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Reasoning of Competitive Non-Functional Requirements in Agent-Based Models

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Declaration

To the best of my knowledge and belief this thesis contains no material previously published by any other person except where due acknowledgement has been made. This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

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Abstract

Modelling and analysis in software system development can be especially challenging in early requirements engineering (RE), where high-level system non-functional requirements are discovered. In the early stage, hard to measure non-functional requirements are critical; understanding the interactions between systems and stakeholders is key to system success. Goal-oriented requirements engineering (GORE) has been successful in dealing with the issues that may arise during the analysis of requirements. While assisting in the analysis of requirements, *i** goal model is the only framework available among the many GORE models, emphasising socio-technical domains such as stakeholders/actors/players, goals/objectives, dependencies and design options/alternatives. Most current approaches to goal-model analysis use quantitative methods or formal information that is hard to gather in early RE, or produce analysis results automatically over models. In real-time competitive applications, the goals of various stakeholders are conflicting in complex systems. Also, each of the system goals have various alternative design options for the systems and optimal selection of goal-oriented requirements faces several challenges in requirements-based engineering.

Hence, effective decision-making frameworks are necessary to capture the real issues to achieve multi-objective optimisation of interdependent actors. To obtain an optimum strategy for interdependent actors in the *i** goal model must balance the opposing goals reciprocally. To achieve this, the model needs to go beyond the analytical decision-making tools such as sensitivity analysis tasks, cost-effective analysis process, game-theoretic concepts and analytical hierarchical process. To

address these requirements, this thesis discusses the design of novel frameworks for an agent-based goal model analysis in requirements engineering.

The major objectives for the proposed work are summarised herewith. This thesis uses a decision-making approach, algorithms and tools to facilitate the reasoning and analysis of non-functional requirements. The thesis also provides analysis, enhances quality, encourages stakeholders' involvement, improves the domain knowledge and captures judgments over important decisions. The optimal design alternatives are discovered in the thesis by balancing their multiple conflicting objectives reciprocally, providing analytical models and performing multi-objective functions for the interdependent actors. Then, the assessment of each actor with the alternative design options is performed according to each opposing softgoal. At the final phase of the proposed approach, an optimal solution is determined for each decision-making method and a model under the conditions of conflicting objectives is adopted.

The proposed goal reasoning method based on the recommended analytical decision-making approaches uses Java Eclipse plugin with the IBM ILOG CPLEX optimisation studio. Also, the validation for different approaches are illustrated with different case studies. The proposed model is applied in a electric power systems that performs reasoning on the impact of non-functional requirements in transactive energy management. The proposed framework also adopts scalable models that are usable and ultimately lead to effective software systems development. To gain better clarity of the problem through analysing published research based, peer-reviewed articles, the analytical decision-making processes were able to enhance the present available knowledge on GORE. This was accomplished by emphasising the significance of the reasoning of conflicting non-functional requirements in agent-based models, particularly in the $i*$ goal model and real-world settings.

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List of publications included as part of the thesis

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Contents

Chapter 1

Introduction

In a global perspective, due to the rapid growth of technology, software systems tend to make greater developments in the open, distributed, decentralised and integrated environments. This influences fields such as e-commerce, e-learning, e-banking, e-healthcare, e-forecasting and so on, because of the advancement from anywhere, at any time and in any form. A newer technology called agent-oriented technology is adopted due to the demand for enabling the system to adapt to environmental variations and higher user requirements. Agent-oriented software engineering has received more research attention (Yu (2001); Krishna et al. (2009); Vilkomir et al. (2004); Goncalves & Krishna (2017)) in the field of software engineering. The following software phases should satisfy the entire software development cycle for the development of any software system, such as design, requirements, evaluation and verification, evolution, deployment, maintenance and so on. Among these factors, requirements engineering (RE) is a very challenging task in agent-based software technology.

Requirements engineering utilises systematic techniques to satisfy the system requirements in terms of completeness, consistency and relevance factors. This type of engineering is utilised by stakeholders, users, developers and analysts to determine each other user's interests, and examines other options for decision making about the systems to be implemented. Based on the software requirements, the system is categorised into functional requirements (FR) or non-functional requirements (NFR). Behavioural/functional requirements define the system's components or functions; whereas non-functional requirements deal with system operation features rather than particular behaviour. Some of the features include usability, while integrity and security of softgoals have more effects on software systems rather than the goals.

Several approaches such as structured modelling, object-oriented, use case, conceptual entity-relationship modelling and goal-oriented approaches have been proposed in the RE literature. Compared with traditional models, goal-oriented requirements engineering (GORE) is appropriate for requirements analysis in terms of the software development cycle of NFR and the computation of alternatives (Mylopoulos et al. (1999)). The GORE approach examines, reveals and expresses stakeholders' goals, which leads to system and software requirements. Several other approaches are employed for the requirements analysis in the software cycle and traceability analysis for the later stage.

Goal models are utilised by analysts for the estimation of goals, evaluation of design alternatives, system design selection, risk analysis and prioritisation of the system requirements. For the purpose of implementation, the best design is selected from different design options. Hence, in the evaluation of design alternatives, different design alternatives are determined, and the best is selected based on selection criteria. In the previous quantitative and qualitative models, softgoals are used as the evaluation criteria (Mylopoulos et al. (1992)). During the validation stage, the values are propagated either by forward (that is, from bottom to top softgoals), or backward (that is, from top to bottom softgoals). Hence, the satisfaction levels of the softgoals and the satisfaction level concerning the selection of top softgoals are estimated based on the selected design alternatives.

Qualitative labels such as partially satisfied, satisfied, partially denied, denied, conflict and unknown are used in the qualitative models. This type of approach has the major drawback of ambiguity problems, which arise due to the same label, and the goal receives an unknown or conflict label during the decision-making process. Therefore, these issues are analysed to improve the conflicting requirements with software development (Mairiza et al. (2014)). In qualitative analysis, the numbers are used instead of qualitative labels. Thus, definite numbers are assigned as per the stakeholders' requirements because the analysis may consider dissimilar stakeholders with different requirements as per the requirements' analysis task. This is because the discrete stakeholders have various knowledge and training levels (Wang & Xiong (2011)). Also, linguistic factors such as minimum cost and maximum profit are considered by the stakeholders to establish communication based on their requirements preferences. However, the representation of these terms in definite numbers is also challenging. Due to those complications, it is necessary to design a novel approach for the goal analysis. When comparing with NFR, knowledge acquisition in automated space (KAOS), Tropos, and i^*, goal-oriented requirements language (GRL) goal models show various actors' dependencies on other actors for achieving the goals. In the decision-making process, these interdependencies are very influential for other design alternatives (Amyot et al. (2010)).

In the literature (Morandini et al. (2007)), the actor dependencies and formalisation approaches have been discussed according to the RE process. Due to incomplete information, the requirements needed for the evaluation by the input data are imprecise. To address RE problems, the analysis deals with more than one goal, which is subjected to multiple-goal models in the real-time environment. However, the priorities of these multiple goals may differ and might be conflicting, but have to be considered simultaneously. Also, scalability is an issue for designing the goals, and when the goal size increases, it is difficult to assign values and complications occur during the decision-making process (Yu (2011); Heaven & Letier (2011); Wang et al. (2021)). Therefore, it is necessary for automation in the goal analysis procedure.

In real-time competitive applications, the goals of various stakeholders are conflicting in complex systems. Also, each of the system goals have various alternative design options for the systems. In addition, optimal selection of goal selection faces several challenges in requirements-based engineering. During the decision-making process, several concerns are considered for the estimation of interdependent interactions among actors. Thus, an effective framework is necessary for learning the issues to attain multi-objective optimisation (Oliveira & Saramago (2010)). The decision-making process in the realistic approach has made the process go beyond the analytical tools such as sensitivity analysis tasks, cost-effective analysis process, game-theoretic concepts and analytical hierarchical process.

In respect of these requirements, this thesis addresses the design of a novel framework for the agent-based goal model analysis in requirements engineering. The major objectives for the proposed work are summarised herewith. The suggested model aims to design a decision-making approach, algorithms and tools to facilitate the reasoning and analysis for the early agent-goal requirements. Further, for the interdependent actors, the optimal alternatives are discovered by balancing their multiple conflicting/opposing objectives reciprocally, providing analytical model analysis and reasoning and performing multi-objective functions. Then, the assessment of each actor with the alternative options is performed according to each opposing softgoal. At the final phase, an optimal solution is determined for each method and a model under the conditions of conflicting/opposing objectives is adopted. Also, a validation for different approaches is illustrated with different case studies. The proposed model is applied in electric power systems that performs reasoning and the impact of non-functional requirements on the transactive energy management system. The proposed framework also adopts scalable models that are usable and will ultimately lead to the development of effective software systems.

1.1 Background

1.1.1 Requirements engineering

In requirements engineering, requirements are defined as the set of a description or specifications in which the system has to perform. During the development stage, these requirements are utilised by the software developer in defining what needs to be developed (Goncalves & Krishna (2015); Affleck et al. (2015); Beydoun et al. (2009)). Various requirements include the specification of features for the system, based on system behaviour, and which represents the general property, as well as constraints, and algorithmic data for system engineers and so on. Generally, the requirements are categorised into functional and non-functional/domain requirements. Functional requirements refer to the system function and its components, whereas non-functional requirements check the system operations rather than the system behaviour. Some of the non-functional requirements factors (such as integrity, usability and security) have a greater effect than the functional requirements on software systems.

Based on the features of an application, the requirements of the domain are determined, and the rules are derived to be applied to that domain. During the earlier stage of software development, the RE involves the characteristics, such as goal elicitation performed by the particular system, goal operationalisation perceived based on constraint specifications, task allocation to the agents, and the development of these requirements in terms of specific intervals. Based on the application, the RE process may vary, including the number of people involved and the development of organisation requirements. Also, RE follows the systematic approach for achieving the complete set of requirements of the goals. In software engineering, retrieving quality requests is an early RE process and a challenging task. Current approaches to requirements analysis claim that RE is an important concern in the research of software engineering (Letier & Van Lamsweerde (2004)). In RE technology, the term "goal" defines the task produced by the system concerned (Van Lamsweerde (2001)).

Usually, the goals are elicited from the stakeholders, and they are found in documents, existing or similar system analysis, and they elaborate other goal models and so on. The level of abstraction for these goals varies from high to low-level strategic and practical considerations. Several other concerns for the goals include behavioural/functional goals related to the services offered by the system; whereas non-functional requirements consider the quality of service parameters such as security, performance, accuracy and so on.

In software engineering, goals are utilised to estimate the earlier non-functional system requirements (Giorgini et al. (2002a); Shofi et al. (2020)). Numerous approaches are proposed earlier in RE, such as goal-oriented, conceptual entity-relationship modelling, use-case approaches and structured modelling. GORE and NFR models are suitable for examining and revealing the stakeholders' goals, which lead to system and software requirements. At the final phase of the software cycle, other approaches are more suitable for requirements analysis and traceability evaluation between requirements and implementation tasks.

1.1.2 Goal-oriented requirements engineering (GORE)

GORE deals with the goals for documenting, negotiating, structuring and requirements reconstruction (van Lamsweerde (2004); Chawla (2020)). Here, stakeholders' objectives define the goals presented by the system where the software is to be integrated under its environment. Goals are specified based on AND-OR representation that defines the functional as well as NFR, and is classified from higher to lower values. Some of the properties of system goals include fault tolerance, survivability, and specific safety achieved for high assurance organisations. The factors affecting such high assurance models are goal modelling and reasoning tasks. Various frameworks of GORE models are Tropos (Bresciani et al. (2004)), KAOS (Dardenne et al. (1991)), NFR (Chung et al. (2012)), $i*$ framework (Yu (2011)), GRL (Amyot et al. (2010)) and attributed goal-oriented requirements analysis (AGORA) (Kaiya et al. (2002)). The detailed explanations for these frameworks are explained below.

1.1.2.1 GORE approaches

KAOS framework

Knowledge acquisition in automated space (KAOS) is RE methodology presented by Van Lamsweerde and several authors in association with the University of Oregon and Louvain (Letier & Van Lamsweerde (2004)). This assists the system analyst to develop the requirements models and documents from KAOS models. To support KAOS, the Objectiver tool is designed. The system goals are estimated based on the consideration of existing technical documents, the current system is examined, future and current users are assessed and so on. The goals are designed in terms of acyclic and directed by the analyst. Each goal, excluding the top level, is rationalised by at least other goals and bottom sub-goals in the graph model. In the graph, the goal at the top indicates the strategic/business goals, and the system requirements are represented by the bottom-level goals. The goals are identified based on either a bottom-down or a top-up approach. The analysis for the goals is determined based on the listed characteristics. Analysis first estimates whether the intermediate goals are determined and asks, "Why do we need that?", for new goals and they look for higher-level reasons. The most specific goals evolved by questioning, "How shall we achieve that objective?" Thus, this model is considered as a group of interconnected goal diagrams for the consideration of the specific issues in the system.

Non-functional requirements framework (NFR)

This framework is represented based on non-functional requirements during the development stage (Mylopoulos et al. (1999, 1992)). Both the functional and non-functional requirements enhance the software system complexity. During the analysis stage, the non-functional requirements are challenging to implement and complex to evaluate at the final state of system construction. This framework is a formal representation tool for non-functional requirements. It is categorised into two approaches: the process-oriented and product-oriented approach. In the product-based model, the formal definitions of non-functional requirements are designed to estimate the degree where the requirements of a software system were met. On the other hand, in the process-oriented model, the design decisions are justified by the techniques developed during the software development phase.

The design decision greatly impacts the specific non-functional requirements either in positive or negative outcome. Based on these dependencies, the software systems were verified to check whether they have met certain criteria of non-functional requirements. These types of requirements, also termed softgoals, are hard to express, although the softgoals express the global qualities of the software system. Some of the qualities include usability, security, accuracy, performance and precision of the given system. To estimate the hierarchy of softgoals, refinement methods are utilised, and the tree structure evaluates the list of NFR, which is assisted by a specific design.

Goal-oriented requirements language (GRL)

GRL is a decision-making modelling language and the representation of documentation as a rationale (Amyot et al. (2010); Daun et al. (2021)). In the graph model, AND decomposition structure is termed for the functionality of the system, and the OR structure defines various guidelines for conducting these goals. In this modelling language, a scenario notation for the analysis of quantitative and qualitative is included in the goal diagram. Also, the separation of GRL elements enables a scalable and consistent representation for the multiple views of the identical goal model.

In quantitative analysis, GRL utilises the values in the range of [-100, ..., 100]) which denotes the satisfaction, contribution and importance of intentional elements to their containing actor. Also, qualitative scales are available for goals, but assigning suitable values to goals is challenging. To solve this issue, the jUCMNav tool is used along with its features. The goal diagram represents the syntax of GRL based on $i*$ language, non-functional requirements, stakeholders' high-level business goals and the facts of the stakeholders.

Attribute goal-Oriented requirements analysis method (AGORA)

AGORA is an improved version of the goal graph in AND-OR structure, which is also termed an attributed-based AND-OR graph (Kaiya et al. (2002)). Nodes and edges with attribute values are the factors of the extended version that include the details of structural characteristics and the values that estimate the requirements of specification quality. The goal decomposition into subgoals is specified by the rationale of the system. This is combined with the attribute as well to the edge and nodes. For the construction of the AGORA graph, the steps represented below are utilised.

1. Prioritise customers' needs as the primary goals
2. Decomposition of goals into subgoals
3. Goals selection from the substitutes of decomposed goals
4. Goals conflicts of are analysed.

i* framework

This framework is designed by Yu (Yu (2011)) where the social elements are modelled and are utilised at the initial stage of requirements analysis. For modelling, two types of diagrams are used, such as strategic dependency (SD) and the strategic rationale (SR) model. SD diagrams define the relationship of the stakeholders, while SR represents the intentional relationships of stakeholders. Nodes in the SD model graph represent the actors, while their interdependencies are termed links. The intentional elements of the model are softgoal, task, goal and resources, in which any of the elements can be a dependency. An SD model has a higher level of abstraction, which represents the actor's dependency on one another. The internal patterns of the SD model are not disclosed, and only the external relationships are explored (Krishna et al. (2004)). The representation in SD goals is presented in terms of actors by circles; hard goals by ovals; tasks by hexagonal pattern; softgoals by cloud; and resources by rectangles. The intentional elements are assigned to the actors that describe how the actors achieve the goals and are linked in terms of MEANS-END relationships, softgoal contributions, and TASK decomposition. Based on MEANS-END relationships, the decomposition of high-level into low-level goals is achieved by the SR model. This also links a task to a goal that indicates that the particular approach is utilised to achieve a goal. To ensure the success of the task, the softgoals, resources and sub-goals are estimated in the task decomposition stage. The types of softgoal contributions include *some+, some-, make, break* and *help.* At the initial stage of the software development stage, the i^* model analysis not only considers the questions like "how" and "what", but also includes the "why" questionnaire. Thus, quality analysis is performed for software dependencies estimation and allows a constant treatment for the NFR and functional requirements.

TROPOS

This is designed by Eric Yu (Yu (2001)) based on an agent-oriented software methodology that uses i^* modelling framework. The primary aim of goal, actor and their dependencies are modelled based on their late and early requirements. This methodology was developed to support various design activities and analyses in the software development activity. Two types of requirements analysis are performed include early and late requirements activity analysis. During the early requirements analysis, the analyst identifies the domain stakeholders in which they model actors with their dependencies on additional resources and actors. On the other hand, in the late requirements stage, the model is extended by the additional new actors with their dependencies. The requirements in terms of both requirements models are included in the system. In the architectural and detailed design phase, the system specifications are included in the requirements phase. After the design specification process, the implementation activity is carried out step-by-step that maps between the implementation and design platform.

In the existing RE literature, various goal analysis procedures proposed for GORE frameworks are explained in the next section.

1.1.2.2 Goal analysis

To support qualitative reasoning of goals, goal models are designed during requirements engineering. This model consists of an AND-OR graph that illustrates how the high-level goals are contributed by the lower ones, and vice versa (van Lamsweerde (2009)). Also, the satisfaction level is estimated by the analyst based on goal models, which also evaluates design alternatives, selects system design, analysis the risk and makes a requirements prioritisation. During the evaluation stage of selection criteria, alternative designs are evaluated, and explore various other designs to select the best one. In the goal model, softgoals are utilised as the evaluation criteria in the earlier qualitative and quantitative estimation approaches (Mylopoulos et al. (1999, 1992)). In the RE literature, several qualitative and quantitative models are proposed to support the goal analysis (Waters et al. (2015); Liaskos et al. (2010); Miller et al. (2014); Horkoff & Yu (2009); Franch et al. (2016); Amyot et al. (2010); Ashamalla et al. (2017)). In the goal model evaluation stage, the qualitative/quantitative measures are transmitted from the bottom to the top softgoal. Also, the depiction of the contribution of goals to softgoals is carried out by assigning the weight values in terms of both positive and negative values. In the goal model, some of the qualitative labels are used for the allocation to the nodes. To determine the satisfaction level, these labels are propagated through link paths for the achievement of the goal. The decision-making process becomes difficult when two or more different options with the same label are considered. In some cases, when an option has an "undetermined" or U label, the decision process is uncertain. To solve these problems of qualitative reasoning, quantitative reasoning (Subramanian et al. (2015c)) has been proposed as a measurable specification in the RE literature. The evaluations are performed to define the contribution from softgoals to goals. In the quantitative model, the labels are transmitted via links to determine the level to which the goal has been satisfied. Based on using qualitative and quantitative labels, several research models are considered relating to goal achievement (Affleck &

Krishna; Amyot et al. (2010); Franch et al. (2016); Horkoff & Yu (2009); Shaked & Reich (2021)).

Table 1.1: Analysis methods in GORE

Qualitative Approaches			
References	Methods	Strengths	Limitations
van Lamsweerde (2009), Giorgini et al. (2002b), Horkoff & Yu (2009), Mylopoulos et al. (1992)	Applied qualitative labels like satisfied, partially satisfied, denied, unkown, conflict and ++, +, − or - in the propagation algorithms	Easy and simple goal analysis	Vague reasoning, Difficult to implement in large systems, requires strong mathematical reasoning, decision making leads to ambiguity
Dybå et al. (2011)	Applied qualitative labels like categorical data and pictures, based on human behaviour	Helps to quantify human characteristics, investigate the complexity of the problem	Results are softer and fuzzier than quantitative results, hard to summarize and simplify
Quantitative Approaches			
References	Methods	Strengths	Limitations
Mairiza et al. (2014), Amyot et al. (2010), Liaskos et al. (2010), Franch (2006)	Applied quantitative labels like numeric values, probabilistic values in the propagation algorithms, single objective and multi-objective optimisation goal analysis	Avoids ambiguity in goal analysis	Requires certain structures to be satisfied for goal analysis, Difficult to implement in large systems, requires strong mathematical reasoning
Lázaro & Marcos (2006)	Applied quantitative labels like data obtained from samples, based on dependent and independent variables	Helps to reduce the complexity of the problem, Results are of great accuracy, avoids personal bias	Results are quantitative results, no real world application, no human perception

1.1.3 Decision-making analytical methods

In this section, the analytical decision-making techniques are briefly explained in detail as follows:

1.1.3.1 Game theory

This is a powerful interdisciplinary tool that analyses the complex situations in multi-agent systems and RE design challenges (Yazdania et al. (2017); Subramanian et al. (2018); Sumesh et al. (2019c)). It has been mainly applied for the fields of mathematics and economics that effectively describes the relationships between decision-makers. The main idea behind this theory is the generation of an ideal solution under specific conditions under the assumption that the players are rational and that they perform based on their interests (Kelly (2003)). Also, a clear mathematical clarification regarding analysing the issues is offered and finds the payoff values from the player's results. This theory is also known as the multi-person decision analysis from the properties like every player has the knowledge of the opposing player's strategies, circumstances, and choices. However, due to the system complexity, there is difficulty while formulating the majority of the player's policies (Law & Pan (2009); Aplak et al. (2014)). Each game consists of a set of players, policies and a payoff for every combination of strategies. An optimal strategy is obtained for the players by the formal reasoning technique during an interactive situation, and the expected results of the game are decided (Aplak et al. (2014)). A special policy called the Nash equilibrium is used where no player attains success by individually separating from it (Law & Pan (2009); Aplak et al. (2014)). A game is said to be stable when it follows the Nash equilibrium, and the saddle point in this equilibrium defines the state where no player can achieve more by changing the policies, provided the other players remain unchanged. Similarly, when no Nash equilibrium is involved, the game is known as an unstable game. These types of games have mixed policies rather than pure policies. In the game theory, the payoff is the assessment of the games when optimally played by the players (Hillier (2012)).

The existing model and its drawbacks in goal analysis methods are explained below.

In RE design, a non-cooperative game theory is introduced by Yazdania et al. (Yazdania et al. (2017)) which enhances the suboptimal performance of the project design. During the development stage, the complex system and its requirements are classified into subsystems and the subsystem-level requirements which is fulfilled by each design team. The performance of the entire system depends on the allocation of the resources shared by the subsystems. The requirements specification should be satisfied by each team, which leads to the reduced decomposition at system-level requirements and also affects the design alternatives. Thus, an optimal design (Subramanian et al. (2015a, 2016a); Goncalves & Krishna (2016)) is not achieved as a result. Hence, to derive an optimal result output, a non-cooperative game theory is applied for the theoretical analysis of RE design. However, this technique cannot be applied to goal analysis while it employs game theory in requirements design-based engineering.

1.1.3.2 Cost-effectiveness analysis (CEA)

For the analysis of strategic decisions, objectively, the CEA tool has been developed which strictly investigates the costs, productivity, performance and system efficiency. In this, the cost investigation is estimated in terms of money and significance using non-monetary terms. For instance, the natural units are computed in physical terms, including prevented, lives saved, cases cured, complications and so on (Boardman et al. (2017); Neumann & Sanders (2017); Sumesh et al. (2018a)). This process results in an accurate cost prediction and the expected result (Robinson (1993)). Hence, a trade-off analysis is involved while choosing between the available options. For the performances of each alternative, gradual expenditures, the total costs and the effects are also computed. The result of CEA is described by a cost-effectiveness ratio (CER); the denominator describes the advantage of selecting particular alternatives; while the numerator defines the cost related to this benefit. This tool helps decision-makers with the selection of the best design alternative that satisfies technical and financial requirements. After the calculation of CERs based on the societal perspective, an alternative design is selected within constraints executed by available resources and the lowest cost per effectiveness. The CEA offers a simple as well as a critical contribution by the computation of overall costs and outcomes. This helps in the selection of design alternatives for a given issue. If the overall cost and the result is misrepresented, then several alternatives cause complications, depending on its application. Thus, the need for the data to be accurate becomes critical because the decision making is directly proportional to it. The inaccurate choice of data leads to the selection of wrong alternatives and causes an impaired decision-making process. Thus, an accurate selection of information helps to derive the best alternatives, which in turn leads to an effective CER. Based on this process, the best cost-effective alternatives with low costs are predicted. In this research work, a CEA-based multi-objective optimisation and the analysis of NFR in the i^* goal model are introduced.

1.1.3.3 Analytic hierarchy process (AHP)

A multi-objective decision-making model was developed by Thomas T Saaty in 1972 based on pairwise assessments between the design alternatives (Saaty (1987)). In this thesis, a hybrid quantitative AHP based satisfaction propagation model is proposed. For the pairwise comparison process, this framework is introduced after the goals' decomposition (goals into sub-goals between the non-functional requirements). Some of the previous AHP based analysis approaches with their limitations are explained below.

For the prioritisation and the preference requirements evaluation, Liaskos et al. (Liaskos et al. (2010)) present a model that obtains the important requirements while satisfying the best preference priorities and requirements. This model distinguishes the mandatory goals from preference goals and suggests a model for finding other ways to accomplish mandatory and the fulfilment/non-fulfilment of preference goals. However, this technique cannot be applied to real time situations where goals are of opposing nature.

For requirements prioritisation, Sadiq and Jain (Sadiq & Jain (2014)) propose a prioritisation of requirements model based on the analysis of AHP. For group decision-making, this model employs a fuzzy model and the set of prioritised requirements obtained by a binary sort tree method. Also, the weight values based on the AHP pair-wise comparison model are assigned to locate the list of prioritised requirements. The integration of experts' preferences with group preferences is performed by fuzzy preference relation. The disadvantage of this approach is that, for the demonstration of this approach, a small number of requirements and criteria are used, and high level mathematical knowledge is required for the prioritisation of goals.

1.1.3.4 Probabilistic mixed strategic Nash equilibrium

In this thesis, a probabilistic mixed-strategy approach is proposed for the selection of the best alternative by various actors for achieving the opposing goals. This model thereby solves the conflicting issues for the result analysis in a competitive situation, especially when applied to conflict scenarios. A mixed strategy is utilised by each player, where the best one is used against the other players' strategies. In the mixed strategy Nash equilibrium, a randomised strategy is applied by at least one player, and no other player can enhance their payoff by playing an alternative strategy. When no player is applied with randomised strategy in the Nash equilibrium, then it is termed as a pure strategy Nash equilibrium. A pure Nash equilibrium is termed as the specification of a strategy for each player in which no player has an advantage by changing their strategy and does not allow the other players to change their strategies. From the set of available actions, unique actions are selected by the game's players are termed as pure strategies. If a random selection of action is played by a player, then it is said to be a mixed strategy. In a mixed strategy, the probability distribution is applied to select a set of actions available to players, while in a pure strategy, a player chooses a particular action. This concept is utilised to analyse critical environments such as wars and arms races, and also conflict may be overcome by repetitive interaction. Also, this strategy is utilised to study to what extent people with various preferences can combine and whether they achieve a cooperative outcome by taking risks. Some of the applications include traffic flow management, education, marketing analysis, environmental regulations, natural resource management, transportation systems, evacuation issues, wireless communications and energy systems.

1.1.3.5 Sensitivity analysis

Sensitivity analysis (SA) is a modelling tool that analyses how the various set of independent variables affects a particular dependent variable under specific environments. This analysis is applied in various fields ranging from geography, biology to economics and engineering. In this thesis, the SA technique in the $i*$ goal modelling is introduced to calculate how the uncertainties of one or more input variables impact the output variables. This analysis benefits in enhancing the prediction task and understood the knowledge of learning the analysis of interactions between variables. From the expected result of various parameters, robustness and sensitivity are evaluated. Also, SA identifies the factors beyond the result that changes significantly. This analysis identifies priority needs and minimises the uncertainties of the parameters, and then decides about the phenomenon under study that can be considered (Subramanian et al. (2016b)).

Table 1.2: Comparative analysis of goal reasoning methods in GORE

References	Approach	Analysis Type	Optimisation	Tool implementation	Sensitivity Analysis	Game Theory	AHP	CEA	Probabilistic Approach
NFR Model									
Affleck et al. (2015)	Non-functional requirements framework: A mathematical programming approach	Qualitative	Yes	No	Yes	No	No	No	No
Goncalves & Krishna (2016)	Optimal Requirements Dependent Model-Driven Agent Development	Quantitative	No	No	No	No	No	No	No
Mairiza et al. (2014)	Utilizing TOPSIS: A multi criteria decision analysis technique for non-functional requirements conflicts	Quantitative	No	No	No	No	No	No	No

Table 1.3: Comparative analysis of goal reasoning methods in GORE (cont...)

References	Approach	Analysis Type	Optimisation	Tool implementation	Sensitivity Analysis	Game Theory	AHP	CEA	Probabilistic Approach
KAOS Model									
Heaven & Letier (2011)	Simulating and optimising design decisions in quantitative goal models	Quantitative	Yes	Yes	No	No	No	No	No
Mylopoulos et al. (2001)	Exploring alternatives during requirements analysis	Qualitative	No	No	No	No	No	No	No
Letier & Van Lamsweerde (2004)	Reasoning about partial goal satisfaction for requirements and design engineering	Quantitative	No	No	No	No	No	No	No
van Lamsweerde (2009)	Reasoning about alternative requirements options	Qualitative	No	No	No	No	No	No	No
GRL Model									
Amyot et al. (2010)	Evaluating goal models within the goal-oriented requirement language	Qualitative, Quantitative and hybrid	No	Yes	No	No	No	No	No

Table 1.4: Comparative analysis of goal reasoning methods in GORE (cont...)

References	Approach	Analysis Type	Optimisation	Tool implementation	Sensitivity Analysis	Game Theory	AHP	CEA	Probabilistic Approach
*i** Model									
Horkoff & Yu (2009)	Evaluating goal achievement in enterprise modeling–an interactive procedure and experiences	Qualitative	No	Yes	No	No	No	No	No
Liaskos et al. (2010)	Integrating preferences into goal models for requirements engineering	Quantitative	No	No	Yes	No	yes	No	No
Liaskos et al. (2011)	Representing and reasoning about preferences in RE	Quantitative	No	No	Yes	No	Yes	No	No
Franch (2006)	On the quantitative analysis of agent-oriented models	Quantitative	No	No	No	No	No	No	No

1.2 Challenges in agent-based goal model reasoning for early requirements engineering

Some of the specific challenges for early requirements analysis have been identified, such as non-functional importance, struggling for adequate accuracy and completeness. These challenges play an important role in making effective reasoning and analysis procedures using agent-based goal models in the analysis of early requirements (Subramanian et al. (2015b)). In this section, several challenges in agent-based goal model reasoning for early RE are outlined below.

1.2.1 Complexity in model analysis

Agent-based goal models can become too complex to be manually reasoned and analysed. One way to ease the complexity of analysis over goal models is to automate the analysis process. However, some level of automation is required to support model structure and content analysis. Although the appropriate level of support is found several times, the level of automation is difficult. Too much automation fails to account for the inherent in-expressiveness and incompleteness model in early RE and may limit the role of the modeller or stakeholders. Also, insufficient automation can lead to a process that is too tedious or time consuming to realistically complete and can produce inconsistent and difficult to reinterpret results later. It can also be challenging to understand the results of the analysis over a complex model. Methods that aid in understanding the model or analysis would help such analysis be more accessible to stakeholders with limited time.

1.2.2 Completeness of modelling

According to the high-level social nature of early RE models, it can be argued that models are never complete in the same way as models used for other purposes. In other modelling contexts, there are often clear requirements for model inclusion. For example, the construction of entity-relationship diagrams (ERD) entities involved in a focus system is very limited in the existing system. When modelling the early requirements, the models represent only a complicated and system interconnected part of the network with people. There are lots of stakeholders, more interacting systems, more goals, dependencies and contributions that can be added to the models. The difficulty of exploiting the modelling lies in two facts:

(a) knowing where to stop modelling

(b) knowing if the amount of information collected is sufficient to support useful analysis, reasoning and understanding of the domain.

1.2.3 Accuracy of model analysis

Model accuracy issues are similar to model completeness issues. To generate a model, the interactions among the social needs are difficult to characterise accurately for analysis and understanding. The model can be argued from a constructionist viewpoint when the model is correct or not. However, the models have sufficient collection modellers from the collective viewpoint regarding the domain. Hence, improving accuracy and generating sufficient accuracy are the challenges in early RE (Kasauli et al. (2021)).

1.2.4 Understanding of the domain

One of the primary aims of modelling, reasoning and analysis is to increase the understanding of the domain in early RE. In the early requirements process, the large, complex and socio-technical organisation are the challenges to understand the domain. Practically, stakeholders want to focus on the technical details without receiving the motivations or conflicting goals that can frequently prevent the technical choices underlying those successful requirements. For an effective technical intervention, the sufficient level is specified by early RE models and analysis. Therefore, it is difficult to know the depth of all technical details for certain project time constraints. However, understanding the domain is complex to balance the requirements in the domain.

1.2.5 Flexibility in modelling

Goal models have been developed specifically to addresses the level of flexibility and in-expressiveness to facilitate the explicit consideration of high-level NFR and social requirements (for example, customer satisfaction, company branding). These requirements are difficult to quantify and formalise, but should be recognised and considered in the early stage analysis. Although clear measures can be assigned to requirements, it is difficult to determine how to combine measures at different scales in an integrated and accurate way. The critical system involves early, inexpressive and ambiguous representations. Once key decisions are obtained, the scope of the critical system becomes restricted or partially sufficient, and its resources can be measured or formalised for later review. However, the goal models of early RE will support reasoning about critical system requirements.

1.2.6 Involvement of stakeholders

An active part of the early RE process is important for stakeholders. Stakeholders already provide the collected information to validate their needs and interactions. The inherent incomplete and inaccurate nature of goal models is especially important to encourage continuous iteration as a means of stakeholder validation. Depending on the domain, system users may be reluctant to support upcoming changes for technical or political reasons. The goal modelling and analysis approach should have a relatively low learning curve. They should have a reasonably transparent rationale and functionality for users with a given shortage of time for stakeholders. Furthermore, stakeholder participation can induce "buy-in" or a sense of ownership in project goals and planned changes to improve the accuracy and completeness of the models in the early system analysis. Stakeholder scheduling makes it difficult to access their time when it is busy. In practice, the stakeholders often have difficulty understanding models due to the complexity of analysis. To solve this issue, an effective method is needed to involve the stakeholder as much as possible for the modelling and analysis process.

1.2.7 Analysis and reasoning on modelling

Without analysis, the process of generating an agent-based goal model can be useful for understanding and agreement. Such models should support reasoning and analysis as much as possible to increase profit for the time invested. In other words, modellers should be able to use the models to answer different types of useful domain questions. Although the structure of goal models allows multiple procedures, most procedures require the addition of specific formal or quantitative information to the goal models (Letier & Van Lamsweerde (2004)). This information is needed to encode the model. To facilitate different types of reasoning and analysis, there is a trade-off to analyse more specific information, including the time and difficulty in finding this type of information to generate the goal model.

1.2.8 Usability and selection of decision-making methodologies for goal analysis

In early RE, the system decisions are prepared by group consensus that implicitly includes and possibly guides without documentation. Various analysis procedures collect some information to make key initial decisions from the usability of goal models. However, the model and analysis may not achieve clear results because certain decisions were made based on judgments expressed about contentious areas and assumptions support the stakeholder choices in the model. Also, it is difficult to know what information needs to be retrieved and associated with the goal-model-aided decision process. In this, the modelling process becomes slightly complex due to a large amount of information and stakeholder leaves their own or other choices due to small amount of information.

For agent-goal model analysis and decision-making process, several existing methods have been introduced, but there is little work focused on the practical usability of existing methodologies. Such methodologies are usable, and it is not clear to express the requirements . The complex analysis methodology (Giorgini et al. (2002a)) is employed by expanding goal model syntax (Gans et al. (2003)) in several goal models approaches. These methodologies mentioned the objective of simplicity and usability requirements. For goal model analysis, a wide range of questions are analysed from the available methodologies below.

1. What procedure would the stakeholder and modeller choose if the performance analysis is based on an early RE content?

2. How can users choose the methodology for analysing the possible goal model suited to their needs?

Therefore, understanding benefits, capabilities, and costs are the challenging issues to make the goal model analysis techniques possible in RE.

1.3 Literature review - Existing approaches to goal model analysis and reasoning of non-functional requirements

1.3.1 Conceptual foundation

In the model analysis, several approaches are identified based on the goal of denial or satisfaction. At the initial stage of the procedure, the model initiates assigned value to propagate either forward or backward for an alternative reflection/question using model links (Chung et al. (2012); Giorgini et al. (2002a); Letier & Van Lamsweerde (2004); Amyot et al. (2010)). These procedures analyse several alternatives of forward and backward questions, such as, "Is it possible to satisfy certain goals?" or "What is the alternative impact of forward? If possible, which alternative would the model meet these goals?" (that is, forward or backward). Typically, some satisfaction procedures represent analysis results using partially satisfied, satisfied, denied and partially denied in terms of qualitative labels (Amyot et al. (2010); Giorgini et al. (2002a); Chung et al. (2012)). To deal with quantitative analysis, the probability of the goal can be represented in the degree of satisfaction/denial (Amyot et al. (2010)) or satisfied/denied (Letier & Van Lamsweerde (2004); Giorgini et al. (2002a))for several procedures. On the other hand, the remaining procedures have only one or two values to produce binary results, whether it is typically satisfied or not.

Among these approaches, the main distinguishing features of multiple incoming values are resolved for the goal model. To various degrees, the contribution links represent positive and negative consequences from the goal models. Different types of contributions receive various goal strength in the formation of positive and/or negative simultaneously. Such situations could be resolved by separating negative and positive evidence regardless of whether it is unnecessary or not for some approaches (Giorgini et al. (2002a)). Other procedures employ predefined qualitative or quantitative rules to combine multiple values (Amyot et al. (2010); Letier & Van Lamsweerde (2004)). Besides, the interactive procedures are used to resolve partial or conflicting evidence with the use of human intervention based on domain knowledge (Chung et al. (2012)). These procedures utilise construct metrics to measure quality in the domain of security, vulnerability and efficiency (Franch et al. (2016)).

The procedures analyse several questions such as, "How does the specific alternative for a specific stakeholder become risky?" or "How does the system become secure by representing the model?" To illustrate, Franch et al. (Franch et al. (2004)) present classifications and weights of actors over $i*$ strategic dependency (SD) models to measure global or local metrics. This approach (Franch (2006)) is expanded to develop the framework that allows interactive metric calculation and give an effort over $i*$ strategic rationale models.

The procedure analyses several questions, such as, "What is the best action plans on certain requirements?" or "What design alternatives need to be taken to meet the goals?" In this instance, the Bryl et al. (Bryl et al. (2006)) analyse plans to determine satisfactory delegations based on dependencies through the goal model in the social network. To fully exploit the potential of the goal model, the evaluation is measured in terms of cost metrics and use similar metrics (Franch et al. (2004)). Many approaches use construct metrics to represent the goal model and allow temporal information for implementation over the network (Wang & Lespérance (2001); Gans et al. (2003)). In this case, the simulated results are tested to obtain unexpected or interesting properties in a particular scenario. These procedures analyse different questions such as, "What particular alternative is selected if the analysis is obtained?". Further methods provide additional information to perform enhanced ways over the models and ask different questions to the users, such as, "What makes the model consistent?" or "What model is particularly possible to achieve a goal?". To illustrate, the desired constraints are represented to add the model for linear-time temporal logic statements and transform $i*$ models to formal TROPOS using first-order logic. Then the model validates the property and verifies the illustration for consistency, Fuxman et al. (Fuxman et al. (2004, 2001)). Instead of analysis, several methods focused on model construction methods to generate models with the help of modellers (Ayala Martínez et al. (2005); Grau et al. (2006); Letier & Van Lamsweerde (2004)). These methods involve process re-engineering $i*$ Method (PRiM) in which $i*$ models employ complementary artifacts (context models and Data Flow Diagrams) and separate processes from intentional content that is systematically constructed for model analysis and reasoning (Grau et al. (2006)).

1.3.2 Identification of research gaps in goal model reasoning

For early RE, several challenges that appeared in agent-based goal analysis are outlined in Section 1.2. Existing methods do not explicitly define early RE challenges. Indeed, most of the works are focused primarily on the analytical power offered by their procedures. Several procedures address the issues faced externally and motivate the scope of goal model analysis for early RE. For example, the system operation could be analysed in detail for simulation. The contributions of existing work challenges are discussed below.

1.3.2.1 Complexity in model analysis

Some level of automation is needed to support model structure and content analysis over complex goal models. In existing procedures, the fully automated process takes particular content as input, and the majority of the model content is used to automatically produce results for goal model analysis. However, the fully automated analysis makes it difficult for user-analysts and stakeholders to trust the results due to incompleteness and inaccuracy. Also, the analysis procedure can be difficult to understand (how the results are achieved), and validation of the results is challenging due to the transparency and complexity of the model. For this purpose, that fully automated analysis is observed as being not ideal for early stage RE analysis. Some analysis procedures have introduced interactive components that allow the modellers to get involved at various points (Asnar & Giorgini (2008); Franch et al. (2004)). For example, analyst intervention is used to promote or demote partial evidence or to decide whether the evidence conflicts with the NFR procedure. Although it is useful for allowing the modeller to intervene in the modelling process with their domain knowledge, the restrictions on user intervention of all values must be specifically promoted. This leads to a limited loss of information. Hence, existing approaches have not focused on supporting knowledge of analysis results over complex models.

1.3.2.2 Completeness of modelling

For the best knowledge of the domain, the goal model analysis procedures do not address model completeness issues. Most of the procedures are processed with model assumptions that can be analysed accurately and completely. Existing procedures focus on analytical power and cannot determine gaps in the model acquisition of the knowledge. Although the analysis procedure can potentially reveal important missing information when the results are examined by stakeholders, finding errors is particularly difficult when analysing the "future" situation. Then it can be useful for modellers to re-examine and question the completeness of the model, especially fragments that have a high degree of uncertainty when analysing early RE models.

Automatic analysis procedures may not motivate a model review. Finding and examining these areas in an ad hoc way may be challenging for modellers, especially if they have already spent a lot of time generating the model and have reached an agreement based on its contents. As a part of the model analysis, the required methods help to deal with important model fragments, finding potential errors and improving the quality of the model. The suggested steps achieve completeness with the help of modellers, and also verify other types of models for model construction using different approaches (Grau et al. (2006)). This can be particularly helpful while constructing the model initially. The generated steps must become a complete model based on the complex nature of agent-based goal models. To improve the completeness of the model, the agent-based goal model focuses on intention and controls against non-intentional models. Hence, further approaches are needed to increase confidence in the completeness of goal-oriented models and help to achieve model stability.

1.3.2.3 Accuracy of model analysis

For any analysis procedure, modellers examine and reveal inaccurate parts corresponding to the completeness of the analysis of a model. But existing methods focus on analysing the domain represented by the model and validate that either the model is correct or not. Initially, the model is generated using the basic "sanity" tests, especially when the correctness of the model has to be verified using analysis procedures. To this end, the user guide requires the use of goal analysis procedures, which includes several analysis questions to ask about the newly finished models. Similar to model completeness, the modellers continually re-examine the model key areas to determine the model inaccuracies in this case. This process will not be supported for fully automated analysis. Hence, there is a need to determine a more appropriate procedure to balance between automation and intervention for goal models used in early RE.

1.3.2.4 Understanding of the domain

To understand the domain, any procedure can help provide analysis results over the domain model. However, existing procedures do not explicitly aim to increase or improve domain understanding, but instead focus on answering specific questions, often selecting the best design alternatives, without ensuring the selection criteria is sufficiently accurate or complete.

1.3.2.5 Flexibility in modelling

Several procedures support reasoning based on flexible and inexpressive models through the use of simple and qualitative labels (Amyot et al. (2010); Chung et al. (2012); Yu (2001)). Such labels can be applied and propagated using a mix of automated rules and stakeholder judgment without forcing users to formalise or quantify high-level model concepts. However, other procedures use a quantitative interpretation over these informal concepts, assuming that the numbers are meaningful; that is, customer satisfaction of 0.7 means that this goal is satisfied on a scale of 7/10 (Kaiya et al. (2002); Amyot et al. (2010); Giorgini et al. (2002a)). On the other hand, other procedures require that the model have a precise formal or quantitative label before undergoing analysis (Bryl et al. (2006); Fuxman et al. (2001); Letier & Van Lamsweerde (2004)). Different approaches require the addition of specific information, such as cost, timing or probability of occurrence, to evaluate a model (Gans et al. (2003); Giorgini et al. (2002a); Letier & Van Lamsweerde (2004); van Lamsweerde (2009)). Demanding formal, quantitative or detailed representations for high-level social concepts helps the flexibility and usability of these approaches for early RE.

1.3.2.6 Involvement of stakeholders

An active part of the early RE process is important to provide and validate domain information for stakeholders. In general, current procedures do not focus on the role of the stakeholder in the analysis. At the beginning of the process, most procedures take input as the first step to frame the query over the model without the modeller and provide analysis results at the end of the output. Some procedures allow for expert intervention at certain points (Asnar & Giorgini (2008); Franch et al. (2016)). Typically, in these procedures, the participation of "experts" is seen as a necessary step to enhance the model or analysis with domain knowledge, but it is not explicitly encouraged as a means for engaging the user. In the goal model analysis, encouraging user involvement in a structured and clear way allows a higher level of user input, encouraging iteration over the correctness and completeness of the model, and increases the chances of obtaining stakeholder consensus in the new system.

1.3.2.7 Analysis and reasoning on modelling

Existing procedures support a wide range of analysis questions over models. However, most procedures require the addition of specific quantitative or qualitative or automatic production of results on high-level models. Procedures provide a wide range of analysis capabilities to keep information available from the user's role for early RE models. Hence, the analysis results may be conflicting, incomplete or inaccurate to a certain degree, and should receive appropriate weight in domain understanding and decision making as part of a methodology for early RE exploration.

Qualitative analysis

In this section, some of the previous qualitative goal analysis methods with their drawbacks are listed.

Van Lamsweerde (van Lamsweerde (2009)) introduces a qualitative reasoning model for the alternative estimation. Initially, the alternative solution for the contribution to different softgoals is assessed qualitatively. Next, these contributions are propagated toward the upper level, and the softgoal graphs are marked as "+" or "++" based on the strength of the positive contribution; whereas the negative contributions in terms of conflict links are termed as "-" or "- -". The propagation is considered recursively till the softgoals at the top level accept a single label. The limitations of this model are listed below.

1. The propagation rule converts the labels into "inconclusive".

2. According to the system-specific phenomena, the link weight and labels have no clear meaning.

3. The evaluation of goals is offered roughly.

Concerning these problems, a lightweight quantitative alternative validation system is proposed by Lamsweerde (van Lamsweerde (2004)), which combines the goals and softgoals into the KAOS model. The alternatives for contributions to all leaf nodes are assessed using quantitative estimations. The relative importance of the leaf softgoals are assigned with different weights. For an overall comparison, the scores and weight matrix are collected in the weighted matrix. For each softgoal, this model uses the variables such as ideal target value, maximum acceptable value and gauge variable. These variables are determined based on the system specifications. Hence, to design a goal model, the system specifications have to be analysed clearly. Some of the limitations of this model cause difficulty in applying for the higher complexity and the large systems, and also when the same label is received by two or more goals, then ambiguity arises in the decision-making process.

Mylopoulos et al. (Mylopoulos et al. (1999)) introduce a business-goals-based goal-oriented analysis technique to explore a design alternative to estimate the feasibility and desirability of the system. The goal structure is represented by AND-OR decomposition and includes five steps below.

1. Analysis of the goal

2. Softgoal analysis

3. Analysis of softgoal correlation

4. Analysis of goal correlation

5. Alternative estimation.

A case study is provided for the evaluation of this approach explained with the meeting scheduler. From the above four steps, the softgoal and goal decomposition has been constructed, and the evaluation of goal decomposition is performed in terms of softgoal hierarchy. Also, a selection of the set of softgoals is made for the evaluation that satisfies all given goals and the overall satisfaction for the top-level softgoals.

Giorgini et al. (Giorgini et al. (2002a)) present a goal model based on a qualitative formalisation and label propagation algorithm for the formal reasoning of goals. They design a model for a goal that incorporates qualitative relationships of goals and contradictory conditions. A goal relationships label with "+", "-" is introduced that defines the positive and negative contributions in the satisfaction of other goals. The labelling of goals uses the semantic representation of the new goal. This is implemented with a Java platform with two different processes; labelling the propagation algorithm with a qualitative and quantitative formalisation. Also, two different sets of experiments are performed for qualitative label propagation and quantitative label propagation algorithms. A set of goals were assigned for the events, and some goals and their significances are eminent in the qualitative algorithm. After five iterations, a steady state is achieved in the qualitative task. On the other hand, the numeric weights are assigned for the relationships "+", "-" and "-s" in the quantitative algorithm task. For each goal, final values are calculated using the propagation algorithm, and the outcome is ensured by the result predicted from the qualitative algorithm. Also, a numerical approach is utilised for the accurate estimation related to the final values of goals/events. For new relationships, quantitative semantics is used, which is obtained from the probabilistic model and also needs mathematical understanding, because it uses first-order logic.

Horkoff and Yu (Horkoff & Yu (2009); Horkoff et al. (2019)) designed goal and agent-oriented models for the qualitative analysis to solve the problem that arises during the initial stage of requirements engineering. Also, to understand the problem domain, an interactive evaluation procedure is introduced for the evaluation of alternatives that require the intervention of a customer (Kavakli (2002); Gaol et al. (2019)). Here, the alternatives are termed as process design or a system, capabilities, courses of actions and commitments. For the manual analysis, an informal process based on the $i*$ framework has been introduced. This analysis is performed based on raising the question, "How alternative design option is an effective one with respect to model goals?" A satisfaction or denial degree is assigned for the intentional elements based on a set of qualitative labels. These labels are propagated via model links using a propagation algorithm. When multiple or partial goals become conflicted, then a human judgment is performed for the analysis of satisfaction or denial of a softgoal. However, the final satisfaction and denial scores for each actor are analysed based on the original queries. The result estimates whether a choice of design is satisfied or not, and then the further analysis and refinement processes are performed. Experimental analyses are evaluated with various case studies to estimate where this process can be applied. The results prove that the procedure could be applied for a better understanding of the model and domain. However, during the decision-making process, ambiguity arises when multiple goals are attained with the same label, and it suffers from validity issues due to a minimum number of participants.

Quantitative analysis

Several existing models related to quantitative goal analysis approaches and their drawbacks are explained below.

Letier and Van Lamsweerde (Letier & Van Lamsweerde (2004)) present a heavyweight model from the number interpretations related to probability. Lamsweerde et al. (van Lamsweerde (2004)) introduce an approach for the goal satisfaction estimation in terms of partial degree, and computed the impact of alternatives for higher-level goals in terms of partial satisfaction. The alternatives of goal satisfaction degrees are evaluated based on qualitative and quantitative reasoning approaches. Softgoal predictions are also made by Bayesian networks techniques. For partial goal satisfaction estimation precision, an objective function and quality variables are utilised. For evaluating alternative design, the quality variables and the objective function are specified using the five heuristics model. The accurate specification of objective functions is specified by the probabilistic extension of temporal logic. For each alternative, the objective function values are computed by propagation rules that combine the quality variables of subgoals to the parent goals. However, the actual estimation of the objective function is performed via ad hoc use of mathematical software. For the complex equations, the estimation leads to difficulty, and hence dedicated tools are provided to handle such computations effectively. Further, this model is improved to overcome the parameter uncertainties on calculations using confidence intervals.

A hybrid approach by the integration of qualitative and quantitative techniques was designed by Amyot et al. (Amyot et al. (2010)) that performs GRL analysis and calculates the satisfaction degree for the intentional elements and actors. The subgroups of intentional elements include the satisfaction scores, and these values are propagated based on propagation algorithm via contribution, dependency links and decomposition to new intentional elements. For the same GRL model, this process performs at several intervals by assigning various intentional strategies with a different subset of intentional elements. Two evaluation procedures, namely qualitative and quantitative, with the range of integer values lies within [-100. . . 100] analysis are selected. Initially, for other intentional elements, these two attribute scores are set to none and 0, respectively. In URN models, an Eclipse-based editor, the jUCMNav tool is employed for the implementation of three algorithms such as qualitative, quantitative and hybrid evaluation. The evaluation of mixed propagation performs from intentional elements, which are neither roots nor leaves. However, this model does not design a better goal model, and also, assigning exact numeric values to requirements is challenging.

Liaskos et al. (Liaskos et al. (2010)) present a model for the prioritisation and the indication of preference requirements. This model distinguishes the mandatory goals from preference goals and also suggests a technique for finding other ways to achieve the mandatory and the preference goals. In preference goals, an optimised preference function is obtained by assigning an analytic hierarchy process (AHP) weights. However, this model cannot be applied to the larger analysis.

Franch (Franch (2006)) proposes an agent-oriented model designed related to the quantitative aspect which is constructed based on the $i*$ language. The conceptual model of this language is expressed based on unified modelling language (UML) and object constraint language (OCL). The structural indicators are adopted to obtain the structural metrics that compute the $i*$ model properties include dependencies, actors and other factors. For the selection of alternatives during decision making, this method requires expert judgment. Also, this model is completely quantitative, because accurate data is obtained based on some degree of qualitative reasoning techniques.

To solve the issues in the decision of NFR analysis, Mairisa et al. (Mairiza et al. (2014)) discusses a multi-criteria decision analysis (MCDA) that performs the analysis and evaluation of alternative design solutions. This model found the best design and satisfies the conflicts on NFRs. Also, an ideal solution is determined to find the alternative based on a goal-based technique named technique for order of preference by similarity to ideal solution (TOPSIS). However, an evaluation analysis of this approach was not provided in this approach.

Goncalves and Krishna (Goncalves & Krishna (2016)) introduce a quantitative-based model for operationalisation in the extended NFR. The suitable operationalisation is determined based on its preferences and the progressive range of values of its children within the extended model. Based on the consideration of complexity, time and space, an optimal path is suggested for the combination of operationalisation at any particular time. Here, a simulation of this model is carried out using a banking system case study. This work is extended by adding change management in agents (Krishna et al. (2016)). Whenever any changes occur, an optimal decision path is determined to estimate the agents with the variations such as softgoal weight or change in contribution values. Based on probability criteria, an optimisation model is designed, and an experimental evaluation is carried out. The result shows that the model cannot be applied directly and requires changes to be made in the original model.

Optimisation in goal analysis In real-time competitive circumstances, decision making encompasses goals, alternative options, actors, decision-makers and criteria. The main factor of decision making depends on finding all the ecological factors and computing based on its objectives. The ideal solution is discovered by the decision-makers in which the optimisation methods determine the optimal alternatives from the list of possible options based on techniques such as linear, quadratic and non-linear programming (Ponsard & Darimont (2020)).

Some of the existing optimisation methods and their limitations in the goal analysis task are listed below:

To determine the alternative design option, Heaven and Letier (Heaven & Letier (2011)) present an extended model from their earlier work by utilising a multi-objective structure from the KAOS model. In their existing goal models analysis, a heuristics set and formal semantics are utilised. However, this model is not applicable for a greater number of design alternatives and does not automate the model analysis. Hence, an automated technique is designed by overcoming these limitations, and identifies the optimal alternatives among them. For the simulation, a stochastic simulation is employed where the input uses the list of design samples and size. For the particular design, the simulation is performed by the probability distributions and quantitative goal model equations. Further, the satisfaction scores are obtained for the simulation process. The simulation is performed based on the MATLAB platform presented based on the London Ambulance Service goal model. However, there is no systematic technique for the computation of objective function.

For the NFR framework, Affleck et al. (Affleck et al. (2013); Affleck & Krishna) present a linear programming optimisation that focuses on operationalisation minimisation. To support the decision-making process, an improved version of the quantitative model from their previous work (Affleck et al. (2014)) is utilised.

Here, the weights are employed to the leaf softgoals and to the links between operationalisation and softgoals. The calculation of the leaf softgoal scores, operational scores, actual attainment and optimal scores are computed using these predicted weight values. Also, the linear programming method is applied for the objective function estimation concerning decision variables. To compute the result, objective functions, variables and constraints are applied as the input to the linear solver. The main objective of this work is to generate an optimal set of operationalisation represented in terms of minimisation or maximisation problem. In the extended goal graph, the propagation procedure from the leaf to the root softgoals is added. The implementation process is carried out using LPSolve, and the outcome shows that the process is better when there is a greater set of relationships between operationalisation and softgoals. For minimum operation, a single-objective optimisation is utilised that increases the overall satisfaction score of the NFR.

The quantitative input values are determined by sensitivity analysis. If the potential value goes beyond the given range, then the required action is performed accordingly. However, the values allowed to leaf softgoals are subjective, and assigning accurate value to leaf goals is difficult.

1.3.2.8 Usability and selection of decision-making methodologies for goal analysis

The analysis results can be used as a form of the rationale for decisions. However, users must be able to easily compare results to understand why it was believed that a particular analysis scenario was preferable to another. If procedures move away from full automation, users need to use their domain knowledge; decisions should be captured and somehow stored on the model. Modellers should be able to return these decisions to remember why they were made and change them if desired. Current interactive goal model analysis procedures do not provide support for organisation on model decisions. It would be particularly useful to allow modellers to capture the free-form rationale for the decision and attach it in some way over the model. Although the work of Maiden et al. (Maiden et al. (2007)) supports storage and management of satisfaction arguments over model decisions, their approach applies these arguments to limited structures and does not emphasise modification to arguments. Hence, existing techniques often review related procedures that aim to specifically guide the selection of techniques for goal analysis based on the requirements or characteristics of the goal model domain.

1.3.3 Problem Statement

From the review of the goal analysis literature and its limitations, we find that there is a need for a method to deal with linguistic terms of requirements. This dissertation aims to fill the research gap by using fuzzy numbers for the linguistic representation of stakeholders' requirements. Furthermore, numerous conflicting and competing objective functions encounter real-world business issues in simultaneous optimisation. For goal analysis procedures, several existing approaches are unable to address these issues examined by the literature. To fill the research gaps, efficient methods are presented to eliminate subjective preference and manage vague requirements based on goal programming and multi-objective optimisation. Also, several approaches are presented based on analytical decision-making techniques to address requirements with opposing objective functions. No research work was identified that focused on quantitative assessment using inter-actor dependencies from the literature review of the $i*$ framework-based goal analysis.

1.4 Reasoning of competitive non-functional requirements in agent-based model

For early REs, previous work of agent-based goal model analysis faces many challenges and limitations. To address these issues, a suitable framework to support the reasoning of competitive NFR analysis over agent-based goal models used in the early RE is provided. The first step reviews the existing literature and summarises its capabilities, including the specific information (for example, quantitative measure, temporal ordering) to perform the analysis.

1.4.1 Research questions

In this thesis, the following main research questions was raised during the development of efficient methods.

1. How to represent, analyse and evaluate the stakeholders subjective linguistic requirements of opposing nature to provide an effective analytical power and optimal decision making in selecting design alternatives when developing the early RE analysis framework?

Following are the sub-questions that were raised during the development of the main contribution:

1. What are the available goal analysis methods needed for goal analysis for early RE?
2. What goal model constructs or notations support the procedure?
3. How can linguistic description (by stakeholders) of requirements in the goal analysis be represented?
4. What are the potential benefits of goal model analysis in the requirements process?
5. How can goal analysis effectively represent a subjective preference of quantitative values?
6. How does the opposite nature effectively implement requirements?

Based on the characteristics of the domain, the above-mentioned information is very helpful to provide a suggestion for methodology selection.

1.4.2 Research methodology

From the research point of view, several methods provide the potential for goal model analysis from the perspective of practitioners, and the available diversity of analysis techniques will be confusing, thus limiting their adoption. Before developing the goal analysis framework, there are two objectives:

1. To understand existing approaches, the available methods are reviewed for the goal model analysis.
2. Procedure selection from responsible initial guidelines.

Next, the characteristics of the early requirements process are examined to derive a list of NFR for early RE analysis. These requirements evaluate the suitability of existing goal model analysis procedures by selecting existing procedures for inclusion in this framework.

1.4.2.1 Backward propagation satisfaction and analysis procedure

As a next step, a detailed analysis of methods is performed for backward satisfaction propagation. From the goal model syntax, different analysis procedures formulate different assumptions concerning the goal model construction, and different interpretations will lead to differing propagation rules for model evidence. The purpose of this analysis illustrates to what extent these different propagation rules affect reasoning and analysis results and to make recommendations concerning the heuristic role of goal model analysis in early RE. To achieve this, the choice of procedure design affects the analysis results, and the comparison results could lead to different recommendations using goal models. Using the satisfaction analysis technique, the comparison results can make recommendations for goal models under the reasoning of the competitive NFR framework. This will support its use as a heuristic guiding domain to explore the emphasising benefits beyond analytical power and decision making.

In other words, the procedure should be able to use the models to answer different types of useful domain questions, such as, "Is it possible?" and "What if?" To illustrate, "Is it possible that certain intentions in the model are satisfied?" And if so, "Which design alternative produce analysis results?" These procedures analyse several alternative questions, where the positioned model produces desired values, and the procedure works backward to determine these values in the model to be considered.

1.4.2.2 Fuzzy numbers to represent linguistic terms of requirements

Previous quantitative and qualitative approaches have addressed the limitations and highlight the requirements. Fuzzy numbers were used to justify these points for backward propagation goal analysis to support decision making during the RE process. Then, in the fuzzy logic process, requirements preferences can be easily examined to represent the linguistic term of stakeholders (Zadeh (1975)). From the research point of view, a quantitative approach employs an improved method called a fuzzy algorithm to determine softgoals satisfaction using inter-actor dependencies based on $i*$ framework. Thus, the quantitative approach employs fuzzy logic concepts to collect the requirements that can be defined in linguistic terms and transform the linguistic terms into quantitative numbers.

1.4.2.3 Requirements of conflicting nature

Numerous reasonable objective functions encounter extremely real-world business issues in simultaneous optimisation (Deng et al. (2017)). The analysis procedure of the goal model considers the type of maximum objective in the existing literature of RE (Heaven & Letier (2011)). In the case of conflict, the concept of different decision making analytical methods is used to determine the optimal solutions based on the assumption that the actors are rational and act in their interests for NFR (Kelly (2003)).

1.4.2.4 Selection of the $i*$ agent-goal modelling framework

Before introducing the specific elements of the framework, let us analyse and review the existing goal model approaches, which include common syntax variations along with the review of the $i*$ syntax. From popular research studies, the $i*$ framework was selected to be used as an illustration of the agent-goal model

according to its ability and balance between expressiveness and flexibility for selecting specific components in early RE (Kelly (2003)). The $i*$ framework aims to define a flexible enough framework to facilitate modelling of early requirements and describes this framework to a certain degree of interpretation and adaptation. Also, it can model and analyse the relationship among the entities considered in a social network, where the entities involve different types of social structures and human organisation (Yu (2011)). Here, common variations made by researchers are surveyed, analysing the motivations behind the variations and classifying the variations as permissible shortcuts (warnings) or incorrect syntax (errors).
From the surveyed results, the variations are used to create a more formal definition of the $i*$ model. This definition is used in the analysis procedures and features in the rest of the work. In the existing RE literature, no work is focused on achieving the quantitative goal analysis on the $i*$ framework. Therefore, an improved framework called $i*$ framework is chosen as a modelling tool and is suitable for the goal analysis. To facilitate reasonable variation, the $i*$ framework provides a more formal description and attempts to balance the need for precision with syntax flexibility to facilitate reasonable variation.

1.4.2.5 Optimisation for incomplete or unobtainable information about requirements

The goal model fails to address the scalability and requirements problem highlighted by existing approaches. To overcome these issues, an operation research framework is designed, namely, a fuzzy-based inter-actor goal analysis procedure, to manage incomplete information and assign weights of the softgoals through model analysis, which is subject to the preference analysis. However, subjective preference is complex for analysis. To evade this problem, an optimisation approach is presented to reduce the analyst's interaction and subjective preference. In this framework, the goal model determines the weight based on the leaf softgoals for analysis. For the requirements analyst, the optimisation model takes data as input and expands to produce useful information in the formation of sensitivity analysis. Then this approach is further improved by a complete optimisation model based on softgoals and leaf softgoals in a more generalised form on the i^* framework. Based on the propagation of values, the improved approach is selected through the whole hierarchy of softgoals within the alternate range. Hence, an improved optimal approach is considered across the whole hierarchy of softgoals.

1.4.2.6 Proposed decision-making methodologies

The suggested analytical approaches such as game theory, CEA, AHP, probabilistic mixed strategic Nash equilibrium, and sensitivity analysis were guided under the application of the i^* framework for reasoning and analysis of NFR in the early RE agent-based goal models. These analytical decision-making approaches specifically guide how to initiate analysis for model generation, including the types of predefined "sanity" questions that can be investigated over goal models.

1.4.2.7 Analysis visualisation

The framework supports several visualisation techniques over goal models to assist the user to initiate and understand analysis results. In particular, the model is highlighted as suggested starting points for model analysis, highlighted intentions involved in a human judgment, and highlighted goals directly involved in conflict situations during backward analysis.

1.4.2.8 Judgment inconsistencies

Consistency presents the judgment model to encourage useful reasoning and highlight areas of interest over the models. Judgments are issued as part of the backward analysis to resolve partial or conflicting evidence over contentious areas of the model. These judgments verify the consistency of the model structure.

1.4.2.9 Implementation

Framework components are implemented based on the Open OME (Organization Modelling Environment) requirements modelling tool. The Open OME implementation supports the backward analysis procedure that includes storing multiple evaluation results, managing human judgments and analysing visualisations. This thesis has proposed reasoning methods based on different analytical decision making approaches using Java Eclipse plugin with the IBM ILOG CPLEX optimisation studio. The developed proposal is able to evaluate the viability and practicability of the proposed optimisation problem on the i^* goal model.

1.4.2.10 Framework validation

In the framework evaluation, the components in the backward procedure were tested across several studies, including the youth counselling system and telemedicine system, to analyse the effectiveness of knowledge transfer and analysis. In a telemedicine case study, quantitative analysis of results is used to compare treatments using various approaches to gather evidence and support or deny claims. Also, it can understand the benefits and barriers to the systematic analysis of the goal model. A large number of experiments conduct different case studies to determine evidence and support the perceived contributions of the analysis procedure on the models. A case study is administered to test the contributions of competitive NFR reasoning and analysis on the electric power system. Using this case study, knowledge is evaluated using subjects in the i^* modelling process.

1.4.3 Research objectives

1.4.3.1 Main objective:

Representation, evaluation and reasoning of stakeholders subjective linguistic requirements of opposing nature to provide an effective analytical power and optimal decision making in selecting design alternatives when developing the early

RE analysis framework.

1.4.3.2 Sub-objectives:

The main objective of this thesis is divided into sub-objectives as summarised below.

1. To evaluate the goal model, the linguistic description of NFR is represented by the use of fuzzy numbers.

2. To avoid subjective preferences, the goal model is analysed using an optimisation technique based on the i* goal model.

3. To implement NFR analysis and reasoning, the goals of opposing objective functions effectively used the procedure based on game theory.

4. To select an optimum strategy, the opposing goals are mutually balanced using a multi-objective zero-sum game-theoretic approach for interdependent actors based on the i* goal model.

5. To select the best alternative design solution, the conflicting NFR are resolved using a mixed strategic probabilistic Nash equilibrium approach.

6. To prioritise each design option, optimal values employ the cost-effectiveness analysis approach that implies optimisation function depends on the interdependence relationships and economic evaluation. Thus, the optimal design is cost-effective and can fulfil conflicting goals.

7. To address the selection of alternative strategy, the evaluation of interdependent actors based on the i* goal model is performed with the use of the analytic hierarchy process for the decision-making process.

8. To perform the reasoning and evaluation of opposing NFR, the performance of the model analysis describes that the final results would have changed if the weights of the non-functional requirements were different through the use of the sensitivity analysis approach on AHP.

9. To obtain the optimal solutions of top softgoals of conflicting nature, the optimal values obtained from the cost-effectiveness analysis-based economic eval-

uation methods would be evaluated, compared, and derived from the reasoning of competitive NFR by the use of a sensitivity analysis approach.

10. To manage the energy system, the transactive structure is used in the application of the goal-oriented requirements engineering approach that is applicable for electric power systems.

11. To analyse the goal model, methods are developed using different decision making analytical procedures based on the i^* framework.

12. To test the experimental analysis, the implemented evaluation conducts different test for the goal analysis in such case studies.

Under this thesis, a total of eight publications present the above objectives based on the report of the overall methods.

1.4.4 Research contributions

1.4.4.1 Main Contribution:

Design and implementation of agent based goal model analysis methods using different quantitative approaches to represent the stakeholders subjective linguistic requirements of opposing nature to provide an effective analytical power and optimal decision making in selecting design alternatives using i^* framework.

1.4.4.2 Sub-contributions:

This PhD thesis comprises of the individual sub-objectives presented in the following eight publications in addition to the overall objectives mentioned in sub-objectives 1, 2, 11 and 12 in order to achieve the main objective listed in 1.4.3.1. This thesis provides the mentioned sub-objectives cited based on the current state-of-art RE literature and highlighted as contributions which are summarised below:

1. Sub-objective 3 is achieved in Publication 1 - "Optimal reasoning of opposing non-functional requirements based on game theory" – An optimum strategy is selected using a multi-objective zero-sum game theory model, which is employed

for the goal model in the i^* framework (Sumesh et al. (2018b)).

2. Sub-objective 4 is achieved in Publication 2 - "Game theory-based reasoning of opposing non- functional requirements using inter-actor dependencies" – A reasoning approach based on game theory is presented to evaluate opposing NFR by Max-Min formulation for the i^* goal model. This Max-Min is mathematically formulated to define the optimisation problem and illustrated as linear programming with the support of multi-objective game model for each player (Sumesh et al. (2019c)).

3. Sub-objective 6 is achieved in Publication 3 - "CEA based reasoning with the i^* framework"- Cost-Effectiveness Analysis, also known as economic-based evaluation technique, is used as an optimisation technique for actors interdependencies in the i^* goal model. Also, it uses economic evaluation and interdependency relationships among actors to optimise each objective function and prioritise choices. This is done by balancing one another's conflicting goals. Therefore, the design is cost-effective and conflicting goals can be accommodated (Sumesh et al. (2018a)).

4. Sub-objective 5 is achieved in Publication 7 - "Mixed-strategic reasoning of the i^* goal model" – A best alternative design is selected using a game-theory-based probabilistic, mixed-strategy approach which is employed to solve the problem of conflicting requirements. Also, an optimum strategy is presented to mutually balance opposing goals and construct the framework related to Nash equilibrium based on multi-objective functions of actors based on their interdependencies in the i^* goal model (Sumesh & Krishna (2019)).

5. Sub-objective 7 is achieved in Publication 5 - "AHP based optimal reasoning of non-functional requirements in the i^* goal model" – An alternative design is proposed to address selection assessment using a modified AHP of decision-making for interdependent actors in the i^* goal model. This approach computes the fulfilment of top softgoals and describes this framework with a certain degree of alternatives. Then it is combined with priority values related to the normalisation of top softgoals. Thus, the combined result evaluates the alternative option based

on the requirements problem concerning each other (Sumesh et al. (2019b)).

6. Sub-objective 8 is achieved in Publication 6 - “Hybrid analytic hierarchy process-based quantitative satisfaction propagation in goal-oriented requirements engineering through sensitivity analysis” – An ideal alternative option is selected using sensitivity analysis process on AHP for interdependent actors in the i^* goal model. This is done by maintaining the opposing goals, and it is useful to perform what-if analysis on the final results. Because the changed results can be viewed as different based on the weights of the criteria. Also, it is useful to understand that how strong the unique decision is and what criteria is subjective to initial results. As part of this thesis, there is no final decision without evaluating the sensitivity analysis process (Sumesh & Krishna (2020)).

7. Sub-objective 9 is achieved in Publication 4 - “Sensitivity analysis of conflicting goals in the i^* goal model” – cost-effectiveness analysis, also known as economic-based evaluation technique, is used as a sensitivity analysis technique to obtain optimal values. This analysis technique supports different input to examine the optimal solution and select if the input agrees the fixed range by analysts (Sumesh & Krishna (2021)).

8. Sub-o1bjective 10 is achieved in Publication 8 - “Requirements analysis in transactive energy management” – An energy management system describes the transactive structure using a goal-oriented requirements engineering approach. This chapter aims to evaluate the impact of NFR and reasoning on the energy management for electric power systems. Thus, the performance deserves better results for decision-makers and provides a reliable and efficient electric power systems (Sumesh et al. (2019d)).

1.4.5 Research outcomes

The research outcomes based on the developed methods are outlined, and challenges of this work are listed below.

1.4.5.1 Complexity in model analysis

In this work, the framework balances the need for automation by developing tools due to model complexity. Also, it is necessary to think about competitive NFR that takes into account the incompleteness and relative accuracy of complex early RE models. Visual interventions help modellers to understand analysis results over complex models. The individual case studies gathered evidence to support the utility of visualisations.

1.4.5.2 Completeness of modelling

The interactive nature of the analysis framework forces modellers to examine key pieces of the model when making judgments over conflicting, competitive or partial evidence. This process can lead to the discovery of important model omissions and can simulate the improvement of reasoning about the completeness of the model. The suggested modelling methodologies instruct users on how to use the analysis procedures to test the basic "sanity" of the models, including completeness and accuracy. Thus, it is necessary to develop and administer various studies to test these claims.

1.4.5.3 Accuracy of model analysis

As the modellers make judgments about the model fragments, they are inherently checking the accuracy of the model contents. When the interactive component of the framework is performed in a group session, judgments over model fragments can lead to the construction of the consensus and the subsequent modification of the model to represent the consensus. The results of the model analysis are used to check the accuracy of the model. If the results are surprising, then either a discovery has been made regarding the domain or the contents of the model are not sufficiently complete or accurate.

1.4.5.4 Understanding of the domain

In this work, the reasoning nature of the framework is introduced that can encourage further requirements elicitation in the domain, increasing domain knowledge and improving model accuracy and completeness. The experiential and concrete evidence involves conditions perceived during the occurrence of the elicitation and explores as part of the framework validation to support these claims.

1.4.5.5 Flexibility in modelling

By expanding the modelling and analysis methods, the developed framework provides flexibility and enables qualitative analysis over high-level domain concepts. Analysis procedures involve flexible and non-quantitative (that is, $i*$) goal model frameworks and do not require additional information (for example, costs, temporal ordering) to produce analysis results.

1.4.5.6 Capturing rationale for decisions

For early RE decisions, the non-functional areas of the model used user judgments in the developed model to capture and manage decisions and provide support for understanding the rationale behind the key. Further improvements may allow users to insert additional text to describe the reasoning and assumptions behind their decisions.

1.4.5.7 Involvement of stakeholders

The incomplete and imprecise nature of early RE models defines that the active participation of stakeholders improves the model in a cycle, and elicitation is the key to getting an accurate and effective high-level view of the future system. Within this developed framework, analysis procedures encourage interactive analysis by acquiring human judgment to resolve partial or conflicting evidence. This increases the role of stakeholders in the analysis process, providing potential by a sense of ownership to the model, and the analysis results can be used as a basis for subsequent decisions.

1.4.5.8 Analysis and reasoning on modelling

The framework defined in this work has provided a unique form of analysis, backward analysis, which allows users to ask, “Is this possible?”, “If so, how?”

and “If not, why?” The framework provides flexibility in performing forward analysis without additional information.

1.4.5.9 Usability and selection of decision-making methodologies for goal analysis

The survey of goal model analysis procedures considers the analytical capability and information required to perform the analysis. A detailed comparison of backward satisfaction procedures provides a better understanding to differentiate existing approaches in this area, including NFR, which could be used to select between methods. Using this information, a potential goal model user could use domain-related knowledge to decide whether existing procedures will fit their purpose or whether the framework is specifically intended for early RE analysis or not. This can be described in detail and suitable for this work.

1.4.5.10 Generalisation

This work used a developed framework, namely, the $i*$ framework, which is an example of an agent-based goal model framework. This $i*$ framework was specially selected for designing early RE analysis, and the modelling framework is generally used as a syntactic superset for several related frameworks (for example, NFR, GRL and Tropos). Generally, the reasoning and analysis of NFR could be useful for other types of models for early RE goal model analysis. In other contexts, these frameworks could be reused and adapted for some components.

1.4.5.11 Feasibility

A fuzzy-based quantitative method is developed using the inter-actor dependencies among the actors for goal analysis of the $i*$ framework. The performance of the approach was simulated by Java Eclipse combined with the IBM CPLEX optimisation platform to obtain better outcomes. The results of the validation studies show that systematic analysis generates a more consistent model interpretation when compared to ad hoc (without a systematic procedure) analysis.

Increasing the consistency of model interpretation will help to build a more consistent consensus among stakeholders involved in early RE elicitation.

1.5 Summary of the research review and the purpose of this research

From the research studies, two main approaches were used: quantitative and qualitative approach, for data analysis in software engineering. The qualitative approach employs attributes of human behaviour, namely, understanding, motivation and communication. Then, the qualitative approach employs image and text to represent the data for analysis. These analysed approaches were developed by social scientists and researchers in the field of education. However, the obtained data samples were examined and presented numerically by statistical methods for quantitative analysis. Because these methods determine dependent and independent variables, the removal of irrelevant variables and reduces complexity. From the surveyed literature, qualitative and quantitative approaches were identified to be used for goal analysis. To determine the variables, the qualitative analysis approach used propagation algorithms in terms of qualitative labels such as denied, partially denied, conflict, satisfied, partially satisfied and unknown for goal satisfaction. Few types of research describe positive ("+") and negative ("-") goal symbols used to contribute toward another goal satisfaction. Performing goal analysis provides a simple, cheap and easy way using qualitative algorithms. However, there are some limitations.

Initially, the risk arises when two or more alternatives provide a similar label and will lead to a decision-making problem while using qualitative approaches. Also, the analysis techniques will be confusing when receiving an unknown label. Then, the second risk arises that the link weights and labels cannot provide a strong position to the specific phenomena of the system. There is a need for sound mathematical knowledge and system knowledge for several approaches.

However, few approaches are applicable due to large and complex systems. To overcome these issues, the qualitative analysis method solves the difficulties with the support of quantitative analysis methods and overcome its limitations. Also, a significant problem arises with quantitative analysis, where the analysis can involve different stakeholders regarding similar requirements and dissimilar preferences. It is also hard to allocate definite numbers to stakeholders' requirements. The stakeholders have commonly used linguistic terms of high profit and low cost to communicate their preference on requirements. These terms become difficult to represent definite numbers used in quantitative analysis and qualitative labels used in qualitative analysis, respectively. Therefore, it is necessary to represent linguistic terms of requirements using an effective method. This thesis employed fuzzy numbers to represent linguistic terms of stakeholders' requirements and fill the gaps discussed in the literature. For evaluation, real-world data is taken as input, and the performance of the requirements becomes vague because of unobtainable or incomplete information. From the requirements point of view, the subjective preference is also taken as an input for the analysis.

Additionally, numerous conflicting and competing objective functions encounter real-world business issues in simultaneous optimisation. For goal analysis procedures, several existing approaches are unable to address these issues examined by the literature. To fill these research gaps, efficient methods are presented to eliminate subjective preference and manage vague requirements based on goal programming and multi-objective optimisation. Also, several approaches are presented based on analytical decision-making techniques to address requirements with opposing objective functions. No research work was identified that focused on quantitative assessment using inter-actor dependencies from the literature review of the i^* framework-based goal analysis. Therefore, the i^* framework is selected as an effective framework and suitable to execute these novel approaches. In the first step, a fuzzy-based quantitative method is developed using the inter-actor dependencies among the actors for goal analysis based on the i^* framework.

The impact of softgoal/goal term relationships contributes to defining the term using fuzzy values. The top softgoal/goal satisfaction process is obtained based on the percentage for the selection of alternative options.
Second, the *i** framework-based optimisation approach is developed for goal analysis. The leaf softgoal weights are allocated using the fuzzy-based quantitative method through analyst of goal analysis . For an alternative selection, the top softgoals get different satisfaction values, and leaf softgoals use different analysts based on different preferences. Such subjective preferences are avoided using the multi-objective optimisation method and determine the weights of the leaf softgoal used in the goal analysis.
Third, an improved optimisation approach is considered across the whole hierarchy of softgoals. For this reason, the alternative design is selected through the score value of all the softgoals in its propagation path.
Finally, the methodology addressed the goal issues to resolve conflicts of opposing objective functions such as the variation of maximum and minimum values. These functions are handled by analytical approaches such as game theory, cost-effective analysis, analytical hierarchical process and sensitivity analysis for goal analysis, reasoning and management. Demanding formal, quantitative or detailed representations for high-level social concepts in the proposed methods helped the flexibility and usability of the approaches for early RE. The methodologies also increase confidence in the completeness of goal-oriented models and thus helped to achieve model stability. In the goal model analysis, encouraging user involvement in a structured and clear way allowed a higher level of user input, encouraged reasoning over the correctness and completeness of the model, and increased the chances of obtaining stakeholder consensus in the new system. The analysis results received appropriate weight in domain understanding and decision making as part of a methodology for early RE exploration. Approaches have focused on supporting knowledge of analysis results over complex models. Also, the performance of the approaches were implemented by using Java Eclipse plugin with

IBM ILOG CPLEX optimisation studio to obtain the simulated results. The methods developed have a built-in goal analysis procedure used for the optimisation approach in the i^* framework.

1.6 Thesis structure

The thesis initially constitutes the Introduction chapter and is followed by two other chapters listed below and the published articles.

Chapter 1: In this chapter, the main theoretical framework describes the research study regarding to its research questions and objectives. Further, the literature review deals with the survey about the recent existing method challenges and issues faced by the system are discussed in detail. This chapter also explains the research questions, research methodologies, research objectives, research contributions and the research outcomes.

Chapter 2: This chapter summarises the eight publication articles, including research work, and the overall contribution of the thesis is presented.

Chapter 3: This chapter provides the overall conclusion of the research methodologies along with the future scope of the research.

The above-mentioned chapters follow the published articles represented by the final version of the authors.

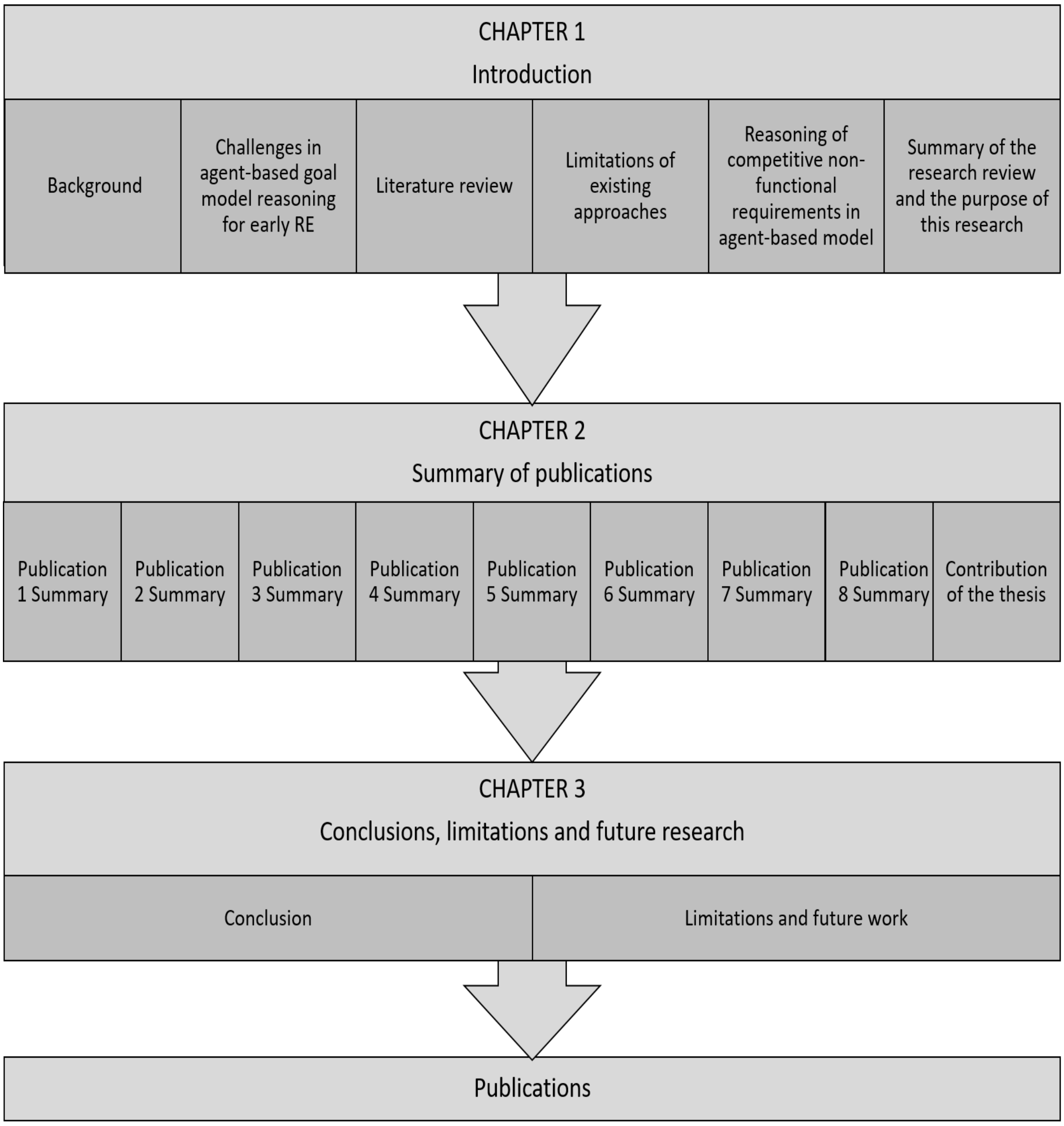

Figure 1.1: Thesis structure

Chapter 2

Summary of publications and contributions

This chapter shows a summary of the eight publications submitted as part of this thesis with full texts available. All publications cohesively contribute to answering the research question of the thesis. They are summarised in this chapter, followed by the overall contribution of the thesis.

2.1 Publication 1: Optimal reasoning of opposing non-functional requirements based on game theory

Bibliographic reference:

S. Sumesh, A. Krishna and C. Subramanian (2018), Optimal Reasoning of Opposing Non-functional Requirements based on Game Theory. In B. Andersson, B. Johansson, S. Carlsson, C. Barry, M. Lang, H. Linger, C. Schneider (Eds.), Designing Digitalization (ISD 2018 Proceedings). Lund, Sweden: Lund University. ISBN: 978-91-7753-876-9. http://aisel.aisnet.org/isd2014/proceedings2018 / General/8.

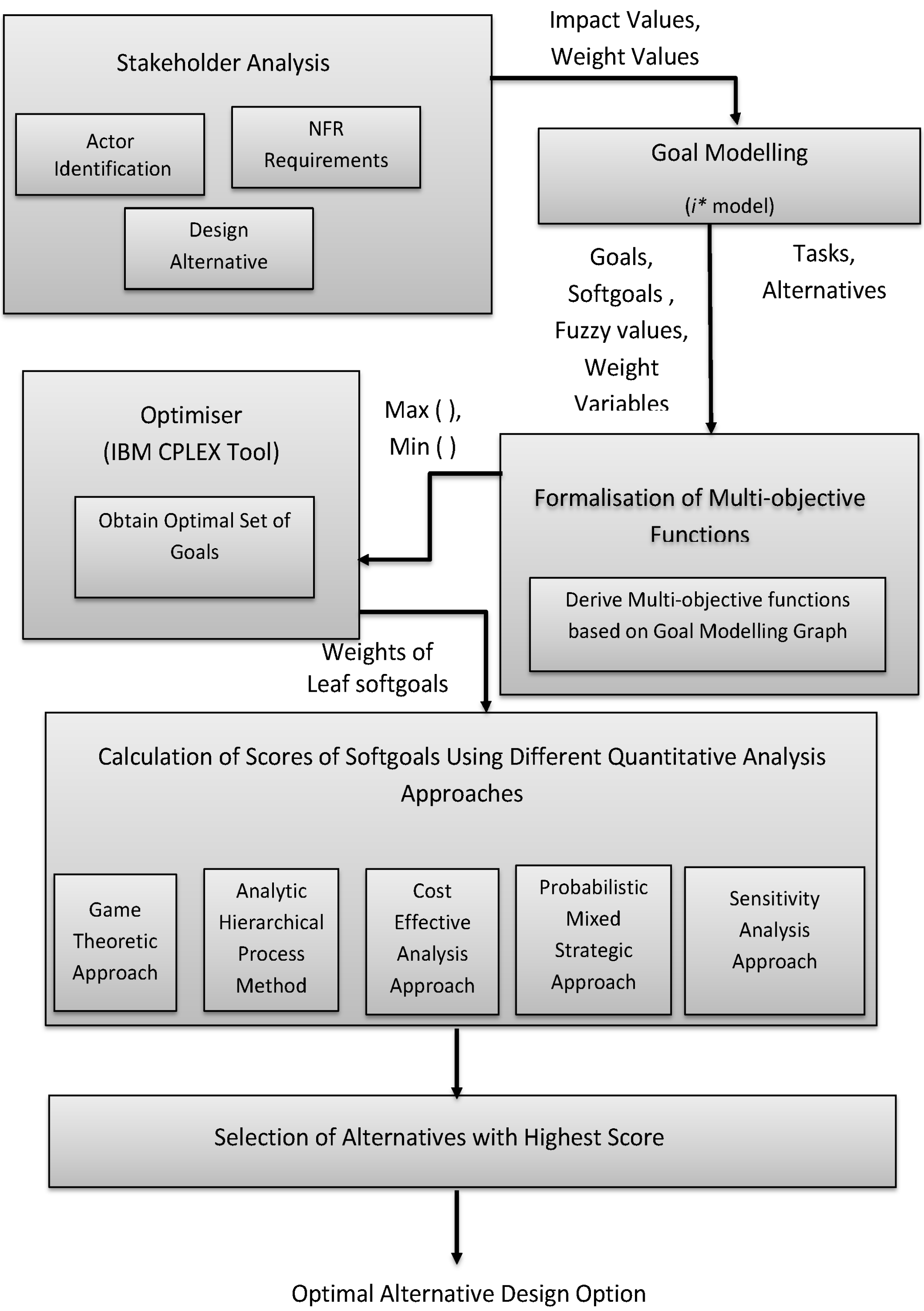

Figure 2.1: Thesis contribution framework with different approaches

Status:

Published refereed conference article.

2.1.1 Abstract

In today's competitive and real-time organisational arrangements, many stakeholders have various interdependent yet conflicting goals and participate in complex systems. A genuine challenge that a requirement analyst faces while dealing with such systems is making sure that each of these interdependent yet conflicting goals are achieved with the use of optimal reasoning techniques while also giving due consideration to all the possible design options. Requirements engineering faces the challenge of finding the most optimal design option for a goal model containing such interdependent and conflicting goals. A novel and viable RE-based framework is proposed in this paper for effectively capturing these real and genuine concerns to accomplish multi-objective optimisation in the $i*$ goal model with interdependent and conflicting goals.

This paper successfully provides a realistic solution to deal with these challenges by implementing a viable decision-making process which goes beyond game-theory-based concepts. This novel decision-making procedure examines and explores the system efficiently by assessing all the alternative design options. This paper discusses the results of experimentation by evaluating the proposed approach using different case studies.

2.1.2 Approach

This paper propounds a systematic and effective approach based on game theory that facilitates the decision analyst in making optimal decisions in the $i*$ goal model with interdependent stakeholders. This is achieved by effectively integrating the significance of the multiple opposing goals after determining the significance of each individual goal. A two-person zero-sum game approach is applied at this juncture to derive the optimal alternative design options. Multi-objective functions have also been advocated at this point, which helps to ascertain a definitive significance of each individual goal. Then, all possible alternative design options (for each stakeholder) are individually assessed by applying game theory. In the final step, the optimal solution is determined in the given conflicting situation.

2.1.3 Methodology and findings

This paper successfully delivers a precise and effective approach to facilitate the decision-analyst in making optimal decisions in today's complex and competitive organisational settings. An easy-to-apply two-person zero-sum game approach is used to derive multi-objective functions, which are then used to calculate the significance of each opposing goal individually.

A formalisation of the opposing NFRs, with regards to goals, softgoals, tasks and resources, based on the strategic rationale model of the i^* goal model is then carried out. This formalisation process helps to evaluate the scores or weights or values of each top softgoal. This process depends completely on the interdependency relationship among the stakeholders. Hence, the objective functions of each top softgoal are successfully propagated while assuming only the softgoal interdependency relationships.

In the next step, the objective functions of the softgoals are individually optimised and ideal solutions are generated. An integration of the objective function solutions of the top softgoals is then carried out for the stakeholders displaying the same nature (for example, maximise). This step helps to generate the payoff matrix for each nature (maximum or minimum) under each alternative. The obtained payoff matrices (which are derived independently for each individual stakeholder) are then integrated to simultaneously derive the overall objective of the multiple opposing goals. Finally, the linear programming technique is applied to obtain the optimal strategy. This step involves an analysis of the integrated decision payoff matrix using the linear programming method. The results obtained, therefore, indicate that by selecting the optimal strategy with a high proportion

value, the system used in the $i*$ goal model, was able to achieve the interdependent and conflicting softgoals of the stakeholders reciprocally. Experiments were then performed to test the viability and efficacy of this technique. These experiments were performed on various case studies such as the telemedicine system and the meeting scheduler system.
Just like in game theory, this approach regards the stakeholders (or game players) as the top softgoals, having conflicting objective functions in the system, and the game strategies are regarded as the alternative design options of the interdependent stakeholders in the $i*$ goal model. An initial examination of the game theory application, from the stakeholder's viewpoint with opposing objective functions, is carried out with the presumption that each stakeholder in the $i*$ goal model contains the same set of alternative design options for the accomplishment of their conflicting goals.

2.1.4 Contributions

This paper presents a goal analysis based on the game theory. Its methodology considers the interdependent relationships among the stakeholders who participate in today's complex organisational setups in which decision-makers must make optimal decisions. This paper propounds a very systematic and effective approach based on game-theory that would facilitate the decision analyst in making optimal decisions in the $i*$ goal model, in which there are various interdependent stakeholders. The multiple conflicting goals of these stakeholders are integrated as per their individual significance. For determining the optimal alternative design options, an approach based on game theory is used in the $i*$ goal model. Multi-objective functions are determined to assess their individual significance and are expressed numerically. The proposed framework is then checked thoroughly and assessed. This evaluation is based on the optimal alternative choice, which in turn is performed by balancing the conflicting goals of dependent stakeholders in the $i*$ goal model. This proposal uses a two-person zero-sum game approach for the multi-objective optimisation process.

2.2 Publication 2: Game theory-based reasoning of opposing non-functional requirements using inter-actor dependencies

Bibliographic reference:

S. Sumesh, A. Krishna and C. Subramanian (2019), Game Theory-Based Reasoning of Opposing Non-functional Requirements using Inter-actor Dependencies, The Computer Journal, Volume 62, Issue 11, November 2019, Pages 1557–1583, https://doi.org/10.1093/comjnl/bxy143.

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2.2.1 Abstract

This study presents an extension of the previous article and proposes an exceptional framework which, when used, captures the decision making problems faced in today's competitive and complex organisational set-ups. Such an organisational setup might comprise of requirements of stakeholders having multiple conflicting goals. A multi-objective zero-sum approach based on the game theory is applied on the $i*$ goal model for obtaining an optimum strategy for the multiple requirements of stakeholders. A simulator was developed on the basis of the proposed approach. This simulation model uses the IBM CPLEX optimisation studio integrated with Java, and helps the users in selecting the optimal alternative design option based on the evaluation results. The choice made was therefore found to be feasible in today's competitive and complex environments having multiple conflicting and interdependent goals.

2.2.2 Approach

This research provides very precise and systematic decision-making tools which are suitable for the present-day complex organisational settings. This was achieved by integrating the many opposing objectives with respect to their significance. A two-person zero-sum theory game-theoretic approach was used to determine the optimal alternative options of the interdependent stakeholders. This was done by simultaneously balancing their conflicting goals in the given $i*$ goal model. This proposal has used multi-objective functions to determine the significance of each conflicting goal and assessed the alternative design options for each stakeholder according to the significance of each opposing softgoal. Game theory was further used to establish the payoff matrices for each top softgoals. For the purpose of exhibiting the applicability of this proposal, two case studies were used in this proposal.

2.2.3 Methodology and findings

For selecting an optimal strategy for interdependent stakeholders in the $i*$ goal model, an approach based on multi-objective two-person zero sum game theory was proposed in this research. First, the proposed approach formalises and generates objective functions for each actor to determine their importance based on the interdependency relationships. In the proposed approach, to obtain quantifiable results, fuzzy values were used. In order to formalise this methodology, the SR model is assumed as a directed graph represented as G(N,R) where N is the intentional elements such as softgoals, tasks and resources and also the tasks which form a set of nodes; R is the means-end link, the task decomposition link, dependency link or contribution link which come together to form the edges of the graphs. A propagation of the impact values or scores with the softgoal presence of each actor constitutes the next step for finding the level of satisfaction or scores of the top softgoals. A backward propagation of the leaf softgoals is computed in two stages, and constitutes the next step of this technique. This computation is done for ascertaining the scores of the softgoals so that their hierarchy can be found in definitive values.

During the earlier phase, the score of each child was multiplied by their impact values. In the second phase, the impacts of all the children were joined together by simply adding them. In the next step, a formalisation of the scores of each top softgoal of each stakeholder based on their inter-actor dependency under each alternative is performed. Objective functions for each alternative design were then generated based on the elements of the graph. The game-theoretic approach was applied as a next step and is used to create a payoff matrix for each stakeholder based on the objective function values and their variation to a final decision payoff matrix.

To obtain the optimal strategies for interdependent actor's having opposing objectives, the following steps were used:

Step 1: Evaluate the optimal solutions of multi-objective optimisation functions of opposing top softgoals.

Step 2: Use objective integrated game-theoretic approach for payoff matrix transformations.

Step 3: Apply the unification process to obtain the decision payoff matrix.

Step 4: Apply the linear programming model to obtain optimal strategy including decision making.

A Max-Min linear programming strategy has been formulated for the proposed multi-objective game model, and it was discovered that a linear programming method could be used for solving the optimisation problem for each player. By solving these formulas, the proportion values of the strategies were obtained. Finally, by applying the IBM ILOG CPLEX optimiser, the most desirable optimal strategies and their proportion values were obtained. Then the optimal strategy, that is, the one with the high proportion value was selected. This selected optimal strategy could simultaneously and easily accomplish the opposing NFRs of each stakeholder or actor.

To check the applicability and scalability of the proposed game theory-based approach, many experiments were performed on different case studies. The proposed goal reasoning method based on the recommended analytical decision-making approaches uses Java Eclipse plugin with the IBM ILOG CPLEX optimisation studio. The developed method is able to evaluate the viability and practicability of the proposed optimisation problem by using game theory on the i^* goal model.

2.2.4 Contributions

The paper proposes a game theory-based reasoning of opposing NFRs for the i^* goal model. A method was devised and implemented for the proposed reasoning technique based on the game theory using Java Eclipse plugin with the IBM ILOG CPLEX optimisation studio. The simulated model has been tested on different case studies drawn from the existing literature, and the proposed methodology has been evaluated based on the optimal alternative selection by balancing the opposing objectives of interdependent stakeholders in the i^* goal model. No previous research efforts have been found in the available literature for developing such a systematic game theory-based method which could find an optimal alternative design option for interdependent stakeholders acting in the i^* goal model. The main concern was to find a technique to reciprocally balance the multiple opposing objectives with their significance. This proposal has successfully examined and found a way by using requirements-based engineering design for delivering the optimal design outcome.

2.3 Publication 3: CEA based reasoning with the i^* framework

Bibliographic reference:

S. Sumesh, A. Krishna and C. Subramanian (2018), CEA Based Reasoning with the i^* Framework (2018). PACIS 2018 Proceedings. 174. https://aisel.aisnet.org/pacis2018/174.

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2.3.1 Abstract

This paper details the economic evaluation-based goal analysis method and proposes an alternative design option which can accommodate various conflicting goals of the interdependent stakeholders that are participating in a particular scenario in a goal model. This paper applies an approach based on an economic evaluation which is referred to as cost-effectiveness analysis. This approach is useful for selecting an optimal strategy for interdependent stakeholders in the $i*$ goal model and works by balancing the opposing goals reciprocally while also optimises each objective function based on their interdependency relationships and the economic evaluation of their optimal values for prioritising each design option. This technique is able to successfully support the decision-maker in choosing the most cost-effective yet optimal design option which also accommodates the multiple conflicting goals even in a complex scenario.

2.3.2 Approach

To discover the optimal alternative options of interdependent actors by balancing their multiple opposing objectives reciprocally, an economic evaluation approach known as CEA was applied to the $i*$ goal model. It was an essential approach for analysing decision-making problems cost-effectively. Overall, no previous research efforts have developed a systematic method for deciding on a cost-effective optimal alternative design option for interdependent actors in the $i*$ model by reciprocally balancing the multiple opposing objectives with their significance. In other words, this proposal examined how requirement-based engineering design can deliver a cost-effective optimal design outcome. In the proposed approach, multi-objective functions were determined in order to decide their significance. Then, the alternative options for each actor were assessed according to each opposing softgoal's optimal CEA values. An optimal, cost-effective solution was found in the final phase which seeks the adoption of a strategy under the circumstances of opposing objectives. A case study from the literature was used to illustrate the applicability of the proposed approach.

2.3.3 Methodology and findings

The main aim of the proposed approach is to accomplish the strategic goals while taking into account the constraints in such a manner that the applied reasoning method would help in optimizing the overall strategy. The given methodology helps in selecting an effective alternative option which is also cost-effective.

At first, the stakeholders who would define the design alternatives are identified. The impacts of different design alternatives of the identified stakeholders' goals are identified. These design alternatives would depend on the stakeholders' subjective preference as per the given problem. A bottom-up approach is used to determine the stakeholders' perspective about the criteria for achieving their goals and consists of discovering the criteria of goals from the consequences and impacts of the alternatives. The next step formalises the conflicting objective functions in terms of softgoals, goals, tasks and resources for modelling a complete generalised structure of an $i*$ goal model. A strategic rationale model was considered as a directed graph which represents goals, softgoals, resources, tasks, means-end, task decomposition, dependency and contribution links. An objective function for each choice was generated based on the elements of this graph. In the next step, the multi-objective optimisation functions of opposing goals (maximum and minimum in nature) were evaluated and optimised. Individually optimising the objective functions for softgoals successfully generated ideal solutions. To evaluate the optimisation process, IBM ILOG CPLEX optimisation studio was used for evaluating this optimisation procedure. The obtained optimal values represent the capacity of each alternative to fulfil the objectives of the stakeholders.

In the next step, CEA was applied for prioritising the alternative options. This realistic decision-making approach helped in prioritising the design alternatives for effectively achieving the softgoals (non-functional requirements). CEA has been helpful in assessing the decisions objectively and is based on different strategies. CEA simultaneously examines the benefits in the light of costs. Hence, this approach provides additional safety and efficacy by comparing the costs of the alternative design options. All these considerations with the decision context and characteristics were reflected in the final decision like the support to the decision-makers, criteria and alternatives while addressing various goals. This step involves a pair-wise comparison among various alternatives based on their efficiency and effectiveness in fulfilling stakeholders' goals. The values obtained by applying CEA procedure provided a hierarchy to the design alternatives for each stakeholder. The final analysis of the decision led to a Pareto optimal final hierarchy since the CEA inputs were optimal values obtained from CPLEX. This step involved a pair-wise comparison between several alternatives based on their efficiency and effectiveness in fulfilling stakeholders' objectives. The outputs of the CEA provided rankings of alternatives for each actor. Because CEA inputs were optimal values from CPLEX, this final decision analysis led to a Pareto optimal final ranking. For evaluating the application provided in the proposed approach, a simple telemedicine system (Yu (2001)) case study was used from the available literature.

2.3.4 Contribution

The objective of this research work is to provide an extension to GORE techniques to facilitate decision-making. This paper uses CEA which is based on the economic evaluation for prioritising alternative design options. This research work has made contributions by designing a CEA model to support decision-making for accomplishing cost-effective strategic goals. The proposed methodology enables reasoning in conflicted circumstances and produces a data-driven conclusion which uses optimization techniques and decision-making techniques. It also examines whether the framework would lead to better quality strategic decision making and also compares its usability and effectiveness while prioritising alternatives. This proposal examines how requirement-based engineering design delivered a cost-effective optimal design outcome. Overall, no previous research efforts were able to develop such a systematic method for choosing a cost-effective optimal alternative design option for interdependent stakeholders in the i^* model by reciprocally balancing the multiple opposing objectives according to their individual significance.

2.4 Publication 4: Sensitivity analysis of conflicting goals in the i^* goal model

Bibliographic reference:

S. Sumesh, A. Krishna (2021), Sensitivity Analysis of Conflicting Goals in the i^* Goal Model, The Computer Journal, 2021;, bxaa189, https://doi.org/10.1093 /comjnl/bxaa189.

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2.4.1 Abstract

This research work has developed a technique for analysing the conflicting objectives of interdependent stakeholders in the i^* goal model. Cost-effectiveness analysis (CEA) is applied to the multi-objective optimisation model for determining the non-functional requirements of the stakeholders in the i^* goal model. The application of CEA at this stage increases the capacity of the model by developing its ability to handle large and complex systems. The requirements analyst can use the information derived from the system after input data is fed into the system. The inclusion of sensitivity analysis of the conflicting goals further facilitates the requirements' analyst in handling the requirements in the i^* goal model. This paper also proposes the optimisation of each objective function based on their interdependent relationships. Sensitivity analysis based on the economic assessment of the optimal derived values is also applied to enable a clear prioritisation of the design options. With the aim of achieving the con-

flicting goals, an optimal and cost-effective design option is selected by using the techniques provided in this approach. Many case studies have been used in this proposal to make assessments through a simulation-based analysis.

2.4.2 Approach

This approach is based on the reasoning that in real-world settings, the goals of multiple stakeholders involved in large and complex system start opposing one another. It was also observed that each goal (or functional requirement) of a system could have many different alternative design options. During the early stages of requirements analysis, an analyst must find the most cost-effective and optimal design alternative, such that the goals of all the interdependent stakeholders can be achieved up to their complete satisfaction.

The challenge of finding the most cost-effective and optimal design option for a goal model must be overcome with the use of requirements-based engineering. In real-world settings, many other concerns may arise while making cost-effective decisions which the decision-makers need to deal with by making effective and capable decisions. Such decisions must give due consideration to the cost per service provided by the various design options based on the interdependent relationships among the stakeholders. This situation requires a very dependable framework which will help in understanding and capturing the real issues for achieving multi-objective optimisation . Adopting a practical and cost-effective decision-making model in such a situation has enhanced this approach by taking it beyond economic evaluation concepts and theories.

CEA is one such approach that has been applied for choosing an optimum strategy for interdependent stakeholders in the $i*$ goal model. CEA operates by constantly balancing the conflicting goals inversely (reciprocally). This approach has become fundamentally important in analysing decision-making problems so that they are the most cost-effective. A novel methodology for exploring a system has been provided in this research, which helps to make a proper evaluation of the most cost-effective alternative design option. However, in earlier works, CEA analysis did not consider cost-effectiveness in terms of the relationships of the interdependent stakeholders. In real-world settings for various design options, decision-makers must consider the economic assessment of goals in view of their interdependent relationships among the stakeholders. A methodical yet economical assessment of goals has been provided in the proposed approach, which, when applied, paves the way toward cost-effective decision-making in real-world situations, where interdependent stakeholders in the i^* goal model exist. This approach further facilitates the optimisation of the multi-layered conflicting goals. A CEA approach was applied to the i^* goal model to find the most accurate optimal design option, for interdependent actors, while also ensuring their objectives were balanced reciprocally (inversely).

In the proposed approach, multi-objective functions were fully computed for determining their individual significance. At this juncture, alternative options for each stakeholder were computed and were based on the CEA values of the opposing softgoals. Finally, an optimal and cost-effective solution was determined in a situation comprising conflicting objectives. An added advantage of the optimisation model was the inclusion of sensitivity analysis. This included indicating the extent to which a variable can be altered without any changes in the final answer. One of the most important aims of applying sensitivity analysis is to test the robustness of the model. A clear understanding of the effect of input parameters is provided by this test, along with the identification of errors in the model on a continuous basis. In addition to the above benefits, this analysis provides an optimal solution which remains optimal until the time the input parameters remain in a certain designated range. Sensitivity analysis has been used as a cost-effective solution to keep track of the system's behaviour every time there is a variation in the input data. A case study has been taken from the existing literature and sensitivity analysis has been applied to this case study. The results were analysed after effectively illustrating the applicability of the proposed approach.

2.4.3 Methodology and findings

A multi-objective and cost-effective reasoning-based approach is presented in this research paper. In this paper, a reasoning technique is provided which helps to optimise the overall strategy when selecting the most cost-effective alternative design option. It is very important to use a quantitative approach for the interpretation of experimental data instances. Such instances involve the modelling of conflicting goals in scenarios containing interdependent stakeholders. This methodology proves helpful in determining an optimal strategy for actors who have conflicting goals. As stated earlier, the main aim of this research work is to implement and execute a new model and viable techniques which result in a theoretical framework for selecting an optimal strategy for stakeholders with conflicting goals. New algorithms and prototypes in congruence with the "making something work" approach is proposed in this paper so that the objectives of this research work can be accomplished effectively.

A notional framework based on GORE was designed for achieving conflicting goals using cost-effectiveness ratio (CER) values. This framework includes stakeholders' analysis, formalisation of multi-objective functions of softgoals, Pareto-optimal propagation of solutions, cost-effective analysis of Pareto-optimal values and sensitivity analysis of NFRs. A multi-objective optimisation model based on the framework has been developed for the $i*$ goal model. This optimisation model cost-effectively evaluates design options by giving due consideration to the impact of alternatives designs on NFRs. After obtaining the CER values, the alternative design options are then ranked from lowest to highest, wherein the option with the lowest CER value is considered to be the most cost-effective option. This option can hence be used to achieve the conflicting goals.

2.4.4 Contributions

Significant contributions have been made by this research by implementing a technique to evaluate the requirements of the stakeholders using fuzzy logic so that the requirements of the stakeholders can be elucidated and evaluated effectively. Previously, these requirements were usually expressed in very subjective and linguistic terms, creating ambiguity in the decision-making process. This research work presents a clear approach to handle this ambiguity, which usually arises due to the subjective preferences of the decision analyst during the goal analysis process. A fuzzy mathematical application and optimisation tool called CEA has been used in this approach to help in the analysis of the quantitative goals so that an optimal strategy can be found to satisfy the opposing objective functions. An investigation was made using this proposed approach for how requirements-based engineering design could provide a design option which is both optimal and cost-effective. Sensitivity analysis is another integral part of this proposal, which has been used in this approach to observe how the system would behave every time there is a variation in input data. This approach provides a significant edge in allowing the calculations of input variables to be examined before making a final decision.

Identifying errors and completely understanding the effects of input parameters in the model are other important tools which are provided in this approach. In the presence of opposing NFRs of interdependent stakeholders, a cost-effective sensitivity analysis on the GORE model has been evolved, implemented and evaluated so that a cost-effective and optimal alternative design option can be quantified and identified optimally. Further application of sensitivity analysis helps the decision analyst to evaluate the range of the input parameters within which the optimal solution does not alter.

A method has been created using the proposed approach for overseeing the compliance of the proposed goal model by using sensitivity analysis. The consistency of the quantified results as compared to the existing approaches is further enhanced. This method contains another important feature that evaluates the practicality of the proposed cost-effective analysis. This approach was among the first deliberate attempts to apply cost-effective analysis to the $i*$ goal model. The problem of ambiguity and uncertainty that arose due to qualitatively analysing goals was successfully overcome with this novel approach.

2.5 Publication 5: AHP based optimal reasoning of non-functional requirements in the *i** goal model

Bibliographic reference:

S. Sumesh, A. Krishna and C. Subramanian (2019), AHP based Optimal Reasoning of Non-functional Requirements in the *i** Goal Model. In A. Siarheyeva, C. Barry, M. Lang, H. Linger, C. Schneider (Eds.), Information Systems Development: Information Systems Beyond 2020 (ISD 2019 Proceedings). Toulon, France: ISEN Yncréa Méditerranée.

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2.5.1 Abstract

A simple telemedicine system was used for illustrating the proposed approach. This case study helps in demonstrating how analytical hierarchical process (AHP) based quantitative reasoning can be applied for optimal decision making. First, the contribution degrees of alternatives towards the fulfilment of top softgoals are calculated and then these values were integrated with the normalised relative priority values of top softgoals. Based on the requirements problem, the result of this integration helped in a very precise and accurate assessment of the alternative design options against one another.

2.5.2 Approach

The proposed approach is based on finding a solution to one serious difficulty faced by decision-makers: - they need to perform 'consistent' decision making every time. Decision-makers try to achieve consistency in decision-making by eliciting the contribution values of various alternative design options toward final goals in the goal models. This approach attempts to help decision-makers to find the best suited alternative option for the stakeholders by using the given methodology. Another reasoning behind this approach is that the stakeholders' requirements need to be assigned quantitative values because the elicitation of requirements may involve more than one stakeholder having diverse preferences for the exact requirements. The reason behind assigning such definitive numbers is the fact that each of the stakeholders has a distinct level of knowledge, training and skills.

The use of AHP, fuzzy mathematical application and optimisation in this study has proved to be a useful tool for quantitative goal analysis. With the use of quantitative goal analysis, this approach helps in finding an optimal strategy with opposing objective functions in the requirements-based engineering design. Due consideration is given to the fact that all the softgoals would not carry the same importance toward the main goal. Hence, in the second step, the relative priorities of the softgoals are ascertained. In the next step, depending upon the impact (value or score or weight) of each alternative on the top softgoals, the priority of the top softgoal is ascertained. In all the previous research works, assigning subjective values to the impacts of alternatives to softgoals did not help to lead to inaccuracies in the i^* goal model.

2.5.3 Methodology and findings

A precise methodology is developed and presented in this paper to enable quantitative assessment of the contribution relationships between functional and non-functional requirements having conflicting goals. To achieve this, AHP has been integrated with the GORE approach in this proposal to help to provide reasoning of non-functional requirements to enable the most informed decision making. This approach prevents the decision analysts from using their own subjective judgement for assigning values while analysing the goals.

In the available literature, the elicitation process of the existing goal-oriented requirements models such as i^* goal model, the prioritisation of the multi-objective requirements of interdependent stakeholders was not supported during the decision-making phase. To overcome this hurdle, the AHP was merged with quantitative satisfaction fuzzy-based propagation approach to enable prioritisation of requirements. None of the previous research work was able to develop a systematic method which allowed a consistent optimal alternative design option for interdependent stakeholders in the i^* goal model. This research work has successfully developed a methodology toward providing consistent decision making.

In this paper, an alternative selection algorithm through AHP is implemented on the i^* goal model. In order to obtain an improved and consistent decision-making process, an integrated AHP with GORE helps in calculating the optimal relative priority of each of the requirements toward the main goal. The decision modelling approach further helps in constructing a hierarchical model for reasoning during the decision-making phase. This important step in the AHP process is taken so that the stakeholders can be asked to guarantee to ensure all softgoals and alternative options have been included.

In this paper, judgment is assigned within a range which can be defined by fuzzy numbers instead of assigning one numerical value. Impacts are represented as triangular fuzzy numbers, indicate the extent to which an alternative design option fulfils the leaf softgoal. After de-fuzzification of fuzzy values, objective functions of top softgoals under each alternative for a stakeholder are created and optimised. After determining the scores (or satisfaction values) of top softgoals with the help of the GORE approach, a pairwise comparison matrix (PCM) is generated by deriving the relative priority of each softgoal.

The AHP process performs averaging over normalised columns to estimate the eigenvalues of the PCM. With this normalised matrix, the overall relative importance of each softgoal can be derived. The consistency of the derived overall relative importance of softgoals is then checked by using a consistency ratio (CR).

After achieving the aim of consistency in decision making, PCM is constructed for each alternative with regards to each specific top softgoal and the local priorities of alternatives are calculated.

Finally, each alternative's overall priority, including the different weight of each softgoal is calculated and shown. The overall priorities are obtained, compared and then tested to verify and confirm whether the variations are large enough to enable a clear choice of the design option.

2.5.4 Contribution

In this research work, an integration of a modified AHP along with the quantitative reasoning of the $i*$ goal model of interdependent stakeholders with conflicting goals has been performed successfully. This integration would help decision-makers consistently choose an ideal alternative design option that is not based on the subjective judgment of decision-makers. Hence, this research work contributes significantly by providing an easy-to-apply decision-making approach that assists the decision-maker in finding precise and consistent judgments.

2.6 Publication 6: Hybrid analytic hierarchy process based quantitative satisfaction propagation in goal-oriented requirements engineering through sensitivity analysis

Bibliographic reference:

S. Sumesh, A. Krishna (2020), Hybrid analytic hierarchy process based quantitative satisfaction propagation in goal-oriented requirements engineering through sensitivity analysis. 1 Jan. 2020 : 433 – 462.

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2.6.1 Abstract

In order to refine the decision-making process in more detail and to provide a quantitative approach, a decision was made to modify the AHP process and integrate it with the GORE model to enable, evaluate and select the most optimal alternative strategies of interdependent stakeholders in the goal model. This paper is an extension of the previous article Sumesh et al. (2019b). This proposal presents a methodology to calculate the contribution degrees of alternatives leading to the satisfactory fulfilment of the top softgoals. In this paper, another significant technique called sensitivity analysis is provided. This important technique helps to check the system's behaviour each time the value of the input parameter varies. To effectively showcase and present the proposed approach, an extended telemedicine system case study is used.

2.6.2 Approach

This approach is based on the need for a systematic methodology that could perform a degree of satisfaction of goals. The given methodology in this approach makes the decision-making process quantitative, easy to understand, optimal as well as consistent. Because it was quite difficult for stakeholders to provide exact contribution values directly, the AHP was used in this approach to encourage quantification reasoning as opposed to using a qualitative approach. Another rationale behind this approach is that different stakeholders have different levels of understanding, education and abilities. Due to the fact that the present GORE model did not assist in prioritising the multi-objective requirements of interdependent actors in the decision-making process, an examination was performed to find out how requirements-based engineering design could deliver a consistent and optimal design outcome. This challenging situation was handled by combining the AHP approach with an approach based on quantitative satisfaction fuzzy-based propagation. By combining the two approaches, it became easy to prioritise the requirements. In order to achieve this, AHP has been modified by calculating the optimal relative priority of each requirement toward the main goal.

This approach is also based on the fact that none of the previous research works could develop a methodical process for deciding a consistent optimal alternative design option for the interdependent stakeholders. This particular notion has led to the novel idea of combining the advantages of AHP and quantitative reasoning. This approach places the primary organisational objective on the top level, while the alternatives are placed at the bottom level. Between the objective and alternatives, the characteristic element of the decision-making problem which is referred to as the softgoals, are placed. Here, each softgoal has a local priority and a global priority to achieve the main goal. The pairwise comparison matrix is used to check the consistency of all its elements which need to follow the transitivity and reciprocity rules.

In addition to the above approach, sensitivity analysis has been applied to assist the developers in finding quantitative input values. The earlier approach of assigning values to leaf softgoals was quite subjective and was making it extremely difficult to assign accurate values. This was one limitation that led to further applying sensitivity analysis. The inclusion of sensitivity analysis has proven to be very useful in checking how the final outcomes differ when any change occurs in the weight of the softgoals. As the weights of top softgoals changed, a change was also observed in the overall priorities of the alternatives.

2.6.3 Methodology and findings

This approach presents a methodology to help elicit the contribution values of different alternatives toward final goals and provide the much-needed support toward consistent decision making within the hierarchies of requirements. In this research work, a systematic methodology is developed for deciding a consistent optimal alternative $i*$ design option for interdependent stakeholders in the model. To enable this feature, the advantages of AHP-based approaches have been combined with the quantitative satisfaction propagation-based approaches. The methodology presents AHP integrated with the GORE approach to help in providing reasoning of non-functional requirements, and hence provides the much-needed support for making informed decisions. In the existing work of Saaty's pairwise comparison scale (Saaty (1987)), an inaccurate subjective judgment is used for goal formulations. Hence, a methodology was developed to provide definite numbers (scores or values) to the stakeholders' requirements, because requirements elicitation may involve various stakeholders.

For analysing goals quantitatively, the AHP method, fuzzy mathematical application and optimisation tools have been used in this study to ascertain an optimal strategy with opposing objective functions in the requirements-based engineering design. An alternative selection algorithm is developed using AHP so as to enhance the consistency of the decision-making process. The decision-making process has been used to enable consistent judgments that significantly improve the precision of decision making and provide accurate priority calculations. Besides providing an objective evaluation approach, AHP also provides decision-makers with a method for checking the consistency of the evaluation and the alternatives. A precise methodology is further presented to decompose the primary objectives into their constituent sub-objectives, progressing from a generic goal to a specific goal while performing complex decision making, which involves multiple opposing goals.

A method is presented to evaluate the contribution of each alternative design option through softgoals toward the high-level goals. It shows clearly how fuzzy values are assigned to the correlation between the alternative design options and the softgoals in the given $i*$ goal model. The derivations show the levels of goal satisfaction or relative priorities of the softgoals to the main goals by using the backward propagation of values to the goals (which are higher in the hierarchy). An important first step in the AHP process shows the decision modelling method of constructing the hierarchical model for the reasoning of the decision-making problem. The second step in the AHP analysis is based on the finding that all the softgoals will not have similar significance toward the main goal. In this step, the relative priorities for the softgoals, by evaluating the contribution of each alternative design options on the top softgoals, are ascertained. The relative priorities of the softgoals to the main goals are then derived by using the backward propagation of these values to the top softgoals. The obtained values of the softgoals are calculated as ratios concerning one another and hence referred to as relative. The complete method is shown for deriving the relative priorities of each softgoal with a generalised yet complete structure of the $i*$ goal model. Labels such as softgoals, goals, tasks and resources have been used for this derivation.

To avoid imprecision, this approach assigns a judgment within a range that can be defined by a fuzzy number rather than using one numerical value. Triangular fuzzy numbers represent the impacts given as *make, help, hurt, break, some-, some+* are used to indicate the extent up to which an alternative option fulfils the leaf softgoal. To find the level of satisfaction or scores of the top softgoals, steps are shown to describe the propagation of the impacts to the top softgoals.

In the next step, the IBM CPLEX optimiser (Lima (2010)) is used to optimise these multi-objective functions of opposing goals, which are maximum as well as a minimum in nature. The multi-objective function values (referred to as scores) for all the stakeholders in the goal model are generated and shown. To enable the fulfilment of the stakeholders' objectives, these optimal values or scores quantitatively show the importance of each top softgoal under each alternative. A formalisation process has been presented to generalise the score of a softgoal at level t for an actor with the dependency relationship, after which objective functions of top softgoals under each alternative for each actor are created and shown in precise steps. The GORE approach helps in finding the scores (satisfaction values) of top softgoals. These scores represent the contribution of each top softgoal to achieve the goal for comparison between softgoals. After this process, PCM (pairwise comparison matrix) is generated by deriving the relative priority of each softgoal and the importance of a softgoal is compared with itself. Then the AHP calculates the overall relative importance of each softgoal. Eigenvalues of the PCM are estimated by averaging over normalised columns. The normalised matrix which is obtained, therefore helps to show the overall relative importance of each softgoal and shows the estimation of eigenvalues of the matrix. After determining the overall relative importance of relative softgoals, their consistency is also checked.

For checking consistency, the consistency ratio (CR) is calculated. As a next step, the derivation of relative local priorities of each alternative is shown and includes each top softgoal in the decision-making model. The derivation of overall priority for each alternative is calculated next and is a crucial method to show how each softgoal has a different weight to achieve the goal. Finally, sensitivity analysis is applied by understanding the various situations that may arise. This was done by asking two questions to understand the given scenarios:

a) What will happen if all the softgoals have the same weight?

b) What is the weight needed to create a tie in the overall priorities of the design options?

2.6.4 Contribution

In this paper, AHP has been modified and integrated with the GORE model to enable the quantitative reasoning of the $i*$ goal model of interdependent stakeholders having conflicting goals. A modified AHP has been proposed to derive the procedure of alternative selection to find an ideal alternative option by balancing the opposing goals reciprocally. The quantitative-based fuzzy judgments made for this study have achieved quite consistent results. A significant contribution has been made by this research work by proposing the AHP methodology, which is easy to apply during the decision-making process and assists the decision-makers in making precise judgments. The main concern while applying AHP to multi-objective functions has been dealt with by using paired comparisons. The relative ease of application has been demonstrated by increasing the number of levels in the hierarchical structure. Another important contribution has been made by adding sensitivity analysis as the next step of the AHP process. This analysis helps in identifying the errors in the model and understanding the changes that may occur when the input parameters vary within a designated change. Another test has been added to this paper to further check the reliability of the sensitivity analysis tests.

2.7 Publication 7: Mixed-strategic reasoning of the *i** goal model

Bibliographic reference:

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2.7.1 Abstract

In a goal model, different interdependent actors have conflicting goals that need to be ascertained, addressed and fulfilled optimally. Simultaneously, the goals of all the involved stakeholders should be satisfied. In this proposal, a probabilistic, mixed-strategy approach based on the Nash equilibrium has been presented to address the uncertainty and resolve the conflicting requirements of the stakeholders. An integration of Java with IBM ILOG CPLEX has been performed in this paper to develop and evaluate the proposed methodology.

2.7.2 Approach

This approach is based on the fact that requirements-based engineering can been used to derive an optimal alternative design option in case there exist conflicting goals among actors. This application of a realistic decision-making process allows us to venture beyond analytical concepts, such as the concept of game-theoretic

Nash equilibrium.

2.7.3 Methodology and findings

The method of goal-oriented requirements engineering has been used for deciphering and deducing the intent of the stakeholders. Since the i^* goal model helps the goal-oriented prototype of socio-technical systems and organisations, it has been one of the most sought-after and accepted goal models in the software engineering field. Based on the assumption that players are rational and behave according to their own individual interests, it was found that game theory is a very useful decision-making and inter-disciplinary tool which helps in finding optimal solutions in conflicting situations (Kelly (2003)).

Precise mathematical solutions have been proposed that help during the problem analysis and in providing the much-needed support in deriving values of payoff matrices that represent the players' outcomes. A unique methodology of the Nash equilibrium structured game theory for system exploration involving alternative design evaluation is presented in this paper. The multi-objective optimisation tool is also used to create a unique structure for achieving the multi-objective optimisation amidst the real challenges faced in the real world. Unlike earlier research work, this study gives due consideration to the interdependent and conflicting nature present among the actors (stakeholders).

In the i^* goal model, the game players are top softgoals, while the game strategy is considered as the alternative design option of interdependent actors. To understand the importance of the i^* goal model, the multi-objective functions are decided on which would facilitate in deriving optimal alternative options of interdependent relationship among the actors considering each conflicting softgoal. At this point, a probabilistic, mixed strategic approach based on Nash equilibrium is applied and as a final step, an optimal solution is derived along with a strategy in a situation of conflicting objectives. This case study clearly and effectively demonstrates the implementation of the proposed approach, along with an overview of the already existing approaches related to GORE and the i^*

goal model.

This study is the first of its kind, in which fuzzy mathematical applications, linear programming optimisation and some very useful tools are presented. This study addresses the actors' interdependency in relationships, which is crucial for decision making in a real-world competitive scenario. To implement this approach, a systematic game theory-based probabilistic mixed strategic Nash equilibrium method has been presented. Nash equilibrium groups strategies effectively to find a solution in the game. In the Nash equilibrium comes the point called the saddle point, wherein any further change in strategies stops affecting the gain of the players. This clearly indicates the steadiness of the game. Hence, the mixed strategy Nash Equilibrium has been adapted for easy calculation and representation and for selecting an alternative design option in case there are goals which conflict with one another.

A completely generalised structure of the $i*$ goal model has been presented by formalising the opposing objective functions in terms of softgoals, goals, tasks and resources. Based on the elements of the graph, an objective function for each choice has been generated. To solve the mathematical business models, the IBM ILOG CPLEX optimiser has been used to obtain accurate and logical decisions. This optimisation toolkit is used for evaluating the optimisation process. In this proposal, the two opposing softgoals of each actor are represented by SG1 and SG2 and the two alternative design options are represented as A1 and A2. This approach has been demonstrated in the given space constraints, with the game theory with an inter-actor dependency relationship from X to Y, of a two-player (X and Y) game theory. If p is the probability that X chooses A1, then (1-p) is the probability that X chooses A2. Similarly, if q is the probability that Y chooses A1, so (1-q) is the probability that Y chooses A2. P-mix and q-mix options are then computed to find mixed strategies. After this step, the optimal choice of each player is found when choosing from the various alternatives, both algebraically and graphically.

A best response function is generated for each actor to depict each player's choice of mixed probability. Hence, this method reveals the mixed strategy Nash equilibrium by combining the best response functions and can discover an intersection point from the combined best response function. At this juncture, the players "arrive" at a profile where every player's strategy is the best response to each player itself. Hence, this point is a "stable" situation called "equilibrium". The final decision must come up with the decision context and characteristics by supporting the decision-makers, criteria and alternatives when addressing the various objectives. At this stage, a pairwise comparison between many alternative design options is carried out to fulfil stakeholders' objectives. Hence, it is clear that with the use of the Nash mixed-strategy equilibrium, how the outputs provide an optimal selection of alternatives for each actor. This final decision analysis hence leads to a Pareto optimal equilibrium because it ensures that the inputs from CPLEX are the most optimal values.

2.7.4 Contribution

In this paper, the probabilistic mixed-strategic approach of the Nash equilibrium-based goal analysis for the $i*$ goal model helps in resolving the conflict which arises at the time of reasoning with the non-functional requirements. This methodology uses the IBM CPLEX optimisation studio within the Java Eclipse environment. This work concludes with the application of sensitivity analysis to further help the decision analyst in selecting the most optimal design alternative. This approach adapts and uses a two-person zero-sum game approach in this $i*$ goal model.

2.8 Publication 8: Requirements analysis in transactive energy management

Bibliographic reference:

S. Sumesh, A. Krishna and C. Subramanian (2019), Requirements analysis in transactive energy management (Power and Energy, 2019), Variability, Scalability and Stability of Microgrids, Chap. 3, pp. 73-97, DOI: 10.1049/PBPO139E-ch3 IET Digital Library, https://digital-library.theiet.org/content/books/10.1049/p-bpo139e-ch3.

Status:

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2.8.1 Abstract

The main objective of this research is to develop an efficient and reliable transactive energy management system (TEM) for electric power system using a goal-oriented RE approach, which is not only efficient and completely reliable but is also economical in distributing and transmitting power effectively. This paper provides a framework of TEM to support the energy service providers, equipment suppliers, regulators and sophisticated users to offset variability and to enhance relationships based on the value in the electric power systems. To fulfil this objective, an assessment of the impact of non-functional requirements on the transactive energy management has been applied.

2.8.2 Approach

An innovative and well-researched goal-oriented requirements engineering approach based on $i*$ goal is used to provide an intelligent and interactive solution. This highly useful approach helps to structure the transactive energy management system for the power system operations in the future smart grid. Transactive energy is explained in detail – what it is?, how it works? and why some experts highly recommend its use? An overview of some of the key non-functional requirements such as scalability, security, inter-operability, reliability and efficiency is also added in this approach.

2.8.3 Methodology and findings

This chapter presents a clear methodology to show the precise usage of requirements engineering model called goal-oriented requirements engineering. Decision-makers can use the application and reasoning of non-functional requirements for implementing the TEM system, which has been explained in detail. To develop the NFR reasoning for TEM system, the requirements engineering model is clearly presented with illustrations.

At this point, a need was discovered for supplementary models which could explore the full potential of future smart grid systems. In the transactive energy management system, "value" is used as a key operational parameter so that an even distribution of supply and demand across the entire electrical infrastructure can take place. To allow an even distribution, a set of economic and control processes have been applied to the three categories of players in the TEM system. These three categories comprise:

1) customers, prosumers, storage, owners, producers and so on, who would be a part of the energy services

2) transmission and distribution owners who would form the transport services

3) exchanges, market makers, system operators and so on, who would form the intermediaries.

There is a clear understanding that requirements play a major role in deciding all the engineering activities. Therefore, a decision was made to use a methodology that can support the accurate detectability of requirements among design decisions and system requirements. In this approach, due consideration is given to failures in the performance of the TEM system because these failures can be very costly. The GORE model can help to ensure such failures do not occur. It also enables the determination and satisfaction of goals of all three categories of players involved. A systematic and effective technique of goal modelling is used, which helps to determine the goals during the very early stages. This technique offers clarity by providing a good knowledge base for the proposed system.

It was further noticed that non-functional requirements influence the TEM system more than the functional requirements (or specific behaviours). For a successful implementation of TEM, only a few significant non-functional requirements have been considered, such as security, active communication, accurate forecasting, scalability, efficiency, inter-operability, reliability and so on.

The IBM ILOG CPLEX optimisation studio (Lima (2010)) is also used to determine an alternative design to optimally fulfil the non-functional requirements, which are represented as softgoals. An $i*$ goal model is incorporated to further optimise the TEM system with a stakeholder through hierarchy of softgoals, goals and tasks. The proposed model depends on the satisfaction scores of the top softgoals of the given $i*$ goal model. A four-step methodology proposed in this chapter assists the user in determining an optimal strategy based on the given requirements in the TEM system with multiple conflicting yet interdependent goals.

In the proposed approach, an updated version of (Sumesh et al. (2019c,a)) has been used. Each leaf softgoal in the TEM system is pre-assigned a unique weight so that an optimal design option for achieving the top softgoal can be chosen easily and effectively. Individual weights of leaf softgoals, such as security, active communication, accurate forecasting, scalability, inter-operability and real-time demand/response have been assigned unique weights. De-fuzzified values are then used to evaluate the score of each top softgoal for the stakeholder (actor) power system in the TEM system. The obtained multi-objective functions of top softgoals are formalised, which are then scalarised (or derived) into a single objective.

This chapter is concluded by incorporating the IBM ILOG CPLEX optimisation studio (implemented in Java code) which evaluates the proposed reasoning method based on the $i*$ goal model. The results clearly show that the alternative smart grid has a higher value than the earlier traditional value.

2.8.4 Contribution

This chapter explains the transactive energy management system for power distribution system by applying it on GORE. This model clearly illustrates the importance of the requirements engineering model called GORE in the TEM system. The aim of this chapter is to provide a concrete methodology for the decision-makers so that they can achieve a very reliable power system with significantly higher efficiency levels.

The most significant contribution of this chapter has been the use of the $i*$ goal modelling, which was used to fulfil the aim of providing more efficient and reliable power distribution and transmission systems. The TEM case study used in this proposal clearly indicates that the proposed methodology can be easily scaled up and applied to reasonably complex scenarios, which was not possible earlier. However, $i*$ goal modelling has certain drawbacks, such as dependence on the requirements on characteristics of the particular domain which is under consideration for developing the TEM system. Therefore, another plan is being explored for developing a tool which can perform optimal goal analysis more efficiently.

2.9 Contribution of the thesis

This thesis has been developed to examine the following research questions:

- How is the linguistic description of the stakeholders' non-functional requirements in an agent-based goal analysis represented?

The eight publications of this thesis clearly answer the above question. These publications provide a multi-dimensional approach that helps gain clarity and discernment with the use of knowledge development. The thesis uses a triangular fuzzy-based backward propagation quantitative approach designed to find the satisfaction of softgoals using inter-actor dependencies in the $i*$ goal model. The non-functional requirements are captured by using fuzzy concepts, which are then stated in linguistic terms. During the RE process in goal analysis, the fuzzy logic tool helps transpose the linguistic terms into quantitative numbers.

• How are the quantitative values of subjective preference used during the goal analysis represented effectively?

This thesis provides a novel perspective, along with a method for managing the subjective preferences (referred to as weights) of the leaf softgoals. This thesis notably handles the subjective weights of the leaf softgoals by using multi-objective optimisation techniques. Each objective function of the alternative design option was generated for each actor depending on the impact of the alternative designs on the leaf softgoal. The multi-objective functions were then combined into an objective function with the use of the scalarisation method. The final single objective function was solved using the IBM ILOG CPLEX optimisation studio to calculate the weights of the leaf softgoals. The weights obtained were therefore used for analysing the procedure to perform the goal analysis of the $i*$ goal model. This optimisation approach was further enriched and upgraded by developing a complete optimisation model, which gave rise to a more generalised yet complete optimisation model based on all softgoals of the $i*$ goal model. This improvement was led by the choices made from the range of alternative designs depended on value propagation throughout the complete hierarchy of softgoals. Therefore, an optimal and novel framework was developed by giving due consideration to all the available softgoals within the hierarchy. To produce practical information that can be used as input data for the requirements analyst, the optimisation model has been further improvised by including sensitivity analysis.

• How are the judgment inconsistencies resolved as a part of the goal analysis procedure?

The application of sensitivity analysis gives this answer by providing the required checks and balances in the model. The introduction of model judgment consistencies in this research study encourages useful reasoning over the models to highlight the areas of interest in the $i*$ goal model. The system behaviour is further checked for determining any change would occur due to variation in the input parameter by using the sensitivity analysis application. The impact of the tasks on the leaf softgoals was represented by the input parameter in the objective function. To find a specific range of impact values for which there was no change in the optimal solution, each impact variable's lower and upper limit were varied. This enabled the decision-maker to make clear judgments as part of backward analysis using reasoning based on the range of impact values that were obtained. These judgments resolved the partial and conflicting evidence over the contentious areas of the model. The consistency of these judgments was further checked in the thesis with the structure of the model.

• How are the results of the quantitative goal analysis validated?

To evaluate the quantitative goal analysis techniques' perceived contributions, several experiments were conducted by means of various case studies using this research model. These experiments helped gain clarity and understand the benefits and impediments and disadvantages present in the analysis of the goal model. In addition to sensitivity analysis, a real case study of GORE in electric power system mainly on transactive energy management, has also been included and demonstrated in this thesis. TEM proved helpful in testing the contributions that are made in reasoning and goal analysis of competitive non-functional requirements. The methods proposed in this research have been implemented on subjects with experience in the $i*$ goal model. Enough experimentation has been done on the case study for checking the viability and soundness of this thesis.

This thesis comprises the individual contributions presented in the following eight publications in addition to the overall contributions mentioned above. The research question answered by these contributions is:

"How can we effectively analyse and implement the non-functional requirements which have a competitive or opposing or conflicting nature in an agent-based goal model?"

This thesis proposes various goal reasoning and analysis techniques in its eight publications, which are based on the analytical decision-making approaches, such as game theory, CEA, AHP, probabilistic mixed strategic Nash equilibrium and sensitivity analysis, so that an alternative design option for a system with goals of opposing or conflicting objectives of interdependent stakeholders in the i^* goal model can be chosen effectively. The proposed analytical decision-making approaches help find optimal solutions in the presence of conflict and assume that actors/stakeholders (agents) are rational and act in their own interests. The rational decision-making approaches give explicit guidance on starting the analysis for created models and include various types of default "sanity" check questions that can be asked about the model.

Publication 1 proposes a novel reasoning technique based on multi-objective zero-sum game theory and can assist in choosing an optimum strategy for stakeholders in the i^* goal model. In this paper, a methodical approach based on game theory has been proposed to promote decision making by combining multiple opposing goals based on their respective significance. The proposed model has been tested, assessed and verified on the basis of the selected optimal design option by balancing the opposing objectives of interdependent stakeholders in the i^* goal model. A multi-objective optimisation technique in a two-person zero-sum game setting has been illustrated in this approach.

Publication 2 provides a game-theoretic approach in the proposed goal analysis method and uses Java Eclipse integrated with the IBM ILOG CPLEX optimisation studio. This exceptional framework brings forth real-time environment issues where stakeholders' requirements may have multiple conflicting goals. In this publication, an approach based on multi-objective zero-sum game theory has been incorporated into the i^* goal model to determine an optimum strategy for multiple non-functional requirements of the stakeholders.

Publication 3 presents the cost-effectiveness analysis approach which is based on GORE, and depends on economic evaluation of NFR to prioritise alternative design options. This research has made contributions by designing a CEA model which supports decision making to achieve the most cost-effective strategic goals.

The proposed approach provides logical reasoning in conflicted settings and gives rise to data-driven inferences by using optimisation and decision-making techniques. The CEA approach further investigates and checks the provided technique to determine whether the framework would indeed lead to better quality decision making or not. It also compares its applicability and capability to prioritise the design alternatives. Therefore, this proposal helps investigate the requirements-based engineering design alternative capable of delivering a cost-effective optimal design outcome.

Publication 4 makes a considerable contribution by proposing a cost-effective sensitive analysis to the GORE process. This proposal administers, evaluates and identifies an optimally quantified cost-effective alternative design option in the presence of opposing NFRs of interdependent stakeholders. Another significant contribution of this research is the application of sensitivity analysis to enable the decision analyst to evaluate the limits of the input parameters within which the optimal solution does not vary. A simulation method was also developed in this thesis to check the compliance of the proposed goal model to further increase the consistency of the quantified results compared to existing approaches. Another advantage of this method is that it helps to assess the practicality of the proposed process of cost-effective analysis.

Publication 5 proposes a quantitative reasoning technique for optimal decision making using the AHP process. In the AHP process, the contribution values of design alternatives are integrated with the normalised relative priorities of top softgoals. This integration can provide concrete support to decision analysts in making decisions without using their own subjective judgment. Decision-makers can use the techniques provided in this approach to consistently select the most appropriate alternative design alternative. This thesis' contribution is significant because it successfully provides an easy-to-apply decision-making methodology that can help decision-makers to find and make consistent decisions.

Publication 6 of this thesis contributes by presenting a hybrid AHP-GORE model.

This model provides a quantitative reasoning technique in the $i*$ goal model for interdependent actors who have conflicting goals, where all these goals must be achieved simultaneously and satisfactorily. Toward this end, AHP was modified and proposed to elicit the procedure of selecting an alternative by balancing the opposing goals reciprocally. The fuzzy judgments based on quantitative reasoning in this study have always and consistently achieved effective outcomes. By proposing a modified AHP technique, this research has made an impressive contribution and is easy to apply during the decision-making phase. The decision-makers can make precise judgments and decisions by using the given methodology. The inclusion of the sensitivity analysis process toward the end of goal analysis is another significant contribution made by this research. The sensitivity analysis has been added to further check the errors in the model to comprehend the changes that might occur each time there is a variation in the input parameters within a specified range of values.

Publication 7 proposes a probabilistic Nash equilibrium based mixed-strategy methodology of analysing goals in the $i*$ goal model. This approach is based on the Nash equilibrium and has proven to help resolve the conflict that arises during the process of reasoning with non-functional requirements. This technique was implemented within the Java Eclipse environment with the use of the IBM CPLEX ILOG optimisation studio.

Publication 8 contributes by presenting a clear, effective and dependable transactive energy management system for the electric power system. This proposal uses the goal-oriented requirements engineering approach, which has proven to be efficient and completely reliable as well as economical in effective power transmission and distribution. This is a case study that uses the GORE approach to carry out the reasoning and impact of non-functional requirements in the $i*$ goal model, has been used to demonstrate the novel approaches.

The most important contribution of this publication has been the application of the $i*$ goal model, which provides an enhanced version of this model that dis-tributes and transmits power most reliably. This TEM system-based case study clearly illustrates and demonstrates the approach which can be scaled up and applied to fairly large, sophisticated and complex scenarios, which was not possible earlier.

Chapter 3

Conclusions, limitations and future research

The intention of developing any software system is considered to be fulfilled depending on the degree up to which it satisfies its purpose. A process which clearly indicates the purpose of a software system and records it in a form that is compliant with intelligent audit and communication followed by an implementation mechanism is termed "requirements engineering" (RE). RE is the most important step during the software development life cycle because the determination of poor requirements is one of the major reasons why software system fails.

To define and analyse the requirements that lead to the growth of modelling languages, the first step involves the identification of these requirements. The analysis of requirements is one of the most crucial challenges in RE. Despite the numerous approaches proposed in the past for analysing requirements, an automated system for analysing requirements has always been a major challenge in RE. Goal-oriented requirements engineering (GORE) is an archetype in RE that has evolved like other traditional, object-oriented archetypes. GORE has been successful in dealing with the issues that may arise during the analysis of requirements. While assisting in the analysis of an organisation, $i*$ goal model is the only framework available among many other GORE models which emphasises socio-technical domains, such as stakeholders (actors or players), goals or objectives, dependencies and design options or alternatives. The i^* goal model is an effective tool that can be used for the reasoning and modelling of organisational settings and their environment. However, a study of the previous literature shows that until now, the i^* goal model enabled only qualitative analysis of requirements with some very apparent drawbacks. Therefore, it is imperative to find techniques that can help improve the existing qualitative methods used for analysing the requirements. This thesis aims to fill these evident gaps and also presents a clear-cut methodology to analyse the requirements with an automated system in the i^* goal model by applying numerous logical decision-making techniques. This chapter concludes the work carried out so far and paves the way for related research which can be carried out in the future.

To gain better clarity on the problem through a sequence of published research articles, the improvised methodical processes were able to enhance the available knowledge present on GORE. This was accomplished by emphasising the significance of the reasoning of conflicting non-functional requirements in agent-based models, particularly in the i^* goal model. As an answer to the ambient research question, "How are the non-functional requirements of opposing or competitive or conflicting disposition effectively analysed and incorporated in agent-based goal models?", the published article discusses the findings which form the foundation of this research. This thesis makes a considerable contribution in the area of GORE by developing various automated techniques for analysing the non-functional requirements in the i^* goal model. Some distinct sub-questions associated with this thesis are:

1) How are the linguistic descriptions of stakeholders' requirements in goal analysis represented?

2) Are the subjective preferences of quantitative values used in the goal analysis represented effectively?

3) How are the judgment inconsistencies resolved as a part of the goal analysis

process?

4) How are the outcomes of quantitative goal analysis validated?

The answers to the above sub-questions have been dealt with by giving due consideration to the various perspectives of the ambient question. The thesis is concluded below.

3.1 Conclusion

The main goal of this thesis is to devise and present a methodology which provides quantitative support for reasoning during the analysis of non-functional requirements in the $i*$ goal model. This thesis successfully assimilates the GORE knowledge to widen the concept of multiple opposing non-functional requirements in the agent-based goal model. To address the ambiguity which arose due to qualitative reasoning of goals, a fuzzy-based quantitative approach was used to accomplish goal analysis which provided much more clarity and proper reasoning techniques. Therefore, instead of representing requirements in linguistic terms, fuzzy numbers were used to depict stakeholders' requirements.

The model proposed here provides a fresh perspective that helps manage subjective preferences (weights) to the leaf softgoals. This aspect was specifically managed by using multi-objective optimisation for assigning subjective weights to the leaf softgoals. Objective functions for each alternative were propagated for each stakeholder depending on its impact on the leaf softgoals. The multiple objective functions obtained were combined in one objective function by applying the scalarisation technique. The IBM CPLEX optimisation studio was then used to solve this single objective function so that the weights of the leaf softgoals could be derived. The obtained weights were then used to analyse the procedure for performing goal analysis of the $i*$ goal model.

To further improvise and augment the operational and conceptual research and practice, sensitivity analysis was then applied for checking the system behaviour each time there was a variation in the input parameter. The impact of the activities of the leaf softgoals in the system is the input parameter in the objective function. The lower and upper limits of each impact variable were altered to find a specific range of input parameters within which no change occurred in the optimal solution.

In an inter-actor dependent framework, analysis of goals in the $i*$ framework was performed by generating the impact and weight values across each actor's hierarchy. Based on the softgoals and leaf softgoals of every stakeholder, an optimisation model has been assembled. The IBM ILOG CPLEX optimiser was then used to solve the multi-objective functions to ascertain the weights of the leaf softgoals. The obtained weights were then applied to analyse the goals in the $i*$ goal model. To achieve further inter-actor goal analysis, the Java Eclipse environment-based tool was devised. In most of the real-world business settings, there is a need to perform concurrent optimisation of multiple competitive objective functions. To overcome this problem, various contrasting analytical decision-making techniques were proposed, such as game theory, CEA, AHP, probabilistic mixed strategy Nash equilibrium and sensitivity analysis for analysing the non-functional requirements and for appropriate reasoning to handle such issues. All these approaches were incorporated in the Java Eclipse based-environment merged with the IBM ILOG CPLEX optimiser. The evaluation procedure was finally implemented to evaluate the efficacy and capacity of the proposed optimal goal analysis model by applying contrasting approaches. This assessment was carried out in place of the present tool used for goal analysis which has been termed Open OME. The next section discusses the outcomes of this assessment which can lead to future potential research.

A new approach in the academic research area has been presented in this thesis by using a "mixed-methods methodology". As shown clearly in all eight published articles, selecting an optimum design approach for interdependent stakeholders in the $i*$ goal model was used as the predominant and all-encompassing core technique that complemented collaborative opinion on fulfilling the promise of a better-informed comprehension of the capacity of the i^* goal model during the decision-making process of non-functional requirements. The quantitative analysis of goals gave way to pursue the study involving social interaction within specific physical settings or scenarios.

With the application of its various analytical approaches, this research devised a new front-line knowledge that simplifies the analysis of non-functional requirements with an opposing nature in agent-based goal models. A data-driven conclusion can be drawn by using optimisation and decision-making techniques as initiated by this research and with the use of its various proposed approaches. This research further investigates whether the proposed framework will pave the way for improved quality of strategic decision making. A comparison of its serviceability and effectiveness was tested for prioritising the design alternatives. This research investigates how RE design can provide support in finding a cost-effective and optimal design outcome. To support the decision-maker in finding the most accurate and reliable judgments, this proposal makes a significant contribution to this thesis by offering easy-to-apply decision-making techniques.

To perform multi-objective inter-actor goal analysis, this thesis develops a number of simulation models for increasing the procedural and conceptual experimentation, research and practice. These models have used the IBM ILOG CPLEX optimisation studio integrated with Java. This research uses a case study of the GORE model to accomplish the reasoning and impact of the non-functional requirements in the transactive energy management system (TEM) for the electric power system. This thesis also re-examines the process of alternative choice by balancing conflicting goals reciprocally by including the analysis of non-functional requirements of interdependent stakeholders. This approach is capable of offering insights into decision-making in relation to requirements analysis.

Demanding formal, quantitative or detailed representations for high-level social concepts in the proposed methods helped the flexibility and usability of the approaches for early RE. The methodologies also increased confidence in the completeness of goal-oriented models and thus helped to achieve model stability. In the goal model analysis, encouraging user involvement in a structured and cleared way allowed a higher level of user input encouraged reasoning over the correctness and completeness of the model and increased the chances of obtaining stakeholder consensus in the new system. The analysis results received appropriate weight in domain understanding and decision making as part of a methodology for early RE exploration. Approaches have focused on supporting knowledge of analysis results over complex models. Also, the performance of the approaches was implemented by Java integrated with the IBM CPLEX optimisation studio to obtain the simulated results. Therefore, a reasonable conclusion is made that this research provides a realistic suggestion for making distinct improvements in the requirements engineering model.

3.2 Limitations and future work

A new frontier has been established by this research related to the analysis of the GORE model. Several limitations were found in this thesis which was eventually resolved by addressing these restrictions. This provides the potential for further research, which can be carried out to create an extension of the $i*$ goal analysis methodology.

There are continuous changes in the models, and this research analysis framework aims to encourage expansions to this framework, which can handle such fluctuations in the models effectively. Specifically, when any changes occur in the model, the analysis results should also reflect them, and which can be handled in several ways. Any change in the system should lead to an automatic re-assessment of the framework and, as far as possible, automatically generate and prompt the user in case a new decision would be required. Nevertheless, in an attempt to encourage a better comprehension of the model, it may be more useful if the user is also shown which fragments of the analysis results are altered over associated fragments of the model when any change occurred in this model. This can be achieved by using either of the visual techniques by using a modelling canvas or by summarising the results of the analysis. This includes the decision of whether or not the change in model would affect the results of the goal analysis (for example, renaming an intention should not ideally affect the outcomes of the analysis). Backward analysis has proved less useful for analysing in the backward direction, because when the backward slice is used to find the affected results of an analysis, it may end up highlighting most parts of the model. Work done in the future can be focused on this area. In a genuine, realistic and sophisticated case study, a further round of verification would be conducted to test the procedure and application of backward analysis and could include innovative interventions such as human decision-making checks and human visualisations. Different types of analysis such as ad hoc analysis, interactive analysis and fully automatic analysis can be tested using such realistic studies. However, some challenges (as mentioned in the first chapter) must be addressed to balance and measure the effects of various types of analysis versus analysing the effects made on false study designs.

The current research has not addressed a scenario in which users would be allowed to alter and modify the degree of automation. Based on the user's confidence in the accuracy and completeness of the model, the user should be able to choose the degree of automation they would like by using established rules to combine evidence. This thesis does not include complete automation in the proposed framework. Even though this approach is somewhat automated, such an option for automation is required to support analysis over large and sophisticated models. Manual propagation will be needed in the absence of complete automation. Manual intervention is complicated and would require an expert to operate the system. Work done in the future should examine situations wherein users can choose whether they should increase or decrease the level/degree of automation. Further studies should also investigate how effectively can such an option lead to much improvised RE analysis.

The aforementioned techniques that emphasised agent-based goal models' analysis during early RE are relevant. The given techniques provide support only with high-level concepts. Work done in the future must be able to guide the users to transition from the kind of model and analysis presented in this study to more detailed RE models that have a more clear-cut scope. Many of the prevailing analysis approaches used in the goal model have introduced and used models that need detailed information on probability, priority or temporal ordering. Even though this early RE analysis techniques are fixated, where there is a lack of proper domain statistics, it may be likely to extract partial, more precise domain statistics and information as a part of this early RE process. However, the main underlying question is whether collecting these definite metrics may take the focus away from comprehending the bigger picture or not, which is supposed to be the main aim of the high-level RE models. However, if detailed information is made available, it could be collected, attached to the model and left for additional examination and development in later RE stages after selecting high-level alternatives and making sure that enough rounds of scoping have happened.

In the $i*$ goal model, only softgoal interdependencies have been used in this fuzzy-based inter-actor quantitative approach. However, it is noteworthy that other kinds of dependencies are also present in the $i*$ goal model such as goal dependency, resource dependency and task dependency, which also contribute to analysing goals in a strategic dependency framework. Consequently, possible future research may comprise of an extension by including all types of inter-actor dependencies.

The goals that contribute to the assessment of the softgoals can also be linked with other parameters, such as time taken to develop the goal, risk involved or other aspects of the development. Such aspects can also be considered during the assessment of the goals, which can then be used to determine the goals with maximum softgoal fulfilment and minimum cost factors.

An extensive study on the optimisation approach's viability and applicability on other models, such as the NFR model, goal-oriented requirements language model and the TROPOS model is planned. This planning includes a verification of the proposed techniques based on machine learning, with respect to their ability to modify or extend the approach as described in this thesis.

During the analysis of real-time software systems, at times, requirements are not clearly specified (or not known) completely. Indicative learning algorithms can therefore be used in this proposal to ascertain how incomplete or inaccurate are the given set of requirements. Rough set-based techniques can also be used in this proposal to be able to deal with ambiguity in data.

To improve the comprehension and application of goal model analysis by applying visualisation methods, future work should continue to devise new techniques. For example, the analysis values of intentions that might be affected could be highlighted for the user each time changes are made, either to the model or a change that occurs due to human judgments.

Publications

Publication 1 [1]

[1] This is the pre-submitted version.

Optimal Reasoning of Opposing Non-functional Requirements based on Game Theory

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Abstract

Goal-Oriented Requirement Engineering is a modeling technique that represents software system requirements using goals as goal models. In a competitive environment, these requirements may have opposing objectives. Therefore, there is a requirement for a goal reasoning method, which offers an alternative design option that achieves the opposing objectives of inter-dependent actors. In this paper, a multi-objective zero-sum game theory-based approach is applied for choosing an optimum strategy for dependent actors in the *i** goal model. By integrating Java with IBM CPLEX optimisation tool, a simulation model based on the proposed method was developed. A successful evaluation was performed on case studies from the existing literature. Results indicate that the developed simulation model helps users to choose an optimal design option feasible in real-time competitive environments.

Keywords: Goal models, Requirements engineering, Game theory.

1. Introduction

Any software system's success depends upon the degree to which its requirements are met. During the last two decades, Requirements Engineering (RE) has progressively been developed as a critical area of the software development lifecycle [23]. The elicitation process (one of the most important phases of RE), discovers the stakeholders and identifies the goals/tasks of the system which in turn indicate the objectives that need to be met by the system. In requirement analysis phase, the requirements analyst examines information received from stakeholders to identify their goals from the collected requirements. Stakeholders have hardgoals which indicate the functions the system has to perform. The non-functional goals of the system are represented as softgoals which relate to the qualities desired for the system (accuracy, reliability, performance, etc.). Furthermore, the requirements analyst examines high-level alternative system design options and decides which system design to implement [10].

Goal-Oriented Requirement Engineering (GORE) is a method that models the software system's requirements using goals by eliciting, elaborating, structuring, specifying, analysing, negotiating, documenting and modifying requirements [23]. In GORE, goals play a critical role in understanding the domain and determining the stakeholders' intentions [22]. Goals are elaborated at different levels of abstraction, from strategic concerns to technical matters. Hence, it is a significant, well-thought-out artefact during the early phases of RE [5], [8]. This use of goals is modeled on a multi-view model or goal model that illustrates the way in which goals, actors, states, objects, tasks, and their domain properties are inter-related for the given system [18].

Ever since the mid-nineties, goal models have been prominent in software engineering discipline. In software engineering literature, the *i** goal model is one of the popular and well-known goal models, because it helps goal-oriented modelling of socio-technical systems and organisations. Organisations and socio-technical systems get support in its essential processes with the use of *i** model, as an intentional structure of actors and their dependencies. Reasoning techniques in the *i** goal model enable all types of qualitative analyses [11, 14] or quantitative analyses [9] or even both [1] to be performed.

In real-world, competitive environments, the goals of many stakeholders of complex systems are of a conflicting or opposing in nature. Furthermore, each goal (functional requirement) of a system may have a number of different alternative design options for achieving it. In the *i** goal model, actors have multiple conflicting goals that are dependent on each other. A requirement analyst has to deal with the challenges of these multiple conflicting goals. Requirement-based engineering faces the challenge of identifying an optimal alternative design option for a goal model with conflicting goals. Hence, a novel framework is needed that captures the real issues behind achieving multi-objective optimisation [7]. The implementation of a realistic decision-making process in our approach allows us to go beyond analytical tools, like game-theoretic concepts. This paper proposes a novel methodology based on game theory for system exploration which involves alternative design evaluation. Game theory is a powerful inter-disciplinary tool for the analysis of competitive situations in multi-agent systems [17]. It can adequately characterise the interaction between decision-makers and find optimal solutions under conflicting circumstances, assuming that players are rational and behaving according to their interests.

In previous research [5], game theory-based goal analysis was proposed for each actor in the *i** goal model without considering the dependency relationships among actors. In a real-world competitive environment, when making decisions, decision-makers have to consider the inter-dependent relationships among actors. In this paper, a systematic game theory-based approach is proposed to facilitate decision-making when there are inter-dependent actors in the *i** model by integrating multiple opposing goals together with their significance. To discover the optimal alternative options, a two-person zero-sum game approach is applied to the *i** goal model. In the proposed approach, multi-objective functions are determined to decide their significance. Then, the alternative options for each actor are assessed according to each conflicting softgoal by applying game theory. In the final phase, an optimal solution is found under the circumstances of conflicting goals. A case study is used to illustrate the applicability of the proposed approach. An overview of the existing approaches, techniques and methods related to GORE and more precisely, *i** model, which are closely associated with our approach are presented in the next section.

The paper is organized as follows. Section 2 presents the existing approaches, techniques and methods related to the *i** model, which are closely associated with our proposed approach. The methodology comprising of various steps in our approach and a brief introduction of the methods used in the study are given in Section 3. The evaluation and simulation of the proposed work are described in Section 4. Finally, conclusions are drawn at the end of the paper.

2. Background and Related works

Recent trends in GORE recommend using goals, as a means of discovering the 'whys' in the functionality as opposed to the notion of 'what'. In this section, an overview of the existing approaches, techniques and methods related to the *i** model, that approximate our approach are presented. An interactive, iterative, qualitative analysis method for *i** goal models was proposed by Horkoff and Yu [15]. The uncertainty of making decisions when more than one goal has the same label is the main limitation of this approach. To analyse alternative design options in the KAOS model, Heaven et al. [12] proposed quantitative reasoning based multi-objective optimisation model. However, the main issue with this model is that it does not consider the non-functional requirements of the system. To deal with the conflicts in NFR decision analysis, Mairiza et al. [21] developed a Multi-Criteria Decision Analysis (MCDA) and applied TOPSIS as an MCDA method for prioritising the alternative options. However, the application of TOPSIS for the selection of preferred design solution against conflicting NFRs was not presented. Using the *i** model [3], an inter-actor quantitative goal analysis method was developed for reasoning with non-functional requirements. This method is enhanced by applying a multi-objective optimisation method to find feasible values of softgoals for an alternative selection in the goal analysis process [6], [7]. This furthermore helps in preventing the stakeholders' from imposing his/her subjective preference of values that are being used for the goal based reasoning. However, all these proposals for goal analysis are based on either quantitative or qualitative values used when choosing an alternative design option based on the maximum satisfaction label of non-functional requirements. However, an ambiguity arises when two or more non-functional requirements receive the same type of label during decision-making [15]. This limitation of the qualitative approach to the *i** framework that causes ambiguity in decision making was overcome by Chitra et al. [6], [7]. Chitra et al. developed fuzzy-based optimal quantitative methods for goal analysis in the *i** model. However, the existing literature does not include goals with opposing objective functions in reasoning goal models. In [5], game theory-based goal analysis was proposed but without considering the dependency relationships among the actors. In a real-world competitive environment, when making decisions, decision-makers have to consider the inter-dependent relationships among actors. Overall, using the *i** model, previous research efforts have not been able to develop a systematic game theory-based reasoning approach by reciprocally balancing multiple opposing objectives with their significance. In the next section, the proposed methodology of reasoning opposing non-functional requirements in the *i** goal model is presented.

3. Game Theoretic Approach for Reasoning Opposing Non-functional Requirements

This study aims to provide a more precise decision-making process in real-time competitive environments by integrating multiple opposing objectives with their significance. For the calculation convenience and easy presentation, a two-person zero-sum game [2] is applied in this paper. In the proposed approach, multi-objective functions are determined to decide their significance. To obtain an optimal strategy for player's having opposing objectives, a methodology has been proposed in this paper. The proposed methodology is presented in the following sub-sections.

3.1. Generation of Multi-Objective Functions

In this section, formalisation approach to the opposing non-functional requirements with respect to softgoals, goals, tasks and resource elements based on the Strategic Rationale (SR) model of *i** framework is explained. A directed graph, *G (N, R)* is represented for SR model in such a way that *N* indicates softgoals, goals, tasks and resources which represents a collection of nodes and *R* indicates the links (means-end, task decomposition, dependency and contribution links) which shows a collection of edges [20]. The task of a decision maker is to choose an ideal alternative option from the given choices.

Given an i^* goal model, we aim to choose an optimal design based on its contribution on the softgoals. Impacts are represented as *Make*, *Help*, *Hurt*, *Break*, *Some-*, *Some+*. They are symbolized as fuzzy triangular numbers that indicate the extent to which an alternative option fulfils the leaf softgoal [4], [8], [24]. The impacts of the softgoal preferences are backward propagated to the uppermost softgoals in order to evaluate the scores of the same and to achieve the level of satisfaction. Furthermore, a weight ω is assigned to each leaf softgoals based on their relative significance in achieving the goal.

Initially, based on the inter-actor dependency relationship among actors, each top softgoal's scores are evaluated. For details on how to generate scores, readers are directed to [3, 4].

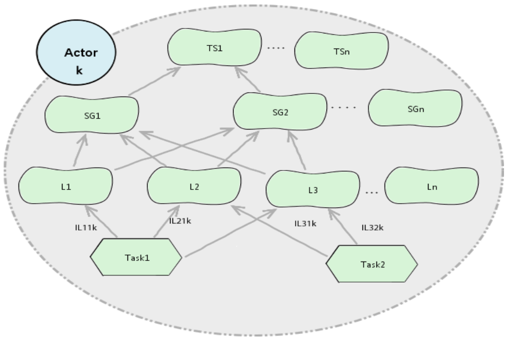

Fig. 1. Directed graph of *i** model

Assume there are *t* hierarchy levels in the directed graph, *G (N, R)* (Figure 1). Let the i^{th} leaf softgoal's weight be $\omega_{L_{ik}}$ and the impact of j^{th} alternative of k^{th} actor on i^{th} leaf softgoal be $I_{L_{ijk}}$. Consider there are *m* softgoals, n_d dependencies and n_c children for the i^{th} softgoal at level 1. Then, at $t > 1$, the score of any softgoal is calculated by multiplying its impact with each child's score. Thus, a dependency relationship can be generalised in Equation 1 for any softgoal at level $t > 1$.

$$S_{SG_{i_t jk}} = \prod\nolimits_{l=1}^{m} I_{ijl} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{ijk}}} \times \omega_{d_{L_{ijk}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\} \tag{1}$$

Consequently, the objective functions of top softgoals are generated with the assumption that only softgoal inter-dependency relationships are considered in this proposed approach. For an actor having *n* alternative options, there will be *n* different objective functions for each top softgoal.

The objective functions under n^{th} alternative for each opposing nature (maximisation and minimisation) are given as,

$$f_{i(n)} = S_{SG_{ink}} = Max \prod\nolimits_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{in}} \times I_{d_{L_{ink}}} \times \omega_{d_{L_{ink}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

$$f_{i(n)} = S_{SG_{ink}} = Min \prod_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{in}} \times I_{d_{L_{ink}}} \times \omega_{d_{L_{ink}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

Such that $0 \le \omega_{d_{L_{jk}}} \le 100 \; for \; d = 1 \; to \; n_c$

(2)

In this paper, the two-person zero-sum game theory approach is applied to choose an ideal strategy for inter-dependent actors. Analogous to game theory, in this proposed approach, game players are considered as the top softgoals with conflicting objective functions of the system and game strategy is treated as the alternative design options of inter-dependent actors in the i^* goal model. Initially, the application of game theory from the actors' perspective having opposing objective functions is investigated with the assumption that each actor in the goal model has the same set of alternative options for achieving his/her opposing objectives.

3.2. Evaluation of the Optimal Solutions of Multi-Objective Optimization Functions

Consider an i^* goal model in which each actor is considered to have two opposing soft goals (SG_1 and SG_2) and two alternative design options (A_1 and A_2). Optimising the objective functions for soft goals individually generates two ideal solutions using Algorithm. 1. The IBM ILOG CPLEX optimisation tool is used for evaluating the optimisation [19].

Let the ideal solutions for the objective functions for softgoals of an actor using two alternative design options, based on Equation 2, is expressed as

$$\left(x_{SG_1A_1}, x_{SG_1A_2}, x_{SG_2A_1}, x_{SG_2A_2} \right) \qquad (3)$$

Likewise, for all the actors in the given goal model, the optimal multi-objective function values are generated.

Algorithm 1: Main Module- Optimal Selection

Input: A collection of directed graphs $S = \{S_1, S_2, \ldots, S_n\}$ where $G \subseteq S$ having same n number of tasks T, where $G = \{G_1, G_2, \ldots, G_k\}$ and each G_i represents $\{T, L, SG, TS\}$ which indicates a set of task, a set of Leaf softgoals, a set of in-between softgoals, a set of top softgoals respectively with each top softgoal associated with opposing variables such as *Max* or *Min.*

for $G_i \in G$ **do**
    for task $t \in T$ **do**
        for top softgoals $t_s \in TS$ **do**
        if t_s is Min **then**
            Generate minimisation objective function;
        end
        if t_s is Max **then**
            Generate maximisation objective function;
        else
            break;
        end

```
        end
    end
end
Let F_Max ← Max{f_max_1, f_max_2, … …, f_max_n };
Let F_Min ← Min{f_min_1, f_min_2, … …, f_min_n };
for f_max_i ∈ F_Max do
      Let x_max_i ← optimal(f_max_i, Max); //finding optimal solutions for
maximum objective functions
end
for f_min_i ∈ F_Min do
      Let x_min_i ← optimal(f_min_i, Min); //finding optimal solutions for
minimum objective functions
end
Generate pay-off matrix, P_TSMax , for maximum objective
function values, by integrating x_max's of all Gi∈G
Generate pay-off matrix, P_TSMin , for minimum objective function
values, by integrating x_min's of all Gi∈G
Generate decision pay-off matrix P by merging pay-off matrices
P_TSMax and P_TSMin
Generate primal linear equation using MaxMin strategy
Generate the optimal solution by solving the primal linear
equation
```

Sub Module - Solving Multi-objective functions to obtain the optimal function value

```
Define the objective functions and their constraints based on
C;
if C is Max then
    Define maximisation objective function;
end
if C is Min then
    Define minimisation objective function;
else
return (cplex.solve( ) → W);
end
```

3.3. Objective Integrated Game Theoretic Approach for Pay-Off Matrix Transformation

In this section, the objective function values of top softgoals are integrated for all actors in the goal model that are of the same nature (for example: maximise) under each alternative to generate the pay-off matrix (for each nature). To understand the formation of the pay-off matrix according to the objective function values, let us assume that there are two actors in the same goal model with an inter-actor dependency relationship from *X* to *Y*. Also, assume that both actors have the same alternative options (A_1 and A_2) for reaching their opposing top softgoals (TS_1 (Maximise) and TS_2 (Minimise)). The optimal function values for each actor are represented in Table 1 as a ready reference.

Table 1. Objective functions values

Optimal Function Values	X	Y
$F_{TS1_{A1}}$	$x_{TS1_{A1}}$	$y_{TS1_{A1}}$
$F_{TS1_{A2}}$	$x_{TS1_{A2}}$	$y_{TS1_{A2}}$
$F_{TS2_{A1}}$	$x_{TS2_{A1}}$	$y_{TS2_{A1}}$
$F_{TS2_{A2}}$	$x_{TS2_{A2}}$	$y_{TS2_{A2}}$

Based on the optimal function values shown in Table 1, the pay-off matrices, TS_{Max} and TS_{Min} are generated for each top softgoal by taking the summation of the objective function values that are of the same nature for all actors based on each alternative. Now the pay-off matrix $P_{TS_{Max}}$ for the top softgoal TS_{Max} which has to be maximised for two actors *X* and *Y* under *n* alternatives is generalised as shown below

$$P_{TS_{Max}} = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \dots\dots & A_n \end{array} \\ \begin{pmatrix} P_{A_1A_1} & P_{A_1A_2} & \dots\dots & P_{A_1A_n} \\ P_{A_2A_1} & P_{A_2A_2} & \dots\dots & P_{A_2A_n} \\ \dots\dots & \dots\dots & \dots\dots & \dots\dots \\ P_{A_nA_1} & P_{A_nA_2} & \dots\dots & P_{A_nA_n} \end{pmatrix} \end{array}$$

where $P_{A_iA_j} = x_{TS_1A_i} + y_{TS_1A_j}$, for *i, j =1 to n* (4)

If there are *s* number of actors in an i^* goal model, in such a way that $k \leq s$ actors have the same set of n number of alternatives, then each element in the final pay-off matrix of top softgoal that has to be maximised is obtained as:

$$\sum_{i,j=1}^{k} a_{A_lA_r}^{ij} \text{ , where } A_l \geq 0 \; for \; l = n \; and \; A_r \geq 0 \; for \; l = n \tag{5}$$

where a^{ij} denote an element of the pay-off matrix of every combination of i^{th} and j^{th} actor of k resulting from choosing the l^{th} and r^{th} alternative of *n*. Similarly, the pay-off matrix $P_{TS_{Min}}$ for the top softgoal TS_{Min} which has to be minimised for two actors *X* and *Y* under *n* number of alternatives can be generalised.

3.4. Decision Pay-Off Matrix Formation

The overall objective of opposing goals simultaneously can be achieved by merging the pay-off matrices that are obtained separately for each player. This process of integrating objectives with their importance based on alternatives is known as the unification process. An optimal strategy is obtained by analysing the unified pay-off matrices. Now, using TS_{Max} and TS_{Min}, the decision pay-off matrix *P* is generated as shown below:

$$P = \begin{array}{c} \\ A_1 \\ A_2 \\ \vdots \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & \dots\dots & A_n \end{array} \\ \begin{pmatrix} Z_{A_1A_1} & Z_{A_1A_2} & \dots\dots & Z_{A_1A_n} \\ Z_{A_2A_1} & Z_{A_2A_2} & \dots\dots & Z_{A_2A_n} \\ \dots\dots & \dots\dots & \dots\dots & \dots\dots \\ Z_{A_nA_1} & Z_{A_nA_2} & \dots\dots & Z_{A_nA_n} \end{pmatrix} \end{array}$$

where $Z_{A_iA_j} = p_{A_1A_j} + q_{A_1A_j}$, for *i, j =1 to n* *(6)*

3.5. Linear Programming Model to Obtain Optimal Strategy and Decision Making

In the last phase, the optimal strategy is obtained by analysing the unified decision pay-off matrix by applying linear programming method [13] to the decision pay-off matrix, shown in Equation 6.

In the case of top softgoal that has to be maximised, (TS_{Max}), follows the Max-Min strategy, the formulation of which is given below as ready reference:
Let the value of the game is *v*; the strategies are $A_1, A_2 ... A_n$; the upper value of the game is $\overline{v}$; the lower value of the game is $\underline{v}$ and the range of the values of the game is $= \overline{v} - \underline{v}$.

$Max\ v,$

Subject to the linear constraints

$$-u \times v + \sum_{i=j=1}^{n} Z_{A_i A_j} \times A_i \geq \overline{v},$$

$$\sum_{i=1}^{n} A_i = 1; \sum_{j=1}^{n} A_j = 1\ A_{i,j} \geq 0\ for\ i,j = 1\ to\ n \qquad (7)$$

From Equation 7 all the values are in linear form, and the solution to the game can be found by using a linear programming method. Similarly, player 2 i.e., top softgoal (TS_{Min}), follows the Min-Max strategy. The linear formulation, TS_{Min} is the dual of $TS_{Max,}$. So the solution to the game is found by solving either the formulation of TS_{Max} or TS_{Min}. Thus, the optimal proportion values of the strategies are evaluated by solving either formulation and the strategy with high proportion value is selected.

4. Simulation and Evaluation

The effectiveness and feasibility of the proposed approach (of the *i**goal model) were tested by performing experiments on different case studies from the literature namely Telemedicine system [26], Meeting Scheduler system [4]. The result of the Telemedicine case study is presented in this paper.

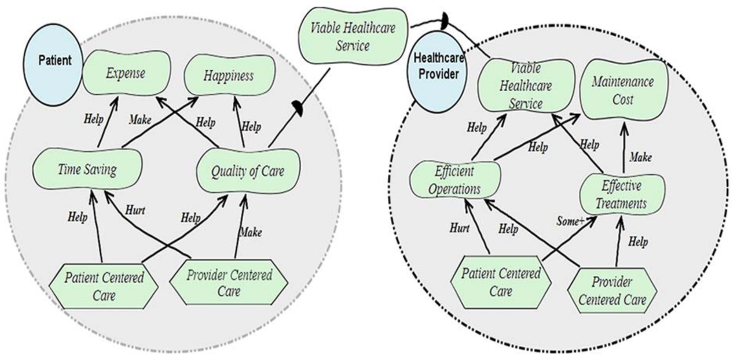

Fig. 2 Simplified SR model for the Telemedicine system (with dependency)

The adapted telemedicine system is shown in Figure 2 with actors, *Patient* and *Health Care Provider*. For more details about the telemedicine system, readers are directed to [26]. The objective of this system is to choose an optimal alternative option regarding its impact on each of the softgoals. The defuzzified values, as shown in Table 2, are used to evaluate the objective functions of each top softgoal.

Table 2. Defuzzified values for impacts

Impact	Defuzzified value
Make	0.8
Help	0.64
Some+	0.48
Some-	0.32
Hurt	0.16
Break	0

The objective function values for both actors, under both alternatives, are given in Table 3 using Equation 2 as a ready reference.

Table 3. Optimal values for the Telemedicine system

Optimal values	Patient	Healthcare Provider
$F_{TS1_{\text{Patient Centered Care}}}$	51.2	30.72
$F_{TS1_{\text{Provider Centered Care}}}$	51.2	40.96
$F_{TS2_{\text{Patient Centered Care}}}$	5.24	12.8
$F_{TS2_{\text{Provider Centered Care}}}$	10.24	51.2

An optimal strategy is obtained using a linear programming model on Equation 7, and the result is shown in Table 4. The results indicate that by choosing the *Provider Centered Care* strategy, the system achieves the opposing top softgoals of inter-dependent actors in the i^* goal model reciprocally.

For evaluating the optimisation model using game theory, a tool was implemented as shown in Figure 3 using Java Eclipse environment integrated with the IBM ILOG CPLEX optimisation tool.

Table 4. Optimal linear formulation for the Telemedicine system

Alternatives	Optimal solution
Patient Centered Care	-9.73
Provider Centered Care	10.73

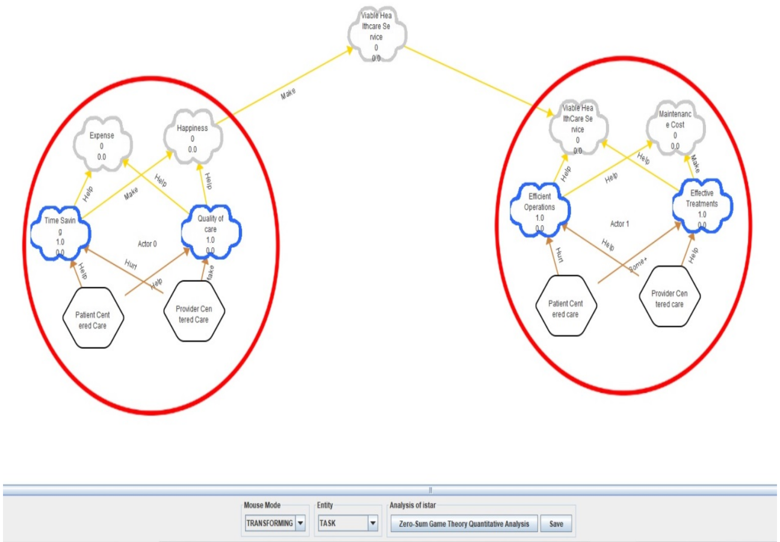

Fig. 3. Tool result for the Telemedicine system (with dependency)

5. Conclusion

A game theory-based goal analysis for the i^* goal model has been proposed in this paper. The proposed model is tested and then evaluated based on the optimal alternative selection by balancing the opposing objectives of dependent actors in the i^* goal model. The proposed approach involves a multi-objective optimisation process in a two-person zero-sum game situation. Further research topics include arriving at optimal solutions for conflicting goals among inter-dependent actors. Also, performing sensitivity analysis, for facilitating valuable input data to help stakeholders in the decision-analysis process.

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Game Theory based Reasoning of Opposing Non-functional Requirements using Inter-actor Dependencies

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Goal-Oriented Requirements Engineering frameworks are used to model stakeholders' objectives and requirements using goals. In a real-time environment, stakeholders' requirements may have opposing objectives. Hence, a novel framework is needed that captures the real issues in order to achieve multi-objective optimisation of inter-dependent actors. For obtaining an optimum strategy for inter-dependent actors in the i^* goal model, a multi-objective two-person zero-sum game theory based approach is applied in this paper, by balancing the opposing goals reciprocally. The proposed approach involves the generation of each objective function based on the inter-dependency relationships, the creation of decision pay-off matrices based on the objective function values and their variation to a final decision pay-off matrix. A Maxmin solution is formulated for the multi-objective game model, in which the optimisation problem for each player is a linear programming problem. Finally, the most desirable strategies and their proportion values are found. By integrating Java with the IBM CPLEX optimisation tool, a simulation model based on the proposed method was developed. A successful evaluation was conducted on various case studies from the existing literature. Evaluation results indicate that the developed simulation model helps users to choose an optimal alternative design option feasible in real-time competitive environments that have goals with opposing objectives.

Keywords: Goals; Goal models; Requirements Engineering; Software systems; Game theory; Multi-objective Optimisation

1. INTRODUCTION

The accomplishment of any software development relies upon the degree to which its requirements are satisfied. In the course of the most recent two decades, Requirements Engineering (RE) has progressively been perceived as a significant part in the software development lifecycle. RE is a cyclic process of eliciting, analysing, modelling, communicating, agreeing on and evolving requirements [1,2]. The initial and most significant phase of RE involves the elicitation of requirements. The elicitation process ascertains the stakeholders and identifies the goals and tasks which indicate the objectives of the system that need to be met. During the requirement analysis phase, the requirements analyst analyses the information received from stakeholders in order to identify their goals. Stakeholders have goals (hardgoal) that indicate the functions the system has to perform. The requirement analyst then analyses the goals in order to develop the system. Furthermore, the requirements analyst examines high-level alternative system design options and decides which system design to implement [1].

Goal-Oriented Requirements Engineering (GORE) models the stakeholders' requirements using goals by eliciting, elaborating, structuring, specifying, analysing, negotiating, documenting and modifying requirements [1, 2]. In GORE, goals play a critical part in understanding the domain and determining the stakeholders intentions [2]. Goals are elaborated at different abstraction levels, from strategic concerns to technical matters. Hence, it is a significant, well-thought-out artefact during the early phases of RE [1,3]. This use of goals is modelled on a multi-view model or goal model that illustrates the way in which goals, actors, states, objects, tasks, and its domain properties are inter-dependent in the given system [4]. Ever since the mid-nineties, goal models have been prominent in the software engineering discipline [5, 6].

GORE approaches/frameworks have a noteworthy part to play in the development of recent emerging technologies, for example, Internet of Things (IoT). These days, computer systems are getting pervasive in nature due to the advent of mobile technologies and the development of the IoT. In IoT systems, applications require high accessibility, reliability, safety, and security as well as administrative consistency, adaptability, and serviceability [7]. Likewise, they may be exposed to uncertainty and variability. Due to the interconnection with the real-world things, IoT requires more systematic techniques for capturing and reasoning about its framework. GORE is a candidate for meeting such requirements by characterising the objectives and stakeholders of IoT systems, together with their relationships like decompositions, contributions, and dependencies. Goal models can help to get the knowledge of who needs what and also help to perform analyses to determine the satisfaction of goals. The early identification of goals help stakeholders, inside and outside of the IoT frameworks. It also leads to a better knowledge and understanding about the system and help to perform reasoning with the specific non-functional requirements (qualities) of the IoT systems. Also, goal modelling can help decision-makers in ensuring whether processes and tools are aligned with the goals of IoT systems. Thus goal reasoning can be performed by systematically identifying and structuring IoT requirements [7].

Some of the more widely-used goal models are Knowledge Acquisition in Automated Space (KAOS) Model [8], i^* goal model [9], Non-Functional Requirements (NFR) model [2], Attributed Goal-Oriented Requirements Analysis (AGORA) Model [10], Tropos Model [11] and Goal-Oriented Requirement Language (GRL) [12] Model. In the software engineering discipline, the i^* goal model is one of the popular and well-known goal models, because it helps goal-oriented modelling of socio-technical systems and organisations. The i^* model supports modelling organisations and socio-technical systems with its essential course of actions, intentional elements and dependencies. The different goal reasoning methods in the i^* goal model enables all types of qualitative analysis [13, 14] or quantitative analysis [15], or even both [12] to be performed.

In real-world competitive environments, the goals of many stakeholders of complex systems are of a conflicting or opposing nature. Moreover, each goal of a system may have several different alternative design options. Requirements-based engineering faces the challenge of identifying an optimal stratagic option to accomplish opposing goals. Decision-making in competitive environments involves various concerns. In the real-world, decision-makers have to consider the inter-dependent relationships among actors. Hence, a novel framework is needed that captures the real issues in order to achieve multi-objective optimisation [16]. The adoption of a realistic decision-making process in our approach allows us to go beyond analytical tools, like game-theoretic concepts.

Game theory is a decision-making tool that offers a scientific mathematical explication. It has a significant part in competing situations for analysing issues and obtaining the pay-off values based on the player's results'. This paper proposes a novel methodology based on game theory for system exploration which involves alternative design evaluation [17].

Game theory is a powerful inter-disciplinary tool for the analysis of competitive situations (or situations of conflict) in multi-agent systems. It was originally developed for the domains of mathematics and economics. It can effectively characterise the interaction between decision-makers. It is an appropriate tool to analyse challenges of requirements-based engineering design [18]. The reason for choosing the game theory idea is that it finds an ideal solution under conditions of conflict assuming that players are rational and act based on their interests [17]. In this paper, analogous to game theory, the game players are considered as the top softgoals having opposing natures and the game strategy is treated as the alternative design options of inter-dependent actors in the i^* goal model.

In previous research [19], game theory-based goal analysis was proposed in the i^* framework without considering the inter-dependency relationships between actors. In a real-world competitive environment, when making decisions, decision-makers have to consider the inter-dependent relationships among actors. In the proposed approach, a systematic decision-making method is developed when there are inter-dependent actors in the i^* model by integrating the multiple opposing objectives together with their significance. To discover the optimal alternative options of inter-dependent actors by balancing their opposing objectives reciprocally, a two-person-zero-sum game method is applied and multi-objective functions are determined in order to decide their significance. Then, the alternative options for each actor are assessed according to each opposing softgoal, and pay-off matrices are formed for each type of top softgoals (by applying game theory). These matrices are transformed to a decision pay-off matrix in the subsequent phase. An optimal solution is found in the final phase that sees the adoption of a strategy under the circumstances of opposing objectives. To illustrate the evaluation of the developed approach, various case studies are applied .

The paper is organised as follows. A motivating example to the proposed approach is illustrated in Section 2. Section 3 presents the existing approaches, techniques and methods related to the i^* model, which are closely associated with our proposed approach. A brief introduction about how game theory and multi-objective optimisation method related to our proposed approach is presented in Section 4. The methodology comprising the various steps of our approach with an example and a brief introduction of the methods used in the study are given in Section 5. The two case studies used for this work are described in Section 6. A tool is designed and implemented to discuss the viability and practicability of the proposed approach and is illustrated in Section 7. Finally, conclusions are drawn at the end of the paper.

2. MOTIVATING EXAMPLE : TELEMEDICINE SYSTEM - CASE STUDY

Consider a telemedicine system [20], where each patient gets remote telemedicine amenities out of one or more healthcare service providers. Such arrangements may perhaps enhance the quality of care and minimise the typical medical costs. Thus permitting the patients to lead a more normal life at home and receive greater personalised care. Also, healthcare specialists are relieved of the more regular factors of their duties. However, certain questions should be considered, such as: how can we reason about the functionalities of the system?, whom must these systems be responsible for?, how duties must be divided among them?, why should tasks be divided?, do the stakeholders hold common goals? and will the system work regardless of continuous changes and conflicting interests? This would lead into specific solutions for each case, based on the situation. Several alternatives should be considered in each case. Initially, some options may work, but later on, they may not work, depending upon more analysis. Some may be technically infeasible, or not acceptable to some stakeholders. So, it is necessary for stakeholders, developers, designers, and analysts to see each other's concerns to discover alternative choices about the system to be built. There is a need for a systematic framework or model which can help in finding all the requirements, perform evaluation or analysis regarding their implications, and resolution based on different alternatives. In such situations, GORE approaches help us to perform identified tasks in an efficient, flexible and accurate manner.

The GORE framework, specifically i^*, is an efficient way for modelling and analysing the dependency between all the elements in a socio-economic communities environment [21–23]. Therefore, the i^* framework is preferred in this proposed approach, for modelling social relationships in the telemedicine system [20]. In this view, the central unit to be modelled is the intentional strategic actor. The intentional aspects of an actor can be characterised by goals, beliefs, ability and commitment [21]. An actor is strategic, means it aims to achieve the goal successfully. Actors are also concerned about the structural relationships with other actors in sharing resources or performing some tasks to accomplish their goals. Explicitly clear representation of goals in the i^* model helps to discover alternative choices through means-end (OR-decomposition) reasoning. A softgoal (non-functional goals) usually captures some preferred behaviours among those captured by functional goals (hardgoals). The i^* goal modelling uses two models for representing the socio-economic systems: the Strategic Dependency (SD) model and the Strategic Rationale (SR) model [20–23].

The SD model represents a graph, which demonstrates a high-level explanation of a process or a system. It portrays the actors dependencies through goals (behavioural goals or softgoals), tasks and resources. For understandability and ease of presentation, the telemedicine case study has been used to describe the i^* goal model. The Figure 1 demonstrates a SD model of a simple telemedicine scenario with actors are portrayed as circles, hardgoals as ovals, softgoals as cloud images, resources as rectangles and tasks as hexagonal shapes. In the example telemedicine model (Figure 1), a $Patient$ depends upon $Healthcare\ Provider$ for $Sickness\ Treated$ and the latter consecutively follow on $Patient$ toward $Follow\ Treatment\ Plan$. If the $Patient$ wants to incorporate treatment plan with some more activities, then it should be $Flexible$. The $Healthcare\ Provider$ monitors $Patient$'s $Vital\ Signs$ remotely through $Monitoring\ Agent$.

While the SD framework centres around the dependency between actors, the SR model helps in demonstrating the modelling and analysis of all actors in the framework based on their internal intentional inter-dependencies. The intended function of the system is represented by behavioural goals. The non-functional goals of the system is represented as a softgoal. The SR model is also represented as a graph where nodes are goals or tasks or resources or softgoals which are inter-connected by means-end links or task decomposition links or contribution links [20, 23]. The goals are connected to one or more tasks through AND (decomposition links) or OR (means-end links) relationships for accomplishing it. The contribution links can be $Make$, $Break$, $Help$, $Hurt$, $Some+$, $Some-$. These notions describe various types of contributions to various softgoals, that leads to the satisfaction of softgoals [9, 20, 23]. The Figure 2 represents a SR framework demonstrating the analysis of a simple telemedicine plan.

For identifying the goals of each actors, a top-down approach is used in the i^* model. The primary goal (hardgoal) is broken-down into a collection of tasks, by answering "how to achieve?" or "what to achieve?" questions. The softgoal is decomposed by answering "how to achieve?". This decomposition repeats till every leaf softgoals are atomic. The following section shows how the goals and the softgoals of an actor are broken down by applying telemedicine case study.

For convenience and explanation purpose, only 2 actors, *Patient* and *Healthcare Provider*, are considered in the Figure 2 of simplified telemedicine model created for this domain. For the ease of illustration, the

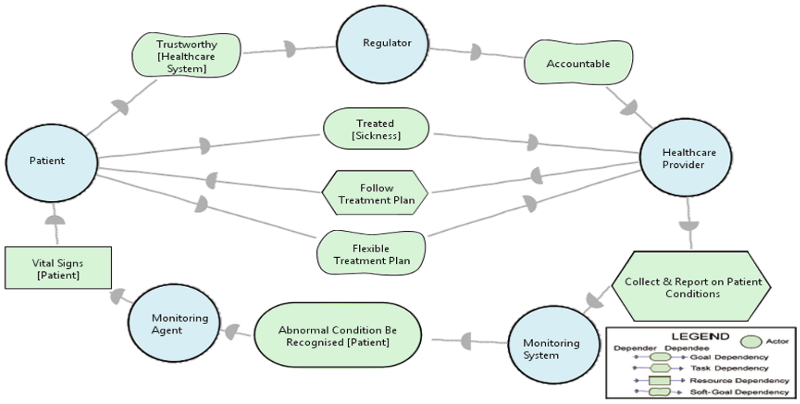

FIGURE 1. Simplified SD model for telemedicine system

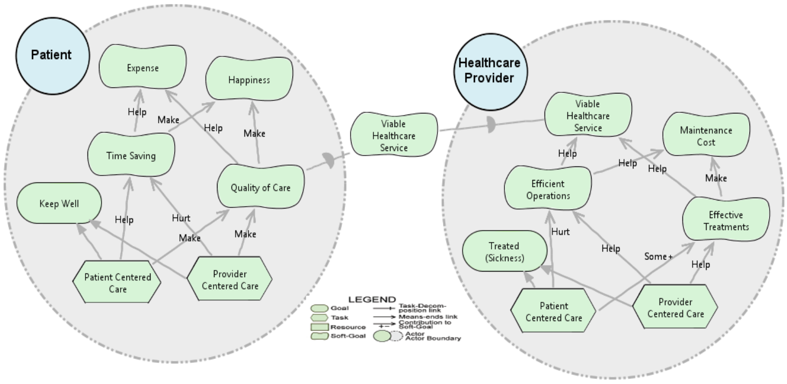

FIGURE 2. Simplified SR model for the telemedicine system

actor *Patient*, has two non-functional requirements (softgoals) namely, *Expense* and *Happiness*, which consequently follow *Time Saving* and *Quality of Care*. The *Patient* has a functional requirement (hardgoal) to *Keep Well*. It can be accomplished through either of two alternative ways *Patient Centered Care* or *Provider Centered Care*. These alternatives impact the *Patient* 's softgoals in various ways. The contribution of *Patient Centered Care* to *Time Saving* is *Help* while contribution from *Provider Centered Care* to *Time Saving* is *Hurt*. The softgoal *Time Saving* which consequently contribute *Help* to *Expense* and *Make* to *Happiness*. The contribution of *Patient Centered Care* to *Quality of Care* is *Make* whereas *Provider Centered Care* to *Quality of Care* is *Make*. The *Quality of Care* which consequently contributes *Help* to *Expense* and *Make* to *Happiness*. The *Patient* has two topmost softgoals of opposing in nature such as *Expense* and *Happiness*. The actor *Patient* depends upon the actor *Healthcare Provider* through the softgoal *Viable Healthcare Service* for its telemedicine services. The actor *Healthcare Provider* also has its own hardgoal (functional requirement) of *Treated* to achieve and explores two options of implementing this goal: *Patient Centered Care* and *Provider Centered Care*. These alternatives impact the *Healthcare Provider*'s softgoals in various ways. The two main non-functional requirements of *Healthcare Provider* are *Viable Healthcare Service* and *Maintenance Cost* which consequently, follow to *Efficient Operations* and

Effective Treatments. To illustrate, the contribution of *Patient Centered Care* to *Efficient Operations* is *Hurt* whereas *Provider Centered Care* to *Efficient Operations* is *Help*. The *Efficient Operations* which consequently contributes *Help* to both *Viable Healthcare Service* and *Maintenance Cost*. The contribution of *Patient Centered Care* to *Effective Treatments* is *Some+* whereas *Provider Centered Care* to *Effective Treatments* is *Help*. The *Effective Treatments* consequently contributes *Help* to *Viable Healthcare Service* and *Make* to *Maintenance Cost*. The *Healthcare Provider* has two top softgoals of opposing in nature, *Viable Healthcare Service* and *Maintenance Cost*. The satisfaction percentage for *Happiness* of *Patient* and *Viable Healthcare Service* of *Healthcare Provider* should be maximised while *Expense* of *Patient* and *Maintenance Cost* of *Healthcare Provider* should be minimised based on the functional and non-functional requirements in the model [19].

The reasoning of this goal model (Figure 2) points to a significant query: which alternative especially *Patient Centered Care* or *Provider Centered Care* is most effective for both actors who are dependent, to achieve their opposing goals simultaneously. The existing goal analysis approach [19] proposed an alternative selection technique based on softgoals having opposing objective functions. But the above approach cannot find a solution when actors have a dependency relationship in order to achieve their opposing softgoals simultaneously. Hence, there is a need for a novel reasoning method for alternative option selection in the situation where actors are inter-dependent for accomplishing their opposing softgoals reciprocally. In this paper, a novel approach is proposed for tackling the above mentioned problem.

An outline of the existing approaches, methods and techniques related to GORE and more precisely, i^* model, which are closely associated with the proposed approach are presented in the next section.

3. BACKGROUND AND STATE OF THE ART

Recent trends in requirements engineering recommend to use goals, as a means of discovering the '*whys*' in the functionality as opposed to '*what*' it has to do. Goals enable the requirements of the organisation to be aligned with the functionality delivered by the system. Hence, an overview of the existing approaches and methods related to the i^* model, that approximate our approach is presented in this section.

First, the approaches that are appropriate for conducting requirements analysis is reviewed, although all the details of a system may have already been finalised. Before applying a lightweight quantitative method, a qualitative propagation algorithm was proposed by Van Lamsweerde for goal analysis of Non-Functional Requirements (NFR) [24, 25]. Based on the requirements specification of the given system, he modified this approach by including certain parameters namely gauge variable, optimal goal variable, and satisfactory variable for each softgoal. A lightweight alternative evaluation system based on quantitative reasoning was developed by incorporating softgoal and goal concepts into the KAOS model. Hence, a complete system specification knowledge is required when designing a goal model. However, this approach cannot be used for large and complex systems [26].

In order to minimise the number of operations/goals for implementation, Affleck et al. [27–29] offered a quantitative goal analysis method for decision-making in the NFR model. Firstly, Affleck proposed a lightweight process-oriented quantitative method as an extension of the NFR model [27]. By applying a single optimisation step, they further improved this method [28, 29].

A qualitative and a quantitative axiomatisation approach was introduced by Giorgini et al. [30] to develop a formal model for the reasoning of goals in the goal model. Based on their axiomatisations, they also presented a label propagation algorithm. Even though this proposal is stable and comprehensive, it still needs a solid numerical understanding.

By assessing the qualitative and quantitative satisfaction values of actors and the intentional elements, Amyot et al. [12] developed an approach to analyse GRL modelling. Despite its simplicity, there arises an ambiguity when selecting numeric figures to represent the requirements.

To prioritise goals, Liaskos et al. [31] developed a quantitative method using an analytical hierarchy process. Liaskos et al. prioritised optional goals for assessing alternative means of achieving mandatory goals. The drawback of this method is that it does not satisfy the specific structural features of a given goal model.

The practical problems in requirements-based engineering design which includes poor or ambiguous requirements, inadequate, unreliable, incomplete, improper and outdated requirements, changing requirements over time, etc are summarised by Firesmith [32]. A broad review of major challenges in requirements engineering design was provided by Shah et al. [33]. Sabaliauskaite et el. investigated a review in large-scale industry domain and discovered the major requirements engineering design problems [32–34]. Past literature shows that the performance of requirements-based engineering designs can be improved by increasing the quality of requirements and more efficient allocation of requirements [35–37]. The limitations of requirements-based design are addressed by [38–45]. All of these studies focus on the implementation challenges of requirements-based engineering design.

Next, in the context of requirements-based engineering design challenges, several goal analysis procedures that were used in the early RE are discussed. An interactive, iterative, qualitative analysis method for i^*

goal models was proposed by Horkoff and Yu [21]. It included goal analysis using methods, algorithms and tools. The uncertainty of making decisions when more than one goal have the same label is the main limitation of this approach.

For the purpose of analysing alternative design options in the KAOS model, Heaven et al. [46] proposed a multi-objective optimisation model based on quantitative reasoning. It analysed a comprehensive range of options for alternative designs in a goal model. By applying probability distribution, the vector values of the quality variables of each leaf were implemented. However, the main issue with this multi-objective optimisation model is that it does not consider the non-functional requirements of the stakeholder.

In order to deal with the conflicts in NFR decision analysis, Mairiza et al. [47] developed a Multi Criteria Decision Analysis (MCDA) and applied TOPSIS as an MCDA method for prioritising the alternative options. The systematic application of TOPSIS for the selection design solution for decision-making was well presented.

In i^* model, Chitra et al. [26, 48] developed an inter-actor quantitative goal analysis method to decide on alternative design options. In order to avoid the ambiguity in selecting numeric numbers during quantitative analysis, fuzzy numbers are used. Later, in order to enhance this method, a multi-objective optimisation method is applied for finding the optimal values of softgoals for alternative selection in goal analysis [16, 49]. It also prevents the decision analyst from imposing his/her own subjective values from being used for goal reasoning.

However, all these aforementioned proposals for goal analysis are based on either quantitative or qualitative values, which are used when choosing a suitable design option for achieving maximum satisfaction of non-functional requirements. However, an ambiguity arises in making a decision when two or more non-functional requirements receive the same type of label [21]. This limitation of the qualitative approach to the i^* framework that cause ambiguity in decision-making was overcome by Chitra et al. [19] who developed fuzzy-based optimal quantitative methods for goal analysis in the i^* model. However, the above mentioned literature shows that the qualitative and quantitative goal reasoning for the i^* and other goal models does not consider non-functional requirements with opposing objectives.

The first research work to apply the game theory-based analysis of goal models using optimisation was conducted by Chitra et al. [19] who identified an alternative design option for each actor in an i^* goal model. Chitra et al. formalises the evaluation of objective functions without addressing the actor's inter-dependency relationships, which are essential for decision-making in a real-world competitive environment. This inability to address the dependency relationship among actors is the major drawback of this proposal. Overall, no previous research efforts have been able to develop a systematic game theory-based method for deciding on an optimal alternative design option for inter-dependent actors in the i^* model. The issue lies in reciprocally balancing the multiple opposing objectives with their significance. The proposal forthwith examines the way requirements-based engineering design can deliver an optimal design outcome. In the next section, a brief introduction about how game theory and multi-objective optimisation method related to our proposed approach is presented before proceeding to the proposed methodology for reasoning opposing goals using inter-actor dependency in the i^* goal model.

4. MULTI-OBJECTIVE OPTIMISATION FOR REASONING OF OPPOSING NON-FUNCTIONAL REQUIREMENTS BASED ON GAME THEORY

This study provides a more precise decision-making in real-time competing environments by integrating multiple opposing objectives with their significance. To discover the optimal alternative options of inter-dependent actors, a two-person zero-sum game theoretic approach is applied by balancing their opposing objectives simultaneously in the given i^* goal model. In the proposed approach, multi-objective functions are determined to decide their significance. Then, the alternative options for each actor is assessed according to each opposing softgoal and pay-off matrices are established for each type of top softgoals by applying game theory. These matrices are converted to a decision pay-off matrix to obtain their optimal strategies and proportion values. To exhibit the applicability of the proposed approach, two case studies are illustrated in this paper. The following subsection gives a brief introduction to the decision-making process using game theory.

4.1. Decision-making using game theory

Game theory is defined as a multi-person decision analysis process based on the assumption that all players in the game know about the circumstances, the opposing player's strategies and their preferences. However, it is impossible to formulate the majority of strategies due to the complexity of real situations [50, 51]. A game involves a set of players, a set of strategies and a pay-off for every strategy combination. When a game involves an interactive situation, a formal reasoning can discover the optimal strategies for players and can decide the expected outcome of the game [51]. In game theory, players' strategies are assessed equally according to environmental factors. It also provides solutions to a game of strategy based on the assumption that each player behaves conservatively and as such would always wish to maximise his/her gains and minimise his/her opponents loss. In the proposed approach, the goals with conflicting objectives are considered as the game players and the alternative design options (tasks) are treated as the game strategies [51]. Initially, game theory is applied, from the actors' perspective having opposing objectives, with the assumption that each actor in the goal model has the same set of alternative options for achieving his/her opposing objectives. Two-person zero-sum game theoretic approach is used in the proposal to find optimal strategies for actors by balancing objectives reciprocally. According to the proposed approach, firstly objectives are evaluated to determine their importance. Then, strategies of players are evaluated for all their combinations according to each objective and then decision pay-off matrices are calculated by applying fuzzy logic mathematical concepts. In the next phase, these matrices are transformed into final decision pay-off matrix. Finally, optimal strategies and their values are found. In this case, players will try to balance all objectives and optimise them according to their importance.

A game solution comprises a specific grouping of strategies known a Nash equilibrium in which no player can achieve success by unilaterally deviating from it [50, 51]. A game which has Nash equilibrium is known as a stable game. The saddle point in the Nash equilibrium is defined as the point where no player can gain more by altering the strategy as long as the other players remain unchanged. An unstable game is a game which has no Nash equilibrium. In such games players have mixed strategies rather than pure strategies. The pay-off to a player is defined as the value of the game when both players play optimally [52]. Nash equilibrium is a point at which the following equation is satisfied.

$$Maximum(RowMinimum) = Minimum(Column\ Maximum) \tag{1}$$

In order to anticipate more practical results using Nash equilibrium, a great deal of psychological work should be done to foresee how much the user tried to compute in specific cases. Another limitation of Nash equilibrium is that it always generates a very situationally dependent outcome. In the proposed decision-making approach, Nash equilibrium is used as a base for the generation of Pareto optimal output for a predefined situation. As long as it is adapted to a specific issue, it does well in discovering an optimal solution. The system where there is a dynamic change of requirements, then Nash equilibrium is not applicable for reasoning around such system. As explained in Section 2, all requirements of the telemedicine system are predefined for the reasoning of opposing goals. For any system with dynamic changes in the requirements, Nash equilibrium will not be an appropriate method for optimal task selection (for achieving the goals of the system).

In competitive circumstances, instead of generating pay-off matrices from single objective function, players may have more than one objective and can be opposing in nature. For the calculation convenience and ease of presentation, two-person zero-sum game is applied in this paper. It also suits to our requirements of choosing an alternative in situation of opposing goals.

The next sub-section provides a short introduction about how multi-objective optimisation helps decision-makers to discover an ideal alternative option for achieving opposing goals.

4.2. Multi-objective Optimisation Problem

Decision-making involves decision-makers, actors, goals or objectives, strategies or alternative options and criteria. In real-competitive circumstances, the effectiveness of decision-making relies upon recognising all ecological factors and assessing them according to the objectives. Decision-makers aim to discover ideal strategies for opposing goals [51]. Optimisation helps to decide optimal or best alternatives on a list of possible options by applying operations research methods namely linear programming, non-linear programming and quadratic programming [47, 51]. For real-competitive problems, single-objective optimisation methods are not adequate for decision-making. So multi-objective optimisation methods have been refined for solving real-world problems [47, 51, 52]. The task of decision-maker is to choose an ideal alternative option from the choices to accomplish multiple objectives. The multi-objective optimisation methods can solve this problem. It creates a set of solutions and an optimal value is chosen named as optimal Pareto solution or optimal Pareto frontier based on the requirements [16].

Mathematically, the multi-objective optimisation functions are represented as:

$$Max/Min[f1(x), f2(x), ., fn(x)] \tag{2}$$

where $f1, f2, ., fn$ are scalar functions, x is an element of Y and Y is the set of constraints.

5. METHODOLOGY

In this paper, a multi-objective two-person zero-sum game theory based approach is proposed, for the optimal strategy selection for inter-dependent actors in the $i*$ goal model. Firstly, the proposed approach generates objective function for each actor to determine their importance based on the inter-dependency relationships. Then the game theoretic approach is applied for the creation of pay-off matrix for each actor based on the objective function values and their variation to a final decision pay-off matrix. A

Maxmin linear programming strategy is formulated for the proposed multi-objective game model. Finally, the most desirable optimal strategies and their proportion values are found. The proposed methodology is presented in the following sub-sections in detail, to obtain an optimal strategy for player's having opposing objectives.

5.1. Formalisation of multi-objective functions

A generalised structure of an SR model is illustrated in this section, by formalising the opposing objective functions in terms of softgoal, goal, task and resource dependencies. Based on the process of generating the scores of leaf softgoals in [26], the proposed approach formalises the multi-objective functions of inter-actor dependencies. For clarity and understanding, a brief introduction on how to generate the scores of softgoals is provided in this section. For easy understanding of the formalisation of our approach, consider a simple SR graph, as shown in Figure 3, of single actor A, whose nodes are goals (G), tasks (T_1, T_2), leaf softgoals (LS_1, LS_2) and top softgoals (TS_1, TS_2). The goal (G) can be achieved by either of the two alternatives (A_1 or A_2). The leaf softgoals (the softgoals that are lower in the hierarchy are called leaf softgoals) are assigned values based on their relative importance in percentage. Let the weights of leaf softgoals LS_1 and LS_2 be ω_{L_1} and ω_{L_2} respectively.

The contributions of tasks to each softgoals is outlined by impacts such as *Make*, *Help*, *Hurt*, *Break*, *Some−*, *Some+*. These uncertain or conflicting linguistic terms are represented as fuzzy numbers [53]. It indicates the extent to which an alternative option fulfils a leaf softgoal (Figure 3). A fuzzy number is considered as a quantity whose value is imprecise rather than certain as in the case of single-valued numbers. It helps us to express the real-world problems in more practical manner than single-valued numbers [53]. In general, a fuzzy set is characterised as a set of items with graded membership between 0 and 1 and is represented by a fuzzy set A as

$$A = (x, \mu A(x)) x \epsilon X, 0 <= \mu A(x) <= 1 \quad (3)$$

where A(x) is a membership function.

The membership function depicting a fuzzy number represents some obscure idea of that fuzzy number and is chosen subjectively. This implies distinctive people may choose diverse membership functions to represent a similar idea.

In the proposed approach, triangular fuzzy numbers are applied because it is the simplest and most efficient approach [27]. The diagrammatic representation of a triangular fuzzy number is shown in Figure 4. Moreover, triangular fuzzy numbers represent fuzzy numbers, whereas other fuzzy representations like trapezoidal fuzzy numbers involve fuzzy intervals. Triangular fuzzy numbers (TFN) are commonly represented as $A = (a_1, a_2, a_3)$, where a_2 is the value where the membership function of a fuzzy number is 1.0, a_1 is the left distribution of the confidence interval and a_3 the right distribution of the confidence interval of the fuzzy number A [54]. The membership function of the interval is given as follows:

$$\mu A(x) = \begin{cases} \dfrac{(x-a_1)}{(a_2-a_1)}, a_1 <= x <= a_2 \\ \dfrac{(a_3-x)}{(a_3-a_2)}, a_2 <= x <= a_3 \\ 0, otherwise \end{cases} \quad (4)$$

In the proposed approach, to obtain quantifiable result, the scores are defuzzified by applying the α-cut operation using an optimal index λ [26]. The α-cut is the set of elements whose membership values exceed the threshold level α. A crisp interval of a fuzzy number A can be obtained by performing α-cut operation. The optimal index λ shows the degree of confidence and it can take esteems λ=0 for a pessimistic index, λ=0.5 for a moderate index and λ=1 for an optimistic index. To acquire the defuzzified value for a fuzzy number $A = (a, b, c)$, the following defuzzification formula is used:

$$\lambda * left + (1 - \lambda) * right \quad (5)$$

where $left = \alpha * (b - a) + a$ and $right = c - [\alpha * (c - b)]$

For moderate decision-making, $\alpha = 0.5$ and $\lambda = 0.5$. Based on this notion, we calculated the defuzzified values for all impacts specified in the i^* model. The fuzzy values and its membership function for the softgoal contribution (impacts) are shown in Figure 5. The impacts with the softgoal preferences are propagated to the top softgoals, to find the level of satisfaction or scores of top softgoals. The leaf softgoal scores are propagated backward to discover the scores of the softgoals that are higher in the hierarchy. Softgoals are the recipients of multiple contribution links. The membership values of each impacts (*Make*, *Help*, *Hurt*, *Break*, *Some−*, *Some+*) are diagrammatically shown in Figure 5.

The scores are computed in two stages. In the initial stage, the score of its children is multiplied by their impact values. In the second stage, the impacts of all the children are combined by using an addition operation. Let us represent the scores of leaf softgoals as $S_{(LS_1)}$, $S_{(LS_2)}$, which are computed based on the weights and the impact of chosen task (alternative) for the leaf softgoals. It also considers all dependency

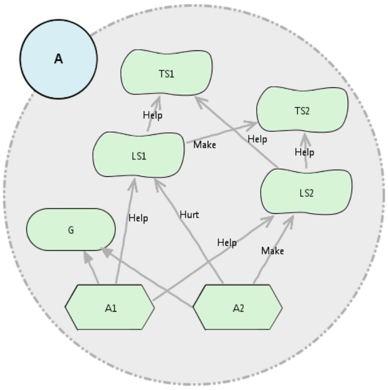

FIGURE 3. A simple SR model

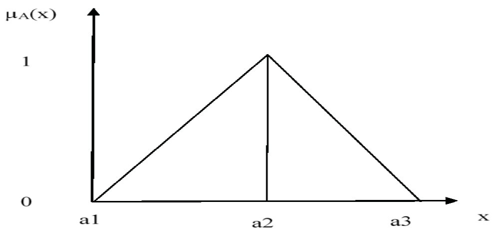

FIGURE 4. Membership functions of triangular fuzzy numbers

relationships with other actors. The score of leaf softgoals $S_{(LS_1)}, S_{(LS_2)}$ for A_1 alternative is represented as follows:

$$S_{LS_{1A_1}} = Help * \omega_{L_1}$$
$$S_{LS_{2A_1}} = Help * \omega_{L_2}$$

The score of leaf softgoals $S_{(LS_1)}, S_{(LS_2)}$ for A_2 alternative is represented as follows:

$$S_{LS_{1A_2}} = Hurt * \omega_{L_1}$$
$$S_{LS_{2A_2}} = Make * \omega_{L_2}$$

The score of top softgoals $S_{(TS_1)}, S_{(TS_2)}$ for alternatives A_1, A_2 is represented as follows:

$$S_{TS_{1A_1}} = Help * S_{LS_{1A_1}} + Help * S_{LS_{2A_1}}$$
$$S_{TS_{2A_1}} = Make * S_{LS_{1A_1}} + Help * S_{LS_{2A_1}}$$
$$S_{TS_{1A_2}} = Help * S_{LS_{1A_2}} + Help * S_{LS_{2A_2}}$$
$$S_{TS_{2A_2}} = Make * S_{LS_{1A_2}} + Help * S_{LS_{2A_2}}$$

For further details on how to generate scores, readers are directed to [26, 48]. These scores of top softgoals are then applied to determine the multi-objective optimisation functions under different alternatives.

For formalisation, Strategic Rationale (SR) model is considered as a directed graph which is represented as $G(N, R)$, where N represents the intentional elements such as goals, softgoals, resources and tasks that form a set of nodes and R represents the means-end link, task decomposition link, dependency link or contribution link that form a set of edges of the graphs [55].

The approach is illustrated with the telemedicine case study (Figure 2) as a running example. The task of a decision-maker is to choose an ideal alternative option from the choices. An objective function for each choice can be generated based on the elements of the graph. Given an i^* goal model, our aim is to select the best alternative option according to each of its impact on softgoals.

Firstly, the scores of each top softgoals of each actor based on its inter-actor dependency under each

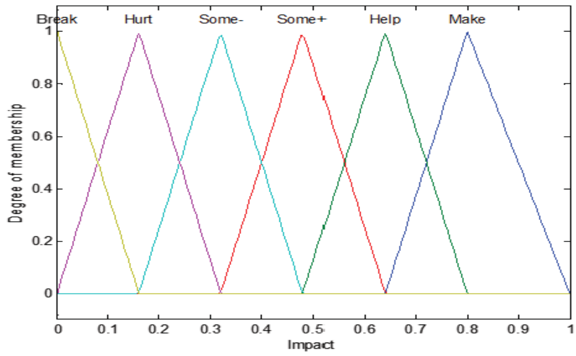

FIGURE 5. Membership function values of impacts adapted from [26]

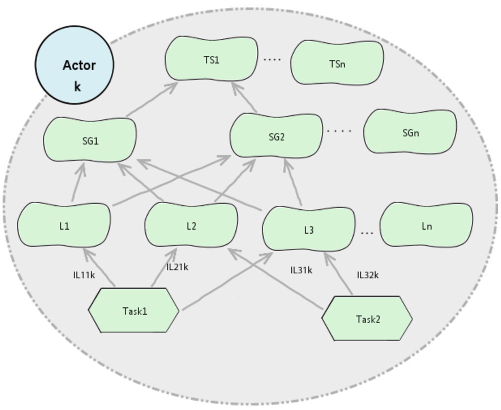

FIGURE 6. Directed graph representation of SR model for an actor with dependency

alternative is calculated. Consider a node that represents a leaf softgoal in the i^* model. Let $\omega_{L_{ik}}$ represents the weight of i^{th} leaf softgoal of k^{th} actor. From Figure 6, $I_{L_{ijk}}$ means the impact on i^{th} leaf softgoal of j^{th} alternative. Let $\omega_{L_{ijk}}$ represents the weight of i^{th} leaf softgoal for actor k at level zero. Then the score of i^{th} leaf softgoal for j^{th} alternative for the k^{th} actor is as follows:

$$S_{L_{ijk}} = I_{L_{ijk}} * \omega_{L_{ijk}} + \sum_{d_{L_i}=1}^{n_{d_i}} (S_{d_{L_i}} * I_{d_{L_i}}) \qquad (6)$$

where $S_{d_{L_i}}$ is the score of $d_L{}^{th}$ dependent for the i^{th} leaf softgoal, $I_{d_{L_i}}$ is the $d_L{}^{th}$ dependent impact for the i^{th} leaf softgoal and n_{d_i} is the number of dependencies for the i^{th} leaf softgoal (i.e., at level zero).

Telemedicine case study: For each actor *Patient* and *Healthcare Provider*, leaf softgoals are assigned an individual weight that can optimally select the best alternative option for achieving the opposing goals. Let the individual weights of leaf softgoals such as *Time Saving*, *Quality of Care*, *Efficient Operations* and *Effective Treatments* be ω_1, ω_2, ω_3 and ω_4 respectively. To improve the readability in writing, certain terms in telemedicine case study are abbreviated as shown in Table 1. The scores of the leaf softgoals for both actors, *Patient* and *Healthcare Provider*, under the alternative, *Patient Centered Care*, are calculated

TABLE 1. Abbreviation of terms in telemedicine system

Terms	Abbreviation
$Patient$	P
$Healthcare\ Provider$	HCP
$Time\ Saving$	TS
$Quality\ of\ Care$	QoC
$Expense$	E
$Happiness$	H
$Viable\ Healthcare\ Service$	VHS
$Maintenance\ Cost$	MC
$Efficient\ Operations$	EO
$Effective\ Treatments$	ET
$Patient\ Centered\ Care$	$PaCC$
$Provider\ Centered\ Care$	$PrCC$

as follows:

$$\begin{aligned} S_{TS_{PaCC}} &= Help * \omega_1 \\ S_{QoC_{PaCC}} &= Help * \omega_2 + make * (S_{VHS_{PaCC}}) \\ S_{EO_{PaCC}} &= Hurt * \omega_3 \\ S_{ET_{PaCC}} &= Some + * \omega_4 \end{aligned}$$

The scores for the leaf softgoals for both actors, $Patient$ and $Healthcare\ Provider$, under the alternative, $Provider\ Centered\ Care$ are calculated as follows:

$$\begin{aligned} S_{TS_{PrCC}} &= Hurt * \omega_1 \\ S_{QoC_{PrCC}} &= Make * \omega_2 + make * (S_{VHS_{PrCC}}) \\ S_{EO_{PrCC}} &= Help * \omega_3 \\ S_{ET_{PrCC}} &= Help * \omega_4 \end{aligned}$$

Consider the case of t hierarchy levels in the directed graph, with leaf softgoals at level zero. Then, at level $t = 1$, the score of the i^{th} softgoal for j^{th} alternative for actor k is shown below.

$$S_{SG_{i_1jk}} = \sum_{x=1}^{n_c} (I_x * S_{L_{xjk}}) + \sum_{d_{i1}=1}^{n_i} (S_{d_{i1}} * I_{d_{i1}}) \tag{7}$$

where n_c is the number of children for each i^{th} softgoal at level $t = 1$ and n_i is the number of dependencies at level $t = 1$ for i^{th} softgoal.

Since the score of softgoals at level $t = 1$ depends on the score of their leaf softgoal, equation 7 can be rewritten as:

$$\begin{aligned} S_{SG_{i_1jk}} &= I_1 * S_{L_{1jk}} + I_2 * S_{L_{2jk}} + \ldots\ldots\ldots \\ &+ I_{n_c} * S_{L_{ncjk}} + \sum_{d_{i1}=1}^{n_i} (S_{d_{i1}} * I_{d_{i1}}) \end{aligned} \tag{8}$$

Substituting with equation 6, equation 8 becomes

$$\begin{aligned} S_{SG_{i_1jk}} = I_1 * (I_{L_{1jk}} * \omega_{L_{1jk}} + \sum_{d_{L_1}=1}^{n_{d_1}} (S_{d_{L_1}} * I_{d_{L_1}})) \\ + I_2 * (I_{L_{2jk}} * \omega_{L_{2jk}} + \sum_{d_{L_2}=1}^{n_{d_2}} (S_{d_{L_2}} * I_{d_{L_2}})) + \ldots\ldots\ldots \\ + I_{n_c} * (I_{L_{n_c}} jk * \omega_{L_{n_c}} jk + \sum_{d_{L_{n_c}}=1}^{n_{d_{n_c}}} (S_{d_{L_{n_c}}} * I_{d_{L_{n_c}}})) \\ + \sum_{d_{i1}=1}^{n_i} (S_{d_{i1}} * I_{d_{i1}}) \end{aligned} \tag{9}$$

In this way it propagates upwards. At level 1, if there are m number of softgoals, n_c children and n_d dependencies for the i^{th} softgoal, then any softgoal's score at higher level ($t > 1$) is found as the product of its impact and each child's score.

Therefore, the softgoal's score at any level t for an actor with a dependency relationship can be generalised as:

$$\begin{aligned} S_{SG_{i_tjk}} = \Pi_{l=1}^{t} I_{ijl} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{ij}} * I_{d_{L_{ijk}}} * \omega_{d_{L_{ijk}}})] \\ + \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (S_{i_{d_{by}}} * I_{i_{d_{by}}})) + \sum_{b=1}^{n_d} (S_{i_{d_b}} \\ * I_{i_{d_b}})] \end{aligned} \tag{10}$$

Then the objective function of top softgoals under each alternative for each actor is created from the scores as shown in equation 10.

As discussed in Section 2, SD model shows a high-end explanation that focuses on the inter-dependency between actors of a system. Also, SR model help in demonstrating the analysis of each actor in the system based on their intentional inter-dependencies. In the proposed approach, the inter-actor dependency relationship is considered for selecting the optimal alternative to achieve the opposing goals. So, it is necessary to consider both SD model and SR model of the i^* goal model with the assumption that only softgoal inter-dependency relationship is taken into account in this approach.

Telemedicine case study: For actor $Patient$, the score of top softgoals, $Expense$ and $Happiness$ under both alternatives $Patient\ Centered\ Care$ and $Provider\ Centered\ Care$ are calculated. Since the actor $Patient$ has a softgoal dependency on the actor $Healthcare\ Provider$, then the score of $Viable\ Healthcare\ Service$ should be considered for calculating the score of top softgoals, $Expense$ and $Happiness$, of actor $Patient$. Also, for simplicity of calculation, defuzzification is used

TABLE 2. Impact values

Impact	Fuzzy value	Defuzzified value
Hurt	(0, 0.16, 0.32)	0.16
Make	(0.64, 0.8, 1)	0.8
Some−	(0.16, 0.32, 0.48)	0.32
Some+	(0.32, 0.48, 0.64)	0.48
Break	(0, 0, 0.16)	0
Help	(0.48, 0.64, 0.80)	0.64

to convert the impacts which are represented in fuzzy numbers to quantifiable values [56]. These defuzzified values shown in Table 2 are used to evaluate the scores of each softgoal.

For actor *Healthcare Provider*, the score of top softgoals, *Viable Healthcare Service* and *Maintenance Cost* under both alternatives are calculated as:

$$\begin{aligned} S_{VHS_{PaCC}} &= Help * S_{EO_{PaCC}} + Help * S_{ET_{PaCC}} \\ &= 0.64 * (0.16 * \omega_3) + 0.64 * (0.48 * \omega_4) \\ &= 0.1024 * \omega_3 + 0.3072 * \omega_4 \end{aligned}$$

$$\begin{aligned} S_{MC_{PaCC}} &= Help * S_{EO_{PaCC}} + Make * S_{ET_{PaCC}} \\ &= 0.64 * (0.16 * \omega_3) + 0.8 * (0.48 * \omega_4) \\ &= 0.1024 * \omega_3 + 0.384 * \omega_4 \end{aligned}$$

$$\begin{aligned} S_{VHS_{PrCC}} &= Help * S_{EO_{PrCC}} + Help * S_{ET_{PrCC}} \\ &= 0.64 * (0.64 * \omega_3) + 0.64 * (0.64 * \omega_4) \\ &= 0.4096 * \omega_3 + 0.4096 * \omega_4 \end{aligned}$$

$$\begin{aligned} S_{MC_{PrCC}} &= Help * S_{EO_{PrCC}} + Make * S_{ET_{PrCC}} \\ &= 0.64 * (0.64 * \omega_3) + 0.8 * (0.64 * \omega_4) \\ &= 0.4096 * \omega_3 + 0.512 * \omega_4 \end{aligned}$$

For actor *Patient*, the score of top softgoals, *Expense* and *Happiness* under both alternatives are calculated as:

$$\begin{aligned} S_{E_{PaCC}} &= Help * S_{TS_{PaCC}} + Help * S_{QoC_{PaCC}} \\ &= 0.64 * (0.64 * \omega_1) + 0.64 * (0.8 * \omega_2 \\ &+ 0.8 * (0.1024 * \omega_3 + 0.3072 * \omega_4)) \\ &= 0.4096 * \omega_1 + 0.512 * \omega_2 \\ &+ 0.0524 * \omega_3 + 0.1573 * \omega_4 \end{aligned}$$

$$\begin{aligned} S_{H_{PaCC}} &= Make * S_{T_{PaCC}} + Help * S_{QoC_{PaCC}} \\ &= 0.8 * (0.64 * \omega_1) + 0.8 * (0.64 * \omega_2 \\ &+ 0.8 * (0.1024 * \omega_3 + 0.3072 * \omega_4)) \\ &= 0.512 * \omega_1 + 0.64 * \omega_2 \\ &+ 0.0656 * \omega_3 + 0.1966 * \omega_4 \end{aligned}$$

$$\begin{aligned} S_{E_{PrCC}} &= Help * S_{TS_{PrCC}} + Help * S_{QoC_{PrCC}} \\ &= 0.64 * (0.16 * \omega_1) + 0.64 * (0.8 * \omega_2) \\ &+ 0.8 * (0.4096 * \omega_3 + 0.4096 * \omega_4)) \\ &= 0.1024 * \omega_1 + 0.512 * \omega_2 \\ &+ 0.2097 * \omega_3 + 0.2097 * \omega_4 \end{aligned}$$

$$\begin{aligned} S_{H_{PrCC}} &= Make * S_{TS_{PrCC}} + Help * S_{QoC_{PrCC}} \\ &= 0.8 * (0.16 * \omega_1) + 0.8 * (0.8 * \omega_2) \\ &+ 0.8 * (0.4096 * \omega_3 + 0.4096 * \omega_4)) \\ &= 0.128 * \omega_1 + 0.64 * \omega_2 \\ &+ 0.2 * \omega_3 + 0.2621 * \omega_4 \end{aligned}$$

Consider that if there are n number of alternative options for an actor, then there are n objective functions for each top softgoal. To obtain maximum score for the top softgoal under each alternative, the n objective functions that have to be maximised are given as:

$$\begin{aligned} f_i(\omega_1) &= S_{SG_{i1k}} \\ &= Max\Pi_{l=1}^{t} I_{i1l} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{i1}} * I_{d_{L_{i1k}}} * \omega_{d_{L_{i1k}}})] \\ &+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i_{d_{by}}})) \\ &+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i_{d_b}})] \\ f_i(\omega_2) &= S_{SG_{i2k}} \\ &= Max\Pi_{l=1}^{t} I_{i2l} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{i2}} * I_{d_{L_{i2k}}} * \omega_{d_{L_{i2k}}})] \\ &+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i_{d_{by}}})) \\ &+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i_{d_b}})] \\ &\ldots\ldots\ldots\ldots \\ &\ldots\ldots\ldots\ldots \\ &\ldots\ldots\ldots\ldots \\ f_i(\omega_n) &= S_{SG_{ink}} \\ &= Max\Pi_{l=1}^{t} I_{inl} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{in}} * I_{d_{L_{ink}}} * \omega_{d_{L_{ink}}})] \\ &+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i_{d_{by}}})) \\ &+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i_{d_b}})] \end{aligned} \tag{11}$$

where

$$0 \leq \omega_{d_{L_{jk}}} \leq 100 \text{ for } d = 1 \text{ to } n_c$$

Correspondingly, the objective functions for all other actors that have to be maximised are formalised. Likewise, the objective functions that have to be minimised for each actor are formalised.

The next section explains how the multi-objective functions of opposing goals (Maximum and Minimum in nature) are optimised using game theory.

5.2. Application of game theory for multi-objective optimisation of the i* goal model

Game theory is a method developed in the mathematics domain whereby players' strategies are assessed equally according to the environmental factors. In the proposed approach, the goals with conflicting objectives are considered as the game players and the alternative design options (tasks) are treated as the game strategies [51]. Initially, the application of game theory from the actors' perspective having opposing objectives is investigated with the assumption that each actor in the goal model has the same set of alternative options for achieving his/her opposing objectives.

Consider that actor X in the i^* goal model has two softgoals TS_1 and TS_2 of opposing objectives. Consider TS_1's objective is to be maximised and TS_2's objective is to be minimised. From the game theory point of view, these top softgoals TS_1 and TS_2 are considered as being the two game players and the alternatives are the strategies of the players. If there are n alternatives, then TS_1 has strategies $A_1, A_2, ..., A_n$ and TS_2 has strategies $A_1, A_2, ..., A_n$. Of these, the best alternative is the one that can maximise TS_1 and minimise TS_2 simultaneously. The multi-objective optimisation function of each opposing goal under each alternative for each actor are generated based on the equation 10.

From equation 11, the multi-objective optimisation function of i^{th} top softgoal for an actor k, with dependency relationship for j^{th} alternative is written as:

$$\begin{aligned} f_i(\omega_j) &= S_{SG_{ijk}} \\ &= Max\Pi_{l=1}^{t} I_{ijl} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{ij}} * I_{d_{L_{ijk}}} * \omega_{d_{L_{ijk}}})] \\ &+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i_{d_{by}}})) \\ &+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i_{d_b}})] \end{aligned} \tag{12}$$

For the first top softgoal, TS_1, of an actor X, the multi-objective optimisation function with first alternative A_1 can be written as:

$$\begin{aligned} F_{TS_1}(\omega_{A_1}) &= S_{TS1_{A_1}} \\ &= Max\Pi_{l=1}^{t} I_{TS1_{A_1}l} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{iA_1}} \\ &* I_{d_{L_{iA_1x}}} * \omega_{d_{L_{iA_1x}}})] \\ &+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i_{d_{by}}})) \\ &+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i_{d_b}})] \end{aligned} \tag{13}$$

Similarly for second alternative, third alternative and so on.

$$F_{TS_1}(\omega_{A_2}), F_{TS_1}(\omega_{A_3}), ..., F_{TS_1}(\omega_{A_n}) \tag{14}$$

Likewise, the multi-objective functions for the second softgoal, TS_2, which is to be minimised can be written as:

$$\begin{aligned} F_{TS_2}(\omega_{A_1}) &= S_{TS2_{A_1}} \\ &= Min\Pi_{l=1}^{t} I_{TS2_{A_1}l} \sum_{i=1}^{m}((\sum_{d=1}^{n_c}(I_{diA_1} * I_{d_{L_{iA_1x}}} \\ &* \omega_{d_{L_{iA_1x}}})) \\ &+ \sum_{i=1}^{m}(\sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{dbyi} * I_{dbyi}))) \\ &+ \sum_{i=1}^{m}(\sum_{b=1}^{n_d}(S_{dbi} * I_{dbi}))) \end{aligned} \tag{15}$$

Similarly for

$$F_{TS_2}(\omega_{A_2}), F_{TS_2}(\omega_{A_3}), ..., F_{TS_2}(\omega_{A_n}) \tag{16}$$

The multi-objective functions of TS_1 that should be maximised (from equations 13 and 14) are written as:

$$Max(F_{TS_1}(\omega_{A_1}), F_{TS_1}(\omega_{A_2}), ..., F_{TS_1}(\omega_{A_n})) \tag{17}$$

where $n > 1$ and w an element of y where y is a constraint set.

Similarly the multi-objective functions of TS_2 (from equations 15 and 16) are written as:

$$Min(F_{TS_2}(\omega_{A_1}), F_{TS_2}(\omega_{A_2}), ..., F_{TS_2}(\omega_{A_n})) \tag{18}$$

where $n > 1$ and w an element of y where y is the set of constraint.

Telemedicine case study: For actor *Patient*, the objective functions for both the top softgoals, under the two alternatives *Patient Centered care* and *Provider*

Centered care, are given using equations 13 and 15, based on their scores are as follows:

$$\begin{aligned} F_{TS_2}(\omega)_{A_1} &= F_E(\omega)_{PaCC} \\ &= Min(S_{E_{PaCC}}) \\ &= Min(0.4096 * \omega 1 + 0.512 * \omega_2 \\ &+ 0.0524 * \omega_3 + 0.1573 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_2}(\omega)_{A_2} &= F_E(\omega)_{PrCC} \\ &= Min(S_{E_{PrCC}}) \\ &= Min(0.1024 * \omega_1 + 0.512 * \omega_2 \\ &+ 0.2097 * \omega_3 + 0.2097 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_1}(\omega)_{A_1} &= F_H(\omega)_{PaCC} \\ &= Max(S_{H_{PaCC}}) \\ &= Max(0.512 * \omega_1 + 0.64 * \omega_2 \\ &+ 0.0656 * \omega_3 + 0.1966 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_1}(\omega)_{A_2} &= F_H(\omega)_{PrCC} \\ &= Max(S_{H_{PrCC}}) \\ &= Max(0.128 * \omega_1 + 0.64 * \omega_2 \\ &+ 0.2621 * \omega_3 + 0.2621 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_1}(\omega)_{A_1} &= F_{VHS}(\omega)_{PaCC} \\ &= Max(S_{VHS_{PaCC}}) \\ &= Max(0.1024 * \omega_3 + 0.3072 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_1}(\omega)_{A_2} &= F_{VHS}(\omega)_{PrCC} \\ &= Max(S_{VHS_{PrCC}}) \\ &= Max(0.4096 * \omega_3 + 0.4096 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_2}(\omega)_{A_2} &= F_{MC}(\omega)_{PaCC} \\ &= Min(S_{MC_{PaCC}}) \\ &= Min(0.128 * \omega_3 + 0.384 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_2}(\omega)_{A_2} &= F_{MC}(\omega)_{PrCC} \\ &= Min(S_{MC_{PrCC}}) \\ &= Min(0.512 * \omega_3 + 0.512 * \omega_4) \end{aligned}$$

To obtain the optimal strategies for player's having opposing objectives, the following listed steps are carried out.

Step 1: Evaluation of the optimal solutions of multi-objective optimisation functions of opposing top softgoals

Step 2: Objective integrated game theoretic approach for pay-off matrix transformations

TABLE 3. Maximum Objective functions values representation

Maximum Objective Function Values	X	Y
$F_{TS1_{A_1}}$	$x_{TS_1A_1}$	$y_{TS_1A_1}$
$F_{TS1_{A_2}}$	$x_{TS_1A_2}$	$y_{TS_1A_2}$

TABLE 4. Minimum Objective functions values representation

Minimum Objective Function Values	X	Y
$F_{TS2_{A_1}}$	$x_{TS_2A_1}$	$y_{TS_2A_1}$
$F_{TS2_{A_2}}$	$x_{TS_2A_2}$	$y_{TS_2A_2}$

Step 3: Unification process for decision pay-off matrix formation

Step 4: Application of linear programming model to obtain optimal strategy including decision-making

Above steps are now explained in detail in the following subsections with the simplified telemedicine system.

5.2.1. *Optimal solutions for multi-objective optimisation functions*

Optimising the objective functions individually can generate ideal solutions. The IBM ILOG CPLEX Optimisation Studio (often informally referred to simply as CPLEX) is used for evaluating the optimisation model using game theory. The IBM ILOG CPLEX Optimisation tool is an optimisation software package. The name "CPLEX" is a combination of two words, Simplex algorithm and C programming language. Simplex algorithm (or simplex method) is a popular algorithm for linear programming as implemented in the C programming language. It is applied for solving mathematical business models by utilising powerful algorithms to acquire precise and logical decisions [57]. Furthermore, IBM ILOG CPLEX has a modelling layer called Concert that empowers interfacing with Java, C++ and C# languages [57].

Let the ideal solutions for the objective functions in equation 17 and equation 18 be expressed as:

$$\begin{aligned} &(x_{TS_1A_1}, x_{TS_1A_2}, x_{TS_1A_3}, ..., x_{TS_1A_n}, \\ &x_{TS_2A_1}, x_{TS_2A_2}, x_{TS_2A_3}, ..., x_{TS_2A_n}) \end{aligned} \tag{19}$$

with

$$(x_{TS_1A_1}, x_{TS_1A_2}, x_{TS_1A_3}, ..., x_{TS_1A_n}) \tag{20}$$

representing the solution to equation 17 and

$$(x_{TS_2A_1}, x_{TS_2A_2}, x_{TS_2A_3}, ..., x_{TS_2A_n}) \tag{21}$$

representing the solution to equation 18.

Likewise, the multi-objective function values are generated for all the actors in the goal model and are

TABLE 5. Maximum objective function values for each actors in telemedicine system

Maximum functions	Patient	Healthcare Provider
$F_{TS1_{A_1}}$	64	30.72
$F_{TS1_{A_2}}$	64	40.96

TABLE 6. Minimum objective function values for each actors in telemedicine system

Minimum functions	Patient	Healthcare Provider
$F_{TS2_{A_1}}$	5.24	12.8
$F_{TS2_{A_2}}$	10.24	51.2

shown in Tables 3 and 4.

Telemedicine case study: The multi-objective function values for each actor for the telemedicine case study is illustrated in Tables 5 and 6.

5.2.2. Generation of pay-off matrices for each player

The pay-off of a game is characterised as the quantifiable value that each player gets by choosing a particular strategy. Pay-off matrix is used for representing all the possible outcomes in the game with both player's possible strategies. By analysing the pay-off matrix, optimal strategy is obtained. In this section, the objective function values of top softgoals are integrated for all actors in the goal model that are of the same nature (for example maximise) under each alternative to generate the pay-off matrix for each nature.

For generating the pay-off matrix according to the objective function values, let's assume another actor Y in the same goal model which has an inter-actor dependency relationship with actor X. Also, assume both actors X and Y has the same alternative options (A_1 and A_2) for reaching their opposing top softgoals (TS_1 and TS_2). The optimal function values that are of maximum in nature for each actor are represented in Table 3. The optimal function values that are of minimum in nature for each actor are represented in Table 4.

According to the optimal function values shown in Tables 3 and 4, the pay-off matrices, TS_{Max} and TS_{Min}, are generated for each top softgoal that has an opposing nature. The sum of the objective function values of the same nature under each alternative for all actors produces the pay-off matrix for each nature.

Now the pay-off matrix $P_{TS_{Max}}$ for the top softgoal TS_{Max} has to be maximised for two actors X and Y under n number of alternatives is generalised as:

$$\mathbf{P_{TS_{Max}}} = \begin{array}{c} \\ A_1 \\ A_2 \\ \\ \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & & A_n \end{array} \\ \begin{pmatrix} p_{A_1A_1} & p_{A_1A_2} & .... & p_{A_1A_n} \\ p_{A_2A_1} & p_{A_2A_2} & .... & p_{A_2A_n} \\ .... & .... & .... & .... \\ .... & .... & .... & .... \\ p_{A_nA_1} & p_{A_nA_2} & .... & p_{A_nA_n} \end{pmatrix} \end{array}$$

where

$$\begin{aligned} &p_{A_1A_1} = x_{TS_1A_1} + y_{TS_1A_1} \\ &p_{A_2A_1} = x_{TS_2A_1} + y_{TS_1A_1} \\ &.. \\ &.. \\ &p_{A_iA_j} = x_{TS_1A_i} + y_{TS_1A_j}, \text{ for } i, j = 1 \text{ to } n \end{aligned} \tag{22}$$

Consider there are s number of actors in an i^* goal model, in such a way that each of the k ($<= s$) actor's has the same set of n number of alternatives. Each element in the final pay-off matrix of top softgoal, that has to be maximised, can be generated as shown below:

$$\sum_{i,j=1}^{k} a^{ij}_{A_l,A_r} \tag{23}$$

where

$$A_l \geq 0 \text{ for } l = 1 \text{ to } n$$
$$A_r \geq 0 \text{ for } r = 1 \text{ to } n$$

where a^{ij} denote an element of the pay-off matrix of every combination of i^{th} and j^{th} actor of k resulting from choosing the l^{th} and r^{th} alternative of n.

Similarly, the pay-off matrix $P_{TS_{Min}}$ for the top softgoal TS_{Min} has to be minimised for two actors X and Y under n number of alternatives is generalised as:

$$\mathbf{P_{TS_{Min}}} = \begin{array}{c} \\ A_1 \\ A_2 \\ .. \\ .. \\ A_n \end{array} \begin{array}{c} \begin{array}{cccc} A_1 & A_2 & .. & A_n \end{array} \\ \begin{pmatrix} q_{A_1A_1} & q_{A_1A_2} & .... & q_{A_1A_n} \\ q_{A_2A_1} & q_{A_2A_2} & .... & q_{A_2A_n} \\ .... & .... & .... & .... \\ .... & .... & .... & .... \\ q_{A_nA_1} & q_{A_nA_2} & .... & q_{A_nA_n} \end{pmatrix} \end{array}$$

where

$$\begin{aligned} &q_{A_1A_1} = x_{TS_2A_1} + y_{TS_2A_1} \\ &q_{A_2A_1} = x_{TS_2A_2} + y_{TS_2A_1} \\ &.. \\ &.. \\ &q_{A_iA_j} = x_{TS_2A_i} + y_{TS_2A_j}, \text{ for } i, j = 1 \text{ to } n \end{aligned} \tag{24}$$

If there are s number of actors in an i^* goal model, in such a way that $k(<= s)$ actors have the same set of n

number of alternatives, then each element in the final pay-off matrix of top softgoal that has to be minimised is obtained as:

$$\sum_{i,j=1}^{k} a^{ij}_{A_l,A_r} \tag{25}$$

where

$$A_l \geq 0 \text{ for } l = 1 \text{ to } n$$
$$A_r \geq 0 \text{ for } r = 1 \text{ to } n$$

where a^{ij} denote the pay-off matrix of every combination of i^{th} and j^{th} actor of k resulting from choosing the l^{th} and r^{th} alternative of n.

Telemedicine case study: Therefore the pay-off matrix that maximises the top softgoals, $P_{TS_{Max}}$ (player 1) of telemedicine system using equation 22 is given as:

$$\mathbf{P_{TS_{Max}}} = \begin{pmatrix} 94.72 & 104.96 \\ 94.72 & 104.96 \end{pmatrix} \tag{26}$$

Therefore the pay-off matrix that minimise the top softgoals, $P_{TS_{Min}}$ (player 2) of the telemedicine system using equation 24 is given as:

$$\mathbf{P_{TS_{Min}}} = \begin{pmatrix} 18.04 & 56.44 \\ 23.04 & 61.44 \end{pmatrix} \tag{27}$$

5.2.3. Generation of decision pay-off matrix

To achieve the overall objective of opposing goals simultaneously, the pay-off matrices which are obtained separately for each player should be merged together. As mentioned in the methodology, objectives have different importance (opposing). The strategies for the opposing objectives are evaluated based on their contributions to them. To discover all objectives simultaneously and to accomplish the overall objective, is the critical task in any decision-making process. Thus, the pay-off matrices formed individually for each player should be integrated together. This process of integrating objectives with their degree of importance based on alternatives is called the unification process. The optimal strategy is then obtained by analysing these unified pay-off matrices that contains both maximising and minimising multi objective function values.

Now, using matrices in equations 22 and 24, the unified pay-off matrix P that contains both the maximising and minimising multi-objective function values is represented as:

$\mathbf{P} =$

$$\begin{array}{c c} & \begin{array}{cccc} A_1 & A_2 & .. & A_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ .. \\ .. \\ A_n \end{array} & \begin{pmatrix} (p_{A_1A_1}, q_{A_1A_1}) & (p_{A_1A_2}, q_{A_1A_2}) & .. & (p_{A_1A_n}, q_{A_1A_n}) \\ (p_{A_2A_1}, q_{A_2A_1}) & (p_{A_2A_2}, q_{A_2A_2}) & .. & (p_{A_2A_n}, q_{A_2A_n}) \\ .. & .. & .. & .. \\ .. & .. & .. & .. \\ (p_{A_nA_1}, q_{A_nA_1}) & (p_{A_nA_2}, q_{A_nA_2}) & .. & (p_{A_nA_n}, q_{A_nA_n}) \end{pmatrix} \end{array}$$

i.e.,

$$\mathbf{P} = \begin{array}{c c} & \begin{array}{cccc} A_1 & A_2 & .. & A_n \end{array} \\ \begin{array}{c} A_1 \\ A_2 \\ .. \\ .. \\ A_n \end{array} & \begin{pmatrix} z_{A_1A_1} & z_{A_1A_2} & .... & z_{A_1A_n} \\ z_{A_2A_1} & z_{A_2A_2} & .... & z_{A_2A_n} \\ .... & .... & .... & .... \\ .... & .... & .... & .... \\ z_{A_nA_1} & z_{A_nA_2} & .... & z_{A_nA_n} \end{pmatrix} \end{array}$$

where

$$\begin{gathered} z_{A_1A_1} = p_{A_1A_1} + q_{A_1A_1} \\ \dots\dots\dots\dots\dots\dots\dots\dots\dots\dots \\ z_{A_iA_j} = p_{A_iA_j} + q_{A_iA_j}, \text{ for } i,j = 1 \text{ to } n \end{gathered} \tag{28}$$

Telemedicine case study: From the above matrices, $P_{TS_{Max}}$ and $P_{TS_{Min}}$, the decision pay-off matrix is created for the telemedicine system using equation 28 and is given as:

$$\mathbf{P} = \begin{pmatrix} 112.76 & 161.4 \\ 117.76 & 166.4 \end{pmatrix} \tag{29}$$

When analysing a game, if player's uses the same strategy at each round of the game, then it is called a pure strategy game. To obtain a solution of a zero-sum game with pure strategies, it is feasible to find out the best strategies for player's through the saddle point calculation which is explained in the next paragraph.

Consider the decision pay-off matrix generated as shown in equation 28. The element $z_{A_iA_j}$ is called a *saddle point* of the matrix P if

$$\begin{gathered} z_{A_iA_j} \leq z_{A_iA_l} \ \forall l = 1, .., n \text{ and} \\ z_{A_iA_j} \geq z_{A_kA_j} \ \forall k = 1, .., n. \end{gathered} \tag{30}$$

That is, the element $z_{A_iA_j}$ is simultaneously a minimum in its row and a maximum in its column. If (i, j) is a saddle point of a given game matrix, then the pay-off that the row player gets in the saddle point is called the value of the game and it corresponds to *pure strategy Nash equilibrium* of the game. In our reasoning, we made a rather subtle assumption that each player uses mixed strategies instead of pure strategies.

In the case of mixed strategy Nash equilibrium, the value of the game can be obtained by applying primal linear programming. The following sub-section explains how the value of the game can be obtained using linear programming.

5.2.4. Linear programming model to obtain optimal strategy and decision-making

In zero-sum games, the total benefit to all players, for every combination of strategies, always adds to zero. The pay-off of one player is the negative of the pay-off of the other player [58]. Two-person zero-sum games play a central role in the development of the theory of games, but it is difficult to solve two-person matrix game with the order m x n ($m \geq 3$, $n \geq 3$). The connection with linear programming was discovered by von Neumann in 1947 [59] helped to solve two-person matrix game of higher order. The Minmax theorem is a simple consequence of the Duality Theorem of linear programming [60]. So using linear programming techniques, two-person zero-sum games can be solved. Mixed strategies must exist for two-player zero-sum games had been proven by John von Neumann and Oskar Morgenstern [61]. In this sub-section, we solve a two-person zero-sum game having mixed strategies by applying linear programming approach.

In the last phase of our proposed approach, we obtained the unified decision pay-off matrix. In order to obtain the proposed optimal strategy, the operation research technique of linear programming is applied. Thus a linear programming model is built in the proposed approach according to the decision pay-off matrix in equation 28, which is formed with the integration of objective function solutions. The value of the game is defined as the pay-off to player 1 when both players play optimally [52].

Based on the two-player zero-sum game theoretic approach, the player 1, who needs to maximise his gain, follows the Maxmin strategy and the player 2, follows Minmax strategy. Based on the decision pay-off matrix given in equation 28, if the softgoal 1 (player 1) uses A_1, $z_{A_1A_1}$ proportion of times, A_2, $z_{A_2A_1}$ proportion of times, ... and An, $z_{A_nA_1}$ proportion of times with softgoal 2 (player 2) consistently having A_1, then player 1's gain will be

$$z_{A_1A_1} * A_1 + z_{A_2A_1} * A_2 + .. + z_{A_nA_1} * A_n \tag{31}$$

Generally, using A_n, then the player 1's gain will be

$$z_{A_1A_n} * A_1 + z_{A_2A_n} * A_2 + .. + z_{A_nA_n} * A_n \tag{32}$$

Softgoal 1 knows that it has to maximise the minimum that it will get. Since it is linear, the minimum that softgoal 1 will get lie in equation 31 or 32 or it is the point of intersection of these equations. This implies that, the top softgoal (TS_{Max}) needs to be maximised. Therefore, player 1 follows Maxmin strategy. The inexact values in the goal programming model reflect the vagueness or tolerance of the decision maker as well as the imprecision of experts knowledge. To obtain the optimum value, we include a tolerance value in each constraints to keep all the constraints with consequent variations inside their bounds. Thus a product of tolerance value and value of the game is subtracted from each constraints to eliminate the maximum acceptable absolute violation in maximum optimal value [62].

Let's assume v be the value of the game, $\bar{v}$ be the maximum value of the game, $\underline{v}$ be the minimum value of the game, $u = \bar{v} - \underline{v}$ be tolerance value for TS_{Max}. The formulation of Maxmin strategy of player 1 is given as follows:

Max v

Subject to the linear constraints

$$\begin{aligned} -u*v + z_{A_1A_1} * A_1 + z_{A_2A_1} * A_2 + ...+ \\ z_{A_nA_1} * A_n \geq \bar{v} \\ -u*v + z_{A_1A_2} * A_1 + z_{A_2A_2} * A_2 + ...+ \\ z_{A_nA_2} * A_n \geq \bar{v} \\ .... \\ .... \\ -u*v + z_{A_1A_n} * A_1 + z_{A_2A_n} * A_2 + ...+ \\ z_{A_nA_n} * A_n \geq \bar{v} \end{aligned} \tag{33}$$

$$\sum_{i=1}^{n} A_i = 1;$$
$$A_i \geq 0 \text{ for } i = 1 \text{ to } n$$

Similarly, in the case of player 2, top softgoal 2 (TS_{Min}), needs to be minimised. Therefore, it follows Minmax strategy. Based on the decision pay-off matrix given in equation 28, if the softgoal 2 (player 2) uses A_1, $z_{A_1A_1}$ proportion of times, A_2, $z_{A_1A_2}$ proportion of times, ... and An, $z_{A_1A_n}$ proportion of times with softgoal 1 (player 2) consistently having A_1, then player 2's loss will be

$$z_{A_1A_1} * A_1 + z_{A_1A_2} * A_2 + .. + z_{A_1A_n} * A_n \tag{34}$$

Generally, using A_n, then the player 2's loss will be

$$z_{A_nA_1} * A_1 + z_{A_nA_2} * A_2 + .. + z_{A_nA_n} * A_n \quad (35)$$

Softgoal 2 knows that it has to minimise the maximum that it will get. Since it is linear, the maximum that softgoal 1 will get lie in equation 33 or 34 or it is the point of intersection of these equations. This implies that, the top softgoal (TS_{Min}) needs to be minimised. Therefore, player 2 follows Minmax strategy. The inexact values in the goal programming model reflect the vagueness or tolerance of the decision maker as well as the imprecision of experts knowledge. To obtain the optimum value, we include a tolerance value in each constraints to keep all the constraints with consequent variations inside their bounds. Thus a product of tolerance value and value of the game is subtracted from each constraints to eliminate the maximum acceptable absolute violation in minimum optimal value [62].

Let's assume w be the value of the game, $\bar{w}$ be the maximum value of the game, $\underline{w}$ be the minimum value of the game, $l = \bar{w} - \underline{w}$ be tolerance value for TS_{Min}. The formulation of Minmax strategy of player 2 is given as follows:

Min w

Subject to the linear constraints

$$\begin{aligned}
-l * w + z_{A_1A_1} * A_1 + z_{A_1A_2} * A_2 + ...+ \\
z_{A_1A_n} * A_n \leq \bar{w} \\
-l * w + z_{A_2A_1} * A_1 + z_{A_2A_2} * A_2 + ...+ \\
z_{A_2A_n} * A_n \leq \bar{w} \\
.... \\
.... \\
-l * w + z_{A_nA_1} * A_1 + z_{A_nA_2} * A_2 + ...+ \\
z_{A_nA_n} * A_n \leq \bar{w}
\end{aligned} \quad (36)$$

$$\sum_{i=1}^{n} A_i = 1;$$
$$A_i \geq 0 \text{ for } i = 1 \text{ to } n$$

By solving either formulations, the proportion values of the strategies are obtained. The optimal strategy, the one with the high proportion value, is chosen. The chosen optimal strategy can accomplish the opposing non-functional requirements of each actor simultaneously. Since the linear formulation of TS_{Min} is the dual of the linear formulation of TS_{Max}, the solution to the game is found by solving either the formulation of TS_{Max} or TS_{Min}. The duality of equations (33) and (36) is demonstrated as below.

Linear programming duality proof of two-person zero-sum game theory

Consider player 1's formulation given by equation 33 (which is called as primal). In order to find the dual of player 1's primal equation, the player 1's formulation given in equation 33 is rewritten as below:

Max v

Subject to the linear constraints

$$\begin{aligned}
\bar{v} + u * v - z_{A_1A_1} * A_1 - z_{A_2A_1} * A_2 - ...- \\
z_{A_nA_1} * A_n \leq 0 \\
\bar{v} + u * v - z_{A_1A_2} * A_1 - z_{A_2A_2} * A_2 - ...- \\
z_{A_nA_2} * A_n \leq 0 \\
.... \\
.... \\
\bar{v} + u * v - z_{A_1A_n} * A_1 - z_{A_2A_n} * A_2 - ...- \\
z_{A_nA_n} * A_n \leq 0
\end{aligned} \quad (37)$$

$$\sum_{i=1}^{n} A_i = 1;$$
$$A_i \geq 0 \text{ for } i = 1 \text{ to } n$$

Also, minimisation formulation given in equation 36 is rewritten as below:

Min w

Subject to the linear constraints

$$\begin{aligned}
\bar{w} + l * w \geq z_{A_1A_1} * A_1 + z_{A_1A_2} * A_2 + ...+ \\
z_{A_1A_n} * A_n \\
\bar{w} + l * w \geq z_{A_2A_1} * A_1 + z_{A_2A_2} * A_2 + ...+ \\
z_{A_2A_n} * A_n \\
.... \\
.... \\
\bar{w} + l * w \geq z_{A_nA_1} * A_1 + z_{A_nA_2} * A_2 + ...+ \\
z_{A_nA_n} * A_n
\end{aligned} \quad (38)$$

$$\sum_{i=1}^{n} A_i = 1;$$
$$A_i \geq 0 \text{ for } i = 1 \text{ to } n$$

The primal has $n + 1$ constraints; hence the dual will have $n + 1$ variables. Let's define dual variables as X_1, X_2, X_n, y for the constraints in equation 37 as shown below:

Max v

Subject to the linear constraints

$$\begin{aligned} X_1 : \bar{v} + u * v - z_{A_1A_1} * A_1 - z_{A_2A_1} * A_2 - ... - \\ z_{A_nA_1} * A_n \leq 0 \\ X_2 : \bar{v} + u * v - z_{A_1A_2} * A_1 - z_{A_2A_2} * A_2 - ... - \\ z_{A_nA_2} * A_n \leq 0 \\ .... \\ .... \\ X_n : \bar{v} + u * v - z_{A_1A_n} * A_1 - z_{A_2A_n} * A_2 - ... - \\ z_{A_nA_n} * A_n \leq 0 \end{aligned} \tag{39}$$

$$y : \sum_{i=1}^{n} A_i = 1;$$
$$A_i \geq 0 \text{ for } i = 1 \text{ to } n$$

The dual will be given as

$y =$ value of the game

$A_1, A_2, ..., A_n$ are the strategies

$\bar{y}$ =maximum value of the game

$\underline{y}$ =minimum value of the game

$l = \bar{y} - \underline{y}$ =tolerance value of the game

Min y

Subject to the linear constraints

$$\begin{aligned} -z_{A_1A_1} * X_1 - z_{A_1A_2} * X_2 - ... - \\ z_{A_1A_n} * X_n \geq \bar{y} + l * y \\ -z_{A_2A_1} * X_1 - z_{A_2A_2} * X_2 - ... - \\ z_{A_2A_n} * X_n \geq \bar{y} + l * y \\ .... \\ .... \\ -z_{A_nA_1} * X_1 - z_{A_nA_2} * X_2 - ... - \\ z_{A_nA_n} * X_n \geq \bar{y} + l * y \end{aligned} \tag{40}$$

$$\sum_{i=1}^{n} X_i = 1;$$
$$X_i \geq 0 \text{ for } i = 1 \text{ to } n$$

Now rewriting equation 36 as

$y =$ value of the game

$A_1, A_2, ..., A_n$ are the strategies

$\bar{y}$ =maximum value of the game

$\underline{y}$ =minimum value of the game

$l = \bar{y} - \underline{y}$ =tolerance value of the game

Min y

Subject to the linear constraints

$$\begin{aligned} \bar{y} + l * y \geq z_{A_1A_1} * X_1 + z_{A_1A_2} * X_2 + ... + \\ z_{A_1A_n} * X_n \\ \bar{y} + l * y \geq z_{A_2A_1} * X_1 + z_{A_2A_2} * X_2 + ... + \\ z_{A_2A_n} * X_n \\ .... \\ .... \\ \bar{y} + l * y \geq z_{A_nA_1} * X_1 + z_{A_nA_2} * X_2 + ... + \\ z_{A_nA_n} * X_n \end{aligned} \tag{41}$$

$$\sum_{i=1}^{n} X_i = 1;$$
$$X_i \geq 0 \text{ for } i = 1 \text{ to } n$$

Comparing the equation 41 with player 2's formulation equation 36, we can say that the dual of player 1's formulation is the player 2's formulation. There is a primal dual relationship between player 1 and player 2.

Hence by solving either player 1's linear formulation or player 2's linear formulation, the proportions for the strategies (in our case the alternatives) can be found. The strategy (alternative) with high proportion is selected.

Hence the linear formulation of TS_{Min} is the dual of the linear formulation of TS_{Max}, the solution to the game is found by solving either the formulation of TS_{Max} or TS_{Min}. Hence by solving either formulations, the proportion values of the strategies are obtained. The optimal strategy, the one with the high proportion value, is chosen. The chosen optimal strategy can accomplish the opposing non-functional requirements of each actor simultaneously.

Telemedicine case study: For obtaining the optimal strategy, a linear programming model is applied on equation 29.

Since player 1, $P_{TS_{Max}}$ knows that it needs to be maximised, it therefore follows the Maxmin Strategy with the formulation given below, using equation 33:

Max v

Subject to,

TABLE 7. Optimal solution of the linear formulation for telemedicine system

Alternatives	Optimal solution
A_1	-9.728
A_2	10.728

$$
\begin{aligned}
&-53.64 * v + 112.76 * A_1 + 117.76 * A_2 \geq 112.76,\\
&-53.64 * v + 161.4 * A_1 + 166.4 * A_2 \geq 112.76,\\
&\textstyle\sum_{i=1}^{n} A_i = 1,\\
&A_i \geq 0 \text{ for } i = 1 \text{ to } n.
\end{aligned}
\tag{42}
$$

Similarly, player 2, $P_{TS_{Min}}$ knows that it needs to be minimised, it therefore follows the Minmax Strategy with the formulation given below, using equation 36:

$$
\begin{aligned}
&\text{Min } w\\
&\text{Subject to,}\\
&-53.64 * w + 112.76 * A_1 + 161.4 * A_2 \leq 112.76,\\
&-53.64 * w + 117.76 * A_1 + 166.4 * A_2 \leq 112.76,\\
&\textstyle\sum_{i=1}^{n} A_i = 1,\\
&A_i \geq 0 \text{ for } i = 1 \text{ to } n.
\end{aligned}
\tag{43}
$$

The above equations 42 and 43 are in linear form, so solving by means of the linear programming method can discover the optimal solution for the game. The IBM CPLEX tool has been used to optimise the linear programming model.

Since the linear formulation of player 1 is the dual of the linear formulation of player 2, the solution to the game is found by solving either the formulation of player 1 or of player 2.

By using the IBM ILOG CPLEX optimiser, optimal proportion values of the strategies for the linear formulation are found. These values are presented in Table 7. The results indicate that the alternative A_2 (*Provider Centered Care*) has a higher value than the alternative A_1 (*Patient Centered care*). This means that by choosing the A_2 strategy, the system achieves the opposing top softgoals of inter-dependent actors in the i^* goal model reciprocally. Hence the approach is evaluated on telemedicine goal model.

6. APPLICATION OF GAME THEORETIC GOAL ANALYSIS IN THE i^* FRAMEWORK

To check the applicability and scalability of the proposed game theory based approach, experiments were carried out on different case studies, namely Extended Telemedicine system [20] and Kids Youth Counselling [21]. The application of our proposed approach on these case studies are explained in this section.

6.1. Case study 1: An extended telemedicine system

In this section, an extended version of the telemedicine system with multiple internal intentional elements, is shown in Figure 7. For both actors, *Patient* and *Healthcare Provider*, the softgoals and goals are decomposed into multiple levels as compared to simplified telemedicine system. In real-time situations, some patients reveal their cultural and spiritual well-beings. For example, each and every religion has got their own cultural preferences. Based on this, the functional requirement (hardgoal) of both actors is *Treatment* decomposed into three alternatives *Patient Centered Treatment* or *Holistic Centered Treatment* or *Provider Centered Treatment*. These alternatives impact each actor's softgoals in various ways. The actor *Patient* has two top-most softgoals of opposing nature such as *Happiness* and *Expense*. For actor *Patient*, the atomic leaf softgoals, *Comfort*, *Cultural Spiritual Well-being*, *Time for Treatment* and *Privacy*, follow to the softgoal, *Fast Recovery*, which consequently follows to the softgoals, *Quality of Care* and *Normal Lifestyle*.

Likewise, the leaf softgoals, *Comfort*, *Cultural Spiritual Well-being* and *Privacy*, leads to the softgoal, *Flexible Treatment*. The *Flexible Treatment* follows *Normal Lifestyle* and *Time Saving*. Subsequently, *Quality of Care*, *Normal Lifestyle* and *Time Saving* leads to the top-most softgoals of *Happiness* and *Expense*. The actor *Patient* depends upon the actor *Healthcare Provider* through the softgoal *Viable Healthcare Service* for providing telemedicine services. Similarly, the actor *Healthcare Provider* achieves the top-most opposing softgoals of *Viable Healthcare Service* and *Cost* through several levels of intermediary softgoals as shown in Figure 7.

The objective of this system is to select the best alternative option based on its impact on each of the softgoals. For illustration and simplicity purpose, the top softgoals with a maximising nature (ie, *Happiness* and *Viable Healthcare Service*) are represented as TS_1 and with a minimising nature (ie, *Expense* and *Maintenance Cost*) are represented as TS_2 under the three alternatives *Patient Centered Treatment*

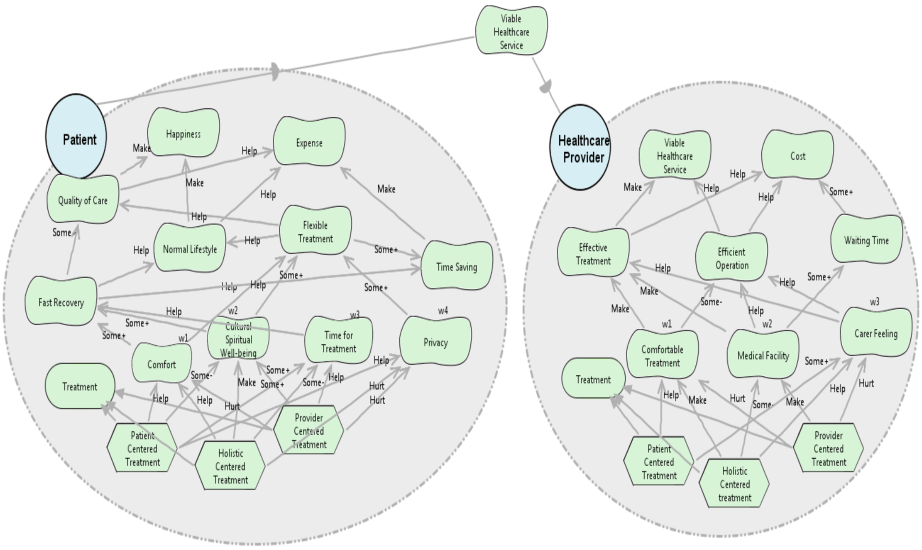

FIGURE 7. SR model of the extended telemedicine system

TABLE 8. Abbreviation of terms used in the extended telemedicine System

Terms	Abbreviation
Happiness	H
Expense	E
Viable Healthcare Service	VHS
Cost	C
Patient Centered Treatment	$PaCT$
Holistic Centered Treatment	$HoCT$
Provider Centered Treatment	$PrCT$

(A_1), *Holistic Centered Treatment* (A_2) and *Provider Centered Treatment* (A_3) (refer to Figure 7).

Terms used in the extended telemedicine system case study are provided as ready reference in Table 8. For the actor *Patient*, objective functions for both top softgoals, under the three alternatives *Patient Centered Treatment*, *Holistic Centered Treatment* and *Provider Centered Treatment*, are derived using equations 13 and 15 (based on their scores) are represented as follows:

$$\begin{aligned} F_{TS_2}(\omega)_{A_1} &= F_E(\omega)_{PaCT} \\ &= Min(S_{E_{PaCT}}) \\ &= Min(0.7457 * \omega 1 + 0.3185 * \omega_2 \\ &\quad + 0.236 * \omega_3 + 0.3224 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_2}(\omega)_{A_2} &= F_E(\omega)_{HoCT} \\ &= Min(S_{E_{HoCT}}) \\ &= Min(0.9018 * \omega 1 + 0.9339 * \omega_2 \\ &\quad + 0.1887 * \omega_3 + 0.9252 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_2}(\omega)_{A_3} &= F_E(\omega)_{PrCT} \\ &= Min(S_{E_{PrCT}}) \\ &= Min(0.1724 * \omega_1 + 0.4779 * \omega_2 \\ &\quad + 0.3146 * \omega_3 + 0.0807 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_1}(\omega)_{A_1} &= F_H(\omega)_{PaCT} \\ &= Max(S_{H_{PaCT}}) \\ &= Max(1.0092 * \omega_1 + 0.4324 * \omega_2 \\ &\quad + 0.4326 * \omega_3 + 0.4326 * \omega_4) \end{aligned}$$

TABLE 9. Maximum objective function values for each actors in the extended telemedicine system

Maximum functions	Patient	Healthcare Provider
F_{TS1A_1}	100.92	54.07
F_{TS1A_2}	108.13	140.8
F_{TS1A_3}	183.66	83.97

$$F_{TS_1}(\omega)_{A_2} = F_H(\omega)_{HoCT} = Max(S_{H_{HoCT}}) = Max(1.0091 * \omega_1 + 1.0813 * \omega_2 + 0.2884 * \omega_3 + 0.1082 * \omega_4)$$

$$F_{TS_1}(\omega)_{A_3} = F_H(\omega)_{PrCT} = Max(S_{H_{PrCT}}) = Max(0.2523 * \omega_1 + 0.649 * \omega_2 + 1.8366 * \omega_3 + 0.1082 * \omega_4)$$

Similarly, for the actor *Healthcare Provider*, objective functions of both the top softgoals, under the three alternatives *Patient Centered Treatment*, *Holistic Centered Treatment* and *Provider Centered Treatment*, are derived using equations 13 and 15, (based on their scores) are represented as follows:

$$F_{TS_1}(\omega)_{A_1} = F_{VHS}(\omega)_{PaCT} = Max(S_{VHS_{PaCT}}) = Max(0.5407 * \omega_1 + 0.3604 * \omega_3)$$

$$F_{TS_1}(\omega)_{A_2} = F_{VHS}(\omega)_{HoCT} = Max(S_{VHS_{HoCT}}) = Max(1.408 * \omega_1 + 0.9344 * \omega_2) + 0.5898 * \omega_3$$

$$F_{TS_1}(\omega)_{A_3} = F_{VHS}(\omega)_{PrCT} = Max(S_{VHS_{PrCT}}) = Max(0.1352 * \omega_1 + 0.8397 * \omega_2 + 0.1474 * \omega_3)$$

$$F_{TS_2}(\omega)_{A_1} = F_C(\omega)_{PaCT} = Min(S_{C_{PaCT}}) = Min(0.4588 * \omega_1 + 0.3932 * \omega_3)$$

$$F_{TS_2}(\omega)_{A_2} = F_C(\omega)_{HoCT} = Min(S_{C_{HoCT}}) = Min(0.5734 * \omega_1 + 0.3686 * \omega_2 + 0.5242 * \omega_3)$$

$$F_{TS_2}(\omega)_{A_3} = F_C(\omega)_{PrCT} = Min(S_{MC_{PrCC}}) = Min(0.1638 * \omega_1 + 0.9216 * \omega_2 + 0.1311 * \omega_3)$$

TABLE 10. Minimum objective function values for each actors in the extended telemedicine system

Minimum functions	Patient	Healthcare Provider
F_{TS2A_1}	23.6	39.32
F_{TS2A_2}	9.25	36.86
F_{TS2A_3}	8.07	13.11

The values of objective functions are obtained by invoking the IBM ILOG CPLEX and are provided in Tables 9 and 10. The sum of the objective function values of the same nature (maximise or minimise) under each alternative for each actor leads to the pay-off matrix of each nature. To achieve the overall objective of conflicting goals simultaneously, the pay-off matrices which are obtained separately for each player should be merged into one. The optimal strategy is then realised by analysing these unified pay-off matrices that contain both maximising and minimising multi objective function values.

Hence, the pay-off matrix that maximises the top softgoals, $P_{TS_{Max}}$ (player 1), of the extended telemedicine system using equation 22 is represented by:

$$\mathbf{P_{TS_{Max}}} = \begin{pmatrix} 154.99 & 141.72 & 184.89 \\ 162.20 & 148.93 & 192.10 \\ 237.73 & 324.46 & 267.63 \end{pmatrix} \tag{44}$$

The pay-off matrix that minimises the top softgoals, $P_{TS_{Min}}$ (player 2), of the extended telemedicine system using equation 24 is represented by:

$$\mathbf{P_{TS_{Min}}} = \begin{pmatrix} 62.92 & 60.46 & 39.71 \\ 48.58 & 46.11 & 22.36 \\ 47.39 & 44.93 & 21.18 \end{pmatrix} \tag{45}$$

From the above matrices, $P_{TS_{Max}}$ and $P_{TS_{Min}}$, the decision pay-off matrix is created for the extended telemedicine system using equation 28 and is represented as:

$$\mathbf{P} = \begin{pmatrix} 217.91 & 202.18 & 224.6 \\ 210.78 & 195.042 & 214.46 \\ 285.12 & 369.39 & 288.81 \end{pmatrix} \tag{46}$$

For obtaining the optimal strategy, a linear programming model is applied on equation 46.

Since $P_{TS_{Max}}$ needs to be maximised, therefore player 1 follows the Maxmin Strategy with the formulation as given below, using equation 33,

$$\begin{aligned}
&\text{Max } v\\
&\text{Subject to,}\\
&-174.348*v+217.91*A_1+210.782*A_2+285.12*A_3 \geq 195.042,\\
&-174.348*v+202.18*A_1+195.04*A_2+369.39*A_3 \geq 195.042,\\
&-174.348*v+224.6*A_1+214.46*A_2+288.81*A_3 \geq 195.042,\\
&\textstyle\sum_{i=1}^{n} A_i = 1,\\
&A_i \geq 0 \text{ for } i = 1 \text{ to } n \text{ and } v \text{ is the value of the game.}
\end{aligned} \tag{47}$$

Similarly, since $P_{TS_{Min}}$ needs to be minimised, therefore player 2 follows the Minmax Strategy with the formulation as given below, using equation 36

$$\begin{aligned}
&\text{Min } w\\
&\text{Subject to,}\\
&-174.348*w+217.91*A_1+202.18*A_2+224.6*A_3 \leq 195.042,\\
&-174.348*w+210.782*A_1+195.04*A_2+214.46*A_3 \leq 195.042,\\
&-174.348*w+285.12*A_1+369.39*A_2+288.81*A_3 \leq 195.042,\\
&\textstyle\sum_{i=1}^{n} A_i = 1,\\
&A_i \geq 0 \text{ for } i = 1 \text{ to } n \text{ and } w \text{ is the value of the game.}
\end{aligned} \tag{48}$$

The values obtained from equations 47 and 48 are linear, so solving by means of the linear programming method can discover the optimal solution for the game. The IBM CPLEX tool has been used to optimise the linear programming model.

TABLE 11. Optimal solution of the linear formulation for the extended telemedicine system

Alternatives	Optimal solution
A_1	0
A_2	-1.134
A_3	2.13

Since the linear formulation of player 1 is the dual of the linear formulation of player 2, the solution to the game is found by solving either the formulation of player 1 or of player 2.

By using the IBM ILOG CPLEX optimiser, optimal proportion values of the strategies for the linear formulation are found. These values are presented in Table 11.

The results indicate that the alternative *Provider Centered Treatment* has a higher value than the other two alternatives, *Patient Centered Treatment* and *Holistic Centered Treatment*. This shows that home-based telemedicine *Patient Centered Treatment* and *Holistic Centered Treatment* would not be able to offer a wide range of viable healthcare services that make patients happy with low cost. Whereas with provider centered care, patients are brought into a room equipped with all the required medical equipment (for example interactive video camera operated by a licensed nurse practitioner) for comfortable and effective treatment. Thus, *Healthcare Provider* can incorporate treatment plan with more flexible options and activities. Hence, both actors who are dependent can achieve conflicting goals simultaneously by selecting *Provider Centered Treatment*. In other words, by choosing the *Provider Centered Treatment* strategy, the system achieves the opposing top softgoals of inter-dependent actors in the i^* goal model reciprocally. This case study illustrates that the proposed approach can be applied to reasonably complex scenarios in practice.

6.2. Case study 2: Youth Counselling System

Consider the Youth Counselling case study shown in Figure 8. Three actors are involved in this model with dependency relationships between them. The opposing multi-objective functions developed for the youth counselling case study (Figure 8) are described in this section. For better counselling services, the following alternative tasks are used for this goal model.

- *Text Messaging* (A_1)
- *Kidsuse Cybercafe portal Chatroom* (A_2)

The actor *Kids and Youth* has two softgoals namely *GetEffectiveHelp* and *DataVisibility*. The non-functional goal, *GetEffectiveHelp*, should be maximised

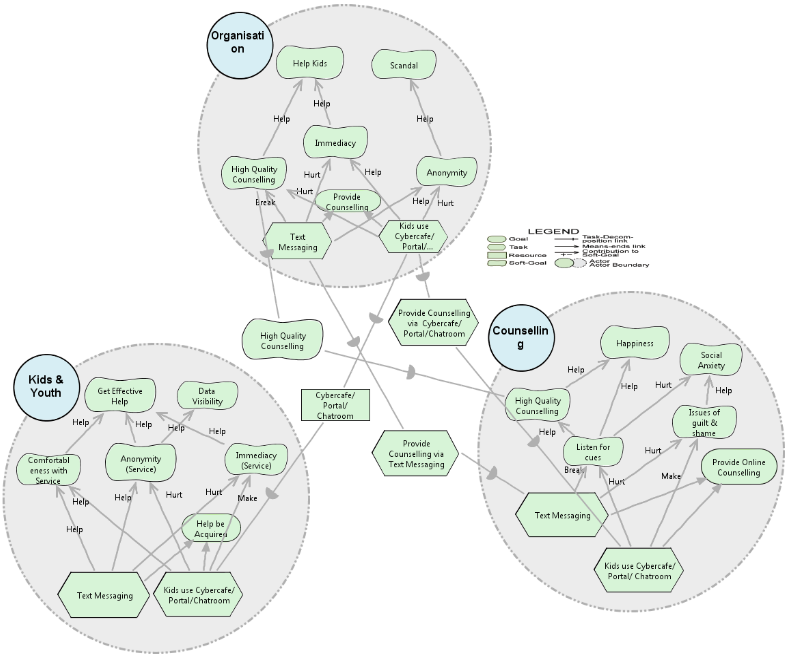

FIGURE 8. Simplified SR model for Youth Counselling with inter-actor dependencies

and the visibility of data (*DataVisibility*) should be minimised simultaneously. The primary objective of *Counsellor* is to make kids/youth happy while reducing the social anxiety. Similarly, the organisation has to provide maximum help to children, and ensure that there are no scandals.

The objective functions of both the top softgoals, *GetEffectiveHelp* and *DataVisibility*, for the actor *KidsYouth* are given below, using equations 13 and 15, as:

$$\begin{aligned} F_{TS_1}(\omega)_{A_1} &= F_{GetEffectiveHelp}(\omega)_{TextMessaging} \\ &= Max\{0.4096 * \omega_1 + 0.4096 * \omega_2 + 0.1024 * \omega_3\} \end{aligned}$$

$$\begin{aligned} F_{TS_1}(\omega)_{A_2} &= F_{GetEffectiveHelp}(\omega)_{KidsuseCybercafePortalChatroom} \\ &= Max\{0.4096 * \omega_1 + 0.1024 * \omega_2 + 0.512 * \omega_3\} \\ F_{TS_2}(\omega)_{A_1} &= F_{DataVisibility}(\omega)_{TextMessaging} \\ &= Min\{0.4096 * \omega_2\} \\ F_{TS_2}(\omega)_{A_2} &= F_{DataVisibility}(\omega)_{KidsuseCybercafePortalChatroom} \\ &= Min\{0.1024 * \omega_2\} \end{aligned}$$

For *Counselling*, the objective functions of *Happiness* and *SocialAnxiety* are shown below , using equations 13 and 15, as:

$$\begin{aligned} F_{TS_1}(\omega)_{A_1} &= F_{Happiness}(\omega)_{TextMessaging} \\ &= Max\{0\} \\ F_{TS_1}(\omega)_{A_2} &= F_{Happiness}(\omega)_{KidsuseCybercafePortalChatroom} \\ &= Max\{0.0655 * \omega_4\} \\ F_{TS_2}(\omega)_{A_1} &= F_{SocialAnxiety}(\omega)_{TextMessaging} \\ &= Min\{0\} \\ F_{TS_2}(\omega)_{A_2} &= F_{SocialAnxiety}(\omega)_{KidsuseCybercafePortalChatroom} \\ &= Min\{0.1024 * \omega_4 + 0.512 * \omega_5\} \end{aligned}$$

For *Organisation*, the objective functions *Helpkids* and *Scandal* are shown below, using equations 13 and 15, as:

TABLE 12. Maximum objective functions values for each actors in Youth Counselling system

Function	KidsYouth	Counselling	Organisation
$F_{TS_1}(\omega)_{A_1}$	40.96	0	10.24
$F_{TS_1}(\omega)_{A_2}$	51.2	6.55	40.96

TABLE 13. Minimum Objective functions values for each actors in Youth Counselling system

Function	KidsYouth	Counselling	Organisation
$F_{TS_2}(\omega)_{A_1}$	40.96	0	40.96
$F_{TS_2}(\omega)_{A_2}$	10.24	10.24	10.24

$$\begin{aligned}
F_{TS_1}(\omega)_{A_1} &= F_{HelpKids}(\omega)_{TextMessaging}\\
&= Max\{0.1024 * \omega_7\}\\
F_{TS_1}(\omega)_{A_2} &= F_{Happiness}(\omega)_{KidsuseCybercafePortalChatroom}\\
&= Max\{0.4096 * \omega_7 + 0.1024 * \omega_6\}\\
F_{TS_2}(\omega)_{A_1} &= F_{Scandal}(\omega)_{TextMessaging}\\
&= Min\{0.4096 * \omega_8\}\\
F_{TS_2}(\omega)_{A_2} &= F_{Scandal}(\omega)_{KidsuseCybercafePortalChatroom}\\
&= Min\{0.1024 * \omega_8\}
\end{aligned}$$

The optimal solutions to the objective functions defined for each actor are generated using CPLEX; the ideal values are presented in Tables 12 and 13. Based on the optimal solutions, pay-off matrix can be formed for each top softgoals: TS_1 and TS_2. The sum of all objective functions of same nature under each alternative gives the pay-off matrix of each nature.

The pay-off matrix that maximises the top softgoals, $P_{TS_{Max}}$ (player 1), of *Youth Counselling* goal model using equation 22 is given as:

$$\mathbf{P_{TS_{Max}}} = \begin{pmatrix} 51.2 & 51.2 \\ 61.44 & 67.99 \end{pmatrix} \tag{49}$$

The pay-off matrix that minimises the top softgoals, $P_{TS_{Min}}$ (player 2), of the *Youth Counselling* goal model using equation 24 is given as:

$$\mathbf{P_{TS_{Min}}} = \begin{pmatrix} 81.92 & 61.44 \\ 51.2 & 30.72 \end{pmatrix} \tag{50}$$

To achieve the overall objective of opposing goals simultaneously, the pay-off matrices which are obtained separately for each player should be combined into one. From the above two matrices, $P_{TS_{Max}}$ and $P_{TS_{Min}}$, the unified decision pay-off matrix P is created for the *Youth Counselling* goal model using equation 28 is given as

$$\mathbf{P} = \begin{pmatrix} 133.12 & 112.64 \\ 112.64 & 98.71 \end{pmatrix} \tag{51}$$

The optimal strategy is obtained by analysing the decision pay-off matrix that contains both maximising and minimising multi-objective function values. In order to obtain an optimal strategy, a linear programming model is created using equation 33 and the decision pay-off matrix given in equation 51.

Since player 1, $P_{TS_{Max}}$, knows that it needs to be maximised, it therefore follows the Maxmin strategy with the formulation given as below:

$$\begin{aligned}
&\text{Max } v\\
&\text{Subject to}\\
&-34.41 * v + 133.12 * A_1 + 112.64 * A_2 \geq 98.71,\\
&-34.41 * v + 112.64 * A_1 + 98.71 * A_2 \geq 98.71,\\
&\textstyle\sum_{i=1}^{n} A_i = 1,\\
&A_i \geq 0 \text{ for } i = 1 \text{ to } n \text{ and } v \text{ is the value of the game.}
\end{aligned} \tag{52}$$

Similarly player 2, $P_{TS_{Min}}$, knows that it needs to be minimised, it therefore follows the Minmax strategy and has a similar formulation given as below:

$$\begin{aligned}
&\text{Min } w\\
&\text{Subject to}\\
&-34.41 * w + 133.12 * A_1 + 112.64 * A_2 \leq 98.71,\\
&-34.41 * w + 112.64 * A_1 + 98.71 * A_2 \leq 98.71,\\
&\textstyle\sum_{i=1}^{n} A_i = 1,\\
&A_i \geq 0 \text{ for } i = 1 \text{ to } n \text{ and } w \text{ is the value of the game.}
\end{aligned} \tag{53}$$

All the values obtained in equations 52 and 53 are in linear form, so an optimal solution for the game can be found with the help of linear programming. Hence, by solving either formulations using the IBM ILOG CPLEX tool, the optimal proportion values

TABLE 14. Optimal solution of the linear formulation for Youth Counselling goal model

Alternatives	Optimal solution
A_1	2.4702
A_2	-1.4702

of the strategies are found and are shown in Table 14. The results indicate that the alternative A_1 (*TextMessaging*) has a higher value than the alternative A_2 (*KidsuseCybercafePortalChatroom*). The three actors can achieve their opposing non-functional goals simultaneously to make kids/youth happy while reducing the social anxiety by selecting *TextMessaging*. Also, the organisation can provide maximum help and support to children, and ensure that there are no scandals. In other words, the system chooses the alternative, A_1 strategy, to achieve opposing top softgoals simultaneously. Hence, the approach is evaluated using the kids youth counselling goal model in an effective manner.

7. TOOL DESIGN AND IMPLEMENTATION

A tool is implemented for the proposed reasoning method based on game theory using Java Eclipse incorporated with IBM ILOG CPLEX optimisation tool. The CPLEX tool solves the unified decision matrix formed using zero-sum game theoretic approach.

The developed tool evaluated the viability and practicability of the proposed optimisation problem using game theory on the i^* goal model. Various case studies, for example, Kids Youth Counselling [21] and Telemedicine [20] from the literature were tested using the developed tool. The pseudo code for the proposed approach is illustrated in Algorithm 1.

The tool evaluation on simplified telemedicine case study is shown in Figure 9.

8. CONCLUSION

A game theory based reasoning of opposing non-functional requirements for the i^* goal model has been proposed in this paper. The methodology for the proposed approach is implemented in Java Eclipse environment incorporated with the IBM CPLEX tool. The simulated model is tested on two different case studies drawn from the existing literature. The proposed approach was evaluated based on the optimal alternative selection by balancing the opposing objectives of inter-dependent actors in the i^* goal model. The requirements from existing work are used in this approach for decision-making. However, these requirements may not be complete in all settings. In particular, new requirements may arise, or existing

Algorithm 1 Pseudo code for the analysis of opposing non-functional requirements in the i^* goal model

Require: A set of directed graphs $S = \{S_1, S_2, ..., S_s\}$ such that G is a subset of S that have same n set of tasks T, where $G = \{G_1, G_2, ..., G_k\}$. Each G_i is a quadruple $\{T, L, SG, TS\}$ where each elements T, L, SG, TS represents alternative tasks, leaf softgoals, in-between softgoals, top softgoals respectively where each top softgoal is related to an opposing variable such as Max or Min.

MAIN MODULE : Reasoning of opposing goals
for all $G_i \epsilon G$ **do**
  for all alternatives $t \epsilon T$ **do**
    for all top softgoals $ts \epsilon TS$ **do**
      if ts is Min **then**
        Generate Minimisation Objective Functions
      else
        Generate Maximisation Objective Functions
      end if
    end for
  end for
end for
Let $F_{Max} \leftarrow Max\{f_{Max_1}, f_{Max_2}, ..., f_{Max_n}\}$
Let $F_{Min} \leftarrow Min\{f_{Min_1}, f_{Min_2}, ..., f_{Min_n}\}$
for all $f_{Max_i} \epsilon F_{Max}$ **do**
  Let $x_{Max_i} \leftarrow optimal(f_{Max_i}, Max)$//finding optimal solutions for maximum objective functions
end for
for all $f_{Min_i} \epsilon F_{Min}$ **do**
  Let $x_{Min_i} \leftarrow optimal(f_{Min_i}, Min)$//finding optimal solutions for minimum objective functions
end for
Generate pay-off matrix, $P_{TS_{Max}}$, for maximum objective function values, by integrating x_{Max_i}'s of all $G_i \epsilon G$ as
for all tasks $t_l, t_r \epsilon T$ where $l, r = 1$ to n **do**
  $P_{TS_{Max}}[i,j] \leftarrow \sum_{i,j=1}^{k} a^{ij}_{Max_{(t_l,t_r)}}$
end for
Generate pay-off matrix, $P_{TS_{Min}}$, for minimum objective function values, by integrating x_{Min_i}'s of all $G_i \epsilon G$ as
for all tasks $t_l, t_r \epsilon T$ where $l, r = 1$ to n **do**
  $P_{TS_{Min}}[i,j] \leftarrow \sum_{i,j=1}^{k} a^{ij}_{Min_{(t_l,t_r)}}$
end for
Generate decision pay-off matrix P by merging pay-off matrices $P_{TS_{Max}}$ and $P_{TS_{Min}}$
for all tasks $t_i, t_j \epsilon T$ where $i, j = 1$ to n **do**
  $P_{t_i t_j}[i,j] = P_{TS_{Max t_i t_j}} + P_{TS_{Min t_i t_j}}$
end for
Generate primal linear equation using Maxmin strategy
Solve the primal linear equation to obtain an optimal Pareto value

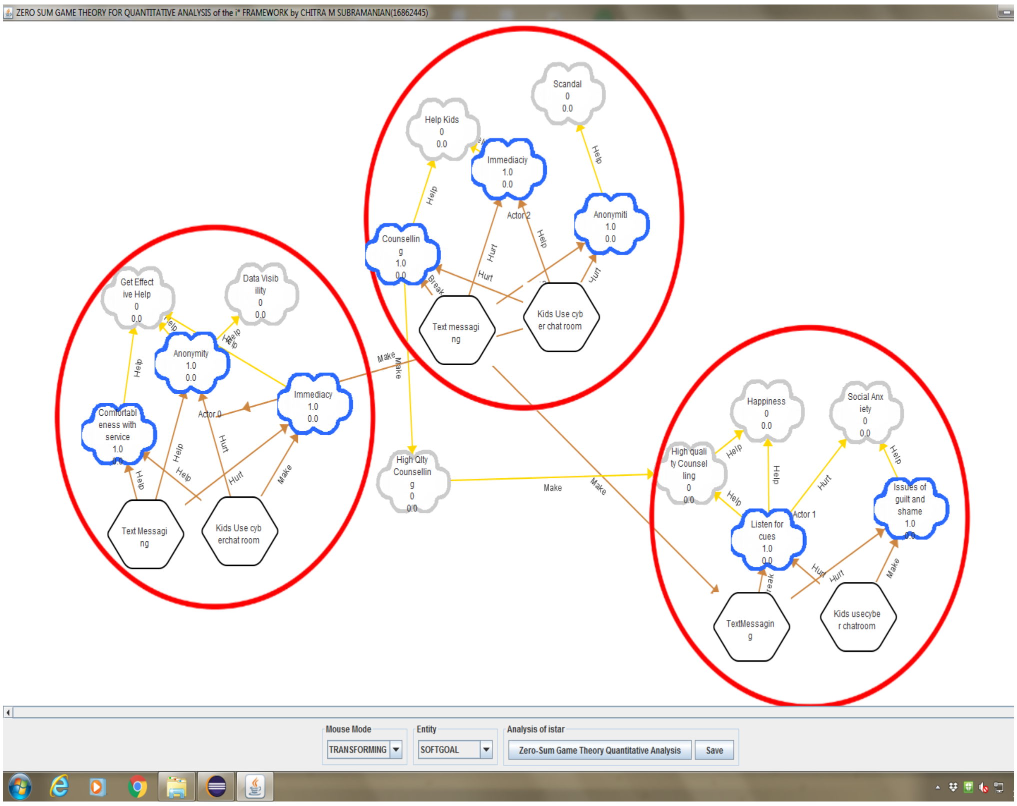

FIGURE 9. Tool result for the Youth Counselling case study with inter-actor dependency

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SUB-MODULE: $Optimal(f, ts)$

Declare and define the variables, the expressions, the objective functions and the constraints based on ts

if ts is Max **then**
  Define maximisation function
else if ts is Min **then**
  Define minimisation function
end if
$CPLEX.solve() \rightarrow W$
return W

---

requirements may become more or less prominent, depending on the characteristics of a particular domain. This is a limitation of this approach. A game theoretic concept known as Nash equilibrium is applied in the proposed methodology for generating and optimising the opposing multi-objective functions. But Nash equilibrium does not hold generally for all repeated game applications. Further research topics include arriving at optimal solutions for conflicting goals among inter-dependent actors. Also, performing sensitivity analysis, for facilitating valuable input data to aid requirements analyst in the overall decision-making process. For future work, it is planned to conduct an empirical validation in order to gain feedback and to evaluate this proposal's viability and usability. Future work in the same area would explore the viability of applying or adapting the optimisation model to similar conceptual models.

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CEA Based Reasoning with the *i** Framework

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Abstract

Goal models in requirement engineering represent stakeholder interests and objectives and help in making decisions when choosing suitable functional requirements based on non-functional requirements. In a competitive environment, stakeholders' requirements may be conflicting and non-functional. Therefore, there is a need for a goal analysis method which offers an alternative design option that can accommodate the conflicting goals of the different inter-dependent actors in a goal model. In this paper, an economic evaluation-based approach known as Cost-Effectiveness Analysis is applied to the selection of an optimum strategy for inter-dependent actors in the i goal model by balancing the opposing goals reciprocally. The proposed approach involves the optimisation of each objective function based on the interdependency relationships and economic evaluation of their optimal values to prioritise each design option. This helps to facilitate the choice of a cost-effective design option that can accommodate conflicting goals.*

Keywords: Goal models, Requirements engineering, Software process
Multi-objective optimisation

Introduction

Any software system's success relies on how its requirements are met in a cost-effective fashion. The failure to perceive and understand customer requirements could lead to issues such as the system running over time, over budget, or even failing completely (Mairiza et al. 2014a). These mistakes once found after implementation are more expensive to fix. Requirements Engineering (RE) is a discipline that aims to improve the early phases of software development, explicitly by finding solutions to requirements elicitation and analysis process. According to (Nuseibeh et al. 2000), RE is characterised by a sequence of decisions that help to solve customer perception of a detailed specification of that problem. A significant issue in RE research is to find appropriate techniques and tools that can support effective decision-making process. Over the last two decades, RE has progressively been perceived as a critical element of the software development lifecycle. Goal-Oriented Requirement Engineering (GORE) is a method that models the software system's requirements using goals by eliciting, elaborating, structuring, specifying, analysing, negotiating, documenting and modifying requirements (Sommerville 2005). In GORE, goals play a critical part in understanding the domain and determining the stakeholders' intentions (Mylopoulos et al. 1999). Goals are decomposed into more specific goals (softgoals) which describe the qualities required by the system (accuracy, reliability, performance, etc.). Furthermore, the requirements analyst examines high-level alternative system design options and decides on the most effective system design to implement (Franch et al. 2016).

A goal model illustrates the way in which goals, actors, states, objects, tasks, and domain properties are inter-related in the given system (van Lamsweerde 2004). Some of the most widely-used goal modelling approaches are Knowledge Acquisition in Automated Space (KAOS) (Dardenne et al. 1991), i^* framework (Yu et al. 1995), Non-Functional Requirements (NFR) framework (Mylopoulos et al. 1999), Attributed Goal-Oriented Requirements Analysis (AGORA) model (Kaiya et al. 2002), Tropos (Bresciani et al. 2004) and Goal-Oriented Requirement Language (GRL) (Amyot et al. 2010). In requirements engineering, the i^* goal model is one of the popular goal models, since it supports goal-oriented modelling of socio-technical systems and organisational context. Reasoning strategies within the i^* goal model enables all types of qualitative (Giorgini et al. 2002; Horkoff et al. 2011) or quantitative analysis (Franch 2006, Subramanian et al. 2015a) or even both (Amyot et al. 2010) to be performed in an effective manner.

In a competitive, real-world environment, goals of many stakeholders of complex systems may be of a conflicting or opposing in nature. Moreover, each goal (functional requirement) of a system may have several different alternative design options to choose from. Hence, during the requirements analysis phase, an analyst has to determine the most cost-effective design option that will achieve the goals of all actors which are dependent on each other in a goal model. Cost-effective decision making in competitive environment involves various considerations. In the real world, when making decisions, decision-makers have to consider cost per service provided by alternative design options based on the interdependent relationships among actors. A novel framework is needed that captures this real issue in order to achieve multi-objective optimisation (Subramanian et al. 2015). Therefore, a realistic and cost-effective decision-making process allows us to go beyond economic evaluation considerations. This paper proposes a novel methodology based on economic evaluation for system exploration which involves cost-effective alternative design evaluation when there are inter-dependent relationships among actors.

To discover the optimal alternative options of inter-dependent actors by balancing their multiple opposing objectives reciprocally, an economic evaluation approach known as Cost-Effectiveness Analysis (CEA) is applied to the i^* goal model. It is an essential approach for analysing decision-making problems cost-effectively. In the proposed approach, multi-objective functions are determined in order to decide their significance. Then, the alternative options for each actor are assessed according to each opposing softgoal's optimal CEA values. An optimal, cost-effective solution is found in the final phase that seeks the adoption of a strategy under the circumstances of opposing objectives. A case study from the literature is used to illustrate the applicability of the proposed approach.

An overview of the existing approaches, techniques and methods related to GORE and more precisely, the i^* framework, are presented in the next section. The paper is organized as follows: Section 2 presents the existing approaches, techniques and methods related to the i^* framework, which are closely associated with the proposed approach. The methodology of reasoning opposing goals using inter-actor dependency is given in Section 3. The evaluation and simulation of the proposed work are presented in Section 4. Finally, conclusions are drawn at the end of the paper.

Background and Related Work

Contemporary GORE approaches focus on reasoning with 'Why' questions as opposed to 'What' (van Lamsweerde 2004, Subramanian et al. 2015). Goals enable the requirements of the organisation to be aligned with the functionality delivered by the system. Hence, in this section, an overview is presented of the existing approaches, techniques and methods related to the i^* model, that approximates with the proposed approach.

An interactive, iterative, qualitative analysis based method for the i^* goal models was proposed by Horkoff and Yu (Horkoff et al. 2016). The uncertainty of making decisions when more than one goal has the same label is the main limitation of this approach. For the purpose of analysing alternative design options in the KAOS model, Heaven et al. (Heaven and Letier 2011) proposed a multi-objective optimisation model. However, the main issue with this model is that it does not consider the non-functional requirements of the system. In order to deal with the conflicts in NFR decision analysis, Mairiza et al. (Mairiza et al. 2014b) developed a Multi-Criteria Decision Analysis (MCDA) and applied TOPSIS as an MCDA method for prioritising the alternative options. The subsequent quantitative results can be used for decision making. In the i^* model, Subramanian et al. (Subramanian et al. 2015) developed an inter-actor quantitative goal analysis method to decide on the alternative design options. Later, in order to enhance this method, a multi-objective optimisation method was applied for finding the optimal values of softgoals for alternative selection in the goal analysis process (Subramanian et al. 2016; Subramanian et al. 2015).

However, all the aforementioned proposals for goal analysis are based on either quantitative or qualitative value used when choosing an alternative design option based on the maximum satisfaction label of non-functional requirements. However, an ambiguity arises in making a decision when two or more non-functional requirements receive the same type of label (Horkoff et al. 2016). This limitation of the qualitative approach to the i^* framework that causes ambiguity in the decision-making process was overcome by Subramanian et al. (Subramanian et al. 2016; Subramanian et al. 2015), who developed fuzzy-based optimal quantitative methods for goal analysis in the i^* model. However, the literature shows that the qualitative and quantitative goal analysis process for the i^* and other goal models do not include goals with opposing objective functions. A game-theory-based analysis of goal models using optimisation was conducted by Subramanian et al. (Subramanian et al. 2018). This approach formalised without any economic evaluation of objective functions. Moreover, it could not address the actors' interdependency relationships, which are essential for decision making in a competitive, real-world environment. Overall, no previous research efforts have been able to develop a systematic method for deciding on a cost-effective optimal alternative design option for inter-dependent actors in the i^* model by reciprocally balancing the multiple opposing objectives with their significance. In other words, this proposal examines how requirement-based engineering design can deliver a cost-effective optimal design outcome.

Research Objectives

The objective of this research is to extend goal-oriented requirements engineering techniques to provide support for decision-making. The research objectives (RO's) are as follows:

RO1: Design a framework that supports decision making to achieve strategic goals.

RO2: Apply the proposed method that enables reasoning under conflict situations and produces a data-driven conclusion using optimisation technique and decision-making techniques.

RO3: Examine whether the framework leads to better quality strategic decision-making and compare its usability and effectiveness in prioritising alternatives.

The next section presents the proposed methodology of reasoning opposing goals using inter-actor dependency using the i^* goal model.

Proposed Methodology

In the proposed approach, the objective is to achieve strategic goals while taking into account the constraints so that the reasoning method helps to optimise the overall strategy by choosing an effective alternative option. To achieve the research goal, a methodology has been proposed and is illustrated below:

Stakeholder analysis

The first step involves identifying the actors (i.e., which stakeholders should be considered), defining design alternatives or options to achieve stakeholders objectives and identifying the impacts of different alternatives, which depend on the stakeholders' subjective preference to the problem. The stakeholders' point of view about the criteria used to achieve their objectives is determined through a bottom-up approach. The bottom-up approach consists of discovering goals criteria from the consequences and impacts of the alternatives.

Formalisation of multi-objective functions

In the next step, a generalised complete structure of an i^* goal model is modelled by formalising the opposing objective functions in terms of softgoals, goals, tasks and resources. For formalisation, a Strategic Rationale (SR) model is considered as a directed graph which is represented as G (N; R), where N represents the intentional elements such as goals, softgoals, resources and tasks that form a set of nodes and R represents the means-end, task decomposition, dependency and contribution links that form a set of edges for the graphs. The task of a decision maker is to choose an ideal, cost-effective alternative option from the available choices. An objective function for each choice can be generated based on the elements of the graph. Given an i^*goal model, our aim is to select the best alternative option according to its impact on the softgoals. Impacts are make; help; hurt; break; some-; some+ which are represented as triangular fuzzy numbers that indicate the extent to which an alternative option fulfils the leaf softgoal. The impacts with the softgoal preferences are propagated to the top softgoals, to find the level of satisfaction or scores of top softgoals. Also, each leaf's softgoals are assigned a weight ω based on their relative importance in achieving the goal.

Firstly, the scores of each top softgoals of each actor based on its inter-actor dependency under each alternative are calculated. For details on representing goals, weights, impacts and alternatives, readers are directed to (Subramanian et al. 2015), this work adapts similar steps in this process.

From Figure 1. $I_{L_{ijk}}$ means the impact on i^{th} leaf softgoal of j^{th} alternative and $\omega_{L_{ijk}}$ represents the weight of i^{th} leaf softgoal for actor k. Then, the score of i^{th} leaf softgoal for j^{th} alternative for the k^{th} actor is as follows:

$$S_{L_{ijk}} = I_{L_{ijk}} \times \omega_{L_{ijk}} + \sum_{d_{L_i}=1}^{n_{d_i}} \left(S_{d_{L_i}} \times I_{d_{L_i}} \right) \qquad (1)$$

where $S_{d_{L_i}}$ is the score of ${d_L}^{th}$ dependent for the i^{th} leaf softgoal, $I_{d_{L_i}}$ is the ${d_L}^{th}$ dependent impact for the i^{th} leaf softgoal and n_{d_i} is the number of dependencies for the i^{th} leaf softgoal (i.e., at level zero).

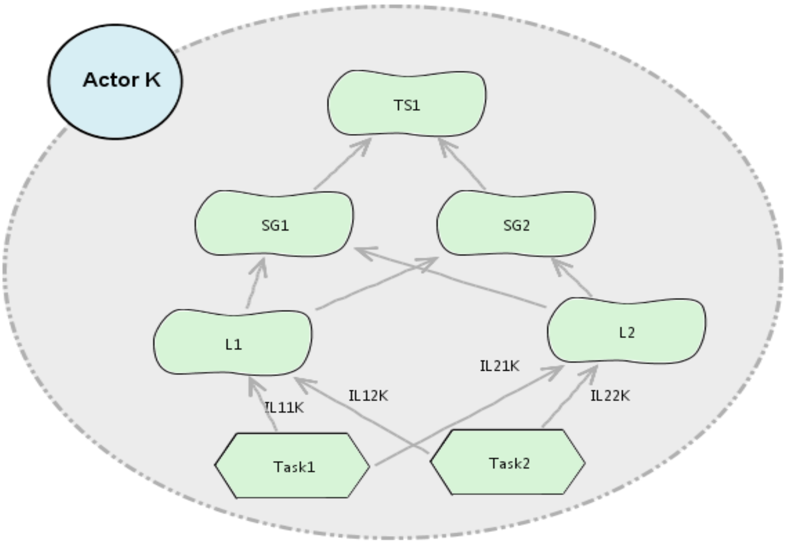

Figure 1 An example directed graph representation of SR model for an actor

Consider the case of t hierarchy levels in the directed graph, with leaf softgoal at level zero. Then, at level $t = 1$, the score of the i^{th} softgoal for j^{th} alternative for actor k is shown as

$$S_{SG_{i_1 jk}} = \sum_{x=1}^{n_c} (I_x \times S_{L_{xjk}}) + \sum_{d_{i_1}=1}^{n_i} (S_{d_{i_1}} \times I_{d_{i_1}}) \quad (2)$$

where n_c is the number of children for each i^{th} softgoal at level $t = 1$, and n_i is the number of dependencies at level $t = 1$ for i^{th} softgoal.

Since the score of softgoals at level $t = 1$ depends on the score of their leaf softgoal, the Equation: 2 can be rewritten as:

$$S_{SG_{i_1 jk}} = I_1 \times S_{L_{1jk}} + I_2 \times S_{L_{2jk}} + \cdots\cdots + I_{n_c} \times S_{L_{n_c jk}} + \sum_{d_{i_1}=1}^{n_i} (S_{d_{i_1}} \times I_{d_{i_1}}) \quad (3)$$

Substituting with Equation: 1, Equation: 3 becomes

$$S_{SG_{i_1 jk}} = I_1 \times (I_{L_{1jk}} \times \omega_{L_{1jk}} + \sum_{d_{L_1}=1}^{n_{d_1}} (S_{d_{L_1}} \times I_{d_{L_1}}))$$

$$+ I_2 \times (I_{L_{2jk}} \times \omega_{L_{2jk}} + \sum_{d_{L_2}=1}^{n_{d_2}} (S_{d_{L_2}} \times I_{d_{L_2}}))$$

$$+ \cdots\cdots + I_{n_c} \times (I_{L_{n_c jk}} \times \omega_{L_{n_c jk}} + \sum_{d_{L_{n_c}}=1}^{n_{d_{n_c}}} (S_{d_{L_{n_c}}} \times I_{d_{L_{n_c}}}))$$

$$+ \sum_{d_{i_1=1}}^{n_i} (S_{d_{i_1}} \times I_{d_{i_1}}) \tag{4}$$

In this way, it propagates upwards. At level 1, if there are m number of softgoals, n_c children and n_d dependencies for the i^{th} softgoal, then the score of any softgoal at $t > 1$ is found by taking the product of its impact and each child score (Subramanian et al. 2015).

Therefore the score of a softgoal at level *t* for an actor with a dependency relationship can be generalised as follows:

$$S_{SG_{i_t jk}} = \prod_{l=1}^{m} I_{ijl} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{ijk}}} \times \omega_{d_{L_{ijk}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\} \tag{5}$$

Then, the objective functions of top softgoals under each alternative for an actor are created from the scores as shown in Equation: 5. If there is an inter-actor dependency relationship, then it is necessary to consider both strategic dependency and strategic rationale diagrams of the i^* goal model with the assumption that only softgoal inter-dependency relationships are taken into account in this approach. Consider that if there are *n* numbers of alternative options for an actor, then there are *n* objective functions for each top softgoal. To obtain the maximum score for the top softgoal under each alternative, the *n* objective functions that have to be maximised are given as:

$$f_{i(\omega_1)} = S_{SG_{i1k}} = Max \prod_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{i1k}}} \times \omega_{d_{L_{i1k}}} \right] \right.$$

$$\left. + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

$$f_{i(\omega_2)} = S_{SG_{i1k}} = Max \prod_{l=1}^{m} I_{i2l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{i2k}}} \times \omega_{d_{L_{i2k}}} \right] \right.$$

$$\left. + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

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$$f_{i(n)} = S_{SG_{ink}} = Max \prod_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{in}} \times I_{d_{L_{ink}}} \times \omega_{d_{L_{ink}}} \right] \right.$$

$$\left. + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

Such that $0 \leq \omega_{d_{L_{jk}}} \leq 100 \; for \; d = 1 \; to \; n_c$ (6)

Similarly, objective functions that have to be minimised are formalised for each actor in the i^* goal model.

The next section explains how the multi-objective functions of opposing goals (Maximum and Minimum in nature) are optimised.

Evaluation of the optimal solutions of multi-objective optimization functions

In the proposed model, each actor is considered to have two opposing soft goals (SG_1 and SG_2) and two alternative design options (A_1 and A_2). Optimising the objective functions for soft goals (SG_1 and SG_2) individually can generate two ideal solutions using algorithm: 1. The IBM ILOG CPLEX optimisation tool is used for evaluating the optimisation process (Lima 2010). The IBM ILOG CPLEX optimizer is used to solve mathematical business models using powerful algorithms to obtain precise and logical decisions. Additionally, IBM ILOG CPLEX has a modelling layer called 'Concert' that enables interfacing with Java, C++ and C # languages.

Let the ideal solutions for the objective functions for soft goals (SG_1 and SG_2) of an actor using the two alternative design options (A_1 and A_2) based on the Equation: 6 is expressed as

$$\left(x_{SG_1A_1}, x_{SG_1A_2}, x_{SG_2A_1}, x_{SG_2A_2}\right) \tag{7}$$

Likewise, the multi-objective function values are generated for all the actors in the goal model. These optimal values refer to the capacity of each alternative to fulfil the stakeholders' objectives.

Cost-Effective Analysis

Cost-Effectiveness Analysis (CEA) is one of the significant approaches for the prioritisation of alternative options (Robinson 1993). The reason for adopting such a realistic decision-making approach is that it can help in prioritising alternatives to achieve the quality requirements (non-functional requirement or softgoal). CEA can assess decisions objectively based on different strategies, by simultaneously examining the benefits in the light of costs. It is a performance efficiency analysis method where cost is measured in terms of money and consequences are measured in non-monetary/ natural units as measured in physical units such as number of cases cured, lives saved, complications prevented etc. It compares alternative options with different safety and efficacy profiles (Boardman 2011; Neumann et al. 2017).

The final decision must reflect these considerations with the decision context and characteristics such as support the decision makers, criteria and the alternatives when addressing the different objectives. This step involves a pair-wise comparison between several alternatives based on their efficiency and effectiveness in fulfilling stakeholders' objectives. The outputs of the CEA provide rankings of alternatives for each actor. Since inputs for CEA are optimal values from CPLEX, this final decision analysis leads to a Pareto optimal final ranking.

Algorithm 1:

Main Module*: Optimal Selection of most effective alternative that represents the best outcome per dollar based on Pareto optimal final ranking for each actor under different alternative options.*

Input: A set of actors $A = \{A_1, A_2, \ldots , A_n\}$ in such a way that *i** model has a set of directed graphs $S = \{S_1, S_2, \ldots , S_n\}$ such that $G = \{G_1, G_2, \ldots, G_k\}$ is a subset of *S* that have same *n* set of tasks *T*, where each G_i is a quadruple $\{T, L, SG, TS\}$ where each element T, L, SG, TS represents a set of task, a set of leaf softgoals, a set of in-between softgoals, a set of top softgoals respectively with each top softgoal associated with opposing variables such as *Max* or *Min.*

$\boldsymbol{for}\ G_i\ \in G\ \boldsymbol{do}$

$\quad \boldsymbol{for}\ task\ t\ \in T\ \boldsymbol{do}$

$\quad\quad \boldsymbol{for}\ top\ softgoals\ t_s\ \in\ TS\ \boldsymbol{do}$

$\quad\quad \boldsymbol{if}\ \ t_s\ is\ Min\ \boldsymbol{then}$

$\quad\quad\quad Generate\ minimisation\ objective\ function;$

$\quad\quad \boldsymbol{endif}$

$\quad\quad \boldsymbol{if}\ \ t_s\ is\ Max\ \boldsymbol{then}$

$\quad\quad\quad Generate\ maximisation\ objective\ function;$

$\quad\quad \boldsymbol{else}$

$\quad\quad\quad Break;$

$\quad\quad \boldsymbol{endif}$

$\quad\quad \boldsymbol{endfor}$

$\quad \boldsymbol{endfor}$

$\boldsymbol{endfor}$

$Let\ F_{Max} \leftarrow Max\{f_{max_1}, f_{max_2}, \cdots, f_{max_n}\};$

$Let\ F_{Min} \leftarrow Min\{f_{min_1}, f_{min_2}, \cdots, f_{min_n}\};$

$\boldsymbol{for}\ f_{max_i} \in\ F_{Max}\ \ \boldsymbol{do}$

$\quad Let\ x_{max_i}\ \leftarrow\ optimal(f_{max_i},\ \ Max);$

$\quad //\ \ finding\ optimal\ solutions\ for\ maximum\ objective\ functions$

$\boldsymbol{endfor}$

$\boldsymbol{for}\ f_{min_i} \in\ F_{Min}\ \ \boldsymbol{do}$

$\quad Let\ x_{min_i} \leftarrow optimal(f_{min_i},\ \ Min);$

$\quad //finding\ optimal\ solutions\ for\ minimum\ objective\ functions$

$\boldsymbol{endfor}$

$Let\ \ X_{min} \leftarrow \{x_{min_1}, x_{min_2}, \cdots\ x_{min_n}\}\ represents\ the\ non-functional\ requirement\ based\ on\ cost;$

$Let\ \ X_{max} \leftarrow \{x_{max_1}, x_{max_2}, \cdots, x_{max_n}\}\ represents\ the\ non-functional\ requirement\ based\ on\ effectiveness;$

$Let\ \ \ CER_{A_{i_t}}\ represents\ the\ cost\ effectiveness\ of\ non-functional\ requirements\ of\ every\ actor,\ \ \ A_i \in A, under\ for\ t\ \in T;$

$\boldsymbol{for}\ A_i \in A\ \boldsymbol{do}$

$\quad \boldsymbol{for}\ task\ t\ \in T\ \boldsymbol{do}$

$\quad\quad CER_{A_{i_t}} \leftarrow \left[\frac{x_{min_i}}{x_{max_i}}\right];\ \ //\ Generate\ optimal\ CER\ values\ for\ each\ actor\ under\ different\ alternative\ options;$

$\quad \boldsymbol{endfor}$

$\boldsymbol{endfor}$

$Let\ T \leftarrow \{t_1, t_2, \ldots, t_n\}, \qquad count = 1, CER_{Min} = 0;$

$\boldsymbol{for}\ A_i \in A\ \boldsymbol{do}$

$\boldsymbol{for}\ task\ t \in T\ \boldsymbol{do}$

$\boldsymbol{while}(count < n)$

$\boldsymbol{if}\ CER_{t_i} < CER_{Min}\ \boldsymbol{then}$

$CER_{Min} = CER_{t_i};$

$\boldsymbol{endif}$

$count++;$

$\boldsymbol{end\ while}$

$\boldsymbol{return}\ t_i;$

$\boldsymbol{endfor}$

$\boldsymbol{endfor}$/

Sub Module: *Solving Multi-objective functions (optimal (f, C))*

ASSERTION: Solves the objective function to obtain the optimal function value:
Declare the variables;

Define the expressions, the objective functions and the constraints based on *C;*

$\boldsymbol{if}\ C\ is\ Max\ \boldsymbol{then}$

Define maximisation function;

$\boldsymbol{end}$

$\boldsymbol{if}\ C\ is\ Min\ \boldsymbol{then}$

Define minimisation function;

$\boldsymbol{else}$

$W \leftarrow cplex.solve();$

$\boldsymbol{end}$

//*invoking CPLEX function*

$\boldsymbol{return}\ W;$

Simulation and Evaluation

In order to illustrate the application of the proposed approach, a generic telemedicine system (Yu 2001) case study is utilised (from the literature). The telemedicine system uses information technology and telecommunication technology to provide remote diagnosis and treatment for patients.

The adapted telemedicine system (Figure 2.) shows two actors, *Patient* and *Healthcare Provider* that are considerably simplified, but nevertheless require some kind of reasoning, namely the identification and exploration of alternatives. The main non-functional requirements or softgoals of the actor *Patient* are the *Expense* of the treatment and *Happiness* obtained from the remote treatment, which depend upon the softgoals *Time Saving* and *Quality of Care*. There are two alternative ways of obtaining treatment for the patient: either via *Patient Centered Care* or by *Provider Centered Care*. The *Patient* has to choose an alternative option so that his/her *Expense* is less and *Happiness* is more.

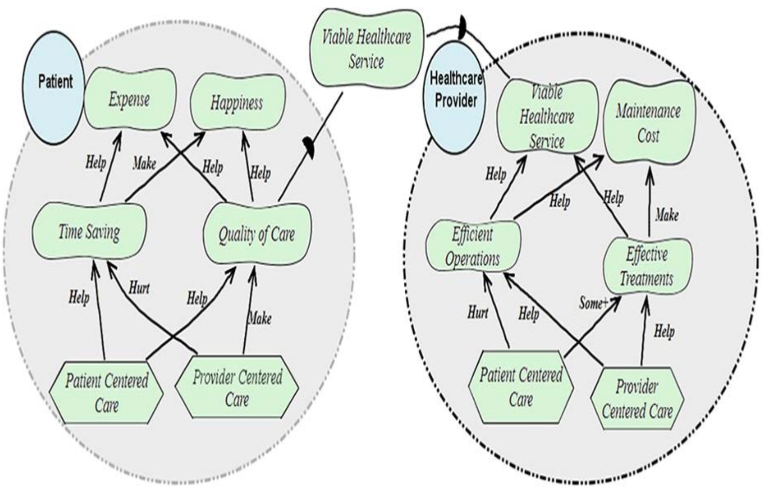

Figure 2. Telemedicine System (adapted from (Yu 2001))

The actor, *Health Care Provider*, has two main non-functional requirements or softgoals namely *Viable Healthcare Service* and *Maintenance Cost* representing the *Health Care Provider*'s aim of providing services within the telemedicine system. The goal *Viable Healthcare Service* can be implemented in one of the two ways; thus, *OR* decomposed into two tasks known as *Patient Centered Care* or by *Provider Centered Care*. The selection of a task for this goal depends on the non-functional goals *Viable Healthcare Service* and *Maintenance Cost* for the satisfaction levels of actor *Health Care Provider*. Here, the task is to select an alternative option that increases the *Healthcare Service* and decreases *Maintenance Cost*. The objective of this system is to select the best alternative option based on its impact on each of the softgoals.

The impacts indicate the extent to which an alternative option satisfies the corresponding softgoal. Impacts such as *make, help, hurt, break, some+, some-* are denoted by fuzzy triangular numbers. Along with the softgoal preferences, these impacts propagate to the top softgoals, to find the level of satisfaction or scores of these softgoals. For each actor, leaf softgoals are assigned an individual weight that can optimally select the best alternative option for achieving the opposing goals.

For illustration and simplicity of calculation, defuzzification is used to convert the impacts which are represented in fuzzy numbers to quantifiable values (Chou et al. 2008). These defuzzified values as shown in Table 1 are used to evaluate the objective functions of each top softgoal.

Table 1. Defuzzified values for impacts

Impact	Fuzzy Contribution	Defuzzified value
Make	(0.64, 0.8, 1)	0.8
Help	(0.48, 0.64, 0.80)	0.64
Some+	(0.32, 0.48, 0.64)	0.48
Some-	(0.16, 0.32, 0.48)	0.32
Hurt	(0, 0.16, 0.32)	0.16
Break	(0, 0, 0.16)	0

The objective function values of the top softgoals for each actor, under both alternatives, are found using Equation: 6. For actor *Patient*, the objective functions for both the top softgoals, *Expense* and *Happiness*, under both alternatives *Patient Centered Care* and *Provider Centered Care*, are found based on their scores which are as follows:

$$F_{Expense}(\omega)_{Patient\ Centered\ Care} = Min(0.4096 \times \omega_1 + 0.4096 \times \omega_2 + 0.0524 \times \omega_3 + 0.1573 \times \omega_4)$$

$$F_{Expense}(\omega)_{Provider\ Centered\ Care} = Min(0.1024 \times \omega_1 + 0.512 \times \omega_2 + 0.2097 \times \omega_3 + 0.2097 \times \omega_4)$$

$$F_{Happiness}(\omega)_{Patient\ Centered\ Care} = Max(0.512 \times \omega_1 + 0.4096 \times \omega_2 + 0.0524 \times \omega_3 + 0.1573 \times \omega_4)$$

$$F_{Happiness}(\omega)_{Provider\ Centered\ Care} = Max(0.128 \times \omega_1 + 0.512 \times \omega_2 + 0.2097 \times \omega_3 + 0.2621 \times \omega_4)$$

Similarly, for the actor *Healthcare Provider*, the objective functions for both the top softgoals, *Viable Healthcare Service* and *Maintenance Cost*, under both alternatives *Patient Centered Care* and *Provider Centered Care*, are generated based on their scores which are as follows:

$$F_{Viable\ Healthcare\ service}(\omega)_{Patient\ Centered\ Care} = Max(0.1024 \times \omega_3 + 0.3072 \times \omega_4)$$

$$F_{Viable\ Healthcare\ service}(\omega)_{Provider\ Centered\ Care} = Max(0.4096 \times \omega_3 + 0.4096 \times \omega_4)$$

$$F_{Maintenance\ Cost}(\omega)_{Patient\ Centered\ Care} = Min(0.128 \times \omega_3 + 0.384 \times \omega_4)$$

$$F_{Maintenance\ Cost}(\omega)_{Provider\ Centered\ Care} = Min(0.512 \times \omega_3 + 0.512 \times \omega_4)$$

The solutions to these objective functions are obtained by invoking the IBM ILOG CPLEX. The obtained function values are given in Table 2. as a ready reference. The paper explains the significance of requirements elicitation and analysis in measuring efficiency regarding the objective of providing efficient services by means of an appropriate efficiency analysis framework. Services are compared based on alternative service providers.

The generic formula for calculating a CE ratio is as follows:

$$CER = Cost/\ Effectiveness\ Measure$$

where the effectiveness measure in this case study are *Happiness* and *Viable Healthcare Service*.

Table 2. Objective functions values and CER values

		Alternatives	
		Patient Centered Care	*Provider Centered Care*
Non- functional goals	*Expense*	5.24	10.24
	Happiness	51.2	51.2
	Maintenance cost	12.8	51.2
	Viable Healthcare service	30.72	40.92
CER values for each actor	*Patient*	0.10	0.2
	Healthcare Provider	0.42	1.25

The cost-effectiveness ratio or the cost per unit of benefit of the healthcare is estimated by dividing the cost of providing service by the degree of service provided. The provision of service is deemed to be cost-effective when the outcome is better when compared with the cost competing alternatives. This approach can compare programs or treatment alternatives with various safety and efficacy profiles. Thus, it helps to identify which treatment alternative will produce the best outcome per dollar.

The results presented in Table 2. indicate that the *Provider Centred Care* has a higher value than the alternative *Patient Centred Care*. This means that by choosing the *Provider Centred Care* strategy, the system achieves the opposing top softgoals of inter-dependent actors efficiently and effectively in the i^* goal model.

Conclusions

The rapid growth in GORE requires careful scrutiny of the requirements with regard to not only effectiveness, but also efficiency. This shift requires decision makers to understand the effectiveness of their chosen alternative and the cost of achieving this. CEAs have become a critical evaluation tool in recent years in many industries. The explicit articulation of comparative cost-effectiveness will help to determine the allocation of limited resources. In this paper, an economic evaluation based on CEA is applied to prioritise alternative design options. Hence, an optimum strategy is chosen for inter-dependent actors in the i^* goal model by balancing the opposing goals reciprocally. Further research work includes performing sensitivity analysis, for facilitating valuable input data to assist the requirements analyst in the decision-making process.

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Sensitivity Analysis of Conflicting Goals in the i^* Goal Model

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Goal Oriented Requirements Engineering is a modelling technique that is used for representing goal models. This technique is used to model software system requirements by evaluating using goals. A goal analysis method helps in choosing an alternative design option. They represent stakeholder objectives. Shareholders' requirements may have conflicting goals in a competitive environment. Goal analysis method helps to achieve the conflicting goals of different inter-dependent actors in a goal model. This paper proposes a framework of multi-objective optimization to evaluate the goal analysis. In this method based on the interdependence relationships between actors, each objective functions are optimised. For the *i goal framework for requirements elicitation, the Cost-Effectiveness Analysis approach is applied to this optimisation method. This approach also includes the sensitivity analysis on the economic evaluation of the obtained optimal values. This helps facilitate useful information on input data for the benefit of requirements' analyst. The proposed approach helps in prioritising design options. It also leads to the achievement of conflicting goals by choosing the cost-effective design option. The proposed approach is applied on the Telemedicine System case study from the existing literature and is evaluated using a simulation based analysis.**

Keywords: Goals; Goal Models; Requirements Engineering; Cost-effectiveness; Multi-objective Optimisation; Sensitivity Analysis

1. INTRODUCTION

Requirements Engineering (RE) is a technique that helps in requirements gathering, analysis, evaluation and management [1]. This technique aims to improve the initial phases of software development life cycle. The success of any software system is measured by its cost-effectiveness. Mistakes made in understanding customer needs during the implementation stage can be catastrophic. Fixing of these errors at a later stage, can prove to be extremely expensive. According to Nuseibeh [2], RE is a series of decisions that helps to identify customer issues to the extent of comprehensive specification and thus helps to solve the issue. A recent work-group article [3] calls for research and experiences of RE decision-making to prescribe methods and tools that can support better and effective decision-making. The key question driving RE activities is: how can businesses make a strong decision to begin designing a new system, a sub-system, or an element?

RE has been viewed as a critical area of the life cycle of system development over the past two decades. RE is a cyclical system of producing, evaluating, modelling, interacting, agreeing and developing [4] requirements, with the most important being the initial elicitation stage of requirements. This elicitation process makes it easier to identify the right stakeholders and identify the system's goals and tasks, thus offering evidence of the system objectives to be accomplished. During the requirements analysis phase, the requirements analyst analyses the information received from the stakeholders. From the analysis of the collected requirements, stakeholder goals are identified. Stakeholders have goals (hardgoal) based on which the system performs its required functions. The requirements analyst then evaluates the goals to design a better software system. In addition, the requirements analyst examines design options for the high-level alternative system and decides on the implementation of an effective system design [5].

Goal Oriented Requirements Engineering (GORE) designs software system requirements by applying goals as staring point. This method involves the requirements specifications being developed, elaborated, organised, defined, evaluated, negotiated, recorded and updated [4]. Goals play a critical part in GORE. Goals help in understanding the domain and determines stakeholder's interests [1]. Goals are drawn up at various layers of abstraction, based on the actors' strategic concerns related to the system being built. It is therefore a well-considered significant artefact during the initial stages of development of RE [5]. A goal model or a multi-view model of goals forms the basis of goal elaboration. The model demonstrates how in the specified system , goals, actors, states, objects, tasks, and domain characteristics are interconnected [6]. Since the mid-1990s, goal models have been a crucial aspect in software engineering. Knowledge Acquisition in Automated Space (KAOS) Model [7], i^* goal model [8], Non-Functional Requirements (NFR) model [1], Attributed Goal-Oriented Requirements Analysis (AGORA) Model [9], Tropos Model [10] and Goal-Oriented Requirement Language (GRL) [11] Model are some of the goal models more widely used. The i^* goal model is one of the prominent and most well-known goal model in the software engineering discipline. By using the i^* model, goal-oriented modelling of social and economic-technical systems and organisations is achieved. This model helps the basic processes of modelling organisations and social and economic-technical systems as an intentional structure of actors and their dependencies. The performance of qualitative analysis [12], or quantitative analysis [5], [13], or even both [11] are based on the reasoning techniques of the i^* model.

Many stakeholders' objectives, during the development of complex systems, are of a conflicting or opposing nature in the competitive environments of the real world. Hence, in a goal model, an analyst must analyse the most cost-effective design option during the requirements analysis process to accomplish the goals of all interdependent actors. Requirements-based engineering is facing the challenge of assessing an optimal alternative design option for a model that is cost-effective. Cost-effective decision-making faces several concerns in a competitive environment. When making decisions effectively in the real world, decision-makers must take into account cost per service provided by alternative design options based on the inter-dependent relationships (among actors). Therefore, to achieve multi-objective optimisation, there is a necessity for a novel framework that can capture these real issues [14, 15]. The implementation of a practical and cost-effective decision-making process in our approach enables us to go beyond economic evaluation concepts that brings about an approach called Cost-Effectiveness Analysis (CEA). In the i^* goal model, the CEA is applied to select an optimal strategy for inter-dependent actors by optimising the opposing goals reciprocally. This approach is essential, therefore, and makes it possible to analyse decision-making problems cost effectively. A novel methodology based on economic evaluation is proposed in this paper. This methodology is beneficial for exploring systems involving cost-effective alternative design evaluations.

In the i^* goal model, the previous research [16] proposed a game theory-based goal analysis for each actor. proposed a game-based goal analysis for each actor. This goal analysis did not take into account the inter-dependency relations among the actors. This paper proposes a systematic economic evaluation approach by optimising the multiple conflicting objectives in turn facilitating cost-effective decision-making when the i^* model includes interdependent actors. A Cost-Effective Analysis (CEA) approach is applied to the i^* goal model that helps the interdependent actors ' optimal alternative options. This is made possible by reciprocally balancing their opposing goals. Multi-objective functions are evaluated to determine their importance in the proposed approach. Each actors' alternative options are then evaluated according to each opponent's optimal CEA values of the softgoals. The final phase leads to an optimal, cost-effective solution that looks at implementing a strategy in the context of competing goals. The inclusion of a sensitivity analysis is an added benefit to the optimisation model. This includes accompanying data indicating the extent to which a input parameter can fluctuate without changing the solution.

The process of sensitivity analysis involves a number of purposes, including checking the reliability of the system, having an overview of the impact of the input variables, and helping to recognise errors in the system. In addition to this, the analysis also provides a space region where the solution is optimal and remains optimal while the input parameters changes within the specified range. The above mentioned analysis is employed in a cost-effective solution and helps in detecting the behaviour of the system when input data are changed.

A case study taken from the literature illustrates the developed sensitivity analysis process. The results are examined by illustrating the applicability of the proposed approach. A summary of the current approaches that are related to GORE are presented in the next section. More precisely, i^* model and the techniques and methods that are closely linked with our proposed method are also presented.

The paper is organised accordingly. Section 2, discusses the existing methods, techniques and approaches on the i^* model, that are very closely associated with approach proposed. Section 3 describes the methodology that includes several steps of the approach proposed and a brief description of the methods used during the study. Section 4 describes the case study used for this work. The conclusions were finally drawn at the end of the paper.

2. RELATED WORKS

The latest Requirements Engineering trends use goals to discover the '*whys*' instead of ''*what*'' [17]. With the help of goals, the requirements of the stakeholder organisation is aligned with its functionality. This section therefore provides an overview of the current i^* goal model-related approaches, strategies, and processes.

The interactive, iterative and qualitative analysis-based approach for the i^* goal model were proposed by Horkoff and Yu [13]. This approach has a limitation of using the same label for more than one top softgoal which causes uncertainty in the decision making process. Heaven et al., [18] suggested a multi-objective optimisation method to evaluate the alternative design options in the KAOS model. This model led to the development of an automated tool for quantitative reasoning. However, the main problem with this model is that the model does not taken into account the non-functional requirements. Mairiza et Al. [19] developed the Multi-Criteria Decision Analysis (MCDA) methodology and applied the TOPSIS model as MCDA to prioritise alternative options to address conflicts in the NFR Decision Analysis. TOPSIS has well been systematically applied to select the preferred solution for designing conflicting NFRs. The quantitative results developed can be used to facilitate decision-making. Chitra et al. [20] has developed an inter-actor goal analysis framework for quantitative evaluation to decide on alternative design options in the i^* model. Fuzzy numbers were used for quantitative evaluation to eliminate the ambiguity in the choice of numerical numbers. Later on, in a goal analysis process to further develop the earlier approach, a multi-objective optimisation approach has been used to find the optimal softgoal values for alternative selection [14, 15]. This approach also prevents the decision-maker to enforce his or her subjective preference on the values for the goal evaluation process. All of the above-mentioned goals analysis proposals are based upon either quantitative or qualitative approaches to select an alternative design option. Also, these proposals evaluate goals according to the maximum satisfaction label of the non-functional requirements. However, there is an ambiguity in deciding when the same type of label is given to two or more non-functional requirements [21]. Chitra et al. [14, 15] has overcome this weakness of the qualitative approach to i^* model which leads to uncertainty in decision-making. Chitra et al. have implemented an optimal quantitative technique based on fuzzy in the i^* model. The above literature shows nevertheless that there are no goals with opposing objective functions in the qualitative and quantitative goal analysis process for inter-actor dependences using i^* or other model goals.

In order to conduct quantitative analysis of goals, CEA, fuzzy mathematical applications and optimisation tools are essential. In this study, these tools are used to develop an ideal strategy in requirements-based engineering design with opposing objective functions. This method thus explains how the requirements-based engineering could evaluate an optimal design result that is cost-effective. Another interesting factor in this proposal is performing sensitivity analysis process. This is applied to detect the behaviour of the system when data input changes. This technique ensures that before a final decision is made, a proper investigation into the calculation of input variables is carried out. It also helps to identify the model's errors and understand the effect of input variables.

Chitra et al. [16] performed the first work on reasoning i^* goal models using optimisation where an alternative design option with opposing objective functions was defined for each actor in a i^* goal model. This approach led to the formalisation of reasoning, but without any economic analysis of the objective functions. The approach proposed could not resolve the inter-dependence relationships of the actor that are important in a competitive environment in a real-world decision-making process. Another drawback of the proposal listed above is the inability to resolve the economic efficiency and dependency relationship between actors [16]. Ultimately, previous research efforts were ineffective in developing a structured method for determining a cost-effective, optimal alternative design option for inter-dependent actors in the i^* model by reciprocally balancing the multiple opposing goals on the basis of their significance. The Section below illustrates how an actor's goals and softgoals are evaluated in the i^* goal model.

3. THE i^* GOAL MODELLING

The GORE framework, specifically i^*, is an effective and efficient method for modelling and analysing the dependencies in a socio-economic community environment [21–24]. Therefore, in this proposed approach, the i^* framework is preferred to model the sensitivity analysis of conflicting goals. The intentional strategic actor is the core entity to be modelled in this view. An actor's intentional aspects can be characterised by goals, values, capability and commitments [21]. An actor is strategic meaning that it intends to effectively achieve the goal. When sharing resources and performing other activities to achieve their goals, actors are also concerned about the structural relationships with other actors. Through means-end (OR-decomposition) reasoning, specifically clear representation of goals in the i^* model helps discover alternative choices. Usually, a softgoal (non-functional goals) captures certain preferred behaviours among those captured by functional goals (hard goals). The goal modelling of i^* framework uses two models to represent socio-economic systems: the model of Strategic Dependency (SD) and the model of Strategic Rationale (SR) [21–24].

The SD model is a graph showing a high-level description of a process or system. This represents the dependencies of the actors by goals (behavioural goals or softgoals), tasks and resources. Figure 1 shows an example of a generic SD model with actors being portrayed as circles, hardgoals as ovals, softgoals as cloud images, resources as rectangles, and tasks as hexagonal shapes. In the example SD model, the actor

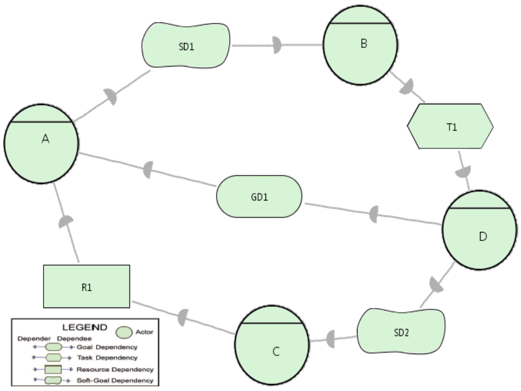

FIGURE 1. An example of a generic SD model in the i^* framework

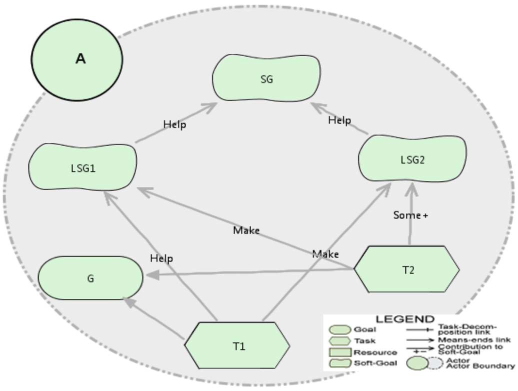

FIGURE 2. An example of a generic SR model in the i^* framework

A is dependent on the actor B to achieve the softgoal $SD1$and the latter is subsequently dependent on D, which in turn depends on C for a softgoal. The actor A has a goal dependency with actor D. Actor A has a goal dependence on actor D.

Even though the SD model focuses on the notion of dependence among actors, the SR model 2 aims to illustrate the modelling and evaluation of all actors within the system based on their internal intended inter-dependencies. Behavioural goals are the intended function of the system. The system's non-functional objectives are defined as a softgoal. The SR model is also described as a graph in which nodes are defined as goals or tasks or resources or softgoals interconnected by means-end links or task links or contribution links [23,24]. To achieve goals, they (goals) are linked to one or more tasks by AND (decomposition links) or OR (means-end links) relationships. The contribution links can be defined as $Make$, $Break$, $Help$, $Hurt$, $Some+$, $Some-$. Such definitions define the different types of contributions to different softgoals, which contribute to softgoals satisfaction [8,23,24].

A top-down approach is applied in the i^* model to identify each actor's goals. The main goal (hardgoal) is divided into a set of tasks by answering to "how to achieve?" or "what to achieve?" questions. By answering "how to achieve?", the softgoal is also further decomposed. This process of decomposition is repeated until each softgoal of the leaf is atomic in nature. The proposed methodology of reasoning opposing goals using inter-actor dependence using the $i*$ goal model is presented in the next section.

4. METHODOLOGY FOR DECISION-MAKING IN CHOOSING ALTERNATIVES UNDER UNCERTAINTY IN ACHIEVING CONFLICTING GOALS

To attain the research goal, a methodology has been proposed and is illustrated in Figure 3.

In the proposed framework, the objective is to achieve strategic goals while keeping into account the constraints so that the reasoning method helps to optimise the overall strategy by choosing an effective alternative option.

4.1. Stakeholder Analysis

In the $i*$ framework, stakeholder analysis involves identifying the actors (i.e., which stakeholders should be considered), defining design alternatives or options to achieve stakeholder's objectives and identifying the impacts of various alternatives based on the stakeholder's subjective preference to the problem. The stakeholder's points of view about the criteria to achieve their objectives are determined through a bottom-up approach. The bottom-up approach is to identify requirements for goals from the implications and impacts of the alternatives.

4.2. Formalisation of Multi-objective Functions

The following Section explains a complete generalised framework of an $i*$ goal model through the formalisation of the opposing objective functions with regard to softgoals, goals tasks and resources. The SR $i*$ model [24] is used for formalisation and is represented as a directed graph. Consider the directed graph be $G(N;R)$, where N represents the intentional elements, (such as goals, top softgoals (TS_1, TS_2, ... , TS_n), intermediate softgoals (SG_1, SG_2, ... , SG_n), leaf softgoals (L_1, L_2, ... , L_n), resources and tasks ($Task_1$ and $Task_2$)), forming a collection of nodes and R, (represents the means-end, task-decomposition, dependency and contribution links), forming a collection of edges of the graphs. The decision-maker has the task of choosing a cost-effective optimal alternative choice. On the basis of the graph structures, an objective function can be developed for each alternative choice.

Based on a $i*$ goal model, we aim to choose an ideal alternative option depending on its softgoals impact. Impacts are defined as fuzzy triangular numbers indicating how well an alternative option meets the leaf softgoal. In order to find the level of satisfaction or scores of top softgoals, the impacts along with the softgoals preferences are propagated to the top softgoals. Based on each softgoals' relative importance in achieving the goal, they are assigned a weight ω.

Initially, each actor's top softgoal scores (based on its inter-actor dependency) are computed under each alternative. Readers are guided to [14, 25, 26] for information on the representation of goals, weights, impacts and alternatives.

Consider there are t hierarchy levels in the directed graph. Leaf softgoals are defined at level zero of the directed graph. Let us aasume $\omega_{L_{ik}}$ refers to the weight of i^{th} leaf softgoal and $I_{L_{ijk}}$ refers to the impact on i^{th} leaf softgoal of j^{th} alternative of the k^{th} actor. Also, consider there exists m number of softgoals, n_c children and n_d dependencies for the i^{th} softgoal at level one. The score of any softgoal at $t > 1$ is determined by taking the product of its impact and its each child score [14].

Thus, the score of a level t softgoal for an actor with a relationship of dependence can be formalised as:

$$\begin{aligned} S_{SG_{i_tjk}} = \Pi_{l=1}^{t} I_{ijl} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{ij}} * I_{d_{L_{ijk}}} * \omega_{d_{L_{ijk}}})] \\ + \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (S_{i_{d_{by}}} * I_{i d_{by}})) + \sum_{b=1}^{n_d} (S_{i d_b} \\ * I_{i d_b})] \end{aligned} \tag{1}$$

Then, as shown in the equation 1, the objective functions of top softgoal under each actor alternative are created from the scores. If there is an inter-actor dependence relationship, then consideration should be given to both strategic dependence and strategic rational diagrams of the $i*$ goal model, assuming that this approach takes into account only softgoal interdependence relationships. If an actor has n number of alternatives, then n objective functions are available for each top softgoal. The n objective functions that need to be maximised to obtain a maximum score for the top softgoal under each alternative are given as follows:

$$\begin{aligned} f_i(\omega_1) &= S_{SGi1k} \\ &= Max \Pi_{l=1}^{t} I_{i1l} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{i1}} * I_{d_{L_{i1k}}} * \omega_{d_{L_{i1k}}})] \\ &+ \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (S_{i_{d_{by}}} * I_{i d_{by}})) \\ &+ \sum_{b=1}^{n_d} (S_{i d_b} * I_{i d_b})] \end{aligned}$$

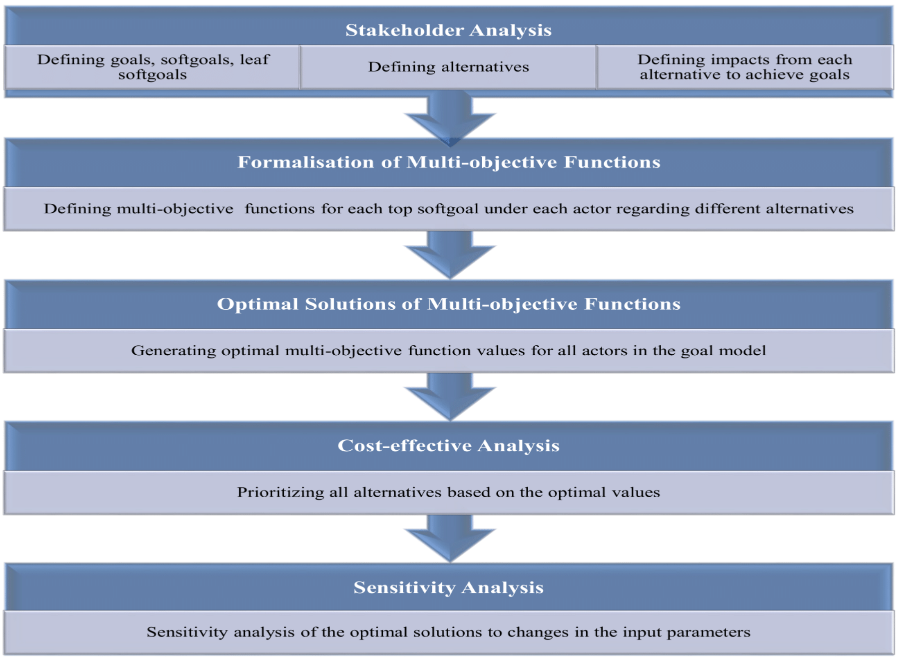

FIGURE 3. Framework for Decision-making in Choosing Alternatives under Uncertainty in Achieving Conflicting Goals using CER values

$$
\begin{aligned}
f_i(\omega_2) &= S_{SGi2k} \\
&= Max\Pi_{l=1}^{t} I_{i2l} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{i2}} * I_{d_{L_{i2k}}} * \omega_{d_{L_{i2k}}})] \\
&+ \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (S_{i d_{by}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d} (S_{i d_b} * I_{i d_b})] \\
&\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots
\end{aligned}
$$

$$
\begin{aligned}
f_i(\omega_n) &= S_{SGink} \\
&= Max\Pi_{l=1}^{t} I_{inl} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{in}} * I_{d_{L_{ink}}} * \omega_{d_{L_{ink}}})] \\
&+ \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (S_{i d_{by}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d} (S_{i d_b} * I_{i d_b})]
\end{aligned} \tag{2}
$$

Such that

$$0 \le \omega_{d_{L_{jk}}} \le 100 \text{ for } d = 1 \text{ to } n_c$$

Likewise, in the i^* goal model, objective functions which need to be minimised are formalised for each actor.

$$
\begin{aligned}
f_i(\omega_1) = S_{SGi1k} \\
&= Min\Pi_{l=1}^{t} I_{i1l} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{i1}} * I_{d_{L_{i1k}}} * \omega_{d_{L_{i1k}}})] \\
&+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i d_b})]
\end{aligned}
$$

$$
\begin{aligned}
f_i(\omega_2) = S_{SGi2k} \\
&= Min\Pi_{l=1}^{t} I_{i2l} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{i2}} * I_{d_{L_{i2k}}} * \omega_{d_{L_{i2k}}})] \\
&+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i d_b})] \\
&\ldots\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots\ldots
\end{aligned}
$$

$$
\begin{aligned}
f_i(\omega_n) = S_{SGink} \\
&= Min\Pi_{l=1}^{t} I_{inl} \sum_{i=1}^{m}[\sum_{d=1}^{n_c}[(I_{d_{in}} * I_{d_{L_{ink}}} * \omega_{d_{L_{ink}}})] \\
&+ \sum_{y=1}^{n_c}(\sum_{b=1}^{n_d}(S_{i_{d_{by}}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d}(S_{i_{d_b}} * I_{i d_b})]
\end{aligned}
\tag{3}
$$

Such that

$$0 \leq \omega_{d_{L_{jk}}} \leq 100 \text{ for } d = 1 \text{ to } n_c$$

Such multi-objective functions are then optimised, to have all the actors in the goal model, with the optimal solution values. The next Section discusses how conflicting goals (Maximum and Minimum in nature) are optimised for multi-objective functions.

4.3. Optimal Solutions Of Multi-objective Optimisation Functions

In the proposed model, each actor is considered to have two conflicting softgoals (G_1 and G_2) and two alternative design options (A_1 and A_2). Two optimal solutions can be generated individually by optimising the objective functions for the top softgoals (G_1 and G_2). To evaluate the optimisation process, the IBM ILOG CPLEX optimisation tool is applied. [27]. In order to discover precise and logical choices, IBM ILOG CPLEX optimiser is applied in business mathematical models. IBM ILOG CPLEX also has a modelling layer called ' Concert ' that allows programming languages such as Java to be interfaced with.

The two alternative design options (A_1 and A_2) based on 2 and 3 equations, express the ideal solutions for the objective functions of softgoals (G_1 and G_2) in the given actor. The optimal solutions are given as

$$
\begin{aligned}
&(x_{G_1A_1}, x_{G_1A_2} x_{G_1A_3}, \ldots\ldots.., x_{G_1A_n}, \\
&x_{G_2A_1}, x_{G_2A_2} x_{G_2A_3}, \ldots\ldots.., x_{G_2A_n})
\end{aligned}
\tag{4}
$$

with

$$(x_{SG_1A_1}, x_{SG_1A_2} x_{SG_1A_3}, \ldots\ldots.., x_{SG_1A_n}) \tag{5}$$

expresses the solution to equation 2 and

$$(x_{SG_1A_1}, x_{SG_1A_2} x_{SG_1A_3}, \ldots\ldots.., x_{SG_1A_n}) \tag{6}$$

expresses the solution to equation 3.

Furthermore, for all actors in the goal model, multi-objective function values are generated.

Such optimal values refer to the potential of each alternative to achieve the objectives of the stakeholder. The approach to cost-effectiveness analyses is used to identify such optimal decision-making values. In multi-objective problems, a set of optimal solution values, is called Pareto optimal set. Pareto Optimal set in the space of objective functions in multi-objective optimisation problems determines a collection of solutions that are not mutually dominant but superior to the rest of the search space. The following Section explains how the Cost-Effectiveness Analysis can be applied to the optimal Pareto values for a final analysis of decisions leading to Pareto optimal final ranking.

4.4. Cost-Effectiveness Analysis

Cost-Effectiveness Analysis (CEA), as the name suggests, is a tool used for objectively analysing different strategic decisions while closely examining the cost involved in the process. The CEA approach has been developed over several decades that analyses the performance and efficiency of the system bearing in mind the cost and consequences involved where cost is measured in terms of money and consequences are measured on non-monetarily terms (for e.g; natural units as measured in physical units like cases cured, lives saved, complications prevented etc) [28, 29]. CEA is considered as one of the key aspects in prioritisation of alternatives, [30]. CEA provides estimates of costs and the related consequences and thus exhibits the trade-off's involved in choosing among alternatives. CEA analyses the net or incremental costs and effectiveness outcome involved in an alternative as compared to other alternatives. The results of the evaluation of cost-effectiveness analysis is demonstrated in terms of cost-effectiveness ratio, where the denominator denotes the gain derived from choosing a particular alternative and the numerator denotes the cost of deriving the gain.

The generic formula used for calculating CER is represented as follows:

$$CER = Cost/EffectivenessMeasure \quad (7)$$

CEA is a very effective tool that guides the decision-makers to sort through various alternatives. The information derived from the cost-effectiveness analysis helps the decision-makers to decide the best alternative that meets their technical and financial needs. Once the cost-effectiveness ratios are determined from the societal perspective and placed in a ranked order, the decision-maker can select the alternative that denotes the lowest cost per effectiveness within the constraint set by available resources. The CEA provides a simple but crucial contribution by estimating the magnitude of costs and outcomes that helps in decision-making and selecting alternatives to a given problem. Most alternatives can be complex in their application. The magnitude of costs and outcome can be wrongly understood or misrepresented and most alternatives can be complex in their application. Therefore, the accuracy of information provided becomes crucial as the effectiveness of decisions is directly dependent on it. Inaccurate information can lead to totally different decisions and deliver wrong alternatives. Accurate information helps with the comparison between right alternatives that in turn provides an effective cost-effectiveness ratio. An alternative is said to dominate all other alternatives when it is more effective and less costly in comparison to others.

CEA is a tool applied to derive quality requirements of the stakeholder (non-functional goal or softgoal). This is achieved by prioritising alternatives. It compares alternative options with different safety and efficacy profiles. A pair-wise comparison between several alternatives is then conducted. The aim is to efficiently and effectively fulfil the objectives of the stakeholders. The final decision must fulfil the decision-makers criteria and the alternatives should address different objectives. The outputs derived by using CEA helps in ranking the alternatives for each actor. Since inputs for CEA are optimal values from CPLEX, this final decision analysis leads to a Pareto optimal final ranking.

4.5. Sensitivity Analysis

Cost-Effectiveness Analysis (CEA) is instrumental in economic evaluation and is based on several assumptions. Therefore, CEA is prone to inaccuracies, leading to uncertainty. This is why Sensitivity Analysis (SA) is important as it formalises different ways to measure and evaluate the uncertainty. CEA is conducted by combining different information where the aim is to achieve effectiveness, preferences regarding effective outcomes, the costs of alternatives and its sequel, and/or any other aspects of the decision-making process. An analyst analyses the true values and relationships of the information based on cost-effective judgements and observational studies in literature or experience. While for many areas (of this information), the analyst may have a good sense of the true values and relationships on the other hand, for some aspects of the study, the correct value or the form of the relationship may be insufficient leading to uncertainty. If the analyst is certain of the true values of all the parameters needed to calculate effectiveness and costs, the true form of the relationships, and the characteristics of the decision-making process, then it would be possible to summarise the Cost-Effectiveness Ratio (CER) with a single set of numbers. However, there will always be some reliance on estimates, hence, there will always be some uncertainty about the true cost-effectiveness of the alternatives.

One way the analyst can hope to have unbiased and relatively precise estimates of cost and effectiveness is by conducting well-designed and randomised trials as well as observational studies. The impact of the uncertainty on the elements of analysis affects the effectiveness in the decision-making process. There are concerns on how to incorporate the uncertainties regarding parameters, relationships and model structure into estimated CER. These concerns have not been properly addressed. Uncertainty about estimates of costs, effectiveness, and the CER can arise in many ways. One of the reasons for uncertainty is known as "Parameter Uncertainty" where the true numerical value of the parameter inputs are not known. For example, what would happen if the true cost or effectiveness were somewhat higher or lower than the optimal or "best" estimate? What is the chance that CER would remain constant for different values of cost and effectiveness?

According to the CEA literature, conducting sensitivity analysis is the standard way of examining and dealing with these uncertainties. Weinstein and Stason [31] argue that for cost-effectiveness analysis, sensitivity analyses are fundamental. A sensitivity analysis is conducted by changing a meaningful amount of some critical component(s) or moving from the worst case to the best case and thus re-calculating the ratio of cost-effectiveness. The sensitivity of the results to the significant but not unplausible change in the parameters are analysed based on the resulting variation in the ratio. If a reasonable variation in the parameters are bringing about insensitive results, then the analyst can be fairly certain that the findings are insensitive to the parameters' working assumptions. If large range of reasonable values or a parameter are giving rise to sensitive results, then the conclusions are not robust. If only some parts of the plausible range is leading to sensitive results whereas other parts of the range are still giving insensitive results, then the analyst may get some clarity about the value for that parameter (that has given sensitive results).

The effects of uncertainty around some variable(s) was examined by using a graphical approach as shown in Figures 4 and 5 adapted from [32]. This helped in illustrating the effects of uncertainty in the components of the CER.

The difference in effectiveness ($\Delta\ E$) between two alternatives on the horizontal axis and the difference in costs ($\Delta\ C$) on the vertical are plotted in the Figures 4 and 5 respectively. The point ($\Delta\ E$, $\Delta\ C$) describes the comparison of the two alternative options, for example, treatments, and the gradient of the straight line from the origin to ($\Delta\ E$, $\Delta\ C$) gives the cost-effectiveness ratio ($\Delta\ C\ /\ \Delta\ E$). The two rays from the origin with gradients $\Delta\ C_L\ /\ \Delta\ E$ and $\Delta\ C_U\ /\ \Delta\ E$ indicate the sensitivity of the cost-effectiveness ratio to a plausible change in the underlying variable C.

Traditionally, optimisation models offer data sets quantifying the optimal solution's sensitivity when adjustments to input parameters are made. This information describes the variation that each parameter makes before the optimal solution changes [33], [34]. Latterly, these data sets can be generated automatically by the optimisation tools while determining the optimal solution. Such data is then used for performing sensitivity analysis, but it is based on continuous variables to obtain sensitivity information. The constraint of the need for integer variables results in the complexity of the problem and reduces the computational efficiency [35].

Study of sensitivity analysis is one of the most interesting and attractive areas in the optimisation process [15] and can assist a decision-analyst in more than one way. In the efforts made to explore the behavioural changes when changes are made to input data, the questions used by the sensitivity analysis process are listed as below:

- What is the input parameter's range?
- What are the results?
- Whether the results are good (positive) or optimal?
- How much will the result get affected if the data changes slightly?
- Would these variations have a minimal or significant impact on the results?
- Is one of the problem coefficients sensitive to an optimal solution for a small change?

Typically, there is a change in the right side of the constraints and/or in the coefficient of the objective function. If the linear program (LP) solution changes, it is referred to as LP sensitive when the initial coefficient is changed.

Consider a linear model,

$$\sum_{j=1}^{n} C_j X_j \tag{8}$$

$$lower - limit \le C_j \le upper - limit \tag{9}$$

where the input parameters are C_j, $lower - limit$ and $upper - limit$.

The process of Sensitivity analysis is done by adjusting input parameter values.

4.6. Implementation

In order to implement the above mentioned problem, a simulation environment was built on the i^* framework to evaluate the scope within which variables (cost and effectiveness) can differ without affecting the optimal solution values. Using Java Eclipse with IBM ILOG CPLEX optimisation tool, a tool is implemented [27]. On the i^* goal model, the developed tool evaluated the feasibility and practicality of the proposed cost-effective sensitivity analysis. 4.6 shows the pseudo code for the proposed approach. The sensitive data includes the scope for input data from which the optimum output value is not changed. If the value exceeds the scope obtained from the sensitivity analysis, the analyst will be alerted. By re-evaluating the input data, an analyst can take further actions.

4.7. Cost-effective Sensitivity Analysis on Telemedicine Case Study

The following literature case studies were considered for the simulation: Youth Counselling System [24], Meeting Scheduling System [36] and Telemedicine System [24]. Due to their simplicity and ease of interpretation, these case studies were selected for simulation.

In this paper, the evaluation of the sensitivity analysis process for Telemedicine case study is discussed. To provide patients with remote diagnosis and treatment, the telemedicine system uses information technology and telecommunication. The adapted Telemedicine model (Figure 6) shows two actors, that are considerably simplified, *Patient* and *Healthcare Provider*, however, involve some kind of reasoning, including identification and alternative exploration. The actor *Patient*'s key non-functional requirements or softgoals are the *Expense* of treatment and *Happiness* of remote treatment, which rely on the *Time Saving* and *Quality of Care* softgoals. Two alternative ways to treat the patient are available: *Patient Centered Care* or by *Provider Centered Care*. The *Patient* must choose

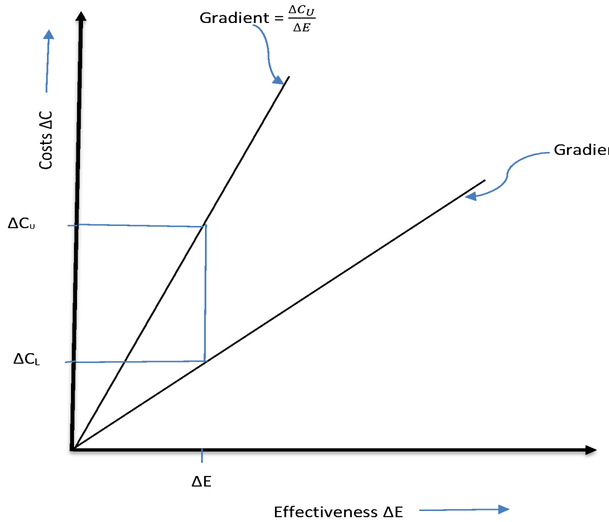

FIGURE 4. Effects of uncertainty adapted from [32]

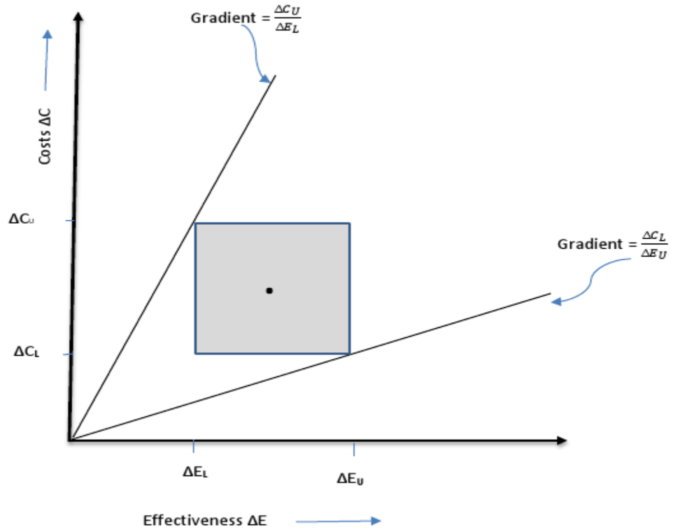

FIGURE 5. Effects of uncertainty adapted from [32]

an alternative option so that it should have less *Expense* and more *Happiness*.

The *Viable Healthcare Service(VHS)* and *Maintenance Cost(MC)* are the two main non-functional requirements or softgoals for the actor *Health Care Provider*, representing the purpose of *Health Care*

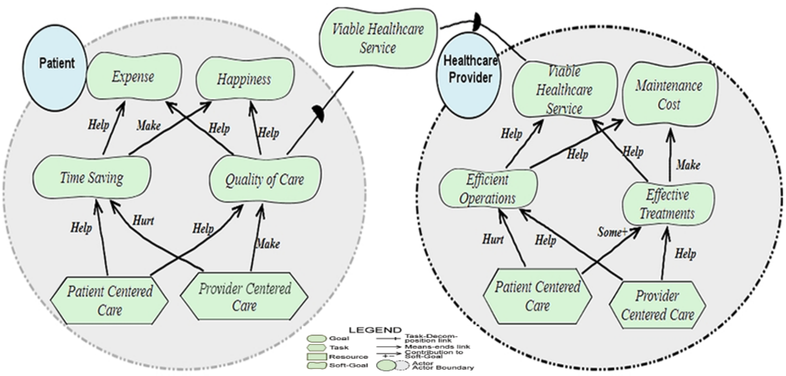

FIGURE 6. Telemedicine Case Study

Provider to provide services in the Telemedicine system. The goal *Viable Healthcare Service* can be achieved in one of two ways and thus *OR* decomposed into *Patient Centered Care* or by *Provider Centered Care* tasks. The task or alternative selection depends on the non-functional goals *Viable Healthcare Service* and *Maintenance Cost* based on the satisfaction levels of actor *Health Care Provider*.

The objective here is to choose an alternative option based on its effect on each of the softgoals, that will increase the healthcare service and reduce maintenance costs. The impacts indicate the degree to which the corresponding softgoal is reached by an alternative option. Fuzzy triangular numbers are used to denote the impacts such as *Make, Support, Hurt, Help, Some+, Some-*. These impacts propagate to the top softgoals along with the softgoal preferences to determine the level of satisfaction or scores of top softgoals. For each actor, leaf softgoals are given an individual weight, so that the best alternative to achieve the opposing goals can be optimally selected. For comparison and calculation simplicity, defuzzification is being used to transform the impacts expressed in fuzzy numbers to quantifiable values [37]. Such defuzzified values are listed in Table: 1 and used for objective functions evaluation of the individual top softgoal.

The objective functions for the top softgoals, *Expense* and *Happiness* for actor *Patient*, based on both alternatives *Patient Centered Care (PaCC)* and *Provider Centered Care (PrCC)*, are defined using equations 1 and 2 (based on their scores) as follows:

TABLE 1. Impact values

Impact	Fuzzy value	De-fuzzified value
Hurt	(0, 0.16, 0.32)	0.16
Make	(0.64, 0.8, 1)	0.8
Some−	(0.16, 0.32, 0.48)	0.32
Some+	(0.32, 0.48, 0.64)	0.48
Break	(0, 0, 0.16)	0
Help	(0.48, 0.64, 0.80)	0.64

$$\begin{aligned}F_{Expense}(\omega)_{PaCC} &= F_E(\omega)_{PaCC}\\ &= Min(S_{E_{PaCC}})\\ &= Min(0.4096 * \omega 1 + 0.4096 * \omega_2\\ &+ 0.0524 * \omega_3 + 0.1573 * \omega_4)\end{aligned}$$

$$\begin{aligned}F_{Expense}(\omega)_{PrCC} &= F_E(\omega)_{PrCC}\\ &= Min(S_{E_{PrCC}})\\ &= Min(0.1024 * \omega_1 + 0.512 * \omega_2\\ &+ 0.2097 * \omega_3 + 0.2097 * \omega_4)\end{aligned}$$

$$\begin{aligned}F_{Happiness}(\omega)_{PaCC} &= F_H(\omega)_{PaCC}\\ &= Max(S_{H_{PaCC}})\\ &= Max(0.512 * \omega_1 + 0.4096 * \omega_2\\ &+ 0.0524 * \omega_3 + 0.1573 * \omega_4)\end{aligned}$$

$$\begin{aligned}F_{Happiness}(\omega)_{PrCC} &= F_H(\omega)_{PrCC}\\ &= Max(S_{H_{PrCC}})\\ &= Max(0.128 * \omega_1 + 0.512 * \omega_2\\ &+ 0.2097 * \omega_3 + 0.2097 * \omega_4)\end{aligned}$$

Algorithm 1 Pseudo code for the sensitivity analysis of opposing non-functional requirements in the i^* goal model using CEA

Require: Consider a set of directed graphs $S = \{S_1, S_2, ..., S_s\}$ so that G is a subset of S with the same n number of tasks T, where $G = \{G_1, G_2, ..., G_k\}$. Every G_i is a quadruple $\{T, L, SG, TS\}$ where each elements T, L, SG, TS represents a set of tasks, leaf softgoals, in-between softgoals and top softgoals respectively with each top softgoal associated with opposing variables such as Max or Min.

MAIN MODULE : Sensitivity analysis on the reasoning of opposing goals
for all $G_i \epsilon G$ **do**
  for all alternatives $t \epsilon T$ **do**
    for all top softgoals $t_s \epsilon TS$ **do**
      if t_s is Min **then**
        Generate Minimisation Objective Functions
      else
        Generate Maximisation Objective Functions
      end if
    end for
  end for
end for
Let $F_{Max} \leftarrow Max\{f_{Max_1}, f_{Max_2}, ..., f_{Max_n}\}$
Let $F_{Min} \leftarrow Min\{f_{Min_1}, f_{Min_2}, ..., f_{Min_n}\}$
for all $f_{Max_i} \epsilon F_{Max}$ **do**
  Let $x_{Max_i} \leftarrow$ *optimal*(f_{Max_i}, Max)//finding optimal solutions for maximum objective functions
end for
for all $f_{Min_i} \epsilon F_{Min}$ **do**
  Let $x_{Min_i} \leftarrow$ *optimal*(f_{Min_i}, Min)//finding optimal solutions for minimum objective functions
end for
Generate optimal CER values and Pareto Optimal Final Ranking for each actor under different alternative options
Choose the most effective alternative that represents best outcome per dollar

SUB-MODULE: $Optimal(f, ts)$
Solves the objective function to obtain the optimal function value
Declare variables, Define expressions, objective functions and the constraints based on C
if ts is Max **then**
  Define maximisation function
else if ts is Min **then**
  Define minimisation function
end if
$CPLEX.solve() \rightarrow W$
return W

TABLE 2. Optimal objective function values for the actor *Patient*

Optimal Values	*Expense(G2)*	*Happiness(G1)*
Patient Centered Care	5.24	51.2
Provider Centered Care	10.24	51.2

TABLE 3. Optimal objective function values for the actor *Healthcare Provider*

Optimal Values	*MC(G2)*	*VHS(G1)*
Patient Centered Care	12.8	30.72
Provider Centered Care	51.2	40.92

Likewise, under both alternatives *Patient Centered Care* and *Provider Centered Care*, objective functions for the top softgoals *Viable Healthcare Service* and *Maintenance Cost* for actor *Healthcare Provider* can also be defined using equations 2 and 3(based on their scores).

$$\begin{aligned} F_{TS_1}(\omega)_{PaCC} &= F_{VHS}(\omega)_{PaCC} \\ &= Max(S_{VHS_{PaCC}}) \\ &= Max(0.1024 * \omega_3 + 0.3072 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_1}(\omega)_{PrCC} &= F_{VHS}(\omega)_{PrCC} \\ &= Max(S_{VHS_{PrCC}}) \\ &= Max(0.4096 * \omega_3 + 0.4096 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_2}(\omega)_{PaCC} &= F_{MC}(\omega)_{PaCC} \\ &= Min(S_{MC_{PaCC}}) \\ &= Min(0.128 * \omega_3 + 0.384 * \omega_4) \end{aligned}$$

$$\begin{aligned} F_{TS_2}(\omega)_{PrCC} &= F_{MC}(\omega)_{PrCC} \\ &= Min(S_{MC_{PrCC}}) \\ &= Min(0.512 * \omega_3 + 0.512 * \omega_4) \end{aligned}$$

Such objective functions are solved by invoking the IBM ILOG CPLEX. The function values obtained are provided as ready reference in Tables: 2 and 3.

In studies involving health care and its efficiency, the objective of analysis is perceived to be either providing services or achieving effective outcomes. Developing an appropriate efficiency analysis framework, as illustrated in this paper, involves collecting and using outcome data that can be used to measure efficiency bearing in mind the objective of providing services.

For calculating CER, the formula is defined as follows:

$$CER = Cost/EffectivenessMeasure \quad (10)$$

where effectiveness measure in this case study are *Happiness* and *Viable Healthcare Service*. The cost-effectiveness ratio (CER) is determined by dividing

TABLE 4. Optimal CER Values for the actor *Patient*

Alternatives	Optimal CER Values
Patient Centered Care	0.10
Provider Centered Care	0.2

TABLE 5. Optimal CER Values for the actor *Healthcare Provider*

Alternatives	Optimal CER Values
Patient Centered Care	0.42
Provider Centered Care	1.25

costs by the degree of service provided in the implementation of the service. The goal is to provide a cost-effective service where the outcome is worth the cost in comparison to other alternatives. The comparison is made on different programs or treatment alternatives with different safety and efficacy profiles to help identify the treatment alternative that represents to the best outcome for every dollar spent. Although CEA is being implemented to achieve cost-effectiveness, it can also help to create better health and/or longer lives. The cost-effectiveness ratio (CER) represents a ratio where the denominator denotes a candidate intervention's health gain (measured for example, in terms of years of life gained) and the numerator denotes the cost of obtaining the health gain / benefit value. Decision-makers may be at federal, state or local level, and could be in the private (or public) sector, and CEA provides them with data that can assist them in searching out options that meet the best technical and financial needs. Decision-makers can monitor dollars or run programmes and pose a range of questions within the context of the CEA. In a broader sense, the purpose of cost-effectiveness analysis is to provide a policy-maker with knowledge about the quality of a specific healthcare program to others interested in the health care industry.

The results from Tables: 4 and 5 indicate that the alternative *Provider Centered Care* has a greater value than the alternative *Patient Centered Care*. This implies that by selecting the *Provider Centered Care* strategy, the system achieves the opposing top softgoals of inter-dependent actors efficiently and effectively in the presented i^* goal model.

Figures 7 and 8 show the graphical representation of the sensitivity analysis process for the actor *Patient* for achieving opposing top softgoals, *Happiness (G1)* and *Expense (G2)* (using the alternative *Provider Centered Care*). As the value of *Happiness* is varied (by increasing and decreasing by a constant amount), it has been seen that optimal CER value of 0.25 remains constant in a range of plausible values from *40.36* to *41.56*. Similarly, the value of *Expense* is varied (by increasing and decreasing by a constant amount), it has been seen that optimal CER value of 0.25 remains constant in a range of plausible values from 10.04 to 10.44.

Figures 9 and 10 show the graphical representation of the sensitivity analysis process for the actor *Healthcare Provider* with the top softgoals, *Viable Healthcare Service (G1)* and *Maintenance Cost (G2)* (using the alternative *Provider Centered Care*). The optimal CER value of 1.25 by choosing *Provider Centered Care* remain constant for different values of *Viable Healthcare Service* from 40.82 to 41.12 and also of *Maintenance Cost* from 51.00 to 51.30.

Sensitivity analysis allows the analyst to determine whether the inputs are within an expected range. This helps analysts analyse and evaluate the solutions obtained from different inputs in order to find the best solution possible. The analyst does not need to carry out the sensitivity analysis each time the optimisation process is carried out. An analyst only needs to perform sensitivity analysis when access to the given data is needed, which ensures that when an effect is checked, the analyst can then request a bound estimate.

5. CONCLUSION

In this paper, CEA is used as a tool for performing economic evaluation in order to prioritise available alternative design options. In the i^* goal model, an optimal strategy is selected for interdependent actors by balancing the opposing goals reciprocally. To analyse the method used for the case study of the Telemedicine System, a cost-effective sensitivity analysis process was developed and implemented. The sensitivity analysis method instructed the analyst to determine the limits of the inputs when there is no change in the optimal solution. For this research, an empirical validation will be carried out in the near future to evaluate this proposal.

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G2/G1	40.06	40.36	40.66	40.96	41.26	41.56	41.86	42.16
9.64	0.24	0.24	0.24	0.24	0.23	0.23	0.23	0.23
9.84	0.25	0.24	0.24	0.24	0.24	0.24	0.24	0.23
10.04	0.25	0.25	0.25	0.25	0.24	0.24	0.24	0.24
10.24	0.26	0.25	0.25	0.25	0.25	0.25	0.24	0.24
10.44	0.26	0.26	0.26	0.25	0.25	0.25	0.25	0.25
10.64	0.27	0.26	0.26	0.26	0.26	0.26	0.25	0.25
10.84	0.27	0.27	0.27	0.26	0.26	0.26	0.26	0.26
11.04	0.28	0.27	0.27	0.27	0.27	0.27	0.26	0.26
11.24	0.28	0.28	0.28	0.27	0.27	0.27	0.27	0.27

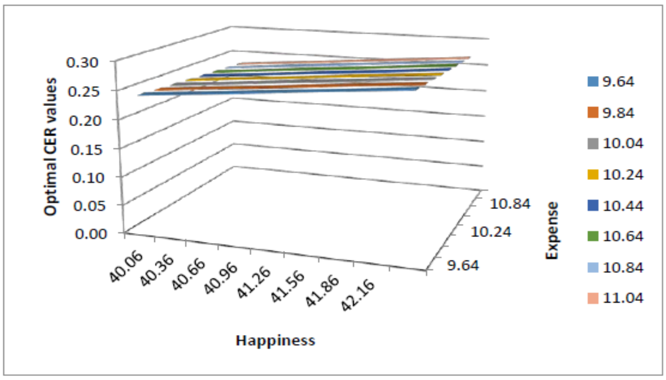

FIGURE 7. Sensitivity Analysis of choosing *Provider Centered Care* by varying *Happiness (G1)* for the actor *Patient*

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G2/G1	40.76	40.86	40.96	41.06	41.16	41.26	41.36	41.46
9.64	0.24	0.24	0.24	0.23	0.23	0.23	0.23	0.23
9.84	0.24	0.24	0.24	0.24	0.24	0.24	0.24	0.24
10.04	0.25	0.25	0.25	0.24	0.24	0.24	0.24	0.24
10.24	0.25	0.25	0.25	0.25	0.25	0.25	0.25	0.25
10.44	0.26	0.26	0.25	0.25	0.25	0.25	0.25	0.25
10.64	0.26	0.26	0.26	0.26	0.26	0.26	0.26	0.26
10.84	0.27	0.27	0.26	0.26	0.26	0.26	0.26	0.26
11.04	0.27	0.27	0.27	0.27	0.27	0.27	0.27	0.27
11.24	0.28	0.28	0.27	0.27	0.27	0.27	0.27	0.27

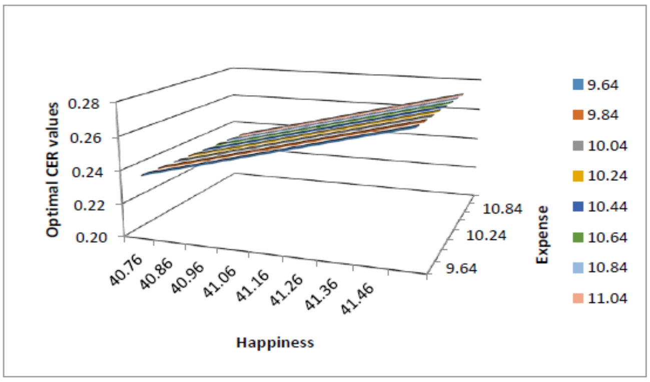

FIGURE 8. Sensitivity Analysis of choosing *Provider Centered Care* by varying *Expense (G2)* for the actor *Patient*

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G2/G1	40.52	40.62	40.72	40.82	40.92	41.02	41.12	41.22
50.80	1.25	1.25	1.25	1.24	1.24	1.24	1.24	1.23
50.90	1.26	1.25	1.25	1.25	1.24	1.24	1.24	1.23
51.00	1.26	1.26	1.25	1.25	1.25	1.24	1.24	1.24
51.10	1.26	1.26	1.25	1.25	1.25	1.25	1.24	1.24
51.20	1.26	1.26	1.26	1.25	1.25	1.25	1.25	1.24
51.30	1.27	1.26	1.26	1.26	1.25	1.25	1.25	1.24
51.40	1.27	1.27	1.26	1.26	1.26	1.25	1.25	1.25
51.50	1.27	1.27	1.26	1.26	1.26	1.26	1.25	1.25
51.60	1.27	1.27	1.27	1.26	1.26	1.26	1.25	1.25

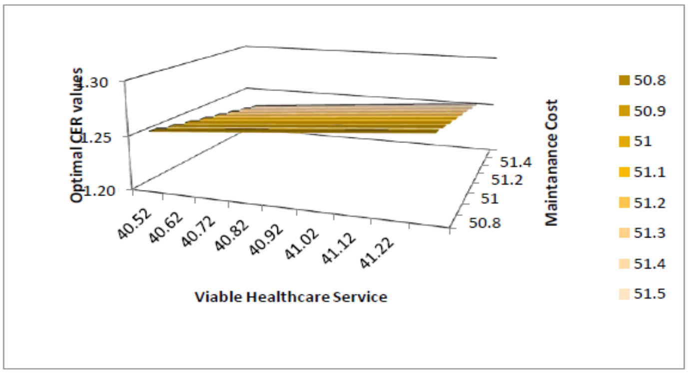

FIGURE 9. Sensitivity Analysis of choosing *Provider Centered Care* by varying *Viable Healthcare Service (G1)* for the actor *Healthcare Provider*

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G2/G1	37.92	38.92	39.92	40.92	41.92	42.92	43.92	44.92
50.80	1.34	1.31	1.27	1.24	1.21	1.18	1.16	1.13
50.90	1.34	1.31	1.28	1.24	1.21	1.19	1.16	1.13
51.00	1.34	1.31	1.28	1.25	1.22	1.19	1.16	1.14
51.10	1.35	1.31	1.28	1.25	1.22	1.19	1.16	1.14
51.20	1.35	1.32	1.28	1.25	1.22	1.19	1.17	1.14
51.30	1.35	1.32	1.29	1.25	1.22	1.20	1.17	1.14
51.40	1.36	1.32	1.29	1.26	1.23	1.20	1.17	1.14
51.50	1.36	1.32	1.29	1.26	1.23	1.20	1.17	1.15
51.60	1.36	1.33	1.29	1.26	1.23	1.20	1.17	1.15

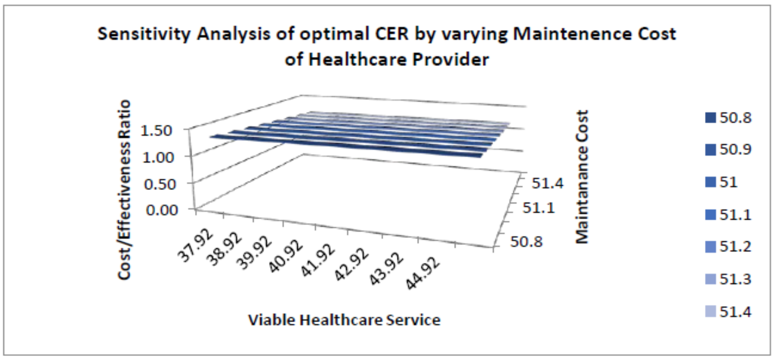

FIGURE 10. Sensitivity Analysis of choosing *Provider Centered Care* by varying *Maintenance Cost (G2)* for the actor *Healthcare Provider*

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AHP based Optimal Reasoning of Non-functional Requirements in the $i*$ Goal Model

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Abstract

Goal-Oriented Requirements Engineering (GORE) has been found to be a valuable tool in the early stages of requirements engineering. GORE plays a vital role in requirements analysis like alternative design/ goal selection during decision-making. The decision-making process of alternative design/ goal selection is performed to assess the practicability and value of alternative approaches towards quality goals. Majority of the GORE models manage alternative selection based on qualitative approach, which is extremely coarse-grained, making it impossible for separating two alternatives. A few works are based on quantitative alternative selection, yet this does not provide a consistent judgement on decision-making. In this paper, Analytic Hierarchy Process (AHP) is modified to deal with the evaluation of selecting the alternative strategies of inter-dependent actors of $i*$ goal model. The proposed approach calculates the contribution degrees of alternatives to the fulfilment of top softgoals. It is then integrated with the normalized relative priority values of top softgoals. The result of integration helps to evaluate the alternative options based on the requirements problem against each other. To clarify the proposed approach, a simple telemedicine system is considered in this paper.

Keywords: Requirements engineering, Goal models, AHP, Decision-making.

1. Introduction

Goal models play a vital role in the early phases of Requirements Engineering (RE) and is a significant tool for alternative design/ goal selection technique [21, 15]. Alternative selection is a decision-making technique in requirements analysis or design alternatives that can be used to assess their achievability and feasibility with softgoals as the choosing criteria [20, 32, 3]. In Goal-Oriented Requirement Engineering (GORE), techniques like i∗ model [9, 35, 10], Tropos model [11, 4], Knowledge Acquisition in Automated Specification (KAOS) [8], and Goal Oriented Requirements Language (GRL) [3] strategy are utilized for refining, decomposing and reasoning the requirements of the stakeholders [20, 14, 12]. Goal models help to achieve top- level objectives within the hierarchies of requirements. Each alternative selection is evaluated by prioritizing quality requirements. The impact of bottom-level requirements are hierarchically structured to satisfactorily achieve top goals. Based on the importance of these contributions, the alternative options that best suit the requirements of the stakeholder is identified and sought after. However, when it comes to the consistency of decision-making, eliciting the contribution values of different alternatives towards final goals is a serious problem. Therefore, the need for a systematic approach that can perform the degree of satisfaction of goals persistently and in a consistent manner becomes important. So, in this paper a systematic method is developed for deciding a consistent optimal alternative design option for inter-dependent actors in the i∗ model by combining the advantages of AHP-based approaches and quantitative satisfaction propagation-based approaches.

2. Background and Related Works

In vast majority of the existing GORE frameworks, requirements analysis is organized and carried out based on qualitative goal models [34, 7, 5, 1, 2]. Qualitative analysis uses qualitative estimations such as 'denied' or 'satisfied' to label goals satisfaction status. In order to label softgoals satisfaction status, the qualitative estimations used are 'satisfied', 'weakly satis- fied', 'undetermined', 'conflicting', 'weakly denied' or 'denied' for assessing the degree of goal satisfaction achieved. Although qualitative reasoning provides a fast approach in evaluating goals in the early stages of requirement engineering, the labels for representing contributions are ambiguous and too coarsely-grained to be able to differentiate among alternatives during propagation [13]. This is because a qualitative propagation method frequently brings about undetermined or conflicting goal satisfaction status; different alternatives usually lead to same results for softgoals for example, both weakly denied or strongly satisfied; qualitative satisfaction status is coarse-grained and correspondingly cannot disclose to what degree the goals are denied or satisfied.

The limitations mentioned above with the qualitative propagation procedure have given rise to the need for addressing quantitative goal models. Letier et.al [16] conducted a dedicated alternative selection based on objective criteria, however, they require particular information, for example, the distribution functions of quality variables. Such extra information, however, is difficult to get in many situations at the early phase of RE. A few works [3, 17] offer quantitative analysis techniques by using numbers to denote the strength of links however they do not provide guided strategies to acquire these strength-value numbers.

In this paper, we depict how the Analytic Hierarchy Process (AHP) is applied in *i*∗ goal model to quantitatively assess the contribution relationships between functional and non-functional requirements with opposing objectives. Thus, AHP integrated with GORE approach helps to provide reasoning of non-functional requirements to make informed decisions. The AHP [22] can be used to encourage the quantification reasoning, since it is hard for stakeholders to provide exact contribution values directly. An existing work incorporate AHP with goal models for alternative selection [18, 36]. In this work, stakeholders are subjectively assigning the relative priority of each softgoals with the main goals based on the Saaty's pairwise comparison scale [22]. Since it is a subjective judgement, it may not be accurate for goal formulations. It is also crucial to assign definite numbers to the stakeholder's requirements, as requirement elicitation may involve distinct stakeholders. They have diverse preferences for the same requirements. The rationale behind this is that distinct stakeholders have different levels of knowledge, training and skills [31].

In *i*∗ goal model, Chitra et al. [25, 28] developed a quantitative goal analysis method to decide on alternative design options. To avoid ambiguity in the usage of numeric numbers for the purpose of quantitative analysis, fuzzy numbers are used. Later, in order to enhance this method, a multi-objective optimization method is applied for finding the optimal values of soft- goals for alternative selection in goal analysis [24, 26]. It also prevents the decision analyst from imposing his/her own subjective preference of values being used for the goal analysis process. However, the literature shows that the qualitative and quantitative goal analysis process for the *i*∗ and other goal models do not include goals with opposing objective functions having inter- actor dependency. In contrast, AHP, fuzzy mathematical application and optimization tool are used in this study as they are essential tools for quantitative goal analysis. The quantitative goal analysis helps to find an optimal strategy with opposing objective functions in the requirement- based engineering design [30, 29]. This proposal examines how requirement-based engineering design can deliver a consistent optimal design outcome. In literature, we identify that the elicitation process of the existing goal-oriented requirements frameworks like $i*$ models do not support the prioritization of the multi-objective requirements of inter-dependent actors in the decision-making process. This problem can be overcome by a combined AHP and quantitative satisfaction fuzzy-based propagation approach to prioritize the requirements.

In the proposed approach, we modified the AHP by calculating the optimal relative priority of each requirements towards the main goal. This will enhance the consistency on decision-making process. Based on the $i*$ goal model, an alternative selection algorithm is designed through AHP. Overall, no previous research efforts have been able to develop a systematic method for deciding on a consistent optimal alternative design option for inter-dependent actors in the $i*$ model by combining the advantages of AHP and quantitative reasoning. In order to illustrate the application of the proposed approach, a simple telemedicine $i*$ goal model adapted from [32] is considered in this paper. The methodology of reasoning opposing goals based on inter-actor dependency by applying AHP is given in Section 3. Conclusions and future works are drawn at the end of the paper.

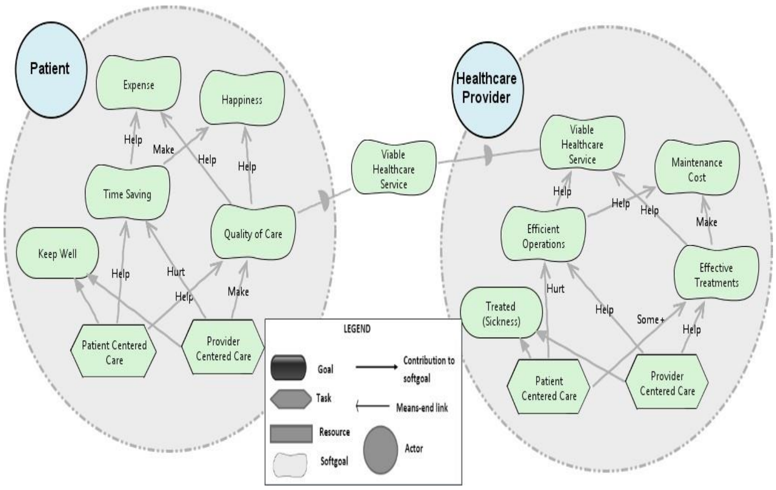

Figure 1. Simplified $i*$ goal model for Telemedicine System [33]

3. Requirements analysis using AHP

The proposed research presents a multi-objective optimization based decision-making approach in GORE by modifying the AHP. Unlike traditional decision-making process, T L Saaty de- signed AHP based on pair-wise comparisons that enable consistent judgements that improve the precision of decision-making, and further, enable accurate priority calculations. The AHP includes an objective evaluation approach. It also provides a method for checking the consistency of the evaluation and alternatives. During complex decision-making that involve multiple opposing goals, the initial step is to decompose the primary objectives into its constituent sub-objectives, progressing from a generic goal to a specific goal. In its simplest form, this hierarchical decomposition involves a goal level, softgoals levels, and an alternative level. Each softgoal can be further decomposed depending on the decision-making problem. To

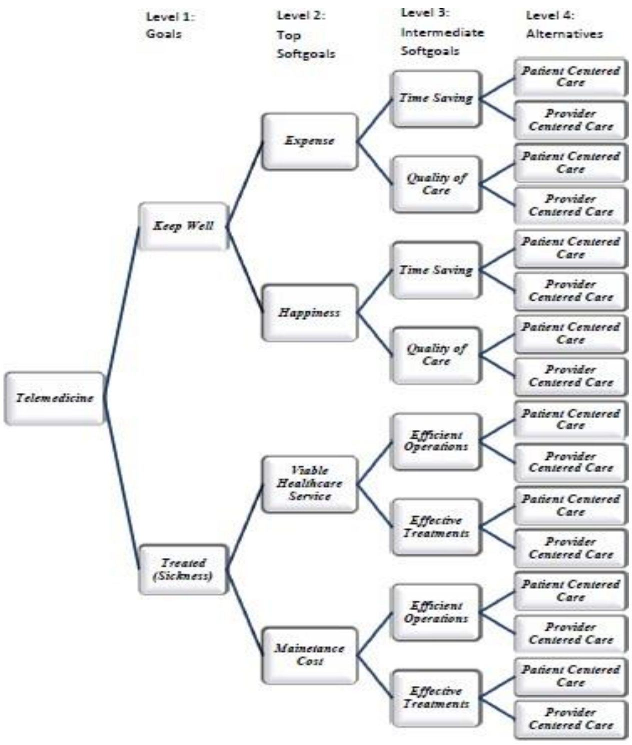

Figure 2. Hierarchical Model of Telemedicine System

explain the proposed method, a simple telemedicine i∗ goal model, as shown in Figure: 1, is considered in this paper. It shows two actors, Patient and Healthcare Provider that are considerably simplified, but nevertheless require some kind of reasoning namely selection of an ideal alternative. The main non-functional requirements or softgoals of the actor Patient are the Expense of the treatment and Happiness obtained from the remote treatment, which depend upon the softgoals Time Saving and Quality of Care. There are two alternative ways of obtaining treatment for the Patient. It is either via Patient Centered Care or Provider Centered Care. The Patient has to choose an alternative option so that his/her Expense should be less and Happiness should be more. The actor Health Care Provider has two main non-functional requirements or softgoals namely Viable Healthcare Service and Maintenance Cost representing the Health Care Provider's aiof providing services in the telemedicine system. The telemedicine system's goals, Keep Well of Patient and Treated (Sickness) of Health Care Provider can be implemented in one of two ways and thus is OR decomposed into two tasks known as Patient Centered Care and Provider Centered Care. The decision-making process of this telemedicine system is to select an alternative option that increases the Viable Healthcare Service of the Health Care Provider and the Happiness of the Patient and at the same time decreases the Maintenance Cost of the Health Care Provider and the Expense of the Patient. Figure: 2 illustrates the typical hierarchical structure of the telemedicine system where the primary organizational objective is placed on the top level while the alternatives are at the bottom level. Between the goal and alternatives lies the characteristic element of the decision-making problem such as the softgoals. Each softgoal has a local, and global priority to accomplish the main goal. The pair-wise comparison judgements about the importance of each softgoal towards main goal and the importance of each alternative towards each goal should be consistent. The pair-wise comparison matrix is said to be consistent if all its elements follow the transitivity and reciprocity rules [22].

In the proposed approach, we evaluate the contribution of each alternative options through softgoals towards the high-level goals as shown in Figure: 2. Given a goal model with alternative design options, fuzzy values are assigned to the correlation between these alternatives and the softgoals. By backward propagation of these values to the goals (that are higher in hierarchy), the levels of goal satisfaction or the relative priorities of the softgoals to the main goal are derived.

3.1. Methodology

The proposed methodology is presented in the following sub-section, to obtain an optimal strategy for inter-dependent actors having opposing objectives.

Framework for the AHP analysis

The initial stage of the proposed approach is called decision modelling. This step involves con- structing a hierarchical model for reasoning of the decision-making problem. Figure: 2 shows the hierarchical model for the telemedicine model. The first level in the hierarchy represents the goals of the system to be modelled; in our example, Keep Well and Treated (Sickness). The top softgoals constitute the second level in the hierarchy. In our example, four top softgoals are mentioned: Expense, Happiness, Viable Healthcare Service and Maintenance Cost. Intermedi- ary softgoals are mentioned in the third level of the hierarchy. The fourth level represents the available alternative ways to achieve the main goal. In the example of the telemedicine model, the Patient Centred Care and Provider Centred Care are the alternatives. This is a crucial step in AHP process. Because, during complex decision-making problems, it is required to ask the stakeholders to guarantee that all softgoals and possible alternatives options have been consid- ered.

Deriving Priorities for the top softgoals

All the softgoals will not have the similar significance towards the main goal. Therefore, the second step in the AHP analysis is to determine the relative priorities for the softgoals. In the proposed approach, we evaluate the contribution that each alternative options have upon the top softgoals.

Given a goal model with alternative design options, fuzzy values are assigned to the correlation between the alternatives and the softgoals. By backward propagation of these values to the top softgoals, the levels of goal satisfaction or the relative priorities of the softgoals to the main goal are derived. It is called relative because the obtained softgoal priorities are calculated as a ratio concerning each other. For deriving the relative priorities of each softgoals, a generalised complete structure of an $i*$ goal model is modelled in terms of softgoals, goals, tasks and resources. Given an $i*$ goal model, our aim is to find the priority of top softgoal according to the impact of each alternative on top softgoals. Assigning values to impacts of alternatives to softgoals can lead to imprecision because many analysts assign different values and sometimes they are subjective. Therefore, the proposed approach assigns a judgement within a range which can be defined by a fuzzy number rather than giving one numerical value. Therefore, impacts are given as *Make; Help; Hurt; Break; Some-; Some+*, which are represented as triangular fuzzy numbers. It indicates the extent to which an alternative option fulfils the leaf softgoal [32]. For simplicity of calculation, de-fuzzification is used to convert the impacts which are represented in fuzzy numbers to quantifiable values [6], shown in Table: 1, which are used to evaluate the scores of each softgoal. The impacts are propagated to the top softgoals, to find the level of satisfaction or scores of top softgoals towards main goal.

Table 1. De-fuzzified impact values in Telemedicine system

Impact	Fuzzy value	De-fuzzified value
Hurt	(0, 0.16, 0.32)	0.16
Make	(0.64, 0.8, 1)	0.8
Some−	(0.16, 0.32, 0.48)	0.32
Some+	(0.32, 0.48, 0.64)	0.48
Break	(0, 0, 0.16)	0
Help	(0.48, 0.64, 0.80)	0.64

In addition to impacts, each leaf softgoals are assigned a weight ω based on their relative importance to achieve the goal. Firstly, the scores of each top softgoals of each actor based on its inter-actor dependency under each alternative is calculated. For details on representing goals, weights, impacts and alternatives, readers are directed to [25, 24]. Consider the case of t hierarchy levels in the hierarchy structure, with leaf softgoal (SG) at level zero. Let $\omega_{L_{ik}}$ represents the weight of i^{th} leaf softgoal and $I_{L_{ijk}}$ means the impact of i^{th} leaf softgoal of j^{th} alternative of k^{th} actor, S_{idby} means the score of the i^{th} softgoal with its b^{th} dependent having y children, I_{dLijk} means the impact of the dependent on i^{th} leaf softgoal of j^{th} alternative of k^{th} actor and I_d is the b^{th} dependent impact.

At level 1, if there are m number of softgoals, n_c children and n_d dependencies for the i^{th} softgoal, then the score of any softgoal at $t > 1$ is found by taking the product of its impact and each child score. For complete details on the formalization of the below equation, readers are directed to [27]. The score of a softgoal at level t for an actor with a dependency relationship can be generalized as:

$$S_{SG_{i_t jk}} = \prod_{l=1}^{m} I_{ijl} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{ijk}}} \times \omega_{d_{L_{ijk}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\} \tag{1}$$

Then the objective functions of top softgoals under each alternative for an actor are created from Equation: 1. If there is an inter-actor dependency relationship, then it is necessary to consider both strategic dependency and strategic rationale diagrams of the i^* goal model with the assumption that only softgoal inter-dependency relationships are taken into account in this approach. Consider that if there are n numbers of alternative options for an actor, then there are n maximum and minimum objective functions for each top softgoal.

In the next step, these multi-objective functions of opposing goals (maximum and minimum in nature) are optimized using IBM CPLEX optimizer [19]. This tool helps to generate the multi-objective function values for all the actors in the goal model. These optimal values refer to the score (importance) of each top softgoal under each alternative to fulfil the stakeholder's objectives.

To improve the readability in writing, certain terms in telemedicine case study are abbreviated as shown in Table: 2. The objective function values for telemedicine system generated from CPLEX are shown in Table: 3. Thus GORE approach helps to determine the scores (satisfaction values) of top softgoals concerning the contribution of each alternative to accomplish the goal for comparison between softgoals. The importance of each softgoal towards main goal is different. So it is required to generate the pair-wise comparison matrix (PCM), by deriving the relative priority of each softgoal, concerning each of the others, towards the main goal by pair-wise comparisons. Elements in PCM have a value obtained from the objective function values as shown in Table: 3 to show the relative importance in each of the compared pairs of softgoals. In PCM, the importance of a softgoal is compared with itself; for instance, *Expense* versus *Expense*; the input value is one which compares to the measure of equal significance towards the main goal. This implies that the ratio of the significance of a given softgoal concerning the importance of itself will always be equal. The PCM shows the pairwise relative priorities among all softgoals involved in the decision-making process.

Table 2. Abbreviation of terms in Telemedicine system

Terms	**Abbreviation**
Patient	P
Healthcare Provider	HCP
Expense	E
Happiness	H
Viable Healthcare Service	V HS
Maintenance Cost	MC
Patient Centered Care	PaCC
Provider Centered Care	PrCC

After constructing PCM, the AHP calculates the overall relative importance of each softgoal. The overall relative importance calculation includes averaging over normalized columns to estimate the eigenvalues of the PCM (divide each element by the total summation of all the elements in each column). Using this normalized matrix, the overall relative importance of each softgoal can be obtained by simply averaging each row and is an estimation of eigenvalues of the matrix.

The PCM representation of the overall relative importance of each top softgoals of telemedicine case study with respect to *PaCC* is given as

$$\text{PCM}_{PaCC} = \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} \begin{bmatrix} 0.0524 \\ 0.5125 \\ 0.308 \\ 0.128 \end{bmatrix}$$

Table 3. Objective function values of each top softgoals in Telemedicine system with respect to each alternative

Top softgoals for actor ***P***	*PaCC*	*PrCC*
H	51.2	51.2
E	5.24	10.24
Top softgoals for actor ***HCP***	*PaCC*	*PrCC*
V HS	30.72	40.96
MC	12.8	51.2

The PCM representation of the overall relative importance of each top softgoals of telemedicine case study with respect to *PrCC* is given as

$$\text{PCM}_{PrCC} = \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} \begin{bmatrix} 0.07 \\ 0.33 \\ 0.27 \\ 0.33 \end{bmatrix}$$

Once the overall relative importance of softgoals have been obtained, it is necessary to check whether they are consistent or not. For this purpose, a consistency ratio (CR) is calculated by comparing the consistency index (CI) of the obtained PCM versus CI of a random-like matrix (RI). Saaty [23] provided the obtained RI value for matrices of various sizes.

Saaty [23] has shown that a *CR* of 0.10 or less is adequate to proceed with the AHP reasoning. In the event that the consistency ratio is more than 0.10, it is required to change the contributions assigned to find the reason for the inconsistency and revise it. The *CI*, which shows the result accuracy of PCM, has to be calculated first for finding *CR*,

$$CI = (\lambda_{max} - n)/\,(n - 1)$$

where λ_{max} represents the maximum principal eigenvalue of the PCM. If λ_{max} is closer to number of requirements (n), then the judgement errors will be less, and the results will be more consistent. For obtaining λ_{max}, firstly multiply PCM by priority column matrix. Secondly, divide each element in the obtained result matrix by the corresponding element in the priority matrix. Thirdly, average all the elements in the result matrix obtained in second step. This average value gives the value of λ_{max} which can then be used for calculating CI. For example, the *CR* of the relative importance of top softgoals with respect to the alternative, *Patient Centered Care* is calculated and its value is 0.0034. As a general rule by Saaty, *CR* of 0.10 or less is considered acceptable. So the obtained result for $PaCC$ is ideal. Similarly, the CR of the relative importance of top softgoals with respect to the alternative, *Provider Centered Care* is calculated and its value is 0.003. This CR value is also considered as acceptable. So the obtained result for $PrCC$ is also ideal. The proposed approach for finding the relative importance of each top softgoals towards main goal is considered as consistent, so the decision-making process using AHP is proceeded to next step.

Table 4. Propagated impact score of alternatives towards top softgoal

	E	H	VHS	MC
$PaCC$	5.12	5.28	1.76	1.92
$PrCC$	5.6	5.76	2.56	2.72

Derive Relative Local Priorities of each Alternatives

In this step, the relative priorities of each alternative are calculated concerning each top softgoal included in the decision-making model. For this, PCM is constructed (using the propagated (summation) impact score of each alternative to top softgoals from Table: 4) for each alternatives, with respect to each specific top softgoal. In the telemedicine example, two alternatives *Patient Centered Care* and *Provider Centred Care*, and four top softgoals are mentioned. So there are four pair-wise comparison matrices.

With respect to *Expense*, the PCM representation of the relative local priority of *PaCC* and *PrCC* is given as,

$$PCM_E = \begin{bmatrix} 0.48 \\ 0.52 \end{bmatrix}$$

With respect to *Happiness*, the PCM representation of the relative local priority of $PaCC$ and $PrCC$ is given as,

$$PCM_H = \begin{bmatrix} 0.48 \\ 0.52 \end{bmatrix}$$

With respect to $V\,iableHealthcareService$, the PCM representation of the relative local priority of $PaCC$ and $PrCC$,

$$PCM_{VHS} = \begin{bmatrix} 0.41 \\ 0.59 \end{bmatrix}$$

With respect to *Maintenance Cost*, the PCM representation of the relative local priority of *PaCC* and *PrCC*,

$$PCM_{MC} = \begin{bmatrix} 0.42 \\ 0.58 \end{bmatrix}$$

By averaging over normalized columns to estimate the eigenvalues of obtained PCM's of each alternatives with respect to all top softgoals, the local priorities of alternatives are calculated. The consistency will be checked only if the number of elements that are compared pairwise are three or more [23]. In this case only two alternatives are compared in PCM, therefore, there is no requirement to calculate consistency. This means, the calculated local priorities are consistent.

Derive Overall Priorities

In this step, the overall priority for each alternative is calculated. This means priorities that take into account not only our preference of alternative options for each softgoal yet in addition the way that each softgoal has a different weight to achieve the goal.

Table 5. Overall Priorities of Alternatives towards Main Goal

	E	*H*	*VHS*	*MC*
Top softgoals priority w.r.t *PaCC*	0.05	0.51	0.31	0.13
***PaCC* local priority**	0.48	0.48	0.41	0.42
Top softgoals priority w.r.t *PrCC*	0.07	0.33	0.27	0.33
***PrCC* local priority**	0.52	0.52	0.59	0.58

Table 6. Overall priorities of alternatives towards main goal

Alternatives	Overall priority
PaCC	0.4505
PrCC	0.5587

For example, the *Expense* top softgoal has a priority of 0.0524 with respect to the *Patient Centered Care* alternative and the *Patient Centered Care* has a local priority of 0.48 relative to *Expense*; therefore, the weighted priority, with respect to *Expense*, of the *Patient Centered Care* is 0.024.

Similarly, it is necessary to obtain the *Patient Centered Care* weighted priorities with respect to *Happiness, Viable Healthcare Service* and *Maintenance Cost*. Now the alternative options can be ordered based on their overall priority as shown in Table: 6.

In other words, given the importance of each top softgoal (*Expense, Happiness, Viable Healthcare Service* and *Maintenance Cost*), the *Provider Centred Care* is preferable (overall priority = 0.5587) compared to the *Patient Centered Care* (0.4505). When the number of the levels in the hierarchy increase, the number of pair comparisons also increase. So to build the AHP model takes much more time and effort but has been demonstrated easy. Another limitation of AHP is that if the consistency index is above 10%, then it is required to reconsider the stakeholder requirements.

4. Conclusion

In this paper, the quantitative reasoning of the *i** goal model of inter-dependent actors that have opposing objectives is integrated with AHP to solve multi-objective decision-making problem of alternative selection. In this paper, a modified AHP is proposed to drive the procedure of alternative selection. Hence an ideal alternative option is chosen using the proposed approach for inter-dependent actors in the *i** goal model by balancing the opposing goals reciprocally. This research showed that quantitative based fuzzy judgements for this study were quite consistent. Thus the proposed AHP methodology is an easy applicable decision-making approach that assist the decision maker to precisely decide the judgements. The primary difficulty in applying AHP to multi-objective reasoning is the potentially large number of paired comparisons, when the number of levels in the hierarchical structure is increased. However, the paired comparisons have been demonstrated to be relatively easy. Further research topics include performing sensitivity analysis to aid requirements analyst in the decision-making process.

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Hybrid Analytic Hierarchy Process-based Quantitative Satisfaction Propagation in Goal-Oriented Requirements Engineering through Sensitivity Analysis

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Abstract. In the early phase of Requirements Engineering (RE), Goal-Oriented Requirements Engineering (GORE) has been found to be a valuable tool. GORE plays a vital role in requirements analysis such as alternative selection decision-making process. This is carried out to determine the practicability and effectiveness of alternative approaches to arriving at quality goals. Most GORE models handle alternative selection based on an extremely coarse-grained qualitative approach, making it impossible to distinguish two alternatives. Many proposals are based on quantitative alternative choices, yet they do not offer a clear decision-making judgement. We propose a fuzzy-based quantitative approach to perform goal analysis using inter-actor dependencies in the i^* framework, thereby addressing the ambiguity problems that arise in qualitative analysis. The goal analysis in the i^* framework was performed by propagating the impact and weight values throughout the entire hierarchy of an actor. In this article, the Analytic Hierarchy Process (AHP) is adapted with GORE to discuss the evaluation of alternative strategies of the i^* goal model of interdependent actors. By using a quantitative requirement prioritisation method such as the AHP, weights of importance are assigned to softgoals to obtain a multi-objective optimised function. The proposed hybrid method measures the degree of contribution of alternatives to the fulfillment of top softgoals. The integration of AHP with goal anlaysis helps to measure alternative options against each other based on the requirements problem. This approach also includes the sensitivity analysis, which helps to check the system behaviour for change in input parameter. Hence, it facilitates decision-making for the benefit of the requirements' analyst. To explain the proposed solution, this paper considers a telemedicine system case study from the existing literature.

Keywords: Goal model, Requirements, AHP

1. Introduction

GORE designs software system requirements by applying goals as the starting point. This method involves the requirements specifications being developed, elaborated, organised, defined, evaluated, negotiated, recorded and updated [68]. Goals play a critical part in GORE. Goals help in understanding the domain and determine stakeholders interests [62]. Goals are drawn up at various layers of abstraction, based on the actors' strategic concerns related to the system being built. It is therefore a well-considered significant artefact during the initial stages of RE [25]. A goal model or a multi-view model of goals forms the basis of goal elaboration. The model demonstrates how, in the specified system, goals, actors, states, objects, tasks and domain characteristics are interconnected [48].

In GORE, techniques such as the i^* model [81], Knowledge Acquisition in Automated Specification (KAOS) model [18], and Goal-Oriented Requirements Language (GRL) [5] strategies are being applied to simplify, decompose and justify stakeholders' requirements. Goal models help to attain top-level objectives within the requirement hierarchies. Each alternative selection shall be assessed by prioritising quality requirements. The impact of the requirements at the bottom level are hierarchically organised in order to achieve the top goals satisfactorily. Based on the importance of the contributions, alternative options are identified and pursued through best match stakeholder requirements. Nevertheless, eliciting the contribution values of different alternatives against final goals is a significant issue when it comes to the quality of decision-making. Hence, the need for a systematic approach that can persistently and reliably satisfy the degree of goal fulfilment becomes essential. Therefore, a systematic method

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for determining a consistent optimal alternative design option for interdependent actors in the i^* model is developed in this paper. The method combines the advantages of AHP-based approaches with GORE-based quantitative satisfaction propagation. The main research contributions proposed in this paper include:

(i) The optimised quantification approach for pairwise comparison, normalisation and validation of relative priorities of softgoals towards the main goal. This approach increases the consistency of quantification results compared to the existing approaches.

(ii) A guide for alternative selection for interdependent actors having opposing non-functional requirements.

The background and related works of GORE-based quantitative and qualitative goal models are explained in the following section. In Section 4, the proposed method of reasoning opposing goals based on inter-actor dependency is explained. A case study of a telemedicine system for the proposed method is demonstrated in Section 5. Conclusions and future works are drawn at the end of the paper.

2. Literature Review

The most important activity during a software engineering process is to obtain the precise requirements. Recent surveys done on requirements have proven that RE is a primary area of study in software engineering research and practice [51]. Nowadays, we use the term “goals” in RE technology. A goal is defined as an objective which needs to be achieved by the software system that is being developed [48]. These goals are obtained from stakeholders and disclosed in the requirements documents along with analysis of similar or existing systems, an explanation of other goal models, etc. We can specify goals at various levels of abstraction from high-level strategic concerns to low-level technical concerns. Behavioural goals or functional requirements determine the services that need to be provided by the system. The softgoals or non-functional requirements are concerned with the quality of service provided, such as accuracy, performance, security, etc. In software engineering, goals have been used to model early requirements and the non-functional requirements [28].

During the early phase of the software development life cycle, RE is used to elicit goals that need to be achieved by the system being developed. These goals need to operate as per the service and constraint specifications. The tasks have to be allocated to agents like humans, devices and software to fulfil the requirements. This system is also used for the evolution of these requirements over a span of time. The process of RE may differ depending on the application domain, the people involved and the organisation which is identifying the requirements. It is however noteworthy, that RE follows a systematic methodology to identify a complete and congruous set of requirements, so that the goals can be reached satisfactorily.

Among the various methods proposed in the RE literature for modelling requirements, GORE was found to be the most suitable approach compared to other traditional approaches, namely conceptual entity-relationship modelling, structured modelling and object-oriented modelling [62]. All these approaches were found to be more appropriate during the later stages of requirement analysis in the software cycle, when they are used to target the traceability between requirements and implementation. Hence, GORE was found to be the most suitable alternative for requirements analysis, especially for identifying the non-functional requirements (NFRs) during the initial phase of the software development cycle.

GORE uses goals for eliciting, elaborating, structuring, specifying, analysing, negotiating, documenting and modifying requirements [48]. The objectives of the stakeholders or the requirements to be accomplished by the system under consideration are referred to as “goals”. We refer to “system” as the software-to-be, together with its environment [51]. We represent goals using AND/OR structures, which show how the goals are refined or abstracted. These goals specify the functional or non-functional requirements and are further categorised as high-level to low-level goals. The system goals specify the application’s specific safety, its fault tolerance and the properties of its survivability. These system goals are meant to develop the software system with high assurance quality, for which goal modelling and reasoning are particularly significant.

During the RE process, goal models are formulated to help in the qualitative or formal reasoning of goals. An AND/OR graph represents a goal model and depicts how higher-level goals are satisfied by the lower-level goals and vice versa [49]. Besides modelling, analysts also use goal models to find the levels of satisfaction of goals achieved, to evaluate alternative design options, to choose the system design, to analyse risk and to ascertain the prioritisation of requirements. During the evaluation of alternative designs, analysts use several evaluation criteria to choose the best design. They use softgoals in goal models as evaluation criteria in existing quantitative and qualitative approaches [61]. To support goal analysis, several quantitative and qualitative methodologies have been proposed in the RE literature [5, 7, 9, 10, 24, 28, 38, 55, 59, 75].

Requirements analysis is structured and carried out in most of the current GORE frameworks based on the qualitative goal models [16, 29, 80]. During the process of evaluation, the quantitative or qualitative values are propagated using bottom softgoals to the top softgoals in the goal model. Qualitative requirements analysis utilises qualitative measures like 'satisfied', 'weakly satisfied', 'undetermined', 'conflicting', 'weakly denied' or 'denied' to mark the fulfilment level of the quality goals. While it offers a quick approach to evaluate goals in the early stages of RE, the labels for representing contributions are optimistic and too coarsely-grained to be able to distinguish between alternatives during propagation [40]. This is based on the premise that a qualitative propagation approach frequently results in unspecified, inconsistent or conflicting goal satisfaction status. Different alternatives usually leads to same results for softgoals (for example, both weakly denied or strongly satisfied). Qualitative satisfaction status is coarse-grained and therefore hard to disclose at what degree the goals are denied or achieved. Such problems with the qualitative propagation approach created the need to address this issue with quantitative goal models.

While Letier et.al [51] performed a dedicated alternative selection based on objective criteria, they required specific details such as the distribution functions of quality variables. Such extra information, however, is hard to get at the early phase of RE in many cases. A few proposals [5, 52] provide quantitative analytical techniques by using numbers to denote the strength of associations, but they do not include directed strategies to obtain such numbers for strength values. Subramanian et al. [14] utilise quantitative fuzzy numbers for decision-making during the RE process. Through fuzzy logic, [15], the linguistic representation of the requirements of the stakeholders are effectively interpreted by Chou et al.

While using the quantitative method, quantitative estimations are used to represent the contribution of goals to softgoals. The quantitative labels are hence generated using link paths to find the satisfaction levels of the goals achieved. Ever since the goal model was conceptualised, a significant amount of research has been put forth on the logic used to achieve goals using quantitative and qualitative labels [2, 3, 5, 24, 28, 30, 38, 55]. In the paragraphs that follow, we have given a brief description of the several research proposals along with their shortcomings so that we can get a better understanding of the reasons which led to the development of this state of the art framework.

A qualitative formalisation and label propagation algorithm was used by [28] to present a formal reasoning of goals in the goal models. The aim of this work was to model a framework for goals to implement qualitative goal relationships and to include contradictory situations. Goal relationship labels (+, -) were used to represent the positive and negative contributions of a goal towards another goal. This labelling needed a definitive representation of semantics of the new goal relationships, which was achieved in two ways: by labelling the propagation algorithm with a qualitative formalisation, and by labelling the propagation algorithm with the quantitative formalisation. The final values for each goal/event are computed using the propagation algorithm. However, the numeric approach is used to obtain precise conclusions about the final values of the goal/event. Additionally, quantitative semantics for new relationships depend on the probabilistic model, which requires solid knowledge of mathematics to apply first order logic.

Horkoff and Yu [38] proposed a qualitative analysis of goal and agent-oriented models models, which aimed to understand the problem domain during the early phase of RE. They introduced an interactive evaluation procedure and also provided alternative evaluation techniques. These alternative evaluation techniques were helpful when the intervention of customers was required to ascertain goals. The alternatives could be a system alternative, a process design alternative or an alternative in terms of course of actions, capabilities and commitments. To make it easier to comprehend and to enable manual analysis, an informal method has been presented using the i^* framework. This goal analysis allows further analysis and refinement of the model by checking whether a design alternative is satisfactory. Several case studies were used in an experimental study. However, this experiment faced many problems of validity and consisted only of a smaller number of participants/stakeholders. One of the main drawbacks of this approach was that it led to ambiguity each time one or more goals received the same label.

As per the proposal of Letier and Van Lamsweerde [51], a heavyweight yet more accurate approach was presented. This approach was based on probability, which requires a good knowledge and support of mathematics. A method was presented for determining the partial degrees of goal satisfaction. This method quantifies the impact of system alternatives on high-level goals which are satisfied partially. To evaluate an alternative design, the appropriate objective functions and quality variables are specified accurately. At the optimal formal layer, probabilistic extension of temporal logic is used to specify objective functions more accurately. An ad hoc use of mathematical software is required to do the calculation of objective functions, which may become difficult when the equations needing refinement are complex in nature. Additional tools dedicated to performing such complex computations need to be provided as well. The author also mentions that this framework should be extended to manage the uncertainties on parameter estimations by using confidence intervals. In the case of a complex system, the application of this approach was very difficult.

A proposal presented by Amyot et al. [5] developed a hybrid approach which combined both the qualitative and quantitative approaches to perform an analysis of the GRL model. This approach evaluates the level of satisfaction of the actors and the intentional elements. The example of a telecommunications system is used to illustrate the algorithms. This approach evaluates satisfaction values by attaching them to a subgroup of intentional elements. Using a propagation algorithm, these values are then propagated through decomposition, contribution and dependency links to other intentional elements. Three evaluation algorithms, namely qualitative evaluation, quantitative evaluation and hybrid evaluation, were implemented using the jUCMNav tool, which is an Eclipse-based editor for URN models. The shortcoming with this work was that it did not address the generation of a goal model, which is usually linked with eliciting requirements and an analysis process. Moreover, it was not possible to assign exact numeric values to requirements using quantitative analysis when the stakeholders' requirements were ambiguous.

The framework proposed by Liaskos et al. [52, 54, 55] indicated preference requirements and their prioritisation. It aimed to examine the similarity between goal hierarchies and criteria hierarchies. They are used to ascertain the specifications that achieve mandatory requirements and simultaneously satisfy preference requirements and priorities in the best possible manner. An experimental study has also been conducted to show the feasibility of the approach. The limitation of this approach is that it requires certain structural features to be satisfied by the model for goal analysis.

Franch [24] presented a proposal which emphasised the quantitative aspect using an analysis of agent-oriented models. He used the i^* language to create agent-oriented models for explaining his approach. UML (Unified Modeling Language) is used to represent the conceptual model of the i^*, and OCL (Object Constraint Language) is used to express the framework. The quantitative method is used to determine the structural indicators. These structural indicators are used to define the structural metrics, as well as to measure properties of the i^* model such as actors, dependencies and other elements. An example illustrates how the indicators are used to derive the properties of a system. However, this method needs some expert yet subjective judgements, when deciding on the best alternative that should be selected. This method is not completely quantitative in nature since it requires some degree of qualitative reasoning to obtain the most accurate information.

Mairiza et al. [58] presented an approach which used Multi Criteria Decision Analysis (MCDA) to settle the conflicts that arise during NFR decision analysis. The evaluation and analysis of alternative design solutions are performed using MCDA. This approach also finds the best design solution to satisfy the conflicting NFRs by using MCDA in the best possible manner. TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) is a goal-based technique in MCDA, which is used to find an alternative closest to the most suitable solution. However, this approach does not provide any tools to evaluate the approach.

Sadiq and Jain [67] presented a technique which prioritises requirements. Prioritisation of requirements, using a fuzzy-based approach in Goal-Oriented Requirements Elicitation, used the concepts of a fuzzy-based AHP for group decision-making. It also used a binary sort tree method to derive the prioritised requirements. The AHP pairwise comparison is used to assign weights to goals/softgoals and hence locate the list of prioritised requirements using the binary sort tree method. The fuzzy preference relation is used to combine the expert preferences with the group preferences. This approach has been illustrated with a small number of requirements and criteria. However, this approach requires a sound knowledge of mathematics during the decision-making process.

Goncalves and Krishna [30] proposed a quantitative approach for operationalisation in the Extended Non-Functional Requirements (ENFR) framework. The preferences of operationalisation and the progressive value of its children within the ENFR model are used to ascertain the most appropriate operationalisation. By incorporating change management in the agents, the authors expanded their work [31, 47]. Whenever any changes occur in an agent (e.g. change in softgoals or change in contribution values), the decision path is used to find the agents affected by these changes. An evaluation of the proposed optimisation model was carried out. This evaluation was based on probability, which indicated that the approach cannot be directly applied to the ENFR. Hence, this process needs changes to be made to the original model so that the proposed concepts can be incorporated.

Heaven and Letier [35] proposed to extend their previous work by applying multi-objective optimisation to the KAOS goal model, so that the alternative design options could be explored. In their previous work, a formal semantics and a set of heuristics for the goal models were proposed. However, the model analysis could not be automated and was not applicable to a model which contained a large number of design alternatives. In the later research, these limitations were addressed by providing and automated technique for the goal model, even when a large number of design alternatives were present. The extended research also enabled the identification of the most optimal design alternative, even in the presence of a large number of design alternatives. A stochastic simulation model is generated to simulate the complete set of alternative designs in the given goal model. A MATLAB simulation-based illustration was presented using the London Ambulance Service goal model. The main drawback of this approach is that there is no systematic method which can specify the objective functions.

Affleck et al.[2, 4] proposed a linear programming optimisation model for the NFR framework, which aimed to minimise operationalisation. The optimisation model is an extended version of their original work [1]. Their earlier work presented a quantitative extension of the NFR framework which supported the decision-making process. In the quantitative NFR framework, weights are assigned to the leaf softgoals in the softgoal graph. Weights are also assigned to the links between leaf softgoals and operationalisation. In the extended version, a linear programming method is used to express an objective function mathematically, in terms of decision variables. The simulation showed that the process was effective in graphs which had a large number of relationships between softgoals and operationalisation. Additionally, sensitivity analysis is used to help the developers find the quantitative input values. The limitation of this approach is that the values assigned to the leaf softgoals are quite subjective, which made it very difficult to assign accurate values to the leaf softgoals.

In this paper, we explain how the AHP method is implemented in the i^* goal model to quantitatively analyse the contribution relationships between functional and non-functional requirements. The Analytic Hierarchy Process (AHP) was developed by Thomas T Saaty in 1972. AHP is a multi-objective decision-making method based on pairwise comparisons among the alternatives [66]. In AHP, the hierarchical framework is designed after the refinement and decomposition of the goals into sub-goals for the pairwise comparison process among the alternatives or non-functional requirements. The AHP method, combined with the GORE methodology, thus helps to provide reasoning of non-functional requirements for informed decision-making. AHP [65] can be used to promote the rationale for quantification, as it is difficult for stakeholders specifically to have exact contribution values. In the proposed method, we adapted AHP by evaluating each requirement's optimum relative priority towards the main goal. This will improve the consistency of the decision-making process. An alternative option selection algorithm is developed by means of AHP, based on the i^* goal model. Ultimately, by integrating the strengths of AHP with quantitative reasoning, no previous research attempts have been able to implement a systematic framework for determining a reliably optimal and consistent alternative design choice for interdependent actors in the i^* model. A simplified telemedicine i^* goal model adapted from [79] is considered in this paper to explain the implementation of the proposed approach.

3. Proposed method of reasoning opposing non-functional requirements

The requirements analysts' decision-making process if complex, and they sometimes find it challenging to arrive at the best decision. With the aim of helping decision-makers cope with complex decision-making, a productive tool known as AHP was introduced. This tool effectively helps the decision-makers to prioritise decisions thus enabling an excellent decision forward. AHP converts complex decisions into a series of pairwise comparisons, and the outcome is synthesised to arrive at both subjective and objective decisions. It compares softgoals' values and alternative options' values to arrive at the decision. One must consider that some of the top softgoals are contrasting and that the best option may not be the one that optimises each top softgoal. Instead, the best option could be the one that achieves the most suitable trade-off among the different top softgoals. AHP also helps to control bias in the decision-making process by monitoring the consistency of the decision-makers' evaluations. AHP prioritises each evaluation top softgoal based on the decision-makers' pairwise comparisons, while the importance of the corresponding top softgoal depends on how high its priority is. If the priority for the evaluation top softgoal is high, more important is the corresponding softgoal. Secondly, AHP allocates a score to each alternative of a fixed top softgoal. The performance of the alternative is based on the score. The higher the score, better the performance of the alternatiave. Lastly, the scores of the top softgoals and their alternative options are combined, arriving at an overall score for each alternative and a resultant ranking. The weighted sum of the scores of a particular alternative, obtained with respect to all the top softgoals, is the global score for the given alternative.

The score values and the final rating are extracted based on the pairwise assessment of both top softgoals and alternative choices, thus making AHP a very versatile yet powerful tool. The evaluations made by AHP are based on the decision-makers' experience. This enables the qualitative and quantitative evaluations performed by the decision-maker to be transferred into a multi-objective ranking. AHP is a simple process, as there is no requirement to build a complex system. Nevertheless, due to the number of evaluations generated by the user, particularly for problems involving comparison of many softgoals and alternative options, the load of evaluations may become irrational as the number of pair comparisons increases quadratically.

The proposed work introduces a decision-making approach based on multi-objective optimisation in GORE by modifying AHP. Unlike conventional decision-making processes, TL Saaty developed AHP based on pairwise comparisons, which lead to clear decisions that enhance decision-making consistency and facilitate accurate priority calculations. AHP provides an objective approach to the evaluation process. AHP methodology includes a tool for testing evaluation accuracy (consistency). Reasoning of opposing non-functional requirements using AHP mainly involves three phases.

First Phase: The first phase identifies the elements of the system and classifies them into a hierarchical structure. Similarly to a goal tree, the elements at a higher hierarchical level work effectively on the elements at a lower level.

Second Phase: The second phase involves the evaluation of each element and its consistency. The process of evaluation involves the comparison of all pairs of elements from a certain level with each element from a level higher in the hierarchical structure that was previously constructed. These comparisons bring about a set of matrices that, after normalisation, is examined for consistency. This consistent set of matrices is used for the final evaluation of the system. There are four steps involved in the successful implementation of the second phase of AHP.
The first step involves computing the priorities of each softgoal.
The second step involves computing the local priorities of each alternative.
The third step involves computing the overall priorities, and the fourth and final step involves ranking the alternatives.
These steps are elaborated in the following sections. Assumptions are made that *m* evaluation top softgoals are to be used and n alternative options are to be evaluated. An explanation of how to implement an effective technique to check the reliability of results will also be provided in the following sections.

Third Phase: The third phase of AHP involves conducting sensitivity analysis. The following sections will explain each step in more detail. A useful method will also be added to test the reliability of the tests.

In the next subsection, we explain the AHP-based methodology of reasoning opposing goals based on inter-actor dependency.

3.1. Methodology

In the subsection below, the suggested approach is provided in different steps for achieving an optimal strategy for interdependent actors with opposing goals. The steps of the proposed methodology are:

Step 1 : Develop a hierarchical framework for the decision-making process.

Step 1.1: Analyse the decision into a hierarchical structure of goals, softgoals and alternatives.

Step 2 : Determination of priorities for each top softgoal.

Step 2.1 : Construction of pairwise comparison matrix (PCM)

: Application of GORE methodology to assess the scores (satisfaction values) of top softgoals for each alternative's contribution to achieve the goal. This step is critical in evaluating the alternative designs. The importance of softgoals is compared pairwise with regard to the main goal to determine their relative importance.

Step 2.2 : Normalisation of PCM

Step 2.3 : Validation of PCM

: Check the consistency of pairwise comparison decisions based on the transitivity and reciprocity rules for each softgoal towards the main goal.

Step 3: Determination of local priorities of each alternative towards each softgoal

Step 3.1: Construction of PCM

Step 3.2: Normalisation of PCM

Step 3.3: Validation of PCM

Step 4: Determination of the overall priorities or model synthesis

Step 4.1: Integration of alternative priority values with relative priority values of the softgoals. The alternative priority values obtained are integrated as a weighted sum by matrix multiplying the relative priorities of each alternative strategy with the priority value.

Step 4.2: Rank the alternatives based on their overall priority values obtained from *Step 4.1*. The alternative option with the highest overall priority value provides the best decision.

Step 5: Perform sensitivity analysis on the obtained overall priorities.

3.1.1. Framework for the analytic hierarchy process analysis:

The initial phase of the approach being proposed is called decision modelling. This stage includes the creation of a hierarchical model for rationalising the question of decision-making. In a complex decision-making process involving multiple competing goals, it is required initially to break down the primary objectives into their constituent sub-objectives, shifting from a general goal to a specific goal. This hierarchical decomposition, in its simplest form, includes a level of top goals, a level of softgoals and an alternative level. Depending on the question of decision-making, each softgoal can be further decomposed. This is a decisive step in the analytic hierarchy process. In the event of complex decision-making challenges, it is necessary to ask stakeholders to ensure that all softgoals and possible alternatives have been considered. It might also be important to progressively incorporate additional levels into the hierarchy. The characteristic element of the decision-making problem, such as the softgoals, lies between the goal and alternatives. To achieve the main goal, each softgoal has a local and global priority.

3.1.2. Deriving priorities for the top softgoals:

Not all of the softgoals will have the same impact towards the main goal. The second step is therefore to assess the relative priorities for the softgoals. To derive the relative priorities of each top softgoal, a generalised complete structure of an i^* goal model is modelled in terms of softgoals, goals, tasks and resources. For formalisation, a Strategic Rationale (SR) i^* goal model is considered as shown in Figure: 1.

In the proposed strategy, we assess each alternative option's contribution towards the high-level goals. Given a goal model with alternative design options, the association between these alternatives and the softgoals is attributed to fuzzy values. The levels of goal satisfaction or the relative expectations of the softgoals to the main goal are determined by the backward propagation of these values to the goals (which are higher in hierarchy).

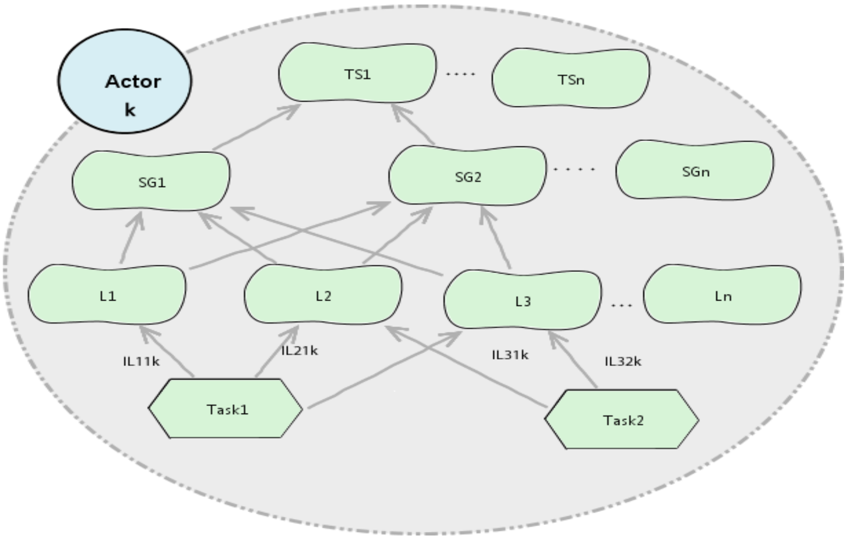

Figure 1. Generalised complete structure of an i^* goal model

The aim is to find the top softgoals' priority. This is deciphered from the kind of impact each alternative has on the top softgoals. If the impacts of alternatives on the softgoals are analysed in terms of values, it may lead to imprecision, as the values can differ depending on the analyst and can lead to a subjective outcome. This is why fuzzy numbers are used in the proposed approach, instead of a numerical value. Thus, the impact of each alternative on the top softgoals is demonstrated as triangular fuzzy numbers such as make, help, break, some- and some+, which give an indication as to what degree an alternative option meets the leaf softgoals.

The top softgoals are evaluated by a simplified calculation. This involves fuzzy numbers that represent the impacts of each alternative on the top softgoals. These numbers are then defuzzified into quantifiable values. Scores of top softgoals are evaluated by propagating the impacts towards them. A weight ω is assigned to each leaf softgoal on the basis of their relative significance in order to achieve the goal. The scores of each top softgoal of each actor are calculated based on its dependency under each alternative. Further information is provided in [11, 12] regarding the representation of goals, weights, impacts and alternatives.

The SR i^* goal model is defined as a directed graph $G(N; R)$, where N represents the intentional elements (such as goals, top softgoals (TS_1, TS_2, ... , TS_n), intermediate softgoals (SG_1, SG_2, ... , SG_n), leaf softgoals (L_1, L_2, ... , L_n), resources and tasks ($Task_1$ and $Task_2$)), forming a collection of nodes, and R represents the means-end, task-decomposition, dependency and contribution links, forming a collections of edges on the graph.

If there are t hierarchy levels in the directed graph, then leaf softgoals are defined at level zero of the directed graph. Let us assume $\omega_{L_{ik}}$ refers to the weight of the i^{th} leaf softgoal and $I_{L_{ijk}}$ refers to the impact on the i^{th} leaf softgoal of the j^{th} alternative of the k^{th} actor. Also, consider there exists m softgoals, n_c children and n_d dependencies for the i^{th} softgoal at level one. The score of any softgoal at $t > 1$ is determined by taking the product of its impact and its each child score [11].

Thus, the score of a level t softgoal for an actor with a relationship of dependency can be formalised as:

Table 1
Optimal values of objective functions

Top softgoals	$Task_1$	$Task_2$
TS_1	S_{11}	S_{12}
TS_2	S_{21}	S_{22}

$$Score_{Softgoal_{i_t jk}} = \Pi_{l=1}^{t} I_{ijl} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{ij}} * I_{d_{L_{ijk}}} * \omega_{d_{L_{ijk}}})] + \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (S_{id_{by}} * I_{id_{by}})) + \sum_{b=1}^{n_d} (S_{id_b} * I_{id_b})] \tag{1}$$

Then, as shown in the Equation 1, the objective functions of the top softgoal under each actor alternative are created from the scores. If there is an inter-actor dependency relationship, then consideration should be given to both strategic dependency and strategic rationale diagrams of the *i** goal model, assuming that this approach takes into account only softgoal interdependency relationships. If an actor has *n* alternatives, then *n* objective functions are available for each top softgoal. The *n* objective functions that need to be maximised to obtain a maximum score for the top softgoal under each alternative are given as follows:

$$\begin{aligned} f_i(\omega_n) &= Max(Score_{SG_{ink}}) \\ &= Max(\Pi_{l=1}^{t} I_{inl} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{in}} * I_{d_{L_{ink}}} * \omega_{d_{L_{ink}}})] + \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (S_{id_{by}} * I_{id_{by}})) + \sum_{b=1}^{n_d} (S_{id_b} * I_{id_b})]) \end{aligned} \tag{2}$$

where $0 \leqslant \omega_{d_{L_{jk}}} \leqslant 100$ for $d = 1$ to n_c

Likewise, objective functions that have to be minimised are formalised for each actor in the *i** goal model.

In the next step, using the IBM CPLEX optimiser [56], these multi-objective functions of opposing goals (maximum and minimum) are utilised to their fullest potential. The optimiser IBM CPLEX is used to solve multi-objective functions for all actors in the goal model. The solved optimal values obtained refer to the score (importance) of each top softgoal under each alternative to meet stakeholders' goals.

Let the optimal values of the objective functions in Eq: 2 be expressed as:

$$(x_{TS_1 A_1}, x_{TS_1 A_2} x_{TS_1 A_3}, ..., x_{TS_1 A_n}) \tag{3}$$

Furthermore, for all actors in the goal model, multi-objective function values are generated on similar lines.

3.1.3. Construction of pairwise comparison matrix

The scores of the top softgoals are thus determined using the GORE approach, which is based on each alternative's contribution to achieve the goal for comparison between softgoals. Therefore, it is important to generate the PCM that varies the importance of each softgoal against the main goal. This is achieved through deriving, by pairwise comparison, the relative importance of each softgoal as opposed to others, and towards the main goal. The objective values for the elements in the PCM obtained using GORE are shown in Table 1. It helps to illustrate the relative importance of each of the softgoal pairs compared. Through the PCM, it contrasts the value of a softgoal to itself. The input value relates to the equally important metric towards the main goal. This proves that the ratio of a given softgoal's importance regarding the importance to itself will always be equal. The PCM shows the relative pairwise preferences between all softgoals engaged in the decision-making process.

As a solution to decrease the decision-makers' workload, AHP can be completely or partially automated. This can be achieved by identifying suitable thresholds so that some pairwise comparisons are decided automatically.

Table 2

Random-like matrix values of different sizes

Order of matrix	1	2	3	4	5
RI value	0.00	0.00	0.58	0.90	1.12

The pairwise comparison judgements about the importance of each softgoal towards main goal and the importance of each alternative towards each softgoal should be consistent. The matrix for a pairwise comparison is said to be consistent if all its elements follow the Saaty rules of transitivity and reciprocity [65].

Let us assume A is the PCM of size n x n, $[a_{ij}]$ are its elements, where $i, j = 1, 2, ...n$. Each element $[a_{ij}]$ indicates how important the i^{th} element is compared to the j^{th} element. If the i^{th} element is x times more important than the j^{th} element, then the j^{th} element is $(\frac{1}{x})$ times as important as the i^{th} element. It is necessary for the comparative values to be inserted above the leading diagonal in the pairwise comparison matrix. Hence, the total number of required comparisons is equal to $\frac{n(n-1)}{2}$.

Normalisation of pairwise comparison matrix:

The AHP measures the overall relative importance of each softgoal after constructing the PCM. The overall measurement of relative importance involves averaging over normalised columns in order to estimate the PCM's eigenvalues (divide each element by summing all the elements in each column in total). As a result of the normalisation process, matrix A is transformed into matrix $B = [b_{ij}]$. Matrix elements in B are computed on the basis of the following equation:

$$b_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \tag{4}$$

Then, the pairwise relative priority (eigenvector) of top softgoals, $W = [w_{ij}]$, is determined by evaluating the numerical averages from the normalised comparison matrix row. These vector components are determined as per the equation shown below:

$$w_i = \frac{\sum_{j=1}^{n} b_{ij}}{n} \tag{5}$$

Validation of pairwise comparison matrix:

Once the overall relative significance of the top softgoal is established, its consistency will be tested. The consistency ratio (CR) is measured. This is performed by contrasting the consistency index (CI) of a random-like matrix (RI) with the CI of the obtained PCM. Saaty [66] has predefined the RI values for matrices of different sizes as shown in Table: 2. According to Saaty [66], a CR of 0.10 or less is acceptable to proceed with the AHP reasoning. In the case that the consistency ratio reaches 0.10 or more, the specified contributions need to be updated, then the reason for the inconsistency must be found and revised. The CI, which indicates the PCM's result accuracy, must be determined first to find the CR:

$$CI = \frac{(\lambda_{max} - n)}{(n-1)} \tag{6}$$

where λ_{max} is the PCM's maximum principal eigenvalue.

When λ_{max} is equal or closer to the number of requirements (n), then there will be fewer decision errors and more reliable results. To get λ_{max}, first multiply the PCM by a matrix of priority columns. Secondly, divide each element in the obtained result matrix by the corresponding element in the priority matrix. Thirdly, calculate the average of all the elements in the resultant matrix, obtained in the second step. This average value gives the value of λ_{max} that can then be used to calculate CI. The maximum eigenvector (λ_{max}) is determined using the equation below:

$$\lambda_{max} = \frac{1}{n}\sum_{i=1}^{n}\frac{(AW)_i}{w_i} \tag{7}$$

3.1.4. Determination of alternatives' local priorities

The next step is to measure each alternative's local priorities with respect to each softgoal. It differentiates the local priorities from the overall priorities. The local priorities are only valid for each softgoal. This enables them to be differentiated from the overall priorities, which have to be determined later. In order to determine the priorities of the alternatives with respect to each of the top softgoals, a pairwise comparison of all the alternatives is performed. In a model consisting of two alternatives, only one comparison needs to be made for each top softgoal: comparison of alternative 1 with alternative 2. Three comparisons are required for a model with three alternatives (alternative 1 and alternative 2, alternative 1 and alternative 3, and alternative 2 and alternative 3).

3.1.5. Determination of overall priorities

The local priorities help identify the preferred alternative to each top softgoal. For each alternative, the overall priority has to be determined. Such preferences take into account not only our preference for alternatives for each softgoal, but also the varying weight of each softgoal. This step is known as *model synthesis*, since all the values given in the model are used. Next, the overall priority is determined using the local priority as the starting point for each alternative. Then, the weights of each top softgoal is taken into account.

3.1.6. Sensitivity analysis

The weights given to the respective softgoals change the overall priorities. A "what-if-analysis" process known as *sensitivity analysis* would be beneficial to check how the final outcomes vary as the softgoals' weights change. This study gives an understanding of which alternatives brought about the original results. Sensitivity analysis is a crucial process and all final decisions are dependent upon the impact of this analysis.

When changes are made to the weights of top softgoals, then changes take place in the overall priorities of the alternatives. This analysis is the sensitivity analysis. To properly demonstrate this notion, the following scenarios can be analysed:

(i) What is the result of having the same weight for all top softgoals?
(ii) What weight is needed to create a tie in the overall priorities of the alternatives?

In order to measure the break-even point, different weights may be used for the top softgoals. When the top softgoal weight is about 0.5 of the total 10, the alternatives have the same value for practical purposes; i.e., all alternatives are preferred equally. After the above processes are finished, a decision can be made. This represents the final stage in our analysis of the AHP method. For this purpose, the overall priorities obtained must be compared and tested as to whether the variations are sufficiently large to make a clear choice.

In the next section, we illustrate the AHP-based methodology of reasoning opposing goals based on inter-actor dependency using a telemedicine system case study.

4. Case Study: Telemedicine System

To illustrate the above proposed approach, this paper considers a simple i^* goal model for telemedicine, as shown in Figure: 2. It presents two actors, *Patient* and *Healthcare Provider*. They are considerably simplified but still require some kind of reasoning, namely selection of an optimal alternative. The actor *Patient*'s key non-functional requirements or softgoals are the *Expense* of treatment and *Happiness* received from remote treatment, which rely on the *Time Saving* and *Quality of Care*. There are two different ways of getting the *Patient* diagnosis. It is either

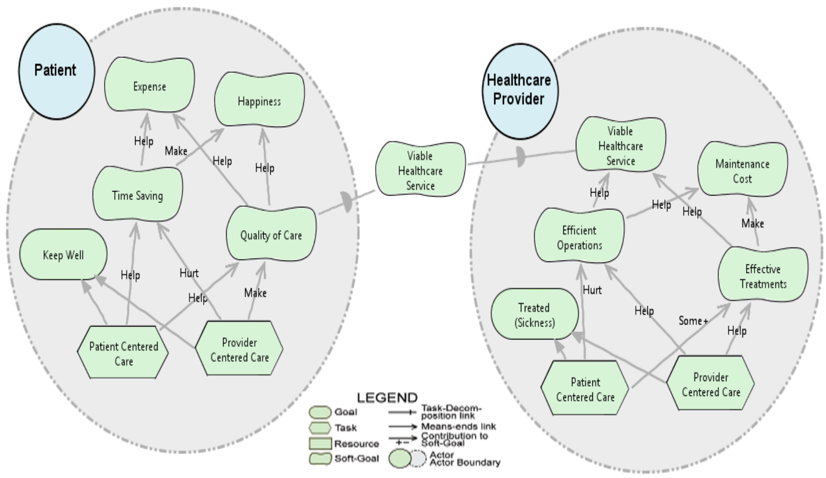

Figure 2. Simplified i^* goal model for the Telemedicine System [71]

through *Patient Centered Care* or *Provider Centered Care*. The *Patient* has to choose an alternative option, so that their *Expense* should be less and their *Happiness* should be greater. The actor *Health Care Provider* has two main non-functional requirements or softgoals, namely *Viable Healthcare Service* and *Maintenance Cost*, representing the goal of providing services in the telemedicine system for the *Health Care Provider*. The goals of the telemedicine system are *Keep Well* of *Patient* and *Treated (Sickness)* of *Health Care Provider*, can be applied in one of two ways and are therefore *OR* decomposed into two tasks known as *Patient Centered Care* and *Provider Centered Care*.

This telemedicine system's decision-making process is to choose an alternative option that increases the *Viable Healthcare Service* of the *Health Care Provider* and *Happiness* of the *Patient*, while also decreasing the *Maintenance Cost* of the *Health Care Provider* and the *Expense* of the *Patient*. Figure: 3 illustrates the typical hierarchical structure of the telemedicine system, where the top softgoals are set at the top level while the alternatives are at the bottom.

The first level in the hierarchy represents the system goals to model (*Keep Well* and *Treated (Sickness)* in our example). The top softgoals constitute the hierarchy's second level. Four top softgoals are listed in our example: *Expense*, *Happiness*, *Viable Healthcare Service* and *Cost of Maintenance*. In the third level of the hierarchy, intermediate softgoals are listed. The fourth level reflects the alternative means available for achieving the main goal. In the telemedicine model example, the alternatives are *Patient Centered Care* and *Provider Centered Care*.

In the case study on telemedicine, some terms are abbreviated as shown in Table: 3. Fuzzy numbers are defuzzified into quantifiable values as demonstrated in Table: 4. In order to improve the readability of the text, Table : 5 shows the objective function values for the telemedicine system. Therefore, the GORE method helps to evaluate the scores (satisfactory values) of the top softgoals based on the contribution of each alternative towards the goal. Each softgoal's importance to the main goal is different. It is therefore necessary to generate the PCM by deriving the relative priority of each softgoal, with regard to each other and towards the main goal, through pair-by-pair comparisons. Elements in the PCM have a value derived from the objective functions, as shown in Table: 5, to display

Table 3
Abbreviation of terms in the telemedicine system

Terms	**Abbreviations**
Patient	*P*
Healthcare Provider	*HCP*
Expense	*E*
Happiness	*H*
Viable Healthcare Service	*VHS*
Maintenance Cost	*MC*
Patient Centered Care	*PaCC*
Provider Centered Care	*PrCC*

Table 4
Defuzzified impact values in the telemedicine system

Impact	Fuzzy value	Defuzzified value
Hurt	(0, 0.16, 0.32)	0.16
Make	(0.64, 0.8, 1)	0.8
Some-	(0.16, 0.32, 0.48)	0.32
Some+	(0.32, 0.48, 0.64)	0.48
Break	(0, 0, 0.16)	0
Help	(0.48, 0.64, 0.80)	0.64

Table 5
Objective function values of each top softgoals in the telemedicine system with respect to each alternative

(a) For actor *Patient*

Top softgoals for actor *P*	*PaCC*	*PrCC*
H	51.2	51.2
E	5.24	10.24

(b) For actor *Healthcare Provider*

Top softgoals for actor *HCP*	*PaCC*	*PrCC*
VHS	30.72	40.96
MC	12.8	51.2

the relative importance in each pair of softgoals compared. In the PCM, the importance of a softgoal is relative to itself, e.g. $Expense$ versus $Expense$. The input value is one that corresponds with the metric of equivalent significance towards the main goal. This means that the ratio of a given softgoal's significance regarding the importance of itself will always be equal. The PCM displays the relative priorities of all softgoals involved in the decision-making process in pairs. AHP measures the overall relative importances of each softgoal after deriving the PCM. The overall calculation of relative importance involves averaging over normalised columns in order to estimate the PCM's eigenvalues (divide each element by summing all the elements in each column in total). Based on the normalised matrix, the overall relative importance of each softgoal can be achieved by simply averaging each row, and it is an approximation of the matrix's eigenvalues. The PCM representation of each top softgoal in the telemedicine case study with respect to the alternative *PaCC* is represented as:

$$\mathbf{PCM}_{PaCC} = \begin{array}{cc} & \begin{array}{cccc} E & H & VHS & MC \end{array} \\ \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} & \begin{pmatrix} 1 & \frac{5.24}{51.2} & \frac{5.24}{30.72} & \frac{5.24}{12.8} \\ \frac{51.2}{5.24} & 1 & \frac{51.2}{30.72} & \frac{51.2}{12.8} \\ \frac{30.72}{5.24} & \frac{30.72}{51.2} & 1 & \frac{30.72}{12.8} \\ \frac{12.8}{5.24} & \frac{12.8}{51.2} & \frac{12.8}{30.72} & 1 \end{pmatrix} \end{array} = \begin{array}{cc} & \begin{array}{cccc} E & H & VHS & MC \end{array} \\ \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} & \begin{pmatrix} 0.0524 & 0.0524 & 0.0524 & 0.0525 \\ 0.513 & 0.513 & 0.512 & 0.512 \\ 0.309 & 0.308 & 0.307 & 0.307 \\ 0.126 & 0.128 & 0.129 & 0.128 \end{pmatrix} \end{array} \tag{8}$$

The PCM sum representation with respect to *PaCC* is given as below:

$$\mathbf{PCM}_{PaCC} = \begin{array}{cc} & Sum \\ \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} & \begin{pmatrix} 0.2109 \\ 2.049 \\ 1.23 \\ 0.511 \end{pmatrix} \end{array} \tag{9}$$

The PCM priority representation with respect to *PaCC* is given as below:

$$\mathbf{PCM}_{PaCC} = \begin{array}{cc} & Priority \\ \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} & \begin{pmatrix} 0.0524 \\ 0.5125 \\ 0.308 \\ 0.128 \end{pmatrix} \end{array} \tag{10}$$

The PCM representation of each top softgoal of the telemedicine case study with respect to *PrCC* is given as below:

$$\mathbf{PCM}_{PrCC} = \begin{array}{cc} & \begin{array}{cccc} E & H & VHS & MC \end{array} \\ \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} & \begin{pmatrix} 1 & \frac{10.24}{51.2} & \frac{10.24}{40.96} & \frac{10.24}{51.2} \\ \frac{51.2}{10.24} & 1 & \frac{51.2}{40.96} & \frac{51.2}{51.2} \\ \frac{40.96}{10.24} & \frac{40.96}{51.2} & 1 & \frac{40.96}{51.2} \\ \frac{51.2}{10.24} & \frac{51.2}{51.2} & \frac{51.2}{40.96} & 1 \end{pmatrix} \end{array} = \begin{array}{cc} & \begin{array}{cccc} E & H & VHS & MC \end{array} \\ \begin{array}{c} E \\ H \\ VHS \\ MC \end{array} & \begin{pmatrix} 0.07 & 0.07 & 0.07 & 0.07 \\ 0.33 & 0.33 & 0.33 & 0.33 \\ 0.27 & 0.27 & 0.27 & 0.27 \\ 0.33 & 0.33 & 0.33 & 0.33 \end{pmatrix} \end{array}$$

(11)

The PCM sum representation with respect to *PrCC* is given as below:

$$\mathbf{PCM}_{PrCC} = \begin{array}{c} \\ E \\ H \\ VHS \\ MC \end{array} \begin{array}{c} Sum \\ \begin{pmatrix} 0.28 \\ 1.32 \\ 1.08 \\ 1.32 \end{pmatrix} \end{array} \tag{12}$$

The PCM priority representation with respect to *PrCC* is given as below:

$$\mathbf{PCM}_{PrCC} = \begin{array}{c} \\ E \\ H \\ VHS \\ MC \end{array} \begin{array}{c} Priority \\ \begin{pmatrix} 0.07 \\ 0.33 \\ 0.27 \\ 0.33 \end{pmatrix} \end{array} \tag{13}$$

Once the overall relative importance of softgoals has been obtained, it is necessary to check whether or not they are consistent. For this reason, a consistency ratio (CR) is determined by comparing the consistency index (CI) of a random matrix (RI) of the obtained PCM versus the CI. Saaty [66] has given the RI value obtained for matrices of different sizes. Saaty [66] has shown that a *CR* of 0.10 or less is appropriate for the AHP reasoning to continue. In the case that the consistency ratio reaches 0.10, the assigned contributions need to be updated, to find the reason for the inconsistency, and revised. The *CI*, which displays the resulting PCM accuracy, must be determined first to find the *CR*.

For example, the *CR* of top softgoals with respect to *PaCC* is calculated as shown below:

$$CI = \frac{4.0094-4}{4-1} = 0.0031$$

$$CR = \frac{CI}{RI} = \frac{0.0031}{0.90} = 0.0034 \tag{14}$$

As a general rule, a *CR* of 0.10 or less is acceptable. So the result obtained is an ideal one.

Similarly, the *CR* of top softgoals with respect to *PrCC* is calculated as shown below:

$$CI = \frac{4.008-4}{4-1} = 0.0027$$

$$CR = \frac{0.0027}{0.90} = 0.003 \tag{15}$$

This CR value is also considered as acceptable. So the result obtained for *PrCC* is ideal too. The suggested approach for determining the relative importance of each top softgoal towards the main goal is considered to be consistent, so that the decision-making process using AHP is transferred to the next stage.

4.1. Derive Relative Local Priorities of Alternatives:

In this phase, the relative priorities of each alternative are determined for each top softgoal shown in the decision-making model. For this purpose, the PCM is built (using the propagated (summation) impact score) for each alternative with respect to each particular top softgoal (Table: 6). Two alternatives, *PaCC* and *PrCC*, are mentioned in the telemedicine example, and four top softgoals. This leads to four matrices for pairwise comparison.

The PCM of *PaCC* and *PrCC* with respect to *Expense* is represented as :

PCM_E =

$$\begin{array}{c c} & \begin{array}{cc} PaCC & PrCC \end{array} \\ \begin{array}{c} PaCC \\ PrCC \end{array} & \begin{pmatrix} 1 & 51.2/5.6 \\ 5.6/51.2 & 1 \end{pmatrix} \end{array} = \begin{pmatrix} 1 & 0.91 \\ 1.1 & 1 \end{pmatrix} = \begin{pmatrix} 0.48 & 0.48 \\ 0.52 & 0.52 \end{pmatrix} = \begin{pmatrix} 0.48 \\ 0.52 \end{pmatrix} \tag{16}$$

The PCM of *PaCC* and *PrCC* with respect to *Happiness* is represented as :

PCM_H =

$$\begin{array}{c c} & \begin{array}{cc} PaCC & PrCC \end{array} \\ \begin{array}{c} PaCC \\ PrCC \end{array} & \begin{pmatrix} 1 & 5.28/5.76 \\ 5.76/5.28 & 1 \end{pmatrix} \end{array} = \begin{pmatrix} 1 & 0.92 \\ 1.1 & 1 \end{pmatrix} = \begin{pmatrix} 0.48 & 0.48 \\ 0.52 & 0.52 \end{pmatrix} = \begin{pmatrix} 0.48 \\ 0.52 \end{pmatrix} \tag{17}$$

The PCM of *PaCC* and *PrCC* with respect to *Viable Healthcare Service* is represented as :

PCM_{VHS}=

$$\begin{array}{c c} & \begin{array}{cc} PaCC & PrCC \end{array} \\ \begin{array}{c} PaCC \\ PrCC \end{array} & \begin{pmatrix} 1 & 1.76/2.56 \\ 2.56/1.76 & 1 \end{pmatrix} \end{array} = \begin{pmatrix} 1 & 0.69 \\ 1.5 & 1 \end{pmatrix} = \begin{pmatrix} 0.4 & 0.41 \\ 0.6 & 0.59 \end{pmatrix} = \begin{pmatrix} 0.41 \\ 0.59 \end{pmatrix} \tag{18}$$

The PCM of *PaCC* and *PrCC* with respect to *Maintenance Cost* is represented as :

$$PCM_{MC} =$$

$$\begin{array}{c c} & \begin{array}{cc} PaCC & PrCC \end{array} \\ \begin{array}{c} PaCC \\ PrCC \end{array} & \begin{pmatrix} 1 & 1.92/2.72 \\ 2.72/1.92 & 1 \end{pmatrix} \end{array} = \begin{pmatrix} 1 & 0.71 \\ 1.42 & 1 \end{pmatrix} = \begin{pmatrix} 0.41 & 0.42 \\ 0.59 & 0.58 \end{pmatrix} = \begin{pmatrix} 0.42 \\ 0.58 \end{pmatrix}$$

The local priorities of alternatives are determined, as shown in Table: 3, by averaging over normalised columns to calculate the eigenvalues of the obtained PCMs of each alternative with respect to all top softgoals. The consistency will only be tested if there are three or more elements that are to be compared pairwise [66]. In the given case study, only two alternatives are compared(pairwise). Therefore there is no need for consistency calculations. This implies that the local priorities being measured are consistent. The pseudo code for the approach proposed is shown in Algorithm: 1 for ready reference.

Table 6

Propagated values of alternatives towards the top softgoal

(a) Propagated impact score

Alternatives	*E*	*H*	*VHS*	*MC*
PaCC	5.12	5.28	1.76	1.92
PrCC	5.6	5.76	2.56	2.72

(b) Propagated local priorities

Alternatives	*E*	*H*	*VHS*	*MC*
PaCC	0.48	0.48	0.41	0.42
PrCC	0.52	0.52	0.59	0.58

4.2. Derive Overall Priorities:

In this step, the overall priority for each alternative is calculated. This means that priorities consider not only our preference of alternative options for each softgoal, but also the fact that each softgoal has a different weight to achieve the goal. For example, the *Expense* top softgoal has a priority of 0.0524 with respect to the *Patient Centered Care* alternative, and the *Patient Centered Care* has a local priority of 0.48 relative to *Expense*. Therefore, the weighted priority of the *Patient Centered Care*, with respect to *Expense* is 0.024. Similarly, it is necessary to obtain the *Patient Centered Care* weighted priorities with respect to *Happiness*, *Viable Healthcare Service* and *Maintenance Cost*. Now the alternative options can be ordered based on their overall priority as shown in Table: 7. In other words, given the importance of each top softgoal (*Expense, Happiness, Viable Healthcare Service* and *Maintenance Cost*), the *Provider Centred Care* is preferable (overall priority = 0.5587) compared to the *Patient Centered Care* (0.4505).

4.3. Sensitivity Analysis

The weights given to the respective softgoals will heavily influence the overall priorities. Therefore, a "what-if" study is useful to see how the final results could have to be adjusted if the weights of the requirements were different. This procedure is called sensitivity analysis, which is the next step in the technique of AHP. Analysis of sensitivity helps us to understand how reliable our original decision is, and what the drivers are (i.e. which requirements influenced the original results). This is an important part of the decision-making process and, generally speaking, no final decision should be made without performing sensitivity analysis. Remember that the *PrCC* in our example, Table

Algorithm 1 Pseudo code for prioritising alternative tasks relative to the opposing non-functional requirements in the i^* goal model

Require: A set of directed graphs S such that G is a subset of S that has same n set of tasks T. G_i is a quadruple $\{T, L, SG, TS\}$ where each element represents alternative tasks, leaf softgoals, in-between softgoals and top softgoals respectively.

```
MAIN MODULE : Reasoning of opposing goals
for all G_i ϵ G do
    for all alternatives t ϵ T do
        for all top softgoals ts ϵ TS do
            if ts is Min then
                Generate minimisation objective functions
            else
                Generate maximisation objective functions
            end if
        end for
    end for
end for
Let F_Max ← Max{f_Max_1, ., f_Max_n}
Let F_Min ← Min{f_Min_1, ..., f_Min_n}
for all f_Max_i ϵ F_Max do
    Let x_Max_i ← optimal(f_Max_i, Max)
end for
for all f_Min_i ϵ F_Min do
    Let x_Min_i ← optimal(f_Min_i, Min)
end for
Generate pairwise comparison matrix of top softgoals under each task, PCM_T_i, for obtaining relative importances to the main goal as
for all tasks t_l, t_r ϵ T where l, r = 1 to n do
    PCM_T_l[i, j] ← TS_i / TS_j where i, j = 1 to size(TS)
    PCM_T_r[i, j] ← TS_i / TS_j where i, j = 1 to size(TS)
end for
Calculate the eigenvalues of PCM by averaging over normalised columns.
Assign each top softgoal its relative importance based on the calculated eigenvalues
Check the consistency of the obtained relative priorities of top softgoals
Repeat the above 3 steps for alternatives
Perform model synthesis by deriving the overall priorities of each alternatives
Perform sensitivity analysis from the derived overall priorities of each alternatives
SUB-MODULE: Optimal(f, TS)
if TS is Max then
    Define maximisation function
else if TS is Min then
    Define minimisation function
end if
CPLEX.solve() → W
return W
```

Table 7
Priorities of alternatives towards main goal

(a) Top softgoals overall priorities

Alternatives	*E*	*H*	*VHS*	*MC*
PaCC	0.05	0.51	0.31	0.13
PrCC	0.07	0.33	0.27	0.33

(b) Overall priorities with respect to alternatives

Alternatives	Overall priority
PaCC	0.4505
PrCC	0.5587

Table 8
Scenario 1:

(a) Pairwise priority(%) with respect to each alternatives

Alternatives	*E*	*H*	*VHS*	*MC*
PaCC	5.24%	51.22%	30.73%	12.81%
PrCC	6.67%	33.33%	26.67%	33.33%

(b) Overall priority(%) with respect to each alternatives

Alternatives	*E*	*H*	*VHS*	*MC*	Overall priority
PaCC	2.5%	24.5%	12.5%	5.3%	45%
PrCC	3.5%	17.4%	15.8%	19.5%	56%

7, is of great importance (priority 0.5587). Since the *PrCC* has a high local priority for this particular criterion, this inevitably affects the final result favourably for the *PrCC*. The queries we should ask ourselves at this point are:

(i) If we modify the importance of the criteria, what will be the best alternative option?

(ii) What happens when all of the criteria are offered equal importance?

(iii) What about when we offer *Happiness* more importance or assume it as important as *Viable Healthcare Service*?

In order to perform sensitivity analysis, it is important to make adjustments to criterion weights to see how they affect the alternatives' overall priorities. To illustrate this, we should examine the following hypothetical situations:

(i) What happens if all the criteria have the same weight?

(ii) How much weight must be assigned to the top softgoals to result in a tie in the alternatives' overall priorities?

The original model synthesis is shown in Table 8, in which the most preferred alternative option is listed as *PrCC*. The case where all three criteria weigh the same value (0.333) is illustrated in Table 9. The most preferred alternative choice in this second situation is *PrCC* too. From the observations, we noticed that on all considered criteria, *PrCC* wins. We should experiment with different weights for the different top softgoals to determine the break-even point.

Table 9
Scenario 2:

(a) Pairwise priority(%) with respect to each alternatives

Alternatives	*E*	*H*	*VHS*	*MC*
PaCC	33.33%	33.33%	33.33%	33.33%
PrCC	33.33%	33.33%	33.33%	33.33%

(b) Overall priority(%) with respect to each alternatives

Alternatives	*E*	*H*	*VHS*	*MC*	Overall priority
PaCC	15.9%	15.9%	13.6%	13.8%	59%
PrCC	17.4%	17.4%	19.8%	19.5%	74%

Table 10
Scenario 3:

(a) Pairwise priority(%) with respect to each alternatives

Alternatives	*E*	*H*	*VHS*	*MC*
PaCC	18%	40%	30.63%	21.80%
PrCC	15.5%	26%	23.3%	26%

(b) Overall priority(%) with respect to each alternatives

Alternatives	*E*	*H*	*VHS*	*MC*	Overall priority
PaCC	8.6%	19.2%	12.5%	9.2%	50%
PrCC	8.1%	13.5%	13.7%	15.1%	50%

Both alternatives are equally preferred by decreasing the weight of *Happiness* (from 0.3333 in the original scenario to 0.26 in the third scenario). This is reflected in Table 10.

4.4. Results

After the above processes are finished, a decision can be made. This represents the final stage in our analysis of the AHP method. For this purpose, the overall priorities obtained must be compared and tested as to whether the variations are sufficiently large to make a clear choice. The findings of the sensitivity analysis should also be analysed (Tables: 8, 9 and 10). From the above study, we are able to say that the final regcommendation is as follows: if more than 50% of the overall importance of the criteria is in the decision of the softgoal *Happiness*, the best alternative is *PrCC* (Table 8). But when cost is substantially less than 50%, the better decision is *PaCC* (from Tables 9 and 10).

5. Critical Discussion of the Proposed Method with Related Work

Ever since the concept of goal modelling was conceived and developed, a lot of research work has been done on the logic and rationale used in achieving goals by assigning qualitative and quantitative values. However, among all the work done previously, very limited research work was based on optimisation of goal models. The steps proposed in our approach have been validated with a telemedicine case study. The following observations have been made about the results obtained. The success of this approach depends on the following features:

i) Appropriate stakeholders' needs to be identified in prioritising softgoals
ii) Optimal selection of alternatives for actors having opposing non-functional requirements.
iii) Subjective quantification approach using AHP helps the consistency of the goal analysis.
In the existing GORE literature, there exists methods which make use of formal techniques in choosing the best alternative. They make use of temporal logic and label propagation algorithms. Our approach differs in adopting a quantitative way of evaluating the alternatives using AHP.

In this section, we present a brief discussion of the proposed method with all relevant earlier research proposals which used a similar qualitative and quantitative approach for goal analysis and optimisation of the *i** goal model.
Lamsweerde et al. [49] proposed an alternative lightweight quantitative analysis of goals in the KAOS framework to overcome the problems related to qualitative analysis. They used parameters such as 'gauge variables', 'idea target value' and 'maximum acceptable value' for each softgoal. Using this approach, they obtained these values from the specification of the system. When using this method, the specification of the system has to be clearly understood before designing a goal model. We also noticed that it might be difficult to apply this approach where the systems are large and complex.
J. Mylopolous et al. [28] presented a proposal with formal reasoning of goals in the goal models. This was achieved by presenting a qualitative formalisation and value propagation algorithm. Quantitative semantics for new relationships were also given, based on the probabilistic model. However, this required a strong knowledge of mathematics since it uses first-order logic, as compared to our approach, which is based on fuzzy logic/reasoning.
Horkoff and Yu [38] proposed a qualitative analysis of goal models to understand the problem domain during the early phase of RE. Additionally, this model is used to perform elicitation, which needs customers' interventions. However, the main problem with this approach is the ambiguity in decision-making when one or more goals receive the same labels. We have successfully resolved this problem of ambiguity in our approach by adopting a quantitative analysis method.
Affleck et al. [1] proposed a linear programming optimisation model to the NFR framework, which aimed to minimise operationalisation. It uses a single objective optimisation to select a minimum number of operations which would maximise the overall satisfaction of the NFRs. However, this approach fails to provide a set of alternative design options which trade different objectives with each other. Our approach addresses this by using multi-objective options. In our approach, the interaction between different objectives gives rise to a set of optimal solutions known as Pareto-optimal solutions. Also, in the design and planning stages, we have given due consideration to many objectives. These significantly improve our procedure and hence directly support the decision-making process in the following ways:
(1) When we use a multi-objective methodology, a wider range of alternatives is usually identified.
(2) When we consider multiple objectives, it promotes more appropriate roles for participants in the planning and decision-making process. The role of the "analyst" or "modeller" here is to generate alternative design options, while the "decision-maker" uses these design options to make better informed decisions.
(3) We can make quite a realistic model of a problem when we consider multi-objectives.
William et al. [35] developed a multi-objective optimisation model based on the KAOS goal model for exploring alternative design options. This approach uses probability distribution to simulate the vector values for each leaf quality variable. However, it does not consider non-functional requirements when evaluating design options.
Subramanian et al. [69] conducted the first research work on reasoning non-functional requirements based on goal models using multi-objective optimisation. However, we observed that this approach could not address the actors' interdependency relationships. These relationships need to be addressed because they are crucial for decision-making in today's competitive real-time and real-world environment. In Subramanian et al.'s [69] proposal, we identified the inability to address economic effectiveness and dependency relationships among actors as the major drawbacks.
Although Sumesh et al. [70] introduced an economic evaluation-based approach for selecting an optimal strategy in the *i** goal model, they did not include the sensitivity analysis of outcomes. This analysis would aid the requirements analyst during the decision-making process.
In [53], an alternative selection process is proposed using the AHP method. Due to the subjective allocation of the relative priorities for each softgoal by the stakeholders in [53], it may not result in accurate goal formulations. Assigning specific values to stakeholders' requirements is crucial, as requirement elicitation can involve different

stakeholders. They have different preferences for the same demands. The reasoning behind this is that different stakeholders [74] have varying levels of knowledge, training and skills [74].

Chitra et al. [12] developed a technique of fuzzy-based quantitative goal analysis between actors to evaluate alternative design options. Later, to improve their approach, a multi-objective evaluation method was introduced in the goal analysis process [11] for alternative selection. Nevertheless, the literature demonstrates the process of qualitative and quantitative goal analysis for i^* and other goal models, but it does not include goals of objectively opposing roles.

In contrast to the above-mentioned goal models, we used AHP, fuzzy mathematical application and optimisation tools. These tools were useful in analysing quantitative goals to find an optimal strategy satisfying opposing objective functions. Hence, this proposal investigated how requirements-based engineering design can provide an effective as well as optimal design outcome. Sensitivity analysis was also an important part of this proposal, as it was used to see how the system behaves as the input data vary. This technique provides a great advantage in allowing estimates of input variables to be thoroughly examined before the final decision is made. Other important aids in this technique include identifying errors in the model, and comprehensively understanding the effects of input parameters. Our work is among the first attempts at applying AHP sensitivity analysis to a quantitative multi-objective optimisation model that addresses actors' interdependency relationships in the *i** framework. Our approach overcomes the problem of uncertainty which arises in qualitative analysis of the *i** goal model. Hence, it is an improvement from existing interactive qualitative analysis of the *i** framework. Even though William et al. and Affleck et al. have also used optimisation, their respective approaches are quite different from our approach. They applied optimisation to the KAOS and NFR frameworks, respectively, while we applied our approach to the *i** goal model. Our paper has proposed a multi-objective optimisation model for the *i** framework, which effectively evaluates alternative design options by considering the impact of alternative designs on non-functional requirements. In particular, the proposed approach uses AHP, fuzzy mathematical implementation and optimisation methods, as they are useful tools for performing quantitative requirements analysis [71, 72]. The quantitative non-functional requirements analysis can evaluate an optimal strategy for opposing objective functions in the requirements-based engineering design. This proposal, in other words, explores how requirements-based engineering design can produce a clear, consistent, optimally designed result. In the literature, we consider that the elicitation mechanisms of existing goal-oriented requirements models, such as the *i** model, do not support the prioritisation of interdependent actors' multi-objective requirements in the decision-making process. A hybrid AHP and a quantitative satisfaction fuzzy-based propagation approach will overcome this problem of prioritising the non-functional requirements.

6. Conclusion

In the proposed approach, the AHP method is incorporated with the quantitative reasoning of the i^* goal model of interdependent actors with opposing objectives. An algorithm is proposed to drive the alternative selection procedure of the decision-making problem. An optimal alternative option is chosen using the proposed approach for interdependent actors in the i^* goal model by balancing the opposing goals reciprocally. The study concluded that quantitative fuzzy assessments were very consistent. In order to help analysts with the final decision-making process, we also performed sensitivity analyses. Our future work may involve an extension of the proposed goal analysis of the i^* goal model, since the main focus of our work is to optimise this framework. We also intend to automate the goal analysis process since, in our present approach, human involvement is required to generate objective functions in the i^* goal model. This is a static way of generating objective functions. Hence, one of the main intentions of our future work is to enable the dynamic generation of the objective functions for the i^* goal model. In the present goal analysis of the i^* framework, our fuzzy-based inter-actor quantitative approach has been limited to softgoal interdependencies. The other types of dependencies which also need to be addressed and used in this framework are: goal dependency, resource dependency and task dependency. This clearly implies that there is a potential for an extension of the present goal analysis to include all forms of dependencies. We also observed that the goals contributing to the evaluation of softgoals can be linked with other parameters, such as cost, time and the risks involved during the development of the goals. The inclusion of these factors during the goal-evaluation process will help in determining the goals which would lead to maximum satisfaction in achieving softgoals, while ensuring that minimum costs are incurred. Hence, we concluded that a thorough modification of this implement is needed so that it can be made available for general use. We also plan to perform a more extensive study on the applicability of our optimisation model as compared to other models, such as the Non-Functional Requirements Framework, the Goal-Oriented Requirements Language Framework and the TROPOS framework. We also intend to analyse these approaches based on machine learning to determine whether these methods can be used to modify (or extend) our approach as explained in this proposal. Sometimes, during the analysis of a real-time software system, a complete set of requirements is not known in advance. In order to deal with this uncertainty in data, inductive learning algorithms and rough set-based approaches can also be incorporated into our proposal, so that a complete and specific set of requirements can be ascertained most effectively.

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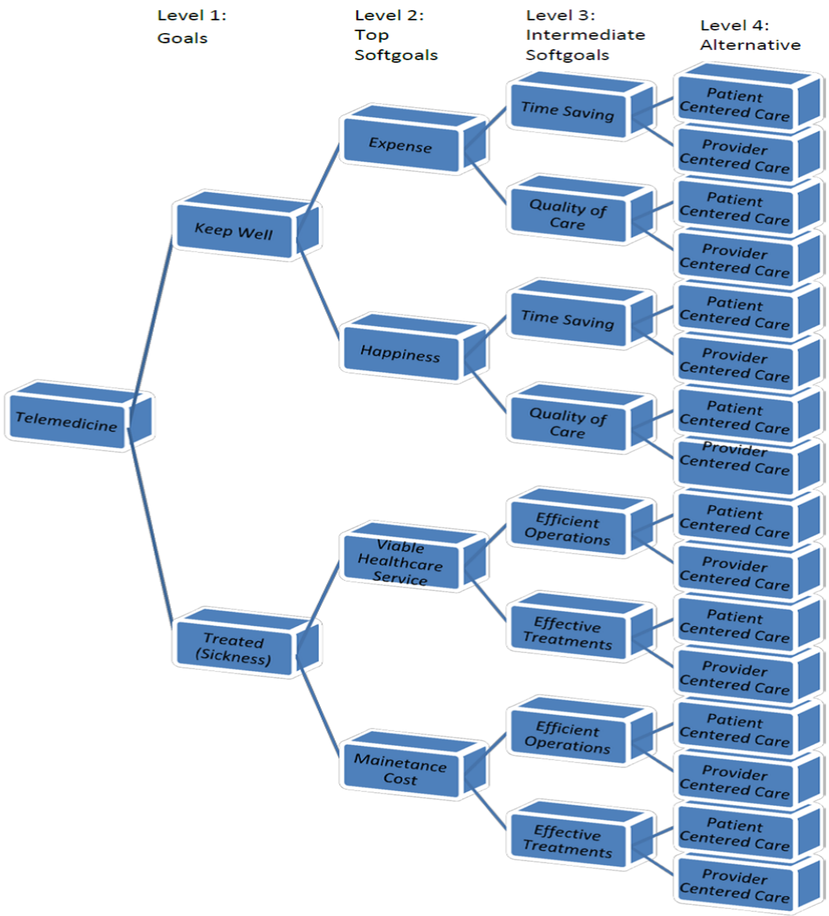


Figure 3. Hierarchical Model of the telemedicine System

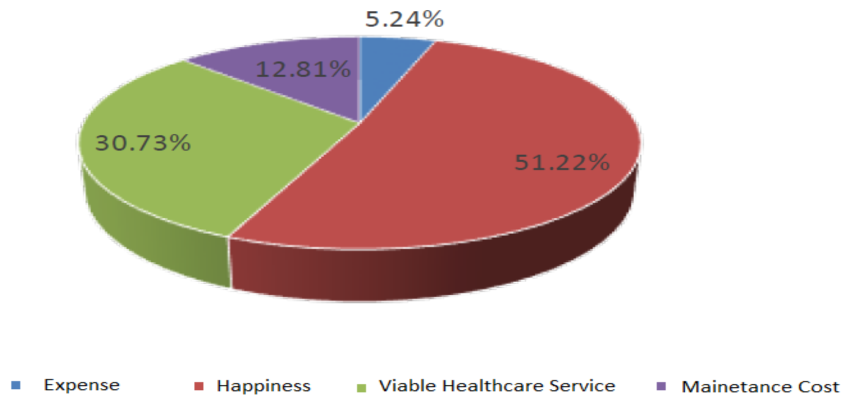


Figure 4. Pairwise relative priority of top softgoals with respect to *Patient Centered Care*

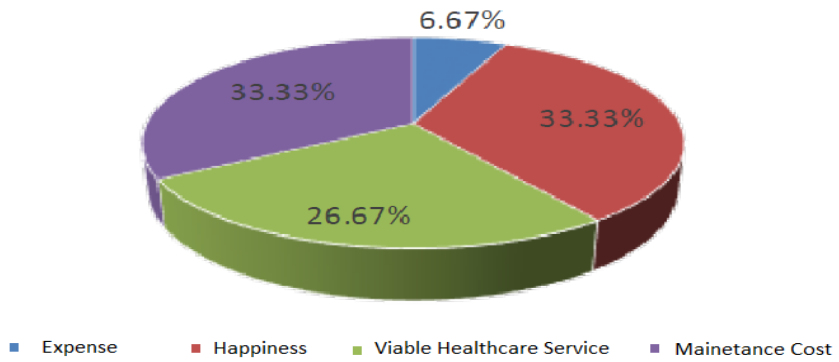
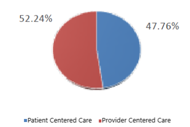
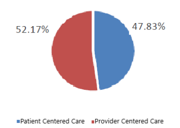


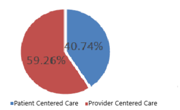
Figure 5. Pairwise relative priority of top softgoals with respect to *Provider Centered Care*



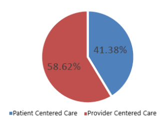
(a) *Expense*



(b) *Happiness*



(c) *Viable Healthcare Service*



(d) *Maintenance Cost*

Figure 6. Local priority of alternatives towards top softgoals

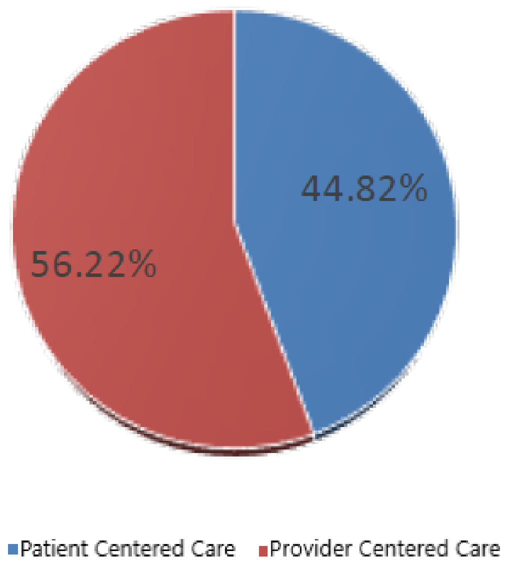
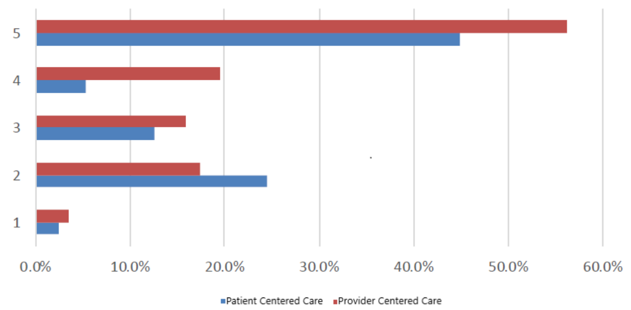
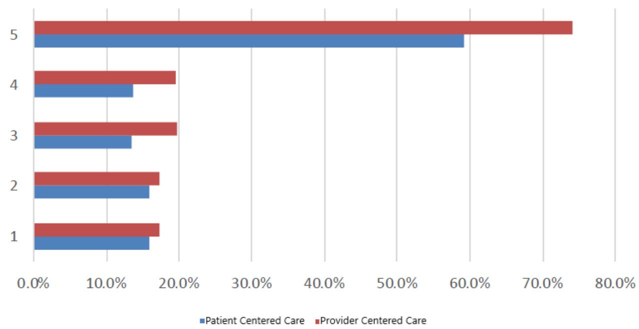


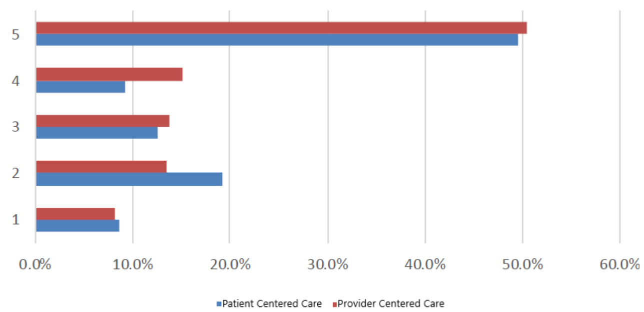
Figure 7. Overall priority of alternatives towards main goals



(a) Scenario: 1



(b) Scenario: 2



(c) Scenario: 3

Figure 8. Different scenarios based on the pairwise relative priority of top softgoals

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[7] This is the pre-submitted version.

Mixed-strategic Reasoning of the *i** Goal Model

Completed Research Paper

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Abstract

Goal-Oriented Requirements Engineering represents the stakeholder objectives using goals for making decisions about the choice of suitable non-functional requirements in view of goal models. In a competitive environment, stakeholders' may have conflicting goals. Therefore, there is a need for a goal analysis method which offers an alternative design option that achieves the conflicting goals of different inter-dependent actors in a goal model. To address circumstances where there is uncertainty, this paper proposes a game-theory based probabilistic, mixed-strategy approach to choose the best alternative to resolve the conflicting requirements issue. In this paper, a framework is proposed that applies Nash equilibrium based on multi-objective values for selecting an optimum strategy in the i goal model by considering the opposing goals reciprocally. By integrating Java with IBM ILOG CPLEX, the proposed method was developed and evaluated successfully using different case studies.*

Keywords: Goal model, Nash equilibrium, Mixed strategy, Optimization

Introduction

The success of any software system depends on the degree to which its requirements are met. The entire phenomenon of software development has increasingly become involved with Requirements Engineering (RE) as its crucial developmental aspect. Amongst the various periodic processes of Requirements Engineering, the beginning and the most important process is the elicitation of requirements. Other processes involved in Requirements Engineering are analysing, modelling, communicating, agreeing on and evolving requirements (Sommerville 2005). First, it is important to identify what are the goals or tasks for the system and keeping goals as the end result, determining what objectives need to be met by the system. This is possible by the process of elicitation. The elicitation process helps in determining the stakeholders and the information received from the stakeholders are analysed by the requirements analyst and goals are identified from the collected requirements. Goals are of two kinds – hardgoals and softgoals. Hardgoals are identified by stakeholders. These hardgoals determine the functions the system must perform. The job of the requirements analyst is to analyse the hardgoals to construct an improvised software system. The hardgoals are disintegrated into specific goals known as softgoals. There are specific goals that relate to the specific attributes such as accuracy, reliability, performance etc that is expected of the system. Alternative superior level options for system design is inspected by the requirements analyst in order to implement the desired system design (Franch et al. 2016).

Goals are used to model the requirements of the software system. This is performed by eliciting, elaborating, structuring, specifying, analysing, negotiating, documenting and modifying requirements. This method of creating a prototype of the software system's requirements is known are Goal-Oriented Requirements Engineering (GORE) (Sommerville 2005). Since the mid-nineties, the software engineering field has been predominantly working with goal models. Goals perform a crucial role in Goal Oriented Requirements Engineering and helps in deciphering the domain and deducing the intent of the stakeholders (Mylopoulos et al. 1999). Goals are developed at various levels of perception and understanding, as of strategic concerns to technical matters. Therefore, it is a very important creation during the early phases of RE (Franch et al. 2016; Karagiannis et al. 2016). Goals are created based on a multi-view representation that exhibits the way in which goals, actors, states, objects, tasks, and domain properties are connected in the given system (Van Lamsweerde 2004). Examples of largely used goal models are Knowledge Acquisition in Automated Space (KAOS) Model (Dardenne et al. 1991), *i** goal model (Yu and Mylopoulos 1995), Non-Functional Requirements (NFR) model (Yu and Mylopoulos 1995), Attributed Goal-Oriented Requirements Analysis (AGORA) Model (Kaiya et al. 2002), Tropos Model (Bresciani et al. 2004) and Goal-Oriented Requirements Language (GRL) (Amyot et al. 2010) Model. The *i** goal model is one of the most sought after and accepted goal models in the software engineering field. This is because it helps goal-oriented prototype of socio-technical systems and organisations. The *i** model is useful in creating prototypes of organisations and aids the essential processes of the socio-technical systems basing the structure on actors and their dependencies.

Goals can be conflicting in nature and each goal i.e. the requirement of a system may have various design options that can be opposing in nature. Therefore, in a realistic competitive scenario, goals of many stakeholders when conflicting in character, an analyst, during the requirements analysis stage, must work with several opposing goals of all actors that are inter-dependent in a goal model. The challenge to derive an optimal alternative design option for a goal model that has conflicting goals forms the nature of Requirements-based engineering. The issues faced by decision makers in the real world scenario, have to consider the inter-dependent relationships between actors. The real challenges faced in the real world have to be taken into consideration by creating a unique structure thus achieving multi-objective optimisation (Subramanian and Kaur 2015). This application of a realistic decision-making process allows to venture beyond analytical concepts, like the concept of game theory.

Game theory is a very useful decision making, inter-disciplinary tool that helps in finding optimal solutions in conflicting situations with the supposition that players are rational and behave according to their own interests (Kelly 2003). At first this theory was formulated for the areas of mathematics and economics. This theory provides mathematical solutions and is useful in problem analysis and deriving values of payoff matrices that represent the players' outcomes. This paper suggests a unique methodology that is structured on game theory for system exploration involving alternative design evaluation. In this paper, the game players are top softgoals that has conflicting natures and the game strategy is considered as the alternative design options of inter-dependent actors in the *i** goal model.

When research was conducted previously on game theory based goal analysis, it was performed without taking into consideration the inter-dependent relationship among the actors. This paper involves the inter-dependent actors in the i* model. The various opposing objectives is combined with their importance in order to arrive at a decision making based on game theory. A two person zero-sum game approach is adapted to the i* goal model. Multi-objective functions are decided upon to understand the importance of the i* goal model. This helps in deriving optimal alternative options of inter-dependent relationship among the actors based on each conflicting softgoal. Then the game theory is applied to assess alternative options for each actor according to each conflicting softgoal. In the final stage, an optimal solution is derived that involves a strategy in a situation of conflicting objectives. The implementation of the proposed approach is demonstrated by a case study. The next section provides an overview of the existing approaches, techniques and methods related to GORE and also the *i** model that are closely associated with our approach. This paper is structured as follows: Section 2 of this paper states the existing approaches, techniques and methods related to the *i** models that are closely connected to our proposed approach. Section 3 provides the methodology encompassing the different steps of our approach and a short introduction of the methods that are used in the study. Section 4 describes the case study used in this work. The end of the paper explains the conclusions drawn from this work.

Related Work

In present times, Requirement Engineering involves the use of goals in order to understand the reason behind the existence of the functionality in comparison to what the role of the functionality would be. Goals play an important role in aligning the organization's requirements along with its functionality. This section presents an overview of the existing methods in connection to the i* model that adapts our approach. Horkoff and Yu proposed a qualitative analysis method that is interactive and iterative for the i* goal models (Horkoff and Yu 2016). This method of goals analysis involved algorithms and tools. The challenge faced by this method is more than one goal having the same label thus leading to uncertainty in decision making. A multi-objective optimisation model was proposed by Heaven et al (Heaven and Letier 2011) for analysing alternative design options in the KAOS model. The multi-objective optimization model does not consider the non-functional requirements of the system. To overcome this NFR issue, Mairiza et al developed a Multi-Criteria Decision Analysis (MCDA) method and applied TOPSIS and MCDA for prioritising the alternative options (Mairiza et al 2014). In order to decide on alternative design options, an inter-actor quantitative goal analysis has been developed by Subramanian et al. (Subramanian and Gopalan 2015). There could arise ambiguity in the selection of numeric numbers and in order to avoid such ambiguity fuzzy numbers are used. The qualitative and quantitative goal analysis process for the i* goal and other models do not include goals with opposing functions. A systematic game theory method for deciding an optimal alternative design option for inter-dependent actors in the i* model by reciprocally balancing the multiple opposing objectives with their significance has not been developed in previous research studies. Fuzzy mathematical applications and a linear programming optimisation tool are useful tools for quantitative goal analysis to find an optimal strategy with opposing objective functions in the requirements-based engineering design and this tool is used in this study. This kind of study was first conducted by Subramanian et al. (Subramanian et al. 2018) where an alternative design option was found for each actor in the i* goal model with opposing objective functions. This did not address the actor's interdependency in relationships that is crucial for decision-making in a real world competitive scenario. This was the negative side of this proposal. The next section gives a brief introduction to the way that game theory and multi-objective optimisation method relates to our proposed approach.

Multi-objective Optimisation for Reasoning of Opposing Non-functional Requirements Based on Game theory

This study uses the concept of game theory in real world competitive scenarios to conduct the decision making process. The method is to combine multiple conflicting objectives based on their importance. This enables a specific decision making process. A mixed-strategic outlook is used to find out the alternative options of inter-dependent actors. By using the concept of game theory the opposing objectives are reciprocally balanced in the i* model. The concept helps in understanding the alternative options for each actor in relation to each opposing softgoal. The subsection given below provides a short introduction to the decision making process using game theory.

Game Theory involves multiple players with multiple strategies that gives an outcome for each strategic combination. Therefore, several people are involved in the decision making process. The process follows the concept that all players in the game are aware of the situation, strategies and selections of the opposing players. However, the complexity of real life situations makes it challenging to formulate most strategies (Law and Pan 2009). When a formal study of a game that involves interactive situations is conducted, optimal strategies for players are derived that helps in understanding the outcome of the game (Aplak et al. 2014). To find a solution to a game, the strategies can be grouped. This is called Nash Equilibrium. Grouping of strategies is crucial in Nash Equilibrium and solutions cannot be derived by singlehandedly deviating from the strategies. Nash Equilibrium is a steady game and at the point when the players cannot gain anything more by changing the strategies and this is called the saddle point in the Nash Equilibrium. In Nash Equilibrium, players cannot be changed, strategies cannot be altered thus making it a very steady game. In this paper, the mixed strategy Nash Equilibrium is adapted for easy calculation and representation. This helps in selecting an alternative in situations of conflicting goals. In the next section, a short introduction is given explaining how to optimise multi-objectives and how this helps decision-makers to find an optimal alternative option for achieving conflicting goals.

In real world scenarios, all environmental factors such as actors, goals, strategies, and decision-makers etc. need to be considered and evaluated based on the objectives. The effectiveness of the decision-making highly depends on this factor. Optimal strategies for opposing objectives have to be found by decision makers (Aplak et al. 2014). Operations research techniques must be applied. Best alternatives to be selected from a list of possible options to derive optimisation as opposed to single objective optimisation methods. Examples of operational research techniques are linear programming, non-linear programming and quadratic programming (Aplak et al. 2014; Mairiza et al 2014). The multi objective optimisation method gives rise to a set of solutions called Pareto solutions or Pareto frontier and the optimal value is chosen based on the Pareto frontier (Subramanian and Kaur 2015).

A multi-objective optimisation problem is represented mathematically as:

$$Max/Min\ [f_1(x), f_2(x), \dots \dots, f_n(x)\ ] \tag{1}$$

where $f_1, f_2, \dots, f_n$ are scalar functions, *x* is an element of *Y* and *Y* is the set of constraints.

Formalization of Multi-objective Functions

A generalised complete structure of the *i** goal model is modelled by formalising the opposing objective functions in terms of softgoals, goals, tasks and resources. For formalisation, Strategic Rationale (SR) model is considered as a directed graph which is represented as G (N;R), where N represents the intentional elements such as goals, softgoals, resources and tasks that form a set of nodes and R represents the means-end, task decomposition, dependency and contribution links that form a set of edges of the graphs. The task of a decision-maker is to choose a cost-effective ideal alternative option from the choices. An objective function for each choice can be generated based on the elements of the graph. Given an *i** goal model, our aim is to select the best alternative option according to its impact on softgoals. Impacts are *Make; Help; Hurt; Break; Some-; Some+* which are represented as triangular fuzzy numbers that indicates the extent to which an alternative option fulfils the leaf softgoal. The impacts of the softgoal preferences are propagated to the top softgoals, to find the level of satisfaction or scores of top softgoals. Also, each of the leaf softgoals is assigned a weight ω based on its relative importance in achieving the goal.

Firstly, the scores for each top softgoal of each actor based on its inter-actor dependency under each alternative are calculated. For details on representing goals, weights, impacts and alternatives, readers are directed to Subramanian et al. (Subramanian and Gopalan 2015).

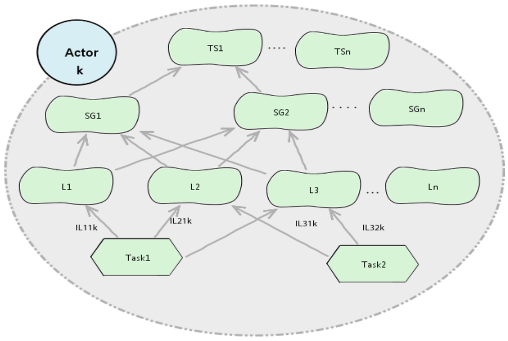

Figure 1 Directed Graph Representation

From Figure 1, consider the case of *t* hierarchy levels in the directed graph, with leaf softgoal at level zero. Let $\omega_{L_{ik}}$ represents the weight of i^{th} leaf softgoal and $I_{L_{ijk}}$means the impact on i^{th} leaf softgoal of j^{th} alternative of k^{th} actor. At level 1, if there are m number of softgoals, n_c children and n_d dependencies for the i^{th} softgoal, then the score of any softgoal at $t > 1$ is found by taking the product of its impact and each child score (Subramanian and Kaur 2016). Then the score of a softgoal at level *t* for an actor with a dependency relationship can be generalised as:

$$S_{SG_{i_t jk}} = \prod_{l=1}^{m} I_{ijl} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{ijk}}} \times \omega_{d_{L_{ijk}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\} \tag{2}$$

Then the objective functions of top softgoals under each alternative for an actor are created from the scores as shown in Equation 2. If there is an inter-actor dependency relationship, then it is necessary to consider both strategic dependency and strategic rationale diagrams of the i^* goal model with the assumption that only softgoal inter-dependency relationships are taken into account in this approach. Consider that if there are *n* numbers of alternative options for an actor, then there are *n* objective functions for each top softgoal. To obtain a maximum score for the top softgoal under each alternative, the *n* objective functions that have to be maximised are given as:

$$f_{i(\omega_1)} = S_{SG_{i1k}} = Max \prod_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{i1k}}} \times \omega_{d_{L_{i1k}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

$$f_{i(\omega_2)} = S_{SG_{i1k}} = Max \prod_{l=1}^{m} I_{i2l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{ij}} \times I_{d_{L_{i2k}}} \times \omega_{d_{L_{i2k}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

………………………………………………………………………..

$$f_{i(\omega_n)} = S_{SG_{ink}} = Max \prod_{l=1}^{m} I_{i1l} \sum_{i=1}^{m} \left\{ \sum_{d=1}^{n_c} \left[I_{d_{in}} \times I_{d_{L_{ink}}} \times \omega_{d_{L_{ink}}} \right] + \sum_{y=1}^{n_c} \left[\sum_{b=1}^{n_d} \left(S_{i_{d_{by}}} \times I_{i_{d_{by}}} \right) \right] + \sum_{b=1}^{n_d} \left(S_{i_{d_b}} \times I_{i_{d_b}} \right) \right\}$$

$$\text{Such that } 0 \leq \omega_{d_{L_{jk}}} \leq 100 \; for \; d = 1 \; to \; n_c \qquad (3)$$

Similarly objective functions that have to be minimised are formalised for each actor in the i^* goal model. The next section explains how the multi-objective functions of opposing goals (maximum and minimum in nature) are optimised.

Evaluation of the Optimal Solutions of Multi-objective Optimisation Functions

In the proposed model, each actor is considered to have two opposing softgoals (SG_1 and SG_2) and two alternative design options (A_1 and A_2). Optimising the objective functions for softgoals (SG_1 and SG_2) individually can generate two ideal solutions using Algorithm 1. The IBM ILOG CPLEX optimisation tool is used for evaluating the optimisation process (Lima 2010). The IBM ILOG CPLEX optimizer is used to solve mathematical business models using powerful algorithms to obtain precise and logical decisions. Additionally, IBM ILOG CPLEX has a modelling layer called 'Concert' that enables interfacing with Java, C++ and C # languages.

Let the ideal solutions for the objective functions for softgoals (SG_1 and SG_2) of an actor using the two alternative design options (A_1 and A_2) based on the Equation 2 is expressed as

$$\left(x_{SG_1A_1}, x_{SG_1A_2}, x_{SG_2A_1}, x_{SG_2A_2} \right) \qquad (4)$$

Likewise, the multi-objective function values are generated for all the actors in the goal model. These optimal values refer to the capacity of each alternative to fulfil the stakeholders' objectives.

Mixed-strategy Equilibrium

Sometimes, decision-analysts should take a "mixed-strategy" approach to address uncertain circumstances. A framework is created in this paper that identifies the mixed-strategy Nash equilibrium based on the multi-objective values. The Nash equilibrium is useful for analysing the result of competitive scenarios, especially when applied to conflict situations. This paper proposes a probabilistic mixed-strategy approach to resolve the conflicting issue in choosing the best alternative by different actors for achieving the opposing goals. To demonstrate this approach given the space constraints, we considered a two-player (*X* and *Y*) game theory with an inter-actor dependency relationship from *X* to *Y*. Also, assume that both players have the same alternative options (A_1 and A_2) for reaching their opposing top softgoals. Based on finding the probability of each player, let *p* be the probability that *X* chooses A_1, so *(1-p)* is the probability that it chooses A_2. Similarly, let *q* be the probability that *Y* chooses A_1, so *(1-q)* is the probability that it chooses A_2. To find mixed-strategies, *p-mix* and *q-mix* options are computed. Then the optimal choice of each player when choosing from the various alternatives is found algebraically and graphically. To depict each player's choice of the mixing probability, a best response function for each actor is generated. The mixed-strategy Nash equilibrium is revealed by combining these best response functions. An intersection point can be discovered from the combined best response functions. At this point, the players "arrive" at a profile where every player's strategy is a best response to every player it self's. At that point, they will be in a "stable" situation called "Equilibrium". The final decision must cope with the decision context and characteristics i.e., supporting the decision-makers, criteria and the alternatives when addressing the different objectives. This step involves a pair-wise comparison between several alternatives to fulfil stakeholders' objectives. By using Nash's mixed-strategy equilibrium, the outputs provide an optimal selection of alternatives for each actor. Since inputs are optimal values from CPLEX, this final decision analysis leads to a Pareto optimal equilibrium.

Algorithm 1: Main Module- Optimal Selection

Input: A set of directed graphs $S = \{S_1, S_2, \dots,\ S_n\}$ such that *G* is a subset of S that have same *n* set of tasks T, where $G = \{G_1,\ G_2, \dots, G_k\}$. Each G_i is a quadruple $\{T, L, SG, TS\}$ where each element T, L, SG, TS represents a set of task, a set of leaf softgoals, a set of in-between softgoals, a set of top softgoals respectively with each top softgoal associated with opposing variables such as *Max* or *Min.*

$\boldsymbol{for}\ G_i\ \in G\ \boldsymbol{do}$
  $\boldsymbol{for}\ task\ t\ \in T\ \boldsymbol{do}$
    $\boldsymbol{for}\ top\ softgoals\ t_s\ \in\ TS\ \boldsymbol{do}$
      $\boldsymbol{if}\ \ t_s\ is\ Min\ \boldsymbol{then}$
        $Generate\ minimisation\ objective\ function$;
      $\boldsymbol{end}$
      $\boldsymbol{if}\ \ t_s\ is\ Max\ \boldsymbol{then}$
        $Generate\ maximisation\ objective\ function$;
      $\boldsymbol{else}$
        Break**;**
      $\boldsymbol{end}$
    $\boldsymbol{end}$
  $\boldsymbol{end}$
$\boldsymbol{end}$
$Let\ F_{Max} \leftarrow Max\{f_{max_1}, f_{max_2}, \dots \dots, f_{max_n}\}$;
$Let\ F_{Min} \leftarrow Min\{f_{min_1}, f_{min_2}, \dots \dots, f_{min_n}\}$;
$\boldsymbol{for}\ f_{max_i} \in\ F_{Max}\ \ \boldsymbol{do}$
  $Let\ x_{max_i} \leftarrow optimal(f_{max_i},\ \ Max)$; //finding optimal solutions for maximum objective functions
$\boldsymbol{end}$
$\boldsymbol{for}\ f_{min_i} \in\ F_{Min}\ \ \boldsymbol{do}$
  $Let\ x_{min_i} \leftarrow optimal(f_{min_i},\ \ Min)$; //finding optimal solutions for minimum objective functions
$\boldsymbol{end}$
$Generate\ each\ player's\ optimal\ best\ response\ function\ graph\ under\ different\ alternative\ options$;
$Combine\ the\ best\ response\ function\ graphs\ to\ obtain\ mixedstrategy\ Nash\ equilibrium\ point\ that\ represents\ the\ Pareto\ optimal\ choice\ for\ each\ player$;

Algorithm 2: Sub Module- Solving Multi-objective functions

ASSERTION: Solves the objective function to obtain the optimal function value:
Declare the variables;
Define the expressions, the objective functions and the constraints based on *C;*
$\boldsymbol{if}\ C\ is\ Max\ \boldsymbol{then}$
  Define maximisation function;
$\boldsymbol{end}$
$\boldsymbol{if}\ C\ is\ Min\ \boldsymbol{then}$
  Define minimisation function;
$\boldsymbol{else}$
$W \leftarrow cplex.solve()$;
$\boldsymbol{end}$
//invoking CPLEX function
return ***W*****;**

Telemedicine System Case Study

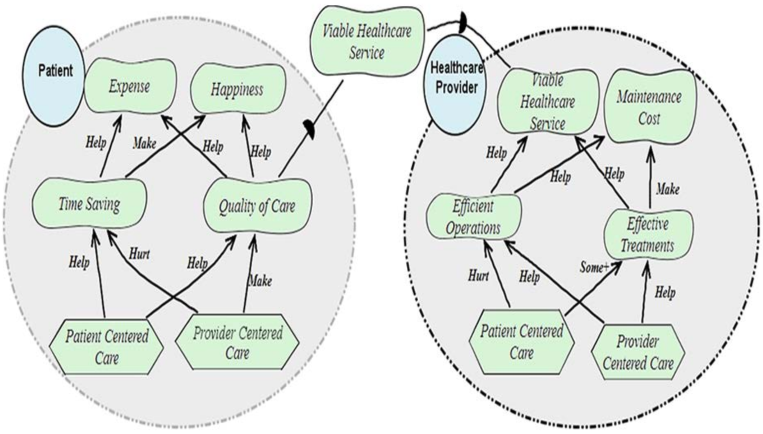

Figure 2 Telemedicine System

The mixed-strategy Nash equilibrium for the *i** framework was evaluated using the goal models from the existing RE literature: Meeting Scheduler System (van Lamsweerde 2004) and Telemedicine (Yu 2001). In order to illustrate the application of the proposed approach within the space restrictions, a generic telemedicine system case study is utilized (from the literature). The telemedicine system combines information technology and telecommunication to provide remote diagnosis and treatment for patients. The adapted telemedicine system (Figure 2) shows two actors, *Patient* and *Healthcare Provider* that are considerably simplified, but nevertheless require some kind of reasoning, namely the identification and exploration of alternatives. The main non-functional requirements or softgoals of the actor *Patient* are the *Expense* of the treatment and *Happiness* obtained from the remote treatment, which depend upon the softgoals *Time Saving* and *Quality of Care*. There are two alternative ways of obtaining treatment for the *Patient*. It is either via *Patient-Centered Care* or by *Provider-Centered Care*. The *Patient* has to choose an alternative option so that his/her *Expense* is less and *Happiness* is more.

The actor *Healthcare Provider* has two main non-functional requirements or softgoals namely *Viable Healthcare Service* and *Maintenance Cost* representing the *Healthcare Provider* aims of providing services in the telemedicine system. The goal *Viable Healthcare Service* can be implemented in one of two ways and thus is *OR* decomposed into two tasks: *Patient Centered Care* or *Provider Centered Care*. The selection of a task for this goal depends on the non-functional goals *Viable Healthcare Service* and *Maintenance Cost* for the satisfaction levels of actor *Healthcare Provider*. Here, the task is to select an alternative option that increases the *Viable Healthcare Service* and decreases *Maintenance Cost*. The objective of this system is to select the best alternative option based on its impact on each of the softgoals. The impacts indicate the extent to which an alternative option satisfies the corresponding softgoal. Impacts such as *Make, Help, Hurt, Break, Some+, Some-* are denoted by fuzzy triangular numbers. Along with the softgoal preferences, these impacts propagate to the top softgoals, to find the level of satisfaction or scores of top softgoals. For each actor, leaf softgoals are assigned an individual weight that can optimally select the best alternative option for achieving the opposing goals. For illustration and simplicity of calculation, de-fuzzification is used to convert the impacts which are represented in fuzzy numbers to quantifiable values (Chou et al. 2008).

These de-fuzzified values as shown in Table 1, and are used to evaluate the objective functions of each top softgoal.

Table 1 Impacts De-fuzzification

Impact	Fuzzy Contribution	De-fuzzified value
Make	(0.64, 0.8, 1)	0.8
Help	(0.48, 0.64, 0.80)	0.64
Some+	(0.32, 0.48, 0.64)	0.48
Some-	(0.16, 0.32, 0.48)	0.32
Hurt	(0, 0.16, 0.32)	0.16
Break	(0, 0, 0.16)	0

For actor *Patient*, the objective functions for both the top softgoals, *Expense* and *Happiness*, under both alternatives *Patient Centered Care* and *Provider Centered Care*, are found using Equation 2 and Equation 3, which are as follows:

$$F_{Expense}(\omega)_{Patient\ Centered\ Care} = Min(0.4096 \times \omega_1 + 0.4096 \times \omega_2 + 0.0524 \times \omega_3 + 0.1573 \times \omega_4)$$

$$F_{Expense}(\omega)_{Provider\ Centered\ Care} = Min(0.1024 \times \omega_1 + 0.512 \times \omega_2 + 0.2097 \times \omega_3 + 0.2097 \times \omega_4)$$

$$F_{Happiness}(\omega)_{Patient\ Centered\ Care} = Max(0.512 \times \omega_1 + 0.4096 \times \omega_2 + 0.0524 \times \omega_3 + 0.1573 \times \omega_4)$$

$$F_{Happiness}(\omega)_{Provider\ Centered\ Care} = Max(0.128 \times \omega_1 + 0.512 \times \omega_2 + 0.2097 \times \omega_3 + 0.2621 \times \omega_4)$$

Similarly, for the actor *Healthcare Provider*, the objective functions for both the top softgoals, *Viable Healthcare Service* and *Maintenance Cost*, under both alternatives *Patient Centered Care* and *Provider Centered Care*, can be generated using Equation 2 and Equation 3, based on their scores.

$$F_{Viable\ Healthcare\ service}(\omega)_{Patient\ Centered\ Care} = Max(0.1024 \times \omega_3 + 0.3072 \times \omega_4)$$

$$F_{Viable\ Healthcare\ service}(\omega)_{Provider\ Centered\ Care} = Max(0.4096 \times \omega_3 + 0.4096 \times \omega_4)$$

$$F_{Maintenance\ Cost}(\omega)_{Patient\ Centered\ Care} = Min(0.128 \times \omega_3 + 0.384 \times \omega_4)$$

$$F_{Maintenance\ Cost}(\omega)_{Provider\ Centered\ Care} = Min(0.512 \times \omega_3 + 0.512 \times \omega_4)$$

The solutions to these objective functions are obtained by invoking the IBM ILOG CPLEX. The obtained function values are given in Table 2 as ready reference. In studies of health care efficiency, the objective of production is perceived to be either providing services or achieving outcomes. By developing an appropriate probabilistic mixed-strategy approach, an optimal selection of the best alternative by different actors for achieving opposing goals can be achieved. Based on finding the probability of each player, *Healthcare Provider (HCP)* and *Patient*, *l*et *p* be the probability that *Healthcare Provider* chooses *Patient Centered Care* (A_1), so (*1-p*) is the probability that it chooses *Provider Centered Care* (A_2) and let *q* be the probability that *Patient* chooses A_1, so *(1-q)* is the probability that it chooses A_2. To find mixed strategies, *p-mix* and *q-mix* options are computed. The *p-mix* and *q-mix* table is shown in Table 2. We can find *Patient* optimal choice of *A1* (*q*) in two ways: algebraically and graphically. In algebraically as shown in Table 3, *Patient* solves for the value of *q* that equates *HCP*'s payoff from choosing A_1 or A_2:

30.72q+40.96(1-q) = 12.8q+51.2(1-q)

q=0.36 i.e., 36 %, so 1-q=64%

Graphically as shown in Figure 3, *q* is chosen so as to equalise the payoff that *HCP* receives from choosing both strategies. This requires the understanding about how the *HCP's* payoff varies with *Patient's* choice of *q*.

If *Patient* choose A_1 with q=36% and A_2 with 64%, then

a) *HCP* success rate of choosing A_1 is *30.72*0.36+40.96*(1-0.36) = 37%*

b) *HCP* success rate of choosing A_2 is *12.8*0.36+51.2*(1-0.36) = 37%*

Table 2 Objective Function Values

			p	*1-p*	
			Healthcare Provider		
			(*Happiness, Viable Healthcare service*)	(*Expense, Maintenance Cost*)	*p-mix*
q	*Patient*	*Patient Centered Care*	(51.2, 30.72)	(5.24, 12.8)	51.2**p* + 5.24*(1-*p*)
1-q		*Provider Centered Care*	(40.96, 40.96)	(10.24, 51.2)	40.96**p* + 10.24*(1-*p*)
		q-mix	30.72**q* + 40.96*(1-*q*)	12.8**q* + 51.2*(1-*q*)	

Since this is a constant sum game, *Patient's* success rate is *100% - HCP's* success rate i.e., *100-37=63%*. Similarly, we can algebraically find *HCP's* optimal choice of A_1 *(p)* as shown in Table 4. *HCP* solves for the value of *p* that equates *Patient's* payoff from choosing A_1 or A_2 :

$$51.2p+5.24(1-p) = 40.96p+10.24(1-p)$$

i.e., p=0.33 i.e., 33%, so 1-p=67%

In graphically as shown in Figure 4, *p* has been chosen so as to equalise the payoff *Patient* receives from choosing both strategies. This requires the understanding about how the *Patient's* payoff varies with *HCP's* choice of *p*. If *HCP* choose A_1 with *p=33%* and A_2 with *67%*, then

a) *Patient* success rate of choosing A_1 is *51.2*0.33+5.24*(1-0.33) = 20%*

b) *Patient* success rate of choosing A_2 is *40.96p+10.24(1-p) = 20%*

Since this is a constant sum game, *HCP's* success rate is *100% - patient's* success rate,

i.e., *100-20=80%.*

Table 3 *HCF*'s Payoff Calculation Based On *q*

Patient's choice of *q*		*HCP* choosing A_1	*HCP* choosing A_2
0%	0	40.96	51.2
5%	0.05	40.45	49.28
10%	0.1	39.94	47.36
15%	0.15	39.42	45.44
20%	0.2	38.91	43.52
25%	0.25	38.40	41.6
30%	0.3	37.89	39.68
35%	0.35	37.38	37.76
40%	0.4	36.86	35.84
45%	0.45	36.35	33.92
50%	0.5	35.84	32
55%	0.55	35.33	30.08
60%	0.6	34.82	28.16
65%	0.65	34.30	26.24
67%	0.67	34.10	25.472
70%	0.7	33.79	24.32
75%	0.75	33.28	22.4

80%	0.8	32.77	20.48
85%	0.85	32.26	18.56
90%	0.9	31.74	16.64
95%	0.95	31.23	14.72
100%	1	30.72	12.8

Table 4 *Patient*'s Payoff calculation based on *p*

HCP's choice of *p*		*Patient* choosing A_1	*Patient* choosing A_2
0%	0	5.24	10.24
5%	0.05	7.54	11.78
10%	0.1	9.84	13.31
15%	0.15	12.13	14.85
20%	0.2	14.43	16.38
25%	0.25	16.73	17.92
30%	0.3	19.03	19.46
35%	0.35	21.33	20.99
40%	0.4	23.62	22.53
45%	0.45	25.92	24.06
50%	0.5	28.22	25.60
55%	0.55	30.52	27.14
60%	0.6	32.82	28.67
65%	0.65	35.11	30.21
67%	0.67	36.03	30.82
70%	0.7	37.41	31.74
75%	0.75	39.71	33.28
80%	0.8	42.01	34.82
85%	0.85	44.31	36.35
90%	0.9	46.60	37.89
95%	0.95	48.90	39.42
100%	1	51.20	40.96

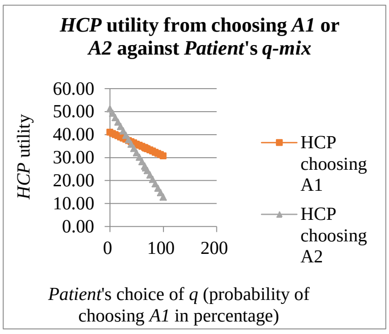

Figure 3 *HCP* utility against *q*

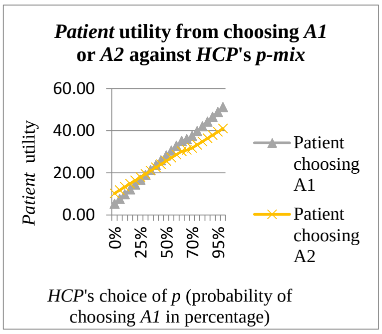

Figure 4 *Patient* utility against *p*

Generation of Best Response Function

Another way to depict each player's choice of the mixing probability is through best response function generation. (Recall p = probability (A_1) by *HCP*, q = probability (A_1) by *patient*). It shows from the Figures 5 and 6 that strategic best response of q = f (p) and p = g (q). If p, q $=0$ means, it always choose A_2; p, q $=1$ means, it always choose A_1. Combining the best response functions to obtain the intersection of two functions reveals the mixed-strategy Nash equilibrium. According to the Figure 7, the mixed-strategy Nash equilibrium is the point when *HCP* choose A_1 *33%* of the time (and A_2 *63%* of the time) while *Patient* choose A_1 *36%* of the time (and A_2 *64%* of time). The mixed-strategy Nash equilibrium is at point $(q, p) = (36, 33)$. At this point, the players "arrive" at a profile where every player's strategy is a best response to every player it self's. At that point, they will be in a "stable" situation called "Equilibrium". That's what a "Nash Equilibrium" is. Both choose the alternative *Patient Centered Care* with the probability of (36%, 33%) and choose alternative *Provider Centered Care* with a probability of (64%, 67%). That means there is a more chance for them to choose the strategy *Provider Centered care.* The Figure 7 indicates that the alternative *Provider Centered Care* (A_2) has a higher optimal value than the alternative *Patient Centered Care* (A_1). Hence by choosing the *Provider Centered Care* strategy, the system achieves the opposing top softgoals of inter-dependent actors in the i^* goal model reciprocally.

Conclusions

In this research a probabilistic mixed-strategic approach has been used for reasoning the non-functional requirements. This mixed-strategic approach of the Nash equilibrium-based goal analysis for the *i** goal model that has been proposed in this paper has helped resolve the conflict issue. This is achieved by choosing the best alternative by various actors for achieving the opposing goals. The proposed methodology is used in the Java Eclipse environment integrated with the IBM CPLEX tool. The optimal alternative selection method is used by balancing the opposing objectives of inter-dependent actors in the *i** goal model. Sensitivity Analysis is performed by way of further research. This provides useful input data to help the requirements analyst with the decision-making process.

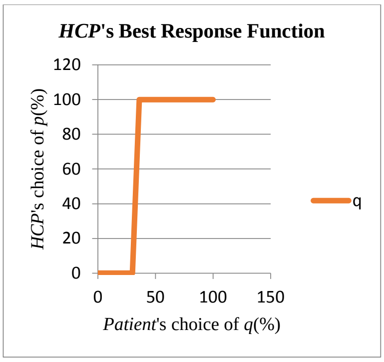

Figure 5 *HCP*'s Best Response Function

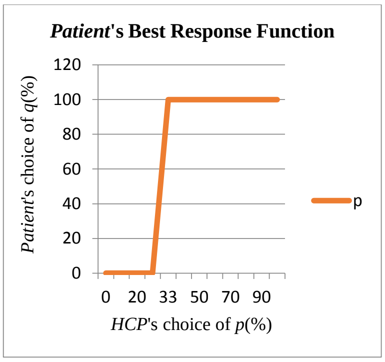

Figure 6 *Patient*'s Best Response Function

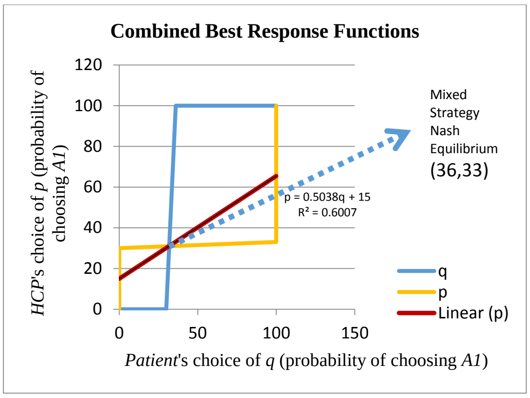

Figure 7 Combined Best Response Functions

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Chapter 3

Requirements Analysis in Transactive Energy Management

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This chapter focusses on the effective usage of transactive energy and the importance of developing an economical transactive energy management process. Transactive energy is a concept that can play a vital role in improving the efficiency and reliability of a power system. This notion is promising for the energy industry in providing an intelligent and interactive future. This concept initiates various requirements for power distribution and transmission that works efficiently and is totally reliable. This leads to the exploration of requirements engineering approaches which can play a vital role in the development of transactive energy and management process. This chapter explains the usage of requirements engineering models in relation to micro-grid and smart-grid development. The wide-ranging development of smart-grid systems demands supplementary software models so that its full potential can be explored and utilised. It only makes sense that consolidation of extensive usage of distributed energy and renewable energy sources is important in relation to the future of smart-grid to bring about an economical and reliable functioning of a power system. An innovative approach in the form of transactive energy towards the future smart-grid is highly beneficial for the power system operations. This novel approach has been extensively researched in recent years around the world. Within this chapter, we are outlining a goal-oriented requirements engineering approach to structure transactive energy management system. The main objective of this chapter is to perform reasoning and impact of non-functional requirements on the transactive energy management. This reasoning will help decision makers in getting the desired outcomes from an efficient and reliable power system

3.1 Introduction

A shift is taking place within the electricity generation systems to use more renewable energy that is collected from renewable sources. This energy is becoming the

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focus of primary energy source thus replacing old generators. The reasons being reduced long-term costs and also less environmental regulation. The intermittent generation characteristics of this system mostly cause added energy storage into the micro-grid installation. This can be challenging in the functioning of the grid. It can affect the efficiency of the energy storing devices and balancing of energy in the process of scheduling non-critical loads. The good news with the use of renewable energy is that there is improved control of individual loads. This is becoming possible through the class of devices belonging to the internet of things [1].

First, let's focus on the various challenges faced by the evolving electricity system. We have witnessed a transformation of the electricity system from a highly centralised structure to a distributed system managed with a diversity of disseminated supply, storage and responsive demand assets [2]. One of the biggest challenges faced and discussed is how to optimise the usage of Distributed Energy Resources (DER) to develop and maintain the efficiency and reliability of the power supply system.

When we use renewable energy as the primary source of energy and to make this efficient and reliable, forecasting becomes inevitable. Foresight and forecast in the planning of the operation becomes crucial to maintain the reliability of the grid as well as efficiency of the power system. This forecasting process involves the installation of complex customised controls. These types of control are in use more often today [2]. This is demonstrated by the usage of transactive energy management to increase the efficiency and reliability of the smart-grid resources [2]. This Transactive Energy Management (TEM) methodology incorporates the valuation of both efficiency and reliability objectives. These changes in the requirements of the power system at a fine-grained nodal level. This has been prevalent in practice for the past decade [2]. The TEM system most efficiently employs DER to get the desired outcomes for both business and operational goals [2]. It helps in balancing renewable intermittency thus aiding to drive better energy management process. The benefit of the TEM system is that it improves the reliability and efficiency of the electric systems. It provides a way for various energy related parties to interact and interoperate. Transactive Energy Systems (TES) can help users like electric grid owners, regulators, and consumers/users to manage the DER. Transactive energy is proposed to be a vital component of the future electric power system. This energy can play an important role in but not limited to supporting the expanding numbers of DER. Transactive Energy (TE) can be an innovative approach for a bright future of the industry. This can be used as a regulatory model for electricity industry to become a very sustainable business. While some perceive TE as a smart-grid application, others point out that the grid cannot be smart-grid without it being transactive [2, 3].

An explanation of the TE concept is provided in this chapter. The application and reasoning of non-functional requirements for implementing TEM that decision makers can consider is also explained and discussed. A smart-grid system based on TEM conforms to not only the functional requirements of system features (and functions) but also the non-functional requirements such as security, reliability, interoperability, efficiency etc. Not a lot of focus has been accorded to the software development life cycle (SDLC) [4] before the design and development stages of the aspects of requirements engineering are carried out. There is also a connection between these notions and safety-critical software systems like smart-grids [1]. A breakdown or failing in the requirements engineering process can be drastic. The Standish Group chaos report [5] identified incomplete requirements, lack of user involvement, lack of resources, unrealistic expectation, lack of executive support, changing requirements and specifications, lack of planning, etc. as causes of many failed projects. The Standish Group Report also revealed that three of the top ten reasons for challenged projects or outright project failure were lack of user involvement, unstable requirements and poor project management practises. The RMS (Royal Mail Steamer) Titanic ship sinking in 1914 was as a result of incorrect steel plating [6] or the market decline of Fords Edsel auto-mobiles owing to the inability to capture end-users needs are examples that resulted in drastic unsafe consequences [1]. Thus, the emphasis on requirements engineering needs to follow best-practices [7]. Some work in requirements engineering for smart-grids has been proposed in the literature. In [8], Information and Communications Technology (ICT) architectures are studied in connection with smart-grids. In [9], case studies have been conducted by authors in connection with security needs of smart-grids. Some of the significant cyber security and communication requirements in relation to smart-grids are listed by Ericsson et.al [10]. Case tools [11] are used by certain researchers with regards to areas of industrial automation software in requirements engineering. In [12], modelling and checking the reliability of safety requirements were conducted by formal modelling and verification techniques. Nevertheless, there is a lack of detailed investigation in regards to the importance of non-functional requirements [13] for the TEM smart-grid systems.

In this chapter, a framework for the transactive energy system in maintaining grid performance and stability has been created to assist energy service providers, equipment suppliers, regulators and complex/sophisticated users. This framework also helps in harnessing flexibility to offset variability and for enabling value-based relationships in the electric power systems.

In the next section, we will explain what transactive energy is; how it works; whether, and if so, how it is different from the smart-grid, and why some experts think we need TE. In Section 3.3, we will provide an overview of some of the key non-functional requirements, such as scalability, security, inter-operability, reliability and efficiency in the case of transactive power system. We also discuss the notion of goal-oriented requirements engineering with respect to this new paradigm in Section 3.4. In Section 3.5, we apply requirements analysis to TEM and will then close with some concluding remarks in Section 3.6.

3.2 Transactive Energy Management

In Transactive Energy Management, value is used as a key operational parameter to establish an even distribution of supply and demand across the entire electrical infrastructure. This is made possible by the use of a set of economic and control processes. Software applications that use economic signals and operational information are used in these scenarios. These applications are used to integrate and control the gadgets for manufacture and/or usage of electricity in the grid [2].

The TE system can be perceived as a notion where an integration of retail and wholesale markets knowledge is studied and explored. Market signals are combined to form a single platform by blending retail and wholesale markets. This is achieved by employing forward and spot transactions. Also, by managing investment and operating decisions [2]. The TE system comprises of three categories of players; one comprising of customers, prosumers, storage, owners, producers etc. that form part of the energy services; second comprising of transmission and distribution owners forming the transport services and third comprising of exchanges, market makers, system operators etc that forms the intermediaries [2]. In contradiction to this notion is the traditional classification of customer types: residential, commercial and industrial. The TE perception constitutes all categories comprising of advanced energy management systems and/or third party assistance. This is beneficial in the optimum use of energy as well as production build on value and grid constraints. When not interested in market exchanges, fixed-price subscriptions on a forward-looking basis can be acquired. Transactions are not risk free. The operation of a TE network is straightforward. Producers offer sell tenders to consumers indicating they have the energy to sell. The consumers then decide whether they want to purchase energy at the suggested price, wait for another offer or not use energy. For example, if a producer advertises to sell 10 MW of electricity at a plant in his city, between a specific time frame. If the selling price is 50 per MWH. Let's assume a consumer wants to buy 5 MWH of the 10 MWH tender; then there is a recorded transaction between the producer and the consumer. A brief comparison between traditional grid and smart-grid is shown in Table 3.1 as ready reference.

Table 3.1 Comparison between traditional grid and smart-grid

Traditional Grid	**Smart-grid**
Centralised generation	Distributed generation
Electromechanical	Digital
Few sensors	Sensors throughout
One-way communication	Two-way communication
Manual monitoring	Self-monitoring
Failures and blackouts	Adaptive and islanding
Manual restoration	Self-healing
Few customer choices	Many customer choices
Limited control	Pervasive control

Few attributes make a smart-grid transactive, and they are: enabling faster transmission of information across the grid, that includes prices; empowering consumers by enabling their active participation; accommodating all new generation devices needed for a functional decentralised supply model; accommodating two-way power flows. Residential customers are having energy management systems and/or third party assistance. This means forward and spot transactions at the retail level being made possible. Retail customers are utilising energy to the maximum potential. All this differentiates TE from smart-grid [2]. The nature of the power grid is ever changing and increasing complexity. There is an improvement in environmental goals and deeper exploration of renewable resources. This in turn is motivating stakeholders to be more proactive and create solutions to foreseen problems. Some renewable resources are variable and unpredictable. Owing to this, greater flexibility and reliable customer resources are sought. With the new demands on the grid, it is becoming difficult for utilities and Independent System Operators (ISO) to manage this complex system. Also, these systems are controlled by consumers and can be difficult to monitor in real time. Distributed systems with a hierarchy of control layers designed comprising of commonly understood sets of data with sufficient interchange of information could enable a steady and universal optimisation in the way of local action. In other words, with the right design, a transactive energy network can create a perfect market with totally rational decisions, benefiting the producers, consumers as well as the grid.

The TE resources allow for more flexibility and reliability by allowing exchanges up to the real time, as opposed to traditional demand response resources. The expectations are high for the new TE grid. Some of the benefits of TE are that optimal usage of Distributed Energy Resources (DER) is viable. The helps in meeting both business and operational goals [2]. The TE increases the soundness and productivity of the electric power systems. The requirements for circulating reserves to bring about an even distribution of restored intermittency is controlled. Consumers are empowered by active participation. Innovation is initiated, and jobs are created. TE enables all parties to transact in the same platform in a transparent environment. This, in turn, increases the efficiency of the market as well as the power distribution network.

3.3 Application of Requirements Engineering approaches in Transactive Energy Management

There is a need for applying Requirements Engineering approaches in Transactive Energy Management. The smart-grid system is highly complex with regards to organisational and technological aspects. Several organisations and engineering domains are involved in the design and development of the system. Thus, the transactive energy management faces an important challenge with regards to integration of these efforts. This affects elements involved in the electrical energy consumption, generation, transportation, distribution, storage, and the supporting information systems and its application. With the transactive energy management, the functionalities and interfaces of its artefacts must be determined in advance [14]. All engineering activities are based on requirements as the decisive factor. Hence, a methodology that fits well in the description and management of requirements is necessary, that should supports detectability amidst design decisions and system requirements. This also aids the association between stakeholders by allocating responsibilities. It also helps to derive the system structure with regards to software and hardware artefacts.

This then assists in the trial of the implementation in comparison to the specification of the system.

One of the important phases in software engineering is Requirements Engineering (RE) [15, 16]. Activities in RE involve requirements elicitation, modelling, analysis, negotiation and validation [17, 18, 19, 20, 21]. Effective RE practises leads to the improvement in software and system development artefacts. The decisions derived using RE techniques aid in identifying customer problems to detailed specification. RE thus helps solve the problem and avoid catastrophic mistakes that could be made during the implementation stage. RE mistakes discovered in later stages could be very expensive to fix. According to Nuseibeh [18], RE represents a series of decisions that helps in recognising customer problems to the extent of detailed specification and therefore, helps solve the problem [22]. The primary question behind RE activities is: How can companies successfully arrive to an effective decision to start developing a new system, a sub-system, or a feature. The past two decades has perceived RE as a vital aspect of the software development life cycle. The most important and initial phase of RE is the elicitation of requirements. Elicitation helps in determining the tasks of the system and the goals that need to be met. This process helps to determine the right stakeholders as well. The requirement analyst is involved in analysing the information received from the stakeholders. After requirements elaborating, the stakeholder goals are determined. The system performs its required function based on the stakeholder goals (captured as 'hardgoals'). The goals analysed by the requirement analyst helps in building an effective software system. The requirement analyst also explores the possibility of implementing an effective system design option for a high-level alternative system [23].

With regards to an already established power system, numerous actors or stakeholders are involved with the management, operation and business aspects of the system. Also, various elements necessary for the generation, transportation and distribution of electrical energy is already established. Failures in the performance of the TEM system especially in its structural and functional planning ends up being costly. An appropriate goal model must be used to model the requirements of the smart-grid and traditional grid system. This will help in implementing a well-structured transactive energy management process. This can be achieved through Goal-oriented Requirements Engineering (GORE) model which can play a significant role in the transactive energy management system. GORE characterises and models the objectives and stakeholders of the TEM systems, together with their relationships like decompositions, contributions, and dependencies. Goal models can help to get the knowledge of who needs what and help to perform analyses to determine the satisfaction of goals [24, 25, 21, 26].

In GORE, the requirements of the system are modelled by using goals. This technique involves eliciting, specifying, structuring, elaborating, analysing, documenting, negotiating and modifying requirements (based on goals) [17, 18, 19, 20]. Goals play the most important role in GORE. Goals aids in establishing a domain and identifies the intention of the stakeholder [24]. Goals can be established at a different abstraction levels, capturing strategic concerns to technical matters. Hence, goals are strategically planned as a very significant artefact in the early phases of

RE [23]. A multi-view model or goal model illustrates the way in which goals, actors, states, objects, tasks, and domain properties are inter-related in the given system [27]. This work focuses on a well-known and popular goal modelling framework known as the *i** model [20]. The *i** goal model [22] supports the essential processes of modelling organisations and socio-technical systems. Some of the other widely-used goal models are Knowledge Acquisition in Automated Space (KAOS) Model [28], Non-Functional Requirements (NFR) model [24], Attributed Goal-Oriented Requirements Analysis (AGORA) Model [29], Tropos Model [30] and Goal-Oriented Requirement Language (GRL) [31] Model.

The *i** goal model supports the essential processes of modelling organisational and socio-technical systems. Hence, it can be used to address all the requirements

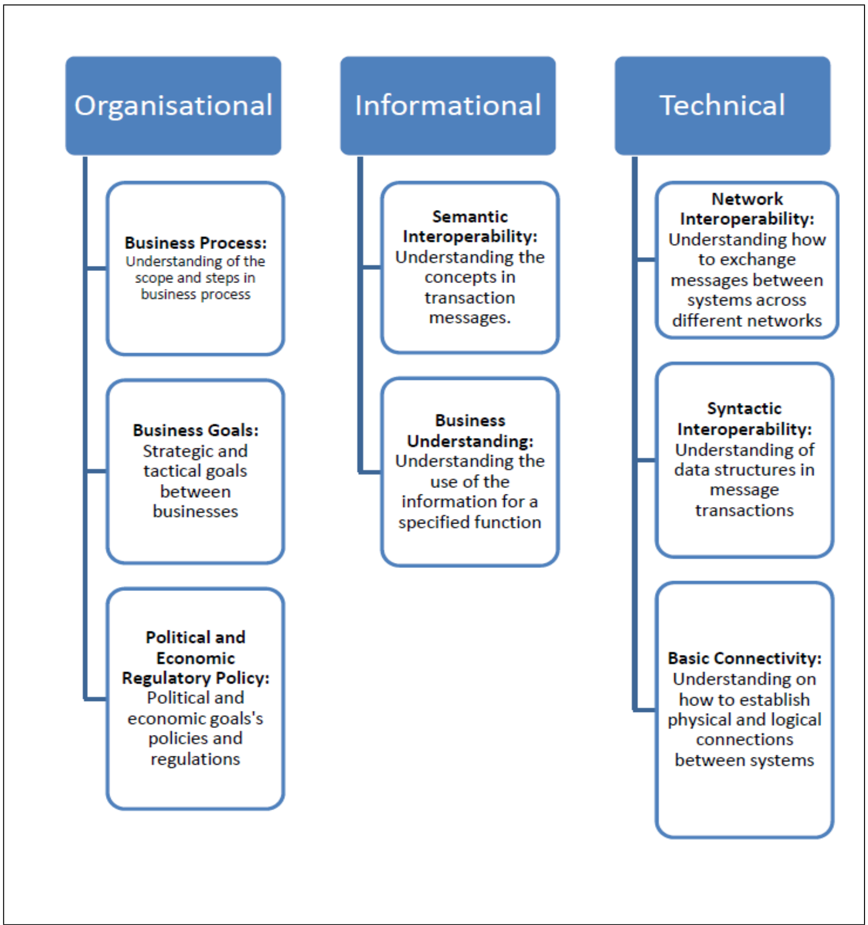

Figure 3.1 Interoperability Levels

of TEM system. Thus, it provides a suitable framework for the elicitation and management of TEM based smart-grid non-functional requirements framework. In goal models, top softgoals are utilised as assessment criteria in existing quantitative [33, 34, 35] and qualitative approaches [24]. The process of goal model analysis involves generation of qualitative or quantitative values in the form of either forward propagation from the bottom softgoals to the top softgoals or backward propagation from the top softgoals to the bottom softgoals. The selected design alternative determines the satisfaction levels of softgoals. The top softgoal design that provides supreme fulfilment is chosen. Qualitative labels cause conflict in the proposed propagation algorithm. These labels are captured as *denied, partially denied, satisfied, partially satisfied and unknown* in the model. The qualitative approach has a downside to it as it delivers vagueness in the decision making process. It leads to confusion when two alternatives have the same label or when a goal receives an unspecified conflict label. Quantitative approach as the name suggests uses crisp numbers. To express a requirement quantitatively, a stakeholder may use phrases which are practical but still vague in nature. These vague, uncertain, inappropriate or conflicting requirements are then expressed in linguistic terms with the representation of fuzzy numbers. Fuzzy numbers and fuzzy values are widely used in this chapter due to their appropriateness for expressing uncertainty[34, 35].

Applications in the TEM system requires high accessibility, reliability, efficiency, inter-operability, and security as well as administrative consistency, adaptability, and serviceability. Applications may be exposed to uncertainty and variability. Due to the interconnection with the real-world notions, TEM system requires more systematic techniques for capturing and reasoning about its framework. The early identification of goals helps the stakeholders inside and outside of the TEM power system. It enables reasoning with the specific non-functional requirements (qualities) of the TEM systems as discussed earlier. With goals being determined and finalised early, it helps in understanding and provides a better knowledge based for the proposed system. The decision makers use goal modelling to determine whether the processes and tools are aligned with the goals of the TEM system. By systematically determining, elaborating and structuring TEM requirements goal reasoning can be performed.

The system performance or elements indicates its functional (or behavioural) requirements. The principle for checking the system performance is based on the non-functional requirements rather than the specific behaviour. Non-functional requirements consist of the system qualities such as accessibility, reliability, inter-operability and security of the system [15]. In comparison to the functional requirements, the non-functional requirements like reliability, efficiency, inter-operability, and security have more influence on TEM system. Non-functional requirement details criteria that can be used to analyse the performance of a system, rather than specific behaviours.

Non-functional requirements complements the functional requirements of a system and are often a result of the analysis of the efficiency, reliability, etc.. But also other aspects such as security, active communication, accurate forecast, scalability, inter-operability, efficiency, reliability may be involved. Many non-functional re-

Table 3.2 Key Elements in Security

Key Elements	Description
Authentication	Use an authentication mechanism
Trust	Earn or give, but never assume trust
Validation	Ensure all data are explicitly validated
Sensitivity	Identify sensitive data and use effective methods to handle it

Table 3.3 Non-functional Requirements Concerned with Scalability

Key Elements	Description
Availability	Integration and verification of various devices to ensure 24/7 operation.
Performance	System should have a real-time Demand-Response within less than 5 minutes response time.
Scalability	1. Development of aggregation, forecasting and scheduling algorithms capable of managing large number of households. 2. Development of a large-scale simulator to emulate the behaviour of large number of households. 3. The complete electrical system and the numerous collection of appliances should be managed by the conception of an architecture that can be parallelisable, scalable, sound, productive and sturdy.

quirements are important for the implementation of a successful TEM system. In this chapter we have considered only a few significant non-functional requirements like security, active communication, accurate forecast, scalability, inter-operability, efficiency, reliability etc. The inter-operability aids to combine various assets and applications into one operational system. A suitable structure has been developed by the GridWise Architectural Council (GWAC) [32] to assist the elicitation and management of inter-operability requirements. It includes eight layers of various inter-operability issues, as shown in Figure 3.1. For more details on inter-operability issues, readers are directed to [32]. Another significant non-functional requirement is security. This ensures the security and privacy of the TEM system. Security should cover all aspects of the TEM system like information security, software security, physical security, hardware security, network and communication security and cloud services security. The key elements that should be considered while providing security are listed in Table 3.2 as ready reference. For providing reliable and efficient power management, the TEM system has to be able to scale to a significant number of households to provide an aggregated demand response. This represents the scalability of the TEM system. The non-functional requirements concerning the scalability of the TEM system is illustrated in Table 3.3.

An effective non-functional requirements elicitation and understanding about the system helps to perform reasoning with the specific non-functional requirements (qualities) of the TEM systems. In the next section, a detailed description of the requirements analysis process is presented for developing an optimised model of the TEM system.

3.3.1 The i Goal Modeling*

The *i** goal model within the GORE framework is an efficient tool utilised for modeling and analysing the dependencies between all the elements in a socio-economic community environment [19, 36, 16, 37, 25]. Hence, *i** framework is the preferred

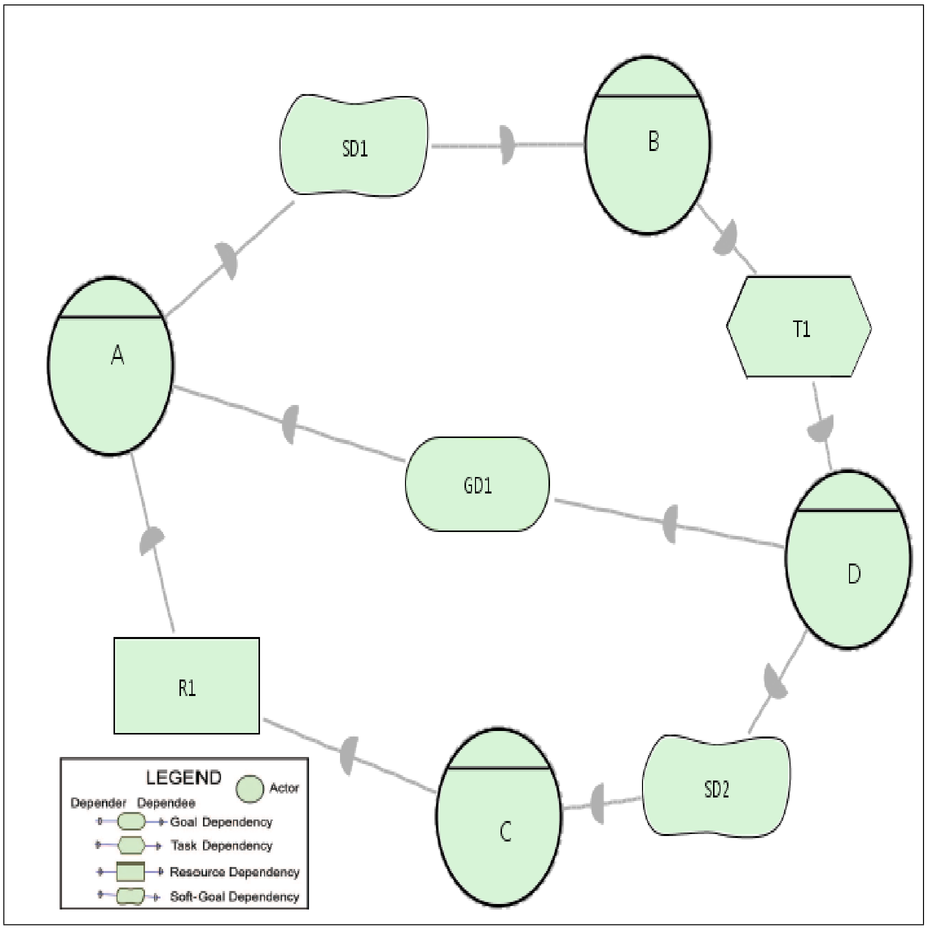

Figure 3.2 An example SD model

approach for modelling social relationships in the TEM system. In this proposed approach, the intentional strategic actor is modelled as the central unit. There are several characteristics that represents the intentional aspects of an actor such as goals, beliefs, ability and commitment [19]. An actor's intention is to successfully and strategically attain the goal. The structural relationship of an actor in comparison to other actors in sharing resources or accomplishing goals by performing some tasks is also a significant aspect. Among functional goals, in other words, 'hardgoals', some preferred behaviours are captured by the non-functional goals also known as 'softgoals'[27]. The i^* model aims at determining alternative choices through means-end (OR-decomposition) reasoning. This is possible with explicit clear representation of the goals in the i^* model. The i^* goal modeling comprises of two models representing the socio-economic systems: the Strategic Dependency (SD) model and the Strategic Rationale (SR) model [19, 36, 16, 37].

The Strategic Dependency (SD) model displays a high-level explanation of a process or a system in the form of a graph. In a graph representation, this model exhibits the actor's dependency through behavioural goals or softgoals, tasks and resources. Figure 3.2 demonstrates an example of SD model where actors are depicted as circles, hardgoals as ovals, softgoals as cloud, resources as rectangles and tasks as hexagonal shapes. In the illustration SD model (Figure 3.2), an actor A depends upon actor B for achieving softgoal $SD1$. Actor B has a task dependency on actor D. Actor D in turn depends on actor C for a softgoal. Actor A has a goal dependency on actor D. Actor C has a resource dependency with actor A. Thus, the SD framework captures the dependency between various actors and hence captures the organisational context.

The Strategic Rationale (SR) model plays the role of capturing and displaying the internal modelling and analysis of all actors in the framework. This is achieved based on the actors internal intentional inter-dependencies. Non-functional goals or softgoals form intended qualities of the system. The SR model like the SD model is also depicted in the form of a graph. Through the graph, nodes are represented as goals or tasks or resources or softgoals that are inter-connected by means-end links or task decomposition links or contribution links [37, 16]. The goals are connected to one or more tasks through *AND* (decomposition links) or *OR* (means-end links) relationships for accomplishing it. The contribution links can be $Make$, $Break$, $Help$, $Hurt$, $Some+$, $Some-$. These notions describe various types of contributions to various softgoals. This in turn leads to the satisfaction of softgoals [20, 37, 16]. Figure 3.3 demonstrates an example of an SR model.

The i^* model uses a top-down approach to identify the goals of each actors. This is achieved by breaking down the primary goals or hardgoals into a group of subgoals or tasks. Reasoning is performed by answering questions like, How to achieve? or What to achieve?. By answering, How to achieve?, the softgoal is decomposed further. This decomposition is repeated till each softgoal is atomic in nature represented as operationalisation of softgoals. The following section displays how the goals and softgoals of an actor are analysed in the TEM system.

3.4 Requirements Analysis and modelling of the TEM system

Requirement analysis and modelling is performed to determine an alternative design that provides an optimum fulfilment of the non-functional requirements that are represented as softgoals [38, 39, 40, 41]. This is achieved by defining a multi-objective linear optimisation function. This helps in determining the maximum satisfaction scores of the top softgoals for each alternatives. Linear weighted sum method is used to integrate these multi-objective functions. The integrated linear function is solved for goal analysis and an optimal design strategy is determined. For this purpose, IBM CPLEX optimisation tool is used [42]. An *i** goal model for TEM system is used with an actor through hierarchy of softgoals, goals and tasks. The proposed optimisation model is based upon the satisfaction scores of the top softgoals of the given *i** framework [43]. This is achieved by taking into consideration other softgoals within the hierarchy. Optimal alternative selection [39] is made on the basis

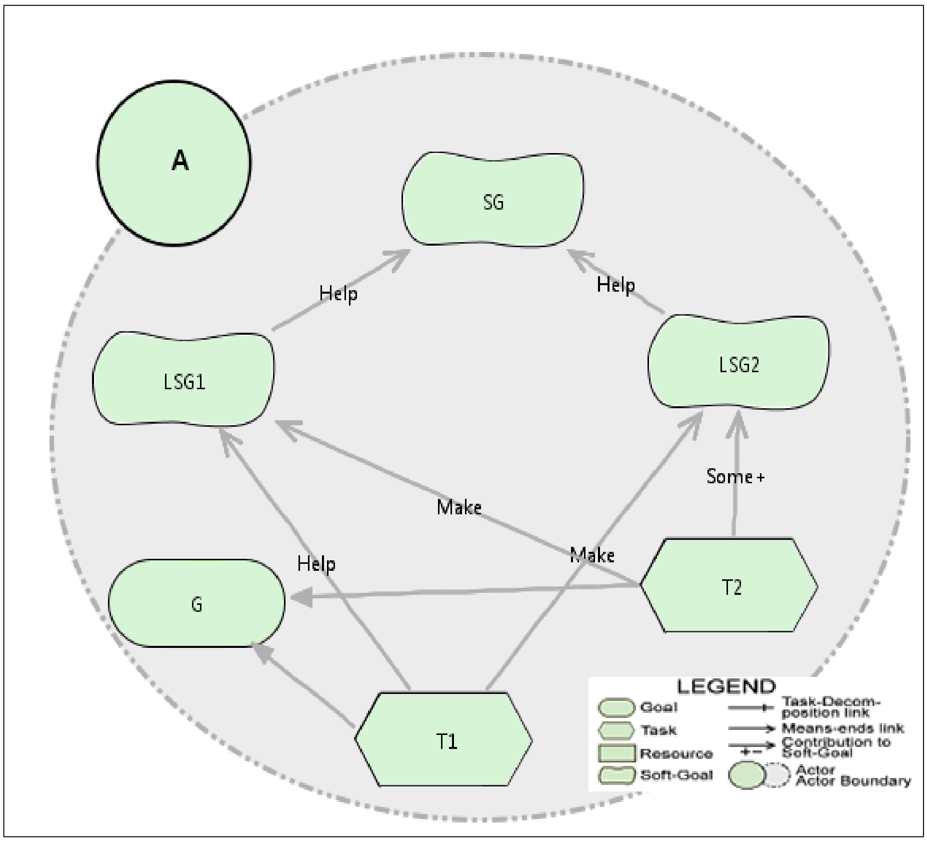

Figure 3.3 An example SR model

of propagation of values through the entire hierarchy of softgoals. For the above process of requirements analysis, an *i** goal model is illustrated for developing an optimisation model of the TEM system.

3.4.1 Goal modelling of the TEM system

To model a generalised *i** framework for the TEM system in terms of softgoals, goals and tasks, let's consider a directed graph, G (N, A) where N as a set of nodes and A as set of arcs (Figure 3.4) [40, 41, 44, 45]. The intentional elements such as softgoals, goals, and tasks form the nodes of graph G and the means-end, task-decomposition and contribution links form the arcs of the graph G. An objective function for the optimisation model is formed in terms of the elements of the graph.

Based on the directed graph in Figure 3.4, an *i** goal model for the TEM system, to achieve an effective power energy management, is developed as shown in Figure 3.5. The developed goal model shows an actor, *Power System* that is considerably simplified, but nevertheless require some type of reasoning namely identification and the exploration of alternatives. The aim of this system is to opt for the best alternative option on the basis of its influence on each of the softgoals. The framework has two alternatives, *traditional grid* and *smart-grid*. The task of the requirement analyst is to choose an alternative that brings about maximum satisfaction to the non-functional requirements that are represented by softgoals. The top softgoals can

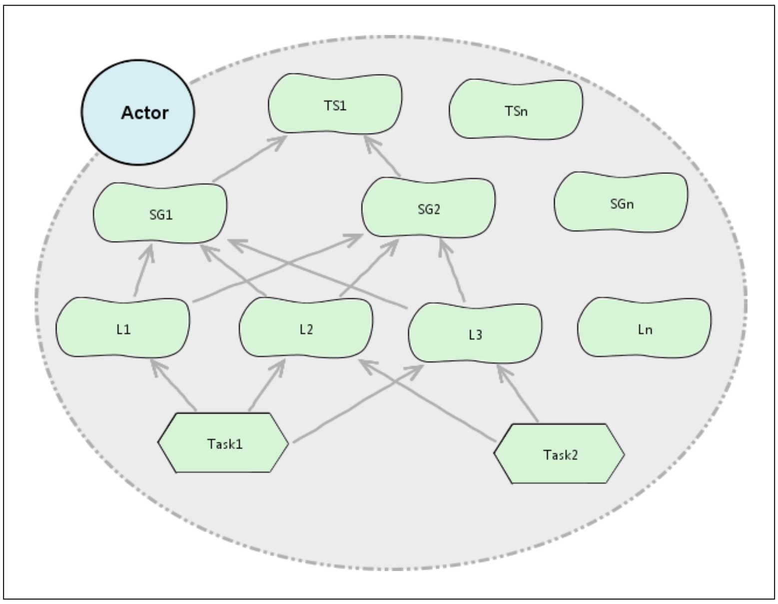

Figure 3.4 Directed graph representation of SR model for an actor with dependency

be thought of as non-functional objectives of the system, and therefore the problem can be viewed as a multi-objective optimisation problem. The selected alternative needs to maximise the satisfaction of the top objectives and hence form the basis for maximisation optimisation problem [40, 41]. A multi-objective maximisation optimisation problem is represented mathematically as follows:

$$Max[F_1(\omega), F_2(\omega), F_3(\omega)....................., F_n(\omega)] \tag{3.1}$$

where $F_1, F_2, F_3, ..., F_n$ are scalar functions, ω is an element of X where X is the set of constraints.

3.4.2 Methodology

A methodology has been proposed in this chapter, to obtain an optimal strategy for the TEM system having multiple objectives.

The proposed method is presented as below:

Step 1: Evaluating the scores of top softgoals based on different alternatives in the goal model

Step 2: Determine multi-objective optimisation functions based on the scores of top softgoals with respect to different alternatives.

Step 3: Scalarisation of multi-objective functions using linear weighted sum optimisation method

Step 4: Applying linear programming model to obtain optimal strategy and decision making

3.4.3 Formalisation of multi-objective optimisation functions of the i goal model*

A generalised complete structure of the TEM *i** framework is modeled in this section by formalising the multiple objective functions in terms of softgoals, goals and tasks.

For easy understanding of the formalisation of our approach, consider a simple directed graph, as shown in Figure 3.4, whose nodes are goals (G) or leaf softgoals ($LS_1, LS_2, ..., LS_n$) or intermediary softgoals ($SG_1, SG_2, ..., SG_n$) or top softgoals ($TS_1, TS_2, ..., TS_n$). The leaf softgoals (the softgoals that are lower in the hierarchy) are assigned values as weights based on their relative importance in percentage. Let the weights of leaf softgoals LS_1 and LS_2 be ω_{L_1} and ω_{L_2} respectively. The goal (G) can be achieved by either of the two tasks (alternatives) (A_1 and A_2). The contributions of goals or tasks to softgoals is represented by impacts that indicates the extend to which an alternative design option fulfils the leaf softgoal. Impacts are *Make, Help, Hurt, Break, Some-, Some+* which are represented as fuzzy numbers that indicates the extend to which an alternative option fulfills the leaf softgoal[34]. Both triangular and trapezoidal fuzzy numbers can be executed easily and can be quickly calculated. In this chapter, triangular fuzzy numbers are used, as to begin with a triangular membership function is the easiest way. Besides, triangular fuzzy numbers denote fuzzy numbers, whereas, trapezoidal fuzzy numbers denote fuzzy intervals.

The effects of the softgoal preferences are disseminated to the top softgoals. This helps in finding the extent of satisfaction or scores of the top softgoals. The leaf softgoal scores are transmitted backwards to find the scores of the softgoals that are higher in the hierarchy. Softgoals receive numerous contribution links. For more details on generating scores, readers are directed to [34, 35]. The proposed approach in this chapter is an updated version of [40].

In the proposed approach, initially each top softgoal's scores are calculated based on its inter-actor dependency under each alternative.

Consider a node that represents a leaf softgoal in the i^* model. Let $\omega_{L_{ik}}$ represents the weight of i^{th} leaf softgoal of k^{th} actor. From Figure 3.4, $I_{L_{ijk}}$ means the impact on i^{th} leaf softgoal of j^{th} alternative. Let $\omega_{L_{ijk}}$ represents the weight of i^{th} leaf softgoal for actor k at level zero. Then the score of i^{th} leaf softgoal for j^{th} alternative for the k^{th} actor is as follows:

$$score_{L_{ijk}} = I_{L_{ijk}} * \omega_{L_{ijk}} + \sum_{d_{L_i}=1}^{n_{d_i}} (score_{d_{L_i}} * I_{d_{L_i}}) \tag{3.2}$$

where $score_{d_{L_i}}$ is the score of $d_L{}^{th}$ dependent for the i^{th} leaf softgoal, $I_{d_{L_i}}$ is the $d_L{}^{th}$ dependent impact for the i^{th} leaf softgoal and n_{d_i} is the number of dependencies for the i^{th} leaf softgoal (i.e., at level zero).

The approach is illustrated with the proposed TEM system as running example shown in Figure 3.5. The decision maker's task is to choose an ideal design (alternative) option from the presented choices. An objective function is generated for each alternative based on the elements of the graph.

In the proposed TEM system, each leaf softgoal is pre-assigned an unique weight that can help to select the best optimal design option for achieving the top softgoal. Let the individual weights of leaf sofgoals such as *Security, Active Communication, Accurate Forecast, Scalability, Inter-operability, Real-time Demand/Response* be ω_1, ω_2, ω_3 , ω_4, ω_5 and ω_6 respectively. For improving the readability of the paper, certain terms in the TEM system are abbreviated as shown in Table 3.4. The scores of the leaf softgoals for actor, *Power System*, under the alternative, *Traditional Grid*, are calculated as follows:

$$
\begin{aligned}
score_{SR_{TraditionalGrid}} &= Hurt * \omega_1 \\
score_{AC_{TraditionalGrid}} &= Break * \omega_2 \\
score_{AF_{TraditionalGrid}} &= Break * \omega_3 \\
score_{SB_{TraditionalGrid}} &= Some - * \omega_4 \\
score_{IO_{TraditionalGrid}} &= Break * \omega_5 \\
score_{RDR_{TraditionalGrid}} &= Break * \omega_6
\end{aligned}
$$

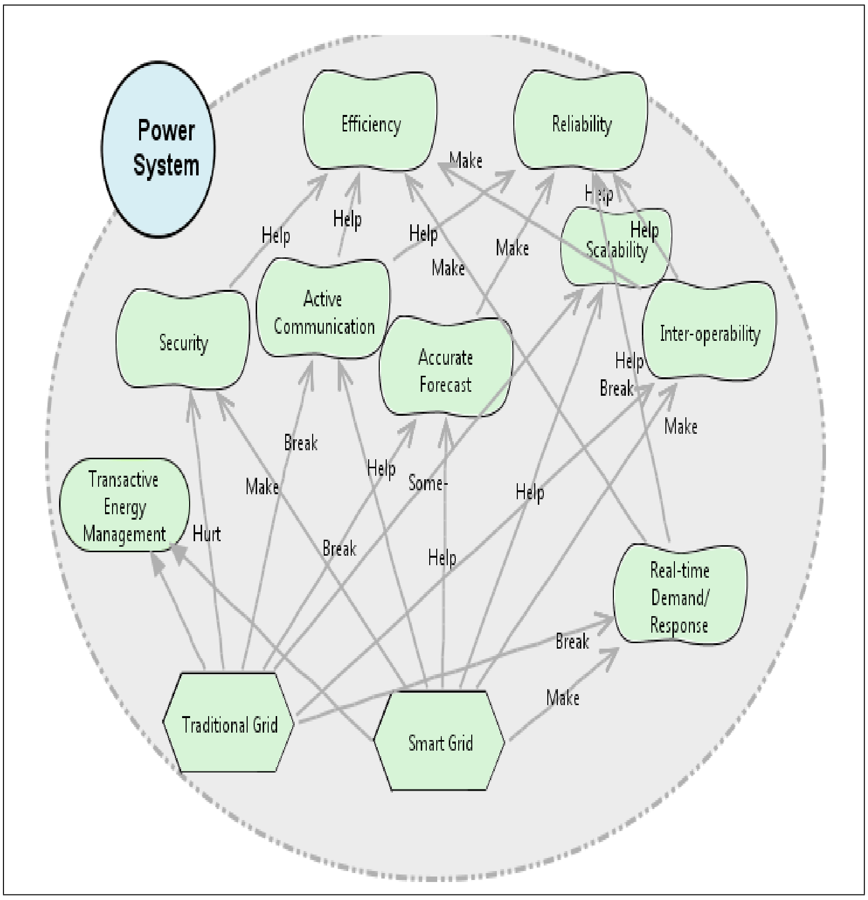

Figure 3.5 The i model of the proposed TEM system*

Table 3.4 Abbreviation of terms in TEM system

Terms	**Abbreviation**
Transactive Energy Management	*TEM*
Security	*SR*
Active Communication	*AC*
Accurate Forecast	*AF*
Scalability	*SB*
Inter-operability	*IO*
Real-time Demand/Response	*RDR*

Similarly, the scores for the leaf softgoals under the alternative, *smart-grid* are calculated and is represented as follows:

$$
\begin{aligned}
score_{SR_{smart-grid}} &= Make * \omega_1 \\
score_{AC_{smart-grid}} &= Help * \omega_2 \\
score_{AF_{smart-grid}} &= Help * \omega_3 \\
score_{SB_{smart-grid}} &= Help * \omega_4 \\
score_{IO_{smart-grid}} &= Make * \omega_5 \\
score_{RDR_{smart-grid}} &= Make * \omega_6
\end{aligned}
$$

Let's assume that there are t hierarchy levels in the directed graph. All leaf softgoals are defined at level zero. Then, at level $t = 1$, the score of the i^{th} softgoal for j^{th} alternative for actor k is defined in Equation 3.3.

$$score_{SG_{i_1 jk}} = \sum_{x=1}^{n_c} (I_x * score_{L_{xjk}}) + \sum_{d_{i1}=1}^{n_i} (score_{d_{i1}} * I_{d_{i1}}) \tag{3.3}$$

where the number of children is represented as n_c for each i^{th} softgoal at level one and the number of dependencies at level one for i^{th} softgoal is represented as n_i.

The score of softgoals at level one depends on the score of its leaf softgoal, Equation 3.3 can be rewritten as:

$$
\begin{aligned}
score_{SG_{i_1 jk}} = {} & I_1 * score_{L_{1jk}} + I_2 * score_{L_{2jk}} + \dots\dots\dots \\
& + I_{n_c} * score_{L_{n_c jk}} + \sum_{d_{i1}=1}^{n_i} (score_{d_{i1}} * I_{d_{i1}})
\end{aligned} \tag{3.4}
$$

Table 3.5 Defuzzified impact values

Impacts	Fuzzy value	Defuzzified value
Make	(0.64, 0.8, 1)	0.8
Hurt	(0, 0.16, 0.32)	0.16
Some+	(0.32, 0.48, 0.64)	0.48
Break	(0, 0, 0.16)	0
Help	(0.48, 0.64, 0.80)	0.64
Some−	(0.16, 0.32, 0.48)	0.32

Substituting with Equation 3.3, Equation 3.4 becomes

$$\begin{aligned} score_{SG_{i_1 jk}} = {} & I_1 * (I_{L_1 jk} * \omega_{L_1 jk} + \sum_{d_{L_1}=1}^{n_{d_1}} (score_{d_{L_1}} * I_{d_{L_1}})) \\ & + I_2 * (I_{L_2 jk} * \omega_{L_2 jk} + \sum_{d_{L_2}=1}^{n_{d_2}} (score_{d_{L_2}} * I_{d_{L_2}})) + \text{.........} \\ & + I_{n_c} * (I_{L_{n_c} jk} * \omega_{L_{n_c} jk} + \sum_{d_{L_{n_c}}=1}^{n_{d_{n_c}}} (score_{d_{L_{n_c}}} * I_{d_{L_{n_c}}})) \\ & + \sum_{d_{i1}=1}^{n_i} (score_{d_{i1}} * I_{d_{i1}}) \end{aligned} \tag{3.5}$$

Thus it propagates upwards. Let's consider that there are m number of softgoals, n_c children and n_d dependencies for the i^{th} softgoal. Then the score of any softgoal at level $t > 1$ is determined by calculating the product of each child score and its impact.

Hence, for an actor at level t, the softgoal's score with a dependency relationship is formalised as follows:

$$\begin{aligned} score_{SG_{i_t jk}} = {} & \Pi_{l=1}^{t} I_{ijl} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{ij}} * I_{d_{L_{ijk}}} * \omega_{d_{L_{ijk}}})] \\ & + \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (score_{i_{d_{by}}} * I_{i_{d_{by}}})) + \sum_{b=1}^{n_d} (score_{i d_b} \\ & * I_{i d_b})] \end{aligned} \tag{3.6}$$

In the TEM system, for actor *Power System*, the score of top softgoals, $Efficiency$ and *Reliability* under both alternatives *Traditional Grid* and *smart-grid* are calculated. For a straightforward calculation, defuzzification is used to translate the effects that are represented in fuzzy numbers to quantifiable values [46]. These defuzzified values as shown in Table 3.5 are used to evaluate the scores of each softgoal. Therefore for actor *Power System*, the score of top softgoals, $Efficiency$ and *Reliability* under both alternatives are calculated as:

$$
\begin{aligned}
score_{Efficiency_{TraditionalGrid}} &= Help * score_{SR_{TraditionalGrid}} + Help * score_{AC_{TraditionalGrid}} \\
&+ Make * score_{RDR_{TraditionalGrid}} + Make * score_{IO_{TraditionalGrid}} \\
&= 0.64 * (0.16 * \omega_1) + 0.64 * (0 * \omega_2) + 0.8 * (0 * \omega_5) + 0.8 * (0 * \omega_6) \\
&= 0.1024 * \omega_1
\end{aligned}
$$

$$
\begin{aligned}
score_{Reliability_{TraditionalGrid}} &= Help * score_{AC_{TraditionalGrid}} + Make * score_{AF_{TraditionalGrid}} \\
&+ Help * score_{SB_{TraditionalGrid}} + Help * score_{IO_{TraditionalGrid}} \\
&+ Help * score_{RDR_{TraditionalGrid}} \\
&= 0.64 * (0 * \omega_2) + 0.8 * (0 * \omega_3) + 0.64 * (0.32 * \omega_4) \\
&+ 0.64 * (0 * \omega_5) + 0.64 * (0 * \omega_6) \\
&= 0.2048 * \omega_4
\end{aligned}
$$

$$
\begin{aligned}
score_{Efficiency_{smart-grid}} &= Help * score_{SR_{smart-grid}} + Help * score_{AC_{smart-grid}} \\
&+ Make * score_{RDR_{smart-grid}} + Make * score_{IO_{smart-grid}} \\
&= 0.64 * (0.8 * \omega_1) + 0.64 * (0.64 * \omega_2) \\
&+ 0.8 * (0.8 * \omega_5) + 0.8 * (0.8 * \omega_6) \\
&= 0.512 * \omega_1 + 0.4096 * \omega_2 + 0.64 * \omega_5 + 0.64 * \omega_6
\end{aligned}
$$

$$
\begin{aligned}
score_{Reliability_{smart-grid}} &= Help * score_{AC_{smart-grid}} + Make * score_{AF_{smart-grid}} \\
&+ Help * score_{SB_{smart-grid}} + Help * score_{IO_{smart-grid}} \\
&+ Help * score_{RDR_{smart-grid}} \\
&= 0.64 * (0.64 * \omega_2) + 0.8 * (0.64 * \omega_3) \\
&+ 0.64 * (0.64 * \omega_4) + 0.64 * (0.8 * \omega_5) + 0.64 * (0.8 * \omega_6) \\
&= 0.4096 * \omega_2 + 0.512 * \omega_3 + 0.4096 * \omega_4 \\
&+ 0.512 * \omega_5 + 0.512 * \omega_6
\end{aligned}
$$

Then the objective function of top softgoals under each alternative for an actor are formalised from the scores as shown in Equation 3.6 with the assumption that no inter-actor dependency relationship is considered. Let's consider that for an actor in the *i** model has *n* number of alternative design options, then there is a need to define *n* number of objective functions (maximum or minimum) for each top softgoal. Hence, to obtain the maximum score for the top softgoal under each alternative, the

n maximum objective functions are defined as follows:

$$
\begin{aligned}
F_i(\omega_1) &= score_{SG_{i1k}} \\
&= Max\Pi_{l=1}^{t} I_{i1l} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{i1}} * I_{d_{L_{i1k}}} * \omega_{d_{L_{i1k}}})] \\
&+ \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (score_{i_{d_{by}}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d} (score_{i d_b} * I_{i d_b})]
\end{aligned}
$$

$$
\begin{aligned}
F_i(\omega_2) &= score_{SG_{i2k}} \\
&= Max\Pi_{l=1}^{t} I_{i2l} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{i2}} * I_{d_{L_{i2k}}} * \omega_{d_{L_{i2k}}})] \\
&+ \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (score_{i_{d_{by}}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d} (score_{i d_b} * I_{i d_b})] \\
&\ldots\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots\ldots \\
&\ldots\ldots\ldots\ldots\ldots
\end{aligned}
$$

$$
\begin{aligned}
F_i(\omega_n) &= score_{SG_{ink}} \\
&= Max\Pi_{l=1}^{t} I_{inl} \sum_{i=1}^{m} [\sum_{d=1}^{n_c} [(I_{d_{in}} * I_{d_{L_{ink}}} * \omega_{d_{L_{ink}}})] \\
&+ \sum_{y=1}^{n_c} (\sum_{b=1}^{n_d} (score_{i_{d_{by}}} * I_{i d_{by}})) \\
&+ \sum_{b=1}^{n_d} (score_{i d_b} * I_{i d_b})]
\end{aligned} \tag{3.7}
$$

Such that

$$0 \leq \omega_{d_{L_{jk}}} \leq 100 \text{ for } d = 1 \text{ to } n_c$$

Based on the objective functions defined in Equation 3.7, objective functions that has to be maximised for actor *Power System* in the TEM system are represented as follows:

$$
\begin{aligned}
F_{Efficiency}(\omega)_{TraditionalGrid} &= Max(score_{Efficiency_{TraditionalGrid}}) \\
&= Max(0.1024 * \omega_1) \\
F_{Efficiency}(\omega)_{smart-grid} &= Max(score_{Efficiency_{smart-grid}}) \\
&= Max(0.512 * \omega_1 + 0.4096 * \omega_2 + 0.64 * \omega_5 + 0.64 * \omega_6) \\
F_{Reliability}(\omega)_{TraditionalGrid} &= Max(score_{ReliabilityTraditionalGrid}) \\
&= Max(0.2048 * \omega_4) \\
F_{Reliability}(\omega)_{smart-grid} &= Max(score_{Reliabilitysmart-grid}) \\
&= Max(0.4096 * \omega_2 + 0.512 * \omega_3 + 0.4096 * \omega_4 + 0.512 * \omega_5 \\
&\quad + 0.512 * \omega_6)
\end{aligned}
$$

In the next step of formalisation, the obtained multi-objective functions of top softgoals, that has to be maximised, are integrated to a single objective function, for optimisation, using linear weighted sum method. By applying linear weighted sum method, the set of multi-objective functions are scalarised into a single objective. This is performed by adding each objective functions pre-multiplied by a user provided weight (W). The weight of an objective is predefined in proportion to its relative importance among all top softgoals in the *i** model. The linear weighted sum scalarisation process is defined as follows:

$$
MaxF(\omega) = \sum_{i,j=1}^{n,k} W_i * F_i(\omega)_{A_j} \tag{3.8}
$$

$$
\begin{aligned}
W_i &\geq 0 \text{ for } i = 1 \text{ to } n \\
A_j &\geq 0 \text{ for } j = 1 \text{ to } k
\end{aligned}
$$

where W_i denote the weight assigned to the each objective function F_i under each alternative A_j.

For obtaining the optimal reasoning for the TEM system, a more subjective preference is given to $Efficiency$ than $Reliability$, therefore different weighting values are set to both objectives. Let's consider that the weights assigned to both top softgoals, $Efficiency$ and $Reliability$ are W_1 and W_2 respectively. Also assume that the objective $Efficiency$ is 3 times as important than the objective $Reliability$. Hence, the scalarised single objective function $F(\omega)$ that needs to be maximised is represented as follows:

$$
\begin{aligned}
MaxF(\omega) &= W_1 * F_{Efficiency}(\omega) + W_2 * F_{Reliability}(\omega) \\
&= 3 * F_{Efficiency}(\omega) + 1 * F_{Reliability}(\omega)
\end{aligned}
$$

Table 3.6 Maximum objective function values for the TEM system

Maximum Objective Functions	Traditional Grid	smart-grid
$F_{Efficiency}(\omega)$	12.4	64
$F_{Reliability}(\omega)$	0	51.2

Therefore, the linearly integrated objective function under the alternative *Traditional Grid* is represented as follows:

$$\begin{aligned} MaxF_{TraditionalGrid}(\omega) &= W_1 * F_{Efficiency}(\omega)_{TraditionalGrid} + W_2 * \\ &\quad F_{Reliability}(\omega)_{TraditionalGrid} \\ &= 3 * F_{Efficiency}(\omega)_{TraditionalGrid} + 1 * \\ &\quad F_{Reliability}(\omega)_{TraditionalGrid} \end{aligned}$$

Similarly, the linearly integrated objective function under the alternative *smart-grid* is represented as follows:

$$\begin{aligned} MaxF_{smart-grid}(\omega) &= W_1 * F_{Efficiency}(\omega)_{smart-grid} + W_2 * F_{Reliability}(\omega)_{smart-grid} \\ &= 3 * F_{Efficiency}(\omega)_{smart-grid} + 1 * F_{Reliability}(\omega)_{smart-grid} \end{aligned}$$

To evaluate the proposed reasoning method based on the *i** goal model, IBM ILOG CPLEX optimisation tool is incorporated. The robust optimisation problems are solved by using the optimisation package CPLEX, implemented in Java code, which guarantees global optimality for mixed integer programming. The optimal values of the unified objective functions optimised by the IBM ILOG CPLEX optimisation tool are provided in Table 3.6 as ready reference.

The results indicate that the alternative *smart-grid* has a higher value than *Traditional Grid*. This means that by choosing the *smart-grid* strategy, the TEM system can achieves the top softgoals in the *i** goal model reciprocally. This case study on TEM system illustrates that the proposed approach can be scaled up and applied to a reasonably complex scenarios in practice.

3.5 Conclusion

This chapter covers transactive energy management and the importance of requirement engineering in TEM, applied to micro-grid and smart-grid. The efficient and reliable functioning of the electric power system by using requirements engineering in transactive energy management has been discussed and analysed. The aim is to help decision-makers to achieve higher efficiency and reliability of the power system. With this aim in mind, an approach to analyse the non-functional requirements for the TEM system has been proposed. The *i** goal modelling approach has been applied to formalise the multi-objective functions of the non-functional requirements. These requirements may be incomplete in some of the settings. In requirements analysis, new requirements may arise, or existing requirements may become more or less prominent. The prominence of the requirements is based on the characteristics of a particular domain. This is the main drawback to this approach. In the future, empirical validation of the proposed approach will be conducted. Plan to develop a tool that can perform optimal goal analysis will also be explored.

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Appendices

Statement of contributions

Appendix A

Statement of contributions

All of the written materials submitted as part of this PhD by Publication were conceived and coordinated by Sreenithya Sumesh. Sreenithya also undertook the majority of the empirical data collection, analysis and writing for each publication.

Signed detailed statements from co-author relating to each publication and the attribution statement are provided at the next pages.

Signed
Sreenithya Sumesh

Signed
Associate Professor Aneesh Krishna
Date: 10-05-2021

Contribution statements

STATEMENT BY CO-AUTHORS

Publication 1

S. Sumesh, A. Krishna and C. Subramanian (2018), Optimal Reasoning of Opposing Non-functional Requirements based on Game Theory. In B.Andersson, B. Johansson, S. Carlsson, C. Barry, M. Lang, H. Linger, C. Schneider (Eds.), Designing Digitalization (ISD2018 Proceedings). Lund, Sweden: Lund University. ISBN: 978-91-7753-876-9. http://aisel.aisnet.org/isd2014/proceeding 2018/General/8.

Contributors	Statement of contribution	% Total contribution
Sreenithya Sumesh	Conceptualization, visualisation, methodology, simulation validation, data analysis and drafting the manuscript	70%
Aneesh Krishna	Supervision and critical revision of the paper	25%
Chitra M Subramanian	Supervision and critical revision of the paper	5%

Sreenithya Sumesh 05 May 2021

I, as a Co-Author endorse that this level of contribution by the candidate indicated above is appropriate.

A/Professor Aneesh Krishna (Co-Author 1) 05 May 2021

I, as a Co-Author endorse that this level of contribution by the candidate indicated above is appropriate.

Chitra M Subramanian (Co-Author 2) 05 May 2021

Publication 2

S. Sumesh, A. Krishna and C. Subramanian (2019), Game Theory-Based Reasoning of Opposing Non-functional Requirements using Inter-actor Dependencies, The Computer Journal, Volume 62, Issue 11, November 2019, Pages 1557–1583, https://doi.org/10.1093/comjnl/bxy143

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Publication 3

S. Sumesh, A. Krishna and C. Subramanian (2018), CEA Based Reasoning with the i* Framework (2018). PACIS 2018 Proceedings. 174. https://aisel.aisnet. org/pacis2018/174

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I, as a Co-Author endorse that this level of contribution by the candidate indicated above is appropriate.

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Publication 4

S. Sumesh, A. Krishna (2021), Sensitivity Analysis of Conflicting Goals in the i* Goal Model, The Computer Journal, 2021, bxaa189, https: //doi.org/ 10.1093/comjnl/bxaa189

Contributors	Statement of contribution	% Total contribution
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Aneesh Krishna	Supervision and critical revision of paper	30%

Sreenithya Sumesh 05 May 2021

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Publication 5

S. Sumesh, A. Krishna and C. Subramanian (2019), AHP based Optimal Reasoning of Non-functional Requirements in the i* Goal Model. In A. Siarheyeva, C. Barry, M. Lang, H. Linger, C. Schneider (Eds.), Information Systems Development: Information Systems Beyond 2020 (ISD2019 Proceedings). Toulon, France: ISEN .

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Publication 6

S. Sumesh, A. Krishna (2020), Hybrid analytic hierarchy process-based quantitative satisfaction propagation in goal-oriented requirements engineering through sensitivity analysis Multiagent and Grid Systems, 16(4), pp.433-462.

Contributors	Statement of contribution	% Total contribution
Sreenithya Sumesh	Conceptualization, visualisation, methodology, simulation validation, data analysis and drafting the manuscript	70%
Aneesh Krishna	Supervision and critical revision of paper	30%

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Publication 7

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Sreenithya Sumesh	Conceptualization, visualisation, methodology, simulation validation, data analysis and drafting the manuscript	70%
Aneesh Krishna	Supervision and critical revision of paper	30%

Sreenithya Sumesh 05 May 2021

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A/Professor Aneesh Krishna (Co-Author 1) 05 May 2021

Publication 8

S. Sumesh, A. Krishna and C. Subramanian (2019), Requirements analysis in transactive energy management Variability, Scalability and Stability of Microgrids, 139, p.73.

Contributors	Statement of contribution	% Total contribution
Sreenithya Sumesh	Conceptualization, visualisation, methodology, simulation validation, data analysis and drafting the manuscript	70%
Aneesh Krishna	Supervision and critical revision of the paper	25%
Chitra M Subramanian	Supervision and critical revision of the paper	5%

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A/Professor Aneesh Krishna (Co-Author 1) 05 May 2021

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Attribution statement

Attribution statement

Publications and titles	% Total contributions	
	Co-Author 1 (Aneesh Krishna)	Co-Author 2 (Chitra M Subramanian)
Publication 1 Optimal Reasoning of Opposing Non-functional Requirements based on Game Theory	25%	5%
Publication 2 Game Theory-Based Reasoning of Opposing Non- Functional Requirements Using Inter-Actor Dependencies	25%	5%
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Co-Authors Names	Contributions	Co-Authors Acknowledgement: I acknowledge that these represent my contribution to the above research output.
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