Department of Construction Management

Meta-heuristic based Construction Supply Chain Modelling and Optimization

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DECLARATION

I affirm that the material in this thesis is the result of my own original research and has not been submitted for any other degree, diploma, or award.

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ABSTRACT

With the competition becoming more severe within the construction industry, the importance of supply chain management for construction projects has been aroused. However, unlike the supply chain in other industries, the attributes of construction supply chain (CSC) is largely dependent on the construction projects, and the relationships between stakeholders are temperate and vulnerable. Therefore, the optimization of CSC is tightly associated with the proper management of construction projects, more specifically, the project planning and scheduling. In this thesis, I analyze the problem of improving the performance of construction supply chain (CSC) and identify the key influencer as the optimization of project scheduling. In order to systematically resolve the construction supply chain optimization problem (CSCOP), I propose mathematical models and meta-heuristic algorithms for coping with three sub-problems under different scenarios, which are deterministic single objective optimization problem, stochastic optimization problem and multi-objective optimization problem respectively.

In Chapter 1, I present a brief review on construction supply chain management and construction project scheduling.

In Chapter 2, I introduce some of the most popular and widely implemented meta-heuristic algorithms.

In Chapter 3, I consider a deterministic construction supply chain optimization problem (DCSCOP). As an extended version of resource constrained project scheduling problem, the DCSCOP aims to minimize the total cost related to CSC that includes material handling cost and labour cost. In this sub-problem, parameters such as activity duration, material demand and workforce allocation are defined as deterministic. Classic constraints including precedence relations and resource constraints are considered. An genetic algorithm (GA) with sequence-based representation of chromosome is proposed for dealing with our proposed DCSCOP. A case study based on a scaffolding construction project is conducted for testifying our proposed mathematical model and GA algorithm. The result of case study indicates that our proposed method is feasible and applicable for resolving the practical problems. The comparisons of

computational results obtained by different parameters and various meta-heuristic algorithms are presented as well.

In Chapter 4, I investigated the CSCOP with three characteristics: stochastic activity durations, budget constraint and alternative solutions for specific operation tasks caused by the selection of rental resources. The proposed stochastic construction supply chain optimization with rental resource selection (SCSCO) problem aims to minimize the total makespan by considering the uncertainty in activity composition of the project and activity duration. A chance-constrained mathematical model is proposed and a hybrid algorithm that integrates sample average approximation (SAA) and particle swarm optimization (PSO) is developed for resolving this sub-problem. A case study based on a maintenance project in a LNG plant is conducted for validating the feasibility and practicability of our prosed model and algorithm. Sensitivity analysis is studied by comparing the results obtained by implementing different values of parameters, and the comparison of performance of different meta-heuristic algorithms is also presented.

In Chapter 5, the third sub-problem specifically focuses on the multi-objective optimization for scaffolding construction project. A multi-objective model is established based on a practical scenario of a mega scaffolding construction project with objectives of minimizing the total project makespan and total supply chain cost and maximizing the workforce utilization rate. A modified non-dominating sorting genetic algorithm (NSGA-II) is developed for searching for the optimal solutions of this problem. The proposed NSGA-II is tested on a case study and the results manifest that accurate and feasible solutions can be produced through our method to assist managers with designing the optimal schedules.

In Chapter 6, some remarkable findings and directions of future research are presented.

To sum up, this thesis provides a thorough review of the characteristics of construction supply chain and previous research about the construction supply chain management and construction project scheduling problems. Based on these background information, this thesis studies the construction supply chain optimization problems under different scenarios, namely, deterministic scenario, stochastic scenario and multi-objective scenario. For resolving these three problems, this thesis proposes three real project-based mathematical models and corresponding meta-heuristic algorithms. The methodology presented by this thesis provides a systematic guideline of implementing mathematical modeling and optimization with real-life industrial application problems, which in this case is the construction supply chain optimization.

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CHAPTER 1

INTRODUCTION

1.1 Background

1.1.1 Construction Supply Chain

As one of the largest industries in the world, construction industry has long been criticized for being less efficient and economical compared to other industrial sectors such as manufacturing industry [1] [2]. Statistics from a marketing report indicate that over 70% of the construction projects suffered from delay, and among these projects, 75% of them spent 50% more than their initial budget [3]. Project delay and budget overrun have been two main prevailing issues that plague the project developers and owners continuously. Over the last few decades, the necessity and needs for implementing the philosophy and methods of supply chain management (SCM) to the construction sector for improving the performance of construction project management and reducing the costs caused by inefficiency have been emphasized by many researchers and industrial professionals [4]. Originated in the manufacturing industry, SCM was initially implemented in the Just-in-Time (JIT) system by Toyota which aimed to regulate the material ordering plan in order to reduce the inventory and manage the production line efficiently [5]. Since then, more and more companies have tended to adopt the supply chain management experience from manufacturing industry in order to drive efficiencies and improvements to the project managements [6]. However, simply transferring the SCM concepts and methodologies initiated in manufacturing industry to construction industry is more difficult than expectation. In contrast to manufacturing which has a comparatively fixed production process, construction is by nature a project-based industry that is characterized with attributes such as labour intensiveness and uncertainty which are caused by the short term relationships among stakeholders, and fragmented structure of the construction supply chain as well as its dependency with operations [7]. Moreover, nowadays, construction projects have become more complex and big than ever before and these projects generally involve large scaled investments and widely dispersed participants including many contractors and subcontractors [6]. Therefore, due to all these characteristics of construction industry, the efficiency of construction supply chain is lagging behind other industries such as manufacturing and the implementation of supply chain management in construction sector is yet challenging.

To our knowledge, the current studies of construction supply chain management (CSCM) have been conducted from two main aspects, namely, management philosophy implementation and information system technology. Speaking of management philosophy, in recent year, lean management has been adopted for improving the supply chain performance in construction industry. Lean management, which was initially developed based on the Toyota production system, represents a series of approaches to continuously eliminate the waste in operations and improve the efficiency and performance of an organization or a system [8]. Erik (2010) investigated the core elements of lean management in construction section which consist of waste reduction, process planning and control, satisfaction of customer needs, continuous improvements and partnership of participants [9]. In order to verify the applicability of lean management in CSCM, the author conducted a pilot study by engaging in a construction project as a facilitator and implemented the core elements in the management of CSC. The results of this study indicated that the construction project was well executed with a high satisfaction in budget and schedule management due to the implementation of lean management [9]. Aziz et al. (2013) examined the perceptions of lean management principles in construction and evaluated the effectiveness of implementing the Last Planner System which is a technique of lean management [10]. Similarly, Deshpande et al. (2011) [11] applied the techniques of lean management in the construction project design including project planning and supply chain design and Shewchuk and Guo (2011) [12] proposed a lean approach for minimizing the quantity of stacks and material handling distance in order to improve the performance of supply chain. Another management improvement methodology that has been developed and applied extensively is six sigma. Six sigma focuses on the reduction of variations, defects measurement and quality improvement for processes, production and supply chain services [13]. In the construction supply chain context, six sigma can contribute to improve the delivery efficiency and cost effectiveness through decreasing the project delays, re-working rate of completed jobs, and the variation of quantity of materials delivered to the construction site [14]. On the other side, with the development of information system (IT), various technologies of IT have been used for CSCM. Building information system (BIM) is a technology that could be used to manage the life cycle of a construction project including design, operation execution, process management, material management and maintenance with visualized representations [15]. Irizarry et al. (2013) integrated BIM and geographic information system (GIS) which is a technology for managing geographic data to track the status of construction supply chain and ensure the supply of materials [4]. Maki and Kerosuo (2015) described the procedure of using the BIM tools and applications for construction site management such as material delivery and inventory storage and provided a guideline of BIM implementation for project managers [16]. There are also other IT technologies that have been used for CSCM, such as radio frequency identification (RFID) [17] [18] and global positioning system (GPS) [19]. Through reviewing these previous studies, I find out that the aforementioned management philosophies and IT technologies seem promising for improving the efficiency and management of construction management, nevertheless, difficulties and problems of implementing these methodologies in CSCM still remain. First of all, the benefits brought by these methodologies might exceed the cost of implementation. Generally, widely adoption of lean and six sigma requires extensive and considerable inputs in terms of personnel training, consulting support, organization and management system restructuring, and information management. According to a report, the average training cost of lean management of an employee is about $50,000 [20]. These investments also apply for IT applications, for example, deploying a RFID system would normally include hardware cost, setup cost, and system service cost [21]. In addition, many of these management philosophies are originated and initially designed in manufacturing industry with the characteristics of assets intensiveness and operations repetitiveness. Notwithstanding some operations within a construction project are repeatable, none of these operations would be executed in the same way with the same performance due to the uncertainty and low level of automation in construction. Hereby, it would be difficult to ensure the accuracy of data collection, process analysis and evaluation of either lean management or six sigma in the construction industry.

In order to adopt a more effective and economically efficient method to improve the performance of construction supply chain, it is vital to identify the goals of construction supply chain management and optimization and the root causes for inefficiency. According to the perception suggested by Vrijhoef et al. (2000), CSCM should focus on the goal of reducing the costs and duration of project activities with the considerations of ensuring the flow of materials and workforce, achieving concurrent execution of activities, and controlling the inventory [22]. Time and cost are commonly recognized as two most critical criteria for evaluating the performance of a supply chain. In the context of CSC, time refers to the duration of a construction project while cost generally stems from material management cost, labour cost and transportation cost. As shown in Figure 1.1, construction supply chain integrates various stakeholders of a construction project including project developers, contractors and subcontractors, and materials and equipment suppliers. In terms of the function, CSC directs construction resources including materials, equipment and workforce from suppliers and contractors to construction sites and manages the allocation of these resources in the construction sites. However, from the perspective of information flow, the demand of resources which is determined at the design phase influences the decision on project planning and scheduling. Afterwards, the subcontractors and suppliers would execute the construction operations and resource arrangement accordingly. It can be concluded that CSC is a project-based supply chain whose performance has a significant interdependency with the effectiveness of project management, especially project planning and scheduling. An appropriate project schedule would avoid the problems in the project management such as project delay and budget overrun. For this reason, optimizing the schedule of a construction project would consequently result in establishing a timely and economically CSC.

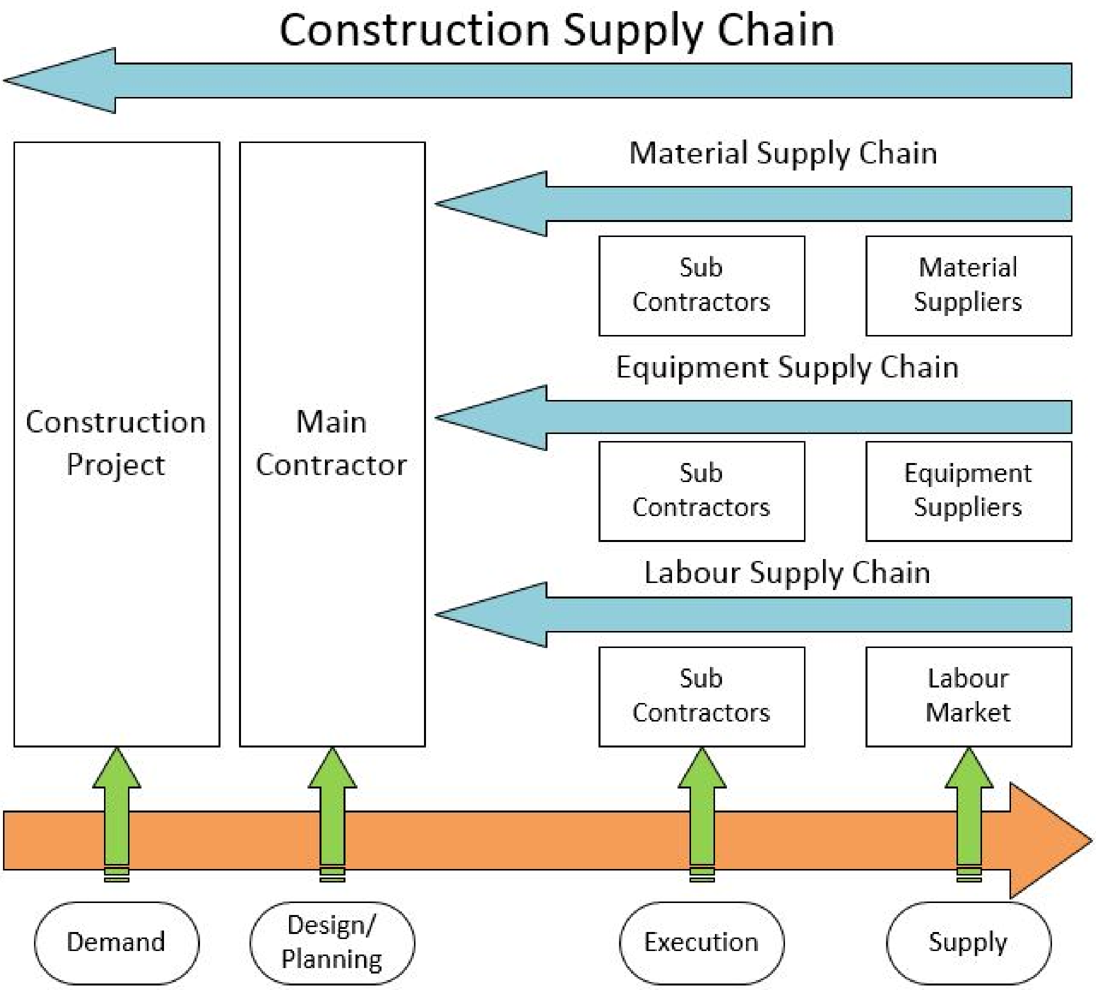

Figure 1.1: Flowchart of Construction Supply Chain

1.1.2 Construction Project Scheduling

Project scheduling deals with the problem of sequencing and planing the project activities and allocating the resources accordingly [23], and it is an important task of project management for ensuring that the project could be completed on time and the cost is controlled within the budget. During the process of scheduling, the availability of resources such as labour and equipment is often limited due to site space restrictions and project budget. These project scheduling problems that consider resource limitations are known as resource constrained project scheduling problems (RCPSP) which have been extensively studied [24]. The objective of RCPSP is normally set as minimizing the total cost or project duration by determining the optimal schedule of activities and allocating the available resources to each activities with the obedience of both the logical relations between activities and the resource constraints.

As a subdivision of RCPSP, construction project scheduling (CPS) shares the similar objectives and considerations. Composed of labour intensive operations, construction projects are characterized by their complexity and difficulties in management [3]. Shorter duration and less expenditure enable the project developers to increase their return on capital and the contractors to gain more profit and avoid the risk of inflation [25]. Therefore, contractors always strive to beat the deadline of project completion and endeavor to crash a project's duration. However, as a consequence, more resources are expected to allocate which could lead to a rise in the total expenditure on project. Hence, the trade-off between time and cost is one of the main challenges for project managers when they encounter the problem of resource constrained project scheduling for a complex project. On most occasions, the project planners would set up their objective of scheduling based on their priority between makespan and expenditure. One of the most adopted objectives is minimizing the total makespan of the project where the total makespan is normally represented as the completion time of the last activity. For example, Van Peteghem and Vanhoucke (2010) [26], Coelho and Vanhoucke (2011) [27] and Cheng et al. (2015) [28] proposed to minimize the total makespan of the project with the consideration of the constraints for both renewable and nonrenewable resources. There are also other time-based objectives for CPS, for example, minimization of weighted tardiness where tardiness means the delay of operations in execution [29] and minimization of the sum of earliness and tardiness [30]. On the other hand, various cost-based objectives have been proposed and studied for CPS. Generally, the total cost of a construction project consists of equipment and resource renting, materials acquisition and transportation, and labor cost [25]. Chen et al. (2010) constructed their mathematical model with the objective to minimize the final net present value (NPV) of the project using discounted cash flow analysis [31]. The delay penalty is another cost-based criterion that would be considered in the real world project management and the objective of minimizing the total cost of tardiness penalty is commonly proposed for the project scheduling [32]. Apart from these single objective formulations, many research have been conducted for multiple objective project scheduling problems as well. For example, Hadjiconstantinou and Klerides (2010) [33], Hazir et al. (2010)[34] and Kazemi and Tavakkoli (2011) [35] studied the discrete time-cost trade-off problems with the objectives of minimizing the total cost and makespan simultaneously, while Al-Fawzan et al. (2005) [36] and Abbasi el al. (2006) [37] considered robustness and makespan as the two objective criteria for their project scheduling problems where robustness represents the ability to cope with the variations in the construction projects. There are also some other formulations of multi-objective project scheduling problems such as time-resource [38] and time-cost-quality [39] [40]. Moreover, while planning the schedule of construction projects, various considerations should be deliberated. Precedence relationship of project activities is one of the most basic factors in a construction project that would affect the results of scheduling. In reality, some activities always have a higher priority of execution compared to others when project scheduling is being conducted [24]. Another type of relationship between activities which is known as mutual exclusion relationship is usually considered[41]. The mutual exclusion relationship means that the execution or selection of one activity will lead to the exclusion of another activity, and likewise, there exists mutual inclusion relationship which means that the selection of one activity will incontestably result in the selection of certain other activities. Resource constraint is undoubtedly the most influential factor for CPS as the execution of any activity is strongly relied on the availability of resources, especially the labours on site. Various resource constraints have been adopted in the research such as renewable and nonrenewable resources [26] [27], cumulative resources [42] and dynamic resource capability [43]. In addition, there are also other factors that would be taken into considerations for CPS including time lags between activities [44] and uncertain activity durations [45] [46].

Critical path (CP), proposed in late 1950s, is one of the most commonly adopted methods for project planning and scheduling in construction industry up to the present. Based on the information of project activities in terms of activity durations and dependencies, CP determines the critical activities by calculating the longest path of project execution from starting activity to the end activity, and the earliest and latest starting time of each activity [25]. Even though CP has been developed and evolved by comprising the representation of resource constraints [47] and various exact algorithms have been applied including dynamic programming [48], branch and bound [49] and minimum bounding algorithm [50], the restrictions of these algorithms limit their applications on large scale construction project with multiple objectives or in uncertain environment. Nowadays, construction projects are becoming more complex and it can be predicted that more mega-projects will be invested in infrastructure sector and energy industry for the next few decades[51]. Besides, as mentioned earlier, CPS is an extended version of RCPSP which is a complicated optimization problem that belongs to the class of NP-hard [52] [53]. It is suggested by Demeulemeester and Herroelen (1997) that the RCPSP with over 60 activities would not able to be solved by exact methods [54]. Therefore, methods that are more intelligent should be adopted for resolving complex CPS problems. In this thesis, meta-heuristic methods are developed and utilized to cope with the proposed construction supply chain optimization problems. The introduction of meta-heuristic optimization is detailed in the Chapter 2.

1.2 Research Objective and Scope

The construction supply chain optimization and construction project scheduling share the same goals according to the above discussion. To be more specific, the performance of a project-specific CSC is largely dependent on the appropriateness of project scheduling in terms of material management and resource allocation. In this research, the construction supply chain optimization problem (CSCOP) is described under three different scenarios and the corresponding mathematical models are constructed with the objective to develop an optimal schedule of the construction project in order to optimize the performance of CSC. These sub-problems represent three main types of optimization problem, namely, deterministic single objective optimization problem, stochastic optimization problem and multi-objective optimization problem respectively. Meta-heuristic algorithms are selected and modified to resolve these three sub-problems, and real project-based case studies are conducted for validating our models and algorithms. The objective of each sub-problem studied in this thesis is introduced as follow:

Deterministic Construction Supply Chain Optimization

The deterministic construction supply chain cost optimization problem (DCSCOP) describes a general scenario of supply chain of a construction project which consists of a series of activities. In the environment of construction, construction materials such as scaffolding components are continuously demanded, and the cost spent on material management including transportation, material leasing cost and inventory holding cost is the main contributor to the total cost of CSC. Therefore, this sub-problem aims to construct a general mathematical model of CSCOP with the objective of minimizing the CSC cost including material handling cost and labour cost based on the RCPSP. In order to generalize the modeling of CSCOP, the parameters of material management cost, activity duration, material demand and workforce requirement are assumed as deterministic. Considering the complexity of DCSCOP, a genetic algorithm is developed and applied. In addition, a case study based on the real world scaffolding construction project is conducted by applying our proposed model and algorithm.

Stochastic Construction Supply Chain Optimization with Rental Resource Selection

The stochastic construction supply chain optimization with rental resource selection (SCSCO) problem considers the fact that the selection of rental resources including equipment and temporary structures could alter the way of executing a targeted task. In reality, a construction task can be conducted in various methods that are triggered by adopting different equipment or materials, and most of these resources are rented instead of purchased. In addition, for a construction project, the budget is always limited and the duration of construction activity is not fixed. Therefore, this sub-problem aims to minimize the total makespan of a construction project under the uncertain environment and control its CSC cost including resource leasing cost and labour cost within the budget. In order to achieve this objective, a hybrid meta-heuristic algorithm that integrates sample average approximation and particle swarm optimization is developed to resolve this stochastic problem.

Multi-objective Optimization for Scaffold Supply Chain of a Mega Construction Project

As a temporary structure, scaffolding has been extensively used in construction industry and has a significant contribution to the total cost of construction projects. Especially for a mega construction project, enormous amount of scaffolding materials is continuously delivered between the supplier's warehouses and construction sites. The leasing cost of scaffolding materials is charged based on their amount and time within the construction site. Therefore, it is vital to work out an optimal schedule of the scaffolding construction that could consequently determine the supplying of scaffolding materials in order to improve the performance of scaffold supply chain. In this sub-problem, the performance of scaffold supply chain (SSC) is expected to be optimize through three aspects: total cost minimization, makespan minimization and workforce efficiency maximization. A multi-objective optimization model for SSC is formulated and a meta-heuristic algorithm based on non-dominated sorting genetic algorithm (NSGA-II) is developed for coping with this problem.

1.3 Structure of Thesis

In previous section, a brief background of construction supply chain (CSC) and construction project scheduling (CPS) is presented and three construction supply chain optimization problems (CSCOP) are also introduced briefly. The purpose of this thesis is to propose novel mathematical models of supply chain optimization problems in construction industry and develop meta-heuristic algorithms for solving these problems. The rest of this thesis is organized as follow.

In Chapter 2, several existing meta-heuristic algorithms are introduced. The mechanisms of three popular and widely used meta-heuristics including genetic algorithm (GA), ant colony optimization (ACO) and particle swarm optimization (PSO) are detailed, and their applications in CPS are presented from the aspects of single objective optimization, uncertainty and multi-objective optimization. The studies regarding to other most recent meta-heuristics are also introduced.

In Chapter 3, a deterministic construction supply chain optimization problem (CSCOP) is considered. This problem describes a general scenario of CSC of a construction project which consists of a series of activities. The parameters of activity duration, material demand and workforce requirement are defined as constant values, and the precedence relations between activities and the limitations on resources are considered in this problem as well. The mathematical model of CSCOP is constructed as a extended version of RCPSP with the objective of minimizing supply chain cost, and a genetic algorithm (GA) is developed and modified to solve this problem. A case study based on a scaffolding construction project is conducted for verifying the feasibility of the model and algorithm.

In Chapter 4, a budget constrained stochastic construction supply chain optimization with rental resource selection (SCSCO) problem is studied. Based on the deterministic CSCOP described in Chapter 3, a more complex construction supply chain optimization problem is formulated by combining stochastic project scheduling with resource selection problem, and the activity duration is considered as a stochastic parameter with a predefined distribution. A chance constrained model of SCSCO with the objective of minimizing the project duration is constructed, and a hybrid algorithm that integrates sample average approximation (SAA) and particle swarm optimization (PSO) is proposed. A case study based on a construction project in a LNG plant is conducted for verifying the feasibility and effectiveness of proposed algorithm and a sensitivity analysis is presented.

In Chapter 5, a multi-objective scaffold supply chain optimization problem is studied. The scenario of scaffold supply chain (SSC) of a mega construction project that comprises several sub-projects is illustrated, and a multi-objective optimization model is constructed with goals of minimizing the total cost, minimizing the project duration and maximizing the workforce efficiency. A non-dominated sorting genetic algorithm (NSGA-II) is modified and proposed for solving this problem, and a real project based scaffolding case study is conducted.

In Chapter 6, the main contributors and the potential directions of future research are presented.

CHAPTER 2

LITERATURE REVIEW: META-HEURISTIC OPTIMIZATION

Undoubtedly, optimization exists in many aspects of our life, from engineering designing to financial planning and from organization management to flight scheduling. People strive to achieve the best results or generate optimal solution for their targeted problems such as budget control, duration management and resource utilization [55]. For some optimization problems, the best solutions can be obtained through using the aforementioned exact algorithms. However, they may not be efficient enough in solving large scale combinational, complex and non-linear optimization problems, and the CSCOP and RCPSP discussed in this thesis are typical examples of these optimization problems. With the increment of the complexity of these problems, especially practical problems that comprise many considerations and restrictions, it is nearly impossible to search and testify every possible solutions and select the optimal one. Therefore, heuristic algorithms which solve problems based on the previous experience are developed to find the good solutions instead of best solutions in a reasonable computational time [56]. According to Beheshiti et al. (2013), meta-heuristics are high-level heuristic procedures which guide the subordinate heuristics by adopting intelligent strategies for exploring and exploiting the searching areas and finding the near optimal solutions efficiently [57]. Meta-heuristics can often generate good solutions with less computational costs compared to simple heuristics, and many of the current meta-heuristic algorithms are inspired by the social or biological behaviors [25]. In this section, a review of several popular meta-heuristic algorithms and their applications in construction project scheduling (CPS) problems is presented.

2.1 Genetic Algorithms

The genetic algorithm (GA) is one of the most well known meta-heuristic algorithms that has been extensively studied and applied in various fields. Developed by John Holland, GA mimics the process of chromosome evolution through genetic operators of selection, crossover and mutation in order to produce better offsprings [58]. According to Juang (2004) [59], GA starts with the problem encoding and chromosome representation. In GA, a chromosome or an individual normally represents a candidate solution for the optimization problem and is formed by a gene string. A fitness function that evaluates the fitness value of each chromosome is defined. In the first stage of GA, a initial population of a certain number of chromosomes will be processed through genetic operations including selection, crossover and mutation, and as a consequence, a new population will be produced and each generated population is called as a generation. The selection operator chooses the higher ranked chromosomes in the current population according to their fitness values and passes these chromosomes to the offspring. The crossover is the process of generating new offsprings by exchanging and combining the genes from their parent chromosomes. The mutation operator changes the value of some genes from a chromosome that are chosen randomly with a probability. The new generation that is obtained through applying these three genetic operators will be assessed by evaluating the criteria of termination. If the criteria are reached, then the solutions can be decoded from the obtained population, otherwise, the GA will be repeated. The general procedure of GA is presented in the Algorithm 1.

Algorithm 1 Pseudo Code of GA

```
For objective function f(x), x = (x_1, x_2, ...x_n)^T
Encode the objective function and the representation of chromosome
Define fitness function F(x)
Generate initial population and define GA parameters
while t < maximum number of iteration
Select the parent chromosomes
Perform Crossover with probability of p_c
Perform Mutation with probability of p_m
Evaluate the fitness of offsprings
Select the best for the next generation
End while
Decode the solutions
```

GA has been developed and applied for solving various construction project scheduling problems since it was introduced. Chan et al. (1996) utilized GA for dealing with the resource scheduling problem in construction which encompasses considerations of both resource levelling and resource restriction [60]. Shadrokh and Kianfar (2007) proposed a resource investment problem in construction with the objective of minimizing the total resource cost and tardiness penalty and applied GA with a schedule generation scheme [32]. In their description of GA, each individual is constructed by the combination of two strings that represents the sequence of activities and the resource capacities respectively [32]. Chen and Weng (2009) introduced a two-phase GA to select the execution mode of each activity and generate a feasible schedule for a resource constrained construction project scheduling problem [61]. The two subsystems of the two-phase GA, namely time-cost trade-off subsystem and resource scheduling subsystem, deal with the cost minimization problem and resource allocation problem respectively [61]. In practical construction projects, uncertainty exists all the time and this would impede the implementation of traditional GA. Ke et al. (2009) adopted GA for solving two stochastic time-cost trade-off models for construction project scheduling problems with uncertainty, which were based on chance-constrained programming and dependent-chance programming respectively [62]. In both of their models, the duration of activity was defined as a stochastic parameter. Ke et al. (2009) integrated stochastic simulation and GA for solving this stochastic problem where stochastic simulation was used for estimating the functions of project cost and makespan [62]. Similarly, GA was implemented for solving uncertain project scheduling problem by Huang and Zhao (2014), while in their model, the risk of investment was considered [63]. In addition, reaching a balance between several criteria including time, cost and quality is another challenge for project manager. In this case, GA has also been utilized for resolving multi-objective construction scheduling problems. Proposed by Srinivas and Deb (1994), non-dominated sorting genetic algorithm (NSGA) has been developed for dealing with multi-objective optimization problems [64]. El-Rayes and Kandil (2005) applied the NSGA on a multi-objective model for the highway construction project scheduling problem with the objectives of minimizing the construction time and cost and maximizing its quality [65]. In 2002, Deb improved NSGA by introducing a new procedure of non-dominated sorting and the new algorithm is called as NSGA-II [66]. NSGA-II has been adopted for coping with various multi-objective project scheduling problems, such as finance-based construction project scheduling problem [67] and multi-mode bi-objective construction project scheduling problem [68].

2.2 Ant Colony Optimization

Proposed by Dorigo in 1992, ant colony optimization (ACO) was inspired by the food searching behaviors of ant colonies [69]. During the process of foraging, ants would leave a chemical pheromone on their paths to mark their trace which would guide the selection of paths for the subsequent ants. Ants tend to follow the routes that have more pheromone and this tendency is normally represented as a probability that changes with the number of ants that have chosen the same route [70]. Consequently, with the paths are searched iteratively, the shortest paths would be marked with the most pheromone. According to Gendreau and potvin (2010) [71], the general procedure of ACO consists of three main stages. In the first phase, the parameters of ACO should be set and the initial pheromone of all paths are assigned to a value τ_0. The parameters of ACO normally include the parameter that controls the influence of pheromone trails (α), the parameter that controls the influence of heuristic values (β), and evaporation rate (ρ). After the initialization of ACO, a set of ant solutions need to be constructed. In the context of project scheduling problems, the solutions are mostly represented by a sequential list of activities. At each step of solution construction, the activity j is selected and placed at ith order in the list with a probability of p_{ij}. The ants that select the path (i, j) will then leave the corresponding pheromone τ_{ij} on their track. The probability of choosing path (i, j) is widely accepted as:

$$p_{ij} = \frac{(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}}{\sum(\tau_{ij})^{\alpha}(\eta_{ij})^{\beta}} \tag{2.1}$$

where η_{ij} stands for a heuristic information that is defined based on specific problems. For example, Zhang (2011) defined the minimum total slack time and the shortest feasible mode of execution as heuristic information in his proposed resource constrained project scheduling problem [70]. After the construction of solutions, the pheromone on each selected path should be updated according to:

$$\tau_{ij} = (1-\rho)\tau_{ij} + \Delta\tau_{ij} \tag{2.2}$$

where ρ represents the evaporation rate of pheromone deposited by previous ants over time. Practically, the consideration of pheromone evaporation could avoid the convergence of the algorithm being too fast [71]. $\Delta\tau_{ij}$ indicates the increment of pheromone on the selection of (i, j). The general procedure of ACO is illustrated in Algorithm 2.

Algorithm 2 Pseudo Code of ACO

Initialize parameters α, β, ρ and pheromone values
while termination condition not satisfied **do**
For $k = 1$ until the number of ants
Construction a solution based on the probability equation 2.1
Update local pheromone based on equation 2.2
End For
Update pheromone for global best solution
End while

ACO is a powerful mega-heuristic algorithm for solving combinational and practical optimization problems due to its attributes of versatility and problem dependency. Up to date, ACO has been adopted to deal with various project scheduling problems. Zhou et al. (2009) applied ACO for solving classic resource constrained project scheduling problems and defined the heuristic information based on the priority rule [72]. Chen et al. (2010) integrated ACO with serial schedule generation scheme (SSGS) for dealing with the construction scheduling problem that takes indirect costs and a bonus-penalty mechanism into consideration [73]. In their work, the performance of eight different heuristics that included two precedence-relation-based heuristics, two time-based heuristic, two cost-based-heuristics and one hybrid heuristic were tested and compared [73]. Huang et al. (2015) discussed the applications of ACO in single resource projects and multiple resource projects [74]. Except for deterministic problems, ACO has also been implemented for tackling problems with uncertainties. Abdallah et al. (2009) developed a ant colony system (ACS) for resolving probabilistic critical path method (CPM) network with fuzzy activity durations for a complex construction project [75], and Huang et al. (2010) modified the definition of pheromone by taking both transportation cost and stockout cost into consideration for coping with the scheduling problem with uncertain demand [76]. In terms of multi-objective problems, Ng and Zhang (2008) optimized a time-cost trade-off problem in construction project scheduling by using ACO [77]. The modified adaptive weight approach was used to transfer the multi-objective problem into a single objective one and a local updating rule and a global updating rule were proposed in their ACO [77]. A non-dominated archiving ant colony algorithm (NA-ACO) was proposed by Kalhor et al. (2011) for solving stochastic time-cost trade-off problems under uncertain activity durations and costs [78]. Their bi-objective model was constructed based on fuzzy sets theory and two colonies which considered the minimization of project's fuzzy cost and the minimization of the project's fuzzy time were comprised [78].

2.3 Particle Swarm Optimization

Particle swarm optimization (PSO) is a global search based optimization algorithm that is inspired by the social behavior of swarms such as bird flocking and bees buzzing [79] [80]. PSO searches the best solutions through iteratively updating the movement of each particle based on its previous local best and global best positions [80]. Each particle posses two key attributes including its position and velocity that adjust the movement of particle towards the best solution. The detailed procedure of PSO is introduced in Chapter 4. Because of the simplicity of implementation and effectiveness in convergence, PSO has become popular for being applied in solving optimization problems including construction project scheduling problems [79]. Guo et al. (2010) modified the conventional PSO by merging a crossover operator and applied the algorithm for optimizing the schedule of a coal mine construction [81]. A justification PSO was proposed by Chen (2011) for dealing with the RCPSP and a mapping scheme which adjusts the position of a particle was designed to improve the efficiency of algorithm [82]. Xu and Feng (2014) presented a priority based PSO which combines the priority representation of particle positions and a schedule generation scheme for a large scare construction project scheduling [83]. Moreover, PSO has been frequently applied for multi-objective problems. Zhang and Li (2010) developed a Pareto-oriented PSO that combined a scheme for determining the best solution from a Pareto front for a construction project scheduling problem with objectives of minimization of time and cost [84]. A hybrid GA-PSO algorithm was introduced by Ashuri and Tavakolan (2011) for tackling a time-cost-resource trade-off problem in construction project planning under a uncertain environment [85].

2.4 Other Meta-heuristics

Apart from the aforementioned algorithms, many other meta-heuristics have been developed and applied for solving project scheduling problems in construction. Simulated annealing (SA) is a probabilistic heuristic algorithm that approximates the global optimum in a given search space [86]. Yannibelli and Amandi (2013) integrated SA algorithm into the framework of an evolutionary-based searching algorithm in order to solve the time-resource trade-off problem in construction planning [87]. In order to overcome the low search efficiency of SA, Bettemir and Sonmez (2014) hybridized SA with GA for coping with the RCPSP and the computational results indicated that the hybrid algorithm outperformed the sole meta-heuristic [88]. Similar to SA, tabu search (TS) is a single-solution-based meta-heuristic for global optimization, and its performance is largely dependent on the quality of initial solutions [80]. Skowronski et al. (2013) adopted two modified TS algorithms with different neighbourhood generation methods for solving a project scheduling problems that considered the constraints of workforce with various skills [89]. The results illustrated that swap-based neighbourhood method could provide better solutions in makespan minimization while random-based neighbourhood method could be more effective in cost optimization [89]. With more research has been conducted in meta-heuristics, there are other algorithms lately developed, such as shuffled frog-leaping algorithm (SFLA) [90], firefly algorithm (FA) [91] [92], harmony search (HS) [93] and bee algorithm (BA) [94]. In the following chapters, various meta-heuristics are selected to optimize the proposed construction supply chain under different scenarios.

2.5 Comprehensive Summary

Table 2.1 summarizes the meta-heuristic algorithms that are applied in the above-mentioned papers. These papers are classified by the types of problems they are dealing with and the meta-heuristic algorithms they developed. There are three main types of project scheduling problems studied in the previous research, namely, single objective problem, multiple objective problem and uncertainty problem. These research provide a great deal of background knowledge for project scheduling problems and meta-heuristic algorithms which are beneficial to the study of this thesis. However, this thesis exhibits its improvement and contribution on the research of supply chain optimization and project scheduling from the following aspects. Firstly, most of the papers I have studied focus on the single objective problem with the objective of minimizing the duration or the cost. However, in reality, the criteria for evaluating the performance of a project are varied and many. As we can observe from Table 2.1, some papers have proposed the multi-objective models to solve time-cost trade-off problems [68] [85]. Nevertheless, workforce utilization is always ignored by these studies. Construction is a labour intensive industry where workforce management is vital. The inappropriate and inefficient workforce scheduling and planning would result in the workforce idling and waste in resources. Therefore, in this thesis, workforce utilization rate will be considered as one of the objectives when resolving the multi-objective optimization for construction supply chain. Secondly, the durations of activities can not be precisely estimated beforehand due to the complexity and uncertainty of projects. Hence, in this thesis, the stochastic activity duration is considered when dealing with the stochastic construction supply chain optimization. Thirdly, few studies have ever conducted regarding to the management of scaffolding activities, even though it is well-known that scaffolding is very important for the safety of a construction project. In order to close this gap, in this thesis, scaffolding construction cases are conducted for evaluating our proposed mathematical models. In a nutshell, this thesis is a comprehensive and systematic study for construction supply chain optimization problems under different scenarios.

Table 2.1: Meta-heuristics for CPS

Meta-heuristic	References	Single-objective	Multi-objective	Uncertainty
GA	Chan *et al.*(1996)	Y	\	\
	Shadrokh & Kiafarn (2007)	Y	\	\
	Chen & Weng (2009)	Y	\	\
	Ke *et al.*(2009)	Y	\	Stochastic Programming
	Huang & Zhao (2014)	Y	\	Stochastic Programming
	El-Rayes & Kandil (2005)	\	Y	\
	Fathi & Afshar (2010)	\	Y	\
	Vanucci *et al.*(2012)	\	Y	\
ACO	Zhou *et al.*(2009)	Y	\	\
	Chen *et al.*(2010)	Y	\	\
	Zhang (2011)	Y	\	\
	Huang *et al.*(2015)	Y	\	\
	Abdallah *et al.*(2009)	Y	\	Fuzzy Sets
	Huang *et al.*(2010)	Y	\	Stochastic Programming
	Ng & Zhang (2008)	\	Y	\
	Kalhor *et al.*(2011)	\	Y	Stochastic Programming
PSO	Pandey *et al.*(2010)	Y	\	\
	Guo *et al.*(2010)	Y	\	\
	Chen (2011)	Y	\	\
	Xu & Feng (2014)	Y	\	\
	Zhang & Li (2010)	Y	\	\
	Ashuri & Tavakolan (2011)	\	Y	Fuzzy Sets
SA	Damodaran & Velez-Gallego (2012)	Y	\	\
	Yannibelli & Amandi (2013)	Y	\	\
	Bettemir & Sonmez (2014)	Y	\	\
TS	Skowronski *et al.*(2013)	Y	\	\
SFLA	Fang & Wang (2012)	Y	\	\
FA	Rizk-Allah *et al.*(2013)	Y	\	\
HS	Pan *et al.*(2011)	Y	\	\
BA	Ziarati *et al.*(2011)	Y	\	\

CHAPTER 3

DETERMINISTIC CONSTRUCTION SUPPLY CHAIN OPTIMIZATION

3.1 Introduction

One of the main contributors for inefficiency and budget overrun of construction industry is the unappropriate management of construction material, workforce and other resources including heavy equipment. Hence, a lot of attention has been aroused for the construction supply chain optimization (CSCO). According to Vrijhoef and Koskela (2000), the goal of construction supply chain management is to reduce the total cost of construction project and duration of activities by ensuring the sufficient material supply and appropriate workforce arrangement [22]. However, the management on material flow and workforce deployment is affected and even determined by the project scheduling to a great extent because the demand of materials and workers during a specific time period would vary due to different project schedules. Thereby, the construction supply chain is dependent and interrelated with project scheduling.

In this chapter, a general scenario of the supply chain for a construction project is described. The construction supply chain (CSC) integrates the flow of materials, money and information in the process of a construction project [95]. It is a temporary and make-to-order supply chain that intends to direct all required materials to various locations inside the construction site [22]. Generally, a CSC involves many participants that provide different construction services, especially for a mega project, and it is formed based on the selection of material and equipment suppliers, management contractors and subcontractors through tendering phase organized by project developers [1]. Figure 3.1 indicates the roadmap of a general construction supply chain including material flow and information flow. As indicated by this roadmap, there are four key stakeholders involved in the CSC, namely project developers, management contractors, subcontractors and material suppliers. To launch a major construction project, the project developers would normally cooperate with large engineering management or consulting companies. These engineering companies would take the responsibilities of planning and managing the project process and monitoring and controlling the budget of project. The developers and management contractors would also divide the whole project into many small parts and choose specific subcontractors as well as material suppliers to take over these tasks through tendering process. In most cases, suppliers would use their own logistics for supplying their products to site which hinders the integration of construction supply chain as a whole. However, the basic elements and flows that form a general construction supply chain are similar. In terms of material flow, construction materials and equipment are transported from corresponding suppliers to the construction site. These resources would normally be stored in a on-site distribution centre or a temporary warehouse. The workers from subcontractors would then retrieve the materials they need from the warehouse and deliver the materials to the workfront area for construction tasks. From the perspective of information flow, subcontractors would be responsible for construction project design and scheduling under the supervision of management contractors and project developers. During the process of scheduling, project managers from subcontractors would take various factors and requirements into consideration, such as cost budget, resource limitations and due dates. Based on the schedule, the subcontractors would then send their material requests to the suppliers and the suppliers would response accordingly.

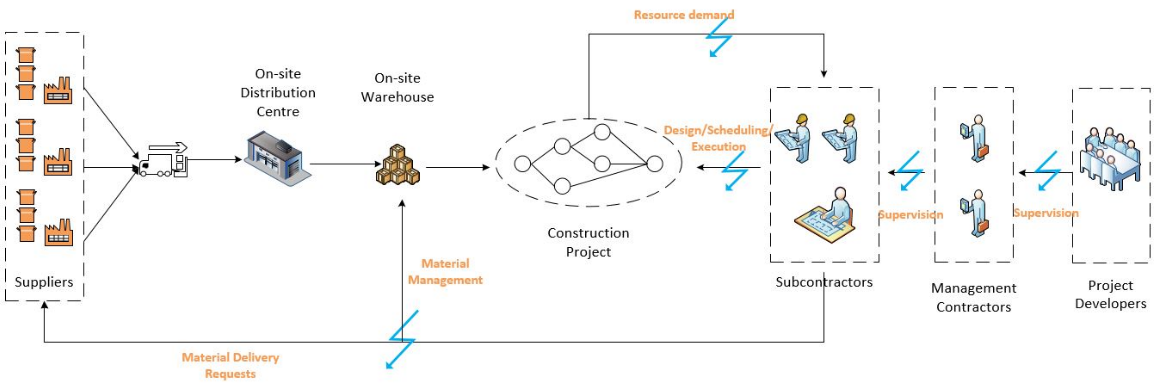

Figure 3.1: Roadmap of a General CSC

On the basis of the scenario of CSC described above, in this chapter, a deterministic mathematical model of construction supply chain optimization problem (DCSCOP) based on the RCPSP is constructed . The aim of DCSCOP is to minimize the total cost related to CSC which includedes material handling cost and labour cost. A modified genetic algorithm based on a permutation-based encoding method is introduced and proposed, and a new fitness function is adopted. The DCSCOP discussed in this chapter lays the foundation for the studies of more complex construction supply chain optimization problems in the following chapters. The reminder of this paper is organized as follows: in Section 3.2, previous studies about construction project scheduling, especially resource constrained project scheduling, and applications of genetic algorithm (GA) are introduced. Section 3.3 presents the formulation of mathematical model for DCSCOP and Section 3.4 illustrated the detailed procedure of our proposed GA. In Section 3.5, our model and algorithm are testified on a real world construction projet and the results are discussed. In Section 3.6, the conclusion of this chapter is indicated.

3.2 Literature Review

Composed of labour intensive operations, construction projects are characterized by their complexity and difficulties in management [3]. While planning the schedule of construction projects, various considerations including working conditions, workforce availability and equipment allocation should be deliberated. As I know, time and cost are the two most critical criteria for evaluating the performance of a project execution and therefore have a significant impact on the decision making for project management. Shorter duration and less expenditure enable the project developers to increase their return on capital and the contractors to gain more profit and avoid the risk of inflation [25]. Therefore, contractors always strive to beat the deadline of project completion and endeavor to crash a project's duration. However, as a consequence, more resources are expected to allocate which could lead to a rise in the total expenditure on project. Hence, the trade-off between time and cost is one of the main challenges for project managers when they encounter the problem of resource constrained project scheduling (RCPSP) for a complex project. Generally, RCPSP aims to generate an optimal schedule for project activities with the objective of minimizing the makespan of whole project, and simultaneously satisfying the precedence relationship between activities and the resource constraints [96]. The precedence relation between activities refers to the sequential order of executing activities or operations. For example, if activity A is a predecessor of activity B, then B can only be conducted after A is completed. Resource availability is another factor that a project manager would encounter in a project, especially for scarce resources such as workers with special skills. On most occasions, the objective of project scheduling is set up based on the priority between makespan and expenditure perceived by the project managers. The general mathematical model of RCPSP can be represented as follow. The objective function is to minimize the total duration of project while equation 3.2 and 3.3 represent the resources constraint and precedence constraint respectively. In this model, r_k^t is the consumption of type k resource at time t while U_k is the maximum usage of resource k. S_i and d_i stand for the starting time and duration of activity i and activity i and j comply the precedence relations denoted by $\mathscr{V}$ which indicated that activity j must start after the completion of activity i.

$$min \;\; f = S_{I+1} \tag{3.1}$$

subject to

$$r_k^t \leq U_k \tag{3.2}$$

$$S_j \geq S_i + d_i, (i, j) \in \mathscr{V} \tag{3.3}$$

As discussed earlier in Chapter 1, one of the most adopted objectives of RCPSP is minimizing the total makespan of the project and the total makespan is normally represented as the starting time of the dummy node $I+1$ as shown in equation 3.1, and this formulation has been widely adopted in many research such as [26], [27] and [28]. Cost-based objectives are also set for dealing with RCPSP, for example, minimization of net present value [31], minimization of total operational costs [25] and minimization of total late penalty [32]. Following Alcaraz et al.(2003) [97], RCPSP is a strong NP-hard problem which is very complicated to be solved. Exact methods for enumerating the schedules such as the precedence tree [98] and exact branch and bound [99] [100] have been proposed and successfully applied for solving RCPSP. However, these exact algorithms are unable to find optimal solutions for a large-sized problem. In this case, meta-heuristic algorithms have been developed and applied for achieving optimal solutions for complex RCPSP within a predefined maximum number of iterations or a limitation of computational time [90]. Genetic algorithm (GA) is one of the most widely studied and used meta-heuristic algorithms. Goncalves et al.(2008) [101] presented a genetic algorithm for an extended version of RCPSP which considered a new project performance measurement. In his GA, a random key alphabet composed by a series of number within the range of $[0, 1]$ was used for chromosome representation and a parameterized active schedule generation procedure was introduced [101]. Wuliang and Chengen (2009) [102] modified the traditional genetic algorithm by proposing a priority based encoding method and applied their GA for solving RCPSP with objective of minimizing the total project cost. In order to improve the efficiency of solution searching, Proon and Jin (2011) [103] incorporated GA with a neighbourhood search strategy which improves the feasibility of solutions by adjusting the scheduling of some activities. A GA was applied for optimizing the construction project scheduling by Faghihi et al.(2014) which is similar to our scenario in this chapter. There are also other meta-heuristic algorithms that have been studied and used for solving various RCPSP over last few years, such as simulated annealing (SA) [104], particle swarm optimization (PSO) [105] and tabu search (TS) [89].

3.3 Problem Mathematical Formulation

In our proposed DCSCOP problem, a construction project that consists of a series of activities is considered and each activity is conducted without interruption. Assuming that activities are represented by a set $\mathscr{I} = \{1, 2, ...i, ..I\}$, where i stands for activity i. For any activity i, there is a set of predecessor activities which have a higher priority for scheduling. The precedence relations among these activities are presented by an activity-on-node network. In our instance, I define that set $\mathscr{V}$ indicates the immediate precedence relations between activities (i, j) where $(i, j) \in \mathscr{V}$ means that activity j must start after the completion of i. The duration of each activity, denoted by ε_i, is given with a known value. There are m types of materials required for this construction project, and the demand of each type material for activity i, d_i^m is estimated at the design phase of project as well as the workforce requirement for each activity, u_i. The objective of our model is to minimize the total cost involved in the construction supply chain management which mainly includes the material life cycle management cost and total labour cost. The material life cycle management cost denotes the general cost in relation to construction material management including material purchasing or leasing cost, inventory holding cost, material transportation cost and material maintenance cost. It is worth mentioning that material maintenance cost would occur even when the materials have been used for construction as protections and maintenance are still necessary until the construction project is completed. Besides, these costs are normally spent at different phases of a construction project. For the purpose of generalization, in our model, a unit cost of material life cycle management l_m is defined. The project is assumed to be scheduled on a discrete time horizon where t is an integer parameter. Hereby, the scheduling of activities on a discrete time line is actually the time allocation process for each activity with the premise that there is no interruption within the procedure of conducting each activity. Therefore, the decision variable for project scheduling in our proposed model is set as a binary variable x_i^t. When $x_i^t = 1$, it indicates that activity i is selected for execution at time t, otherwise, $x_i^t = 0$. Another decision variable that determines the material ordering plan is defined as the quantity of each type material delivered to the site at time t, represented as p_m^t. The other notations including sets and indices, parameters and decision variables used in our mathematical model are shown in Table 3.1.

According to the assumptions and notations described above, the mathematical model for DCSCOP is formulated as a mixed integer programming model as follow:

$$min \;\; C_{Total} = \sum_{m=1}^{M}\sum_{t=1}^{T}(T-t+1)p_m^t l_m + \sum_{t=1}^{T}\sum_{i=1}^{I} u_i x_i^t \gamma \tag{3.4}$$

Subject to

$$S_j \geq S_i + \varepsilon_i, \forall (i,j) \in \mathscr{V} \tag{3.5}$$

$$C_i \geq x_i^t * t, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} \tag{3.6}$$

$$\sum_{i=1}^{I} u_i x_i^t \leq U, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} \tag{3.7}$$

$$\sum_{t=1}^{T} x_i^t = \varepsilon_i, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} \tag{3.8}$$

Table 3.1: Notations for Mathematical Model

Sets and indices:	
$\mathscr{I} = \{1, \cdots, I\}$	set of all project activities indexed by i, j.
$\mathscr{V} \subseteq \mathscr{I}^2$	Immediate precedence relations among project activities, where $(i, j) \in \mathscr{V}$ indicates activity j must start after activity i's completion.
$\mathscr{M} = \{1, \cdots, M\}$	set of material types indexed by m.
$\mathscr{T} = \{1, \cdots, T\}$	set of discrete time slots indexed by t which represents time interval $[t-1, t)$.
Parameters:	
d_i^m	demand of material m for activity i
ε_i	duration of activity i.
u_i	workforce required for activity i.
l_m	material life cycle management cost per unit time per unit of material type m.
γ	labour cost per unit time per person.
U	Maximum available workforce at any time of the project.
Variables:	
S_i	start time of activity i.
C_i	completion time of activity i.
P_m^t	quantity of material m delivered at time t.
$x_i \in \{0, 1\}$	$x_i = 1$, if activity i is executed at time t; otherwise, $x_i = 0$.

$$\sum_{t=1}^{T} p_m^t = \sum_{i}^{m} d_i^m, \forall i \in \mathscr{I}, \forall m \in \mathscr{M} \tag{3.9}$$

$$x_i^t \in \{0, 1\}, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} \tag{3.10}$$

$$p_m^t = \sum_{i=1}^{I} (d_i^m / \varepsilon_i) x_i^t, \forall i \in \mathscr{I}, \forall t \in \mathscr{T} \tag{3.11}$$

$$s_i \geq 0, c_i \geq 0, \forall i \in \mathscr{I} \tag{3.12}$$

The objective function 3.4 aims to minimize the project operational cost which in this case comprises the total material handling cost and total labour cost. The material handling cost is charged for all materials delivered on site per unit quantity per unit time. For example, when the time horizon $T = 4$, the total cost for type m material over this discrete time period would be $\{4p_m^1 + 3p_m^2 + 2p_m^3 + p_m^4\}l_m$. Constraints 3.5 and 3.6 shows that the precedence relations among all activities should be satisfied. If activity i is the predecessor of activity j, the starting time of activity j should be greater than the completion time of activity i. Constraint 3.7 defines that the total number of active workers working on site at any time of project should not exceed the limitation of maximum number of workforce U. Constraint 3.8 ensures that the execution of any activity is continuous and every activity is selected while constraint 3.9 makes sure that the demand of materials is fulfilled. Constraints 3.10, 3.11 and 3.12 are intrinsic variable constraints. According to constraint 3.11, the materials are assumed to be delivered at the end of every unit time t and the amount of delivery equals to the total demand over that period.

3.4 Genetic Algorithm Implementation

Genetic Algorithm (GA) is one of the most widely applied meta-heuristic algorithms and has been proven to be effective for solving complex optimization problems by obtaining optimal or sub-optimal solutions [106]. According to Deb et al. (2000) and Detta et al. (2011), the searching mechanism of GA is inspired by Darwinian Evolution theory which states the concept of survival of fittest [107] [108]. Generally, a GA starts with a randomly generated population which consists of N individuals or chromosomes. An individual or a chromosome in the GA represents a solution for the optimization problem. The initial population evolves by applying the selection operator and genetic operators including cross-over operator and mutation operator over a predefined iterations until better solutions are achieved. The selection operator selects the individuals with better fitness for the further genetic operations. The fitness of an individual is evaluated through calculating the value of a objective function. After the operations of cross-over and mutation, an offspring population that inherits the genes from its parental population is generated. By repeating this evolutionary process, the population with the optimal objective value is expected to be obtained. In this section, a modified genetic algorithm is proposed for resolving CSCCOP problem. A sequence-based representation for chromosome is introduced and the detailed procedure of algorithm which includes algorithm initialization, fitness evaluation, cross-over and mutation operations is presented as follow.

3.4.1 Solution Encoding

In GA, the way how solutions are represented has a significant impact on the performance of the algorithm [97]. In our proposed DCSCOP problem, even though the objective aims to minimize the total expenditure on material handing and workforce, the schedule of the project is actually the determinant. Therefore, every individual or chromosome in the GA should represent a feasible schedule. In this section, a permutation-based encoding method which translates each individual as a priority list of activities is adopted. The permutation-based encoding is widely used for project scheduling problems. For example, Paraskevopoulos (2012) [109] and

Bettemir (2014) [88] solved the multi-mode resource constrained project scheduling problem by representing the project schedule as a two-row activity list in which the first row indicates the order of activities while the other row stands for their corresponding mode selections. In our CSCOP problem, as the single mode situation is considered, hereby, the solution is encoded as an priority list of activity $\lambda = \{j_1, j_2, ..., j_n, ..., j_N\}$ where $j_n \in \{1,2,3,...,i,...,I\}$ and $|N| = |I|$. For example, a individual $\{2,6,3,5,1,4\}$ represents the ordering of 6 activities in which activity 2 should start first while activity 4 is the last one to be executed.

Due to the restriction of activity precedence relations and resource constraints, the randomly generated individuals might be infeasible. Therefore, with the method of individual representation determined, a schedule generation scheme (SGS) for initializing a feasible individual should be developed and applied. In the proposed DCSCOP problem, the precedence relations among activities is presented in the form of an activity-on-node network, as shown by the example in Figure 3.2. The activities are represented by the nodes while the arrows stand for the sequence of activity execution. For example, activity 4 can not start if activity 2 has not completed and activity 5 has the same level of priority with activity 6. The numbers in the boxes indicate the duration and workforce demand for each activity from left to right respectively. In this section, the activity network is encoded into two lists, namely an available activity list AAL and a predecessor list of activity i, PL_i. The available activity list is initialized as $AAL = \{0,1,2,...,i,...,I,I+1\}$ which contains all available activities that can be chosen for scheduling. Activity 0 and $I+1$ are two dummy nodes which indicate starting and finishing of project respectively. AAL would update with the process of scheduling by excluding the selected activities. The predecessor list PL_i consists of the immediate predecessors of activity i which would update after each selection as well. Activity i would be available for selection only when all its immediate predecessors are selected, in this case, $PL_i = \emptyset$. For dummy activity 0 and $I+1$, the respective predecessor lists are $PL_0 = \emptyset$ and $PL_{I+1} = \{0,1,2,...,i,...,I\}$.

During the process of schedule generation, an activity should be selected and executed at its earliest starting time with respecting to the precedence relations and workforce constrains in our proposed CSCOP problem. The detailed procedure of SGS is described as follow:

1. Step 1: Assign the first element of priority list with dummy node 0 with starting time and completion time equal to 0, denoted by $j_1 = 0$ and $S_0 = 0$. Initialize the $\lambda = \{0\}$ ($j_0 = 0$), $AAL = \{1,2,...,i,...,I,I+1\}$ and PL.

2. Step 2: For $n = 1$, starting from activity 1 in AAL, search for the activity i with $PL_i = \emptyset$ and assign the first found activity to j_1, calculate the starting time S_{j_1}, completion time $C_{j_1} = S_{j_1} + \varepsilon_{j_1}$ and the residual workforce for time interval [0, C_{j_1}]: $R(t) = U - u_{j_1}$.

3. Step 3:For $n \geq 2$, starting from the first element i in AAL, evaluate predecessor list of i, PL_i; If $PL_i = \emptyset$, then goes to Step 4; Otherwise, repeat Step 3 for activity $i+1$.

4. Step 4: Calculate the early start time of activity i, $S_i = maxC_j; j \in PL_i$; evaluate the work-

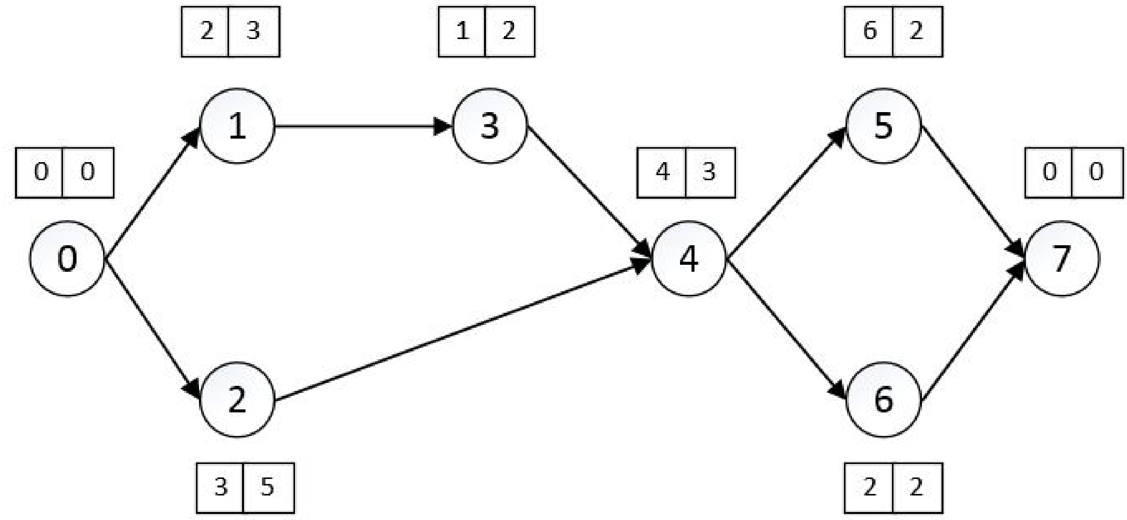

Figure 3.2: Example of an Activity-on-node Network

force availability by comparing $R(S_i)$ with u_i, if $R(S_i) \geq u_i$, then assign activity i to element j_n and update S_{j_n}, C_{j_n}, $R(t)$, AAL, PL and λ ; otherwise update start time of activity by adding one unit time: $S_i = S_i + 1$ and repeat Step 4.

5. Step 5: Repeat Step 3 and Step 4 until $AAL = \emptyset$, record the starting time and completion time for each j_n.

In order to illustrate the procedure of SGS, an example of generating a feasible individual is presented. According to the activity network shown in Figure 3.2, the $AAL = \{0,1,2,3,4,5,6,7\}$ in which activity 0 and 7 are dummy nodes and the maximum number of workers is set as 8. At the beginning, activity 0 is assigned to the first element in the priority list, hereby I have $\lambda = \{0\}$ and $AAL = \{1,2,3,4,5,6,7\}$. Then, I check the feasibility of activity 1 through Step 3 and Step 4. As $PL_1 = \emptyset$ and the workforce demand of activity 1 is less than 3, therefore, activity 1 is selected. By selecting the activity 1, the available activity list is updated as $AAL = \{2,3,4,5,6,7\}$ and the priority list is updated as $\lambda = \{0,1\}$. The residual workforce is calculated as $R(t) = U - u_1 = 8 - 3 = 5$ where $t \in [0,2]$. Activity 2 is the next one with its predecessor list empty and its workforce demand less than $R(t)$, hence, activity 2 is selected with starting time $S_2 = 0$ and $C_2 = 3$. Similarly, I repeat the step 3 and 4 for the rest of activities and I can have the final priority list of the example. The schedule of this example is presented in Figure 3.3 which indicates the starting time of each activity.

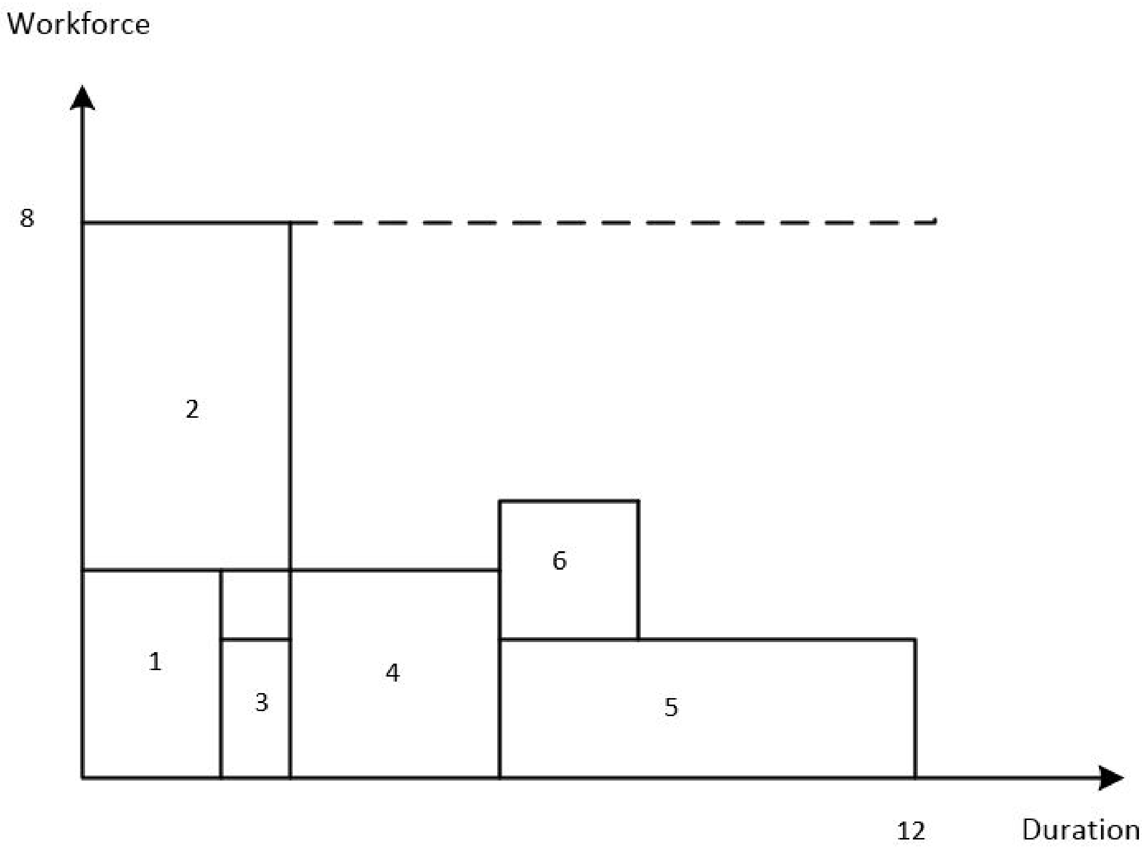

Figure 3.3: A Feasible Schedule of the Example

3.4.2 Initialization

Generally, in the phase of initialization, there are two tasks that need to be taken into consideration. First of all, before running the GA algorithm, various parameters including model parameters and algorithm parameters are required to be defined. Typically, the model parameters normally include the number of constraints and number of decision variables while the GA parameters would consist of the size of population, maximum number of iteration, cross-over rate and mutation rate. Secondly, initial population is expected to generate. According to Ahn and Ramakrishana (2002), two approaches are usually adopted for population initialization, namely random initialization and heuristic initialization [110]. Obviously, the individuals generated by random initialization might be infeasible which consequently increases the complexity of computation. As described in Section 4.1, the SGS performs as a way of heuristic initialization to generate a feasible initial population and helps to converge to the optimal solution more easily due to the high fitness for feasible individuals.

3.4.3 Fitness Evaluation and Selection

With the initial population generated, the performance and quality of each individual should be evaluated through computing its corresponding fitness value. Hereby, the fitness function is introduced for fitness computation. In our proposed DCSCOP problem, the fitness value can obviously represented by the total project operational cost which comprises material handling cost and labour cost. In order to formulate a fitness function that accords with the objective function of the mathematical model and the representation form of chromosome, I assume that the population of individuals is defined as $\mathscr{H} = \{1, 2, ..., h, ..., H\}$, and the hth individual is expressed as $\lambda_h = \{j_1^h, j_2^h, ..., j_N^h\}$. Let $\varphi_{j_n^h}^t$ denotes the execution status of activity j_n^h at time t. If $\varphi_{j_n^i}^t = 1$, then activity j_n^i is being executed at time t; otherwise, $\varphi_{j_n^i}^t = 0$. In this case, the fitness function is formulated as below:

$$f(h) = -C_{Total}(h) = -\{\sum_{m=1}^{M} \sum_{t=1}^{S_{j_{N+1}^h}} \sum_{n=1}^{N} d_{j_n^h} \varphi_{j_n^h}^t l_m + \sum_{t=1}^{S_{j_{N+1}^h}} \sum_{n=1}^{N} u_{j_n^h} \varphi_{j_n^h}^t \gamma\} \tag{3.13}$$

where $S_{j_{N+1}^h}$ denotes the finish time of hth individual and fitness function $f(h)$ gives the negative value of total project cost under the solution represented by hth individual. The individual with a higher fitness value is better performed than others, and the fitness value provides a criterion for parent individuals selection.

The selection operation is the process of selecting the individuals from the population for producing better offsprings through genetic operations. Generally, the selection operation determines the which individuals would be preserved and which ones would be eliminated in a population [111]. Several selection strategies have been developed and extensively used for GA. Roulette wheel selection is one of the most frequently adopted strategy of individual selection in GA which decides the probability of selecting a individual into offspring generation based on the proportion of the fitness values of this individual to the total fitness values of whole population [112]. Razali (2011) [113] introduced a linear ranking selection strategy which ranks the individuals according to their fitness values and allocates the selection probabilities linearly to these individuals. Similarly, exponential ranking selection is another method of ranking selection which differs with linear ranking on the calculation of selection probabilities [111]. Tournament selection strategy is a different selection scheme because it does not contain any arithmetical computation related to fitness values which significantly eliminates the disadvantages of proportionate selection strategies mentioned earlier [112]. The conceptual idea of tournament selection is to compare the fitness values of s randomly picked individuals from the population and select the one with better fitness value. The selected individual is then put into a mating pool for further operations. In this section, due to the high efficiency and low complexity of implementation, the binary tournament selection strategy with tournament size s equals to 2 is applied in our proposed GA.

3.4.4 Crossover and Mutation

Crossover operation is the process of generating feasible offspring individuals by exchanging and inheriting the genes from two parental individuals. In this operation, two parental individuals are chosen randomly with a probability of p_c from the mating pool generated from the selection operation. Here, p_c is the crossover rate. Subsequently, the characteristics from parental individuals are combined according to the mechanism of the designed crossover operator and a new offspring individual is produced resultantly. In this section, a one-point crossover described by Montoya-Torres et al. (2010) [114] and Sastry (2014) [115] is adopted. Firstly, two parental individuals $\lambda_a = \{j_1^a, j_2^a, ..., j_N^a\}$ and $\lambda_b = \{j_1^b, j_2^b, ..., j_N^b\}$ are selected randomly with a probability of p_c and an integer number q is selected randomly within the range $[1, N]$. The first q elements from parental individual λ_a are preserved in the offspring individual λ_c with their positions unchanged. As in the project scheduling problem, each activity can only be scheduled once. Therefore, the rest $N-q$ positions in λ_c can only simply inherit the last $N-q$ elements from individual λ_b. In order to ensure that the generated offspring individual is feasible, the last $N-q$ elements of λ_c is filled by the elements of λ_b excluding the q selected elements from λ_a, $\{j_1^a, j_2^a, ..., j_q^a\}$, with their corresponding positions unchanged. A simple example is presented for illustrating the procedure of crossover. Assuming that $\lambda_a = \{1,3,2,6,4,5,7\}$, $\lambda_b = \{2,4,1,7,6,3,5\}$ and $q = 3$, the generated offspring individual $\lambda_c = \{1,3,2,4,7,6,5\}$. As I can observe, the first 3 elements of λ_c is directly inherited from its parental individual λ_a. By eliminating the selected elements, the individual $\lambda_b = \{4,7,6,5\}$ and these elements are filled into the last 4 positions in λ_c with sustaining their original sequence.

Thereafter, mutation operation that alters one or more elements in the selected individuals is executed. The mutation operator could enhance the diversity of new generations and might create the schedules that could not be engendered by crossover [106]. The mechanism of mutation adopted in this section is elucidated as follow: for every elements in λ_c, two adjacent elements j_i^c and j_{i+1}^c exchange their positions with a probability of p_{mu} where p_{mu} is the mutation rate of GA. However, as I know, the resulting sequence might not comply to the precedence relations. Therefore, a checking procedure based on the SGS is required after each mutation operation. If the offspring individual violates the precedence constraints, the mutation operation would be repeated until a feasible individual is generated.

3.4.5 Termination Criteria

The GA algorithm terminates under different preset termination criteria which normally include the number of iterations, the pre-defined objective value and the optimal solutions are reached. The procedure of proposed GA algorithm is interpreted in Figure 3.4. The procedure starts from the initialization of parameters of the algorithm which include the size of population, maximum number of iteration, cross-over rate and mutation rate. The determination of these parameters can be changed based on different scenarios. The second phase is encoding and generating feasible individuals. The chromosome is encoded as a two-row activity list which represents the sequence of activities. The initial population will then be processed through GA operations including cross-over and mutation. During the process, the performance of individuals is evaluated through fitness function. When the termination criteria is reached, the circulation will stop and the best individuals will be selected. Otherwise, the circulation will keep going.

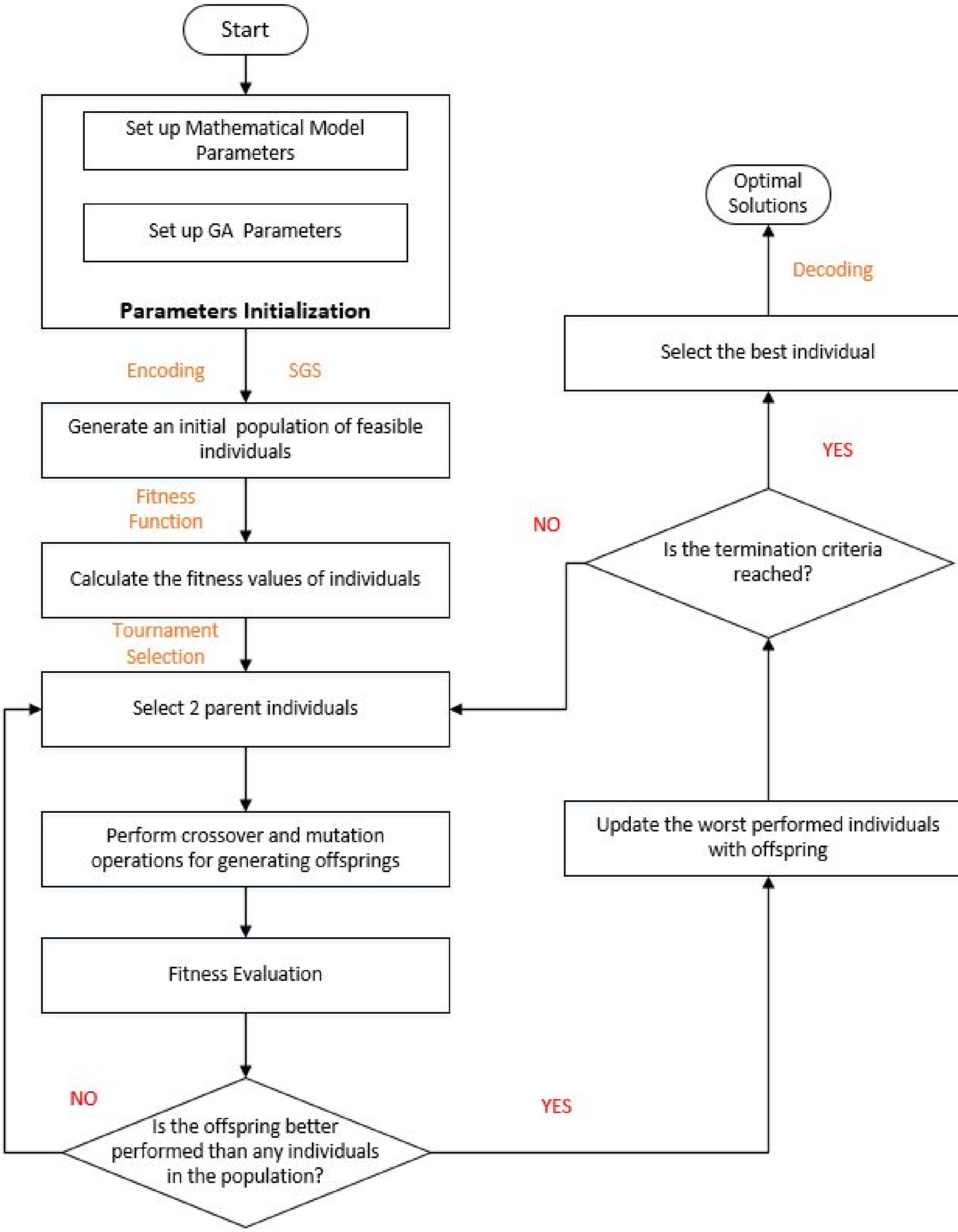

Figure 3.4: The Procedure of Proposed GA

3.5 Case Study

In this section, I validate the feasibility of our proposed genetic algorithm (GA) by solving a designed case study problem based on the practical scaffolding construction project. The proposed GA has been coded and complied in MATLAB R2015a on a computer under windows 7 system with Intel i5 CPU and 4GB RAM. First of all, the case study problem is described in detail in terms of the scenario of project and the corresponding data that is required for solving this problem. Secondly, the GA is applied for solving the case study problem and the optimal solution is presented. In addition, the influence of parameter U, the maximum number of workers, on the results of the case study problem is analyzed.

3.5.1 Case Study Description

Scaffolding is a temporary structure extensively applied in construction industry, which provides the platform for material placement and supports aerial construction activities [116]. As the scaffolding structures would not remain after the completion of a construction project, therefore, people held the belief that scaffolding is not as important as other construction resources. As a consequence, less attention has been given to the the supply chain cost optimization of scaffolding materials. However, due to the great amount of scaffold materials for a construction project, the impact of scaffolding supply chain management on the total cost of project is enormous. Hence, in our case study, I design a scenario of scaffolding supply chain cost optimization problem and implement our proposed GA to solve this problem thereafter. In our case study, a scaffolding construction project that consists of 15 activities is considered. The information in regard to the workforce demand, the planned duration and the demand of each category of scaffolding material for each activity is provided. Table 3.2 shows the workforce demand and duration for each activity while Table 3.3 indicates the demand of 6 categories of scaffolding material for each activity. The precedence relation among these activities is presented by an activity-on-node network as shown in Figure 3.5 and Table 3.4 displays the immediate predecessors for each activity. The maximum number of workers for project is set as 12 which means that the total number of active workers at any time during this project should less or equal to 12. The cost related to the management of scaffolding materials including material leasing cost, material handling cost and transportation cost is defined as 60 per ton per day and the labour cost is set as 80 per worker per day.

3.5.2 Computational Results

Before running our proposed genetic algorithm for solving the case study problem described above, parameters of the GA should be configured. The maximum number of iteration and population size is initiated as 100 respectively. The crossover rate p_c and mutation rate p_{mu} are set as 0.7 and 0.1. The optimal solution of the case study problem obtained through

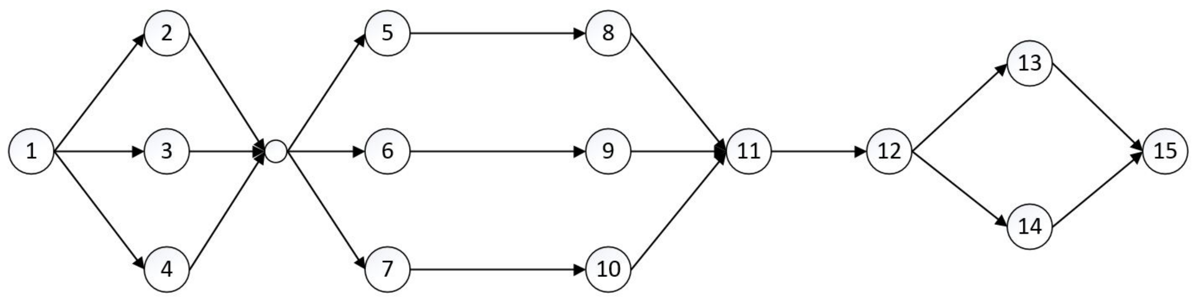

Figure 3.5: The Activity-on-node Network for Scaffolding Construction

Table 3.2: Workforce Demand and Duration for Each Activity

Activity	Workforce	Duration(day)
1	6	3
2	2	15
3	7	12
4	3	25
5	9	7
6	3	21
7	7	7
8	2	4
9	3	18
10	1	14
11	6	14
12	7	20
13	5	23
14	4	11
15	6	7

implementing our proposed GA indicates that the minimum scaffolding supply chain cost is $C_{Total} = 2.067 \times 10^6$ with the optimal scheduling of scaffolding activities represented by the priority list $\lambda = \{1,2,4,3,7,5,6,9,10,8,11,12,13,14,15\}$. The project schedule is decoded from the priority list λ based on the aforementioned SGS and the resulted optimal project schedule is presented by Figure 3.6. As we can observe from the Figure 3.6, activities are planned in a manner that no interruption occurs and the starting time of an activity equals to the latest completion time of its predecessors. The areas marked by yellow lines indicate that only activity 4 and activity 10 are being conducted during that periods due to the precedence constraints. Activities can be operated at the same time if they satisfy both precedence relations and the workforce constraint, for example, activity 2, 3 and 4 start at the same time and the workers arranged for these three activities equals to 12 at the peak time. The total duration of the scaf-

Table 3.3: Demand of Scaffolding Materials for Each Activity (Tonnage)

Activity	Tube	Board	Hyplank	Coupler	Hook	Fencing
1	1.02	2.21	4.22	1.28	3.07	2.91
2	2.71	4.35	1.32	1.59	0.59	4.69
3	3.22	2.39	3.19	2.72	3.23	2.72
4	2.61	3.61	4.97	1.09	0.53	0.55
5	0.38	2.23	2.24	1.82	3.82	3.14
6	3.86	4.66	4.86	0.96	0.69	3.48
7	0.47	2.62	2.65	4.31	2.42	1.97
8	3.36	3.71	2.6	1.74	0.75	2.93
9	1.32	0.22	3.77	1.21	2.12	3.44
10	1.79	3.68	1.97	3.42	3.52	2.21
11	0.97	1.65	2.12	1.35	0.98	4.11
12	2.14	4.43	1.95	3.84	1.98	4.04
13	3.77	1.88	1.08	3.95	4.75	1.63
14	3.36	2.2	4.17	3.84	0.84	4.31
15	4.95	2.57	4.42	2.94	0.77	0.99

folding construction is 138 days. The project duration might not be the shortest as the objective of our mathematical model prioritize the optimization of total cost of supply chain. However, in reality, a deadline of project is always preset due to the estimation on project scheduling.

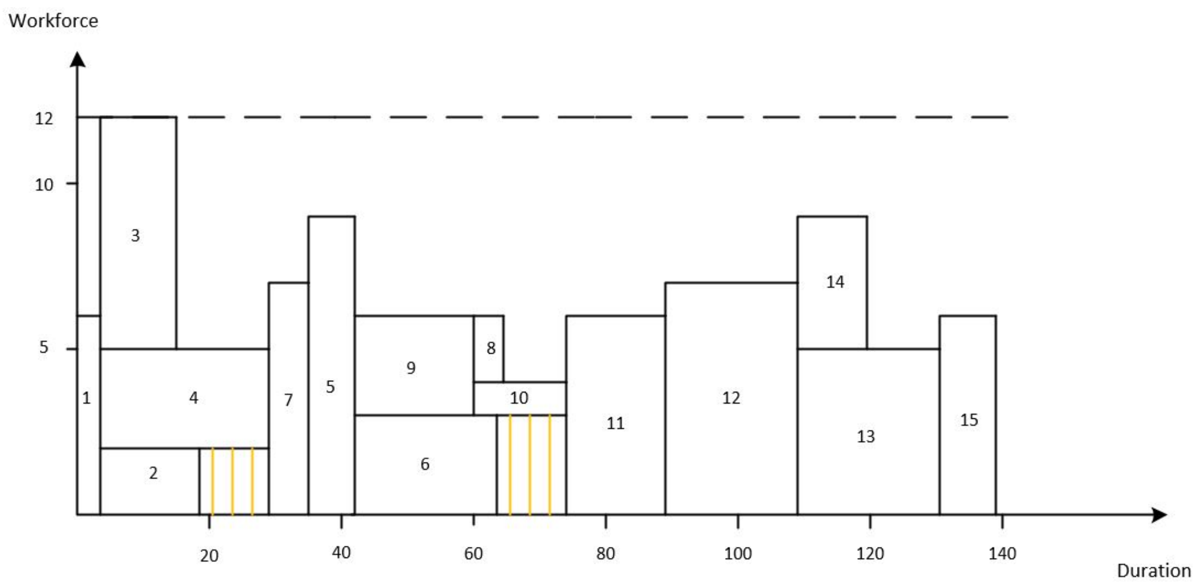

Figure 3.6: Optimal Project Schedule for the Case Study

Table 3.4: Immediate Predecessors for Each Activity

Activity	Immediate Predecessors
1	–
2	1
3	1
4	1
5	2,3,4
6	5
7	2,3,4
8	7
9	2,3,4
10	9
11	6,8,10
12	11
13	12
14	12
15	13,14

3.5.3 Algorithm Performance Analysis

There are many factors that would have an impact on the performance of the genetic algorithm including problem parameters such as maximum number of workers as well as algorithm parameters such as population size. Therefore, to analyze the influence of these parameters on our proposed GA, four experimental instances which consist of 15, 20, 25 and 30 activities respectively with randomized activity durations, workforce demands and material demands are designed and abbreviated as $J15$, $J20$, $J25$ and $J30$. The objective values under different maximum number of workers and different population size are calculated and compared. Table 3.5 shows the optimal cost for four instances with different value of workforce limitation U while Table 3.6 indicates the optimal cost under different population size of GA. By analyzing these results, I find that the total cost would decrease with the increment of the maximum number of workers and reach a lowest point when $U = 12 or 13$. After that, the cost would increase and tend to be stable when U is big enough. This comparison illustrates that when a restricted limitation of available workforce is imposed, that is when U is small, there is little flexibility for scheduling and activities would need to be planned one by one. As a consequence, the makespan of project would be extended and the cost would be high. The cost and the duration can both be reduced when the workforce constraint is getting loose, and there is an optimal value of U which makes the total cost minimum. However, when U is big enough, the workforce constraint would have no restriction or influence on the result of project scheduling and the total cost would stay unchanged. Nevertheless, in real world construction project, the maximum number of workers is normally represented by the budget of labour cost. Instead of being stable for the total cost, allocating excessive budget on labour usage would result in the high idling rate of workforce and contribute to the overall cost consequently. Therefore, it is important to estimate the accurate labour budget which could not only assist our proposed algorithm to produce a better solution but also prevent the budget overrun in a construction project. Table 3.6 gives the comparison between the objective values ($\times 10^6$) obtained by different population size of GA. It is clear that, in general, the total cost falls when the population size raises. Figure 3.7 and Figure 3.8 show the variation of total cost ($\times 10^6$) with different workforce limitation and population size respectively.

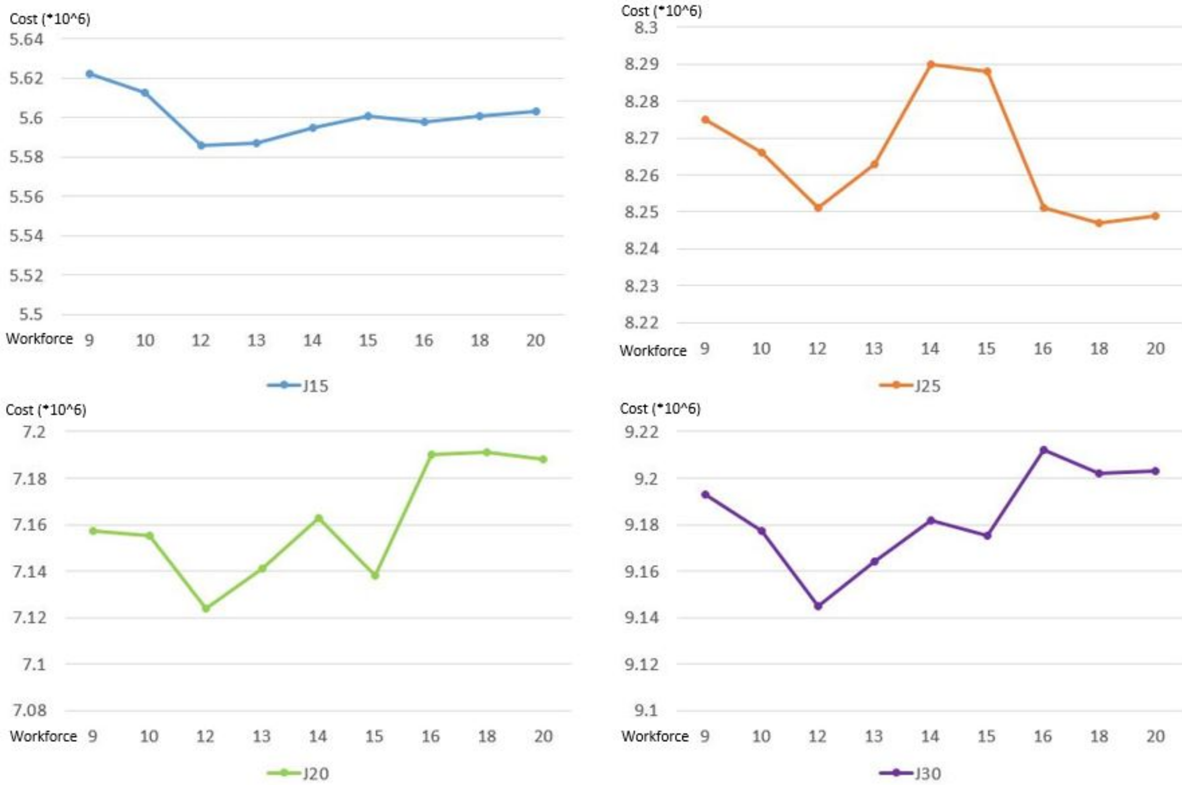

Figure 3.7: Results Comparison with Different Workforce Limitation

The performance of our proposed GA is compared with other meta-heuristic algorithms, which in this case, are ant colony optimization (ACO) presented by Zhang (2011) [70] and particle swarm optimization (PSO) introduced by Chen (2011) [82]. For GA, the crossover rate p_c and mutation rate p_{mu} are set as 0.7 and 0.1 and population size is 100. For the PSO algorithm, the cognitive parameter and social parameter are defined as $c_1 = c_2 = 1$, and the population size is set as 100. For the ACO algorithm, the parameter of pheromone trails (α), the parameter of heuristic values (β) and the evaporation rate (ρ) are defined as 1, 5 and 0.5 respectively. Table 3.7 lists the results of best objective value, standard deviation of objective values and computational time obtained by applying each algorithm to randomly generated instances with 30, 40, 50 and 60 activities. As I can observe, all these three algorithms lead to similar best objective values while ACO method has a lowest computational time and PSO has a

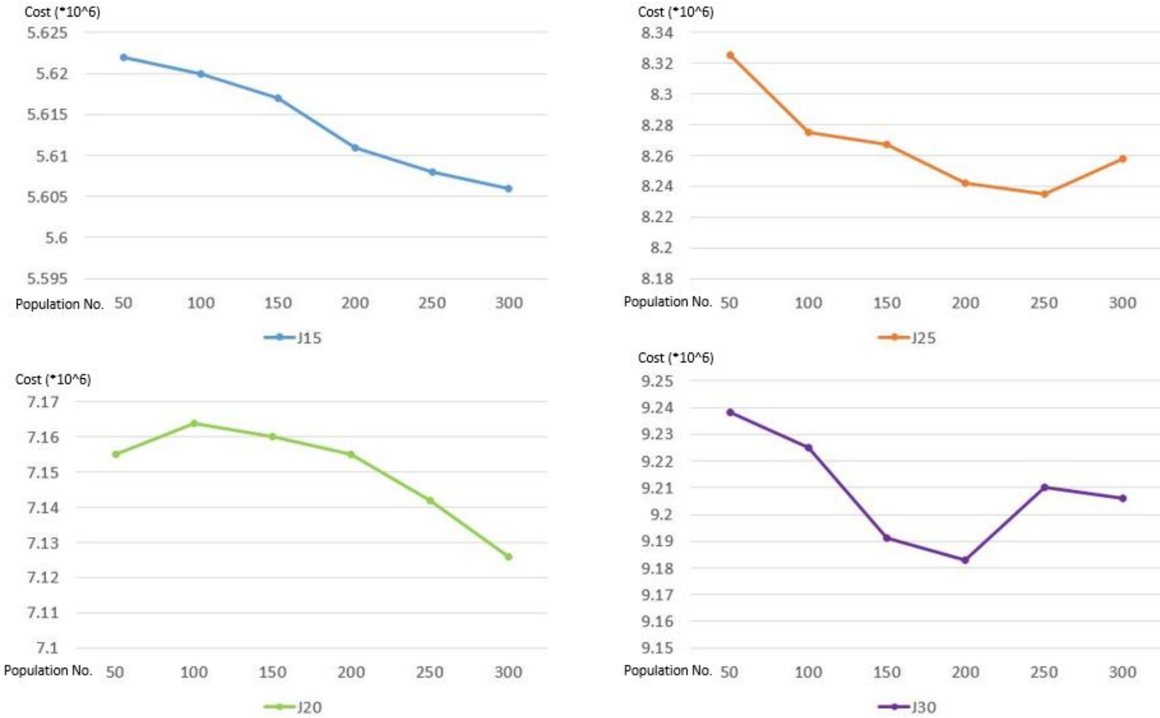

Figure 3.8: Results Comparison with Different Population Size

Table 3.5: Results of J15, J20, J25, J30 with different U

U	J15	J20	J25	J30
9	5.622	7.157	8.275	9.193
10	5.613	7.155	8.266	9.177
12	5.586	7.124	8.251	9.145
13	5.587	7.141	8.263	9.164
14	5.595	7.163	8.290	9.182
15	5.601	7.138	8.288	9.175
16	5.598	7.190	8.251	9.212
18	5.601	7.191	8.247	9.202
20	5.603	7.188	8.249	9.203

Table 3.6: Results of J15, J20, J25, J30 with different Population Size

Population Size	J15	J20	J25	J30
50	5.622	7.155	8.325	9.238
100	5.62	7.164	8.275	9.225
150	5.617	7.160	8.267	9.191
200	5.611	7.155	8.242	9.183
250	5.608	7.142	8.235	9.210
300	5.606	7.126	8.258	9.206

lowest standard deviation. The computational performance of our proposed GA stands between the other two algorithms. However, when dealing with deterministic construction supply chain optimization problems, GA has a clear and straight-forward representation of solutions, which is the sequence of activities. In addition, PSO and ACO are normally used for solving continuous problems, while in this chapter, the DCSCOP is formulated as a mix-integer problem. Therefore, even though GA does not outperformed PSO and ACO in terms of computational performance, it is more convenient to implement GA for solving the DCSCOP in a practical context.

Table 3.7: Comparison among GA, PSO and ACO Methods

	GA			PSO			ACO		
Instance	Best Obj (10^6)	Stad.Dev	CPU(s)	Best Obj (10^6)	Stad.Dev	CPU(s)	Best Obj (10^6)	Stad.Dev	CPU(s)
30	12.92	0.52	19.82	12.83	0.61	22.63	12.93	1.02	12.53
40	27.41	1.69	25.63	27.53	1.55	28.5	27.55	2.25	18.61
50	31.19	2.25	32.45	30.61	1.92	34.53	31.07	3.61	25.37
60	33.51	3.77	42.87	32.35	2.64	45.17	33.42	3.87	33.4

3.6 Conclusion

This chapter interprets the proposed deterministic construction supply chain optimization problem (DCSCOP) as an extended version of resource constrained project scheduling problem (R-CPSP), which aims to minimize the supply chain cost of a construction project with restrictions of activity precedence relation and available workforce. A mathematical model with a binary variable for DCSCOP is formulated and a genetic algorithm (GA) is developed for resolving this problem. In our GA, the solution is encoded as a priority list and a schedule generation scheme (SGS) is introduced for generating feasible individuals. A case study based on a scaffolding construction project is conducted for verifying the feasibility of the proposed mathematical model and genetic algorithm. The impact of different values of both problem parameters and algorithm parameters on the performance of GA is identified. Through analyzing the results of a comparison of four experimental instances, it can be demonstrated that the best configuration of maximum number of workforce, which is represented by the budget of labour cost in reality, could assist the project managers or planners to obtain a better project schedule. In addition, the performance of our proposed GA is compared with ACO and PSO. By running four groups of instances, the results indicate that GA shows a moderate performance while ACO performance better in terms of computational time and PSO has a lower standard deviation. Nevertheless, the implementation of GA is much easier to be achieved.

CHAPTER 4

BUDGET CONSTRAINED STOCHASTIC CONSTRUCTION SUPPLY CHAIN OPTIMIZATION WITH RENTAL RESOURCE SELECTION

4.1 Introduction

In Chapter 1, the construction supply chain optimization problem (CSCOP) focuses on the construction projects with fixed activity tasks and durations. However, in reality, the activity tasks involved in a project and their corresponding durations would actually change due to various factors. On one hand, in a real project, especially a complex construction project, there are always several potential solutions to choose from for accomplishing a particular task. As I know, for applying different methods or solutions, the activities involved might be different, which would eventually lead to different activity durations and resource requirements for completing the same task. At most of the time, these solutions are related to the adoption of different equipment or resources. In addition, most equipment utilized in a construction project, including temporary materials such as scaffolding and fences, are rented instead of purchased or owned. Therefore, the adoption of different equipment would result in a variation on the resource leasing cost. Furthermore, due to the high amount of equipment rented in a complex construction site, such as cranes and trucks, the decisions on equipment selection could consequently have an crucial impact on the total project cost. In this case, the proper selection of rental resources including equipment and temporary materials could not only produce a better project schedule but also reduce the total project cost. Moreover, it is worth mentioning that the budget for a construction project is normally estimated before the commencement of operations and plays a vital role in controlling the expenditure on equipment rental and other resources such as workforce. The project contractors strive to accomplish the tasks on time without overrunning the budget in order to impress the project owners or developers and make more profit out of the project. Hence, in real life project management, complying with the estimated budget is one of the main criteria for making decisions on the aforementioned equipment and resources selection. On the other hand, construction projects are less predictable compared to other industries in terms of project makespans due to their complexity and highly heterogenous activities [117]. Each project is unique in nature and its performance is affected by many factors, such as human behaviors and weather conditions. Therefore, the duration of a activity should not be deemed as fixed, conversely, it is a uncertain parameter. This uncertainty may caused by unexpected severe weather, inappropriate human behaviors or delays of material transport [118]. Hence, taking uncertain activity durations into consideration would make the CSCOP more reliable and realistic. However, to our knowledge, even though few studies have been conducted for solving the resource renting problem in project scheduling which could provide us some relevant and useful references which are introduced in Section 2, none of the studies in regard to the integrated problem of stochastic project scheduling and rental resources selection can be found. In order to close this gap, in this chapter, an extended problem of CSCOP considering the alternative operating methods which are caused by selecting different rental resources, project budget limitation and stochastic activity durations is proposed and studied. This extended problem is named as budget constrained Stochastic Construction Supply Chain Optimization with Rental Resource Selection Problem and abbreviated as SCSCO problem.

In our proposed mathematical model for SCSCO, the objective aims to minimize the project makespan with fulfilling the budget constraint. The total cost of a construction project in this chapter is assumed to consist of resource renting cost and labor cost, which should not exceed the total budget. Activities involved in a project are divided into necessary activities and optional activities, where necessary activities are those mandatory activities that would not be influenced by the decisions on resource selection and optional activities are those triggered and required by different rental resources. Precedence relations between all activities are required to be met and the parameter of activity duration is defined as a stochastic variable with randomly generated distribution. Encompassing all these considerations, the SCSCO has become a NP-hard problem as a extension of RCPSP [119]. Therefore, an hybrid metaheuristic algorithm based on sample average approximation (SAA) and particle swarm optimization (PSO) is developed to cope with this problem. The main contributions of this chapter would be that I extend the RCPSP by presenting a novel mathematical model that integrates stochastic scheduling problem with resource selection problem. This novel model and the proposed algorithm could provide a more reliable and practical approach of project scheduling problem to project managers.

The rest of this chapter is organized as follows. In Section 4.2, relevant researches on project scheduling with uncertain activities, equipment selection and applications of SAA and

PSO are reviewed. Section 4.3 describes the SCSCO problem in detail and proposes the formulated mathematical model. The hybrid algorithm that integrates SAA and PSO is introduced, proposed and applied for coping with the SPSRS in Section 4.4. In Section 4.5, a case study is conducted for validating the proposed model and algorithm. Finally, the conclusion of this chapter is presented in Section 4.6.

4.2 Literature Review

For a construction project, the demand of nonrenewable materials such as concrete and pipes is generally determined in design phase, hereby, the cost on these materials would not change significantly. On the contrary, the expenses spent on construction equipment and other renewable resources, such as scaffolding materials and mobile work platforms, would contribute to a higher project cost if the duration of operations is greatly extended. This is because that most of these rental resources, especially heavy equipment and large trucks, are normally rented instead of purchased and owned. In this case, the longer duration the project lasts, the higher rental cost is expected to spend. Similarly, the labor cost would also vary with the extension of project makespan. In this chapter, our target is to minimize the total project makespan with the constraint that the operation cost including resource rental cost and labor cost does not excess the budget. As indicated in many papers, rental resource including equipment and manpower is denoted by renewable resource which is associated with time dependent costs such as leasing cost and labour cost. Therefore, resource renting problem is tightly bound with project scheduling which has drawn attentions from both industrial professionals and academics. Yamashita et al. (2006) studied a project scheduling problem with the objective of minimizing the total resource renting cost which considered the deadline of project and precedence relations simultaneously [120]. Ranjbar et al. (2008) solved an extended problem on the basis of Yamashita's work, however, in their models, fixed demand of resources and zero time lag among activities were assumed [121]. Ballestin (2008) modified the traditional resource renting problem by defining the maximum and minimum time lags between two activities [122]. The objective of his model was to generate an optimal renting policy for minimizing the total renting cost and this renting policy is determined by the schedule of activities [122]. Apart from defining the minimization of direct resource cost as the goal of problem, optimizing the net present value (NPV) of discounted cash flow is commonly taken into consideration. Najafi and Niaki (2006) constructed a resource investment problem which set the decision variable as the availability level of renewable resource and the objective as maximizing the NPV of project cash flow [123] [124]. With more works regarding to resource renting problem have been conducted, researchers have been endeavoring to improve the mathematical model of the problem by considering more realistic and practical scenarios. Inflation as a unavoidable factor that could have a non-negligible impact on project scheduling is contained in the study of Shahsavar et al. (2010) as well as the bonus-penalty policy that stimulates the project to be completed before due date [125]. Multi-mode which indicates that each activity can be conducted in various modes is another popular scenario studied throughout last decade, and it is similar with the our proposed scenario that each rental resource would trigger a series of activities. Afshar-Nadjafi (2014) [126] and Qi et al. (2014) [127] solved the multi-mode resource renting problem with the objective of minimizing the resource availability cost of a project with a given due date. Most recently, Afshar-Nadjafi et al. (2017) presented a novel model for resource renting in project scheduling problem which encompasses the considerations of the availability cost of rental resource and the tardiness penalty of project [96]. In contrast to the fixed rental cost, the authors assumed that the renting cost is associated with the availability length of the resource.

Unfortunately, all these studies deemed the duration of an activity as a deterministic parameter. In contrast to fixed duration, in reality, the durations of activities can not be precisely estimated beforehand due to the complexity and uncertainty of projects. One of the most accepted approaches for dealing with uncertain activity duration is assuming that the parameter of activity duration is a stochastic variable with a predefined probability distribution [128]. Ke and Liu (2005) discussed a stochastic project scheduling problem (SPSP) with the objective of minimizing the total cost of project with taking interest rate and limited completion time into consideration [129]. They presented three most frequently adopted models for SPSP: expected cost model (ECM) for minimizing the expected cost of project [130], chance constrained model (CCM) with a predetermined confidence level for constrains [131] and probability maximization model (PMM) for maximizing the probability that the total cost would not exceed the budget [129]. In this chapter, the a chance constrained model for SCSCO problem is constructed. Another challenge for coping with stochastic durations is seeking for appropriate methods. Sample average approximation (SAA) method is an approach for solving large scale stochastic optimization problem based on Monte Carlo simulation, it approximates the expected value of objective function by a sample average generated from a group of random samples [132]. SAA has been widely used for various stochastic problems, such as resource constrained project scheduling problem [128], stochastic routing problem [132], and supply chain design [133]. Other than SAA, estimation of distribution algorithm (EDA) which predicts the promising search area based on statistical information is also used for solving stochastic optimization problem, for example, EDA is applied for stochastic resource constrained project scheduling problem [134] [135]. As alternatives for these sampling methods, meta-heuristic algorithms such as tabu search (TS) [136] [137], genetic algorithm (GA) [138] and particle swarm optimization (PSO) [139] have also been implemented for solving uncertainty problems. Considering the complexity of our SCSCO problem, a hybrid method that integrates SAA and PSO algorithm is adopted. The exterior SAA method transfers the stochastic problem into its corresponding sample average optimization problem, and this sample average optimization problem will be resolved by the interior PSO algorithm.

4.3 Problem Statement and Mathematical Modeling

This chapter aims to deal with the integrated problem of stochastic project scheduling and rental resource selection under the restriction of estimated project budget. In our proposed scenario, resource selection should subject to the budget constraint and consequently triggers a series optional activities that need to be conducted. These optional activities along with the necessary activities of the project will then be planned and scheduled according to their precedence relations. By knowing these interaction and interior relations among these three considerations, which in this case are project schedule, resource selection and project budget, I are able to solve these two problems as a whole. In this section, the scenario of SCSCO problem is described and the corresponding mathematical model is proposed.

4.3.1 Problem Statement

In this chapter, a complex construction project that consists of various activities and tasks is considered. For some particular tasks, they can be completed by various methods through adopting different rental resources. As a consequence, each alternative method would lead to a series of new activities which may vary with the selection of different rental resources. Therefore, there will be two sets of activities involved in the construction project, namely, necessary activities and optional activities. Here, necessary activities refer to those not influenced by the decisions on the resource selection for different tasks, while the optional activities are those triggered by alternative rental resources. Once the decision on resource selection is made, the involved optional activities would need to be scheduled along with necessary activities and only one alternative resource can be selected for each task. During the process of activity scheduling, the precedence relations among both necessary activities and optional activities should be satisfied. In order to better explain this scenario, an example of pipe valve replacement is illustrated. In a liquefied natural gas (LNG) plant, pipe valve replacement is one of the most regular tasks for facility maintenance. However, as most of the pipes in a gas plant are suspended in the air, hereby, workers have to be lifted to a height where they can access to the valves. In reality, several methods for height access can be adopted. For example, scaffolding structure can be built to provide a working platform, alternatively, mobile elevator can be used for lifting up the operators. Apparently, in order to apply either of these two methods, scaffold components and mobile elevators should be rented and the different optional activities for utilizing these two resources are triggered consequently. The optional activities for implementing scaffolding and mobile elevator are shown in Table 4.1, and Figure 4.1 presents a real life example of scaffolding construction for LNG facility maintenance. The photo was taken inside a LNG plant in Karratha, Australia. As I can see that, 6 optional activities are triggered if scaffold is applied while only 4 optional activities are required for using a mobile elevator. Apart from these alternative activities, some activities involved in valve replacement are mandatory for either option. For example, inspecting the working condition before and after the valve replacement are necessary for ensuring the quality of work. As each activity may possess different duration and workforce requirement, and the leasing cost of these two resources are different, hence, the selection of resources will have a substantial impact on the total cost and duration of the task. In addition, the precedence relations among these activities should be considered as well. For instance, scaffolding platform has to be built from bottom to top, hereby, activity 1 should definitely be executed before activity 5. Therefore, two considerations should be taken into considerations for scheduling the work of value replacement, and they are resource selection and activity ordering. Figure 4.2 shows the activity network for this example, and the activities are represented by the numbers in the circles. The yellow circles represents the optional activities for scaffolding while the red circles are the activities triggered by using mobile elevator. Necessary activities are shown by blue circles. The priority of activities are indicated by the arrows and dummy node 15 in the network stands for the finish of the task. From the network, I can find out that there are two alternative schedules for valve replacement. The determination on selection of best schedule is based on the performance of objective for these two alternatives, which in this case is the shortest duration. This example only presents us the scenario of a single task, while in a complex project, many tasks as such are involved and plenty of decisions of resource selection need to be made. Hereby, the network for a complex project will be more sophisticated and the alternative solutions for project scheduling are manifold. Before proceeding to the mathematical modeling of SCSCO, there are several assumptions and premises need to be clarified:

(a) At each decision making moment, only one type of alternative resources can be selected.

(b) Each decision making moment is independent from others, therefore, the former decision on resource selection would not interfere the latter ones.

(c) The workforce requirement for adopting each alternative resource for a specific task is assumed as a known parameter as well as the demand of each resource.

(d) The duration of each activity is assumed as a stochastic parameter with a known distribution.

4.3.2 The deterministic model

Before considering the uncertainty conditions, I start with the construction of the deterministic model for SCSCO problem. In our instance of the deterministic SCSCO problem, a construction project that contains a set of activities is considered. Here, both necessary activities and optional activities are integrated into a set of activities represented by $\mathscr{I} = \{1, \cdots, I\}$, where i stands for activity i. Dummy activities 0 and $I+1$ which represent the starting and completing of the project respectively are added in the set of project activities. Therefore, the set of activities is extended as $\mathscr{I} = \{0, 1, \cdots, I, I+1\}$. The precedence relations among different activities are

Table 4.1: Example of Rental Resource Selection.

Rental Resource	Optional Activity
Scaffold	1. Erect the scaffold level (0-1) 2. Set up drop objective protection level (0-1) 3. Erect the scaffold level (1-2) 4. Set up drop objective protection level (1-2) 5. Erect the scaffold level (2-3) 6. Dismantle scaffold platform
Mobile Elevator	7. Set up the base 8. Locate and secure the mobile elevator 9. Lift up the elevator 10. Remove the base and return the elevator
	Necessary Activity
Scaffold/Mobile Elevator	11. Clear the working area 12. Inspect the condition of failed valve 13. Replace the valve 14. Testify the condition of new valve

Figure 4.1: Scaffolding Construction for Facility Maintenance

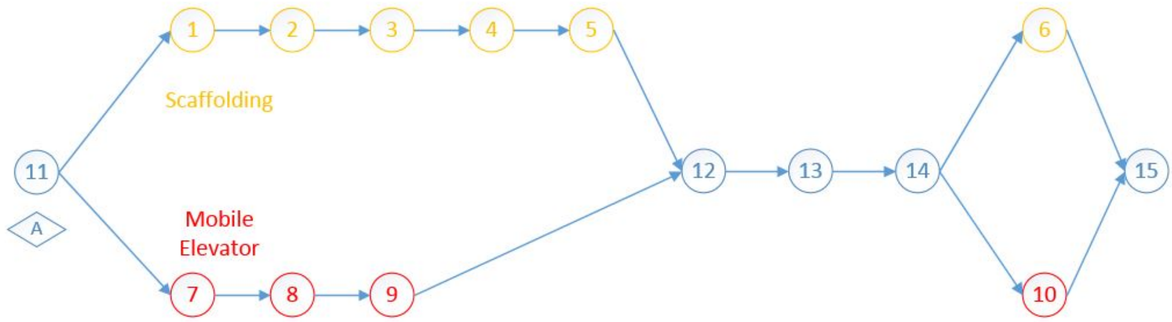

Figure 4.2: Activity Network for Example

shown by an Activity on Node graph $G = (\mathscr{I}, \mathscr{V})$, where each activity is represented by a node $i \in \mathscr{I}$ correspondingly. As I can find in the Figure 4.2, point A represents the task or the moment that the decision on resource selection needs to be made. In our model, these decision making moments are defined as decision points $m \in \mathscr{M}$. The set of options of alternative rental resources at decision point m is described as $\mathscr{O}_m \subset \mathscr{N}$, where $\mathscr{N} = \{1, \cdots, N\}$ represents the set of all types of potential rental resources. As I explain above, by adopting each rental resource, a set of optional activities would be required to operate. Hence, I assume that $\mathscr{H}_n \subset \mathscr{I}$ stands for the set of optional activities when resource n is selected. Workforce is the most important resource that need to be considered throughout the project scheduling process, and the number of workers available for a specific job is always limited due to the restricted working space and budget allocation. In our model, the workforce is restricted by the project budget L. The other notations including sets and indices, parameters and variables used in the deterministic model are listed as Table 4.2 below.

Time and cost are always the most straightforward criteria for evaluating the performance of a project. In our model, the aim is to minimize the total makespan of a project with the total operation cost which consists of resources renting cost and labour cost controlled under the budget. Rather than these two costs, in reality, the sources that contribute to the total cost of a project are many. However, in our scenario, the resource leasing cost and labour cost are the main compositions that would vary with the changes of resource selection and project schedule in a wide range. Therefore, I set our decision variables as S_i, x_i and y_n, which represent the starting time of activity, the selection of activities and the selection of rental resources respectively. In this case, the objective function and constraints can be expressed as:

$$min \;\; f = S_{I+1} \tag{4.1}$$

Subject to

$$C_{Total} = C_{lease} + C_{labour} \leq L \tag{4.2}$$

Table 4.2: Notations for Mathematical Model

Sets and indices:	
$\mathscr{I} = \{1, \cdots, I\}$	set of all possible project activities indexed by i, j.
$\mathscr{V} \subseteq \mathscr{I}^2$	Immediate precedence relations among project activities, where $(i, j) \in \mathscr{V}$ indicates activity j must start after activity i's completion.
$\mathscr{M} = \{1, \cdots, M\}$	set of decision point indexed by m.
$\mathscr{N} = \{1, \cdots, N\}$	set of all candidate alternative resources indexed by n.
$\mathscr{T} = \{1, \cdots, T\}$	set of time slots indexed by t which represents time interval $[t-1, t)$.
Parameters:	
$\mathscr{O}_m \subset \mathscr{N}$	The set of candidate alternative resources at decision point m.
$E_i \in \{0, \mathscr{N}\}$	The rental resources that activity i belongs to. If activity i is necessary, $E_i = 0$; otherwise, $E_i \in \mathscr{N}$.
$\mathscr{H}_n \subset \mathscr{I}$	The optional activities when resource n is selected.
d_n^m	demand of resource n if n is chosen at decision point m.
ε_i	duration of activity i.
u_i	workforce required for activity i.
l_n	leasing cost per unit time per unit of resource n.
γ	labour cost per unit time per person.
L	Operation budget.
Variables:	
S_i	start time of activity i.
f_i	completion time of activity i.
P_t	Set of activities that are underway at time t.
$x_i \in \{0, 1\}$	$x_i = 1$, if activity i is selected; otherwise, $x_i = 0$.
$y_n \in \{0, 1\}$	$y_n = 1$, if the alternative resource n is selected; otherwise, $y_n = 0$.

$$C_{lease} = \sum_{m=1}^{M} \sum_{n \in \mathscr{O}_m} \sum_{i \in \{\mathscr{H}_n\}} d_n^m * \varepsilon_i * y_n * l_n \tag{4.3}$$

$$C_{labour} = \sum_{m=1}^{M} \sum_{n \in \mathscr{O}_m} \sum_{i \in \{\mathscr{H}_n\}} u_i^n * \varepsilon_i * \gamma \tag{4.4}$$

$$(S_i + \varepsilon_i) * x_i * x_j \leq S_j, \forall (i, j) \in \mathscr{V} \tag{4.5}$$

$$\sum_{n \in O_m} y_n = 1, i \in \mathscr{I}, m \in \mathscr{M}, n \in \mathscr{N} \tag{4.6}$$

$$x_i = y_{E_i}, \forall E_i \neq 0, i \in \mathscr{I} \tag{4.7}$$

$$S_i \geq 0, i \in \mathscr{I} \tag{4.8}$$

$$x_i \in \{0, 1\}, \forall i \in \mathscr{I}, m \in \mathscr{M} \tag{4.9}$$

$$y_n \in \{0, 1\}, \forall n \in \mathscr{N} \tag{4.10}$$

In the objective function 4.1, the aim of minimizing the total makespan is expected to be achieved with the premise that the total operation cost should not exceed the budget. Hence, constraint 4.2 should be satisfied, where the leasing cost and labour cost are presented in constraint 4.3 and 4.4. Constraint 4.5 shows that activity j can only start when activity i is completed if activity i and j are all selected, this constraint makes sure that the precedence relations among all possible activities are satisfied. Constraint 4.6 means that only one rental resource can be selected at each decision point. When a resource is selected, the optional activities triggered by this resource should also be selected. Hence, the selection of activities and selection of resources should be kept consistent, which is represented by constraint 4.7. The definitions of decision variables are identified in constraint 4.8, 4.9, 4.10.

4.3.3 The chance-constrained model

The chance constrained programming (CCP) was initially proposed by Charnes and Cooper in 1959 for dealing with optimization problems with uncertainty [140]. Over the past few decades, CCP has been constantly applied for coping with stochastic project scheduling problems. For example, Bruni et al. (2011) [45] and Ma et al. (2016) [141] proposed the chance-constrained models for resource constrained project scheduling problems with stochastic activity durations. The main feature of CCP method is that the constraints with uncertainty will hold with a confidence level, which is denoted as $1-\alpha$ [128]. The constraints 4.2 and 4.5 can then be replaced by following constraints:

$$\Pr\{C_{lease}+C_{labour}\leq L\}\geqslant 1-\alpha, \forall i\in\mathscr{I}, \forall n\in\mathscr{N}, \forall m\in\mathscr{M} \tag{4.11}$$

$$\Pr\left\{x_i\cdot x_j\cdot(S_i+\varepsilon_i)\leqslant S_j\right\}\geqslant 1-\alpha, \forall i\in\mathscr{I}, (i,j)\in\mathscr{V} \tag{4.12}$$

Constraints 4.11 and 4.12 states that the probability of the satisfaction of either budget constraint or precedence constraint should be greater or equal to confidence level $1-\alpha$ respectively. ε_i stands for the duration of activity i, which is a stochastic parameter with a randomized probability distribution. By altering the constraints, the chance-constrained model for SCSCO problem is presented as: minimize 4.1 subject to 4.3, 4.4, 4.6 - 4.10, 4.11 and 4.12.

4.4 Proposed Hybrid Algorithm

In this section, a hybrid algorithm that incorporates sample average approximation (SAA) method and particle swarm optimization (PSO) algorithm is proposed and described in detail. Firstly, the brief introduction on general procedures of SAA method and PSO algorithm are illustrated in subsection 4.1 and 4.2. Then, the detailed description of our proposed hybrid algorithm is stated in subsection 4.3 which includes the solution encoding and decoding, algorithm initialization, PSO implementation, objective value estimation and optimal solution selection.

4.4.1 General SAA Algorithm

The Sample Average Approximation (SAA) Method is commonly used for solving large scale stochastic optimization problems by converging the objective values and optimal solutions of problems with probabilistic conditions from a set of scenarios [139][142] . In traditional SAA method, M independent and random samples are generated and each sample consists of N scenarios with independent and identically distribution. In the first stage, the optimization problems from these samples will be solved and the optimal solutions will be recorded. In the second stage, the recorded optimal solutions will be brought into a sufficiently larger set of samples for further testing. In this case, the better performing solutions obtained in the second stage will be selected as the final optimal solutions. In this section, the conventional procedure of SAA is introduced.

The general stochastic optimization problem with probabilistic constraints is present by the form of equation 4.13 as follow, where W is a random vector with a predefined probability distribution P. $H(x,W)$ is the objective function with variables of x and w. Assuming that $W_1, W_2, ...W_N$ be a random sample from M with N scenarios, the stochastic optimization problem can be transferred into a sample average approximation (SAA) problem as shown in equation 4.14. In the equation, I define that $v^* = min\, f(x)$ denotes the optimal value of objective function of problem (12) and $\hat{v}_N = min\, \hat{f}_N(x)$ represents the optimal value of objective function for problem 4.14. After solving the SAA problem in 4.14 for each sample $m = 1, 2, ...M$, I can have the objective value $\hat{v}_N^m$ and optimal solution $\hat{x}_N^m$. The average of all sample objective function values $\bar{v}^M$ is then calculated, and according to Kleywegt et al.[142], the average objective values of SAA problem could provide a statistical lower bound of v^*. The optimal solutions obtained earlier will then be applied into a sample with a much larger size, N'. In order to testify the quality of the obtained results, the optimality gap need to be estimated as well as the variance value. When the stop criteria is reached, which in this case is that the optimality gap is small enough, the optimal solution x^* can be selected from all potential solutions $\hat{x}_N^m$. The procedure of general SAA is shown in Algorithm 3.

$$\min \quad f(x) = H(x, W) \tag{4.13}$$

$$\min \quad \hat{f}_N(x) = \frac{1}{N} \sum_{j=1}^{N} H(x, W_j) \tag{4.14}$$

Algorithm 3 Procedure of SAA

1: Generate M independent random samples $m = 1, 2, ...M$ with sample size of N
2: Select a reference sample with a large sample size N' where $N' \gg N$
3: **Stage 1**
4: For $m = 1, 2, ...M$, solve the SAA problem $min\, \hat{f}_N(x)$ and record the optimal objective value $\hat{v}_N^m$ and the optimal solution $\hat{x}_N^m$
5: Compute the average of all obtained sample optimal objective values, $\bar{v}^M$
6: $\bar{v}^M = \frac{1}{M} \sum_{m=1}^{M} \hat{v}_N^m$;
7: **Stage 2**
8: Estimate the objective value of the SAA problem in a large sample N' by applying feasible solutions $\tilde{x}$ selected from $\hat{x}_N^m$:
9: $\tilde{v}_{N'} = min\tilde{f}_{N'}(\tilde{x}) = \frac{1}{N'} \sum_{j=1}^{N'} H(\tilde{x}, W_j)$
10: **Stage 3**
11: Compute the optimality gap as $\tilde{v}_{N'} - \bar{v}^M$
12: If the gap is small enough, then stop; Otherwise, increase the sample size N and repeat Stage 1 and Stage 2
13: Choose the best solution x^* from the solutions with the best objective value $\tilde{v}_{N'}$ generated in Stage 3
14: End

4.4.2 General PSO Algorithm

In the Stage 2 of SAA method described above, an stochastic optimization problem $min\, f(x) = H(x,W)$ is expected to be solved. In the context of the SCSCO problem discussed in Section 4.3, the problem encompasses the considerations of precedence relations, budget constraints and stochastic durations that makes it a rather complex NP-Hard problem. Therefore, an intelligent algorithm should be fitted in the Stage 2 and Stage 3 of SAA method in order to resolve the SCSCO problem. In this section, particle swarm optimization (PSO) algorithm is introduced and integrated with SAA method.

PSO is an evolutionary computation technique initially developed in 1995 by Eberhart and Kennedy [143], the concept of which was inspired by social behaviors such as bird flocking. Similar to other evolutionary algorithm, GA for instance, PSO initializes with a population of solutions which is called as swarm and each solution is called as individuals or particles. However, the method of searching for optimal solutions for PSO is different from the cross-over and mutation operations of GA. In PSO, each particle possesses two main characteristics, which are position and velocity. During the process of searching for optima, particles will move towards best known positions which are attained by any other particle of the swarm [144]. Therefore, P-SO has the advantage to explore the global optimal solutions because of the information sharing among particles from the swarm and the experience inherited from previous generations [145].

Assuming that the size of swarm is M, hence, there are M particles and each particle i can be represented as a point in a N-dimensional space with two main characteristics, namely position X_i and velocity V_i. For each iteration, the position and velocity of each particle will be updated based on its previous velocity, the best position it has ever obtained (local best) and the best global position from its group (global best). The mechanism of updating the particles' velocities and positions is presented as the equations below respectively [144]:

$$V_i^t = w^t V_i^t(t-1) + c_1 r_1 (p_{best\,i}^t - X_i^t) + c_2 r_2 (g_{best}^t - X_i^t) \tag{4.15}$$

$$X_i^t = V_i^t + X_i^{t-1} \tag{4.16}$$

where $X_i^t = \{x_{i1}^t, x_{i2}^t, ..., x_{iN}^t\}$ and $V_i^t = \{v_{i1}^t, v_{i2}^t, ..., v_{iN}^t\}$ represent the N-dimensional position and velocity for ith particle at tth generation. $p_{best\,i}^t$, called as local best position, is the best position of ith particle for all previous t generations, while the global best position, g_{best}^t, is the best position of the whole swarm for all previous t generations. w^t stands for inertia weight that controls the effect of previous velocities on the current ones and balance between the abilities of exploring the global optima and local optima. Positive constants c_1 and c_2 are cognitive parameter and social parameter, while r_1 and r_2 are random numbers in the range of [0,1]. According to above description, the procedure of PSO algorithm can be illustrated as shown in Algorithm 4:

Algorithm 4 Procedure of PSO

1: **Step 1: Initialization**
2: Generate a population of particles with size of M, confirm their initial positions and velocities in the feasible region.
3: Evaluate the fitness of each particle through objective function $f(X)$, record the local best $p^0_{best\,i}$ and global best g^0_{best}.
4: **Step 2: Position and Velocity Updating**
5: For iteration $t \geq 2$, update the velocities and positions of each particle through formula 4.15 and 4.16.
6: If the updated position of the particle violates the limits of position range, then the position of this particle is fixed to its maximum or minimum bound.
7: Update particle best local position $p^t_{best\,i}$ and global local position g^t_{best} by evaluating the fitness of each particle.
8: **Step 3: Termination Criteria**
9: The algorithm stops if a maximum number of iterations or a sufficiently good fitness is reached, otherwise, repeat **Step 2**.

4.4.3 Hybrid SAA-PSO Algorithm for BCSPSRS Problem

The proposed hybrid SAA-PSO algorithm that applies PSO as the inner layer algorithm for obtaining the candidate optimal solution for SAA method is developed in this chapter to deal with SCSCO problem. In reality, the distribution of uncertain activity durations is deduced from historical data on most occasions. Hence, in our SAA method, I represent the original distribution of the activity durations by an empirical distribution concluded from a random sample based on the method presented by Luedtke and Ahmed [128] [146] [147]. A set of scenarios $\mathscr{K} = \{1, 2, ..., K\}$ and the vector $\varepsilon^k = \{\varepsilon^k_1, \varepsilon^k_2, ..., \varepsilon^k_I\}$ are generated by Monte Carlo simulation method. ε^k_i represents the duration of activity i in scenario k where $i \in \mathscr{I}$. For each activity duration ε_i, there is a predefined range $[\varepsilon^{min}_i, \varepsilon^{max}_i]$ that limits the variation of the parameter. For each scenario, ε^k_i is generated as a integer varied between the range with a randomized possibility and the equation $\sum^K_{k=1} p(\varepsilon^k_i) = 1$ holds for each activity. For example, the duration of activity 1 varies between the range of $[3, 6]$ and the possible activity durations can be $\{3, 4, 5, 6\}$ with the possibilities of $\{0.2, 0.5, 0.1, 0.2\}$. Therefore, the chance constraint 4.11 and 4.12 can be transferred into 4.17 and 4.18 respectively:

$$(1-\delta_k)\,(\sum_{m=1}^{M}\sum_{n\in\mathscr{O}_m}\sum_{i\in\{\mathscr{H}_n\}} d^m_n * \varepsilon^k_i * y_n * l_n + \sum_{m=1}^{M}\sum_{n\in\mathscr{O}_m}\sum_{i\in\{\mathscr{H}_n\}} u^n_i * \varepsilon^k_i * \gamma) \leqslant L, \quad \forall i \in \mathscr{I}, \forall n \in \mathscr{N}, \forall m \in \mathscr{M}, \forall k \in \mathscr{K} \tag{4.17}$$

$$(1-\beta_k)\cdot x_i \cdot x_j \cdot \left(s_i + \varepsilon^k_i\right) \leqslant s_j, \forall i \in \mathscr{I}, (i,j) \in \mathscr{V}, \forall k \in \mathscr{K} \tag{4.18}$$

where β_k and δ_k are two binary variables which represent the feasibility of precedence constraint and budget constraint. When $\beta_k = 1$ and $\delta_k = 1$, the precedence relations and budget constraint are not fulfilled in scenario k, otherwise, these two variables should equal to 0. Meanwhile, the chance constraints 4.11 and 4.12 are constructed with the confidence level of $1-\alpha$, hence, the infeasibility (number of infeasible scenarios) for both precedence constraint and budget limitation should be lower than $K \cdot \alpha$:

$$\sum_k \beta_k \leqslant K \cdot \alpha, \forall k \in \mathscr{K} \tag{4.19}$$

$$\sum_k \delta_k \leqslant K \cdot \alpha, \forall k \in \mathscr{K} \tag{4.20}$$

$$\beta_k, \delta_k \in \{0,1\}, \forall k \in \mathscr{K} \tag{4.21}$$

In this case, the chance constrained model is transferred into a SAA problem: minimize (4.1) subject to (4.3) - (4.4), (4.6) - (4.10), (4.17) - (4.21).

Solution Encoding and Decoding

Based on the transformation scheme proposed by Zhang et al. [144], the solutions of SCSCO problem discussed in this chapter should be presented with two characteristics that could be transformed into feasible schedules, namely, the selection of potential activities and the starting time of each activity. According to the description of SCSCO problem in section 4.3, the activity-on-node (AON) network is known before scheduling, and one of the alternative methods should be selected at each decision making point. Therefore, the schedule of project can be generated directly from the selection of activities. In this section, a priority value q_i would be assigned to each activity i based on the precedence constraints and the higher value of q_i stands for a higher priority level. The vector of priority value at tth iteration in sample h can be indicated as $Q_h^t = \{q_1 h^t, q_2 h^t, ..., q_I h^t\}$. On the other hand, the selection of activities is interpreted as a vector $\Theta = \{\theta_1, \theta_2, ..., \theta_I\}$, where $\theta_i = 1$ means that activity i is selected, otherwise, $\theta_i = 0$. For necessary activities, they should always be selected and therefore, their corresponding value of θ_i should equal to 1 at any time. Besides, it is worth mentioning that some optional activities are mutually exclusive to others according to the premise (a) of SCSCO problem which states that only one method or rental resource can be selected at any decision point. At decision point m, there are $|\mathscr{O}_m|$ alternative equipment or rental resources available for selection. For a rental resource $n \in \mathscr{O}_m$, the optional activities belonging to n, $\mathscr{H}_n$ is mutually exclusive to activities triggered by other resources. Therefore, $\mathscr{H}_n \cap \mathscr{H}_{n=\mathscr{O}_m \setminus \{n\}} = \emptyset$, hence, I define these activity sets as homogeneous groups which work for same tasks but are also mutually exclusive. There is another special occasion that should be taken into consideration. Sometimes, different activities/methods may be triggered by choosing the same resource. For example, resource n would trigger two sets of optional activities for operating a same task. In this case, I assume that these two sets of activities are caused by two different resource or equipment with same characteristics in terms of unit cost, notated as n_1 and n_2. These two sets of optional activities would be represented by $\mathscr{H}_{n_1}$ and $\mathscr{H}_{n_2}$ which are mutually exclusive. With all aforementioned premises and definitions, a schedule generation scheme (SGS) is developed as follow:

1. Step 1: Generate a activity set $\mathscr{I} = \mathscr{H}_0 \cap \mathscr{H}_n$ where $\mathscr{H}_0$ represents the necessary activity set and $\mathscr{H}_n$ indicates the optional activity sets for different rental resource. Identify the set of homogenous groups for decision point m as $\mathscr{H}_{n=\mathscr{O}_m}$.

2. Step 2: Generate a priority value vector $Q_h^t = \{q_1 h^t, q_2 h^t, ..., q_I h^t\}$ based on the predefined precedence relations and a activity selection vector $\Theta = \{\theta_1, \theta_2, ..., \theta_I\}$ with all elements equal to 0 at the beginning. The duration of activity i is assumed as φ_i.

3. Step 3: Search from the activities with higher priority value, if activity i is mandatory, then assign θ_i with 1; For optional activity i, check the selection status of its immediate predecessor b_i. If none of its immediate predecessors is selected, then repeat Step 3; Otherwise, go to Step 4.

4. Step 4: Check the selection status of the activities from homogenous group $\mathscr{H}_{n=\mathscr{O}_m \setminus \{E_i\}}$, if any activities with a higher priority value are selected, assign θ_i with 0; Otherwise, $\theta_i = 1$; Record the starting time of i, $S_i = S_{b_i} + \varphi_{b_i}$ and the rest of budget $L - C_{lease} - C_{labour}$, update the selected activity set P. Here, C_{lease} and C_{labour} represent the leasing cost and labour cost that have been spent for selected activities till time $\sum_{i \in P} \varphi_i$.

5. Step 5: Repeat Step 4 until all decision points m are scanned and make sure the budget constraint is satisfied.

As PSO algorithm is selected as the inner algorithm for computing the SAA problem stated above, the project schedule in SCSCO problem should be able to be translated from the particle represented solutions. In our algorithm, the particle position is presented as a vector with $2I$ elements. The particle position for hth particle at tth generation is set as $X_h^t = \{x_{h1}^t, x_{h2}^t, ..., x_{hI}^t, ..., x_{h2I}^t\}$, where the first I elements stand for the priority values for activities and the last I elements present the selection status for activities. Here, x_{hi}^t indicates the decision on the selection of activity i at t generation in sample h. As the updating of velocities and positions of particles is based on the calculation of equation 4.15 and 4.16, the results of calculation are not necessarily binary integers. Hence, I assume that the value of x_{hi}^t would vary between [-1, 1]. By doing this, the decoding process that translates the particle representation into a selection list of activity is fairly easy and straightforward. For the first I elements, the higher value the element is, the higher priority the corresponding activity has. However, the activity selection status should be represented as binary numbers in Θ, hence, for the last I elements in the particle position, I define that when $x_{hi}^t \in (0,1]$, $\theta_i = 1$, on the contrary, $\theta_i = 0$ if $x_{hi}^t \in [-1,0]$. The example of solution encoding and decoding is shown in Figure 4.3. As I can find out, two adjustments are conducted for an initial representation of a particle position. In the first stage, the particle position values for the last 5 elements are adjusted to 0 and 1 based on the rule described above. In stage 2, the values of first I elements are adjusted to integers based on their priority ranking in a descending order. In the example, activity 1 has the highest priority values which is ranked as the fifth position in a descending order, therefore, the particle position value for activity 1 is assigned as 5. In addition, the activity selection interpreted from the original particle position may not be feasible. Therefore, the selection status is amended in the example and a feasible solution can be generated.

Duration	3	2	3	5	1					
Activity	1	2	3	4	5	1	2	3	4	5
Particle Position Element	1	2	3	4	5	6	7	8	9	10
Particle Position Value	0.82	0.56	0.61	0.32	0.2	-0.6	-0.5	0.3	-0.7	0.6

Stage 1

Activity	1	2	3	4	5	1	2	3	4	5
Particle Position Element	1	2	3	4	5	6	7	8	9	10
Particle Position Value	0.82	0.56	0.61	0.32	0.2	0	0	1	0	1

Stage 2

Activity	1	2	3	4	5	1	2	3	4	5
Particle Position Element	1	2	3	4	5	6	7	8	9	10
Particle Position Value	5	3	4	2	1	1	0	1	0	1

Figure 4.3: Example of Particle-represented Solution

Initialization

In the first phase of hybrid SAA-PSO algorithm, H independent random samples with sample size of K are generated, where these K scenarios are independently and identically distributed (i.i.d.). A reference sample with a larger size K' is selected for evaluating the best solutions obtained, where $K' \gg K$. In this phase, the parameters for PSO algorithm should also be initialized. These parameters may include the maximum number of iterations, values for cognitive parameter c_1 and social parameter c_2, inertia weight w_t, values for random numbers r_1 and r_2, and confidence level $1-\alpha$.

Candidate Optimal Solutions obtained by PSO

PSO algorithm is adopted to obtain the candidate optimal solutions for the SAA problem for every sample h with K scenarios. For each scenario k, the duration of activity i, ε_i, is randomly generated within the range $[\varepsilon_i^{min}, \varepsilon_i^{max}]$. The vector $\hat{\varepsilon} = (\varepsilon_1, \varepsilon_2 \cdots \varepsilon_K)$ is independently and identically distributed (i.d.d). Considering there are H independent samples with the sample size of K, the computation will be extremely complex and tedious if PSO algorithm is applied for each scenario. In order to reduce the complexity of calculation, in this part, I define that the discrete duration of activity i, denoted as φ_i , equals to the maximum value of the potential duration from a randomly selected scenario set in sample h [147]. The selected scenario set in sample h is denoted as $\hat{\mathscr{K}_h}$, and the cardinality of scenario set should comply the confidence level as shown in constraint 4.23. Under such circumstance, for sample h, PSO algorithm would be applied for solving the following deterministic problem: minimize (4.1) subject to (4.6) - (4.10), (4.22) - (4.25).

$$\varphi_i = \max\{\varepsilon_i^k\}, \forall i \in \mathscr{I}, \forall k \in \hat{\mathscr{K}_h} \tag{4.22}$$

$$|\hat{\mathscr{K}_h}| \geqslant K \cdot (1-\alpha) \tag{4.23}$$

$$\sum_{m=1}^{M} \sum_{n \in \mathscr{O}_m} \sum_{i \in \{\mathscr{H}_n\}} d_n^m * \varphi_i * y_n * l_n + \sum_{m=1}^{M} \sum_{n \in \mathscr{O}_m} \sum_{i \in \{\mathscr{H}_n\}} u_i^n * \varphi_i * \gamma \leqslant L, \forall i \in \mathscr{I}, \forall n \in \mathscr{N}, \forall m \in \mathscr{M} \tag{4.24}$$

$$x_i \cdot x_j \cdot (s_i + \varphi_i) \leqslant s_j, \forall i \in \mathscr{I}, (i,j) \in \mathscr{V} \tag{4.25}$$

Based on the particle representation described in Section 4.3.1, all elements of particle position should be limited to $[-1,1]$. During the process of particle movement, the particles with their positions fall out of the limitation should be adjusted as follow [144]: if $x_{hi}^t > 1$, then I assume $x_{hi}^t = 1$; if $x_{hi}^t < -1$, then $x_{hi}^t = -1$. Similarly, the particle velocity should also be limited in order to prevent the particles move beyond the feasible region. In this section, the maximum velocity $V_{max} \leqslant X_{max}$, hence, the particle velocity is controlled with in the range of $[-1,1]$. The procedure of implementing PSO algorithm for each sample consists of 5 steps, which is similar to the general PSO discussed in section 4.2. However, as the updated particles may not necessarily be feasible, a checking and adjusting process should be conducted when a new particle is generated to ensure the accuracy of our solutions, and the procedure of particle checking and adjusting is shown in Algorithm 5. The details of PSO algorithm in SAA method is shown as below:

1. **Step 1:Initialization**: Generate a selected scenario set $\hat{\mathscr{K}_h}$ randomly and identify the discrete duration of activities φ_i. Generate M particles with feasible initial positions and velocities limited to $[-1,1]$ based on the SGS presented in Section 4.3.1. Evaluate the fitness value for each particle according to the objective function (4.1) and record the local best $p_{best\,i}^0$ and global best g_{best}^0.

2. **Step 2:Position and Velocity Updating**: For iteration $t \geq 2$, update the velocities and

positions of each particle through formula 4.15 and 4.16. Go to Step 3.

3. **Step 3:Checking and Adjusting**: For each new particle generated in Step 2, decode the particle solutions based on the process described in Section 4.3.1 and assess the feasibility of each particle. Three criteria are applied in this step: 1) The range of velocity and position should be limited to [-1, 1]; 2) Precedence constraints including the mutually exclusive conditions for homogenous groups should be satisfied; 3) The operational cost should be controlled under budget. The detailed checking and adjusting procedure is presented in Algorithm 5.

4. **Step 4:Fitness Evaluation**: For the adjusted particles, evaluate their fitness values and update the local best $p^t_{best\,i}$ and global best g^t_{best}. Then $t = t+1$, repeat Step 2 to 4.

5. **Step 5:Stop Criteria**: The algorithm stops when maximum iteration is reached and the optimal solutions for sample h is obtained.

Algorithm 5 Procedure of Particle Checking and Adjusting

Step 1: Limitation Check and Adjust
Check every element of the chosen particle position X^t_h and velocity V^t_h.
If any $x^t_{hi} > 1$, then adjust the value of x^t_{hi} as 1; if $x^t_{hi} < -1$, then $x^t_{hi} = -1$.
Similarly, for any v^t_{hi}, if $v^t_{hi} > 1$ or $v^t_{hi} < -1$, then $v^t_{hi} = 1$ or $v^t_{hi} = -1$.
If none of these particle exist, go to step 2.
Step 2: Precedence Constraint Check and Adjust
Rank the last I elements according to their corresponding priority values in a descending order.
Check the selection status for necessary activities and amend $x^t_{h(I+j)}$ to 1 if $j \in \mathscr{H}_0$.
For the first optional activity i in the order, check the selection status of its resource group $\mathscr{H}_n$ where $n = E_i$.
If $x^t_{hi}(i \in \mathscr{H}_{E_i}) = 1$, then amend the values for its homogenous group $\mathscr{H}_{n=\mathscr{O}_m \setminus \{E_i\}}$ as 0.
Otherwise, check if any of its homogenous group satisfies $x^t_{hi}(i \in \mathscr{H}_{n=\mathscr{O}_m \setminus \{E_i\}}) = 1$.
If none of such group $\mathscr{H}_{n=\mathscr{O}_m}$ exist for decision point m, calculate the selection rate of each group:
$\lambda_{n=E_j} = \frac{\Sigma x^t_{h(I+j)}}{|\mathscr{H}_{E_j}|}$
Chose the group with highest selection rate, and assign 1 to its corresponding elements. For its homogenous groups, amend their selection status as 0.
Step 3: Cost Budget Check
Calculate the C_{Total} and compare it with budget L
If $C_{Total} > L$, for each m, replace the selected group with its homogenous groups and recalculate the C_{Total}.
Repeat Step 1 to 3 until a feasible particle is generated

Objective Value Estimation

In this phase, the optimal solutions $\hat{x}_K^h$ and optimal objective values $\hat{v}_K^h$ obtained by solving the discrete SAA problem with PSO algorithm are evaluated in a sufficiently large sample K'. Before that, the average $\bar{v}^H$ of all obtained sample optimal objective values is calculated by equation 4.26 which provides a lower bound of the final optimal objective value v^*. In the next step, the objective value of original problem in the sample K',$\tilde{v}_{K'}$, is evaluated by applying the optimal solutions $\hat{x}_K^h$ obtained by PSO, as shown in 4.27. The evaluated value $\tilde{v}_{K'}$ provides a upper bound for optimal objective value.

$$\bar{v}^H = \frac{1}{H} \sum_{h=1}^{H} \hat{v}_K^h \tag{4.26}$$

$$\tilde{v}_{K'} = \min \frac{1}{|K'|} \sum_{k=1}^{|K'|} S_{I+1}^k \tag{4.27}$$

Optimal Solution Selection

The optimal solution x^* is selected from the obtained optimal solutions $\hat{x}_K^1, \hat{x}_K^2, ..., \hat{x}_K^H$ for H samples of SAA problem. In this chapter, I selected the solution $\hat{x}_K^h$ that has the smallest objective value in the large sample K', which is represented by 4.28. The optimality gap is the difference between upper and lower bound of objective values, which in this case is the difference between $\tilde{v}_{K'}$ and $\bar{v}^H$. The SAA-PSO algorithm stops when the optimality gap is small enough or the maximum number of iterations is reached, otherwise, repeat the algorithm until the stopping criteria are achieved. The flowchart of SAA-PSO algorithm is presented in Figure 4.4.

$$x^* = \hat{x}_K^h | h = \arg \min_{h=1,2,...,H} \tilde{v}_{K'} \tag{4.28}$$

$$Gap = \tilde{v}_{K'} - \bar{v}^H \tag{4.29}$$

4.5 Computational study

In this section, our proposed mathematical model and intelligent algorithm are applied on a case study which is constructed partially based on a real maintenance project in a LNG plant. The computational results of the example are discussed and the sensitivity analysis regarding to the parameters of our proposed algorithm is conducted. The code of SAA-PSO algorithm is compiled in MATLAB $R2015a$ on a computer under windows 7 with Intel $i5$ CPU and $4GB$ RAM.

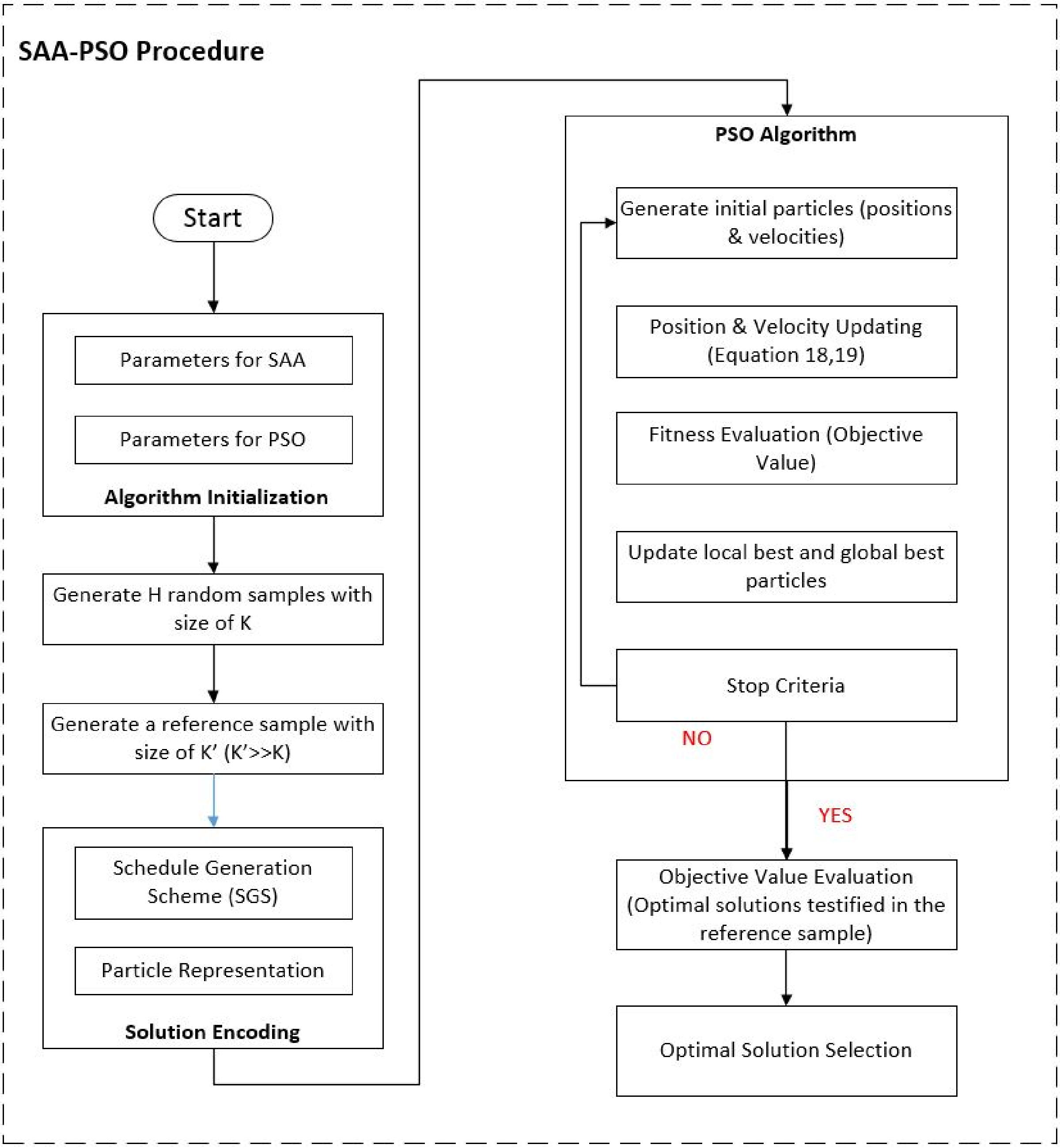

Figure 4.4: Flowchart of SAA-PSO Algorithm

4.5.1 Case Study Description

As aforementioned in the example of valve replacement in Section 4.3, there are several methods that can be adopted for accessing to height. For each method, the utilized equipment or rental resource and the involved activities are varied. As a consequence, by choosing different methods for the same task, the resulted makespan and total cost would be different. In the case study, a maintenance project that consists of 25 activities including mandatory and optional activities is expected to be planned through choosing the optimal methods of height access for each task that minimizes the total makespan of this project. Figure 4.5 indicates the network of the project where the circles represents the activities and the arrows shows their precedence relations. Optional activities are illustrated by yellow circles while blue circles stand for mandatory circles. As I can see, there are three decision making point (tasks) indicated by orange parallelograms. In this case study, there are six alternative methods for tasks 1, 2 and 3, namely scaffolding structure, podium step, mobile elevated work platform (MEWP), remote operated air vehicle (ROAV), rope access and magnetic anchoring. Table 4.3 lists the demand of equipment or rental resources for each method for different tasks, the optional activities for each method and the corresponding leasing cost for each equipment. As predefined in our assumptions, the duration of each activity is deemed as stochastic. Hence, in this case study, I present the duration of each activity as an integer that varies between its range $[Min(duration), Max(duration)]$ and the probability of each possible integer is generated randomly. The range of each activity along with the workforce required for each activity are listed in Table 4.4 and the difference between $Min(duration)$ and $Max(duration)$ is set as the same value 5 for each activity. The possibility of each potential duration is generated randomly and Table 4.5 gives an example of the randomly generated possibilities for the durations of first 10 activities. In this project, the total budget for operational cost which includes resource rental cost and labour cost is limited to 2000 and the unit labour cost is set as 1.5 per worker per unit time.

4.5.2 Case Study Analysis

The proposed SAA-PSO algorithm is applied to generate an optimal schedule for the problem described above by selecting the best rental resources or equipment to access to height for facility maintenance. Before running the algorithm, the values of various parameters need to be set up. For solving this particular problem, I initialize the number of samples as $H = 100$ with the sample size of $K = 100$. As the obtained solutions will be tested in a sufficiently large sample K' where $|K'| \gg |K|$, therefore, I set $N' = 10000$. For the inner PSO algorithm, the maximum number of iterations is designed as 100 while the inertia weight $w = 0.6$. The other parameters such as cognitive parameter and social parameter are presented in Table 4.6.

By implementing the SAA-PSO algorithm on the case study, the optimal solution can be obtained. The optimal duration of the case study project is $S_{26} = 52$ with the activity selection vector {1, 1, 1, 1, 0, 1, 1, 0, 1, 0, 1, 0, 0, 0, 1, 0, 0, 0, 0, 1, 1, 0, 0, 1, 1 }. The Network of

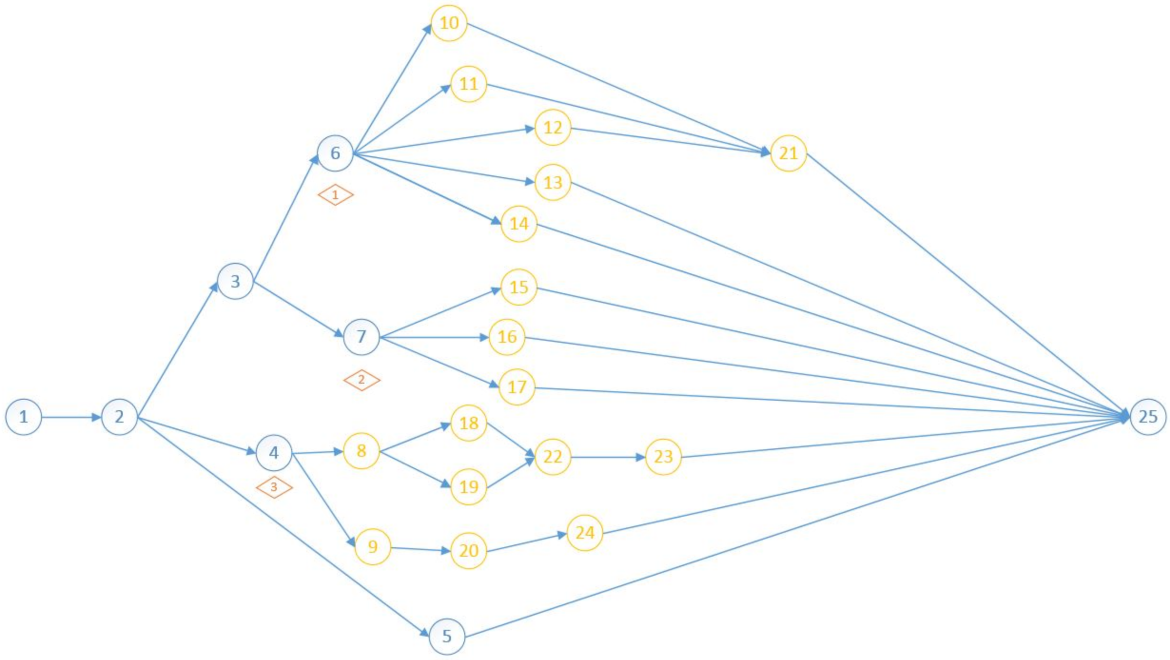

Figure 4.5: Activity Network of Case Study

Table 4.3: Information of Alternative Methods

Tasks	Method/Rental-Equip	Optional Activities	Demand	Unit Cost
Task-1	Podium Step (1)	10, 21	4	2
	MEWP (2)	11, 21	3	5
	ROAV (3)	12, 21	2	8
	Rope Access (4)	13	6	2
	Magnetic Anchoring (5)	14	4	3
Task-2	Podium Step (1)	15	3	2
	MEWP (2)	16	2	5
	ROAV (3)	17	1	8
Task-3	Scaffolding (1)	8, 18, 22, 23	3	3
	Scaffolding (2)	8, 19, 22, 23	2	3
	ROAV (3)	9, 20, 24	2	8

Table 4.4: Duration of Activities

Activity	Min Duration	Max Duration	Workforce	Activity	Min Duration	Max Duration	Workforce
1	3	8	7	14	9	14	1
2	8	13	2	15	3	8	7
3	3	8	7	16	7	12	3
4	2	7	8	17	6	11	4
5	7	12	3	18	6	11	4
6	5	10	5	19	9	14	1
7	5	10	5	20	3	8	7
8	7	12	3	21	4	9	6
9	8	13	2	22	2	7	8
10	4	9	6	23	10	15	1
11	7	12	3	24	7	12	3
12	5	10	5	25	5	10	5
13	9	14	1				

Table 4.5: Possibility of possible durations

Activity	P1	P2	P3	P4	P5	P6
1	3(0.1767)	4(0.1505)	5(0.1789)	6(0.1503)	7(0.1993)	8(0.1444)
2	8(0.5241)	9(0.1153)	10(0.0558)	11(0.0579)	12(0.0335)	13(0.2134)
3	3(0.1147)	4(0.0935)	5(0.1952)	6(0.1606)	7(0.1974)	8(0.2386)
4	2(0.3714)	3(0.0733)	4(0.0530)	5(0.2658)	6(0.0358)	7(0.2006)
5	7(0.1440)	8(0.2338)	9(0.1317)	10(0.1068)	11(0.1823)	12(0.2013)
6	5(0.2722)	6(0.1820)	7(0.0785)	8(0.3068)	9(0.1372)	10(0.0233)
7	5(0.2342)	6(0.0753)	7(0.1372)	8(0.2134)	9(0.1114)	10(0.2284)
8	7(0.1533)	8(0.2654)	9(0.2734)	10(0.1718)	11(0.0076)	12(0.1285)
9	8(0.1400)	9(0.0892)	10(0.0650)	11(0.2711)	12(0.1418)	13(0.2929)
10	4(0.1118)	5(0.2199)	6(0.1134)	7(0.2311)	8(0.2159)	9(0.1079)

Table 4.6: Parameters Initialization of SAA-PSO for Case Study

Parameter	Value	Parameter	Value
H	100	c_1	2
K	100	c_2	2
K'	10000	r_1	0.5
α	0.01	r_2	0.5
Max Iteration	100	w	0.6

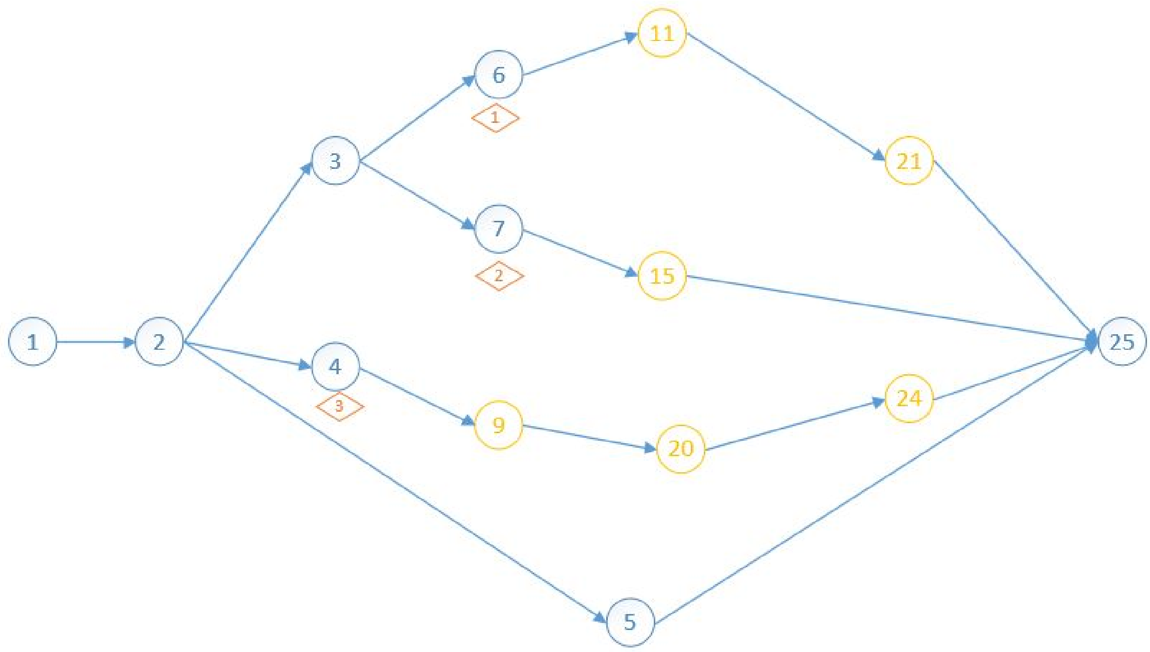

Figure 4.6: Activity Network of Optimal Solution

activity selection is illustrated in Figure 4.6 by eliminating the unselected activities. As I can observe, at the first decision point $m = 1$, the method of MEWP is selected for conducting the first task after activity 6. Therefore, mobile elevators are the rental resource that is needed and activity 11 and 21 are the optional activities triggered by the method of MEWP. As the premises have stated that only one method or rental resource can be selected for each task, therefore, for task 1 ($m = 1$), the activities that are triggered by other methods should be eliminated from the network. Similarly, podium step is selected for task $m = 2$ and remote operated air vehicle (ROAV) is selected at decision point $m = 3$ respectively. As a consequence, activities included by these two methods, which are activity 15, 9, 20, 24, are selected and scheduled. The schedule of this maintenance project is presented in a form of Gantt Chart as shown in Figure 4.7. The total operational cost, which consists of resource leasing cost and labour cost, should always be less than the budget $L = 2000$. By calculating with the possible maximum duration for each chosen activity, the maximum operational cost for the optimal selection is 1857. Apparently, the optimal solution might be different when the total budget varies as the budget limits the maximum usage of rental resources and workforce. Table 4.7 shows the optimal duration for this case study under different budgets. As I can see, in general, the average makespan of project would decrease with the increment of budget. The 'Nil' in the Table 4.7 means that there is no feasible solution can be found when the project budget is 1000. In addition, when the budget is over 2000, the average makespan stays unchanged. That means the budget is greater than the maximum cost for the project. Therefore, having an accurate and appropriate budget estimation would have an important impact on the project scheduling and rental resource selection. The project managers make their decisions on resource selection and project scheduling subject to their preference and priority between cost and time.

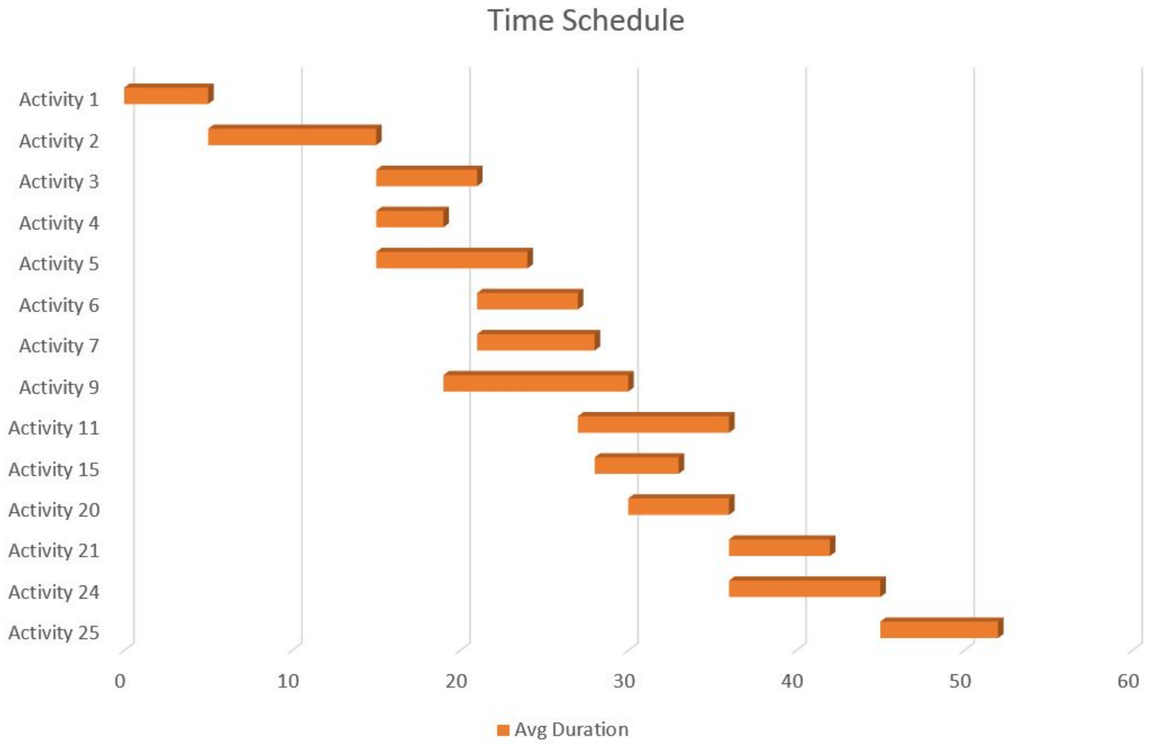

Figure 4.7: Schedule of Case Study

Table 4.7: Makespan under Different Budget Constraint

Budget	Average Makespan
1000	Nil
1200	62.12
1400	62.17
1600	58.82
1800	56.59
2000	52
2200	52

4.5.3 Algorithm Performance Analysis for Parameters

The performance of an algorithm would largely be influenced by the values of parameters, therefore, in order to testify the performance of our proposed SAA-PSO algorithm, a randomly generated instance with 15 activities is constructed for the computational experiment. I will analyze the computational results of the instance under different values of three key parameters which are sample size K, number of samples H and confidence level $1 - \alpha$. The activity network for this instance is presented in Figure 4.8 and the parameters of duration of activities ε_i, workforce requirement u_i and demand of rental resources d_n^m are generated randomly in Matlab. Two criteria will be utilized for this analysis, namely objective value and proportion of infeasible solutions. The objective value is indicated by average makespan and the proportion of infeasible solutions is the average of the proportion of infeasible solutions to all generated solutions. In this experiment, I only change the value of one parameter at a time while other parameters keep unchanged and hold their initial values. The initial values for these three parameters are $K = 100$, $H = 100$ and $\alpha = 0.01$.

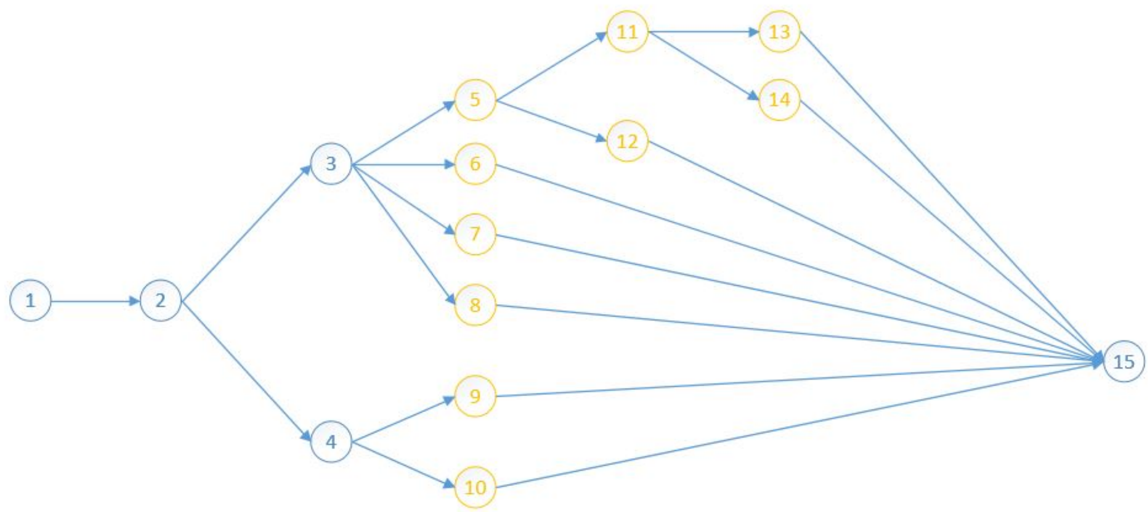

Figure 4.8: Activity Network for Testing Example

Table 4.8 presents the results for different sample size K which varies from 10 to 100 with a interval of 10. As I can observe, the values of proportion of infeasible solutions for $K = 10$ and $K = 20$ are 0, which means that all generated solutions are feasible. This could be resulted from limited number of initial solutions generated under small sample size. Starting from $K = 30$, the average proportion of infeasible solutions increases along with the ascending of sample size K. When the sample size $K = 100$, the infeasibility is 0.01 which is a comparatively small figure. Therefore, as I can expect, when the sample size K is big enough, the algorithm will perform well in generating feasible solutions. From Table 4.8, there is not a significant correlation between the sample size K and objective value (makespan).

Table 4.9 presents the results for different number of samples H which varies from 10 to 100 with a interval of 10. It is clearly indicated that the average proportion of infeasible solutions decreases generally with the increment of the number of samples H. When the number of samples $H = 10$, the proportion of infeasibility equals to 63.14% which indicates that the algorithm fails to converge to feasible regions. However, the value of infeasibility drops dramatically with the increasing H. When $H = 100$, the proportion of infeasible solutions is 3.8%. In addition, the average makespan reduces with the rise of H. Hence, the proposed algorithm will have a better performance on both achieving smaller objective value and searching for feasible solutions

Table 4.8: Analysis Results for Sample Size K

K	Makespan	Proportion of Infeasible Solutions
10	50	0
20	51.25	0
30	48.7	0.093
40	50.825	0.072
50	50.54	0.088
60	49	0.065
70	50.17	0.057
80	49.03	0.042
90	49.19	0.024
100	50.13	0.01

when a large number of samples is applied.

Table 4.9: Analysis Results for Number of Samples H

H	Makespan	Proportion of Infeasible Solutions
10	49.34	0.6314
20	49.36	0.1314
30	48.6	0.0622
40	49.08	0.089
50	49.69	0.077
60	48.21	0.066
70	48.55	0.07
80	48.23	0.066
90	48.55	0.055
100	47.23	0.038

Table 4.10 presents the results for different significance level α which varies from 0.05 to 0.5 with a interval of 0.05. Obviously, the increase of significant level α will result in a larger proportion of infeasible solutions. Therefore, in other word, the confidence level α and rate of feasibility for generated solutions share a positive correlation. Figure 4.9 and 4.10 show the variation of average makespan and average proportion of infeasible solutions, the value in the bracket represents the value of $1-\alpha$. Through analysis, I can found out that larger sample size K, greater number of samples H and larger confidence level $1-\alpha$ would enable the proposed SAA-PSO to have a better performance on searching for feasible solutions.

Table 4.10: Analysis Results for Significance Level α

α	Makespan	Proportion of Infeasible Solutions
0.05	50.09	0.024
0.10	49.35	0.03
0.15	49.35	0.022
0.20	46.85	0.022
0.25	49.52	0.033
0.30	50.79	0.09
0.35	50.65	0.088
0.40	48.77	0.093
0.45	50.25	0.12
0.50	49.36	0.14

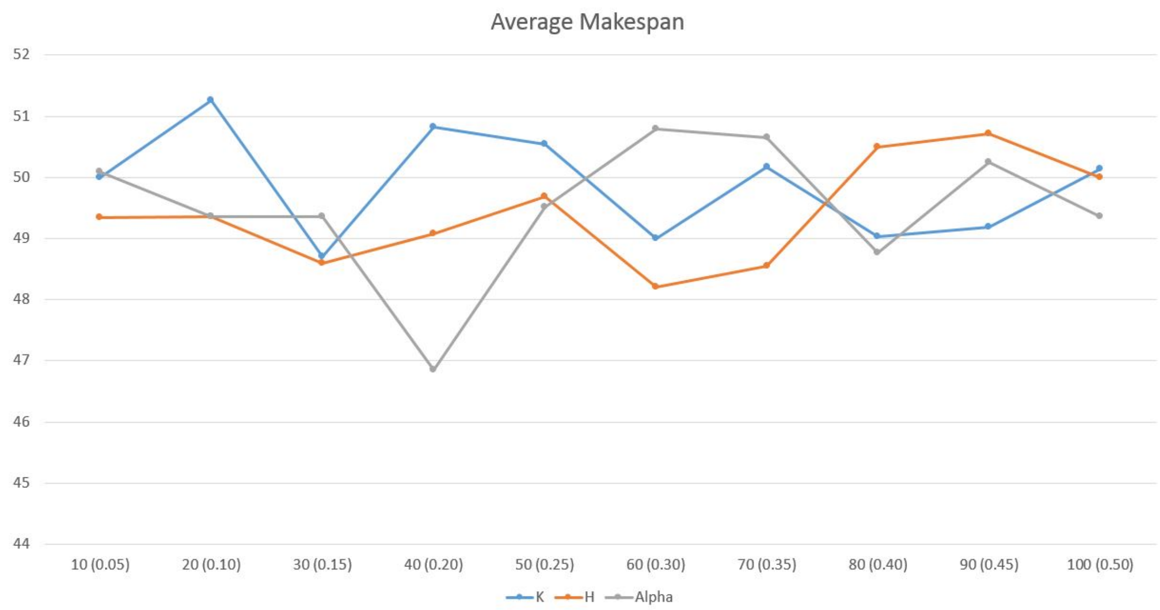

Figure 4.9: Makespan under different values of parameters

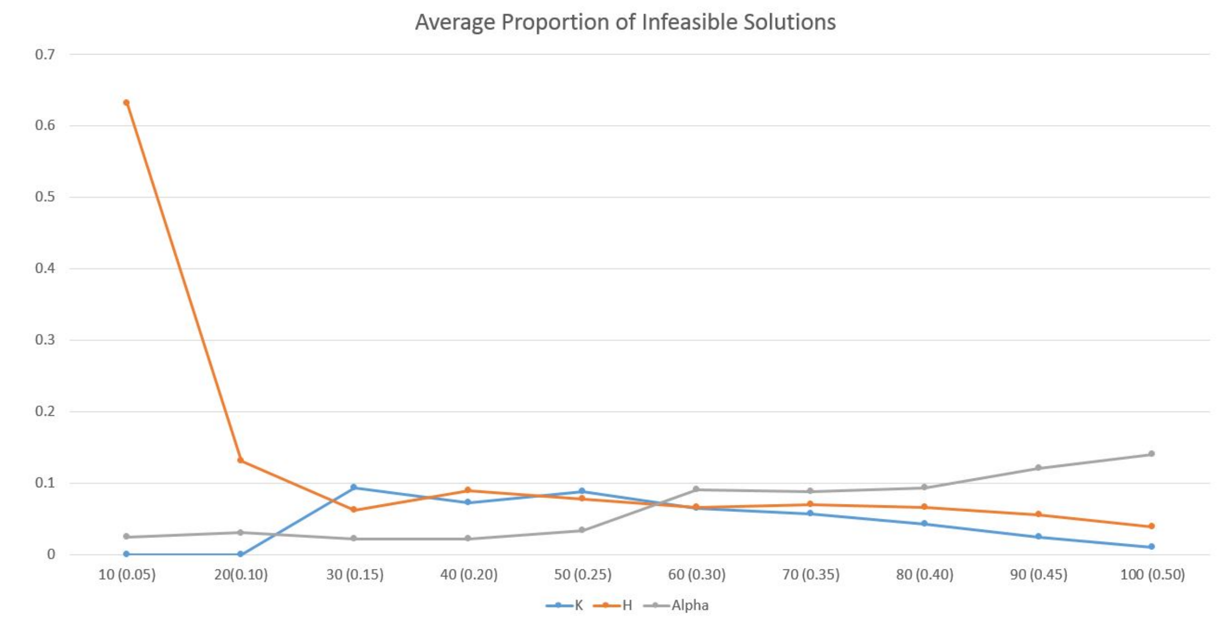

Figure 4.10: Proportion of Infeasible Solutions under different values of parameters

4.5.4 Comparison with Other Meta-heuristics

In our proposed hybrid SAA-PSO algorithm, PSO plays a role of the inner algorithm for solving the discrete deterministic problem for each sample. However, there are other meta-heuristic algorithms that can be utilized as an alternative for solving the proposed SCSCO problem. Hence, in this section, the performance of SAA-PSO should be evaluated by comparing to other algorithms. Two typical and well-known meta-heuristic algorithms, which are the genetic algorithm (GA) proposed in Chapter 3 and the ant colony algorithm (ACO) proposed by Zhang (2011) [70], are selected to substitute PSO in our hybrid algorithm for comparison. Therefore, three hybrid algorithms, namely SAA-PSO, SAA-GA and SAA-ACO, are implemented for coping with five pre-designed experiments with 50, 75, 100, 125 and 150 activities respectively. Four criteria including the average objective value (Avg.), standard deviation of objective value (Std.), infeasibility rate (Inf) and computational time (CUP) are utilized to indicate the performance of these three algorithms.

Table 4.11: Performance Comparison among SAA/PSO, SAA/GA and SAA/ACO

	SAA-PSO				SAA-GA				SAA-ACO			
Inst.	Avg.	Std.	Inf	CPU	Avg.	Std.	Inf	CPU	Avg.	Std.	Inf	CPU
50	80.15	2.7464	0.0132	557.92	82.16	7.5381	0.010453	548.39	82.85	7.9625	0.0128	208.78
75	146.31	6.1112	0.047071	1149.99	147.37	7.8672	0.074133	969.43	146.64	8.6673	0.077151	414.84
100	186.53	6.5226	0.051247	1401.04	182	18.245	0.067797	1218.7	192.64	22.9257	0.072885	505.44
125	227.54	8.4798	0.045555	1667.37	228.45	22.8203	0.034242	1471.95	225.16	23.3997	0.052731	722.68
150	248.5	19.6235	0.041409	2241.78	252.17	32.4593	0.047135	1738.69	251.43	31.0158	0.056671	1106.04

Table 4.11 represents the results of three hybrid algorithms with different instances. With the increment of number of activities involved in an experiment, the complexity of the problem increases dramatically which leads to the rise of the computational time for all algorithm. As I can observe, in terms of computational time, SAA-PSO is the most time consuming algorithm followed by SAA-GA and SAA-ACO. When the number of activities equals to 150, the CPU for SAA-PSO is 2241.78 which is greater than 1738.69 for SAA-GA and double of the time for SAA-ACO. As for the standard deviation of objective value, the values for all three algorithms rise with the increasing of the complexity of instances. Amid these algorithms, SAA-PSO has a comparatively lower standard deviation. For example, when the number of activities is 125, the standard deviation for SAA-PSO is 8.4798 while the figures for SAA-GA and SAA-ACO are 22.8203 and 23.3997 respectively. This implies that SAA-PSO tends to generate more stable and convergent solutions comparing to other two algorithms. As indicated by the table, these three algorithms have little difference on the performance of infeasibility rate. However, to be more precise, the SAA-PSO produces less infeasible solutions than the other two algorithms. For instance, when the number of activities is 100, the infeasibility rate for SAA-PSO is 0.051247 which is slightly smaller than 0.067797 for SAA-GA and 0.072885 for SAA-ACO. Similarly, for instance 150, the infeasibility rate for SAA-PSO is the smallest with the value of 0.041409. Therefore, on the basis of this comparison, I can reach the conclusion that SAA-PSO has a better performance comparing to SAA-GA and SAA-ACO in the aspect of generating solutions especially for large complex problem, but with the sacrifice of computational efficiency.

4.6 Conclusion

A mega construction project management normally comprises the arrangement and deployment of various resources and workforce. Instead of purchasing and owning all resources needed for the project, many resources such as heavy equipment and temporary scaffolding materials are rented from suppliers. While it is commonly known that various methods based on the adoption of different rental resources are available for selection for dealing with the same tasks and each method would trigger a series of optional activities, hereby, the selection of rental resources would have a significant influence on the project scheduling. Therefore, in this chapter, I studied the budget constrained construction supply chain optimization with rental resource selection (SCSCO) problem. Firstly, this chapter proposes a novel mathematical model of this extended resource constrained project scheduling problem (RCPSP) by having three main factors into considerations: 1) the policy of rental resources selection: in contrast to the traditional RCPSP where all activities are encompassed in the project, two sets of activities including necessary activities and optional activities that are triggered by the selected resources are required for scheduling and only one type of rental resources can be chosen for a single task; 2) stochastic activity durations: in our proposed model, activity durations are defined as stochastic variables with known probability distributions; 3) budget constraint: in reality, the arrangement of either workforce or other resources is generally restricted by the estimated budget, hereby, instead of setting up the resources constraints, the constraint for project budget is considered in our mathematical model. The second contribution of this chapter is that a hybrid algorithm that integrates Sample Average Approximation (SAA) method with Particle Swarm Optimization (PSO) algorithm is proposed for coping with the SCSCO problem. A case study based on a maintenance project in a LNG plant is conducted for verifying the effectiveness and feasibility of our proposed hybrid algorithm and a sensitivity analysis based on a randomly generated problem is proceeded. The results manifest that the proposed mathematical model and hybrid algorithm could solve complex stochastic project scheduling problem effectively and the configuration of parameters including project budget, sample size, number of samples and confidence level would affect the performance of proposed algorithm dramatically. In addition, the method described in this chapter could help project planners and managers with generating an appropriate schedule and resource allocation plan which consequently reduces the total makespan and cost of project.

CHAPTER 5

MULTI-OBJECTIVE OPTIMIZATION FOR SCAFFOLD SUPPLY CHAIN OF A MEGA CONSTRUCTION PROJECT

5.1 Introduction

Over the last decade, especially in recent years, the worldwide business environment has become more competitive and the benefits of supply chain management (SCM) have been emphasized by both industry professionals and academic researchers. The philosophy of SCM has been introduced to and applied in various industries, such as construction industry, for improving the performance of product or material management and eliminating the corresponding wastes [4]. The supply chain of a construction project, known as construction supply chain (CSC), concatenates each component from suppliers, contractors to the project owners, and associates the flow of materials, equipment, resources and the transformation of information through each stage [148] [149]. The CSC has drawn a great attention in the construction industry as the need to tackle the challenges such as low productivity, excessive inventory, resource waste and inefficient management of materials has been recognized throughout the industry [4] [149]. Scaffolding system, as a kind of temporary structure applied in construction industry, provides the platform for material placement and supports workers for aerial construction activities [150]. It is commonly known that scaffolding system would not be remained within the final construction structure, therefore, the importance and necessity of scaffolding construction management have not been realized by industry practitioners and researchers. In fact, scaffolding activities have a substantial impact on the safety, quality, productivity and total operational cost of a construction project. According to the report by Construction Industry Institute (CII), the construction and disassembly of scaffolding system has become one of the most wasteful components that contribute to the high indirect construction cost [151]. The evidence can be found in oil and gas industry in Australia. The maintenance cost of the facilities in a LNG plant is estimated to account for 11.47% to 15.36% of the total operational cost, and scaffolding is one of the main contributors as scaffolding materials are needed in a great demand for building supporting platforms [152], and approximately 15% of project budget would be assigned to s-caffolding, while the proportion is still growing [153]. The rental of scaffold materials (leasing cost) is one of the prominent contributors to the staggering cost of scaffolding activities. The leasing cost will occur once the ordered scaffolding materials are delivered to the construction areas and these materials will normally be charged by their weight and the length of leasing. Hence, given that the total scaffold material demand of a project is fixed, the way of how to manage the delivery of material would have a great impact on the leasing cost. Therefore, optimizing the material supply plan is one of the critical issues for optimizing the performance of scaffold supply chain (SSC) and minimizing the total cost of scaffolding construction projects consequently. As I know, the longer the scaffolding structures remain, the greater amount of expense would be spent by the project owner. In this case, appropriate planning of scaffolding construction and disassembly activities would manage to return the dismantled scaffolds timely and shorten the length of a project, which hereby reduce the leasing period of scaffold materials. This leads us to another critical issue of scaffold supply chain optimization - the project scheduling problem. Material supply strategy optimization, which can be comprehended as material ordering optimization, is actually interrelated to project scheduling. Assuming the material demand of each activity is fixed, the schedule of activities would alter the total demand of the project in a given period which correspondingly affects the decision on material ordering. Consequently, project scheduling and material ordering should be considered simultaneously for achieving a better performance of SSC.

To our knowledge, the studies related to scaffold are very limited, let alone those related to SSC optimization. Ratay (2004) discussed and introduced the design philosophies, construction guidance and safety requirements of scaffolding structures [154], while Rubio-Romero et al. (2012) analyzed the relationship between the work safety conditions and the standardization of scaffolding equipment [155]. Building Information Modeling (BIM) has been used for scaffolding construction management in terms of safety risks mitigation [156] and automatic design [131] [157]. More recently, Chai (2017) applied the Radio Frequency Identification (RFID) technology for tracking the transportation of construction materials including scaffold components in a Liquefied Natural Gas (LNG) plant [158]. Apart from these, few studies about scaffold related optimization can be found. Jin et al. (2017) presented a simulation-based optimization model and a multi-attribute utility based decision making model for scaffolding structure space planning [159]. In their research, a two-phase scaffolding structure planning system was proposed, where the first phase was using the multi-objective optimization for determining the optimal location of scaffolding structure and the simulation model for generating feasible scaffolding alternatives. In the second phase of this system, a multiple attribute utility based model was built to help the practitioners to select the best decision on scaffolding plan [159]. Hou et al. (2016) optimized the problem of scaffolding construction scheduling and resource allocating by applying discrete firefly algorithm. They proposed a multi-objective optimization model for the time-cost trade-off resource-constrained scaffolding project scheduling which considered the precedence relationships between different working zones and the selection of modular scaffolds [153]. However, in their model, the cost function was simplified without considering different sources of cost. In order to construct a more realistic and practical optimization model, in this chapter, the problems of scaffolding project scheduling and material ordering are integrated based on the scenario of a mega scaffolding construction and disassembly project which can be named as multi-objective scaffold supply chain optimization problem (MOSSCOP).

In our proposed MOSSCOP, multiple sub-projects and their corresponding scaffolding activities are considered which makes the problem more complex than a single project scenario. The objectives of our model comprise minimizing the total duration and total cost of the project simultaneously, as well as maximizing the utilization rate of workforce. The total cost is broken down into several categories including material leasing cost, transportation cost and labour cost. Precedence relationships between sub-projects and scaffolding activities are incorporated as well as the resource constraints such as available workforce. By encompassing these aforementioned considerations, this SSC optimization problem has become a rather complicated and complex NP-Hard problem [40]. Therefore, an intelligent algorithm is proposed and applied to solve this SSC optimization problem. With the assistance of the proposed model and algorithm, project manager could manage a good balance among time, cost and resource utilization of scaffolding construction and disassembly.

The rest of this chapter is organized as follows. Section 5.2 reviews the relevant researches on construction supply chain, resource-constrained project scheduling and material ordering. A detailed description on general scenario of scaffold supply chain is presented in section 5.3, as well as the formulation of a multi-objective optimization model in section 5.4. In section 5.5, the modified non-dominated sorting genetic algorithm (NSGA-II) is introduced, developed and applied for solving the optimization model. A real project based case study is conducted for validating the proposed model and algorithm in section 5.6, and the conclusion of this chapter is presented in section 5.7.

5.2 Literature Review

Scaffold Supply Chain (SSC) is an area that most researchers have not paid enough attention to, as a consequence, the studies related to scaffolding optimization is very limited. However, the previous studies on construction supply chain (CSC) management and optimization could provide relevant references to our work. Material management is one of the key factors that influence the performance of CSC management, Tesrng et al. (2006) studied the steel rebar production and supply chain and proposed an optimization model with the objective of minimizing the integrated inventory cost of supply chain [160]. On the basis of their optimization model, a decision making system for generating the optimal supply plan was created which could help suppliers with reducing the inventory of construction materials [160]. Both building information modeling (BIM)and geographic information system (GIS) are two information system technologies widely used in various industries, and they were integrated into a construction supply chain management system by Irizarry et al. (2013) for tracking the status of CSC, especially the delivery of construction materials [4]. Liu et al. (2017) integrated the operations within CSC for prefabrication companies, such as procurement, material transportation, inventory management, and preproduction by building up a multi-objective fuzzy optimization model to minimize the partner costs and improve the service levels at the same time [149]. Other fields related to CSC are also studied, such as information sharing for inventory management [161] and quality control for labour productivity improvement [162]. As described in the last section, the SSC studied in this chapter is an integration problem of resource-constrained project scheduling (RCPS)[163] and material ordering (MO), thus, looking into the researches that combine these two problems would be vital to our work. The integrated problem of project scheduling and material ordering (PSMO) was firstly investigated by Aquilano and Smith-Danials in 1980, and a critical path method was proposed and applied for solving this problem [164]. After that, Smith-Daniels et al. (1987) developed mix integer programming models for resource-constrained project scheduling and material ordering (RCPSMO) problem under different considerations and premises, and they found that the optimal solution of R-CPSMO can be determined by the latest starting time [165]. In recent years, the mathematical model for RCPSMO has been developed and improved by either considering more practical and realistic constraints and conditions or being implemented in different fields. Zoraghi et al. (2012) presented a RCPSMO mathematical model with the objective of minimizing the total material holding and ordering cost. In their model, starting time of activities was set as the decision variable and constraints such as allowable completion time and precedence relationships were also included [166]. Afterwards, they improved their model by applying bonus and penalty policies when the project was completed before or after its due date respectively [167]. Shahsavar et al. (2016) studied the RCPSMO problem for nonrenewable resources and formulated an optimization model with the aim of minimizing the costs related to renewable materials. The price of nonrenewable resources is volatile and influenced by the order quantity due to their scarcity, hence, in their model, quantity discount policy was involved [168]. In the context of construction projects, optimization of RCPSMO problem has also been conducted. Ashuri et al. (2013) proposed a shuffled frog-leaping model that addressed the time-cost-resource trade off issue in a construction project, where the objectives of minimizing total cost, total duration and variation of resource allocation were considered simultaneously [169]. A more typical and realistic mix integer programming model of RCPSMO problem for a construction project was presented by Fu (2014) which comprised various trade-offs among various costs such as material price, ordering cost, back-ordering cost, inventory holding cost and bonus-penalty cost as well [170].

Through reviewing the above-mentioned articles related to RCPSMO , I found that time and cost are always the most critical indicators for evaluating the performance of most construction projects including scaffolding projects. However, in most cases, the reduction in the duration of a project would imply the need to invest more on necessary resources, such as workforce and equipment. For these time-cost trade-off problems in the context of construction projects, they are normally formulated as multi-objective optimization problems that aim to screen out the best fit balance between these objectives. Over the past decades, many researches in terms of evolutionary algorithms have been carried out to deal with multi-objective optimization in project scheduling. Abbasi et al. (2006) utilized the simulated annealing (SA) algorithm to solve a bi-objective project scheduling problem with the goal to minimize the makespan and maximize net present value of project [37]. Similarly, SA algorithm was applied for solving multi-objective flowshop scheduling problems [171]. The multi-objective particle swarm optimization (PSO) algorithm was first studied by Parsopoulos and Vrahatis (2002) [172], since then, it has been adopted and modified for solving various scheduling problems [173]. Zhang et al. (2009) proposed a hybrid PSO for multi-objective job shop scheduling problem [174], while Kazemi and Tavakkoli (2011) implemented PSO to optimize the resource constrained project scheduling problem with objectives of minimizing the makespan and floating time [35]. There are also other natural based algorithms that have been applied for similar problems, such as ant colony optimization (ACO) [175], Binary search algorithm [176] [177], firefly algorithm (FA) [178] and genetic algorithm (GA) [179],[180],[147]. Among these evolutionary algorithms, GA would be one of the most popular algorithms that have been improved and modified into different forms specifically suitable for multi-objective problems. Srinivas and Deb (1994) introduced a non-dominated sorting genetic algorithm (NSGA) which remains the genetic operations from conventional GA and identifies the Pareto front solutions at each iteration through fitness calculation and non-dominated sorting operation [64]. Deb (2002) proposed an improved version of NSGA, called NSGA-II, which has a lower computational complexity for non-dominated sorting operation, and a better performance on diversity preservation and Pareto optimal solutions [66]. Jensen (2003) developed a new algorithm for non-dominated sorting which reduced the complexity of NSGA-II [181], and Wei et al. (2009) created a new chromosome selection procedure which hereby improved the performance of NSGA-II [182] which followed by the application of an effective data structure, called dominance tree, proposed by Shi et al. (2009) [183]. Other studies related to the improvement and development of NSGA-II include the improvement on genetic operators [184] [185] and controlled elitism [186]. At the same time, NSGA-II has been used to cope with various scheduling problems because of these merits, such as resource constrained project scheduling [187] and robust job-shop scheduling [188]. In this chapter, the conventional NSGA-II algorithm is modified and applied for the proposed SSC optimization problem by introducing a new method of individual representation.

5.3 Scenario Description

This chapter focuses on a scaffold supply chain (SSC) of a mega construction project that consists of several sub-projects. From an broader perspective, a general CSC could comprise many different stakeholders such as producers of raw materials, manufacturers, wholesalers, retailers, and customers which create a complex network, and most of the related studies laid their emphasis on the optimization of supply chain network or information sharing [161, 149]. However, from an operational perspective, the primary goal of CSC management is to optimize the material flow associated with various operations or activities, such as designing a cost-efficient material ordering plan and controlling the best level of inventory. Nevertheless, the designing of such an appropriate material ordering plan is determined by the demand of materials from construction activities. In this case, generating an optimal schedule for a mega construction project and its corresponding material ordering plan in the scaffold supply chain (SSC) context would be our target.

In this chapter, a mega project that consists several scaffolding construction sub-projects is considered, and the material flow in SSC is described as shown Figure 5.1. For each sub-project, there is a set of activities that need to be executed. Therefore, when the project manager commences the task of scheduling, two classes of priority relationships should be taken into consideration - the priorities between sub-projects and the precedence relationship between activities for each sub-project. However, these two classes of relationships are slightly different. The priority relationship between sub-projects in real life tends to be linear, and the sub-projects with higher level of priority would have the right to use the resources prior to other sub-projects. These sub-projects can be conducted at the same time. In our occasion, I assume that the sequence of operating these sub-projects is fixed. On the other hand, the precedence relationship between activities determines that the successors can only be carried out after the completion of predecessors. The SSC studied in this case would start from material suppliers and end at construction contractors or project owners, where scaffold materials would be delivered directly from supplier warehouse to the project area and transferred around within the area for the operations of sub-projects. In addition, as a specific example of construction supply chain, SSC shows its difference comparing to the general CSC shown in Figure 3.1. The scaffolding structures would be dismantled and returned to the suppliers, hence, the scaffold supply chain starts from suppliers and ends at suppliers which makes it a closed loop supply chain. When the project starts, scaffold materials will be delivered from supplier to the construction area based on the orders placed by construction contractors. Instead of transporting the whole amount of material demand, the construction contractors would normally order the components they need over a certain period in advance, they call this material ordering method as 'drip-feed'strategy. The quantity of material order is decided on the basis of the estimation of construction supervisors or team leaders. The scaffold materials would not be shipped to working area directly, instead, they would be placed temporarily in a dedicated area, called 'Laydown Area'. These inventory would be distributed to the workfront areas for each sub-project and used for construction. Different from most other construction materials, scaffold materials are recyclable. When one of the construction project is completed, the scaffolding structure would be dismantled and the components would be sent back to the supplier. In the operational flow of SSC described above, material ordering is vital to the management of scaffold inventory on-site and the control of total operation costs. As a matter of fact, if excessive amount of materials are ordered, high scaffold material leasing cost and inventory holding cost would occur. While on the contrary, not enough inventory would result in the delay of project. Thus, increasing the frequency of delivery would actually reduce the inventory on site at a single period. However, as a consequence, more transportation cost is expected. Hence, planning the best time and quantity for material delivery would ensure the operations being conducted on time by fulfilling the demand of materials with lower cost. On the other hand, the demand of materials at any time during the project is determined by the schedule of operations. Hence, as aforementioned, this SSC optimization problem can be transferred to the integration of resource-constrained project scheduling problem and material ordering problem in scaffold supply chain (SSC) context. Nevertheless, in real life, the productivity of workers is not always consistent which would result in the variation of material demand from time to time. Therefore, in this chapter, the assumption that the productivity for each scaffolding activity remains the same over its period. As a consequence, the material demand per unit time for each activity keeps stable over the activity execution period.

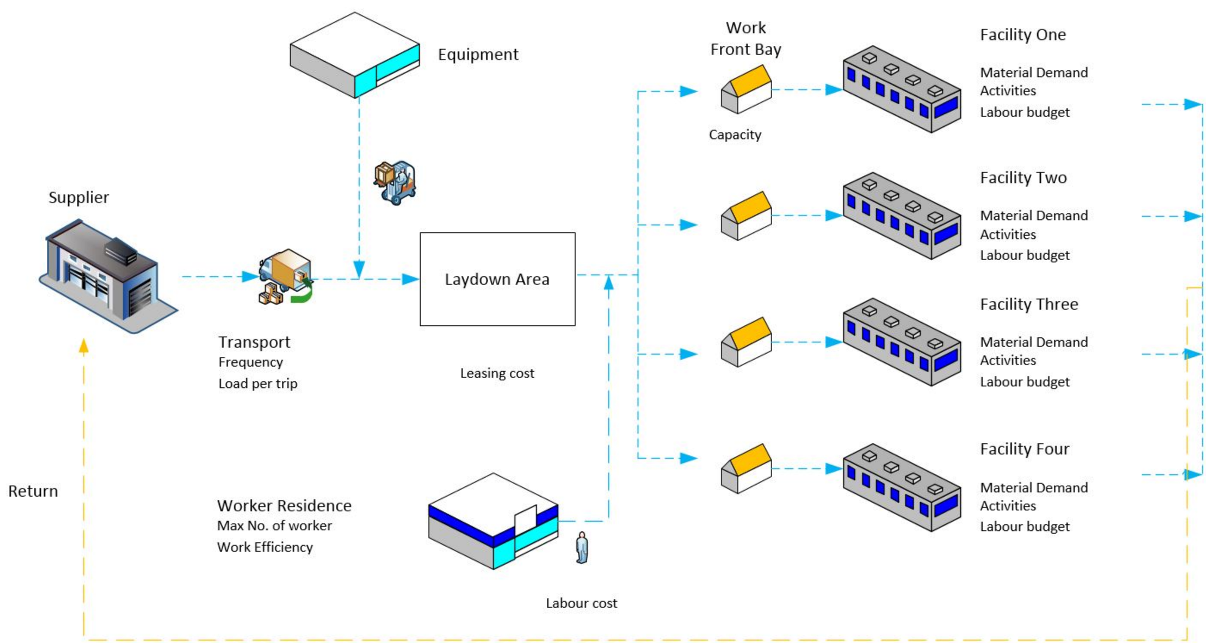

Figure 5.1: Roadmap for general Scaffold Supply Chain

5.4 Mathematical Model Formulation

5.4.1 Assumption and Notation

Assumption

(a) There are various types of scaffold component, and for each component, the leasing cost per unit weight per unit time is assumed to be the same. The transportation cost per unit weight per trip keeps the same for all scaffold materials, while it varies with the quantity delivered each trip.

(b) At the design phase, the contractor has designed the structure of scaffolding construction and estimated the detailed demand of scaffolding materials. Hence, the demand of scaffold materials for each activity of a particular sub-project is assumed as fixed and known.

(c) The workforce required for each activity of a particular sub-project is assumed as fixed and provided due to the same reason as above. There is a limitation on the total number of workers allowed to work at the same time.

(d) This mega project is assumed to be scheduled on a discrete time horizon with a longest allowable total duration.

(e) The demand of scaffold material per unit time for each activity is assumed to be consistent.

Notation

Before proceeding the mathematical modeling for MOSSCOP, the involved notations are displayed in Table 5.1.

5.4.2 Mathematical Model for SSC Optimization

Objective Functions

According to the problem described in Section 5.3, in order to optimize the performance of SSC of a mega project, an optimal scheduling for scaffolding activities associated with the the corresponding scaffold material ordering plan should be designed. Hence, our intention in this section is to construct a mathematical model for the resource-constrained project scheduling problem in the scaffolding supply chain context. Time and cost are two critical indicators for evaluating the performance of the project management, while resource utilization, especially the workforce efficiency, is another importance consideration for project managers. Therefore, in this chapter, a multi-objective mathematical model for SSC optimization problem is proposed

Table 5.1: Notations for SSC Optimization Problem

Set and indices:	
$\mathscr{I} = \{1, \cdots, I\}$	set of scaffolding sub-projects indexed by i.
$\mathscr{J} = \{1, \cdots, J\}$	set of activities for each sub-projects indexed by j.
$\mathscr{V}_1 \subseteq \mathscr{I}^2$	Immediate precedence relations among sub-projects, where $(i,k) \in \mathscr{V}_\infty$ indicates sub-project k must start after sub-project i's completion.
$\mathscr{V}_2 \subseteq \mathscr{J}^2$	Immediate precedence relations among activities, where $(j,h) \in \mathscr{V}_\in$ indicates activity j must start after activity h's completion.
$\mathscr{M} = \{1, \cdots, M\}$	set of types of scaffold component indexed by m.
$\mathscr{T} = \{1, \cdots, T\}$	set of time slots indexed by t which represents time interval $[t-1, t)$.
Parameters:	
p_{ij}^m	demand of scaffold component m for activity j in sub-project i.
d_{ij}	duration of activity j in sub-project i.
u_{ij}	workforce required for activity j in sub-project i.
l_m	leasing cost per unit time per unit weight for scaffold component m.
γ	labour cost per unit time per person.
q^t	quantity of material delivery at time t.
β	transportation cost per unit weight per trip. When $q^t \in [0,a)$, $\beta = \beta_1$; when $q^t \in [a,b)$, then $\beta = \beta_2$; when $q^t \in [b, +\infty)$, $\beta = \beta_3$.
U	Maximum available workforce.
Variables:	
F	project makespan.
s_{ij}	start time of activity j in sub-project i.
c_{ij}	completion time of activity j in sub-project i.
$x_{ij}^t \in \{0,1\}$	$x_{ij}^t = 1$, if the activity j of sub-project i is executed at time t; otherwise, $x_{ij}^t = 0$.
y_m^t	the quantity of type m scaffolding component supplied at time t.

with goals of minimizing the total duration and total cost and maximizing the workforce usage efficiency simultaneously. The total duration can be comprehended as the latest completion time of the sub-projects, hereby, the first objective function can be presented as:

$$min \;\; F_t = s_{I+1,j} \tag{5.1}$$

Here, $s_{I+1,j}$ stands for the starting time of sub-project $I+1$ which is a artificial node.

The second objective is to minimize the total cost which consists of scaffold material leasing cost, labour cost and transportation cost. The leasing cost is charged for the scaffold materials either stored in the laydown areas or used for the construction. In another word, once the scaffold materials arrive the laydown area, leasing cost would occur. Hence, the amount of scaffold materials inside the construction area is the result of the total amount of shipment subtracting the amount of returned materials. In this case, I have the equation for the total leasing cost as below.

$$C_{Lease} = \sum_{m=1}^{M} \sum_{t=1}^{T} [\sum_{k=1}^{t} y_m^k - \sum_{k=1}^{t} \sum_{i=1}^{I} \sum_{j=1}^{J} max(0, -p_{ij}^m * x_{ij}^k)] * l_m \tag{5.2}$$

The labour cost is calculated based on the active workforce at anytime of the project and the transportation cost is the cost for delivering the materials from supplier to the laydown area and recycling the dismantled scaffold components back to warehouse. The equations for total labour cost and total transportation cost are displayed.

$$C_{Labour} = \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} u_{ij} * x_{ij}^t * \gamma \tag{5.3}$$

$$C_{Transp} = \sum_{t=1}^{T} \sum_{i=1}^{I} \sum_{j=1}^{J} \sum_{m=1}^{M} max(0, -p_{ij}^m * x_{ij}^k) * \beta + \sum_{t=1}^{T} \sum_{m=1}^{M} y_m^k * \beta \tag{5.4}$$

Therefore, I have the second objective function is minimizing the sum of total leasing cost, total labour cost and total transportation cost.

$$min \;\; C_{Total} = C_{Lease} + C_{Labour} + C_{Transp} \tag{5.5}$$

In addition to the time and cost, the efficiency of resources utilization, especially the workforce arrangement, is a critical indicator for the performance of both project management and supply chain management. In the mathematical model, the fluctuation of workforce usage is expected to keep stable, which helps project manager to arrange appropriate number of workers on site and reduce the budget for labour cost correspondingly. The utilization rate of workforce at time t is calculated as follow:

$$r^t = \frac{1}{U} \sum_{i=1}^{I} \sum_{j=1}^{J} u_{ij} * x_{ij}^t \tag{5.6}$$

Hence, the third objective function is to maximizing the workforce utilization rate, which equals to minimizing the variation of workforce utilization rate:

$$min \;\; F_r = \sum_{t=1}^{T} (r^t - \frac{1}{T}\sum_{t=1}^{T} r^t)^2 \tag{5.7}$$

Precedence Constraints

As aforementioned, in a mega construction project, some sub-projects need to be executed before the others because of the considerations related to locations, safety requirements and functions of different facilities. This kind of precedence relationship also applies to scaffolding activities, as there is a restricted procedure for scaffolding construction and disassembly. In our model, the precedence constraints between different sub-projects is considered, as well as the relationships between different scaffolding activities for each sub-project are taken into consideration, which are shown by the inequalities as below. It needs to be mentioned that, in our model, the time horizon is assumed to be discrete.

$$s_{ij} \geq c_{kj} + 1, \forall (i,k) \in \mathscr{V}_1 \tag{5.8}$$

$$s_{ij} \geq c_{ih} + 1, \forall (j,h) \in \mathscr{V}_2 \tag{5.9}$$

$$c_{ij} \geq x_{ij}^t * t, i \in \mathscr{I}, j \in \mathscr{J}, t \in \mathscr{T} \tag{5.10}$$

Workforce Constraints

Due to the restricted working space and budget allocation, the maximum number of workers that can be assigned to the project is limited, therefore, the availability of workforce should be considered when schedule of project is being planned. The active workers at any time during the project should not exceed the limitation.

$$\sum_{i=1}^{I}\sum_{j=1}^{J} u_{ij} * x_{ij}^t \leq U, i \in \mathscr{I}, j \in \mathscr{J}, t \in \mathscr{T} \tag{5.11}$$

Intrinsic Variable Constraints

$$\sum_{t=1}^{T} y_m^t = \sum_{i=1}^{I}\sum_{j=1}^{J} p_{ij}^m, i \in \mathscr{I}, j \in \mathscr{J}, m \in \mathscr{M} \tag{5.12}$$

$$\sum_{t=1}^{T} x_{ij}^t = d_{ij}, i \in \mathscr{I}, j \in \mathscr{J}, t \in \mathscr{T} \tag{5.13}$$

$$x_{ij}^t \in \{0,1\}, i \in \mathscr{I}, j \in \mathscr{J}, t \in \mathscr{T} \tag{5.14}$$

$$s_{ij} \geq 0, s_{ij} \geq 0, i \in \mathscr{I}, j \in \mathscr{J} \tag{5.15}$$

Constraint (12) ensures the demand of scaffold materials is always satisfied, while constraint (13) makes sure that every activity is executed. Constraint (14) and (15)are binary and non-negative constraints.

Integrated SSC Optimization Model

To sum up, the integrated SSC optimization problem can be formulated as a multi-objective model displayed as follow

$$\begin{cases} \min & F_t = s_{I+1,j}, \\ \min & C_{Total} = C_{Lease} + C_{Labour} + C_{Transp}, \\ \min & F_r = \sum\limits_{t=1}^{T} (r^t - \frac{1}{T} \sum\limits_{t=1}^{T} r^t)^2. \\ \text{s.t.} & (2) - (4), (6), (8) - (15) \end{cases} \tag{5.16}$$

5.5 Modified Non-dominated Sorting Genetic Algorithm (NSGA-II)

The multi-objective optimization model described above has transferred the scaffold supply chain optimization problem into a time-cost-resource trade-off problem in the context of scaffolding construction. Total duration, total cost and the workforce usage fluctuation are conceived to be minimized simultaneously by searching for optimal schedules of project and better plan of material ordering. Nevertheless, in most cases of a multi-objective problem, some criteria are actually conflicting with others. For example, in our SSC problem, shortening the duration of project may lead to more workers involved in order to improve the total workload per day, which could result in higher labour cost consequently. Instead of obtaining a single best solution, for a multi-objective optimization model, there usually exists a set of optimal solutions (also well known as non-dominated solutions or Pareto-optimal solutions) as it is not necessarily possible to find out a single solution that satisfies all objectives and criteria [66], and the Pareto-optimal solutions are obtained when there is not any objective functions can be improved in values without deteriorating any other objectives. In order to address the proposed multi-objective SSC optimization problem, a modified elitist non-dominated sorting genetic algorithm (NSGA-II) is introduced and applied.

NSGA-II was initially introduced by Deb et al. (2002), which aims to search for a set of solutions that are sorted and organized in Pareto fronts [66]. As aforementioned in the section of literature review, NSGA-II has several advantages compared to other evolutionary algorithm

(EA) for solving multi-objective problems, such as fast computation, elitism incorporation and better convergence in the Pareto fronts [189]. Traditionally, NSGA-II starts with an initialization procedure where a population of feasible solutions with size N is generated randomly, which is call the parent population P_t. Genetic Algorithm (GA) operations - individual selection, crossover and mutation - are conducted for creating an offspring population Q_t from the parent population P_t. A larger population R_t with size $2N$ is then generated by combining P_t and Q_t, followed by selection procedure using non-dominated sorting and crowding distance sorting to filter out the population of elitist individuals with size N. Non-dominated sorting is the procedure of ranking the individuals into different fronts with different non-domination levels, while crowding distance sorting refers to the ranking between different individuals in a front [190]. In the procedure of selection, the solutions that are better ranked and more dispersive are preferred. The new generation of feasible solutions would repeat the procedure of NSGA-II until there is no more improvement or alterations can be seen in the Pareto fronts or the pre-set maximum iterations have reached. In this chapter, I make some modifications on the procedure of NSGA-II in order to fit the proposed SSC problem better.

5.5.1 Parameters Initialization

Before the algorithm is implemented for SSC optimization, various parameters including the model parameters and NSGA-II parameters need to be set up, and the corresponding data should be gathered and sorted. The model parameters could include the number of objective functions, the number of constraints and the number of decision variables, and the size of population, maximum number of iteration for algorithm termination as well as the crossover rate and mutation rate need to be pre-defined as NSGA-II parameters. The data required would vary from different projects, which in this case, could refer to project parameters including the number of sub-projects, the number of scaffolding activities, number of scaffolding component types, duration of each activity in different sub-projects, demand of each scaffold component for each activity in different sub-projects, workforce demand for each activity and various unit costs.

5.5.2 Solution Encoding

The precedence relationships among different activities from different sub-projects can normally be displayed in a form of network. In this section, the precedence network is encoded as three lists: A)An activity pool list for sub-project i at time t, which can be represented as $PL_{i,t}$. The activity pool list includes the available activities that can be selected for scheduling at time t. $PL_{i,t}$ is initially formed by including all activities at time $t = 0$, and each activity in the pool can be repeated. As in this chapter, time t is considered as discrete and integral, hereby, the number of same element for a specific activity appears in $PL_{i,t}$ is based on its duration. For example, if activity j of sub-project i has a duration of $5t$, there will be 5 elements that represent activity j included in the initial pool list; B) A selected activity list for sub-project i at time t, which can be represented as $SL_{i,t}$. The selected activity list is updated by adding the selected activities at time t; C) A predecessor list of activity j for sub-project i, which can be represented as $O_{i,j}$. For each activity j from sub-project i, it can only be chosen when the activities included in the list $O_{i,j}$ are all completed. The predecessor list $O_{i,j}$ would be updated after each selection by eliminating the completed activities from the list. Hence, activity j is available for scheduling when $O_{i,j} = \emptyset$. A dummy node 0 is set as the starting point of this list, where $O_{i,j} = 0$ means that activity j can be scheduled as the first activity for sub-project i.

In the procedure of activity selecting, two rules are worth mentioning. First of all, only one activity for any sub-project can be selected at time t. Secondly, as each activity is duplicated into several same elements in the activity pool list, in order to keep the process of job consistent, the same elements are preferred to be selected and placed next to each other if this particular activity has not completed yet, which makes sure that one single activity would not be operated separately. Thirdly, when scheduling the activities, the priority relationships between different sub-projects as well as between activities have to be satisfied.

The solution of SSC optimization problem, which in this chapter is the schedule of the mega project, can be encoded as a time axis matrix, $TS = [a_{i,t}] \in \mathscr{R}^{I \times T}$. The time axis matrix has I rows and T columns, where each element $a_{i,t}$ represents an activity from sub-project i entitled with the series number $a_{i,t}$ that is conducted at time t. For example, $a_{i,t} = j$ means that activity j from sub-project i is selected for operation at time t. None of the activities would be carried out for sub-project i at time t when $a_{i,t} = 0$. A simple example is provided to illustrate the procedure of solution encoding. Assuming that there are two sub-projects, and the precedence relationships among their activities are represented as networks shown in Figure 5.2, the numbers in the circles represent the codes of activities while the numbers in boxes above stand for the duration and the workforce demand for each activity respectively. From the networks, I can have the predecessor lists for each activity from both sub-projects. For instance, the predecessor list for activity 1 from sub-project 1 is $O_{1,1} = \{0\}$ and the predecessor list for activity 4 from sub-project 2 is $O_{2,4} = \{1,2,3\}$.

In this example, I assume that the maximum allowable duration $T = 12$, and the duration of each activity is assumed to be constant. In this case, the activity pool lists for these two sub-projects at time $t = 1$ are $PL_{1,1} = \{1,1,2,3,3,4,4,4,5,5\}$ and $PL_{2,1} = \{1,2,2,3,3,4,4\}$ respectively. Consequently, the time axis matrix $TS = [a_{i,t}] \in \mathscr{R}^{2\times 12}$, and the structure of the time axis matrix can be illustrated by the example in Figure 5.3. In this example, the length of the time axis matrix is T and all the elements from the pool lists are selected and placed in each row of the matrix accordingly. The unselected positions of the matrix is filled with the dummy node 0.

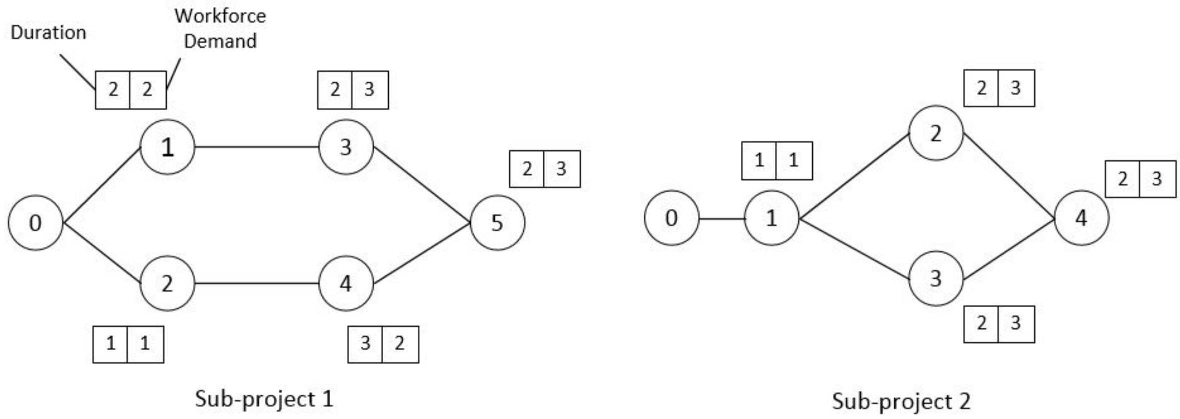

Figure 5.2: Example Activity Netwroks

i \ t	1	2	3	4	5	6	7	8	9	10	11	12
1	2	0	3	1	4	4	3	1	5	4	5	0
2	4	1	2	2	0	0	3	4	3	0	0	0

Figure 5.3: Example of Time Axis Matrix

5.5.3 Initial Feasible Population

For conventional NSGA-II, the initial population of solutions, which in this case is the time axis matrices, is created with the size of N randomly. In order to generate better offsprings, in our algorithm, a random population with the size of $2N$ is generated at the initial stage. To transfer this initial population into feasible solutions, a new schedule generation scheme (SGS) is presented and applied.

As mentioned previously, the priority relationship between sub-projects tends to be linear, therefore, sub-projects are ranked based on their priority levels in the time axis matrices. For example, sub-project $i = 1$ in the time axis matrix means the sub-project that has the highest priority level. Starting from the first element in the time axis matrix, $a_{1,1}$, the feasibility of each element need to be verified by three criteria: 1) Suitability, the element $a_{i,t}$ should be included in the activity pool list $PL_{i,t}$ and consistent with element $a_{i,t-1}$ if the chosen activity has not been completed by time t; 2) Priority, the element $a_{i,t}$ must satisfy the precedence relationship with its predecessors. Hence, in another word, $a_{i,t}$ can only be placed when the activities from its predecessor list $O_{i,a_{i,t}}$ are all selected, which means its updated list $O_{i,a_{i,t}} = \emptyset$; 3) Resource Availability, the total number of workers working at any single time during the project should be limited under the maximum allowable workforce. The starting time of time axis matrix is set as $t = 1$ and the suitability, priority and resource availability for each element $a_{i,t}$ should be checked in the sequence in terms of time and priority of sub-projects. The original $a_{i,t}$ will be kept in the feasible time axis matrices only when $a_{i,t}$ satisfies all three criteria. If there is not any such activities in the activity pool list $PL_{i,t}$, then $a_{i,t} = 0$. When the activity pool list $PL_{i,t}$ is empty, all the unfilled elements are assigned with zeros, and a feasible solution is generated. The pseudo code of the procedure of generating a feasible solution is shown in Algorithm 6.

Following up with the example mentioned above, in this case, I define that the maximum available workforce equals to 5. The detailed procedure of generating a feasible solution is presented as below:

1. Step 1: Generate a initial time axis matrix randomly.

2. Step 2: For $t = 1$, check the feasibility of current elements $a_{1,1}$ and $a_{2,1}$. For $a_{1,1} = 2$, it satisfies three criteria, hereby, it stays unchanged. The remaining available workforce is $U - u_{1,2} = 5 - 1 = 4$. For $a_{2,1} = 4$, it violates the priority constraint. Hence, $a_{2,1}$ should be replaced by an activity with highest priority level from $PL_{2,1}$. In this case, $a_{2,1} = 1$. As $u_{2,1} = 1 < 4$, $a_{2,1}$ satisfies the resource availability constraint. Figure 5.4 shows the procedure of solution updating.

3. Step 3: Repeat step 2 for every elements ($t > 1$) of the time axis matrix until all activities are selected. The third Time Axis Matrix in Figure 5.4 shows the generated feasible solution.

Algorithm 6 Pseudo code of generating a feasible solution

Initialize activity pool list $PL_{i,t}$, selected activity list $SL_{i,t}$, predecessor lists $O_{i,a_{i,t}}$, maximum available workforce U and maximum time horizon T
Generate initial population with size of $2N$ randomly
Select one candidate individual randomly
For $i \in \{1, ..., I\}$, $t \in \{1, ..., T\}$
Check the suitability, priority and resource availability for each element $a_{i,t}$

(a) Suitability
If $a_{i,t-1} \in PL_{i,t}$
replace $a_{i,t}$ with $a_{i,t-1}$
Otherwise
If $a_{i,t} \in PL_{i,t}$
$a_{i,t}$ stays, goes to stage (b)
Otherwise replace $a_{i,t}$ with the next element from $PL_{i,t}$, goes to stage (b)

(b) Priority
If $O_{i,a_{i,t}}=\emptyset$
$a_{i,t}$ stays, goes to stage (c)
Otherwise, replace $a_{i,t}$ with the next element from $PL_{i,t}$
Goes to stage (c)

(c) Resource Availability
Calculate total workforce allocated at time t
If $\sum_{i=1}^{I} u_{i,a_{i,t}} \leq U$
$a_{i,t}$ stays, update $PL_{i,t}$, $SL_{i,t}$ and $O_{i,a_{i,t}}$
start to check the criteria for element $a_{i+1,t}$
Otherwise, replace $a_{i,t}$ with the next element from $PL_{i,t}$
repeat stage (a), (b) and (c) until such element is found
Otherwise, assign $a_{i,t}$ with 0

Until $PL_{i,t} = \emptyset$
Assign unfilled elements with zeros
Stop, a feasible individual is generated

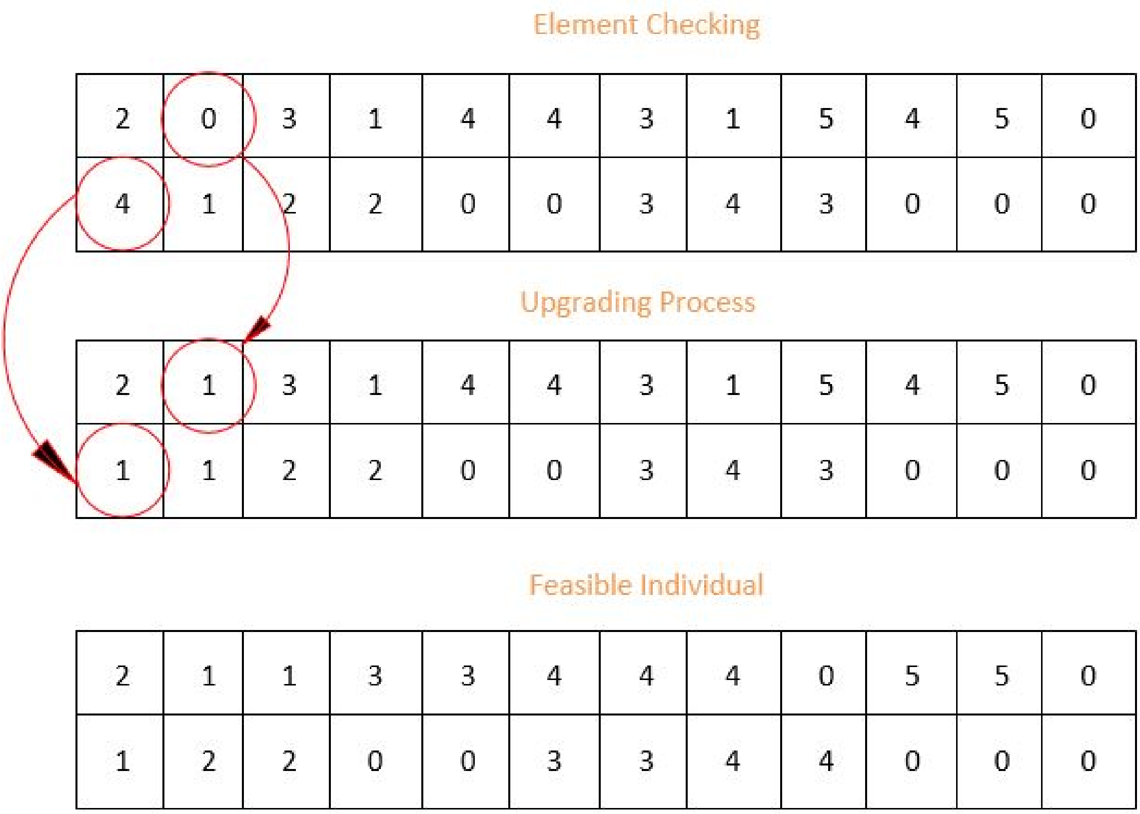

Figure 5.4: Illustration of Individual Upgrading

5.5.4 Fitness Evaluation

In the process of algorithm implementation, the values of objective functions are required to be computed for selecting better solutions. There are three objective functions stated as above: the total duration F_t, the total cost C_{Total} and the workforce efficiency F_r. As the schedule is encoded as a time axis matrix, the latest finish time of sub-projects actually represent the total duration. Hence, I search for the last element that is greater than zero from each row of the matrix, the time t associated with the last non-zero element $a_{i,t}$ is the finish time of sub-project i. The greatest t I find among all sub-projects equals to the value of the first objective function. The total cost C_{Total} is comprised of the leasing cost, the transport cost and the labour cost. For every unit time horizon, the increasing leasing cost is contributed by the previous delivery materials that are either used for construction or stored in the laydown area and the newly delivery materials at the beginning of time t. Transportation fee is charged every delivery based on the amount of materials, therefore, a decision on the unit transportation cost will be made each time I update the transportation cost. Finally, the work efficiency F_r is estimated by calculating the variance of workforce utilization rate.

5.5.5 Selection

The way of selection may vary from different algorithms, and the selection mechanism for NSGA-II proposed by Deb et al. (2002) is adopted in our algorithm [66]. All individuals from initial feasible population are ranked into different dominated fronts based on non-dominated sorting procedure. For each individual q from this $2N$ population, the number of individuals that dominate q and the set of individuals that q dominates are calculated. By updating these two entities for every individual, the solutions are classified into different fronts and ranked from better to worse [191]. The qualities of individuals from a same front is estimated by their crowding distances, where a greater crowding distance gives a better quality. The crowding distance of a individual measures the density of its surrounding solutions, which can be calculated by using the following algorithm. Algorithm 7 shows the Pseudo code of crowding distance sorting. In the algorithm 7, F is a Pareto front that consists of N individuals, while $F[i]^m$ represents the mth objective value for ith individual in this front. f_m^{max} and f_m^{min} stand for the maximum and minimum values for mth objective value.

Once non-dominated sorting is completed, the tournament selection mechanism would start to be performed. A new parent population with N individuals is expected to generated through selection procedure from the initial feasible solution with size of $2N$. Individuals from different non-dominated fronts are selected based on the rankings of these fronts, where better ranked fronts will be selected before others until N individuals are all achieved. If the size of last selected front is greater than the the number of individuals needed, individuals with better qualities, which in this case is greater crowding distances, will be chosen first. Figure 5.5 shows the selection procedure.

Algorithm 7 Pseudo code of crowding distance sorting

1: Initialize F, i, m, and $F[i]_{distance}$
2: Set $F[i]_{distance} = 0$
3: For each objective m
4: Sort(F, m) based on the objective function value in ascending order
5: $F[1]_{distance} = F[N]_{distance} = \infty$
6: For $i = 2toN - 1$
7: $F[i]_{distance} = F[i]_{distance} + (F[i+1]^m - F[i-1]^m)\backslash(f_m^{max} - f_m^{min})$
8: End

5.5.6 Genetic Algorithm Operators

Crossover Operator and Mutation Operator

In our proposed algorithm, the single-point crossover proposed by Hartmann (2001) [192] and Ghoddousi et al. (2013) [189] is applied. As the solutions are encoded as time axis matrices and each column represents the activity arrangement for each sub-project at the same time, therefore, only one integer q_1 is selected randomly. The elements from first q_1 positions in the father

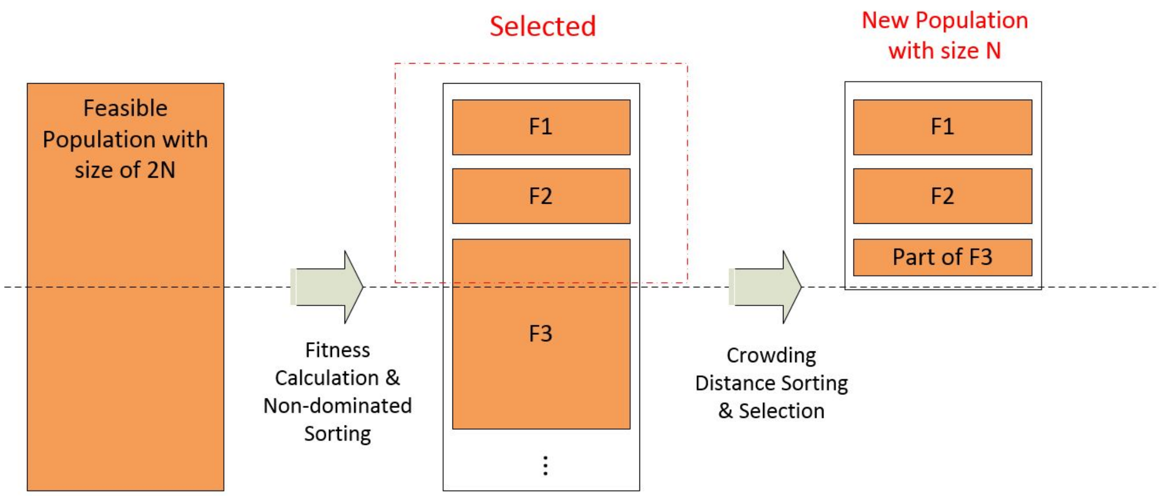

Figure 5.5: Selection Procedure

chromosome would pass to the daughter chromosome with positions and values unchanged. The positions from $q_1 + 1$ to T in the daughter chromosome are inherit from mother chromosome by excluding the the chosen elements that are transferred from father chromosome. The crossover procedure for generating daughter chromosome is illustrated in Figure 5.6, assuming that $q_1 = 4$. The mutation operation will be applied for every row in the time axis matrix. For all elements $a_{i,t}, t = 1,2,3...T$ of each sub-project $i = 1,2,3...I$, two adjacent activities $a_{i,t}$ and $a_{i,t+1}$ would exchange with a probability of $p_{mutation}$ [192]. In this case, a new solution that might not be obtained by crossover is generated through mutation, and the diversity of solutions is improved consequently.

Feasible Offspring Generation

The solutions produced by crossover and mutation are not necessarily feasible as they might not satisfy all three criteria described above. Therefore, every individual obtained through crossover and mutation need to be checked and modified by applying the procedure of feasible solution generation presented in Section 5.3, and a feasible offspring population with size N will be produced. By combining the parent population and the offspring population, I could have a combined population with size $2N$. This combined population will stay in the loop of algorithm for evolution until an optimal solution is produced or the termination conditions are reached.

5.5.7 Procedure of Modified NSGA-II

The procedure of modified NSGA-II is shown in Figure 5.7. Five main processes are included in this algorithm, which are parameters initialization, solution encoding, fitness evaluation, in-

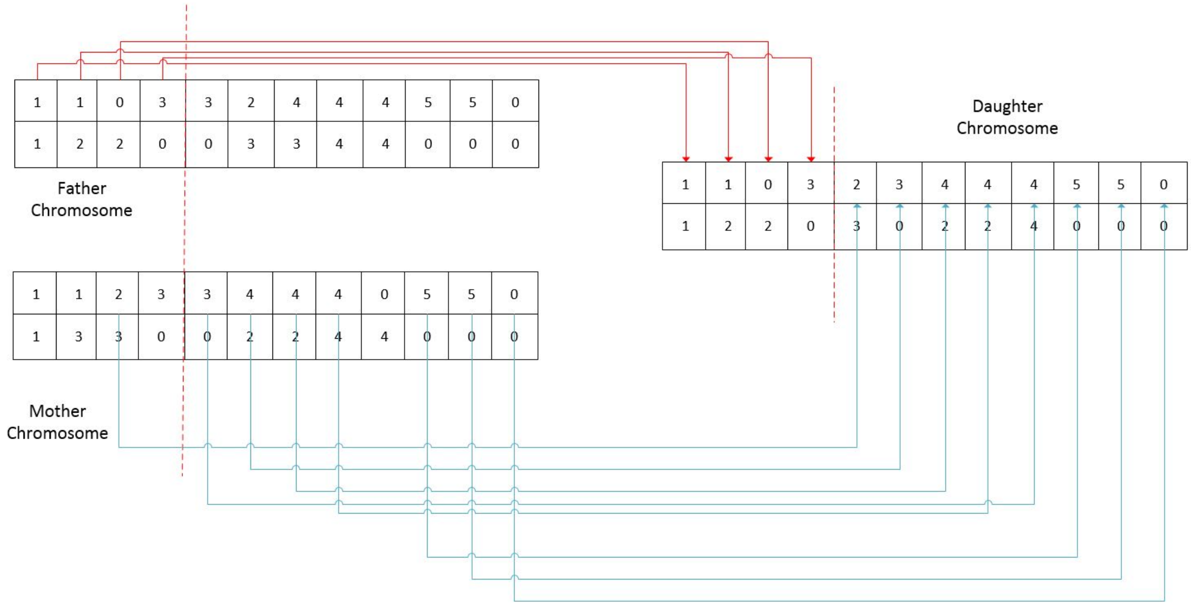

Figure 5.6: Example of Crossover

dividual selection and GA operations. The iteration process in the procedure, which comprises fitness evaluation, individual selection and GA operations, is kept ongoing as long as the Pareto front solutions are obtained or the termination conditions are reached.

5.6 Scaffolding Project Case Study

5.6.1 Scaffolding Project Description

In order to verify the feasibility of our proposed mathematical model and algorithm, an industrial scaffolding project conducted for maintenance purpose in a LNG plant in Western Australia is selected as a case study. According to our observation on site, I have discovered that there are excessive unnecessary scaffold materials stored inside the gas plant which resulted in a great waste in terms of cost on material leasing and the space utilization. In addition, the inappropriate material management and project scheduling would consequently cause operation delays.

In order to reduce the overall cost on scaffolding construction and disassembly, an optimal schedule with a demand driven material ordering plan should be designed. In this case study, three scaffolding sub-projects are considered, namely $A04$, $A03$ and $A02$. As the scaffolding construction for these three sub-projects follow a standard design, therefore, the scaffolding activities are assumed to be the same for all sub-projects. The information regarding to the demand of workers, planned duration as well as the demand of different types of scaffold components for each activity is provided. Table 5.2 presents the number of required workers and the total working hours for each activity from each sub-project. These activities are classified into five stages, which are JCA-1 preliminary activity, JCA-2 scaffold construction, JCA-3 facility

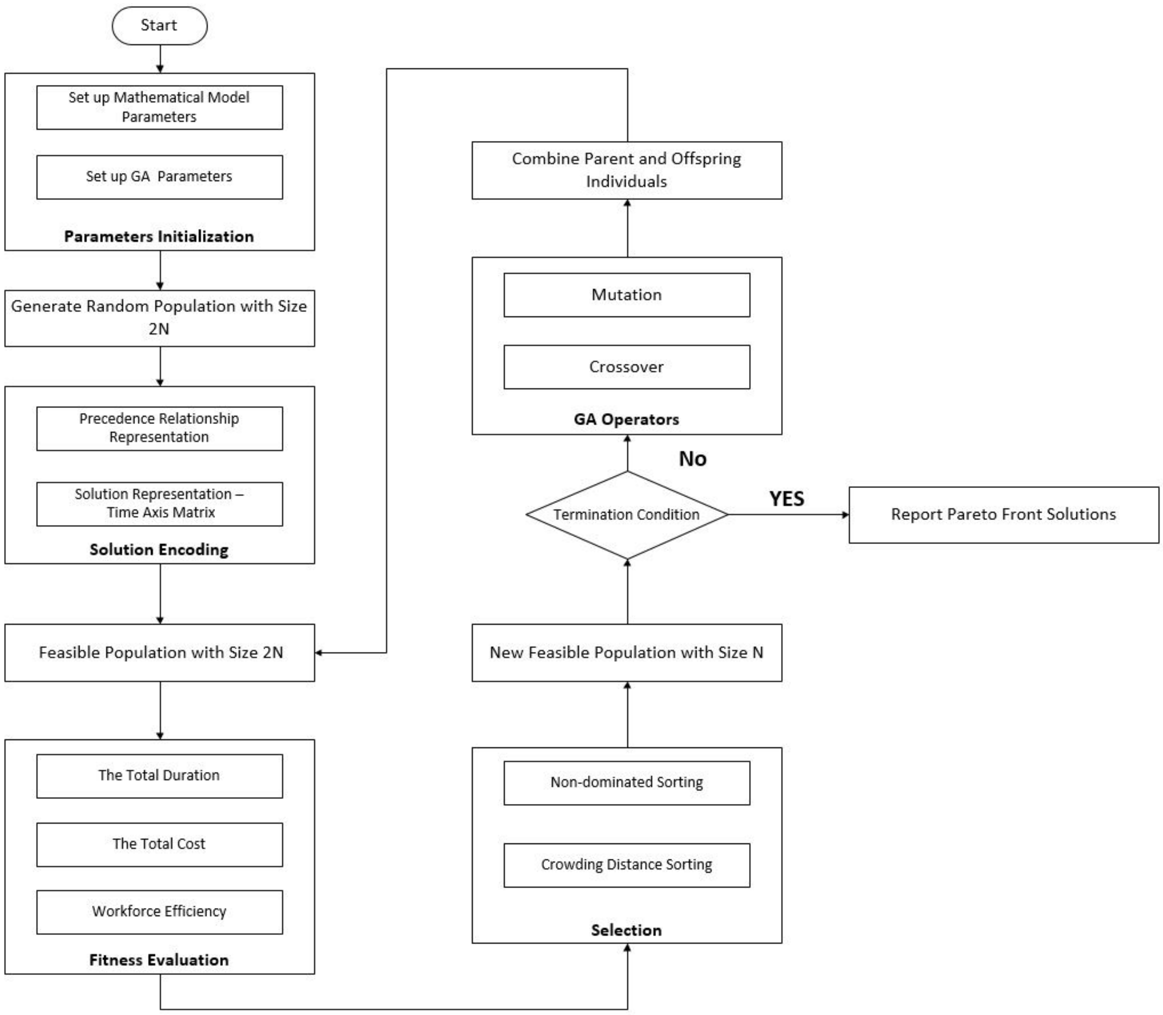

Figure 5.7: Flowchart of NSGA-II

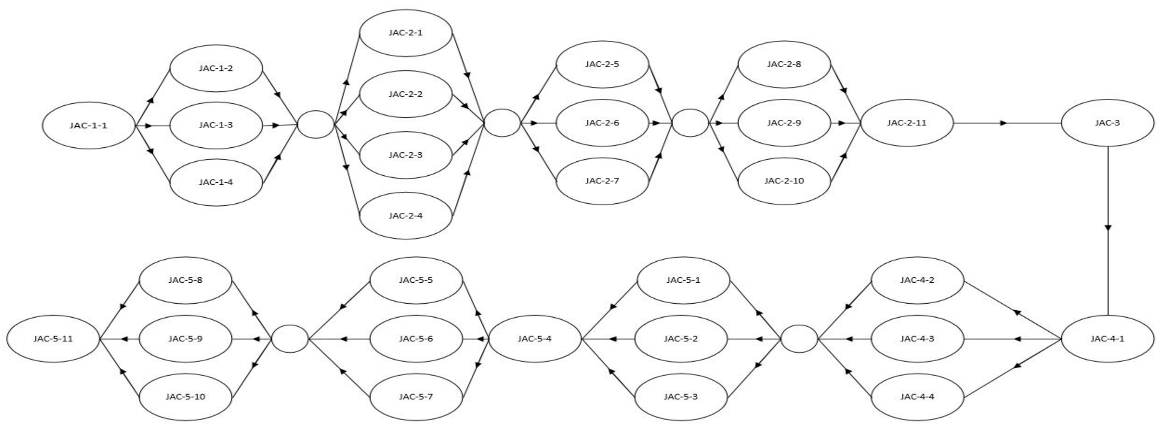

Figure 5.8: Precedence Network of Scaffolding Activities

Table 5.2: Workforce and Duration

Stage	Activity Series No.	Activity Description	Workforce Requirement A04	A03	A02	Duration(Hour) A04	A03	A02
JCA-1	JCA-1-1 (1)	Sign onto Permit	1	1	1	1	1	1
	JCA-1-2 (2)	Complete temporary access	2	2	2	2	3	2
	JCA-1-3 (3)	Mobilise tools and equipment	3	3	3	3	3	2
	JCA-1-4 (4)	Erect suitable barricading	2	2	2	2	2	2
JCA-2	JCA-2-1 (5)	Erect scaffold level (0-2)	10	5	10	55	157	46
	JCA-2-2 (6)	Erect scaffold sair access to loading bay	3	5	5	184	243	173
	JCA-2-3 (7)	Erect scaffold tubing for DOP level (0-2)	10	1	10	2	14	2
	JCA-2-4 (8)	Drop objective protection level (0-2)	10	1	10	3	25	5
	JCA-2-5 (9)	Erect scaffold level (2-3)	10	5	10	79	308	85.5
	JCA-2-6 (10)	Erect scaffold tubing for DOP level (2-3)	10	1	10	2.5	27	3
	JCA-2-7 (11)	Drop objective protection level (2-3)	10	2	10	4	24	9
	JCA-2-8 (12)	Erect scaffold level (3-4)	10	5	10	38	137	23
	JCA-2-9 (13)	Erect scaffold tubing for DOP level (3-4)	1	10	10	12	1	1
	JCA-2-10 (14)	Drop objective protection level (3-4)	1	10	10	19	2	2
	JCA-2-11 (15)	Conduct final inspection	2	2	2	1	2	1
JCA-3	JCA-3 (16)	Scaffold inspection and maintenance	0	1	1	952	498	500
JCA-4	JCA-4-1 (17)	Sign onto Permit	1	1	1	1	1	1
	JCA-4-2 (18)	Complete temporary access	2	2	2	1	2	1
	JCA-4-3 (19)	Mobilise tools and equipment	3	3	3	2	2	1
	JCA-4-4 (20)	Erect suitable barricading	2	2	2	1	2	1
JCA-5	JCA-5-1 (21)	Remove drop objective protection level (3-4)	10	10	10	1	1	1
	JCA-5-2 (22)	Dismantle scaffold tubing for DOP level (3-4)	10	10	10	1	1	1
	JCA-5-3 (23)	Dismantle scaffold level (3-4)	10	9	9	19	39	13
	JCA-5-4 (24)	Dismantle scaffold sair access to loading bay	3	4	4	92	155	95
	JCA-5-5 (25)	Remove drop objective protection level (2-3)	10	9	9	2	3	5
	JCA-5-6 (26)	Dismantle scaffold tubing for DOP level (2-3)	10	9	9	1	2	2
	JCA-5-7 (27)	Dismantle scaffold level (2-3)	10	9	9	40	86	48
	JCA-5-8 (28)	Remove drop objective protection level (0-2)	10	9	9	2	2	3
	JCA-5-9 (29)	Dismantle scaffold tubing for DOP level (0-2)	10	9	9	1	1	1
	JCA-5-10 (30)	Dismantle scaffold level (0-2)	10	9	9	28	44	26
	JCA-5-11 (31)	Stack scaffold material and send back to warehouse	2	2	2	3	3	2

Table 5.3: Unit Weight for Scaffold Components

Series No.	Component Type	Unit Weight(KG)	Series No.	Scaffold Type	Unit Weight (KG)
1	Scaffold Tube 0300	1.35	2	Scaffold Tube 0600	2.7
3	Scaffold Tube 0900	4.05	4	Scaffold Tube 1200	5.4
5	Scaffold Tube 1500	6.75	6	Scaffold Tube 1800	8.1
7	Scaffold Tube 2100	9.45	8	Scaffold Tube 2400	10.8
9	Scaffold Tube 2700	12.15	10	Scaffold Tube 3000	13.5
11	Scaffold Tube 3300	14.85	12	Scaffold Tube 3600	16.2
13	Scaffold Tube 3900	17.55	14	Scaffold Tube 4200	18.9
15	Scaffold Tube 4500	20.25	16	Scaffold Tube 4800	21.6
17	Scaffold Tube 5100	22.95	18	Scaffold Tube 5400	24.3
19	Sole Board	2.57	20	Hyplank 900	5.13
21	Hyplank 1200	6.84	22	Hyplank 1500	8.55
23	Hyplank 1800	10.26	24	Hyplank 2100	11.97
25	Hyplank 2400	13.68	26	Hyplank 2700	15.39
27	Hyplank 3000	17.1	28	Coupler Double	1.3
29	Coupler Girder	1.5	30	Coupler Putlog (Hook) Square	0.6
31	Coupler Putlog (Half)	0.7			

maintenance, JCA-4 preliminary activity (2) and JCA-5 scaffold dismantling. As the time t considered in our mathematical model is defined as an integer, therefore, the duration of each activity is rounded up to its nearest integer. Table 5.3 indicates the unit weight for 31 types of scaffold components used for the scaffolding project, and each type of component is assigned with a series number. The demands of 31 types of scaffold component for each activity from each sub-project are shown in Tabel 5.4, Table 5.5 and Table 5.6 respectively in the form of sparse matrices where only none-zero entries are presented. The position (a,b) in these Tables represents the demand of b^{th} scaffold component for a^{th} activity. For example, position $(5,1)$ and value 6 in Table 5.4 means the demand of $1st$ component for $5th$ activity in sub-project $A04$ is 6 pieces. The series numbers for activities and components can be found in Table 5.2 and Table 5.3. The leasing cost is defined as 4.5 dollars per ton per hour and the labour cost γ equals to 90 dollars per hour per worker. For transportation cost β, when $a = 3$ and $b = 6$, I have $\beta_1 = 65$, $\beta_2 = 55$ and $\beta_3 = 45$. The maximum number of available workers is set as $U = 20$ and the maximum project makespan is $F = 2000$ where the unit time is defined as an hour. The precedence network of scaffolding activities for each sub-project is shown in Figure 5.8. One activity can only be conducted when all its predecessors are completed, for example, only when activity JAC-3 is finished can activity JAC-4-1 be started.

Table 5.4: Material Demand for Each Activity of A04

A04									
Position	Value	Position	Value	Position	Value	Position	Value	Position	Value
(5,1)	6	(9,6)	33	(9,11)	77	(10,17)	8	(31,24)	-55
(9,1)	11	(12,6)	12	(12,11)	63	(13,17)	6	(5,25)	11
(12,1)	6	(31,6)	-67	(31,11)	-173	(31,17)	-20	(9,25)	33
(31,1)	-23	(5,7)	6	(5,12)	33	(6,19)	38	(12,25)	11
(5,2)	110	(6,7)	48	(9,12)	77	(31,19)	-38	(31,25)	-55
(9,2)	220	(9,7)	11	(12,12)	68	(5,20)	6	(5,26)	11
(12,2)	13	(12,7)	6	(31,12)	-178	(9,20)	11	(9,26)	33
(31,2)	-343	(31,7)	-71	(5,13)	55	(12,20)	6	(12,26)	11
(5,3)	6	(5,8)	33	(9,13)	165	(31,20)	-23	(31,26)	-55
(9,3)	11	(9,8)	77	(12,13)	30	(5,21)	6	(5,27)	165
(12,3)	6	(12,8)	58	(31,13)	-250	(9,21)	11	(9,27)	385
(31,3)	-23	(31,8)	-168	(5,14)	11	(12,21)	6	(12,27)	232
(5,4)	22	(5,9)	6	(9,14)	11	(31,21)	-23	(31,27)	-782
(7,4)	22	(9,9)	11	(12,14)	7	(5,22)	6	(5,28)	1551
(9,4)	33	(12,9)	6	(31,14)	-29	(9,22)	11	(6,28)	296
(10,4)	24	(31,9)	-23	(5,15)	33	(12,22)	6	(7,28)	42
(12,4)	12	(5,10)	22	(9,15)	77	(31,22)	-23	(10,28)	45
(13,4)	20	(7,10)	6	(12,15)	4	(5,23)	6	(13,28)	42
(31,4)	-133	(9,10)	33	(31,15)	-114	(9,23)	11	(31,28)	-1976
(5,5)	6	(10,10)	6	(5,16)	22	(12,23)	6	(5,29)	343
(9,5)	11	(12,10)	12	(9,16)	33	(31,23)	-23	(31,29)	-343
(12,5)	6	(13,10)	6	(12,16)	19	(5,24)	11	(5,30)	220
(31,5)	-23	(31,10)	-85	(31,16)	-74	(9,24)	33	(6,30)	40
(5,6)	22	(5,11)	33	(7,17)	6	(12,24)	11	(31,30)	-260
								(5,31)	1155
								(31,31)	-1155

Table 5.5: Material Demand for Each Activity of A03

A03									
Position	Value	Position	Value	Position	Value	Position	Value	Position	Value
(5,1)	11	(31,8)	-11	(5,14)	66	(31,21)	-22	(31,27)	-1760
(31,1)	-11	(5,9)	55	(9,14)	88	(5,22)	11	(5,28)	550
(5,2)	110	(9,9)	110	(12,14)	23	(6,22)	10	(6,28)	200
(6,2)	61	(12,9)	58	(31,14)	-177	(9,22)	11	(7,28)	35
(9,2)	330	(31,9)	-223	(5,15)	110	(31,22)	-32	(9,28)	1650
(12,2)	114	(5,10)	33	(9,15)	165	(5,23)	11	(10,28)	32
(31,2)	-615	(7,10)	6	(12,15)	55	(6,23)	10	(12,28)	1342
(5,3)	11	(9,10)	77	(31,15)	-330	(9,23)	11	(13,28)	35
(6,3)	61	(10,10)	6	(5,16)	55	(31,23)	-32	(31,28)	-3844
(31,3)	-72	(12,10)	9	(9,16)	46	(5,24)	11	(5,29)	110
(5,4)	11	(13,10)	6	(31,16)	-101	(9,24)	11	(7,29)	42
(7,4)	24	(31,10)	-137	(7,17)	10	(12,24)	4	(9,29)	330
(10,4)	21	(5,11)	55	(10,17)	8	(31,24)	-26	(10,29)	35
(13,4)	24	(9,11)	110	(13,17)	10	(5,25)	11	(12,29)	114
(31,4)	-80	(12,11)	51	(31,17)	-28	(9,25)	33	(31,29)	-631
(5,5)	11	(31,11)	-216	(5,19)	40	(12,25)	11	(5,30)	55
(9,5)	44	(5,12)	88	(6,19)	62	(31,25)	-55	(9,30)	110
(12,5)	12	(9,12)	132	(31,19)	-102	(5,26)	22	(12,30)	55
(31,5)	-67	(12,12)	88	(5,20)	11	(9,26)	22	(31,30)	-220
(5,6)	11	(31,12)	-308	(6,20)	10	(12,26)	11	(5,31)	330
(31,6)	-11	(5,13)	44	(9,20)	11	(31,26)	-55	(9,31)	770
(5,7)	11	(9,13)	66	(31,20)	-32	(5,27)	330	(12,31)	394
(31,7)	-11	(12,13)	46	(5,21)	11	(9,27)	990	(31,31)	-1494
(5,8)	11	(31,13)	-156	(9,21)	11	(12,27)	440		

Table 5.6: Material Demand for Each Activity of A02

A02									
Position	Value	Position	Value	Position	Value	Position	Value	Position	Value
(5,1)	11	(5,6)	11	(31,12)	-79	(6,19)	62	(9,26)	33
(9,1)	17	(9,6)	11	(5,13)	33	(31,19)	-62	(31,26)	-55
(31,1)	-28	(12,6)	11	(9,13)	33	(5,20)	11	(5,27)	220
(5,2)	11	(31,6)	-33	(12,13)	33	(6,20)	10	(9,27)	550
(6,2)	61	(5,7)	11	(31,13)	-99	(9,20)	11	(12,27)	85
(9,2)	11	(6,7)	48	(5,14)	11	(31,20)	-32	(31,27)	-855
(12,2)	11	(9,7)	11	(9,14)	33	(5,21)	11	(5,28)	440
(31,2)	-94	(12,7)	11	(12,14)	12	(9,21)	11	(6,28)	296
(5,3)	11	(31,7)	-81	(31,14)	-56	(31,21)	-22	(7,28)	34
(6,3)	61	(5,8)	24	(5,15)	55	(5,22)	11	(9,28)	550
(9,3)	11	(9,8)	33	(9,15)	110	(6,22)	10	(10,28)	35
(12,3)	11	(12,8)	22	(12,15)	36	(9,22)	11	(12,28)	163
(31,3)	-94	(31,8)	-79	(31,15)	-201	(31,22)	-32	(13,28)	34
(5,4)	11	(5,10)	11	(5,16)	33	(5,23)	11	(31,28)	-1552
(7,4)	23	(7,10)	6	(9,16)	110	(6,23)	10	(5,29)	220
(9,4)	11	(9,10)	28	(12,16)	32	(9,23)	11	(9,29)	220
(10,4)	24	(10,10)	6	(31,16)	-175	(31,23)	-32	(12,29)	35
(12,4)	11	(13,10)	6	(5,17)	11	(5,24)	22	(31,29)	-475
(13,4)	24	(31,10)	-57	(7,17)	8	(9,24)	33	(5,30)	55
(31,4)	-104	(5,11)	13	(9,17)	11	(31,24)	-55	(6,30)	40
(5,5)	11	(31,11)	-13	(10,17)	8	(5,25)	22	(9,30)	55
(9,5)	11	(5,12)	24	(12,17)	11	(9,25)	33	(31,30)	-150
(12,5)	11	(9,12)	33	(13,17)	8	(31,25)	-55	(5,31)	110
(31,5)	-33	(12,12)	22	(31,17)	-57	(5,26)	22	(9,31)	220
								(12,31)	132
								(31,31)	-462

5.6.2 Scaffold Case Study Analysis

The proposed optimization model presented in Section 4.2 and the NSGA-II algorithm described above are applied to generate the optimal solutions for the scaffold case study. The model and algorithm has been programmed in Matlab $R2015a$ with the population size of 100 and maximum iteration of 100. Table 5.7 shows the various parameters that need to be initialized before running our proposed algorithm. As the maximum duration of project makespan is preset as $F = 2000$, therefore, the optimal schedule generated would be produced in the form of a time axis matrix, $TS = [a_{i,t}] \in \mathscr{R}^{3\times 2000}$, which is too large to present in this chapter, hereby, a compiled timetable is presented instead. The best 30 solutions obtained by the proposed NSGA-II algorithm for the scaffold case study is shown in Table 5.8, and the range of project duration, total cost and the variation of workforce usage in the these solutions are $1791 - 1803$, $6.6003 - 6.603$ and $0.0532 - 0.0546$ respectively. It has to be mentioned that the value of total cost presented in Table 5.8 is the logarithm to base 10 of the actual total cost. Figure 5.9 indicates the dispersion of these 30 solutions correspondingly, and the figure on the right shows the Pareto-optimal solutions for scaffold case study.

Table 5.7: Parameters Initialization

Model Parameters:	
Number of objective functions:	3
Number of constraints:	12
Number of decision variables:	3
Algorithm Parameters:	
Number of Population:	100
Maximum number of iterations:	100
Crossover rate:	0.7
Mutation rate:	0.1
Problem Parameters:	
Number of sub-projects:	3
Number of activities for each sub-project:	31
Duration of each activity:	d_{ij}
Demand of scaffold component:	p^m_{ij}, shown in Table 5.4
Demand of workforce:	u_{ij}
Leasing cost:	\$ 4.5 per ton per hour
Labour cost:	\$ 90 per worker per hour
Transport cost:	$\beta_1 = \$65, \beta_2 = \$55, \beta_3 = \$45$ where $a = 3, b = 6$

As it can be seen from the Table 5.8, the optimal durations for these 30 solutions varies between $1791 - 1803$. For achieving a shorter makespan, it tends to have either a higher total cost

Table 5.8: Results for Scaffold Case Study

Solution No.	Duration	Variation of Workforce Efficiency	Total Cost
1	1791	0.053574681	6.6025259
2	1792	0.053674626	6.6005049
3	1791	0.054610771	6.6015335
4	1794	0.053704123	6.6004969
5	1798	0.053473899	6.6003281
6	1792	0.053582112	6.6013129
7	1798	0.053353285	6.6003603
8	1795	0.053754458	6.6003725
9	1799	0.053388927	6.6003386
10	1800	0.053475072	6.6003177
11	1798	0.053640827	6.6003030
12	1802	0.053269486	6.6003762
13	1791	0.053506637	6.6025371
14	1796	0.053608927	6.6004005
15	1801	0.053292614	6.6003748
16	1791	0.054146469	6.6031579
17	1793	0.053645575	6.6005079
18	1791	0.053875408	6.6026596
19	1793	0.053611832	6.6015111
20	1801	0.053552894	6.6003071
21	1802	0.053542447	6.6003123
22	1801	0.053378482	6.6003374
23	1803	0.053444234	6.6003348
24	1798	0.053444905	6.6003438
25	1798	0.053483229	6.6003184
26	1800	0.053589207	6.6003035
27	1797	0.053581609	6.6003693
28	1794	0.053624123	6.6005071
29	1797	0.053371497	6.6003373
30	1791	0.053420938	6.6028026

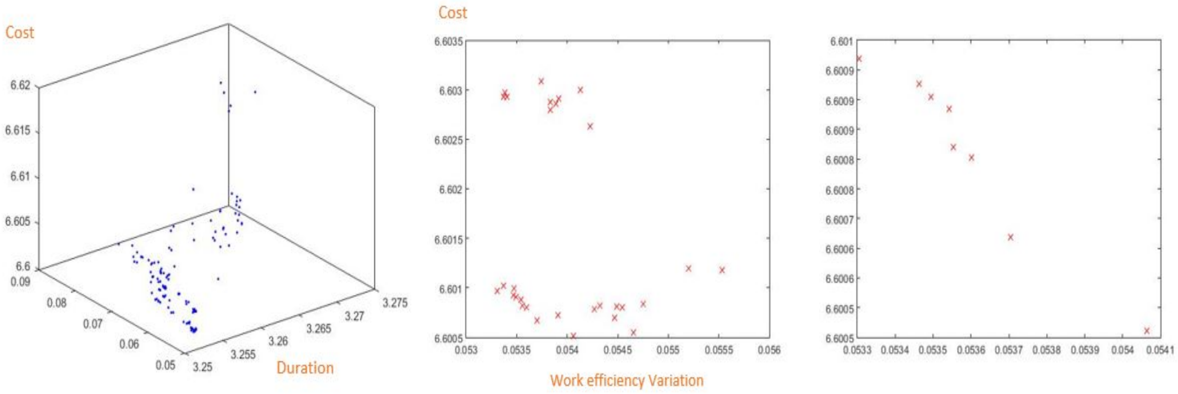

Figure 5.9: Pareto front solutions of the scaffold case study

or a greater variation of working efficiency. For example, the comparison between the results of solution 1 and solution 23 demonstrate this trend. Solution 1 provides the shortest project duration of 1791 while solution 23 has the longest duration of 1803. However, the total project cost for solution 23 is 6.6003 which is smaller than 6.6025 for solution 1 and the variation of working efficiency for solution 23 is slightly smaller than that of solution 1. Similarly, as indicated by Figure 5.9, it can be also found that, when the duration is the same, the total project cost would increase when the variation of working efficiency decreases. For example, solution 20 has a higher variation of working efficiency but a lower total cost comparing to the results of solution 22 while they have the same duration of 1801. Therefore, the selection of the best solution to be executed can be dependent on the priority among duration, working efficiency and total cost. Figure 5.10 presents the compiled timetable of the scaffolding case study for solution 1 with duration of 1791. It can be found that the sub-project $A03$ has the latest completion time while sub-project $A02$ would be finished first. There are interruptions within the sub-project $A02$ and $A04$, which indicate that during these periods, the workforce resource is not enough for operating 3 sub-projects simultaneously. As commonly understood, the best material ordering plan is delivering the exact amount of demand. With the timetable generated, the demand of scaffold material at any time can be estimated by adding the demand for all activities scheduled at that time. In order to show the variation of demand over the project, Figure 5.11 presents the demand of scaffold material in tonnage per day during the scaffolding construction phase. As I can see from Figure 5.10, the construction phase in this case would be the first 1000 hours, and I assume that the available working hours per day are 10 hours. These results reveal that our model and algorithm is feasible to solve the practical problems and achieve the expected solutions.

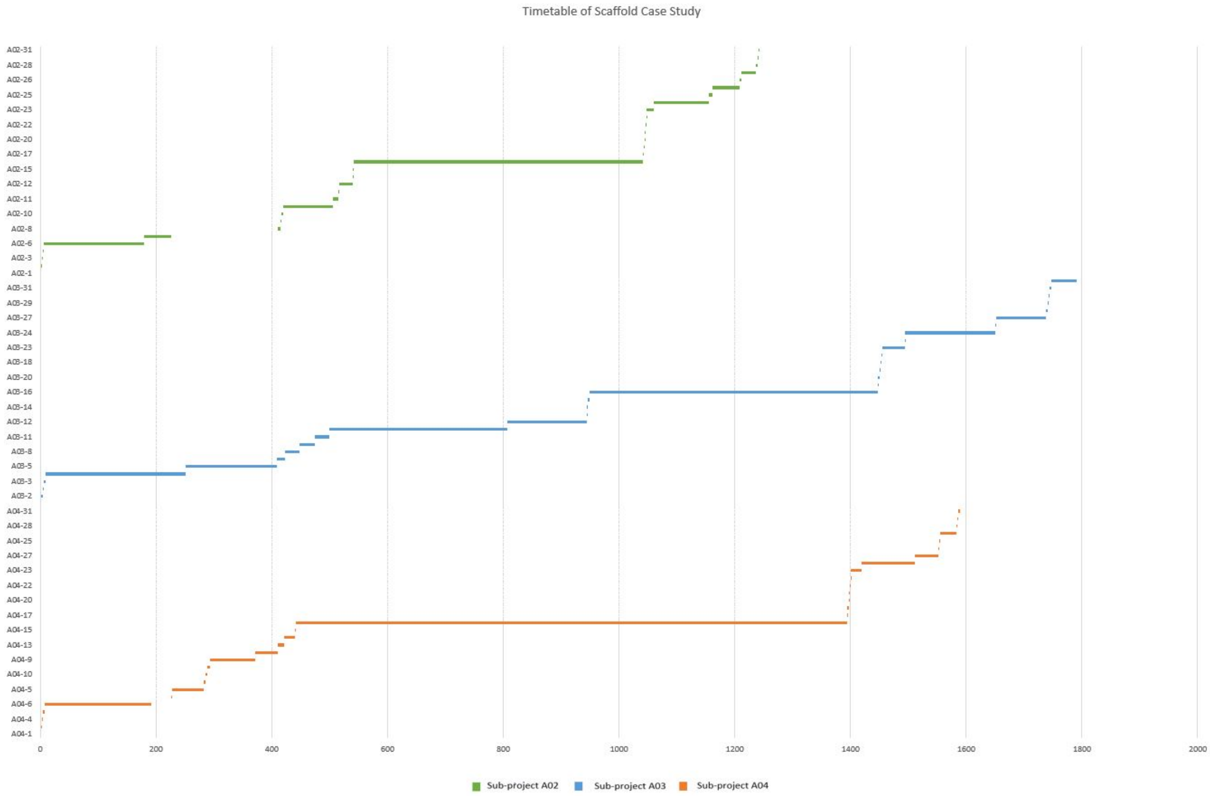

Figure 5.10: Timetable for Scaffold Case Study

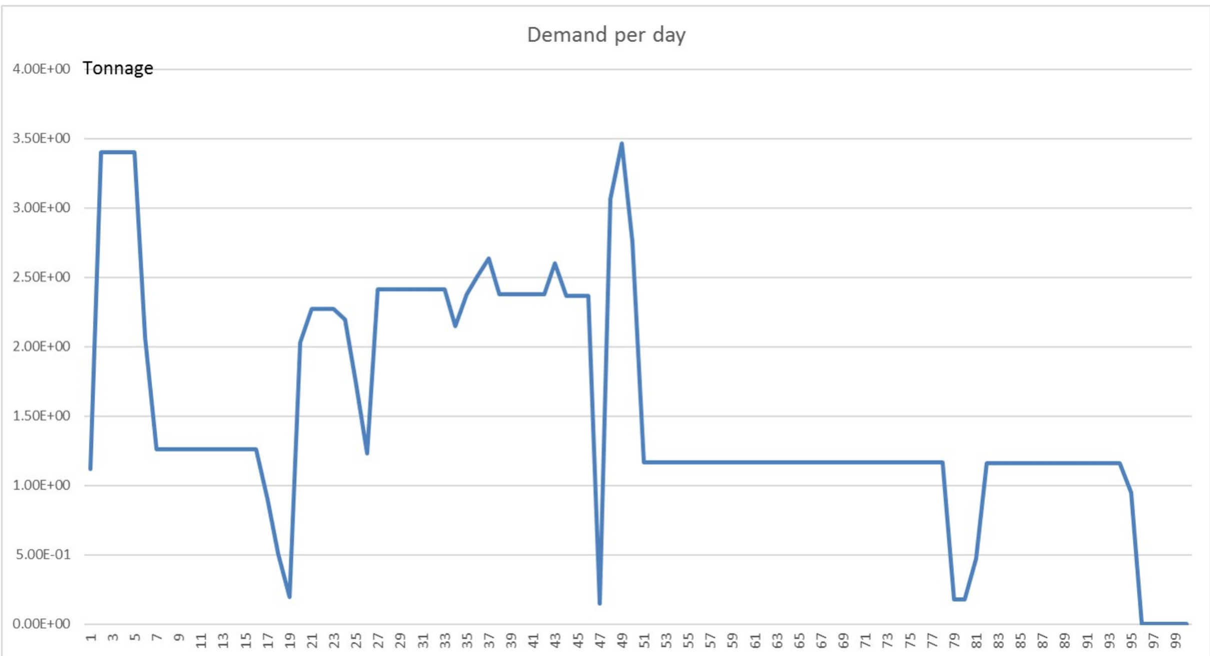

Figure 5.11: Demand per day for Scaffold Material

5.6.3 Parameter Sensitivity Analysis

In order to verify the performance of the proposed algorithm, I generated 10 best solutions resulting from running the algorithm after the $10th$, $20th$, $30th$, $40th$, $50th$ and $100th$ iterations, which are shown in Figure 5.12, Figure 5.13 and Figure 5.14 respectively. Throughout comparison, it can be seen that the results converge towards the Pareto-optimal fronts with keeping the diversity in solutions with the increasing of iterations. Better solutions are produced with the running of the algorithm and the dominated solutions are eliminated until the Pareto-optimal solutions are obtained. As shown in Figure 5.14, most of the non-dominated solutions are found after $50th$ generation.

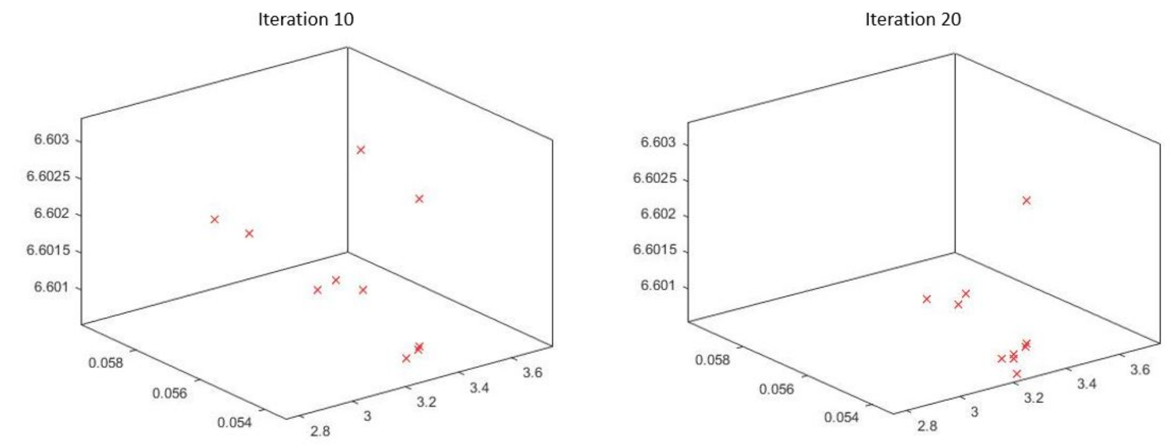

Figure 5.12: 10 Best solutions after 10th and 20th generation

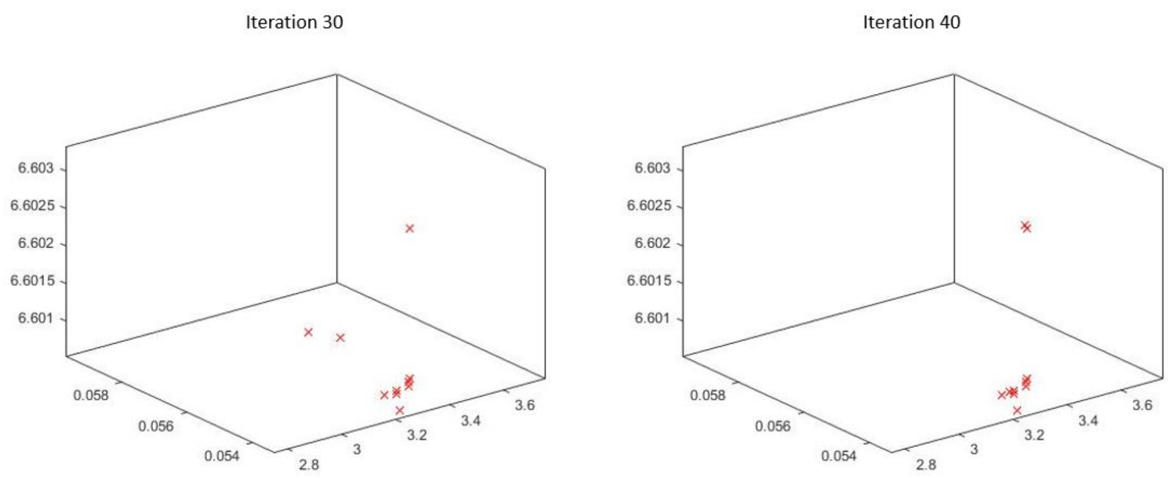

Figure 5.13: 10 Best solutions after 30th and 40th generation

The maximum number of available workers is one of the most important constraints in the proposed SSC optimization model, and it has a critical impact on the optimal solutions gener-

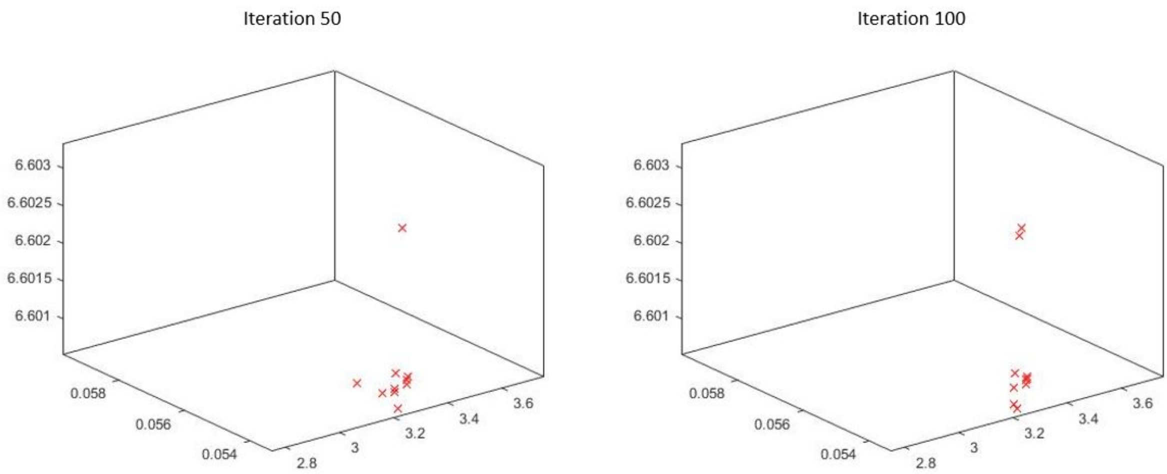

Figure 5.14: 10 Best solutions after 50th and 100th generation

Table 5.9: Results under Different Available Workforces

Maximum Workforce	Duration	Variation of Workforce Efficiency	Total Cost
15	1893	0.046675	6.52838
16	1865	0.048139	6.540316
17	1811	0.050706	6.549362
18	1812	0.05214	6.571704
19	1791	0.053352	6.583021
20	1791	0.053296	6.602984
21	1791	0.053573	6.620042
22	1791	0.053788	6.636457
23	1791	0.054436	6.650454
24	1791	0.06093	6.665693
25	1791	0.096416	6.680481

Figure 5.15: Objective values under different workforce allocations

ated through our algorithm. In order to verify the flexibility of our model and algorithm and investigate the influence of different workforce constraints on the generation of solutions, I calculated the values of objective functions with different U, where U varies from 15 to 25. For each U, I select one of the best Pareto-optimal solutions, and the variations of the values are shown in Table 5.9 and Figure 5.15. In Figure 5.15, the X axis represents the number of maximum workforce while the Y axes represent the variation of workforce efficiency, the logarithm to base 10 of the total cost, the logarithm to base 10 of the total duration respectively. As I can see that, with the increase of U, the total duration of the scaffold project would decrease first and then keep unchanged, while the variation of workforce efficiency and the total cost would increase steadily. This comparison reveals the fact that when there are more available resources to be utilized and allocated, more activities can be conducted simultaneously and the total duration of project could be reduced. As a consequence, the total cost would increase caused by the increment of the investment on resources. However, on the other hand, providing excessive amount of available resources would result in the wastes, such as idling workforce, which is demonstrated by the increasing of the variation of workforce efficiency in Figure 5.15. It is worth mentioning that, providing more available resources would not necessarily reduce the duration of project. For example, in real life, the number of workers assigned to a construction activity is restricted by many factors, such as the working space. Even though more workers can be utilized for the job, the working space limits the maximum number of workforce allocated. This comparison also demonstrates that our proposed model and algorithm could not only help the project managers with the scheduling of activities but also the designing of project parameters. The managers could choose the the proper solutions according to their preference between time, cost and the efficiency of resource utilization.

5.7 Conclusion

This chapter studies the supply chain optimization problem in a scaffolding construction and disassembly context. The proposed scaffold supply chain (SSC) optimization problem aims to deal with the resource constrained project scheduling problem and material ordering problem simultaneously. A multi-objective optimization model for SSC optimization problem is constructed to generate optimal solutions of project scheduling with the goals to minimize the project makespan, total cost and maximize the efficiency of resource utilization. According to the characteristics of our proposed optimization model, a modified non-dominated sorting genetic algorithm (NSGA-II) is presented to seek for the Pareto-optimal solutions. Based on a real life scaffolding project, the effectiveness and feasibility of our proposed model and algorithm for solving practical problems are verified. A comparison between the values of objectives under different limitations of available workforce has been conducted, which indicates that by providing more available resources, the duration of project and the workforce efficiency would reduce correspondingly while the total cost would increase. However, the duration tends to keep unchanged when the excessive resources are provided. These results manifest that the proposed SSC optimization model and the modified NSGA-II are practical in solving the time-cost-resource trade-off problems and would be beneficial to the project managers.

CHAPTER 6

CONCLUSION AND FUTURE RESEARCH

6.1 Findings and Contributions

In this thesis, I identified that optimizing the construction project scheduling is the key to improve the performance of construction supply chain (CSC). On this basis, three practical sub-problems of construction supply chain optimization are considered, and the corresponding mathematical models are proposed with the intention of optimizing the values of CSC performance indicators such as time and cost. These three sub-problems are described under different scenarios and considerations respectively, and meta-heuristic algorithms are developed to generate the most effective project schedules. Our main contributions are summarized as follow.

In Chapter 3, I considered a general problem of the construction supply chain optimization. In our description of general CSC, construction materials flow from the suppliers to the construction projects, while contractors take the responsibilities of the construction project management. Based on this scenario, the deterministic construction supply chain optimization problem (CSCOP) was formulated, which considered the precedence relations between activities and the resource constraints. In our proposed mixed integer programming model, the objective was set as the minimization of total CSC cost which included material management cost and labour cost. As the extended version of RCPSP, the CSCOP is a NP-hard problem. Therefore, I proposed a modified genetic algorithm (GA) that introduced a sequence-based representation of chromosome and a schedule generation scheme for generating feasible individuals. A case study based on a practical scaffolding construction project was conducted, and the results indicated that our proposed model and algorithm can solve real world problems in relation to construction supply chain cost optimization. In addition, the impact of parameters including the maximum number of workforce on-site and population size of GA was identified. By conducting four experimental instances which consisted of 15, 20, 25 and 30 activities, the results illustrated that the best allocation of the budget on labour cost could assist the project managers to produce a better project schedule. The formulation of the deterministic CSCOP discussed in this chapter identified the main contributors of the total CSC cost and the general constraints that should be taken into consideration in the context of construction supply chain optimization.

In Chapter 4, I considered the integration of the CSCOP and resource selection problem in an uncertain environment. In reality, for accomplishing the same task, there are always several alternative methods available. Especially for construction operations, these alternative methods are normally based on the selection of different resources including equipment and materials, and each method would trigger a series of activities. Based on this scenario, the budget constrained construction supply chain optimization with rental resource selection (SCSCO) problem was formulated. The SCSCO extended the model of CSCOP by considering the resource selection, stochastic activity durations and budget constraint. A stochastic mathematical model of SCSCO was constructed based on the chance-constraint programming with the objective of minimizing the total makespan while the total CSC cost was controlled within the budget. A hybrid algorithm that integrated sample average approximation (SAA) and particle swarm optimization (PSO) was proposed for dealing with the SCSCO. The SAA acted as the external algorithm for sampling and the scenarios of our proposed SCSCO and converting the stochastic model into the deterministic model, while the PSO was utilized as the internal algorithm to cope with the deterministic SAA problems. A novel representation of particle for PSO was introduced and a checking and adjusting procedure was designed for generating feasible particles. A case study that consists of five optional rental equipment was conducted and the results showed that our proposed model and algorithm were effective for dealing with the practical SCSCO problems. The formulation of SCSCO problem was the upgraded version of CSCOP which considered the uncertainty in construction projects and alternative execution methods for construction operations, which could assist the project managers to make the decisions on the selections of execution methods and generation of appropriate project schedules that could optimize the CSC.

In Chapter 5, I considered a multi-objective problem of the construction supply chain optimization, specifically for scaffolding construction projects. The expenditure on scaffolding construction has long been regarded as one of the main contributor for the operational cost of construction projects, especially for mega-projects that consist of multiple sub-projects. Based on this scenario, a multi-objective scaffold supply chain optimization problem (MOSSCOP) that considered the recycling of scaffolding materials was formulated. In our mathematical model, three criteria were proposed for evaluating the performance of scaffold supply chain (SSC), namely, time, cost and workforce efficiency. The composition of total SSC cost was identified as the sum of material leasing cost, transportation cost and labour cost. A non-dominated sorting genetic algorithm (NSGA-II) was modified and applied for resolving MOSSCOP which introduced the time axis matrix for solution encoding. A real project based case study that comprises 31 activities was conducted and the results manifested the feasibility and effectiveness of our proposed model and algorithm. As the extended version of CSCOP, our model and algorithm for MOSSCOP provided the solution for tackling the time-cost-efficiency trade-off problems in SSC, and even in CSC and construction project management.

In summary, this thesis investigated the problems existed in CSC and the methodologies for optimizing the performance of CSC. The nature of CSC, that is the dependency with specific construction projects, reveals the fact that a better construction project schedule could lead to a efficient management of CSC. In this case, I developed three mathematical models of CSCOP that contain the deterministic single-objective model, stochastic model and multi-objective model respectively, and each model was formulated based on practical scenarios. Meta-heuristic algorithms were chosen as the methodology for resolving these three models with data input from real life projects. Hence, this thesis will contribute in providing a practical solution for optimizing the performance of CSC under different scenarios and with different considerations.

6.2 Directions of Future Research

This thesis represents three formulations of construction supply chain optimization problem (CSCOP), which has resulted in a new path and a novel solution to improve the integration and performance of CSC. It can be observed that our three proposed mathematical models contain the main practical considerations in the context of construction projects and the adopted meta-heuristic algorithms are computationally effective for solving these three sub-problems of CSCOP. Despite these contributions, this research also has some limitations that need to be addressed in the future research in order to make a further advancement.

First of all, the lateness of materials or resources supply are not considered. In the three sub-problems discussed in this research, I assumed that all required materials were delivered on time regardless of the ordering plan. However, in reality, there might exist the early or late arrival of construction materials. Therefore, the research can be extended by considering the penalty of lateness of material delivery. Secondly, none of the three sub-problems considered uncertainty and multi-objective simultaneously. The SCSCO problem in Chapter 4 was formulated as a single objective model with stochastic activity durations, while the MOSSCOP in Chapter 5 considered three objectives with fixed activity durations. As such, in our future research, an extended model that comprises the considerations of multi-objective and uncertain duration activities will be developed. Last but not least, new meta-heuristic algorithms with better performance are expected to be developed and implemented. The meta-heuristic algorithms adopted in this research were based on classic algorithms such as GA and PSO, however, there are also many newly developed meta-heuristics that can be applied to deal with our CSCOP. In this case, I will develop and testify these novel meta-heuristics on our problems and select the best performed ones.

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