School of Information Systems

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Intelligent Decision Support System for Energy Management in Demand Response Programs and Residential and Industrial Sectors of the Smart Grid

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DECLARATION

To the best of my knowledge and belief, this thesis contains no material previously published by any other person except where due acknowledgement has been made.

This thesis contains no material which has been accepted for the award of any other degree or diploma in any university.

Omid Ameri Sianaki

Signature: . . . .

Date: 1 October 2015

Abstract

In the Smart Grid (SG), the consumption information is provided for end-users in order to help them to change their consumption behaviour. However, this goal will not be achieved if the consumers do not engage in the energy management process; in this case, they require a decision-making system that will assist them. This PhD thesis addresses the complexity of the energy efficiency control problem in the home of a residential customer of SG, and examines the main factors that affect energy demand, and proposes an intelligent Home Energy Management System (HEMS) for applications of demand response in the SG. Subsequently, the proposed methodology is deployed in the industrial sector to assist operations managers to decide whether to accept Demand Response Programs (DRPs) with or without obtaining energy from distributed energy resources or rejecting the DRPs. The thesis comprises five main Chapters:

- Chapters 1 and 2- These chapters presents a comprehensive introduction to the Smart Grid and review of the literature pertaining to HEMS components, SG regulations and standards, as well as demand response programs, energy scheduling and optimization. The main variables affecting energy consumption in the residential sector and comfort management are identified.
- Chapter 3- The variables (identified in Chapter 2) are utilized to propose and model a novel intelligent decision support system (IDSS) for the users. The developed expert IDSS is intended to assist householders to manage DRPs. Three techniques –the analytic hierarchy process, elimination and choice expressing reality, and the technique for Order of preference by similarity to ideal solution- are proposed and implemented.
- Chapter 4 - A versatile scheduling algorithm and methodology is proposed and implemented to schedule energy consumption in different DRPs. A combinatorial optimization technique based on knapsack is proposed and tested for scheduling energy according to the householder’s budget.
- Chapter 5- The TOPSIS methodology is applied in order to assess the effects of engaging in a smart grid DRP on operational and production management in the industrial sector. The Delphi method was introduced to determine the criteria for assessing the effect of energy curtailment during DRP. A combinatorial optimization model is proposed to utilize those ranking values to optimize energy consumption that will satisfy the energy limit imposed by production demands and DRP.

The contribution of this research can be significant for system designers, researchers and policy makers who want to develop the SG for residential and industrial customers.

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List of Acronyms

AC: Air Conditioner

ADR: Automated Demand Response

AHP: Analytic Hierarchy Process

AHURI: Australian Housing and Urban Research Institute

AMI: Advanced Metering Infrastructure

ANP: Analytic Network Process

ARRA: American Recovery and Reinvestment Act

ASHRAE: American Society of Heating, Refrigerating and Air-Conditioning Engineers

BACnet: Building Automation and Control Network

BAS: Building Automation System

BEMS: Building Energy Management System

CCU: Central Control Unit

CEM: Consumer Energy Manager

CPP: Critical Peak Pricing (CPP)

DERs: Distributed Energy Resources

DLC: Direct Load Control

DOE: Department of Energy

DR: Demand Response

DRP: Demand Response Program

DSM: Demand Side Management

EIA: Energy Information Administration

ELECTRE: Elimination et Choix Traduisant la Réalité

EMA: Energy Management Agent

ESI: Energy Services Interface

FERC: Federal Energy Regulatory Commission

GHG: Greenhouse Gas

GUI: Graphical User Interface

HAN: Home Area Network

HEMS: Home Energy Management System

HES: Home Electronic System

HVAC: Heating, Ventilation, and Air Conditioning

IAQ: Indoor Air Quality

ICT: Information and Communication Technology

IDSS: Intelligent Decision Support System

IEC: International Electro-technical Commission

IEEE: Institute of Electrical and Electronics Engineers

ISO: International Organization for Standardization

KP: Knapsack Problem

MCDM: Multi-Criteria Decision Making

NIST: National Institute of Standards and Technology

OpenADR: Open Automated Demand Response

PCS: Power Conditioning Systems

PEVs: Plug-in electric vehicles

PMV: Predicted Mean Vote

PPD: Predicted Percentage Dissatisfied

PROMETHEE: Preference Ranking Organization Method for Enrichment Evaluation

PV: Photo-Voltaic

RTP: Real-Time Pricing

SG: Smart Grid

SoS: System of Systems

SR: Spinning Reserve

TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution

TOU: Time of Use

TPB: Theory of Planned Behaviour

List of Publications

Conference Papers

		Cited by (Ref: Google Scholar)
1	Sianaki, O.A.; Masoum, M.A.S., "Versatile energy scheduler compatible with autonomous demand response for home energy management in smart grid: A system of systems approach," in Power Engineering Conference (AUPEC), 2014 Australasian Universities , vol., no., pp.1-6, Sept. 28 2014-Oct. 1 2014 doi: 10.1109/AUPEC.2014.6966523 URL:http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6966523&isnumber=6966468	1
2	Sianaki, O.A.; Masoum, M.A.S., "A fuzzy TOPSIS approach for home energy management in smart grid with considering householders' preferences," in Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES , vol., no., pp.1-6, 24-27 Feb. 2013 doi: 10.1109/ISGT.2013.6497819 URL:http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=6497819&isnumber=6497783	5
3	Sianaki, O.A.; Hussain, O.; Dillon, T.; Tabesh, A.R., "Intelligent Decision Support System for Including Consumers' Preferences in Residential Energy Consumption in Smart Grid," in Computational Intelligence, Modelling and Simulation (CIMSiM), 2010 Second International Conference on , vol., no., pp.154-159, 28-30 Sept. 2010 doi: 10.1109/CIMSiM.2010.84 URL:http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5701838&isnumber=5701812	31
4	Sianaki, O.A.; Hussain, O.; Tabesh, A.R., "A Knapsack problem approach for achieving efficient energy consumption in smart grid for endusers' life style," in Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES), 2010 IEEE Conference on , vol., no., pp.159-164, 27-29 Sept. 2010 doi: 10.1109/CITRES.2010.5619873 URL:http://ieeexplore.ieee.org/stamp/stamp.jsp?tp=&arnumber=5619873&isnumber=5619765	25

Journal Papers

1	O. A. Sianaki and M. A. S. Masoum, "A Multi-agent Intelligent Decision Making Support System for Home Energy Management in Smart Grid: A Fuzzy TOPSIS Approach," *Multiagent and Grid Systems - An International Journal*, vol. 9, pp. 181–195, 03/11/2013 2013.	2

Chapter 1

Introduction

1.1. Introduction

According to the Energy Information Administration (EIA) report [1], it is estimated that the global demand for energy will rise by 56% by the year 2040. As shown in Figure 1, in order to meet that demand, renewable sources of energy are the fastest-growing source of world energy, with consumption increasing by 2.8% per year from 2010 to 2040; meanwhile, the rate is 2.5 % for nuclear power and natural gas. This shows that the dependence on resources to meet the energy demand is shifting from non-renewable to renewable sources to utilize green energy. Consequently, with such a shift, there has been an increase in the costs of upgrading the old electricity delivery system, pricing and service networks, as these systems have the traditional supply-side options and an inadequate central capacity plan to meet the growing demand and energy shift. The new system demands a framework in which people, systems, solutions, and business processes are dynamic and flexible in responding to changes in technology, customer needs, prices, standards, policies, and other requirements [2]. This is achieved through the Smart Grid. The ***Smart Grid is*** an electricity network that can intelligently integrate subsystems of generation, transmission, distribution and customer services and utilize distributed energy resources [3]. The actions of all subsystems are integrated in order to efficiently deliver sustainable, economic and secure electricity supplies [4].

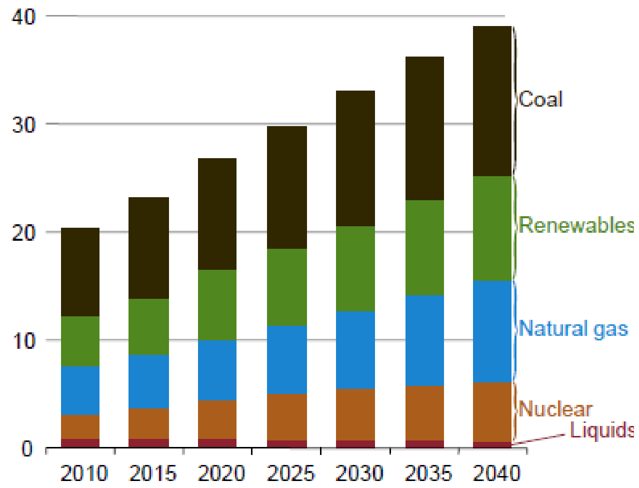

Figure 1.1. World Net Electricity Generation by Fuel, 2010-2040 (Trillion kilowatthours) [1]

In this system, the consumers who are equipped with different forms of distributed energy resources such as roof-top photovoltaic panels or wind turbine (call them “prosumer”) are able simultaneously consume the energy from different sources and produce and return it to the grid or use it during peak times when the price of energy is increased. The need for two-way communication between the utility and its customers lies at the heart of all Smart Grid initiatives. In this fashion, both parties work synergistically to manage the cost, delivery and environmental impact of power generation and energy services delivery. But to achieve energy efficiency, apart from having such architecture, mechanisms are needed that add intelligence to it at different levels. This additional intelligence varies according to the level at which it is being considered. For example, if considered from the generation side, one of the areas in which intelligence has to be added is dynamic pricing; whereas, from the consumer’s perspective, it may be in the efficient utilization of energy at home level based on the price. This is supported by Schneider Electric which states that energy management needs intelligence not only to reduce energy consumption, but also to reduce operational costs[5]. Once developed, the approaches will add intelligence at the end-user level and will encourage customers to change their energy consumption behaviour in order to achieve energy efficiency. It has been mentioned in the literature that consumers are ready to change when they are presented with the appropriate information, but they lack the data or tools to do so [6].

Therefore, an approach is required whereby I can investigate, identify and address the issues which arise for the consumers, and which adds intelligence for efficient and smart energy consumption in line with the real costs and environmental impact which will encourage consumers to utilize energy efficiently. Therefore, the aim of this thesis is to develop an intelligent energy management system at the smart home level in Smart Grid. Such a system takes into account the consumers’ preferences and life styles, and assists them to efficiently utilize energy in the Smart Grid.

This Chapter is organized as follows. It begins with a definition of the smart grid and its architecture, and describes the system’s components. Then, I specify the section of this network that is the focus of this thesis by introducing demand-side management and its components. Certain infrastructures are required for the implementation of energy management techniques in a home, and these will be discussed subsequently. This will be followed by a discussion of the important parameters of energy demand in the residential sector and optimization and scheduling methodologies. Finally, the research objectives and its significance along with the overall structure are presented.

1.2. Smart Grid (SG) Goals

Smart Grid is a novel initiative the aim of which is to deliver energy to the users and to achieve consumption efficiency by means of two-way communication. The Smart Grid architecture is a combination of various hardware devices, and management and reporting software tools that are combined within an ICT infrastructure. This infrastructure is needed to make the smart grid sustainable, creative and intelligent while the various components of this system have been developed independently by many suppliers and they must operate and work together in this domain. This interoperability of system components needs to be outlined and achieved with "architectural guidance". Hence, according to the U.S. Energy Independence and Security Act of 2007-section 1305, the responsibility for coordinating the standards and protocols for an SG interoperability framework resides with the U.S National Institute of Standards and Technology (NIST)[7]. So in late 2009, NIST established the SG interoperability panel (SGIP) to develop support for the mission. Subsequently, an architectural framework was created in order to achieve a common understanding about smart grid elements, the relationship amongst stakeholders and a technical roadmap for integrating domains, companies, and businesses. According to this report, the fundamental goals of constructing the smart grid framework are as follows [7]:

1. *Options:* The smart grid must have a wide range of standard options so that new technologies can be incorporated without incurring huge capital investment and customization.
2. *Interoperability*: Interfacing of subsystems and interoperability of other products outside of the smart grid domain are the other specifications of the SG structure.
3. *Maintainability*: Maintaining system safety, security, and reliability during the period of the SG's life time is another fundamental goal of the SG.
4. *Upgradeability:* It is important that the system remain operational when a part of the grid is being upgraded.
5. *Innovation*: SG must have the capacity to sustain innovation in "regulations and policies; business processes and procedures; information processing; technical communications; and the integration of new and innovative energy systems"[7].
6. *Scalability*: A lifetime of five to thirty years must be considered for system elements when smart grid is under development and the elements must survive and operate in a secure way for the duration.
7. *Flexibility*: SG must have flexibility in type and order of implementation without facing the disadvantage of having to select an alternative implementation.
8. *Legacy integration and migration:* In terms of compatibility of new innovations with existing and old technology, it is very important that the SG framework address the

legacy devices, systems, protocols, syntax, and semantics. These are the components of the framework which were designed and used in the past. Sometimes the compatibility and integration is possible by means of an adapter or by creating an "intervening layer" that must be examined case by case.

9. *Governance*: This goal involves compliance with policies when designing and managing the smart grid system.
10. *Cybersecurity:* Protecting the system against physical and cyber-attack is another goal of SG architecture. The computerized electrical grid must have strong protection for its power systems. Cyber security must reliably cover customer privacy and all communication and automation sectors.
11. *Affordability*: This goal concerns the creation of a reliable energy market for multi-vendors in which capital savings can occur in both national and international markets.

Furthermore, NIST divided the domains of smart grid according to customers, markets, service provider, operations, generations, transmission, and distribution as shown in Figure 1.2. Each domain comprises groups with similar requirement characteristics; they can be organizations, individuals, systems and devices. The information network among these domains and groups is shown in Figure 1.2 and the groups in the customer domain have been shown in Figure 1.4.

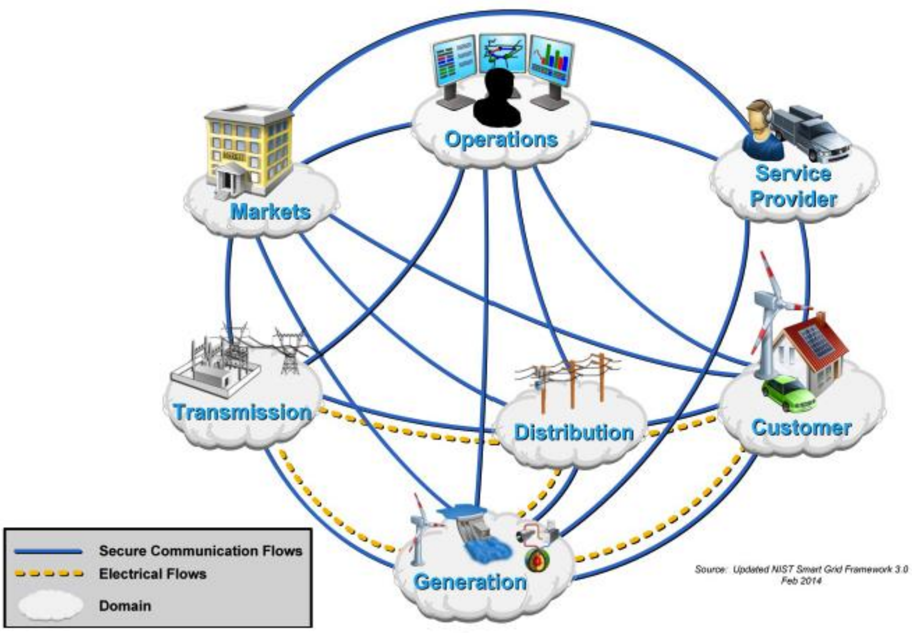

Figure 1.2. Interaction of Actors in Different Smart Grid Domains through Secure Communication [7]

As will be shown in the literature review presented in Chapter 2, the term “smart” in smart grid terminology indicates “intelligence” in functionality, communication and integration of all network domains. The U.S. Department of Energy (DOE) [8] indicates that the smarter grid uses tools, techniques and technologies to add knowledge to power in order to make it more efficient. This knowledge is supposed to be provided by means of two-way digital information and communication technology, so a key feature of smart grid infrastructure is the modern automation technology for conveying data and computerizing information. In this fashion, the important section is the transformation of the information into knowledge in order to make efficient decisions that in this thesis will be addressed in terms of the residential sector.

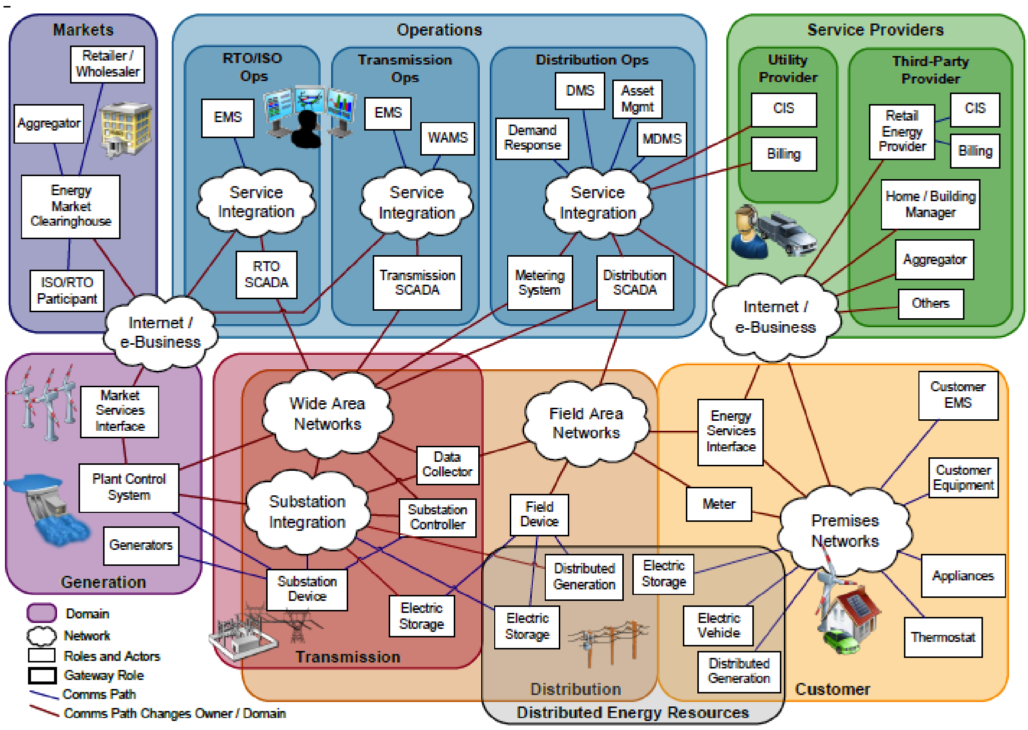

Figure 1.3. Conceptual Domains for Smart Grid Information Networks [9]

1.2.1. Smart Grid Characteristics

According to section 1301 of the Energy Independence and Security Act of 2007, issued by the U.S. DOE, future Smart Grids should have ten characteristics as follows [10]:

1. Digital information and controls technology are employed to make the electric grid more reliable, secure, and efficient.

2. The optimization of operations and pervasive cyber security systems have been utilised dynamically across the grid.
3. Distributed renewable and non-renewable resources are coupled together for electricity generation.
4. In demand-side management, demand response programs are integrated with other energy-efficient resources.
5. "Deployment of `smart' technologies (real-time, automated, interactive technologies that optimize the physical operation of appliances and consumer devices) for metering, communications concerning grid operations and status, and distribution automation"[10].
6. "Integration of `smart' appliances and consumer devices"[10].
7. " Provision to consumers of timely information and control options"[10].
8. The infrastructures and standards have to be prepared and enacted for interoperability of electrical devices and their communication with the grid network.
9. Applying technologies to shift the demand from peak time to off-peak period (Peak shaving) for Plug-in electric vehicles (PEVs), air conditioners (AC) and using modern storage system.
10. Recognition of unreasonable obstacles to the development of SG technologies and practices.

Characteristics five, six, and seven pertain to the consumers' interaction with the utility and optimization of electrical devices, and these play a critical role in ensuring a robust future smart grid. In addition, by studying customer domain groups presented in Figure 1.4, the interconnection of buildings with smart grid has three key features. The first one is a renewable distributed and decentralized power generation strategy. Smart grid customers are able to generate electricity locally, preferably from renewable resources such as solar photo-voltaic (PV) panels or wind turbines, which can be stored in batteries or sent back to the grid. In this scenario, they are called "prosumers" (producers and consumer). The second feature is demand response programs and their associated hardware and software on the end-user side such as a smart meter and Energy Services Interface (ESI) for establishing communication and a data stream between service provider and customer. This interface is a gateway for measuring and recording consumption data and communication purposes such as remote control and outage management. In some cases, the ESI is embedded in the smart meter that will be discussed in the literature review in Chapter 2.

Finally, the third feature is the use of plug-in vehicles or hybrid automobiles which can be charged by connecting them to building outlets.

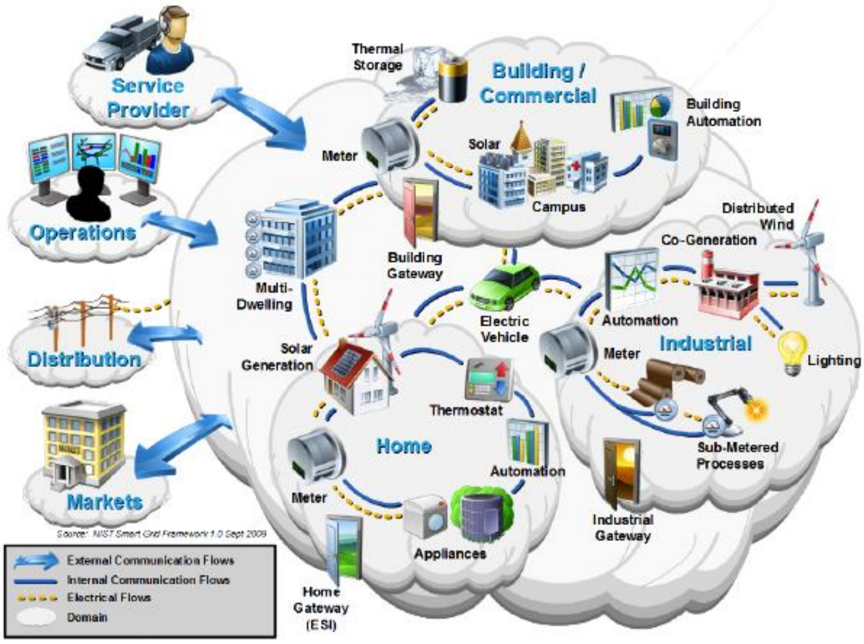

Figure 1.4. Overview of Customer Domain in SG [9]

Thus, the emergence of the smart grid has leveraged the building automation systems in order to achieve efficient energy targets in the customer domain (Figure 1.4). However, future building energy management systems will be more efficient if they are integrated with a smart grid communication system and conform to smart grid infrastructures, standards, and regulations. The following section presents the energy management systems in the smart grid.

1.3. Building Energy Management System (BEMS) and Demand Response (DR) Programs

1.3.1. BEMS

A building automation system (BAS) can be set up to automate a building to make work more efficient for occupants. A BEMS or home energy management system (HEMS) in the residential sector is a subset of BAS. Also, it focuses on automating the building to run as energy-efficiently as possible. BEMS is able to optimize indoor air quality, temperature control, and lighting. For example, optimization in lighting can provide the appropriate level of light by effective control through scheduling or by active energy efficiency measurement such as daylight harvesting. This process can be implemented by either utilizing a photo-electric sensor to detect daylight level entering through windows and dim lights to ensure the space is not over-illuminated, or by using occupancy sensors or stand-alone sensors to turn off lights when the space is unoccupied. Lighting control will be explained in subsequent sections.

The standardization of communication protocols and widespread adoption of the Building Automation and Control Network (BACnet) protocol has enabled the integration of products and connectivity among systems made by different manufacturers [8]. BACnet which achieved the ISO 1648-4 standard in 2003, is a communication protocol developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) for use in control networks and building automation [11]. The acceptance of Zigbee, as the only BACnet approved wireless mesh network standard for building systems for connecting appliances in residential buildings, is increasing at a rapid rate [12].

Buildings play a significant role in the context of smart grid as this sector is responsible for 38% of the total energy consumption in the world [13]. This rate differs among countries. For example, in Europe it is 40% [14] and 39% in the UK (2004) [15]. Consequently, there is great potential for research and development of energy-saving approaches in demand-side management. The next section explains the association of demand response programs and HEMS in SG.

1.3.2. DR Programs and HEMS

Demand-side management (DSM) comprises those technologies, activities and strategies used by the utility in the demand side of the energy network in order to achieve goals including emission reduction, load management, improved energy efficiency and conservation, balancing of supply and demand, increasing consumer participation in energy management and generation, and reduction in operation costs for the total network. So demand response is one of the demand-side management mechanisms.

The U.S. Federal Energy Regulatory Commission, FERC, defines DR as “changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [16].

It is widely agreed that the cost of energy is the most powerful incentive to encourage consumers to curtail their consumption. So in demand response programs, the aggregators or service providers use this incentive to achieve their aims in regard to load management. The most important objective of these programs is to make the demand curve flat by offering a high-priced energy unit during peak periods and lower prices during off-peak periods in order to stabilize the volatile energy demand so as to make it more predictable and controllable.

Albadi and El-Saadany [17] classified DR programs according to two categories: incentive-based and price-based programs. The authors define DR as the changes in power consumption by end-users from their normal consumption patterns in response to changes in the price of electricity over time. These classifications are shown in Figure 1.5 and each program will be discussed in detail in Chapter 2.

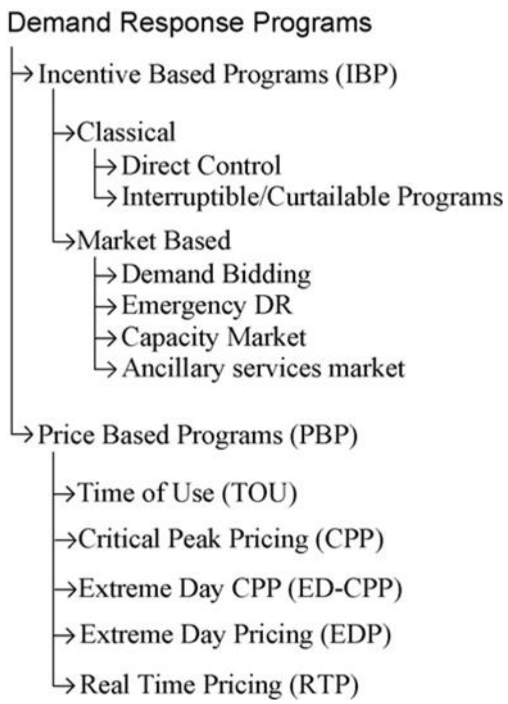

Figure 1.5. Demand Response Programs [17]

The International Organization for Standardization (ISO) and International Electro-technical Commission (IEC) issued ISO/IEC 15067-3 standard as the information technology necessary for the home electronic system (HES) application model, and in the third part, the standards present a model of a demand-response energy management system for HES[3]. A high-level energy management model presented in this document focusses on three primarily demand-response methods: 1) direct, 2) local (time of use), and 3) distributed control (real-time pricing).

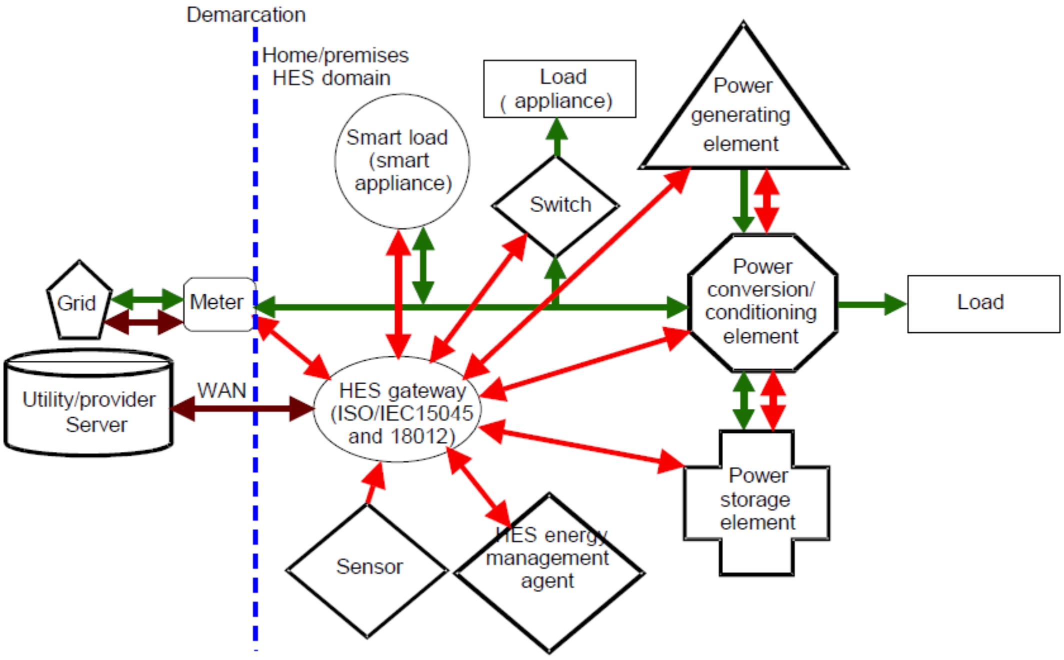

Figure 1.6. HES Energy Management Model Presented by ISO/IEC 15067-3 [3]

A *Direct Load Control (DLC)* program is essentially for the low energy consumers such as residential and small commercial users. In this program, the service provider has the authority to shut down, remotely, several appliances such as air-conditioners, pool pumps, and water heaters at short notice. In a Real-Time Pricing (RTP) program, changes in the wholesale energy market will be reflected and the energy unit price fluctuates hourly or a day ahead. RTP is one of the most efficient DRPs [11]. Another RTP approach is known as *prices to devices* whereby smart appliances will receive the energy price signals and they will adjust themselves accordingly. For example, a program may be embedded in the appliances by the manufacturer to adjust the load based on the price of energy. In air-conditioners, the operation and temperature set point may be modified by changes in energy price. In this case, the communication can be made directly between the utility's wide area network and the home area network, or directly to smart appliances, or via a gateway like HES.

The Australian standard, AS4755 [18], is an operational instruction for demand-response capabilities and supporting technologies for electrical products that can be remotely controlled. The third part of this document is concerned with demand-response-enabling for air conditioners, swimming pools, and electric water heaters.

According to the Australian standard AS 5711-2013, smart appliances in SG are [19]:

a) Those appliances which react with a demand response program combined with an inverter energy system and an appliance energy manager; or

b) An electrical appliance that has the function of changing the operation modes automatically in response to either instruction from sources other than the user, or, is programmed by the user to monitor and react to changes in grid conditions.

The standard states “an appliance that is capable of being remotely interrogated or controlled by the user or that is able to modify its operation through monitoring its own pattern of use is not a smart appliance, unless it also has the characteristics above.” [19]

By referring to the functions explained by the standards and published articles for EMS, the sophisticated software algorithms for scheduling and optimization are at the core of EMS vision. As a result, a major focus of smart grid research has been the design of an intelligent scheduling algorithm and optimization techniques. Considering the outlined smart grid network, demand response and customer domain, home energy management is the area on which this thesis will focus.

Hence, in this thesis, the research has been carried out to design a novel framework for proposing an energy management system compatible with demand response, smart grid infrastructure and standards.

Furthermore, the proposed methodologies in [20-22] and the agent-based approach presented in [23] are enhancements that will be explained in more detail in Chapter 3.

In the literature, the field of HEMS in SG can be categorised according to five main areas of research:

1. comfort management,
2. consumption behaviour and preferences,
3. consumption optimization by load scheduling and control systems,
4. demand response, and
5. information and communication technology.

As mentioned previously, ICT is inherent in SG. Hence, in the next section, the communication network between utility and home, comprising the advanced metering infrastructure in SG, will be described.

1.4. Advanced Metering Infrastructure (AMI) and Home Area Network (HAN)

One of the fundamental parts of the smart grid is the advanced or smart metering infrastructure. This is responsible for metering operations, communication systems, collecting data, managing business arrangements, and supporting the contractual arrangements. Smart electricity meters are electronic devices which the utility installs on the customer's premises for the purpose of recording flows of electric energy at intervals of 30 minutes or less. This device is capable of two-way communication, directly and/or remotely, of:

(a) a range of data for monitoring and billing;

(b) information for energy management purposes; and

(c) any change in the state of the smart meter (e.g. for the purposes of demand response actions) [19].

Synchronization, power management, information display, communication, control and calibration, and quantitative measurement are the expected functionalities of smart meters. Accordingly, the significant features of smart meters can be outlined as follows [24]:

1. Time-based pricing.
2. Providing consumption data for consumer and utility.
3. Net metering.
4. Failure and outage notification.
5. Remote command operations.
6. Load limiting for DR purposes.
7. Power quality monitoring including: phase, voltage and current, active and reactive power, power factor.
8. Energy theft detection.
9. Communication with other intelligent devices.
10. Improvement of environmental conditions by reducing emissions through efficient power consumption.

In AMI, the Home Area Network (HAN) [19] is a network on the premises of an energy consumer which enables electrical products (whether smart or not) to interact with the smart grid connection point (via the home energy gateway) and/or in-home displays.

As demonstrated by [24] and shown in Figure 1.7, utility networks comprise four levels:

1. A core backbone which interconnects utility and aggregation point
2. Access points or smart meters where information provided by a HAN passes through it to backhaul distribution.
3. Backhaul distribution that passes information received from backhaul distribution and smart meters to core backbone and utility.

4. A HAN which is connected to the appliances and in their immediate above layers to the smart meters.

HANs connect smart meters, smart appliances, energy storage and generation, and plug-in electric vehicle (PEV). In this communication, the data flow is more instantaneous rather than continuous, and the data bandwidth of 10 to 100 Kbps for each device depends on the task.

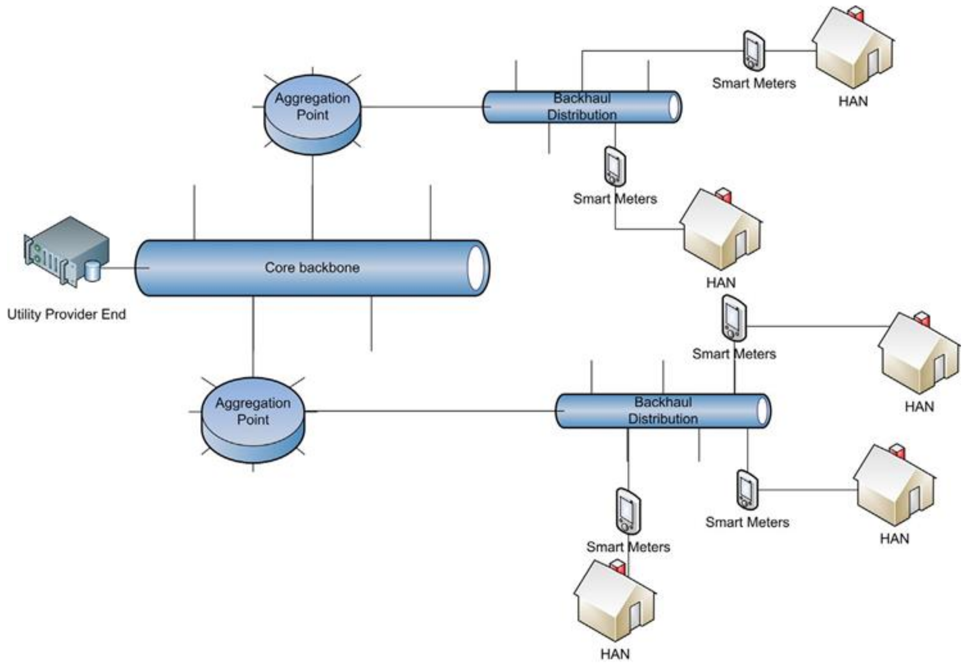

Figure 1.7. Utility Network Proposed by [24]

This network at the domestic level has been delineated by Australian standard AS 5711-2013 and is shown in Figure 1.8. CEM in this figure is the Consumer Energy Manager which is a device connected to the smart grid for the purpose of controlling the appliances. In the standard, the difference between HEM and CEM is just the connection point to the home energy gateway. It means that HEM will convert to CEM if it is directly connected to the gateway. The vertical line in Figure 1.8 indicates the SG connection point.

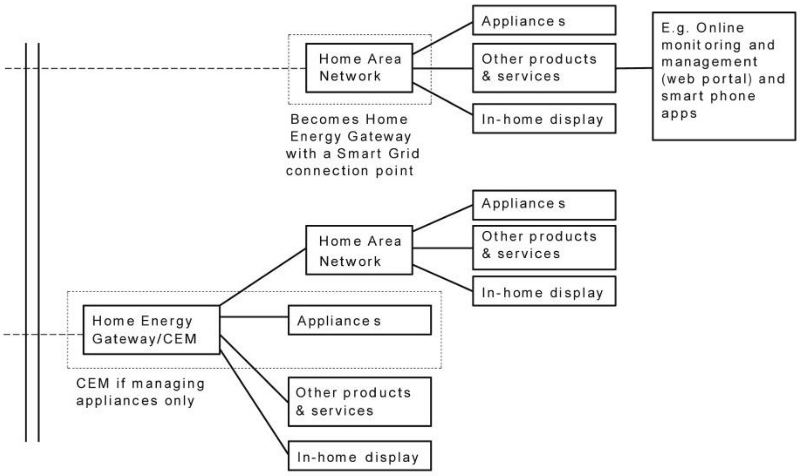

Figure 1.8. Consumer Side Element of Smart Grid [19]

The communication structure described above facilitates the flow of information so as to better monitor the householders' consumption behaviour. Hence, householders are provided with information which may be used in their decision-making process pertaining to the ways in which they could change their life style to achieve a more efficient level of energy consumption, or which kind of DRP may less compromise their comfort level or benefit them financially. The next section presents a discussion of the role of BEMS in comfort management.

1.5. Building Energy Management Systems (BEMS) and Comfort Management

1.5.1. Budget and Energy Cost versus Comfort and Convenience

The developers of smart grid systems must give serious consideration to the issue of whether the customers' comfort level and lifestyle will be compromised or disrupted by the utilization of automated control and scheduling techniques for energy management. The demand-response program is a mechanism whereby customers are encouraged to modify their usual consumption behaviour in favour of saving money, or avoiding cost and penalty consequences in their bills. This is intended to encourage customers to relinquish some of their habits and conveniences, or pay the price for retaining the same consumption habits during the high pricing times.

The user's preferences and energy budget are two inputs to energy management system, so the question is: how do these two inputs affect each other since the adjustment of preferences may be interpreted as adjusting cost which is directly related to budget? Moreover, this becomes more complicated when the dynamic-pricing is considered, demand-response program when the market-based energy price is variable. In this situation, controlling the budget and adjusting the preferences would be more complex as explained by the Standard [3].

Issues arise and arguments may occur between users or family members when making decisions regarding the kind of interface that is appropriate for them and includes their preferences. How can conflict of preferences be avoided? Which methodologies can be used to analyse and integrate all sorts of preferences? If users decide to allocate their budget for a billing period in different forms of demand response, what kind of system and methodology can best accomplish this?

1.5.2. Comfort Management by BEMS

A great deal of research has been conducted into methodologies for measuring comfort and its effect on energy consumption in buildings [25-36]. Dounis et al. [35] undertook a comprehensive survey of control systems for comfort management in buildings and stated that three aspects of comfort -thermal comfort, visual comfort and indoor air quality- indicate the comfort level or quality of life in a building.

Huebner et al. [25] studied the effect of human factors on energy consumption. These factors included comfort, habit and behavioural intention, socio-demographic and psychological variables, building characteristics and external impact factors. The article demonstrates that different understandings of comfort affect consumption behaviour and it is difficult to break habits in order to modify patterns of energy consumption. Wang et al. [27, 29, 30, 36] propose a hierarchical multi-agent intelligent control system which considers comfort management in smart buildings. Their parameters for comfort management consist of illumination for light control, CO_2 concentration for indoor air quality, and temperature for thermal control. Their model architecture is based on the smart grid framework. They utilised the particle swarm optimization technique; the optimizer was an agent and their model included a graphical user interface (GUI) for setting preferences. In their approach, they established a composite comfort index for maximizing it in their objective function as it is based on maximization. They claim that their intelligent system is capable of achieving the control goals.

An approach proposed by [37] is intended to minimize energy cost via a multi-agent system that includes a fuzzy controller for comfort management in a home. Several heaters have communication with Zigbee technology and a central control unit (CCU) measures maximum power to reach a set temperature point for each room according to the comfort level required. They used a fuzzy controller to distribute power to heaters.

As will be shown in the literature review (Chapter 2), researchers use different variables when measuring comfort levels. For example, in the aforementioned article, the variable for measuring comfort is temperature. However, three aspects of comfort are evident in the various researches [35, 38]: thermal comfort, visual comfort and indoor air quality (IAQ). Therefore, this thesis studies comfort management in terms of these three aspects.

1.5.3. Comfort Management: Thermal Comfort

The best references for measuring thermal comfort is the standard of ISO 7730: 2005(or I.S. EN ISO 7730:2006) and ANSI/ASHRAE Standard 55-2013, "Thermal Environmental Conditions for Human Occupancy" issued by the American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE) [39, 40].

According to ANSI/ASHRAE Standard 55-2013, there are six factors which may vary with time that address the conditions for acceptable thermal comfort. They comprise characteristics of occupant factors such as:

1- Metabolic rate (met): "the rate of transformation of chemical energy into heat and mechanical work by metabolic activities of an individual, per unit of skin surface area (expressed in units of met) equal to 58.2 W/m2 (18.4 Btu/h·ft2), which is the energy produced per unit skin surface area of an average person seated at rest."

2- Clothing insulation (I_{cI}): its unit for measurement is "clo" and it is a unit used to express the thermal insulation provided by garments and clothing ensembles, where 1 clo = 0.155 m2·°C/ W (0.88 ft2·h·°F/Btu).

The thermal factors include:

3- Air temperature

4- Mean Radiant temperature $\overline{t_r}$: " the temperature of a uniform, black enclosure that exchanges the same amount of heat by radiation with the occupant as the actual enclosure. It is a single value for the entire body expressed as a spatial average of the temperature of surfaces surrounding the occupant weighted by their view factors with respect to the occupant."

5- Air speed: "the rate of air movement at a point, without regard to direction."

6- Humidity: "a general reference to the moisture content of the air. It is expressed in terms of several thermodynamic variables, including vapour pressure, dew-point temperature, wetbulb temperature, humidity ratio, and relative humidity. It is spatially and temporally averaged in the same manner as air temperature. Note: Any one of these humidity variables must be used in conjunction with dry-bulb temperature in order to describe a specific air condition."

[40] defines thermal comfort as a "condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation." This standard states that "Due to individual differences, it is impossible to specify a thermal environment that will satisfy everybody". Therefore, three classes of thermal environment for a space such as A, B and C are presented. Each class prescribes different thermal states of the body and local discomfort parameters. These classes have been used for measuring the thermal comfort (room temperature set point) in the approach presented by [41]. This study evaluated the energy efficiency aspect of demand-side management and considered a single-dwelling family as a prosumer using structural thermal mass in a heat pump and simulating the building-envelop characteristic in the TOU demand response scheme.

In the ISO 7730 standard, the effective factors that determine the body's thermal sensation comprise physical activity and clothing, and environmental factors include air temperature, mean radiant temperature, air velocity and air humidity. By measuring them, the Predicted Mean Vote (PMV) index can be calculated. But for thermal discomfort or thermal dissatisfaction, the index is the predicted percentage dissatisfied (PPD). This factor can be calculated from the PMV.

The PMV index was utilized in research conducted by [42]. The authors divided appliances into two groups, thermal and non-thermal. By calculating building thermal mass thermodynamically and integrating this factor with customers' comfort preferences, they produced an optimization model for scheduling appliances in peak and off-peak demand response periods of the smart grid. The authors used ISO 7730 to calculate the PMV comfort level. The objective function of their optimization model is to minimize energy cost by scheduling appliances according to a time-varying scheme DR and by taking into account the PMV constraint.

Although the effect of thermal comfort in residential energy consumption is significant, the study of comfort management in the field of residential energy management and energy cost is not limited to this factor. Variables such as "*visual comfort*" and "*indoor air quality*" have been identified by many researchers as a comfort index [43, 44].

1.6. User Activities, Consumption Behaviour and Preferences in EMS

Recognition of user activities in favour of energy consumption monitoring and studying householders' consumption behaviour and preferences have been a major focus of research. For example, research conducted by [45] considers human behaviours in an individual building as primary factors for predicting energy usage. The authors analysed patterns of energy consumption by monitoring activities as well as collecting energy consumption data from several smart environments. They analysed the energy patterns by identifying frequent sequences of energy consumption ranges and identifying outliers in the data. In this research, the role of behaviours in terms of energy consumption has been identified by utilizing machine learning methods to map activities performed in the environment with their corresponding energy consumption.

The research conducted by [46] focuses on the impact of householders' behaviour on building energy performance. Their model shown in Figure 1.9 demonstrates the relationship between the determinants of householders' consumption behaviour and the building.

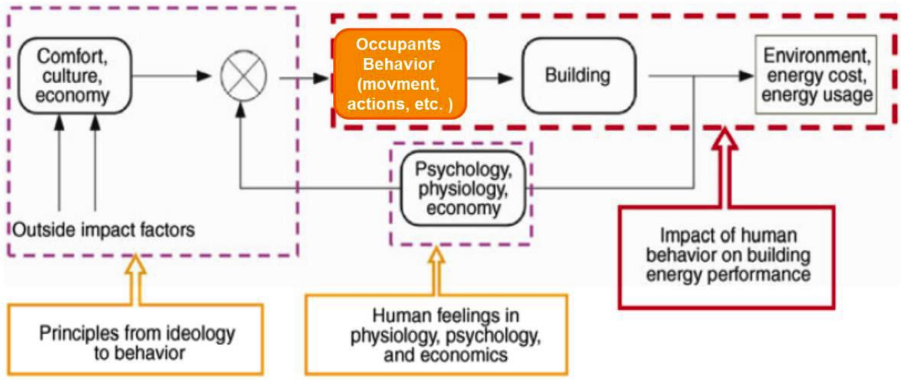

Figure 1.9. The Impact of Householders' Behaviour on Building Energy Performance [46]

The Australian Housing and Urban Research Institute (AHURI) conducted a research study into the attitudes and behaviours of Australian households regarding consumption reduction of energy and resources usage (electricity and water). The researchers utilized a decision-making model, theory of planned behaviour (TPB), to investigate the social and psychological determinants of behavioural intentions and actions. The research finding shows that householders have positive attitudes to practices and actions which minimise waste and conserve energy. Using efficient appliances, providing feedback about usage, and engaging in household sustainability practices in the community, all lead to an efficient level of energy consumption. The variables used in this research are mainly the same variables as those used in the study undertaken by [47] and they comprise age, gender, household tenure (owner/tenant), type of dwelling, annual household income, number of adults in house, number of children in house, highest level of education, and number of bedrooms in dwelling. Similarly, the research results in [48] reveal that providing information about household behavioural conservation actions is as significant as a home energy performance retrofit.

As discussed in section 1.4, the AMI and HEMS are able to provide real-time and online information about consumption rate, energy price or other measurable factors. [44] conducted a survey into the effect of householders' consumption behaviour in DR. The results show that consumers' attitudes to the signals and willingness to modify their consumption behaviour greatly affect the load shift in DR, cost saving and emission reduction.

Scrutinizing the factors that affect users' behaviour is not the only means of achieving energy conservation and efficiency. Consumption optimization and energy scheduling are also significant factors. Productivity will be created when the outcome of that study utilizes optimization techniques. The next section provides a further explanation of energy efficient behaviour.

1.7. Consumption Optimization and Load Scheduling for EMS in SG

SG revolution and emerging new demand response programs have revealed new circumstances and factors that influence the methodologies which have been applied for energy optimization and scheduling. Some of these circumstances are as follows:

1. Effects of the dynamic and real-time DR on householders' consumption behaviour [49, 50].
2. Development of DERs which have enabled consumers to become prosumers [51-53].
3. Enhancing the data availability and visibility by real-time monitoring whereby the utility has the capability of making deals and trading with end-users [54].
4. Enabling mutual communication between end-users and the utility by means of smart meters [55, 56].
5. Development in technologies which enable the system to better monitor and identify appliances [57, 58].
6. Development in technologies and methodologies which enables the system to better predict the available resources and effective parameters in energy demand [59-63].
7. Emerging smart appliances compatible with modern ICTs and home automation [64-66].

Home energy scheduling in the SG can be defined as an offline, semi-online, or online process of allocating energy resources to supply the energy demand of various electrical devices in a time scale of short, medium and long term in order to:

a) satisfy the regulations of demand response programs,
b) optimize the householder's comfort level, and
c) produce energy cost savings.

The term 'optimization' refers to the process of searching for the best value that can be realized or attained [67]. In HEMS, optimization is the process of seeking and finding the minimum or maximum value of the cost or saving function associated with energy consumption or generation given the feasible constraints. The cost and saving are dependent on the objective function.

According to the guidebook provided for ARRA[1] [68], one of the thirteen functions of a modernized electricity delivery and the use of electricity in SG, is customer electricity consumption optimization that provides information enabling consumers to make educated decisions about their electricity use. Householders should have this ability to optimize in order to achieve multiple goals such as reduced cost, reliability, comfort, and decreased environmental impact.

Energy-efficient behaviour may be encouraged by making available to consumers adequate information about energy prices and the energy consumption of appliances. Energy-efficient behaviour [19] is defined as the operation of appliances by consumers in a way that optimizes energy efficiency while reducing energy wastage.

Hence, in Chapters 2 and 4, the most significant methodologies proposed in the literature are presented for four categories: scheduling, optimization, appliance identification, and resource allocation.

1.8. Distributed Energy Resources (DERs) in SG

DERs are defined by [19] as "spatially dispersed power generation or storage units that are connected directly to the distribution network or connected to the network on the consumer side of the meter. These energy sources can include micro turbines, fuel cells, wind power, solar power, and both direct and indirect forms of energy storage".

According to this definition, electric power conversion, from DC (direct current) to AC (alternating current) may occur in DERs. So, power conditioning systems (PCSs) which are power electronics technologies designed to increase the penetration level of renewable resources will be utilized to increase the power quality and to compensate for the intermittency of renewable resources. The power quality in an electric power system depends on the

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[1] American Recovery and Reinvestment Act

characteristics of the electric current, frequencies, voltage, and waveforms at a particular point, evaluated against a set of technical reference parameters.

Renewable resources like the sun and wind are the cleanest means of generating energy; meanwhile, other distributed power plants utilize a combination of renewable (e.g. solar and wind), fossil-fuel-driven generators, and a diesel generator. These hybrid power systems use a fossil-fuel generator to reduce effect of intermittency of renewable resources. The various electricity storage systems include [69]:

- Pumped hydro storage
- Thermal energy storage
- Compressed air energy storage
- Small-scale compressed air energy storage
- Energy storage coupled with natural gas storage
- Energy storage using flow batteries
- Fuel cells—Hydrogen energy storage
- Chemical storage
- Flywheel energy storage
- Superconducting magnetic energy storage
- Energy storage in super-capacitors.

Renewable technologies used in the residential sector can be incorporated in new buildings during construction and some of them can be installed externally. These technologies include:

- Passive solar heating and daylighting
- Biofuels
- Biomass energy heating
- Wind energy
- Geothermal heat pumps
- Photovoltaic (solar cell) systems
- Solar hot water systems
- Geothermal direct use

1.9. The scope of the thesis

In the thesis, the focus is on proposing an energy management system for the residential sector of smart grid. The variables which affect household energy consumption and demand response will be investigated. I intend to address the fundamentals of a knowledge-based system whereby householders are able to make decisions regarding efficient energy consumption using a variety of demand response programs. The focus will be on optimization and scheduling methods that take into account the users' life style, preferences and desired comfort level.

1.10. Research objectives

The main objectives of this thesis are to research the home energy management system characteristics and functionality that are generally incorporated in demand response programs of the smart grid, and to develop a set of advanced solutions to address the following issues:

1. The development of an intelligent decision support system to help users to manage their energy consumption according to their preferences and DR regulations.
2. The development of a home energy management system by proposing methodologies in which intelligence is added to this system.
3. The development of a mathematical optimization algorithm that takes into account users' preferences and comfort level, besides utilizing the maximum amount of distributed energy resources.
4. The development of scheduling methodologies to encourage users to shift their consumption from on-peak period to off peak periods in demand response programs.
5. The deployment of the decision making methodology to industrial sector of smart grid in order to assist the operation manager to decide whether to participate in DRP or use distributed energy resources.

1.11. Structure of the thesis

The thesis has six Chapters. In this section, a brief outline of each Chapter is presented.

Chapter 1 is an introduction to the subject of this thesis. In this Chapter, I explain the concept of smart grid, demand response programs, smart building management system and effective parameters. This introductory Chapter provides a necessary explanation of the main objectives of this dissertation.

Chapter 2 discusses the recent and the most significant related researches in the field of building energy management systems in the context of the smart grid. The research review leads us to the issues which this thesis will address.

Chapter 3 introduces the decision-making frameworks which can support the energy management strategies applied by energy managers or consumers. Here, various examples and scenarios are presented to illustrate the frameworks.

Chapter 4 of this thesis proposes the scheduling algorithm by which the users are able to save on their electricity costs when the price of electricity is dynamic. The proposed optimization is examined using different scenarios.

In Chapter 5, a decision-making framework is proposed that can be used in the industrial sector of the smart grid; this a combination of the methodologies proposed in Chapter 3 and a linear programming optimization technique. This Chapter proposes a methodology which supports the decision-making of industrial energy managers, whether they have to participate in a demand response program or use the distributed energy generation.

Chapter 6 concludes this thesis by recapitulating and explaining the potential future work raised by this doctoral dissertation. This Chapter also addresses the limitations of this research.

1.12. Conclusions

This research thesis focuses on the development of a novel and improved decision-making framework for a home energy management system that is compatible with the smart grid infrastructure. This research area and the general area of smart grid is in its infancy so a brief introduction to the concepts of smart grid, demand response, smart home and energy management systems was provided.

This introduction provided the necessary background to the research motivations, its significance, and the objectives of the improved energy management system which is proposed.

The following Chapter presents a literature review of research in the area of smart grid and evaluates existing building energy consumption control models and related technologies.

Chapter 2

Literature Review For BEMS

2.1. Introduction

In this Chapter, I provide an overview of the literature surveyed and an evaluation of the state-of-the-art elements of an energy management system in the micro grid of the smart grid. Substantial progress has been made in providing a practical basis for a number of problems that are associated with energy optimization and scheduling methodologies in residential sector.

A number of energy efficiency tools and techniques have been documented in the literature. In the following sections, I discuss the works that have been previously undertaken to resolve some of the issues outlined in Chapter 1.

The research literature pertaining to the smart grid could be reviewed from an interdisciplinary perspective because this is a complex domain that involves human, socioeconomic, hardware, and software factors. However, in this Chapter, the literature review is limited to the micro level of the smart grid since this is more relevant to the subject of this thesis. The research areas investigated by this dissertation can be classified into six categories:

1. Demand-side management and demand response programs
2. The role of smart meters in DR
3. Building an energy management system
    a. Energy consumption scheduling and optimization methods
    b. Prediction of building energy consumption
    c. Load demand identification
4. The effect of consumers' behaviour and their preferences on energy demand
    a. Energy consumption behaviour and activities related to energy demand
    b. The consumers' consumption behaviour effect in optimization models
5. Comfort management
    a. Comfort management: Thermal Comfort
    b. Comfort Management: Indoor Air Quality
    c. Comfort Management: Visual Comfort
        i. Visual comfort: Electric Lighting Control by Switching Method

ii. Visual Comfort: Electric Lighting Control by Dimming Method

6. Decision-making approaches in energy management and smart grid

2.2. Demand Side Management (DSM) and Demand Response Program

2.2.1. Demand Side Management (DSM)

Clark W. Gellings [70, 71] who originally coined the term "demand side management" in 1984 introduces DSM as a first marketing strategy that focus on technology, customers' and utility's needs. The author defined DSM as "DSM activities are those which involve actions on the demand (i.e. customer) side of the electric metre, either directly or indirectly stimulated by the utility. These activities include those commonly called load management, strategic conservation, electrification, strategic growth or deliberately increased market share"[72].

Demand-side management (DSM) includes those technologies, activities and strategies that will be employed by the utility provider in the *demand side of the energy network* in order to achieve the following goals:

- emission reduction,
- load management,
- improving energy efficiency and conservation,
- balancing supply and demand,
- increasing consumers participation in energy management and generation, and
- reduction in operational costs for the entire network.

The aim of DSM is to balance demand with available supply that it is in direct opposition to the traditional policy in which supply was matched with the existing demand [73].

In addition, researchers have studied DSM in terms of different categories. For example, [74] places DSM into the four categories mentioned below according to the timing and the effect of the applied measures on the customer process as demonstrated by Fig 2.1, where energy efficiency is defined as those actions which bring permanent energy savings for consumers, such as adding insulation to a building shell to save energy. Moreover, the authors indicate that an energy information system is a prerequisite for analysing and improving energy efficiency in order to discover any potential and hidden wastage.

a) Energy Efficiency (EE)

b) Time of Use (TOU)

c) Demand Reponses (DR)

d) Spinning Reserve (SR)

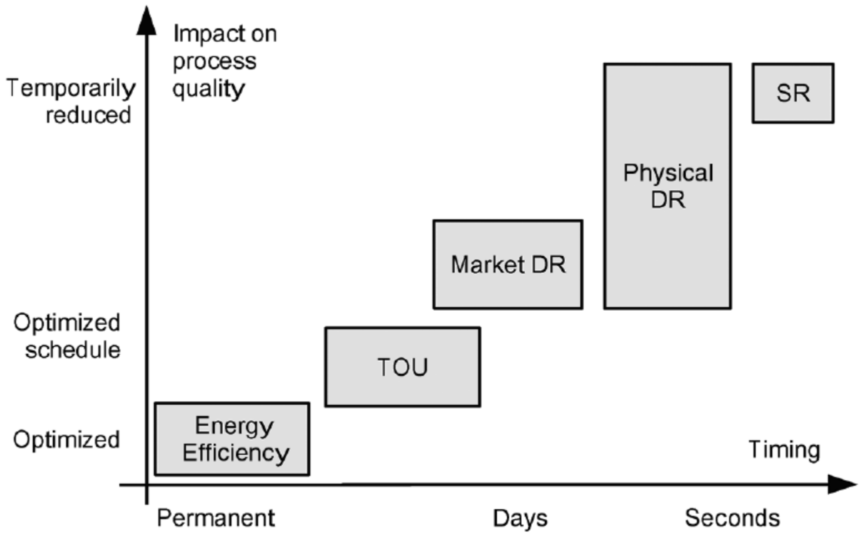


Figure 2.1. Demand-side Management Categories [74]

Moreover, the strategies, technologies and programs that are applied in order to achieve the aforementioned targets vary from country to country as demonstrated in [3-7].

The author of [73] conducted a thorough literature survey on DSM policy, analysed UK DSM policy, and examined the influence of EU directives on UK DSM policy. The author investigated DSM in three broad sections comprising DSM categories, policies, and implementers as shown in Figure 2.2. In the proposed definition, the DSM policy objectives include:

a) Carbon emissions reduction,

b) Energy security,

c) Demand response programs,

d) Energy efficiency, and

e) Energy storage.

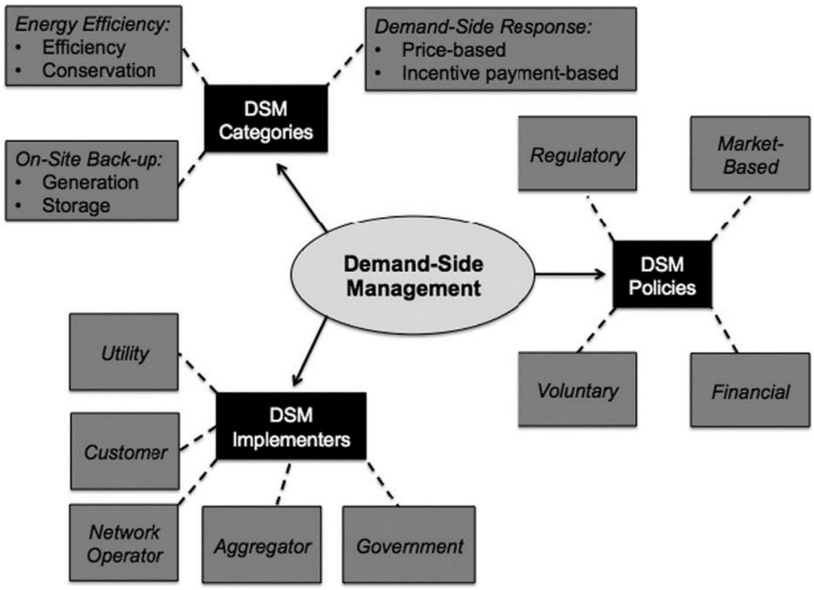


Figure 2.2. Demand-side Management Elements [73]

In addition, the major benefits and challenges of electricity demand-side management (DSM) in the context of the UK electricity system are discussed by Strbac [75]. The author identified a number of reasons for the difficulties and delays encountered in the UK during the implementation of DSM. These reasons are as follows:

- lack of ICT infrastructure;
- lack of understanding of the benefits of DSM solutions;
- DSM-based solutions are often not competitive when compared with traditional approaches;
- DSM-based solutions tend to increase the complexity of the system operation when compared with traditional solutions; and
- inappropriate market structure and lack of incentives.

In the following section, I review surveys conducted on demand response programs and their evolution in the context of the smart grid.

2.2.2. Demand Response (DR) Programs

As was discussed in the previous section, demand response is one of the DSM programs that will be described in detail in this section. However, before going into the DRP survey, I would like to present some preliminary information about DRPs.

Demand response is one of the electricity market mechanisms by which the aggregators or utilities are able to manage power consumption. So demand response is a response to a demand made by utilities. Therefore, responsive demand is ascribed to the changes in a consumer's expected load pattern for improving efficiency in electricity demand and supply by receiving notifications provided by the consumer [76].

The Federal Energy Regulatory Commission, FERC, defines DR as “changes in electric use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized” [16].

It is widely agreed that the cost of energy is the most powerful incentive to encourage consumers to curtail their consumption. So in demand response programs, the aggregators or service providers use this policy to achieve their aims in regard to load management. The most important objective of these programs is to make the demand curve flat by offering a high-priced energy unit during peak periods and lower prices during off-peak periods in order to stabilize the volatile energy demand so as to make it more predictable and controllable.

Many definitions of DR are presented in the literature. DR can be defined as actions voluntarily taken by a consumer to adjust the amount or timing of his/her energy consumption [21]. Demand response is a reduction in demand designed to reduce peak demand or avoid system emergencies. Hence, demand response can be a more cost-effective alternative than adding generation capabilities to meet the peak and or occasional demand spikes[77].

In Chapter 1, Figure 1.5, I discussed Albadi and El-Saadany [17]’s two classifications of DR programs: incentive-based and price-based.
Price-based programs are based on a dynamic or variable pricing scheme in which electricity tariffs are not flat; the rates depend to the real-time price of the electricity market and it fluctuates accordingly. These rates take into account the Time of Use (TOU), Critical Peak Pricing (CPP), and Real Time Pricing (RTP).

TOU is a simple type of DR which rates electricity price per unit of energy (kWh), and is substantially different during some periods. The rate in peak periods fundamentally is higher than the rate during off-peak periods. For example, the Ausgrid Company, the power provider for 1.6 million users in Sydney, has three different tariffs for three time periods as Peak from 2:00p.m to 8:00 p.m., Shoulder as 7:00 a.m. to 2:00 p.m. and 8:00 p.m. to 10:00 p.m. and off-Peak period that is from 10:00 p.m. to 7:00 a.m. Consumers pay different amounts for electricity in each tariff. The company advises its users to save money by shifting their usage from peak periods to off-peak and shoulder periods when energy consumption is less expensive.

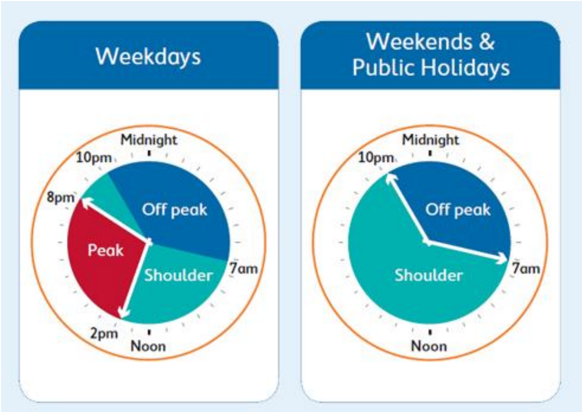


Figure 2.3. Ausgrid TOU Time Periods [4]

Pipattanasomporn et al. [78] categorize DR programs according to two groups: incentive based and time-based programs. They present fourteen DR classifications eight of which are incentive-based and comprise 1- direct load control, 2- interruptible load, 3- load as capacity resource, 4- spinning reserve, 5- non-spinning reserve, 6- emergency demand response, 7 - regulation service, and 8- demand bidding and buy back.

Incentive-based means reduction in demand by receiving load control signals that come from an incentive-based payments system or within a contractual agreement. Time-based DR programs are those that reduce demand by means of different types of time varying price signals. These types are classified as 1- critical peak pricing with direct load control, 2- time-of-use pricing, 3- critical peak pricing, 4- real-time pricing, 5- peak-time rebate and 6- system peak response transmission tariff.

FERC's DRP survey in 2012 categorised time-based and incentive-based programs as listed in Table 2.1[16] :

Table 2.1. Demand Response Programs

Incentive-Based Programs	Time-Based Programs
1- Demand Bidding and Buyback 2- Direct Load Control 3- Emergency Demand Response 4- Interruptible Load 5- Load as Capacity Resource 6- Non-Spinning Reserves 7- Regulation Service 8- Spinning Reserves	1- Critical Peak Pricing with Control 2- Critical Peak Pricing 3- Peak Time Rebate 4- Real-Time Pricing 5- Time-of-Use Pricing 6- System Peak Response Transmission Tariff

DRPs have been defined by FERC, North American Electric Reliability Corporation (NERC) and The U.S Green Building Council (USGBC) as follows:

- *Direct Load Control (DLC):* This program is essentially proposed for the low consumers such as residential and small commercial users. In this program, the service provider has the authority to shut down remotely several appliances such as the air-conditioner, pool pump, and water heater at short notice.
- *Interruptible Load:* This program is a contract between aggregator and consumers that has an established special tariff as a rate discount if consumers reduce and regulate load when the utility is facing a system contingency situation. When a system operator makes this demand, it is called *"remote tripping".*
- *Critical Peak Pricing:* This program is a kind of price structured tariff. During certain hours of the day, the energy unit price rate is high according to the energy wholesale market, or the aggregator foresees the system's critical contingencies and accordingly during those times, the electricity rate would be encouraging strong encouragement for consumers to reduce their consumption.
- *Critical Peak Pricing (CPP) with Direct Load Control:* As its name suggests, this program is a combination of CPP and DLC. If a pre-specified high electricity rate during critical peak period does not lead to load curtailment, then the aggregator will switch the equipment off remotely.
- *Load as a Capacity Resource*: This demand response is a kind of demand-side resource and it is a pre-determined load reduction on the demand-side when the system encounters contingencies.
- *Spinning Reserves:* This is a synchronized demand side resource prepared to balance a demand and supply quickly when system encounters with contingency situation.
- *Non-Spinning Reserves:* This has been considered as an ancillary service [76]. It is a demand-side resource that will not immediately fulfil the demand; but it may supply energy at ten-minute intervals for balancing.
- *Emergency Demand Response:* This is a DRP whereby the aggregator will offer incentive payments to end-users to curtail the load when an emergency event demands response.
- *Regulation Service (up-regulation and down-regulation):* This program was previously considered as an ancillary service. It is a type of Demand Response service whereby, in response to a real-time signal, an Automatic Generation Control (AGC) provider will continuously increase or decrease end-users' load during a commitment period.

- *Demand Bidding and Buy Back:* In both the retail and wholesale markets, this DRP will offer a price for a specific amount of load reduction.
- *Peak Time Rebate:* In a calendar year, there are some days and hours when customers can earn a rebate by consuming less energy than a baseline because of system reliability concerns or high supply prices.
- *System Peak Response Transmission Tariff:* This program is a means of reducing transmission charges and it includes all terms, conditions, and rates and/or prices for customers with interval meters who decrease load during peaks periods[16].
- *Real-Time Pricing (RTP):* In this DRP, changes in the wholesale energy market will be reflected and the energy unit price fluctuates hourly or a day ahead. RTP is one of the most efficient DRPs [76].
- *Time-of-Use Pricing:* This means that there are different electricity prices for different periods of time. This DRP reflects the average cost of power generation and delivery for each time interval.

According to the NIST report [7], one of the eight priority areas whose functionality is critical to deployments of SG technologies and services is “Demand response and consumer energy efficiency”. In this regard, this report states that “Mechanisms and incentives for utilities, business, industrial, and residential customers to cut energy use during times of peak demand or when power reliability is at risk. Demand response is necessary for optimizing the balance of power supply and demand. With increased access to detailed energy consumption information, consumers can also save energy with efficiency behaviour and investments that achieve measurable results. In addition, they can learn where they may benefit with additional energy efficiency investments.”

According to the authors of [38], there are technologies to further advance demand response. These technologies include:

- Interval meters with mutual communications capability which allow customer utility bills to reflect their actual usage pattern and provide consumers with continuous access to their energy consumption data.
- Multiple, user-friendly, communication networks to make consumers aware of real-time pricing conditions, potential power shortages, as well as emergency load curtailment circumstances.
- An energy information mechanism that enables real- or semi-real-time access to interval load data, analyses load curtailment performance relative to baseline usage, and provides diagnostics to facility operators of potential loads to target for curtailment.

- Demand reduction strategies that are optimized to meet differing high price or electric system emergency scenarios.
- Load control automation and building of energy management systems in order to optimize demand response at the end-use level.
- On-site generation equipment used either for emergency backup or to meet the primary power needs of a facility.

The benefit and cost of DRP have been investigated by [17, 76]. Aghaei and Alizadeh [76] assessed the DR advantages according to seven categories: economic benefits, pricing, risk management and reliability, market efficiency impacts, lower cost electric system and service, customer services, and environmental. The authors state that economic benefits are one of the most important benefits of DR. Customers can receive a rebate on their electricity bill if they reduce the consumption rate or shift their demand from peak to off-peak periods.

Similarly, Albadi and El-Saadany [17] identified the same demand response benefits for participants. However, the authors believe that the DRP produces benefits for five categories of participants, market-wide, reliability and market performance. In both researches conducted by [7, 11], the exponential effect of demand reduction on energy generation cost and the market has been highlighted. This phenomenon leads to a reduction in energy price volatility.

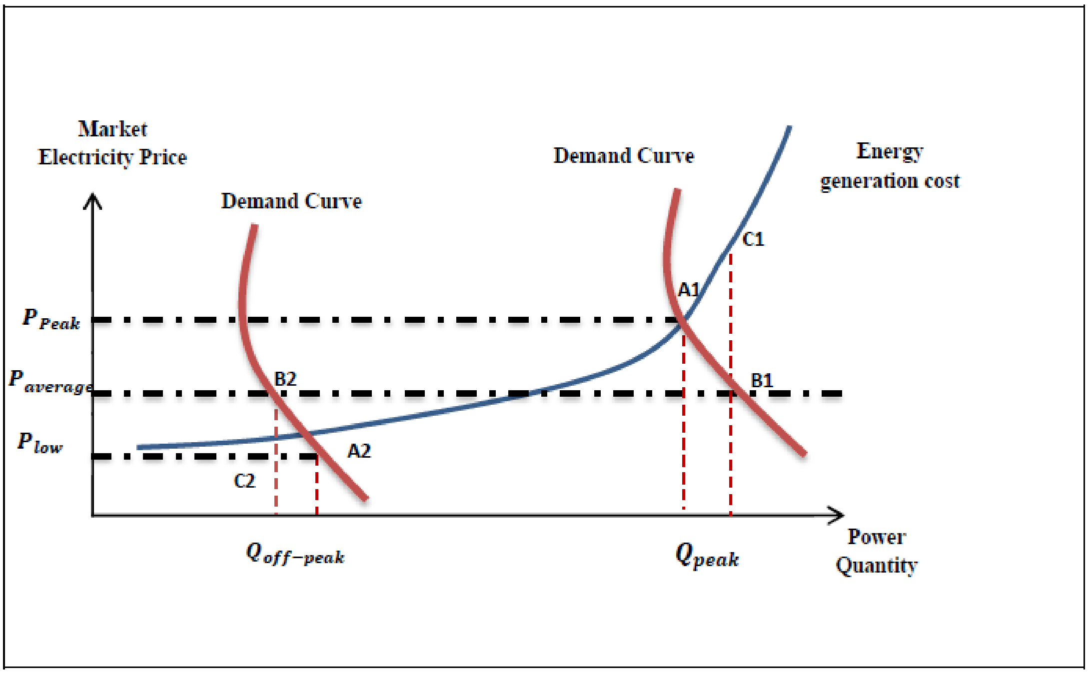


Figure 2.4. Price Volatility Reduction by DRPs [76]

Figure 2.4 shows that when the demand during the peak period from A1 to B1 shifts to the off-peak period from A2 to B2, then the energy generation cost during peak period A1 to C1 decreases to A2 to C2. This phenomenon has been reported during the California Power energy supply crisis during 2000-2001 [79] when five percent demand reduction led to a fifty percent reduction in the cost of electricity energy generation. Hence, the price volatility reduction of demand response demonstrates the significance of the role of participants and their demands in the electricity energy market.

2.3. The Role of Smart Meters in DR

At the micro level of the smart grid, in terms of a smart home, there are various sophisticated and ubiquitous electronic devices with the ability to communicate with each other and with a smart meter.

Smart meters are microprocessor-based devices providing two-way communication capability, and will help home owners to manage their electricity usage. Through a website, for example, or a customer portal, parameters could be set that control when loads in the home turn on and off, based on the price of electricity. The dishwasher, for instance, could be loaded and set to stand-by until the price of energy is below a certain level – typically off peak – when it would start automatically. The aim of a smart meter is to act as a central point connecting all such internal devices with the outside world. The smart meters integrate data collected from the meters into billing, customer service, field services and energy-demand management. This gives a real-time view of a greater volume of data at a more granular level, leading to faster analysis and better decision-making regarding capacity demand, and the carrying out of other business processes.

The recent researches on smart meters can be classified according to the three groups below:

1. Smart meter, communication network and security [80-83]
2. Smart meter and privacy [84-89]
3. Smart meter and Load scheduling and control [62, 83, 90-102]

According to [103], there are technologies to further advance demand response. These technologies include:

- Interval meters with mutual communications capability which makes it possible for customer utility bills to reflect their actual usage pattern and provide consumers with continuous access to their energy consumption data.

- Multiple, user-friendly, communication networks to make consumers aware of real-time pricing conditions, potential power shortages, as well as emergency load curtailment circumstances.
- Energy information mechanism that enables real or semi-real time access to interval load data, analyse load curtailment performance relative to baseline usage, and provide diagnostics to facility operators on potential loads to target for curtailment.
- Demand reduction strategies that are optimized to meet differing high price or electric system emergency scenarios.
- Load control automation and building energy management systems in order to demand response optimization and at the end-use level.
- On-site generation equipment used either for emergency backup or to meet primary power needs of a facility.

2.4. Building Energy Management System

2.4.1. Energy Consumption Scheduling and Optimization Methods

In the existing literature, energy optimization and load scheduling for consumers in demand-side management can be classified as: first, those researches which focus on the end-user sector and aim to optimize energy consumption for a single house or building; and second, those researches which are concerned with demand response and concentrate on the micro grid where a trade-off occurs between the utility provider (independent service provider) and a group of users.

Smart grid has many characteristics that have been comprehensively discussed in the introductory Chapter. However, there are three particular and unique specifications in this computerized grid which require complex algorithms and robust techniques in order to optimize energy consumption efficiently. These specifications are discussed in the following:

1. Demand response programs which are more dependent on the decision-making of the householder make the consumption behaviour factors more significant in optimization constraints and functions. These optimization and scheduling approaches include variables which are mainly about end-users' preferences for operating the electrical devices and comfort terms for the householder's activities and lifestyle. The researches that can be considered in this category are [20, 22, 27, 35, 50, 104-121].

2. As mentioned in the introduction and the previous section, modern ICTs have made the electrical grid more flexible, responsive, smart and intelligent. On the other hand, the development in "internet of things" and ubiquitous smart devices such as the mobile handset has facilitated the flow of information in communication systems with end-users. As a result, the real-time measuring, monitoring, and computing of the effective parameters on energy consumption required new robust techniques and algorithms which are respectively online and stochastic. Some of these approaches can be pointed as [49, 50, 122-130].

3. Changing the end-users' role in the electrical grid from consumer to prosumer and developing the distributed energy generation have caused more parameters to be added to the optimization models where the end-users are able to trade off with the utility provider in energy market. So, optimization techniques are required in order to take into account the parameters such as game theory that affect a group of consumers. The researches in this category include [51, 85, 131-142].

In my literature survey, the technical papers are concerned with the issues and problems which have emerged as a result of the aforementioned characteristics being added to the grid. Some of these issues related to the building energy management systems before the invention of the smart grid. For example, the householder's activities have a direct effect on energy demand (without considering the demand response context) and therefore, many researchers have focused on this means of predicting the building energy demand, recognising that by imposing the demand response programs, these activities will be compromised. Hence, the researchers are examining the ways in which DRP affects users' activities, energy demand and the balancing of demand and supply [38]. As a result, the variety of optimization problems for smart homes and demand response in the context of energy management can be classified under four main categories with total twelve subcategories as follows.

A. Problems on the householders' side:
    1. Compromising the comfort [27, 120]
    2. Consumers' consumption behaviour, activity recognition, occupancy, and users' preferences [38, 121, 143]
B. Problems in scheduling:
    3. Establishing energy demand prediction [14, 144-146]
    4. Shifting load from on-peak to off-peak periods
    5. Load identification and prediction [57, 62, 91, 95, 99, 147-149]

6. Diversity of electrical devices employed by users for different purposes with different functions. Each research has focused on a specific domain of appliances.

C. Problems of distributed energy generation:

7. Availability of renewable energy sources (wind and solar) [137, 150]
8. Deregulated energy market (trade-off with ISP) [151]
9. Distribution network congestion during peak hours by energy storage systems (e.g. vehicles to the grid) [104, 137, 152]

D. Problems in DRP:

10. Predicting energy price in a dynamic pricing scheme [153]
11. Autonomous DRP and customers' participation [85, 142]
12. The variety of DRPs: the proposed solutions cannot provide a universal remedy and be applicable to all DRPs.

In the literature, because it is not feasible to conduct a study that addresses all of the aforementioned issues, scholars have generally attempted to address one or a combination of some of the above problems. However, it is inevitable to assume that the data from the other domain is available. For instance, in a research conducted by [125], a multi-stage stochastic optimization is employed for considering the power procurement by a HEM in a community of users for a dynamic pricing demand response program. The optimization objective of this paper is to minimize the electricity cost based on operator expectation and the customer's degree of comfort which determines a maximum delay for each appliance in different states of a stochastic model. The purpose of the research is to coordinate HEM units in order to balance the demand and supply. The appliances include washing machine, dishwasher, tumble dryer and PHEV, all assumed to have a single operation mode and a single power profile.

Because of the diversity of optimization approaches, in this section I focus on optimization and scheduling approaches for building energy management and demand response programs. In the following, I explore in detail the most significant and related approaches and explain the problem definitions, objective functions, constraints and the optimization methods of this group of researches. I present our literature survey on load identification and prediction in subsequent sections. A summary of my survey on optimization approaches is presented in Table 2.2.

In the literature, several papers focus on the scheduling of appliances and devices such as HVAC and PHEV while taking into consideration the service constraints. This kind of research, such as [130, 137, 153-157], generally focuses on load management. There are many and various parameter-related appliance operation conditions which have been considered in scheduling approaches. The time horizon planning approach is mainly discrete and divided into a specific number of timeslots. The optimization techniques allocate the number of timeslots to the operations and specify in which one of these timeslots an operation shall start and finish. For some appliances, such as a washing machine, different tasks must be undertaken in order to complete a job. So the other parameters are the number of shiftable timeslots or the sequential order of these tasks. For this reason, load commitment which is the operating status of the appliances in an allocated timeslot, has been considered as a significant parameter in scheduling approaches such as those of [50, 156, 157].

[158] is an extended research of [157] where a home outage (home load interruption) has occurred in TOU DRP and the payment and interruption costs must be minimized. The value of lost energy (load) for each appliance is an index for measuring the cost of interruption and the authors claim that in order to maximize customer comfort, these costs must be minimized.

The authors in [130] employed Earliest Deadline First, a real-time scheduling algorithm from the computer science domain, uniprocessors, to propose a method to coordinate the activation/deactivation of the load set to control the peak load of power usage. The proposed model is as follows:

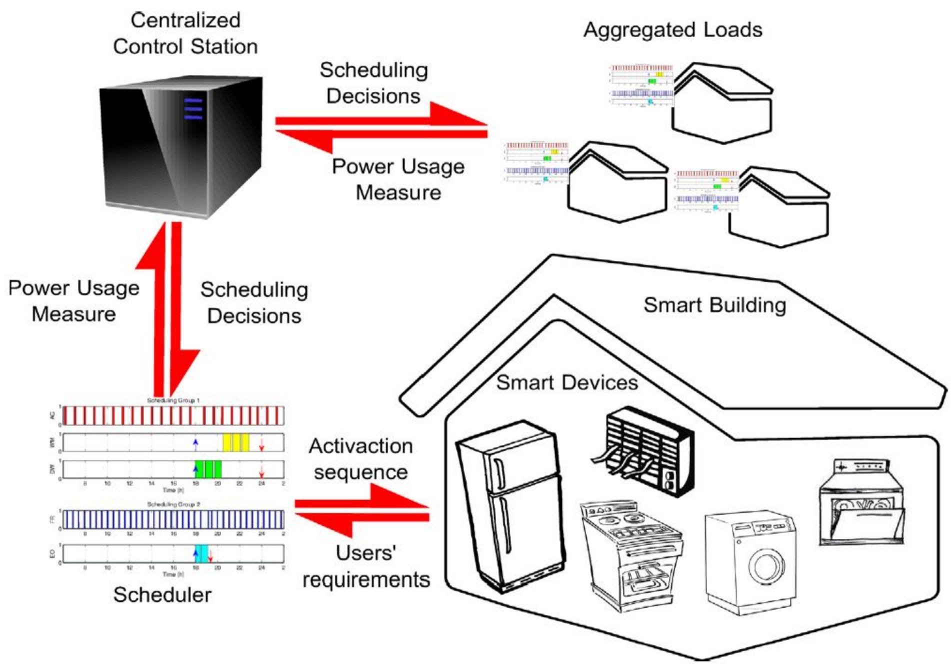


Figure 2.5. HEM based on real-time control techniques [130]

Loads in [130] are divided into two groups: time-triggered and event-triggered. The appliances in time-triggered loads are classified as either cooling or heating appliances. The authors defined the state variables for modelling the power profile of such appliances. For example, temperature is the state variable of a refrigerator and HVAC. They modelled the convection heat transfer of refrigerator and HVAC units according to thermodynamics laws for achieving the temperature and power profile. They used the same techniques for a dishwasher and washing machine. The user characterization in this research is demonstrated by designing a table with the value of usage probability of an event-triggered load in timeslots equal to two hours on the time planning horizon. This paper has not considered the impact of load and associated energy cost in the scheduling or presenting a method to calculate the usage probability. The management of energy in smart homes according to energy prices is a research conducted by [120]. This research analysed a BEMS in the context of a dynamic pricing demand response program. For this purpose, a reference virtual dwelling model was developed in the Matlab Simulink, “SIMulator for building and devices” (SIMBAD) for modelling local control system. The Global Model Based Anticipative Building Energy Management System (GMBA-BEMS) has been analysed for configuration of thermal comfort and cost criteria by comparing four different models. The paper presents a case study and its objective is to analyse the strategy of the BEMS and compare it with the choice of the occupant and examine whether they benefit from dynamic pricing DRP. The paper studied two cases. The first is when consumers accept a decrease in their comfort level in order to decrease the energy cost and energy cost is as an optimization constraint. In the second case, only the comfort criterion is considered as a constraint. The best solutions based on the consumer preferences should be selected by BEMS. This research does not present mathematically an optimization algorithm or new approach; it only analyses an existing BEMS in a DRP.

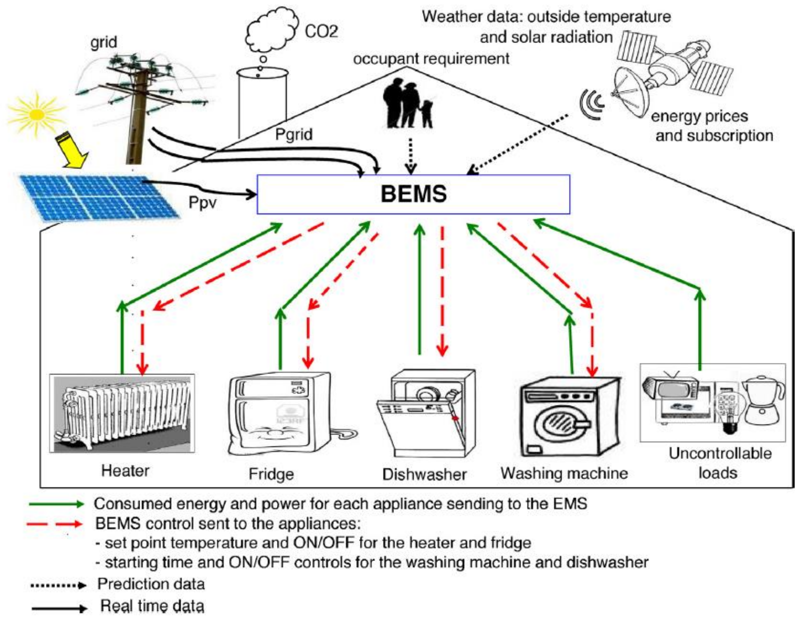


Figure 2.6. BEMS Information System Model Presented by [120]

Similarly, a strategy-based approach for managing the flow of energy by a BEMS in a day-ahead DRP is proposed by [159]. The paper proposed the BEMS framework shown below, and built a photovoltaic and wind prediction with a load and price-forecasting mechanism.

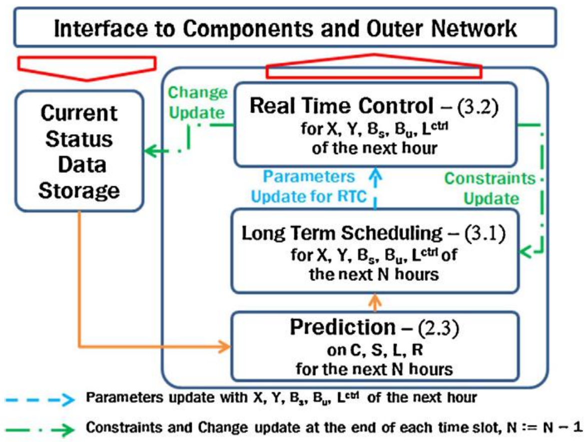


Figure 2.7. The Proposed Framework of BEMS by [159]

In the above model, X and Y are the amount of energy from and to the grid. C, S, L and R are grid energy pricing, sales pricing to the grid, total load, and the amount of energy from renewables. B_s and B_u are the amount of energy to and from energy storage system and L^{ctrl} is controllable load. This paper does not present a scheduling method for appliances, but focused mainly on energy flow control.

Similarly, in [107] it is focused on developing a control strategy in RTP DRP for the HVACs in order to achieve peak load reduction. A proposed dynamic demand response controller (DDRC) changes the consumer-adjusted set-point temperature according to the electricity retail price at 15-minute time intervals in order to control the HVAC loads and shift the loads from on to off peaks.

HVAC controller calculates the associated energy consumption for adjusting the set-point indoor temperature. For this, outdoor temperature, ground temperature, indoor activities, internal load (number of occupants, lighting and electrical equipment energy), and building size are considered in EnergyPlus and OpenStudio tools simulation. Figure 2.8 shows a dynamic demand response controller implemented in MATLAB/ SIMULINK and connected to EnergyPlus by a building controls virtual test bed (BCVTB).

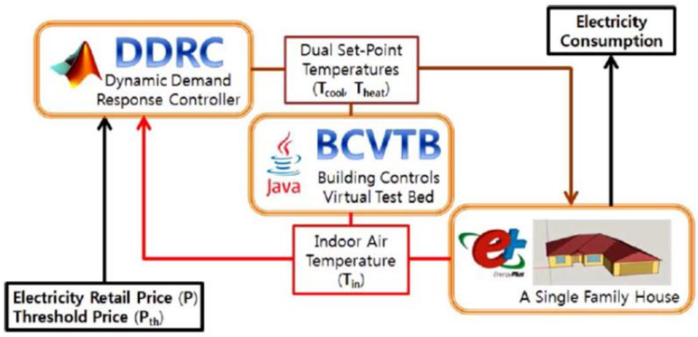


Figure 2.8. Framework of Dynamic Demand Response Controller [107]

Energy box (eBox) is a scheduler device proposed by [55] and its architecture is shown in the figure below. The paper used a novel decision model based on Mixed Integer Linear Programming and a heuristic allocation algorithm for energy household management in terms of cost, minimization, maximization of scheduling preferences and maximization of climatic comfort. The research divided loads into two groups of manageable and non-manageable loads, the former being divided into shiftable, interruptible and thermal loads.

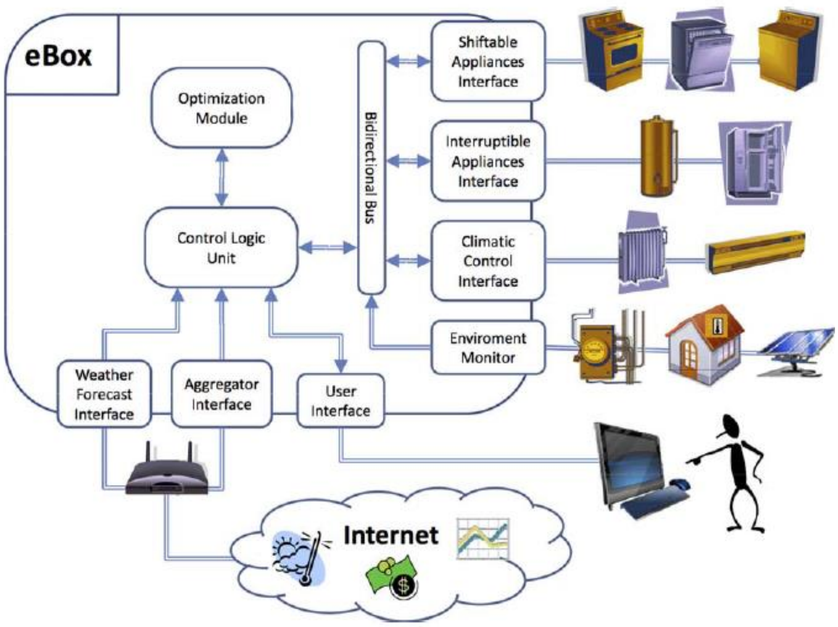


Figure 2.9. eBox Architecture Proposed by [55]

One of the uncertainties in demand-side management is the unavailability of householders or their lack of knowledge to appropriately respond to grid signals. Autonomous appliance scheduling by a smart scheduler for a prosumer is a solution addressed by [160] for this issue.

The smart scheduler is an intelligent monitoring device for aggregating demand with a pre-defined limit of the household's energy consumption. In DRP, the scheduler is able to predict appliances' corresponding probability for each hour based on calculating and monitoring the information such as the day of the week, weather conditions, degree of penetration of the appliances and the level of occupancy of the house. The probability of time of use of each appliance in each time cluster is calculated and scheduling is based on clusters where this value is high. The optimization function minimizes the energy cost and maximizes the energy exchange between user and grid under feed in a tariff plan. So, appliances are grouped based on their preferred time of use and ranked in that cluster.

In comparison, the uncertainty in scheduling has been considered in a research conducted by [49]. The paper assumes a consumer with a solar panel and battery storage system and aims to minimize the costs incurred by the customer by optimally scheduling the operation and energy consumption of each appliance while taking into consideration the uncertainties related to real-time pricing DRP. In this paper, distributed renewable generations, energy storage, and the customer-defined target trip rate are considered. A stochastic scheduling algorithm has incorporated an energy adaptation variable in order to handle uncertainty. The paper compares the result of scheduling in two modes: offline and online. Firstly, linear programming is used to minimize the costs of grid electricity, solar operation and maintenance, the battery, and the one-time installation of the solar panel. Secondly, an offline stochastic methodology recalled from [161] is used for measuring the desired adaption variable for the trip rate. By trip rate, the author aimed to control customer comfort when the home power network trips out by exceeding the given load limit of the household. Finally, the optimality in offline scheduling is tackled by considering the uncertainty of the energy consumed by the appliances and the energy generated by solar panels. This has been done by adding an offset to the variation of these two parameters in the model. To simulate this uncertainty, the Monte Carlo technique is used to generate the appliance operation samples and evaluate the trip rate of samples by Latin hypercube sampling (LHS) [162] , a developed Monte Carlo method. The energy consumption scheduling algorithm in [49] is depicted in Figure2.10.

Our survey of the literature pertaining to energy consumption optimization and appliances scheduling in the residential sector of the smart grid indicates that the goal of these researches is mainly to minimize the energy cost incurred by residents in order to balance the demand with supply based on available resources. However, several researches such as [114, 118, 137, 163] focus on the users’ comfort, preference, satisfaction, and convenience by employing the *utility function* in optimization modelling.

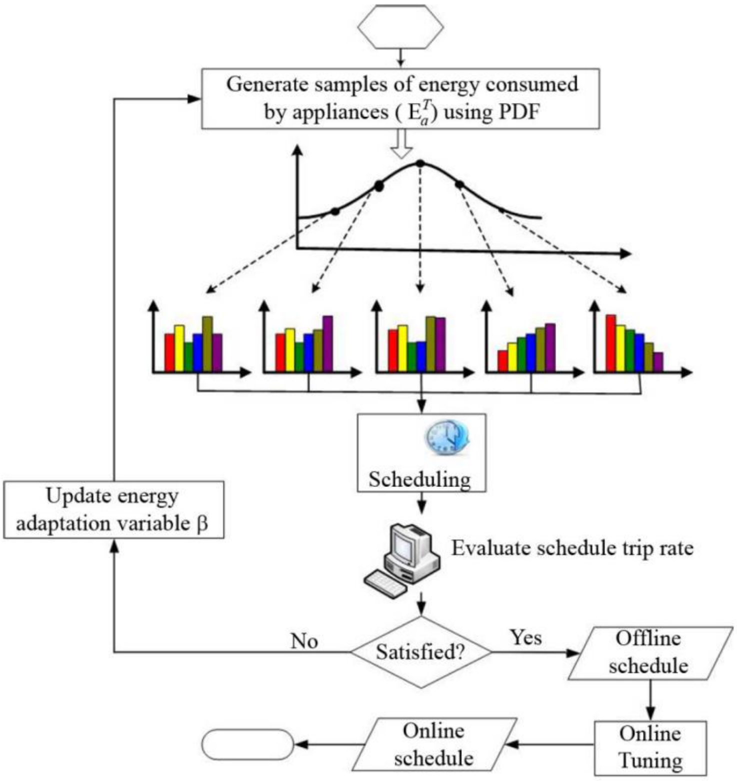


Figure 2.10. Energy Consumption Scheduling Algorithm in [49]

In particular, [164] is a research in which the users' preferences have been modelled in an optimization function in a smart home. The paper proposes a convex programming optimization framework for the automatic load management in demand response. The objective function is intended to minimize the total cost of energy consumed by appliances, and the users' dissatisfaction. The appliances have been categorized as schedulable and interruptible, schedulable and uninterruptible, battery-assisted, and model-based appliances. The latest ones are those appliances which have direct load control. Each class of appliances, particularly in terms of battery storage, renewable (solar, wind) resources, and air-conditioner has been mathematically modelled by using the auxiliary binary decision variables. In order to avoid the computational complexity and difficulty of the N-P problem in mixed integer nonlinear programming, the paper used the L_1 regularization technique. By means of this method, the convexity of the optimization function has been maintained. In this paper, the authors do not present a method whereby users' preferences are taken into account regarding the operation of appliances and the preferred time of operation. For example, for scheduling the appliances with schedulable and uninterruptible load, the preferred time period is indicated by a binary decision variable by which if the value is equal to 1 then the schedule is selected; otherwise, the appliance is off. The DRP optimization model in a smart home proposed by [164] has been shown in Figure2.1.

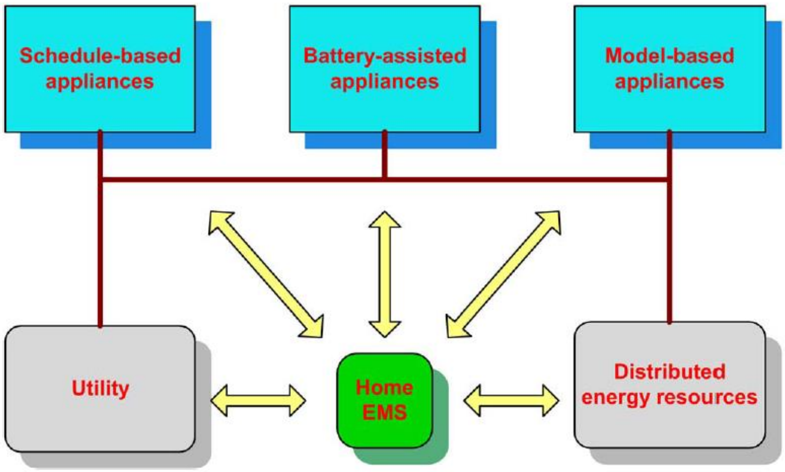


Figure 2.11. DRP Optimization Model in a Smart Home [164]

As mentioned previously, several researches such as [114, 118, 163] [114], have considered the effect of users' preferences as a utility function in their optimization models and have formulated the optimization models based on minimum energy which is provided in response to a demand by an energy provider in a power system. Afterwards, each resident is considered as a subscriber which can behave independently based on energy price, climate change and time horizon. So, the different responses by different subscribers are considered as their utility function. Hence, the authors aim to maximize the utility function and minimize the quadratic cost functions in their proposed optimization models. However, that paper does not focus on scheduling of a single home in smart grid and it focuses mainly on utility provider. Similarly, [163] is a research which focuses on utility maximization by means of a storage system and have PHEV. The objective function in this model is utility maximization (or social well-being maximization) and cost minimization. The paper considered appliances under four types, each of which has a specific utility function:

1) Appliances such as air conditioners and refrigerators which control the temperature of a customer's environment.

2) Deadline-based appliances such as PHEV, dishwasher, washing machine that require scheduling a task so that it is done before a certain time.

3) Appliances such as lighting that must be on for a specific period of time.

4) Entertainment appliances such as TVs and computers.

Despite researches [163] and [114] which have focused on the utility function of a group of customers, the research in [118] focused on consumers in terms of an hourly electricity price of DRP. In this paper, the energy supplier provides the energy according to an RTP scheme and the consumer provides his/her demand one hour in advance. This can occur via a mutual communication system between them. The objective function is to minimize the energy cost and maximize the consumer's utility. The utility of customers has been defined in terms of the minimum level of energy required at certain times each day. The authors used a robust optimization for improving the price uncertainty in RTP.

Distributed energy generation and the effect of the end-users' decision in an energy management system is investigated by [137]. A decision support tool has been proposed in order to maximize the net benefits to consumers. The net benefit refers to the benefit derived from the total energy services minus the cost of energy consumption. An optimization problem is modelled for finding the DER operation schedules by employing canonical particle swarm optimization (divide-and-conquer approach) to determine the value added to the consumer's net benefit by the coordination among the DER . This has enabled consumers to identify two types of scenarios in which DER should work together or can be independently scheduled. The paper determined the value of coordination in terms of the tariffs such as a combination of TOU and CPP and 16 scenarios. The proposed approach is a heuristic approach that provides a near-optimal solution.

As discussed, the distributed renewable resources are a significant contribution to smart grid energy management. Research such as that of [59] and [165] proposes that appliance priority scheduling be based on the prediction of these resources. [165] proposes the intelligent cloud home energy management system comprised of an intelligent cloud management server, intelligent power monitoring device (iPMD) and intelligent environmental device. The paper classified the appliances and prioritized them according to their classifications. The first category of appliances is closely related to the resident's behaviour. Hence, by predicting the behaviour, it is expected that the related appliances can be predicted. The second type of appliances, such as cooling systems, is related to the environmental factor; the third type is the appliances whose operation depends on the state of the embedded battery; for example, a laptop belongs to this category. Afterwards by prioritizing this classification, the appliances can be scheduled under the two categories of stand-alone and server-based architectures. The latest group algorithm is shown in Figure2.12.

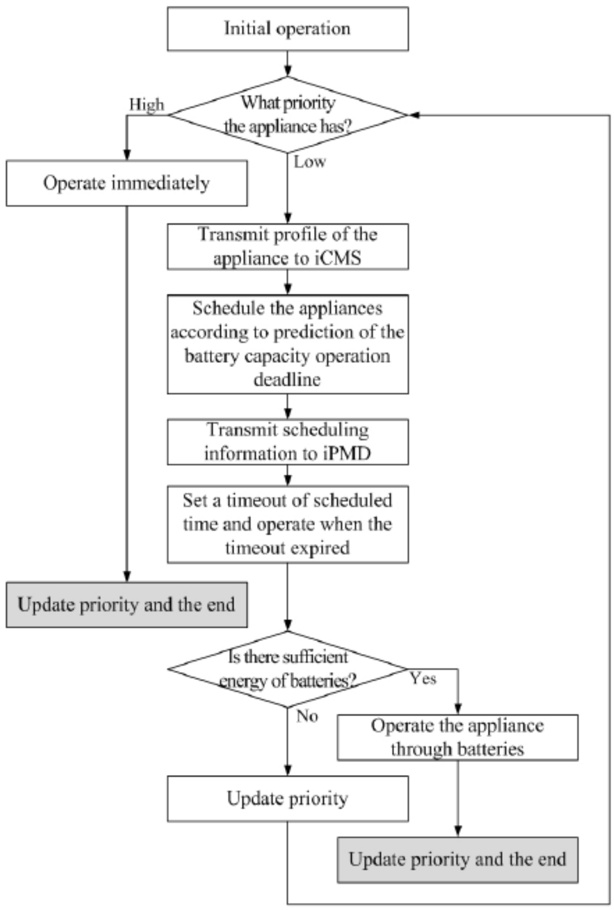


Figure 2.12. Server Based Type of Priority-based Scheduling Algorithm [165]

The optimization method for a building energy management controller based on “model predictive control” is that proposed by [42]. In this paper, the customers’ thermal comfort and building thermodynamics model are integrated into the optimization model. For modelling the thermal flexibility of the customer, the authors employed the predictive mean vote index (PMV) which can be calculated using [39]’s approach. This factor is explained in more detail in Chapter 3. [42] categorized appliances according to three groups as shown in Figure2.14 and the objective function is formulated for each type individually. The first group includes “delay flexible appliances” such as washing machines; the second group is “delay and power consumption flexible appliances” such as a PHEV battery and the third group are “thermostatically controlled appliances” such as air conditioners. [42] categorized appliances according to three groups as shown in Figure2.14 and the objective function is formulated for each type individually. The first group includes “delay flexible appliances” such as washing machines; the second group is “delay and power consumption flexible appliances” such as a PHEV battery and the third group are “thermostatically controlled appliances” such as air conditioners.

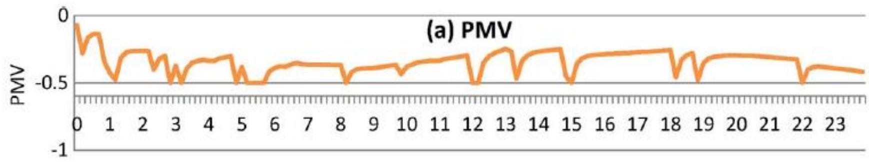


Figure 2.13. PMV Index During Time Planning Horizon Proposed by [39]

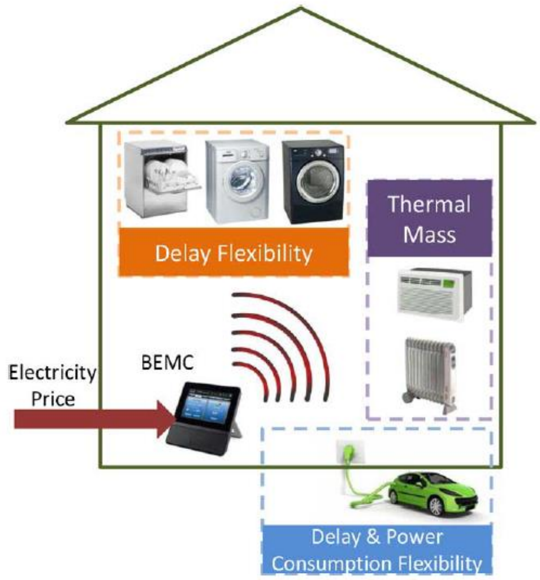


Figure 2.14. Residential Building Energy Management System [42]

2.4.2. Load classification in Scheduling and Optimization

In scheduling, each research has its own load classification but generally they have been categorised as schedulable or non-schedulable. For example, [160] divide loads into two groups of "preemptive and non-preemptive" or [157] called the groups "responsive or non-responsive" or [50, 55, 164] divide loads into "interruptible and non-interruptible". The purpose of this classification is to distinguish loads which are schedulable with non-schedulable ones. Therefore, they classified the appliances according to this classification. However, in some researches such as [164] and [163], the appliance classification is not merely based on load but goes beyond load classification in the scheduling model.

Table 2.2. A Summary of Optimization and Scheduling Approaches in Residential Customers

Ref.	Optimization Objective	Optimization Method	Appliances	DRP
[55]	- Cost minimization - Maximization of scheduling preferences - Maximization of climatic comfort	- Mixed Integer Linear Programming - heuristic allocation algorithm	Randomly-generated loads	TOU
[39]	Energy cost minimization	Linear Programming	PHEV, consumer thermal comfort, thermal dynamics of building room, dish washer, cloth dryer and washing machine	Real-time pricing
[49]	- minimize the monetary expense of the customer	- Linear Programming - Offline and Online stochastic scheduling	Solar rooftop, battery storage system	day-ahead pricing
[50]	Minimizing the electricity bill in different time slots.	- Scenario-based Stochastic optimization - Mixed integer linear programming	PHEV, water heater, air conditioner, dishwasher, oven , cloth dryer	real-time pricing
[114]	Utility maximization and cost minimization	Linear programming	N/A	Real-time pricing
[118]	Minimizing energy cost and maximizing the consumer utility	Linear Programming	N/A	Real-time pricing
[120]	N/A	N/A	washing machine, dishwasher, heater	time varying price
[130]	Peak load shaving	- Combinatorial Optimization (First fit decreasing height) - Earliest deadline first scheduling algorithm	washing machine, dishwasher, electric oven, refrigerator	N/A

Table 2.2.Continue. A Summary of Optimization and Scheduling Approaches in Residential Customers

Ref.	Optimization Objective	Optimization Method	Appliances	DRP
[137]	Determine the distributed energy resources operation schedules (maximize the end-users' net benefits)	Particle Swarm Optimization	PHEV, space heater, storage water heater, pool pump, solar rooftop	TOU and CPP
[156]	Minimizing the energy cost	Linear sequential Optimization	water heater	real-time pricing (day-ahead)
[157]	Minimizing the payment and inconvenience functions	Linear programming	PHEV, storage system, washing machine, cloth dryer, dishwasher, other appliances	time- varying price
[158]	Minimizing the payment and interruption cost at the time of outage occurrence	Mixed integer programming	PHEV, washing machine, dryer, dishwasher, other appliances	time of use
[159]	Minimizing energy to the grid and maximizing the energy to grid	Linear programming	N/A	day-ahead pricing
[160]	- Cost minimization - Maximizing the financial gain for selling energy to grid	Linear programming	Other appliances	dynamic pricing scheme
[163]	Utility maximization (or welfare maximization) and cost minimization	Linear programming	A/C , PHEV, washing machine, lighting, entertainment appliance, battery storage	real-time pricing
[164]	Minimizing the total cost of energy and the users' dissatisfaction	Convex programming with L_1 regularization	- Solar rooftop - Small wind turbine - Air conditioner - other appliances	real-time pricing

2.4.3. Prediction in Building Energy Management

The prediction or forecasting of the energy consumption in a (residential) building has been considered as a significant function in the domain of energy management of buildings for the reasons below:

1- In energy resource allocation, it is essential to forecast the future amount of demand in order to supply energy because insufficient or superfluous energy both impose a cost on the utility provider.
2- In the smart grid and energy market, the demanded energy must be supplied by generation from main resources or distributed resources [153]. Consequently, the prediction of energy demand is essential for improving the energy performance throughout network and achieving an appropriate compromise between energy supplier and customers.

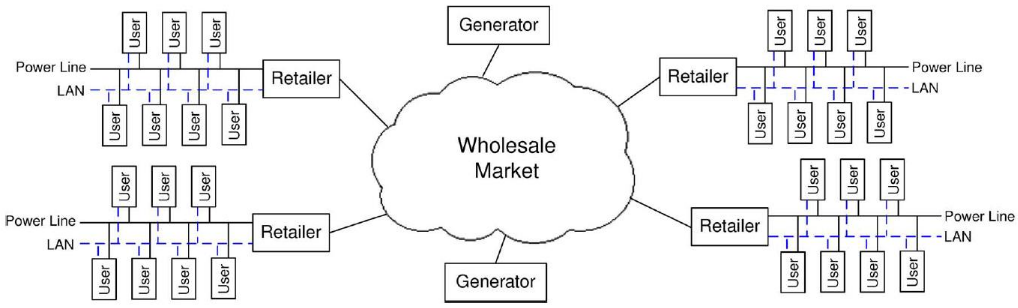


Figure 2.15. Wholesale Electricity Market [153]

3- Precise scheduling and the efficient reduction of the cost of energy in a smart grid smart home are highly dependent on the prediction of appliance energy [166].
4- Taking into consideration the destructive environmental effects of energy consumption such as global warming, CO_2 emissions, and mitigating these effects, the energy consumption prediction can help to achieve efficiency and sustainability in energy management.

A review of methodologies used to predict building energy consumption has been conducted by [14]. This study grouped the relevant methods under three categories: engineering (elaborative and simplified), statistical and artificial intelligence which the latest one includes artificial neural networks (ANN), and support vector machine (SVM) methods. The advantages and disadvantages of ANN and a comparison between forecasting methods have been presented by [167] and are shown in Table 2.3 below.

Table 2.3. Comparison between Forecasting Methods Proposed by [14, 167]

Forecasting Methods	Model complexity	Easy to use	Running speed	Inputs needed	Accuracy
Elaborate engineering	Fairly high	No	Low	Detailed	Fairly high
Simplified engineering	High	Yes	High	Simple	High
Statistical	Fair	Yes	Fairly high	Historical data	Fair
ANNs	High	No	High	Historical data	High
SVMs	Fairly high	No	Low	Historical data	Fairly high

The prediction of building energy consumption in the reviewed researches by [14, 167] includes a broad field of applications, from prediction of environmental parameters to demand for lighting or cooling operations. However, a few papers dealt with appliance usage prediction. A learning algorithm for predicting appliance usage for the next 24 hours has been proposed by [61]. The study used the data about the amount of energy and the operating time of appliances. The paper firstly created a knowledge-based system by an Oracle data management system and using data from a project called IRISE collected by Residential Monitoring to Decrease Energy Use and Carbon Emissions in Europe (REMODECE); and secondly, it proposes three methodologies for designing predictors called "classifiers" in order to extract the knowledge from this database; thirdly, these proposed techniques are intended to predict the appliance consumption usage; and fourthly, it examines the accuracy of prediction models by simulating three different types of appliances which have different functions. The techniques which are proposed for classifiers are decision tree, decision table, and Bayes net. ConsH in Figure 2.16 means the consumption at time H.

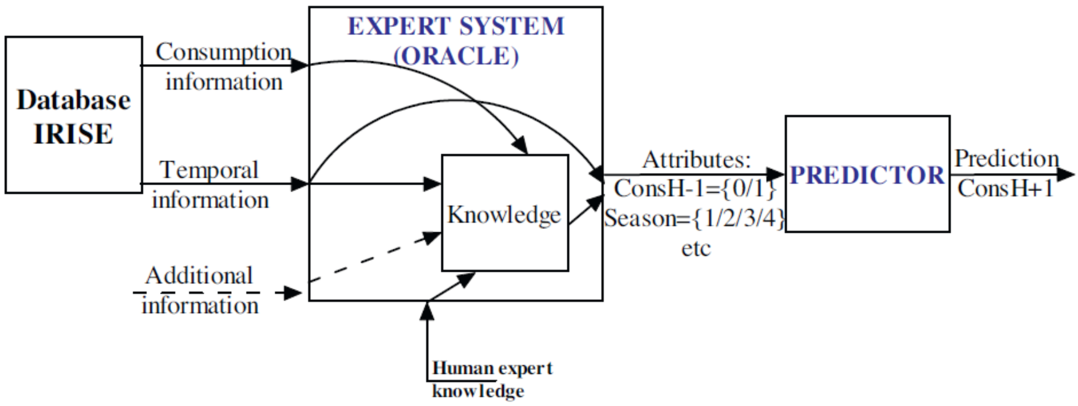


Figure 2.16. Prediction Architecture Presented by [61]

The prediction of the energy consumption of a single appliance is more difficult than the prediction of total energy consumption [61], [166] proposes a methodology for forecasting the energy usage of different appliances in the smart homes in smart grid. This study used a predictor to ascertain the probability of the appliances being operated on an hourly basis. The paper utilises the clustering technique to tackle the precision of the proposed method. In the context of prediction of energy uses, there are many researches which have focused on load forecasting in terms of short, medium and long term. For example, [168-172] employed a support vector machine (SVM) to predict short-term load of industrial and residential consumers in an electrical energy network. It is worth mentioning that the prediction load is different from load identification. The identification is essential for consumption monitoring during energy scheduling. In the next section, I present my survey of literature on this subject.

2.4.4. Load Identification

Load identification is a major function in an energy management system in the SG; hence, the relevant literature comprises studies which aim to identify the appliances individually. It is worth remembering that I cannot control a parameter without measuring it; so the load identification when scheduling and managing building energy is essential in energy monitoring and control systems; thanks to the smart meter, an appropriate communication infrastructure is provided for developing the data-driven methodologies in this field. A research which used the data provided by the meter for monitoring the residential loads by using load signatures is [173]. These data comprise

- The effective current value ($I = \sqrt{1}/T \int i^2 \, dt$)
- The effective voltage value ($V = \sqrt{1}/T \int v^2 \, dt$)
- Active power ($p = \sqrt{1}/T \int vi \, dt$)

The electrical appliance energy signature can be recognizable by different parameters such as the following:

1. the duration and shape of the current transient,
2. the appliance’s current harmonics, and
3. the appliance’s power.

In a more comprehensive study presented by [174], an appliance signature has been defined as “a measurable parameter of the total load that gives information about the nature or operating state of an individual appliance in the load”.

The study proposes the signature taxonomy as shown in Figure 2.17.

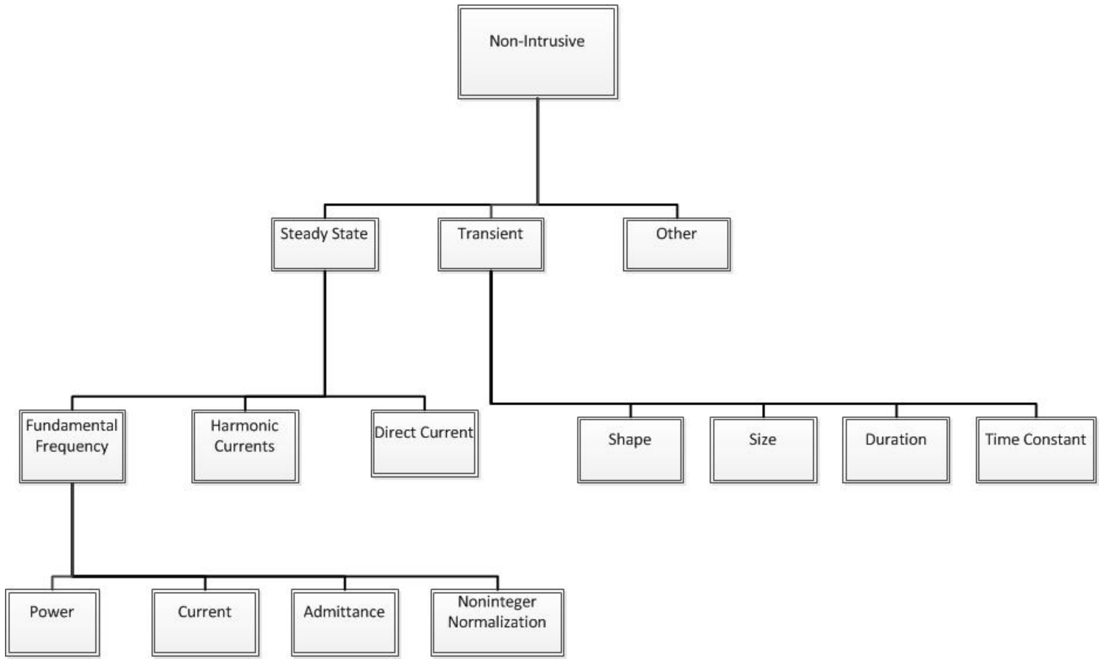


Figure 2.17. Signature Taxonomy Proposed by [174]

This study categorized the household appliances based on the load signatures in six groups such as resistive, pump-operated, fluorescent lighting, motor-driven, electronically-fed, and electronic power control appliances. In literature, load monitoring (LM) methods can be implemented through the direct monitoring of appliances by means of wires or signal processing [38] that it is more dependent on the hardware mechanisms because the identification mechanism like sensors must be connected to the power flow of appliances that cause an *intrusion* into the consumers' devices [174]. Conversely, the other method utilizes *non-intrusive* load monitoring (NILM) which is more dependent on software mechanisms whereby appliances are able to be identified from the total consumption load profile and less consideration is given to individual appliance behaviour. This method is called "load disaggregation or separation" [175, 176]. In the literature, several studies such as [177, 178] have reviewed to some extent the state-of-the art load identification approaches.

2.5. The Effect of Consumer Behaviours and Preferences on Energy Demand

2.5.1 Energy Consumption Behaviour and Activities Related to Energy Demand

The role and effect of consumer behaviour in demand response programs have been investigated by many researchers. Due to the unstable, unpredictable, and unexpected behaviour of customers, [179] constructed a reliability model of DR that takes into consideration the customers' behaviour based on the aggregated demand resources from the historical Demand response data. In this research, the two and a multi-state model of demand resources have been considered. Moreover, the customer behaviour effect is where the customer in the energy market responds to the programs. Furthermore, authors aim to mathematically formulate the transition rate of the states in demand reduction such as success, failure, and derated. The authors present the integrated power energy market structure shown in Figure 2.18. In this model, generation companies (Gencos) with several generators and customer service providers (CSP) constitute the energy market, while each has its own available and unavailable capacities. Generally, the aggregation of individual generation units in Genco is represented by an equivalent multi-state generation provider (EMGP) and for demand resources is called 'equivalent multi-state demand response provider' (EMDRP); the available capacity probability table (ACPT) is provided to demonstrate the availability of resources. So the research into the uncertainty of customer behaviour indicates the uncertainty of responses by customers during demand response events.

[180] examines the effects of occupant characteristics on residential electricity consumption patterns by analysing data from a smart metering survey of approximately 4200 domestic Irish dwellings. Four parameters have been analysed by a multiple linear regression model: total electricity consumption, maximum demand, load factor and TOU of maximum electricity demand for a number of different dwellings and socioeconomic occupant variables. These variables include: dwelling type, number of bedrooms, head of household (HoH) age, household composition, social class, water heating and cooking type, all had a significant influence on the total consumption of domestic electricity. By this methodology the research concludes a relationship exists between these variables and the amount of energy consumption. For example, consumers of the greatest amount of energy are those families whose HoH ages range from 36to 55, since tumble dryers and dishwashers consume the most energy.

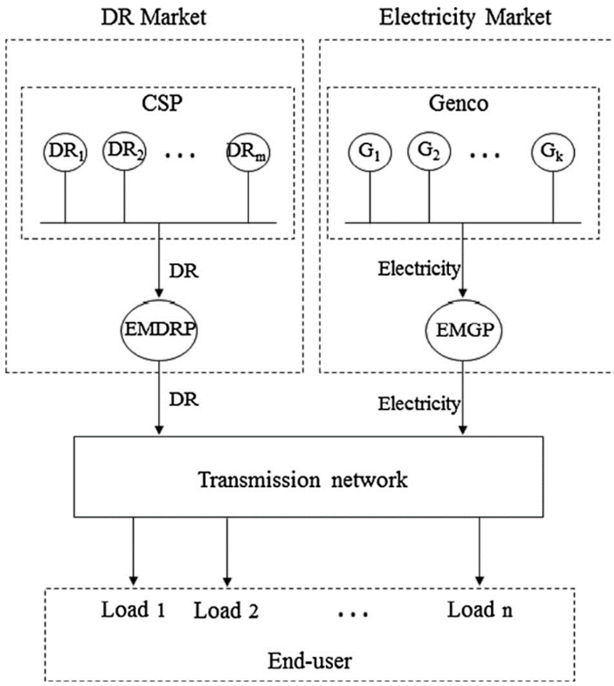


Figure 2.18. The Integrated Power Energy Market Structure Proposed by [179]

The authors of [38] conducted a significant survey which investigated the approaches and methodologies in the field of occupant behaviour's impacts on HVAC, energy consumption of lighting, and appliances. This literature survey has summarized the researches in which occupants' activities are studied by measuring occupancy, occupants' preferences and number of detailed activities as shown in Table 2.4. As It can be seen from this table and as demonstrated in research conducted by [181], occupancy is one of the significant independent parameters which affects energy demand in a dwelling. In some research such as that of [182], the occupancy is modelled in three states: unoccupied, occupied but the residents are awake, or all are asleep.

Table 2.4 Effect of Activities for Energy Demand for Lighting, HVAC and Plug Loads Presented by [38]

Application	Occupancy		Occupants 'preferences	No. of more detailed activities	
	Real-time	Pattern prediction		Single user	Multi Users
Lighting	[183, 184]	[185, 186]	[183, 186]	[187]	
HVAC	[188, 189]	[183, 185, 186]	[189, 190]	[187]	
Plug Loads	[191]	[185]	[181]	[192]	[193]

2.5.2. The Consumers' Consumption Behaviour Effect in Optimization Models

The consumers' consumption behaviour effect in optimization has been modelled in the comfort term or preferences. Some researchers such as [114, 152] have employed the utility theory when examining the consumers' willingness to participate in DRP ; meanwhile, other researches such as [125] considered preferences in terms of comfort where the customer's degree of comfort is defined as the maximum delay time for shifting each appliance when scheduling in different states of a stochastic model. The same term has been defined by [55] where maximization of scheduling preferences is defined as specifying the preferred timeslot for shifting (load) an appliance; similarly in [194], the user time preference is considered as the preferred set-up time in scheduling. In [42], the human comfort level is defined as the thermal flexibility of the consumers and it is demonstrated by a PMV index which is considered as a constraint in the optimization model. In some research, the willingness of consumers has been considered as an important factor and it has been projected in scheduling models such as those in [142, 195]. In [50] the preferences of consumers have been indicated where consumers specify the predefined temperatures for air conditioner and temperature and hot water volume limitations in optimization. The comfort factor is an operational constraint in [156] where it has been defined as the preferable temperature range for adjusting the water heater. The household consumer preferences in [157] are interpreted as inconveniences imposed on users during participation in direct load control DRP and it is equal to the amount of shed load for the number of appliances to be switched off during the program. As can be seen from the literature review, every approach has defined comfort based on its proposed problem definition. So, terms 'comfort' and 'preferences' are different in each research. In [130] it is stated that "it is necessary to characterize the users' behaviour" and for this reason, the value of usage probability of appliances in different timeslots for the purpose of load scheduling is presented by the authors.

In [160], the effect of customer preferences has been considered as the average hourly probability of using an electrical appliance during a timeslot, and users are able to group appliances according to their preferred time of use in the proposed scheduling model. In [49], the customers' level of comfort is correlated with an index as a "trip rate" as it is the number of times that, at certain time intervals, the load demand of appliances exceeds the maximum power level. The trip rate is determined by consumers and it is a constraint in the optimization model.

2.6. Comfort Management

Comfort management, and the part it plays in energy consumption in buildings, has attracted many researchers during last decade [25-36]. As discussed in the introductory Chapter, comfort management in buildings can be classified according to thermal, visual (illuminance) and indoor air quality. Occupants' comfort variables are inherent of building energy management.

The human factors that affect energy consumption include comfort, habit and behavioural intention, socio-demographic and psychological variables, building characteristics and external impact factors [25]. The different understandings of comfort affect consumption behaviour and it is difficult to break habits in order to modify patterns of energy consumption.

As stated in the Introduction and the literature review Chapter, several multi-agent approaches have been taken for comfort management based on the smart grid framework. For example, a hierarchical multi-agent intelligent control system proposed by [27, 29, 30, 36] considers several parameters for comfort management including illumination for light control, CO_2 concentration for indoor air quality, and temperature for thermal control. An optimizer that uses the particle swarm optimization technique is an agent which uses a graphical user interface (GUI) to set preferences. The approach proposed by [37] is intended to minimize energy cost via a multi-agent system that includes a fuzzy controller for comfort management in a home. Several heaters communicate with Zigbee technology, and a central control unit (CCU) measures maximum power in order to reach a set temperature point for each room according to the comfort level required. As a result, the information and communication technologies are inherent to comfort management.

As has been shown in the literature review (Chapter 2), researchers use different approaches when measuring comfort levels. However, three categories of comfort are evident in the various researches [35, 38]: Thermal comfort, Visual comfort and Indoor Air Quality (IAQ). Therefore, this thesis studies comfort management in terms of these three categories.

2.6.1. Comfort management: Thermal Comfort Measurement

The American Society of Heating, Refrigerating and Air Conditioning Engineers (ASHRAE) [16] defines thermal comfort as "condition of mind that expresses satisfaction with the thermal environment and is assessed by subjective evaluation." This standard states that "Due to individual differences, it is impossible to specify a thermal environment that will satisfy everybody".

In general, comfort occurs when body temperatures are maintained within a narrow range, skin moisture is low, and the physiological effort of regulation is minimized. Comfort also depends on behavioural actions such as altering clothing, altering activity, changing posture or location, changing the thermostat setting, opening a window, complaining, or leaving a space.

Thermal comfort is an indispensable part of comfort management. The two standards used for measuring thermal comfort are:

1- ISO 7730: 2005(or I.S. EN ISO 7730:2006)," Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria" [39].

2- ANSI/ASHRAE Standard 55-2013[40], "Thermal Environmental Conditions for Human Occupancy" issued by the American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE) [40].

There are six effective factors that determine the body's thermal sensation [39, 40, 196]:

a) Factors relating to the characteristics of the occupant:
    1. Physical activity or metabolic rate
    2. Clothing insulation
b) Environmental factors:
    3. Air temperature
    4. Radiant temperature
    5. Air velocity (speed)
    6. Air humidity

In this Chapter, the standard reference for thermal environmental conditions is ANSI/ASHRAE Standard 55-2013. The methods used to determine thermal environmental conditions stipulated by this Standard are listed as follows:

- *Method for determining occupant characteristics:* metabolic rate for each representative occupant, rate determination, time-weighted averaging; high metabolic rates, clothing insulation for each representative occupant, insulation determination, limits of applicability
- *General method for determining acceptable thermal conditions in occupied spaces:* graphic comfort zone method applicability and methodology; analytical comfort zone method, elevated air speed limits to average air (va) speed with/without occupant

control; local thermal discomfort applicability, radiant temperature asymmetry, draft, vertical air temperature difference, floor surface temperature; temperature variations with time applicability, cyclic variations, drifts or ramps

- *Determining acceptable thermal conditions in occupant-controlled naturally conditioned spaces:* applicability and methodology

In the literature, there are two types of approaches that address the issue of thermal comfort: heat-balance approaches which are based mainly on Fanger's study [197, 198], and adaptive approaches which rely heavily on occupants' behaviour, characteristics, sensations and backgrounds.

Generally, metabolism, or the process of ingesting food and converting it to energy in the human body, generates heat continuously. The energy produced will create heat, and therefore body temperature varies from that of internal organs (37º C) to that of the skin's surface which is 35º C.

This metabolic rate can be slow or fast depending on a person's age, gender, health and wellbeing, body mass, and type of activity in which the person is engaged. Consequently, this amount of heat differs from person to person. According to the second law of thermodynamics, generated heat has to spread out from body; hence, the body's efficiency (η) can be calculated by the formula below [199] :

$$\eta = 1 - \frac{T_a}{T_b} \tag{2.1}$$

where T_a is the ambient and T_b is the body temperature (º C). Principally, thermal discomfort occurs when the ambient temperature (T_a) is higher than the body temperature (T_b). In order to prevent this thermal disturbance and maintain the body temperature at 37ºC, the human thermoregulatory system shown in Figure 2.19 takes one or more autonomic control actions such as adjusting [200, 201]:

- heat production by shivering;
- internal thermal resistance by vasomotion: i.e. control of skin blood flow;
- external thermal resistance by control of respiratory dry heat loss; and
- water secretion and evaporation by sweating and respiratory evaporative heat loss.

The thermal heat exchange between the body and its environment can be mathematically formulated in terms of of conductive, convective, radiative, moisture, clothing and metabolic effects [202]

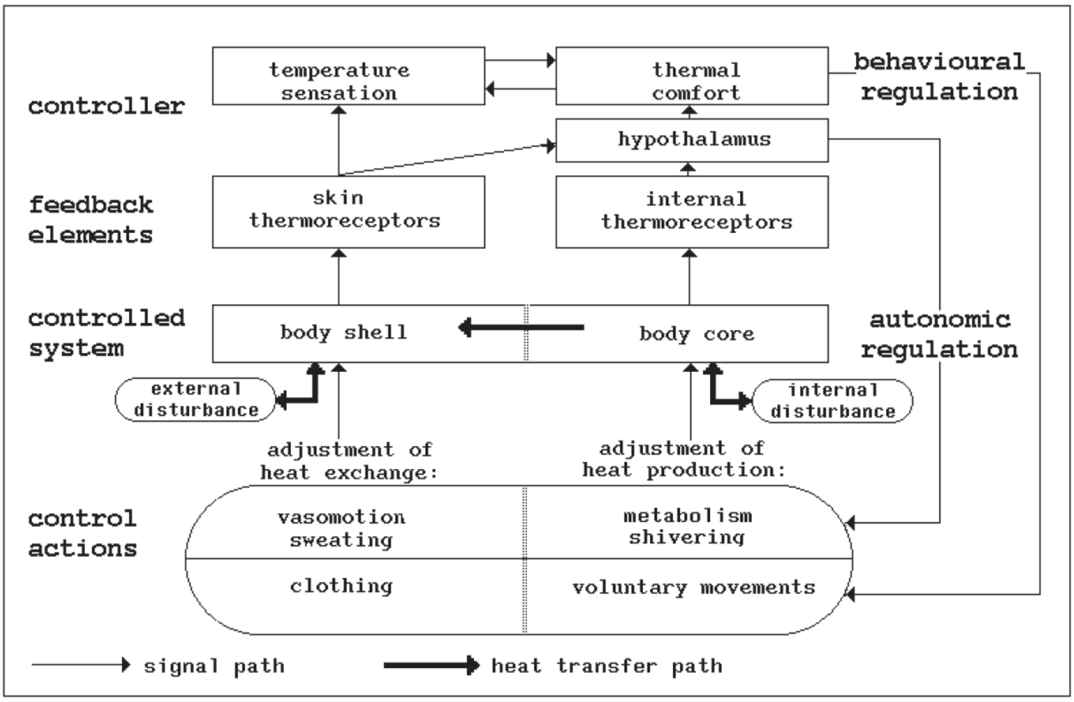


Figure 2.19. Diagram of autonomic and behavioural human temperature regulation [201]

The Predicted Mean Vote (PMV) index can be calculated by measuring the above factors. But for thermal discomfort or thermal dissatisfaction, the index of the predicted percentage dissatisfied (PPD) can be calculated from the PMV.

2.6.1.1. Predicted Mean Vote (PMV) Index

A human being's thermal sensation is related mainly to the thermal balance of his or her body as a whole. This balance is influenced by physical activity and clothing, as well as environmental parameters such as:

a) air temperature;
b) mean radiant temperature;
c) air velocity; and
d) air humidity.

When these factors have been estimated or measured, the thermal sensation for the body as a whole can be predicted by calculating the predicted mean vote (PMV).

The PMV is an index based on the heat balance of the human body that predicts the mean value of the votes of a large group of persons on the seven-point thermal sensation scale shown in Table 2.5. Thermal balance is obtained when the internal heat production in the body is equal to the loss of heat to the environment. In a moderate environment, the human thermoregulatory system will automatically attempt to modify skin temperature and sweat secretion to maintain heat balance.

Table 2.5. Seven-Point Thermal Sensation Scale

+ 3	Hot
+ 2	Warm
+ 1	Slightly warm
0	Neutral
- 1	Slightly cool
- 2	Cool
- 3	Cold

The PMV is calculated by using the following equations:

$$PMV = \left(0.303 \times e^{(-0.036 \times M)} + 0.028\right)L = \alpha L \quad (2.2)$$

$$L = \{(M - W) - 3.05 \times 10^{-3} \times (5733 - 6.99 \times (M - V) - p_a) - 0.42 \times \left((M - V) - 58.15\right) - 1.7 \times 10^{-5} \times M \times (5867 - p_a) - 0.0014 \times M \times (34 - t_a) - 3.96 \times 10^{-8} \times f_{cl} \times ((t_{cl} + 273)^4 - (\bar{t}_r + 273)^4) - \left(f_{cl} \times h_c \times (t_{cl} - t_a)\right)\} \quad (2.3)$$

$$t_{cl} = 35.7 - 0.028 \times (M - V) - I_{cl} \times \{3.96 \times 10^{-8} \times f_{cl} \times ((t_{cl} + 273)^4 - (\bar{t}_r + 273)^4) + \left(f_{cl} \times h_c \times (t_{cl} - t_a)\right)\} \quad (2.4)$$

$$h_c = \begin{cases} 2.38 \times |t_{cl} + t_a|^{0.25} \; for \; 2.38 \times |t_{cl} + t_a|^{0.25} > 12.1 \times \sqrt{v_{ar}} \\ 12.1 \times \sqrt{v_{ar}} \; for \; 2.38 \times |t_{cl} + t_a|^{0.25} < 12.1 \times \sqrt{v_{ar}} \end{cases} \quad (2.5)$$

$$f_{cl} = \begin{cases} 1.00 + 1.290 \times I_{cl} \quad for \; I_{cl} \leq 0.078 \quad m^2.K/W \\ 1.05 + 0.645 \times I_{cl} \quad for \; I_{cl} > 0.078 \quad m^2.K/W \end{cases} \quad (2.6)$$

where L is the thermal load on the body defined as the difference between internal heat production and heat loss to the environment for a person hypothetically kept at comfort values of temperature of the skin layer and evaporative heat loss of regulatory sweating at the activity level, and

α is the sensitivity coefficient;

M is the metabolic rate, in watts per square metre (W/m^2);

W is the effective mechanical power, in watts per square metre (W/m^2);

t_a is the air temperature, in degrees Celsius (°C);

$\bar{t}_r$ is the mean radiant temperature, in degrees Celsius (°C);

t_{cl} is the clothing surface temperature, in degrees Celsius (°C);

f_{cl} is the clothing surface area factor;

I_{cl} is the clothing insulation, in square metres kelvin per watt ($\frac{m^2.K}{W}$);

h_c is the convective heat transfer coefficient, in watts per square metre kelvin ($\frac{W}{m^2.k}$) ;

v_{ar} is the relative air velocity, in metres per second (m/s);

p_a is the water vapour partial pressure, in Pascals (Pa).

And each unit's correlation is as follows:

1 metabolic unit = 1 met = 58.2 W/m^2

1 clothing unit = 1 clo = 0.155 $\frac{m^2 \times °C}{W}$

PMV may be calculated for different combinations of metabolic rate, clothing insulation, air temperature, mean radiant temperature, air velocity and air humidity [203].

The detailed information for calculating PMV is presented in Appendix 01.

2.6.1.2. Predicted Percentage Dissatisfied (PPD) Index

The PPD predicts the percentage of people who feel more than slightly warm or slightly cold. The PMV predicts the mean value of the thermal votes of a large group of people exposed to the same environment. But individual votes are scattered around this mean value and it is useful to be able to predict the number of people likely to feel uncomfortably warm or cool.

The PPD is an index that establishes a quantitative prediction of the percentage of thermally dissatisfied people who feel too cool or too warm. With the PMV value determined by Eqs.2.2-6, the PPD will be calculated by using Equation

$$PPD = 100 - 95 \times e^{(-0.03353 \times PMV^4 - 0.2179 \times PMV^2)} \quad (2.7)$$

The details for calculating PPD are presented in Appendix 01.

2.6.2. Comfort Management: Indoor Air Quality

The measurement of IAQ is an ongoing process of the HVAC system in a building for managing comfort level. The carbon dioxide (CO_2) concentration is an index used for monitoring this comfort factor. This index is affected by the presence of occupants and air pollutant sources such as total volatile organic compounds (TVOCs) , NO_x (mono nitrogen oxides (NO) and nitrogen dioxide(NO2)) [35].

The ventilation function of the HVAC system supplies fresh air from outdoors and removes polluted indoor air and odours in order to maintain the standard IAQ level. However, this process counteracts the cooling or thermal control functions, so the ventilation rates must be decreased in order to achieve an efficient energy load. On the other hand, the effect of weak ventilation may cause ‘sick building’ syndrome that occurs as a result of poor IAQ. Hence, achieving an appropriate level of ventilation with efficient level of heating and cooling is a major and significant challenge facing building designers. Demand-controlled ventilation (DCV) is an energy-efficient method that monitors and controls CO_2 concentration by CO_2 or infrared or wireless occupancy sensors [204, 205]. The Standard, ISO 16814:2008(E) [206] for building environment design and IAQ introduces three methods for determining the quality of indoor air for human occupancy which are based on health, perceived air quality, and the ventilation rate. In the Standard [206], the target concentration for target indoor air quality comfort is based on $CO_{2.}$ for which an acceptable value has been determined by the EN 13779 standard and these levels from most to least acceptable levels are as follows:

a) $< 400\mu\ \mathrm{l}/\ \mathrm{l}$

b) $400\mu\ \mathrm{l}/\ \mathrm{l}$ to $600\mu\ \mathrm{l}/\ \mathrm{l}$

c) $600\mu\ \mathrm{l}/\ \mathrm{l}$ to $1{,}000\mu\ \mathrm{l}/\ \mathrm{l}$

d) $> 1{,}000\mu\ \mathrm{l}/\ \mathrm{l}$

“The units ‘ $\mu\ \mathrm{l}/\ \mathrm{l}$’are equivalent to volume parts per million(ppm), a deprecated unit” [206].

2.6.3. Comfort Management: Visual Comfort

According to an Australia pilot project report known as the Residential Energy Monitoring Program (REMP) issued in 2012, “residential lighting in Australia consumes more than 700 kWh pa per household” [207].

The AS/NZS 1680.1: 2006 standard [208] for interior and workplace lighting has established general principles and a framework for performance and comfort when installing interior lighting.

Various factors affect the good quality of lighting for comfortable visual conditions. Some of these factors must be considered when designing an interior feature such as shade for windows. However, a study of these is not within scope of this thesis. An energy-efficient lighting approach can be associated with a lighting system by considering the following parameters:

1. General measures for energy saving include:
   1.1. Daylight and energy conservation: Effect of an energy-efficient fenestration system on energy consumption and visual comfort and increasing air conditioning energy consumption by increasing daylight.
   1.2. Integration of lighting and air conditioning: Three forms of heat dissipation of the lighting are convection, conduction and radiation, all of which affect the air conditioning's energy consumption.
   1.3. Maintenance: Glazing and surface reflections are important factors in daylighting systems. Also, an energy-efficient globe can reduce energy cost.
2. Energy Saving from reduction in electrical load
   2.1. Lamps and control gear: In order for a lighting system to achieve the highest efficacy, several lamp properties should be taken into consideration including: colour appearance, colour rendering, luminance; luminous flux; lamp lumen depreciation; life; size; available luminaire type; starting and running up characteristics; and dimming possibilities.
   2.2. Luminaires: Luminaires should be selected according to their applications.
   2.3. Arrangement of luminaires: At a given place, luminaires can be arranged in a fixed location or on a flexible mounting system.
   2.4. Room surface reflectance: High reflectance finishes on walls, ceilings, floors and furniture use light more efficiently.

Energy saving by reducing usage time: Control of the electric lighting according to the required level at a given time and at a given place. The interior, the nature of the task, and the available daylight are important factors to consider in this approach.

Additionally, other factors may be considered when evaluating efficient lighting energy consumption such as the parameters used by Energy Efficiency Strategies (EES) [207] (suggested by the Department of Climate Change) to model lighting energy consumption in 2008. They comprised:

• technology efficacy;

• lighting levels (lux);

• resulting power density for each lighting type;

• technology share by floor area for living and non-living areas;

• average floor area per house (from building stock model); and

• usage.

However, the control system is a fundamental part of an electric lighting system. Lighting control means using appropriate lighting as required. Therefore, it is expected that the control mechanism adjusts the output light by switching off or dimming the lamp. However, it must be considered that the enforced switching off of lights may meet with resistance from occupants and therefore a range of choices must be provided for the control of lights. According to [209], switching off and dimming are two forms of control systems for electric lighting. These methods can be combined in order to achieve an efficient level of control.

2.6.3.1. Visual Comfort: Electric Lighting Control by Switching Method

Controlling light by means of switches has two noticeable principles. The first is the immediate availability of a certain amount of light after switching on, and the second is the appropriate interval between switching on and off which depends on the globe type. Various methods of switching include manual switching, remote switching, time switch, daylight-based switch and occupancy-based switch [210-212].

For daylight-based switches, photocells are used to measure the daylight level, whereas occupancy-based switches rely on sensors to sense the noise level or reflected radiation of human presence such as in PIR motion detectors [213-215].

2.6.3.2. Visual Comfort: Electric Lighting Control by Dimming Method

The control which allows the dimming of light is a method whereby the illumination can be decreased until it reaches a desirable level. Tungsten filament globes and some types of discharge lamps can be dimmed. According to the time of day or amount of daylight, dimmers can be controlled either manually or automatically [214].

Many researchers have focused on modelling the comfort parameters related to home energy management. Their research studies can be classified into three groups: those that have studied the notion of comfort in terms of visual, thermal and air quality comfort, those that have used the comfort parameter as a thermal comfort factor in their modelling, and finally, those researches who have focused on just one dimension such as the visual comfort.

In recent years, an agent-based approach has been applied that models energy management systems that take into consideration the comfort management factors. [27] proposes a hierarchical multiagent control system with partial swarm optimization (PSO) to balance the energy for an integrated building and micro grid as shown in Figure 2.20 below.

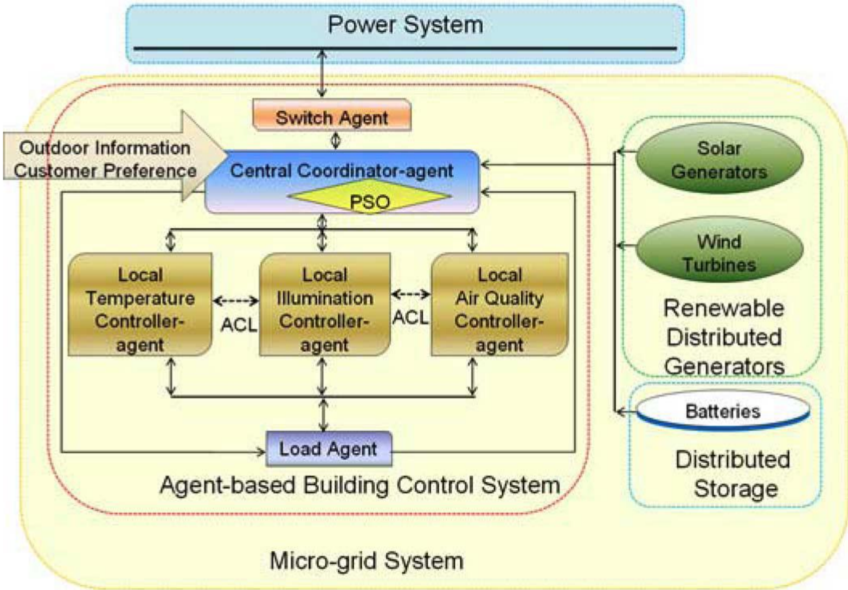


Figure 2.20. Agent-based Building Control System Proposed by [27]

The authors defined the overall comfort index for measuring the overall comfort that consists of thermal, visual and indoor air quality as follows.

$$\text{Comfort}= \mu_1\left[1-\left(\frac{e_T}{T_{set}}\right)^2\right]+\mu_2\left[1-\left(\frac{e_L}{L_{set}}\right)^2\right]+\mu_3\left[1-\left(\frac{e_A}{A_{set}}\right)^2\right] \quad (2.8)$$

In the formula above, the overall comfort index value is within the range of [0,1] where:

- μ_1, μ_2 and μ_3 are the user-defined weight factors that can be set by consumers.
- $e_T = T_{set} - T_{measured}$, is the error between the set point of the temperature and the measured value.
- $e_L = L_{set} - L_{measured}$, is the error between the set point of the illumination and the measured value.
- $e_A = A_{set} - A_{measured}$, is the error between the set point of the indoor air quality and the measured value.

As can be seen, this index is based directly on the weighting input data which have been set by users. The same authors proposed a similar approach in [29].

2.7. Decision-making Approaches in Energy Management and Smart Grid

The application of decision-making methods has been widely considered by researchers for solving and addressing energy management issues such as demand response, building performance assessment, storage system, and renewable energy sources. These methods can be investigated in the domain of multi-criteria decision making (MCDM) that comprises two main categories of multiple attributes and objectives decision-making methods (MADM and MODM). In the next chapter, a comprehensive explanation of the application of these techniques is presented in the field of energy management systems in the smart grid. MADM methods include techniques such as:

- The analytic hierarchy process (AHP)[216, 217],
- The analytic network process (ANP)[218],
- the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [219],
- Elimination and Choice Expressing Reality or ELECTRE (Elimination et Choix Traduisant la Réalité) [220]
- VIKOR[221, 222], and a
- Preference ranking organization method for enrichment evaluation (PROMETHEE) [223, 224]

Multi-Criteria Decision Making (MCDM) techniques have been increasingly employed for decisions relating to energy planning. These methods can be classified into three main groups: a) value measurement models, b) goal and reference models, and c) outranking models [225].

The application of MCDM methods to sustainable energy planning has been reviewed by [226]. Additionally, [225] described the application of these techniques in the field of energy planning problems.

My literature survey has identified researchers who have used MCDM methods in demand response programs for various purposes. Alami et al. [14] used the analytic hierarchy process (AHP) for choosing the most effective DRP in power market; Kim et al.[227] employed the same technique for designing of the emergency DRP which took into account the degree of importance of load reduction criteria. Shengnan et al. [228] determined a resource allocation model for assigning load to the users in a multi-layer DRP by applying AHP. Shimomura et al. [229] used the AHP method to determine the importance of the comfort model in their research on the design of a customer-oriented DR aggregation service. Chen and Gu [230] built a fuzzy analytic network process (ANP) model for integrating the opportunities and risk prioritization in the smart grid. In research conducted by [231], TOPSIS is employed for selecting the best solution of the multi-objective generation scheduling model where incentive-based DR programs are considered as a reserve resource in wind power forecasting in SG. These objective functions include minimizing emissions and the cost of power generation.

On the other hand, the application of MCDM in the field of building energy performance and assessment is addressed by [232-236].

Xu et al. [232] employed an ANP and energy performance contracting mechanism in order to examine the interrelationships of sustainable building energy efficiency retrofit in a hotel building. Chen et al. [233] propose the TOPSIS methodology for benchmarking whole-building energy performance with consideration given to the seven efficiency criteria: energy use intensity, cooling degree day efficiency, heating degree day efficiency, total degree day efficiency, bathroom-oriented efficiency, and occupants-oriented efficiency. In the other research, [236] used a total of 25 criteria under six categories when assessing the energy efficiency of residential buildings in China: space heating and cooling load, efficiency of building facilities, use and reuse of construction material, operation and management, use of renewable energy, and indoor comfort and health.

The intelligent building assessment presented by [234, 235] employed fuzzy AHP and TOPSIS, the criteria of which are represented by five main categories as shown in Table 2.6.

The evaluation of storage systems in SG by decision-making problem approaches has been conducted by [237, 238]. Daim et al. [237] employed Fuzzy Delphi and AHP methods to evaluate multiple energy storage technologies in order to choose the best alternative for the application to intermittency of renewable energy in the Northwest US region.

In terms of the sustainability aspect of SG and the use of renewable sources, MADM are widely used for the selection of suitable technologies and locations for the installation of solar or wind power plants. Aragones-Beltran et al. [239] employed both AHP and ANP techniques when selecting solar-thermal power plant investment projects.

T. Kaya and C. Kahraman [240] propose VIKOR and AHP for selecting the most appropriate renewable energy technology option in Turkey. Similarly, Sengul et al.[241] employed fuzzy TOPSIS in order to rank renewable energy supply systems in Turkey. [242] apply the ELECTRE method when selecting a suitable wind farm site. Also, Beccali et al. [243, 244] employed the ELECTRE III method to select the most appropriate technologies for a renewable energy diffusion plan and compared it with the fuzzy sets logic method.

In all of the approaches mentioned earlier, the decision makers have to select different alternatives by considering a finite set of evaluation criteria in order to achieve the objective. These methodologies help the decision maker, chronologically, to observe how his/her preferences impact on the final decision regarding a problem.

Table 2.6. Intelligent Building Assessment Criteria Proposed by [234, 235]

Main Criteria	Sub-criteria
1. Engineering	1. Functionality 2. Safety and structure 3. Working efficiency 4. Responsiveness 5. Office automation 6. Power supply 7. System integration
2. Environmental	1. Energy consumption 2. Water and water conservation 3. Materials used, durability and waste 4. Land use and site selection 5. Greenhouse gas emissions 6. Indoor environmental quality
3. Economical	1. Economic performance and affordability 2. Initial costs, operating and maintenance costs 3. Life cycle costing
4. Socio-Cultural	1. Functionality, usability and aesthetic aspects 2. Human comfort 3. Health and sanitation 4. Architectural considerations
5. Technological	1. Work efficiency 2. Use of high-tech system 3. Use of advanced artificial intelligence 4. Telecom and data system (Connect-alibility) 5. Security monitoring and access control system 6. Addressable fire detection and alarm system 7. Digital addressable lighting control system

2.8. Research Issues

As mentioned earlier, there is no such technique in the literature that aims to intelligently achieve demand response at the consumer level by actively involving end-users during this process. This is different from the other areas of smart grid that use efficient techniques to achieve demand response. So the main issues identified in the literature and that will be addressed in this research are:

a. No approach has been proposed that measures consumers' preferences and consumption profiles in order to efficiently utilize energy.

b. Much research has been done to achieve efficiency in demand response and price. However, none has studied the effectiveness of such systems when customers are not well-trained, unwilling or passive in responding to price signals. To overcome this, an intelligent decision support system for energy management is required to assist customers to make decisions according to their criteria for demand response.

c. As shown in optimization and scheduling literatures, the study of the preferences of consumers has been limited to the preferred set-up time for the scheduling of appliance operations or air or water temperatures, so there are no any approaches in the literature that assist the end-user to aggregate the total preferences regarding all effective parameters in energy consumption, and employ them in optimization models that demonstrate the effect of these preference changes on the optimization of energy consumption.

d. In the reviewed literature, no approach has been proposed that uses an algorithm to facilitate the decision-making process for end-users when they have decided to participate in DRP and wanted to reduce energy consumption.

The next Chapter discusses the decision-making process and techniques applicable to end-users, and presents a solution for consumers' decision-making in DRP and their energy management.

2.9. Conclusions

In this Chapter, I addressed the most significant elements of electrical energy management systems in terms of the end-users of the smart grid, and I examined those studies most relevant to the topic of this thesis. The creation of an energy management system in the context of the smart grid needs new approaches as the smart grid has added many new parameters in control methodologies and shifted the traditional paradigm to new and modern concepts associated with management. Hence, the authors examined the recent challenges in this field. Their survey showed that the literature to date has not considered all these aspects because the effective parameters in energy management systems belong to different domains of science such as science and engineering or even sociology and economics.

In this thesis which pertains to energy management, methodologies are more dependent on users' decisions or are more customer-oriented. This is an important consideration since the smart electrical network essentially has been created to benefit the end-users and they are the main customers of this provided service; so if customers are to contribute to this service management, they have to possess the facilities, technologies and methodologies enabling them to monitor the effects of the decisions they make regarding energy consumption; In the next Chapter, the decision-making models which can be supportive and applicable in this regard are presented.

Chapter 3

Decision-Making Framework to Support End-users' Energy Management in DRP

3.1. Introduction

An effective approach for successful demand response programs requires techniques at the consumption level. This can be done by creating an intelligent decision-making framework at the end-users' side. For example, at the home level, energy price signal as an input is taken from the grid and, depending on various underlying factors, the decision-making framework assists the end-users to achieve demand response. The importance of such work has been discussed by Hopper et al. [245] who state that there is a role for targeted technical assistance programs to help customers to develop more sophisticated price response strategies. So, participating in DRP and having efficient energy consumption behaviour is a dilemma for end-users as these programs are complicated. Specifically, a dynamic pricing demand response program is one in which the market-based energy price signal varies over time, making it very difficult for end-users to save on the cost of energy during billing periods. I have depicted this dilemma in Figure 3.1. This figure shows that there is a utility provider which sends price signals to end-users and receives the consumption information by means of a smart meter and wireless communication of the sensors (smart appliances). The consumer mutually receives some information from the utility provider about consumption profile and price signals from various portals. It can be expected that the consumers change their consumption behaviour by receiving consumption information in order to mitigate cost and save on their power bills.

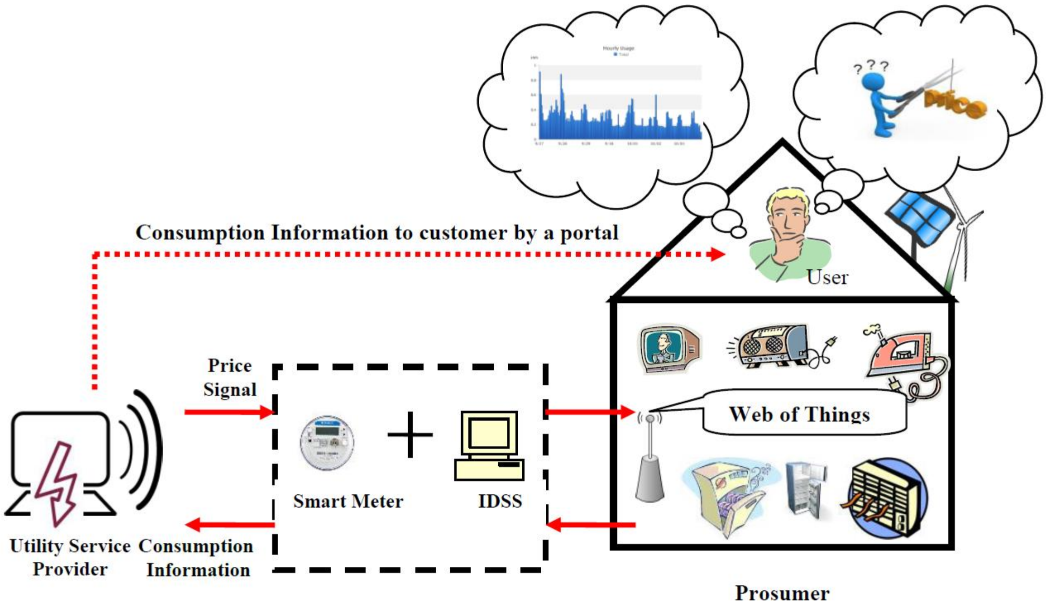


Figure 3.1. Aggregating an IDSS to HEM in SG

However, in a dynamic pricing system, the consumers have no way of knowing whether or not their decision to modify their energy consumption is effective and efficient. This is overcome by adding intelligence to each home level energy management system that is expected to assist householders or energy managers to make decisions about the choice of the best policy, consumption behaviour, or even equipment during participation in DRP. In this Chapter, I will develop decision-making models by which such intelligence is added at each home level on a continuous basis by which demand response is achieved. I will propose our model in the following sections by firstly presenting a primary introduction to the decision-making process and methodologies. Secondly, the appropriate criteria and decision making methodologies for decision-making in the residential sector will be discussed and, thirdly, application of those methodologies are discussed by presenting different scenarios and, fourthly, an intelligent decision-support system in the context of smart grid and smart home will be proposed.

3.2. Decision Making Process and Methodologies

Decision-making processes comprise a series of steps as follows [246]:

1. Problem Identification;
2. Preferences Construction;
3. Alternatives Evaluation;
4. The best alternatives Determination.

Considering the above stepwise, our problem identification in the context of energy management in demand response participation in the residential sector can be explained in terms of the ambiguity, complexity and conflict that end-users face when managing their consumption since such programs involve many regulations and expectations for the curtailment of energy. As stated by O. Svenson [247] “the perceptual, emotional, and cognitive process which ultimately lead to the choice of a decision alternative must also be studied if I want to gain an adequate understanding of human decision making.” Principally, there are three types of formal analysis employed for solving decision-making problems [248-250]:

1. *Descriptive analysis* is concerned with the problems that decision-makers (DMs) actually solve and it is especially addressed in the fields of behaviour decision research such as psychology, marketing, and consumer research [251].
2. *Prescriptive analysis* considers the methods that DMs ought to use to improve their decisions.
3. *Normative analysis* focuses on the problems that DMs should ideally address.

In this thesis, I limit our studies to normative and prescriptive analysis which focuses on the fields of decision science, economics, and operations research (OR). Decision-making is very simple when there is just one criterion; in this case, the alternative with the highest preference rating would be chosen. However, when decision-making is based on evaluating alternatives with multiple criteria, many difficulties will arise that require more sophisticated methods and approaches in order to overcome these difficulties in the evaluation of criteria. Problem identification, constructing the preferences and selecting the appropriate decision-making tools are the three main steps in the decision-making process [250].

Multi Criteria Decision Making (MCDM) can be classified into two main categories [252]:

1. Multiple objective decision making (MODM)
2. Multiple attribute decision making (MADM)

On the other hand, some of the MCDM problems are regarded as problems of subjective uncertainty and vague information and involve fuzzy numbers and variables when dealing with more extensive problems in MCDM [253, 254]. So, MCDM problems based on the concepts of MODM and MADM in an uncertain and fuzzy environment can be classified into two categories, respectively:

1. Fuzzy multiple objective decision making (FMODM)
2. Fuzzy multiple attribute decision making (FMADM)

MODM or vector programming is a mathematical decision-making model in which decision-makers tackle the optimal design problems with high complexity and several objectives that are mainly incorporated into the optimization process. Basically, the problem consists of several conflicting objective functions in maximization and/or minimization forms with a given set of well-defined linear and nonlinear constraints. MADM is defined as making preference decisions such as evaluation, prioritization, selection) over the multiple and conflicting attributes. There are the common characteristics for all MADM problems[252]:

1. *Alternatives*: The number of alternatives is finite, from several to thousands which must be considered and selected.
2. *Multiple Attributes*: Depending on the nature of the problem, many relevant multiple attributes must be set by the decision-maker.
3. *Incommensurable Units*: Each attribute has different units of measurement.
4. Attribute Weights: Almost all MADM methods require information regarding the relative importance of each attribute, which is usually supplied by an ordinal or cardinal scale.
5. *Decision Matrix*: A MADM problem can be concisely expressed in a matrix format, where the columns indicate attributes considered in a given problem and the rows list the competing alternatives.

The application of MCDM methods to sustainable energy planning has been reviewed by [226]. Additionally, Loken [225] described the application of these techniques in the field of energy planning problems. The decision-making process shown in Figure 3.2 shows that this process takes place after indicating the appropriate criteria and specifying the alternatives. Moreover, there are several considerations when choosing these techniques for solving the problems. These are as follows [225]:

1- Provided that a methodology of a technique is expected to measure what it is supposed to determine, so different methodologies give different results. Therefore, a method should be chosen which reflects the true values of users in the best feasible and possible way.

2- The method must be able to provide all the information required for decision-makers and be compatible with available data.

3- The method should be straightforward and easy to understand by users; otherwise, they will not trust the results of decision-making and any recommendations.

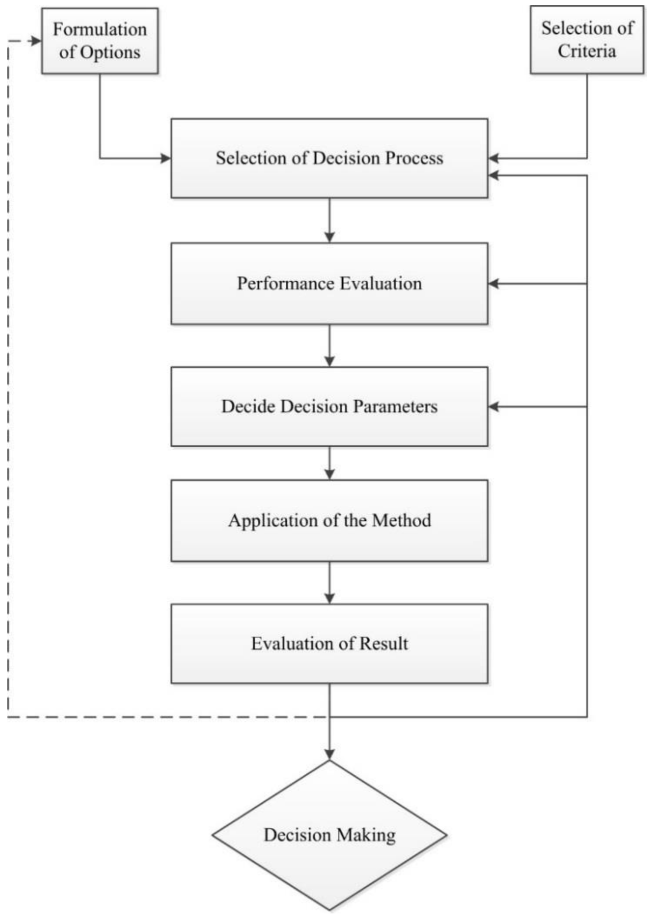


Figure 3.2. Decision-making Process

The MADM problems have been thoroughly resolved and developed by various techniques and methodologies, the most significant of which are briefly explained in the following section and summarized in the table below. The main purpose of reviewing these techniques is to determine which technique is the most appropriate for energy managers of buildings or householders in a decision-making framework (model) in order to manage the flow and amount of energy on their premises (residential, commercial and industrial) during different demand response programs of the smart grid. As a result, I aim in this Chapter to:

- Firstly explain the most effective MADM methods applicable in energy management;
- Secondly, explore the appropriate criteria for decision-making in the residential sector of the smart grid by studying the standards and reviewed literatures;
- Thirdly, present an intelligent decision-making support system in the smart grid structure;
- Fourthly, propose an intelligent decision-making model for energy management that takes into account the established parameters at the smart home level.

3.3. Multi Attribute Decision Making

3.3.1. Analytic Hierarchy Process (AHP)

AHP is a descriptive decision analysis and weighted sum method proposed by Thomas L. Saaty [216, 217]. In this method, the criteria and alternatives are evaluated by the pairwise comparison method. This analytic hierarchy process has an objective at the top and decision alternatives at the bottom while in the middle levels there are criteria and sub-criteria as shown in Figure 3.3. The steps for implementing this methodology are described below:

Step 1) Set up a target: This step is about the purpose of decision-making and is usually about selecting something among many for a reason based on criteria.

Step 2) Select appropriate criteria for achieving the target and structuring the hierarchy.

Step 3): Use pairwise comparison of alternatives based on each criterion by using a scale for qualitative indexes or the real value for quantitative indexes.

Table 3.1. Pairwise Comparison Scale for Qualitative parameters

Scale (a_{ji})	**Description**
1	Equal importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Extreme importance

The comparison matrices [a_{ij}] is formed for each criteria which have reciprocal properties. It means that for each matrix member a_{ij}, the a_{ji} is equal to $\frac{1}{a_{ij}}$. For example, if the criterion i has moderate importance over criterion $a_{ij} = 3$, then the result of comparison of criterion j to criterion i is $a_{ji} = \frac{1}{3}$.

Step 4) Compare and sort the alternatives according to the criteria.

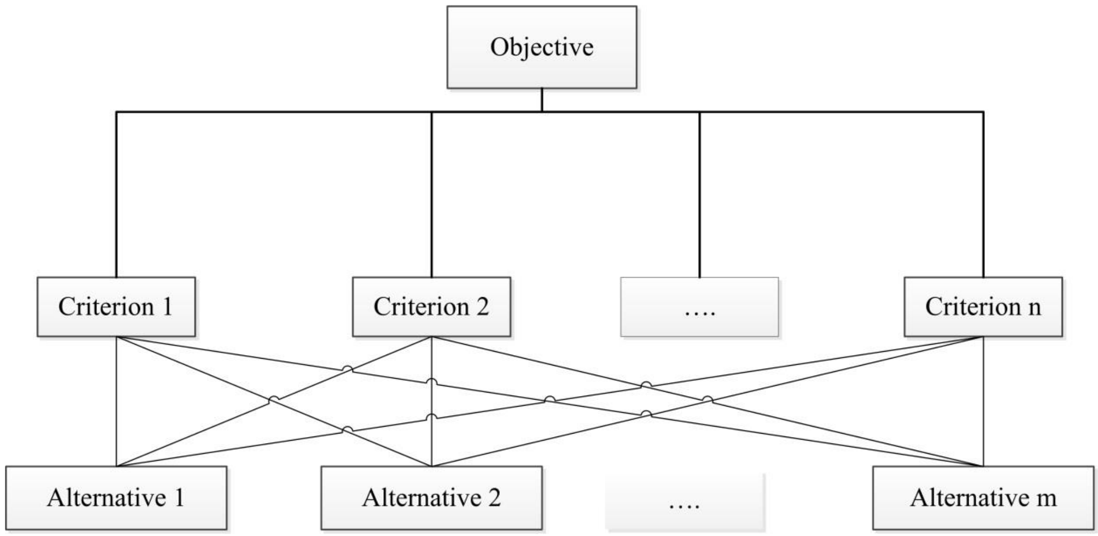


Figure 3.3. AHP Hierarchy Diagram

For each alternative, the consistency ratio, CR, is measured by the ratio of Consistency Index (CI) to Random Index (RI).

$$CR = \frac{CI}{RI} \tag{3.1}$$

where CI is calculated by measuring, Λ_{max} ,the maximum eigenvector of each comparison matrix with "n" alternatives, as follows

$$CI = \frac{\Lambda_{max} - n}{n-1} \tag{3.2}$$

RI is an index obtained from a randomly generated pairwise comparison matrix proposed by Saaty [255] as shown in the table below:

Table 3.2. RI Index proposed by Saaty [255] for Calculating Consistency Index

N	1	2	3	4	5	6	7	8	9	10
RI	0	0	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

$CR \leq 0.1$ implies a satisfactory degree of consistency in the pairwise comparison matrix; otherwise, serious inconsistencies might exist.

3.3.2. Analytic Network Process (ANP)

The Analytic Network Process (ANP) proposed by Saaty [217, 218] is an extension of AHP for studying the dependency and interdependency among criteria in different forms of structure (network) such as hierarchy, holarchy, suparchy,and intarchy [250]. ANP has four main steps as follows:

Step 1: Model construction and problem decomposition by forming clusters and nodes

Step 2: Pairwise comparisons for decision elements in each cluster and among clusters. In this step, a decision maker is asked to evaluate the importance of a criterion or a cluster compared to another criterion or cluster with respect to his/her preferences. For this, the ration scale is employed to compare from 1 to 9 where 1 is equal and 9 is extreme importance.

Step 3: Super matrix formation: The network or structure of the problem consists of the clusters and each cluster consists of the elements. The rows and columns of this matrix comprise comparison vectors, each of which compares the elements of each cluster .The general form of this supermatrix is:

$$W = \begin{array}{cc} & \begin{array}{cccc} c1 & \cdots & c_j & cm \end{array} \\ \begin{array}{c} c1 \\ \vdots \\ ci \\ cm \end{array} & \begin{bmatrix} w11 & \cdots & & w1m \\ \vdots & \ddots & & \vdots \\ \vdots & & wij & \vdots \\ wm1 & & \cdots & wmm \end{bmatrix} \end{array} \tag{3.3}$$

$$C_m = [e_{m1}, \quad \dots, \quad e_{mn_m}] \tag{3.4}$$

Where w is a supermatrix with $m \times m$ dimension, and w_{ij} is the principal eigenvector that denotes the pairwise comparison result of elements in the jth cluster to the ith cluster. C_m denotes the mth cluster with elements from $[e_{m1}, \dots, e_{mn_m}]$ where e_{mn_m} is nth element of cluster m. Assuming that the network structure below has three clusters, the supermatrix w can be expressed as

$$W = \begin{array}{c} \\ c1 \\ c2 \\ c3 \end{array} \begin{array}{c} \begin{array}{ccc} c1 & c2 & c3 \end{array} \\ \begin{bmatrix} w11 & w12 & w13 \\ 0 & 0 & w23 \\ 0 & w32 & w33 \end{bmatrix} \end{array}$$

where arcs represent the interaction of the elements in a cluster.

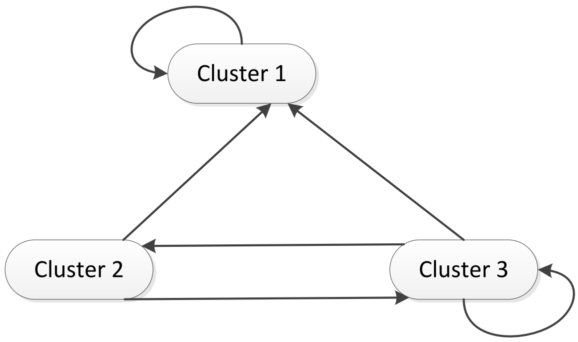


Figure 3.4. ANP Cluster Interactions Diagram

After forming the supermatrix, all columns add up to form the weighted supermatrix and afterwards the weighted supermatrix will be raised to limiting powers to achieve the global priority vectors as shown with the following equation:

$$\lim_{k\to\infty} W^k \tag{3.5}$$

Step 4: Selecting the best alternatives or weighting attributes when the convergence occurs in limiting supermatrix.

3.3.3. TOPSIS: Technique for Order Preference by Similarity to Ideal Solution

Of the numerous criteria decision-making (MCDM) methods, TOPSIS is a practical and useful technique for ranking and selecting a number of possible alternatives by measuring Euclidean distances. TOPSIS, developed by Hwang and Yoon [219], is a simple ranking method in conception and application.

The TOPSIS method [256] based on information entropy is proposed as a decision support tool for an energy manager to determine the effects of DRP on productivity and energy efficiency. In this section, ‘alternative’ refers to all the equipment and ‘criteria’ indexes determined in the previous section. There are two types of criteria. Positive criteria are those that should be increased and negative ones are those which need to be decreased in order to mitigate risk.

The purpose of this methodology is to first arrive at an ideal solution and a negative ideal solution, and then find a scenario which is nearest to the ideal solution and farthest from the negative ideal solution. This methodology can be implemented by taking the following steps:

Step 1: *Specify alternatives and criteria* for the equipment to which the energy must be allocated. This step is explained in the previous section. Assume that there are m possible alternatives called $A = \{ A_1, \dots, A_m\}$ which are to be evaluated against "c" criteria $C = \{C_1, \dots, C_c\}$.

Step 2: *Assign ratings to criteria and alternatives* using matrix X presented in (3.6) where x_{ij} indicates the value of alternative A_i for criterion C_g:

$$X_{m\times c} = \begin{array}{c} \\ A_1 \\ A_i \\ \vdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & C_g & C_c \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1c} \\ . & . & x_{ig} & . \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mc} \end{bmatrix} \end{array}. \qquad (3.6)$$

Step 3: *Calculate weight of criteria by entropy technique* to normalize the decision matrix (3.6) using formula (3.7):

$$q_{ig} = \frac{x_{ig}}{(x_{1g}+\cdots+x_{mg})}\ ; \qquad \forall g \in \{1, .., c\}. \qquad (3.7)$$

The information entropy of criterion g is given by definition of information entropy presented in (3.8):

$$\Delta_g = -k \sum_{i=1}^{m} q_{ig} \,.\ln q_{ig}\ ;\ \forall g \in \{1, .., c\} \qquad (3.8)$$

where $0 \leq \Delta_g \leq 1$ can be ensured with the coefficient k, through $k = 1/ln(m)$.

The Entropy technique for measuring the weights of criteria is an objective weight method which is determined by data statistical properties. This method is introduced and explained comprehensively by Shannon [257]. Generally, the index with bigger information entropy Δ_g has greater variation. Therefore, the weight through deviation degree d_g can be computed by (3.9):

$$d_g = 1 - \Delta_g\ , \qquad (g = 1, \dots, c). \qquad (3.9)$$

Finally, the weight for criteria by the entropy technique can be calculated as follows:

$$w_g = \frac{d_g}{(d_1+\cdots+d_c)} \qquad (3.10)$$

Eqs. (3.10) and (3.11) are used to aggregate the energy manager's weight vector λ_g and obtain the aggregated weight w'_g:

$$w'_g = \frac{\lambda_g . w_g}{(\lambda_1 . w_1 + \cdots + \lambda_c . w_c)} \tag{3.11}$$

$$w' = \{w'_1, w'_2, \ldots, w'_c\} \tag{3.12}$$

Step 4: *Construct a normalized decision matrix* using the vector normalization method, calculate normalized value r_{ig} by (3.13) and construct matrix $N_{m\times c}$ presented by (3.14):

$$r_{ig} = \frac{x_{ig}}{\sqrt{(x_{1g}^2 + \cdots + x_{mg}^2)}} \tag{3.13}$$

$$N_{m\times c} = [r_{ig}]_{m\times c}\,, \quad (i = 1, \ldots, m\,; g = 1, \ldots, c). \tag{3.14}$$

Step 5: *Construct the weighted normalized decision matrix* by building the diagonal matrix $w'_{c\times c}$ with element w'_g in 3.11 to reach the V matrix:

$$V = N_{m\times c} . w'_{c\times c} = (v_{ig})_{m\times c} \tag{3.15}$$

$(i = 1, \ldots, m\,;\ g = 1, \ldots, c)$.

Step 6: *Compute the positive ideal solution (PIS) A^+ and the negative ideal solution (NIS) A^-* of the alternatives:

$$A^+ = \left\{\left(\max v_{ig}\,|g \in G\right); \left(\min v_{ig}|\ g \in G'\right)\right\} = ({v_1}^+, {v_2}^+, \ldots, {v_c}^+) \tag{3.16}$$

$$A^- = \left\{\left(\min v_{ig}\,|g \in G\right); \left(\max v_{ig}|\ g \in G'\right)\right\} = ({v_1}^-, {v_2}^-, \ldots, {v_c}^-). \tag{3.17}$$

where G and G' are the subsets of positive and negative criteria, respectively.

Step 7: *Compute the distance of each alternative from PIS (${d_i}^+$) and NIS (${d_i}^-$):*

$${d_i}^+ = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^+\right)^2} \tag{3.18}$$

$${d_i}^- = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^-\right)^2} \tag{3.19}$$

Step 8: *Compute the closeness coefficient of each alternative:*

$${CC_i}^+ = \frac{{d_i}^-}{({d_i}^- + {d_i}^+)} \quad ; \quad i = 1, 2, \ldots, m \tag{3.20}$$

Step 9: *Rank the alternatives:*

$$v = \left\{v_i|\ \max_{1\leq i\leq m}({CC_i}^+)\right\} \tag{3.21}$$

Table 3.3. Matlab Programming Function Code for TOPSIS Method

```
function [ cc ] = topsis(decisionMakingMatrix,landaWeight,criteriaSign )
 %-Technique for Order of Preference by Similarity to Ideal Solution
 % -Author: Omid Ameri Sianaki
 %-This function implements TOPSIS method with Information entropy
 % weighting Method
% - criteriaSign is a vector specifying whether a criterion has to be maximized
% or minimized . +1 is for positive criterion and -1 for negative criterion
%%%%%%%%%%%%%%%%%%%%%%%
sumDmm=sum(decisionMakingMatrix())
sumDmmMatrix=repmat(sumDmm,size(decisionMakingMatrix,1),1)
pij=decisionMakingMatrix./sumDmmMatrix
lnm= -1 / log(size(decisionMakingMatrix,1));
lnNormDmm = log(pij)
E=lnm .* sum(pij .* lnNormDmm)
dj=ones(1,size(E,2))-E
weightEntropy=dj ./sum(dj)
wt=landaWeight .*weightEntropy ./sum(landaWeight .*weightEntropy)
sqrtxij=sqrt(sum(decisionMakingMatrix().^2)) ;
N=decisionMakingMatrix./repmat(sqrtxij,[size(decisionMakingMatrix,1) 1]);
Wj=eye(size(wt,2)) .* repmat(wt.*criteriaSign,size(wt,2),1)
V=N*Wj;
Apositive=max(V);
Anegative= min(V);
ApositivMtrix=repmat(Apositive,size(V,1),1);
AnegativeMtrix=repmat(Anegative,size(V,1),1);
s1=(V-ApositivMtrix).^2
s2=(V-AnegativeMtrix).^2;
for (j=1:1:size(s1,1))
sumAPositive(j)=sum(s1(j,:));
end
for (j=1:1:size(s2,1))
sumANegative(j)=sum(s2(j,:))
```

Table 3.3. Continue. Matlab Programming Function Code for TOPSIS Method

```
end
dpositive=sqrt(sumAPositive);
dnegative=sqrt(sumANegative);
sumD=dnegative+dpositive;
cc=dnegative./sumD
```

The final step takes us to the ranking of alternatives. This ranking indicates that the alternative with the higher value has greater importance and priority.

The above formulas and steps have been programmed in Matlab software as shown in Table 3.3.

3.3.4. Fuzzy TOPSIS Method

The working principle of fuzzy TOPSIS is based on the fact that the selected alternative should have the shortest distance from the fuzzy positive ideal solution (FPIS) and the farthest from the fuzzy negative ideal solution (FNIS) for solving MCDM problems. As a result, the ideal solution comprises all the best criteria, whereas the negative ideal solution is made up of all the worst criteria [258].

The stepwise procedure for implementing fuzzy TOPSIS is presented in Fig 3.5. By forming an initial decision matrix, the normalizing procedure of the decision matrix will be started. This is followed by building the weighted normalized decision matrix in Step 5, compute the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) in Step 6, and calculating the separation measures for each alternative in Step 7.

The procedure ends with the computation of the relative closeness coefficient in Step 8. The set of alternatives can be ranked according to the descending order of the closeness coefficient in Step 9. The steps of the fuzzy TOPSIS algorithm are as follows:

Step 1*: Assign ratings to the criteria and the alternatives.*

Let us assume that there are m possible home areas called $A = \{A_1, A_2, .. A_m\}$ which are to evaluated against c criteria, $C = \{C_1\ , C_2, \dots, , C_c\}$. The criteria weights are denoted by $w_g\ (g = 1, 2, \dots, c)$. The ratings of each decision-maker $D_k = (k = 1, 2, \dots, k)$ for each alternative $A_{ki} = (i = 1, 2, \ldots, m)$ with respect to criteria C_g $(g = 1, 2, \ldots, c)$ are denoted by $\tilde{R}_k = \tilde{x}_{igk}$ with membership function $\mu_{\tilde{R}_k}(x)$.

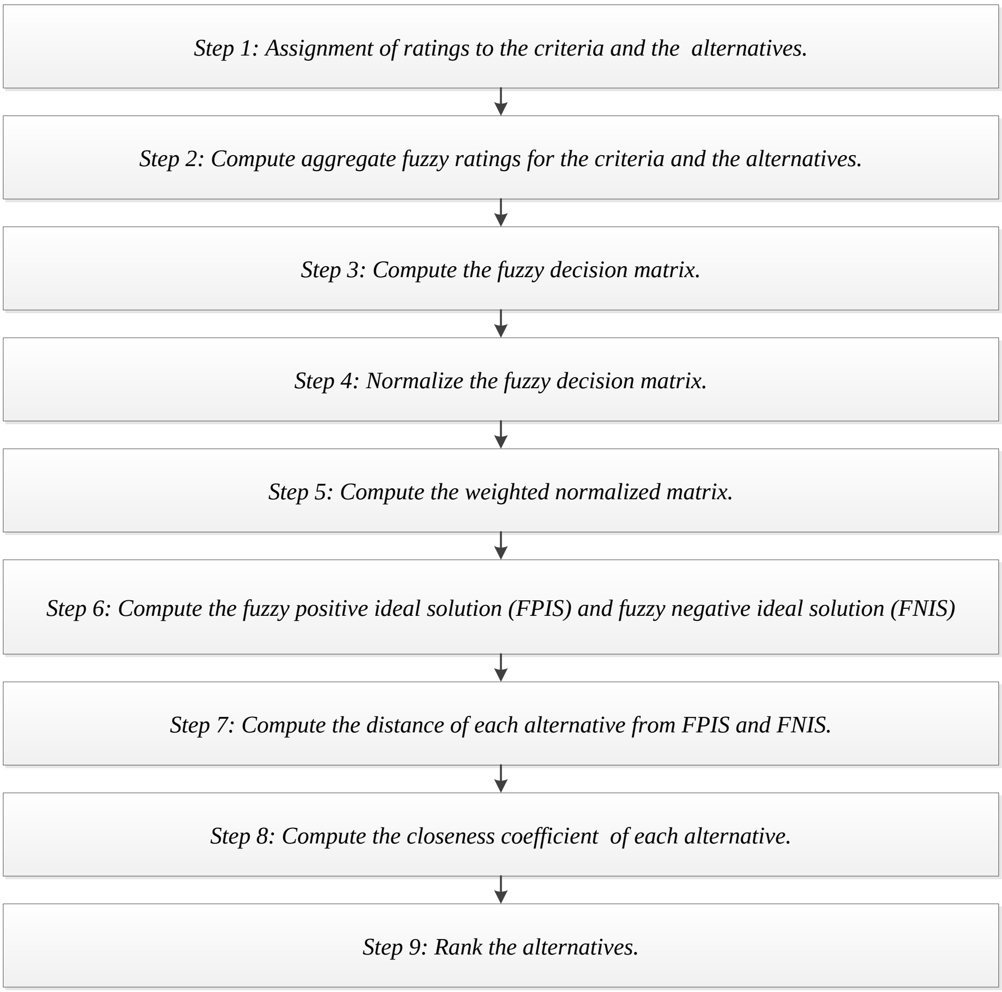


Figure 3.5. The Steps of the Fuzzy TOPSIS Algorithm

Step 2*: Compute aggregate fuzzy ratings for the criteria and the alternatives.*

If the fuzzy rating of all consumers or family members is represented as a triangular fuzzy number

$$\tilde{R}_k = (a_k, b_k, c_k), k = 1, 2, \ldots, K \tag{3.22}$$

then the aggregated fuzzy rating is given by $\tilde{R} = (a, b, c), k = 1, 2, \ldots, K$ where

$$a = min_k\{a_k\} \quad b = \frac{1}{k}\sum_{k=1}^{k} b_k \quad c = max_k\,\{c_k\} \tag{3.23}$$

If the fuzzy rating and importance weight of the kth decision maker are

$$\tilde{x}_{igk} = (a_{igk}, b_{igk}, c_{igk}) \tag{3.24}$$

and

$$\tilde{w}_{igk} = \left(w_{gk1}, w_{gk2}, w_{gk3}\right), \quad \mathrm{i} = 1, 2, \ldots, \mathrm{m}\ ,\ \mathrm{g} = 1, 2, \ldots, \mathrm{n} \tag{3.25}$$

respectively, then the aggregated fuzzy ratings $\tilde{x}_{ijk}$ of alternative with respect to each criterion are given by

$$\tilde{x}_{ij} = \left(a_{ig}, b_{ig}, c_{ig}\right); \tag{3.26}$$

where,

$$a_{ig} = min_k\{a_{igk}\} \tag{3.27}$$

$$b_{ig} = \frac{1}{k}\sum_{k=1}^{k} b_{igk} \tag{3.28}$$

$$c_{ig} = max_k\,\{c_{igk}\} \tag{3.29}$$

The aggregated fuzzy weights $(\widetilde{w}_{ij})$ of each criterion are calculated as $\widetilde{w}_{ig} =$

$$\left(w_{g1}, w_{g2}, w_{g3}\right) \tag{3.30}$$

where

$$w_{g1} = min_k\{w_{gk1}\};\ w_{g2} = \frac{1}{k}\sum_{k=1}^{k} w_{jk2}\ ;\ w_{g3} = max_k\,\{w_{jk3}\} \tag{3.31}$$

Step 3*: Compute the fuzzy decision matrix.*

The fuzzy decision matrix for the alternatives $(\widetilde{D})$ and the criteria $(\widetilde{W})$ is constructed as follows:

$$\widetilde{D} = \begin{array}{c} A_1 \\ A_{..} \\ A_m \end{array} \begin{bmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1c} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mc} \end{bmatrix} \tag{3.32}$$

$$\widetilde{W} = (\widetilde{w}_1, \widetilde{w}_2, \ldots, \widetilde{w}_c) \tag{3.33}$$

Step 4*: Normalize the fuzzy decision matrix.*

The raw data are normalized to bring the various criteria scales into a comparable scale. The normalized fuzzy decision matrix is $\tilde{R}$ given by:

$$\tilde{R} = \left[\tilde{r}_{ig}\right]_{m\times c},\ i = 1, 2, \ldots, m;\ g = 1, 2, \ldots, c \tag{3.34}$$

Where for benefit criterion

$$\tilde{r}_{ig} = \left(\frac{a_{ig,}}{c_g^+}, \frac{b}{c_g^+}, \frac{c_{ig,}}{c_g^+}\right) \tag{3.35}$$

and

$$c_g^+ = max_i\, c_{ig} \text{ (Benefit criterion)} \tag{3.36}$$

and for cost criterion:

$$\tilde{r}_{ig} = \left(\frac{a_g^-}{c_{ig}}, \frac{a_g^-}{b_{ig}}, \frac{a_g^-}{a_{ig}}\right) \tag{3.37}$$

and

$$a_g^- = maxmin_i \; a_{ig} \quad \text{(Cost criterion)} \tag{3.38}$$

***Step 5**: Compute the weighted normalized matrix.*

The weighted normalized matrix $\tilde{V}$for criteria is computed by multiplying the weights ($\widetilde{w}_j$) of the evaluation criteria with the normalized fuzzy decision matrix normalization of the decision matrix $\tilde{r}_{ij}$

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m\times c} \; i = 1, 2, \dots, c; j = 1, 2, \dots, m \tag{3.39}$$

where $\tilde{v}_{ij} = \tilde{r}_{ij} \times \; \widetilde{w}_{ij}$ (3.40)

***Step 6**: Compute the fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS)*

The FPIS and FNIS of the alternatives are computed as follows:

$$A^+ = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_m^+) \tag{3.41}$$

Where

$$\tilde{v}_i^+ = max_i \left\{v_{ig3}\right\}, \quad \text{g} = 1, 2, \dots, \text{c} \;, \; \text{i} = 1, 2, \dots, \text{m} \tag{3.42}$$

and

$$A^- = (\tilde{v}_1^+, \tilde{v}_2^+, \dots, \tilde{v}_m^+) \tag{3.43}$$

Where

$$\tilde{v}_i^- = min_i \left\{v_{ig1}\right\}, \; \text{g} = 1, 2, \dots, \text{c} \;, \; \text{i} = 1, 2, \dots, \text{m} \tag{3.44}$$

***Step 7**: Compute the distance of each alternative from FPIS and FNIS.*

The distance(d_i^+,d_i^-) of each weighted alternative $i = 1, 2, \dots, m$ from the FPIS and the FNIS is computed as follows:

$$d_i^+ = \sum_{i=1}^{m} d_v \left(\tilde{v}_{ig}, \tilde{v}_{ig}^+\right), \; i = 1, 2, \dots, m \; ; \text{g} = 1, 2, \dots, \text{c} \tag{3.45}$$

$$d_i^- = \sum_{i=1}^{m} d_v \left(\tilde{v}_{ij}, \tilde{v}_{ig}^-\right), \; i = 1, 2, \dots, m \; ; \text{g} = 1, 2, \dots, \text{c} \tag{3.46}$$

Where $d_v\ (\tilde{a}, \tilde{b})$ is the distance measurement between two fuzzy numbers $\tilde{a}$ and $\tilde{b}$.

***Step 8**: Compute the closeness coefficient* (CC_i) *of each alternative.*

The closeness coefficient CC_i represents the distances to the fuzzy positive ideal solution (A^+) and the fuzzy negative ideal solution(A^-) simultaneously. The closeness coefficient of each alternative is calculated by:

$$(CC_i) = \frac{d_i^-}{d_i^- + d_i^+} \quad \mathrm{i} = 1, 2, \dots, \mathrm{m} \tag{3.47}$$

***Step 9**: Rank the alternatives.*

In Step 9, the different alternatives are ranked according to the closeness coefficient (CC_i) in decreasing order. The best alternative is closest to the FPIS and farthest from the FNIS.

3.3.5. ELECTRE Method

The acronym ELECTRE stands for "ELimination Et Choix Traduisant la REalité" that in English translates to "Elimination and Choice Expressing the Reality". This method is included in the concordance subgroup, one of the multi-criteria decision-making compensatory types and is considered as an outranking method.

The methodology developed by [259] uses binary outranking relations, "S", for modelling the preferences as it has been described by [260] ."S" means "at least as good as" and for outranking two alternatives such as "a_1" and "a_2", four situations may occur:

1. $a_1\mathrm{S}a_2$ & -($a_2\mathrm{S}a_1$) : this relationship can be stated as "a_1" is at least as good as "a_2" and "a_2" is not at least as good as "a_1" or, "a_1" is strictly preferred to "a_2" that it can be shown by '$a_1\mathrm{P}a_2$'.
2. $a_2\mathrm{S}a_1$ & -$a_1\mathrm{S}a_2$: "a_2" is strictly preferred to "a_1" or $a_2\mathrm{P}a_1$.
3. $a_1\mathrm{S}a_2$ & $a_2\mathrm{S}a_1$: "a_1" is indifferent to "a_2": $a_1\mathrm{I}a_2$
4. -($a_1\mathrm{S}a_2$) & -($a_2\mathrm{S}a_1$): "a_1" is incomparable to "a_2" : $a_1\mathrm{R}a_2$

By this comparison, a major concept is concordance for asserting $a_1\mathrm{S}a_2$ which means that this outranking relation is valid when the majority of the criteria support this assertion [260]. So in this approach when a decision maker accepts $a_1\mathrm{S}a_2$, it means the DM is accepted the risk of a_1 in which it dominates a_2.Moreover, the *concordance* criterion is defined by Roy [220] as " the j th criterion is in concordance with the assertion $a_1\mathrm{S}a_2$ if and only if $a_1S_ja_2$", and similarly the *discordance criterion* or *index* is defined as "the jth criterion is in discordance with the assertion $a_1 S_j a_2$ if and only if $a_1 P_j a_2$." So constructing the subsets of concordance and discordance of all criteria (called *coalition*) by a systematic comparison of alternatives to each criterion is inherent to this methodology.

The objective of the ELECTRE method is to assist DMs to choose a subset of alternatives, as limited as possible, by means of which a single alternative may finally be selected [260]. The ELECTRE methodology is similar to steps 1 to 5 in the TOPSIS methodology in which t*he weighted normalized decision matrix* V is built. The other steps are as follows:

Call the TOPSIS method, $A = \{ A_1, \dots A_m\}$ is a set of alternatives which are to be evaluated against c criteria $C = \{C_1, \dots, C_c\}$. "g" is a subset for criteria and "i" is a subset to include alternatives. By implementing steps 1 to 5 of the TOPSIS method, the V matrix is calculated using:

$$V = N_{m\times c}.w'_{c\times c} = (v_{ig})_{m\times c}$$
$$(i = 1, \dots, m\,;\; g = 1, \dots, c).$$

Step 6: *Forming the concordance and discordance subsets*

I define the subscripts "l","k" for showing the alternatives which are being outranked with regard to criterion "j" in matrix "V". So "l" and "k" cannot be equal and the concordance subset of alternatives "l" and "k" can be shown

$$S(l,k) = \{C, V_{lj} \geq V_{kj}\}\,;\, j \in g \tag{3.48}$$

The above relation indicates a set of criteria (in matrix"V") in which the value of alternative "l" is preferred to alternative "k". The complement of the concordance set is the discordance set which is a set of criteria where the alternative "k" is preferred to alternative "l".

$$D(l,k) = \{C, V_{lj} < V_{kj}\} \tag{3.49}$$

Step 7: *Forming the Concordance Index and Matrix*

$$I_{lk} = \sum_{j\in S(l,k)} w_j\,,\quad 0 \leq I_{lk} \leq 1 \tag{3.50}$$

$$I = [I_{lk}]_{m\times m} \tag{3.51}$$

Step 8: *Forming the Discordance Index and Matrix*

$$NI_{lk} = \frac{max_{j \in D(l,k)} |V_{lj} - V_{kj}|}{max_{j \in g} |V_{lj} - V_{kj}|} \tag{3.52}$$

$$NI = [NI_{lk}]_{m \times m} \tag{3.53}$$

***Step 9**: Determining the threshold concordance and discordance Matrices*

In this step, the threshold concordance and discordance values by forming the matrices $\bar{I}$ and $\overline{NI}$ are determined for evaluation of outranking the alternatives. Afterwards, the result of this evaluation can be summarized in the Boolean matrices F and G.

$$\bar{I} = \sum_{k=1}^{m} \sum_{l=1}^{m} {I_{l,k}}/{m(m-1)} \tag{3.54}$$

$$\overline{NI} = \sum_{k=1}^{m} \sum_{l=1}^{m} {NI_{l,k}}/{m(m-1)} \tag{3.55}$$

The binary relation of concordance values by forming Boolean matrix F is as follows:

$$f_{lk} = \begin{cases} 1 \rightarrow I_{lk} \geq \bar{I} \\ 0 \rightarrow I_{lk} < \bar{I} \end{cases} \tag{3.56}$$

$$F = [f_{lk}]_{m \times m} \tag{3.57}$$

The binary relation of concordance values by forming Boolean matrix G is as follows:

$$g_{lk} = \begin{cases} 1 \rightarrow NI_{lk} \geq \overline{NI} \\ 0 \rightarrow NI_{lk} < \overline{NI} \end{cases} \tag{3.58}$$

$$G = [g_{lk}]_{m \times m} \tag{3.59}$$

***Step 10**: Determining the total outranking relation matrix*

Matrix H is formed to achieve the final outranking of the alternatives by comparing the Boolean matrices F and G.

$$h_{lk} = f_{lk} \times g_{lk} \tag{3.60}$$

$$H = [h_{lk}]_{m \times m} \tag{3.61}$$

I have programmed the aforementioned formulas and steps in Matlab software as shown in Table 3.4.

Table 3.4. Matlab Programming Function Code for ELECTRE Method

```
function[h]=electreEntropy(decisionMakingMatrix,lambdaWeight,criteriaSign)
% Author: Omid Ameri Sianaki
%This function implements ELECTRE I method with Information Entropy
 % weighting Method
%%%%%%%%%%%%%%%%%%%%%%%%
sumDecisionMaking = sum(decisionMakingMatrix())
sumDecisionMakingMatrix=repmat(sumDecisionMaking,size(decisionMakingMatrix,1),1)
decisionMakingMatrixsumNorm=decisionMakingMatrix./sumDecisionMakingMatrix
lnm=-1/log(size(decisionMakingMatrix,1))
lnDecisionMakingMatrixsumNorm = log(decisionMakingMatrixsumNorm);
E=lnm.*sum(decisionMakingMatrixsumNorm.*lnDecisionMakingMatrixsumNorm);
d=ones(1,size(E,2))-E;
weightEntropy=d ./sum(d);
wt=lambdaWeight .*weightEntropy ./sum(lambdaWeight .*weightEntropy);
clsm=sqrt(sum(decisionMakingMatrix().^2));
nDecisionMakingMatrix=decisionMakingMatrix./repmat(clsm,size(decisionMakingMatrix,1),1);
wtmat=eye(size(wt,2)) .* repmat(wt.*criteriaSign,size(wt,2),1);
v=nDecisionMakingMatrix*wtmat;
concordance=zeros(size(decisionMakingMatrix,1))    ;
for(i=1:1:size(decisionMakingMatrix,1))
  for(j=1:1:size(decisionMakingMatrix,1))
  concordance(i,j)=sum(double(v(i,:)>=v(j,:)).*wt);
 end
end
discordance=zeros(size(decisionMakingMatrix,1)) ;
for(i=1:1:size(decisionMakingMatrix,1))
 for(j=1:1:size(decisionMakingMatrix,1))
  discordance(i,j)=max(abs(double(v(i,:)<v(j,:)).*(  v(i,:)-  v(j,:))))/max(abs(  v(i,:)-v(j,:)));
   end
```

Table 3.4. Continue. Matlab Programming Function Code for ELECTRE Method

```
end
concordance(isnan(concordance)) = 0 ;
concordance=concordance.*(eye(size(decisionMakingMatrix,1))-1) .*-1;
discordance(isnan(discordance)) = 0  ;
discordance=discordance.*(eye(size(decisionMakingMatrix,1))-1) .*-1;
alpha=sum(sum(concordance ./(size(decisionMakingMatrix,1)*
(size(decisionMakingMatrix,1)-1))));
beta=sum(sum(discordance ./(size(decisionMakingMatrix,1)*
(size(decisionMakingMatrix,1)-1))));
f=concordance>=alpha;
g=discordance<=beta;
h=(f.*g ).*(eye(size(decisionMakingMatrix,1))-1) .*-1
xlswrite('excelFile.xlsx',h, 'sheetName', 'cellAddress')
end
```

3.4. Criteria for Decision Making on Energy Management

As discussed, and shown in Fig 3.2, the selection of criteria is the first step in the decision-making process. In this approach, the selection of appropriate criteria can be done by referring to the literature review presented in Chapter 2. Table 3.5 shows a list of criteria can be applied to the decision-making process regarding energy consumption in the residential sector. In the following, I show how these criteria may be utilized by users in different approaches.

Table 3.5. The List of Criteria for Assessing Energy Consumption in a Residence

	Criterion	**Definition**
$\mathbf{c_1}$	Energy Cost	Energy consumption cost of all electrical devices in area A_i in time slot t_1
$\mathbf{c_2}$	Budget	The amount of budget that users are prepared to expend on utilizing the appliances in area A_i
$\mathbf{c_3}$	Urgency	Energy demand necessity for each area in time slot t_1
$\mathbf{c_4}$	Thermal Comfort	The level of thermal comfort for each area in time slot t_1
$\mathbf{c_5}$	Visual Comfort	The level of visual comfort for each area in time slot t_1

Table 3.5. Continue. The List of Criteria for Assessing Energy Consumption in a Residence

	Criterion	Definition
c_6	IAQ Comfort	The level of indoor air quality for each area in time slot t_1
c_7	GHG emission	Greenhouse gas emissions produced by consumption in areas
c_8	Energy efficiency score	Energy efficiency rate provided for users that can be compared with data for neighbors and other households (in social network or in a region)
c_9	Carbon tax	The amount of carbon tax allocated to areas by consumed energy
c_{10}	Occupancy level	Amount of time that a dwelling is occupied.
c_{11}	Power (watt)	Amount of power required for an appliance to operate a task
c_{12}	Operation time	The time of doing a task by using an appliance
c_{13}	Enjoyment	The amount of amusement and/or happiness achieved by using an appliance
c_{14}	Welfare	The well-being condition attained by using an appliance
c_{15}	Energy (kw.h)	The amount of energy required for an appliance to execute a task

For criteria that are qualitative, I use a rating scale as shown in Table. 3.6.

Table 3.6. Rating Scale for Qualitative Criteria

	Much less		**Less**			**Average**	**More**			**Much More**
Value	0	1	2	3	4	5	7	8	9	10

In the following section, I present various scenarios in which the above methodologies and criteria are used to help consumers to have an overview of their energy consumption.

3.5. Application of Decision Making Methods in Energy Management in Demand Response of Smart Grid

3.5.1. AHP Application

Structuring any decision problem hierarchically is an efficient way of dealing with complexity and identifying the major components of the problem [261]. As earlier discussed, the Analytic Hierarchy Process (AHP) is a common theory of measurement. It is used to derive ratio scales from both discrete and continuous paired comparisons. These comparisons may be taken from actual measurements or from a fundamental scale which reflects the relative strength of preferences and feeling [262].

In this approach, I present a scenario that provides a good example of AHP application for ranking the consumers' preferences regarding the use of some typical appliances during peak hours when the price of electricity has increased. I have assumed that there is an end-user who judges seven appliances. These appliances, as shown in Table 3.7, are Dishwasher (DW), Home computer (HC), Hair dryer (HD), Iron (IR), Spa Bath (SB), Television (TV), and Vacuum Cleaner (VC). Our goal in this scenario is to rank the appliances according to several criteria that will be used by the consumer to ascertain their level of importance to him. I asked the consumer to compare his use of electrical devices based on priority in a pairwise comparison, according to criteria during peak hours when the price increased from \$0.15 kW.h to \$0.2 kW.h at peak period. The criteria are: Urgency, welfare and enjoyment derived from using appliances, and the cost of electricity as shown by a hierarchy model in Figure 3.6. The consumers use appliances for their essential requirements, welfare or enjoyment needs. For example, from a student's perspective, using a computer during peak hours can be considered as an urgent and imperative need, whereas it may be an enjoyment for a mature adult. In the next sections, I will expand on our methodology.

After creating a hierarchical model, the priorities are established among the elements of the hierarchy by making judgments based on the pairwise comparisons. For example, by comparing the appliances, the consumer might say he prefers to have imperative use of appliances during peak hours even if the price increases, or he might prefer to enjoy using appliances regardless of the cost, or conversely, he might prefer to save money and not to use the appliances that bring him enjoyment during peak hours.

Then, in order to arrive at a set of overall priorities for the hierarchy of all appliances, the judgments will be synthesized for each criterion. For example, the consumer will judge the level of emergent use of his seven appliances according to the most emergent to less emergent one according to his preference. I used the Expert Choice software, EC11.5 [263] to arrive at the consumer judgment about each element and also to process and to measure the hierarchy. The results of the numerical priority of criteria and alternatives are presented at Figure 3.10. The inconsistency value of judgment in this scenario for all measurements was less than 0.0002, meaning that the user has an acceptable level of consistency in his judgment.

Table 3.7. Appliance Specifications

	Appliance	***Power - kW***	***Hour of usage***	***Off-peak time cost- $***	***On-peak time cost- $***
1	Iron	0.933	0.5	0.07	0.093
2	Television	0.200	1.0	0.03	0.40
3	Spa bath with 5 kW heater	4.933	0.5	0.373	0.493
4	Vacuum cleaner	0.933	0.5	0.07	0.093
5	Dishwasher	1.867	1.0	0.28	0.373
6	Hair dryer	1.467	0.3	0.066	0.088
7	Home computer	0.067	1.0	0.01	0.013
The cost of electricity for one-hour use				0.896	1.195

As a result, it is specified that according to four criteria of emergency usage of appliances, welfare and enjoyment derived from them and the electrical cost of usage, when the electrical price increases from 0.15$/kW.h to 0.2 $/ kW.h or 0.33 percent during peak hours, the consumer prefers to use the Spa Bath with highest priority and the Iron with lowest priority. The final preference ranking is presented in Table 3.8.

In this scenario, the user is able to input the preferences in order to compare the appliances based on a criterion by adjusting a graphical control scrollbar (horizontal slider) as shown in Figure 3.7. As can be seen, in each step the user has to input data for pairwise comparison. However, in demand response programs, it is difficult and overwhelming for consumers to input data continuously. Moreover, the number of appliances is not limited to five or six as presented in the scenario; it can be an unlimited number. So, I offer decision-making methods that can be applied by users who wish to have control over consumption, and which are less dependent on decision-maker interaction. Hence, in the next section, by means of various scenarios, I explain how the ELECTRE and TOPSIS methods may assist users.

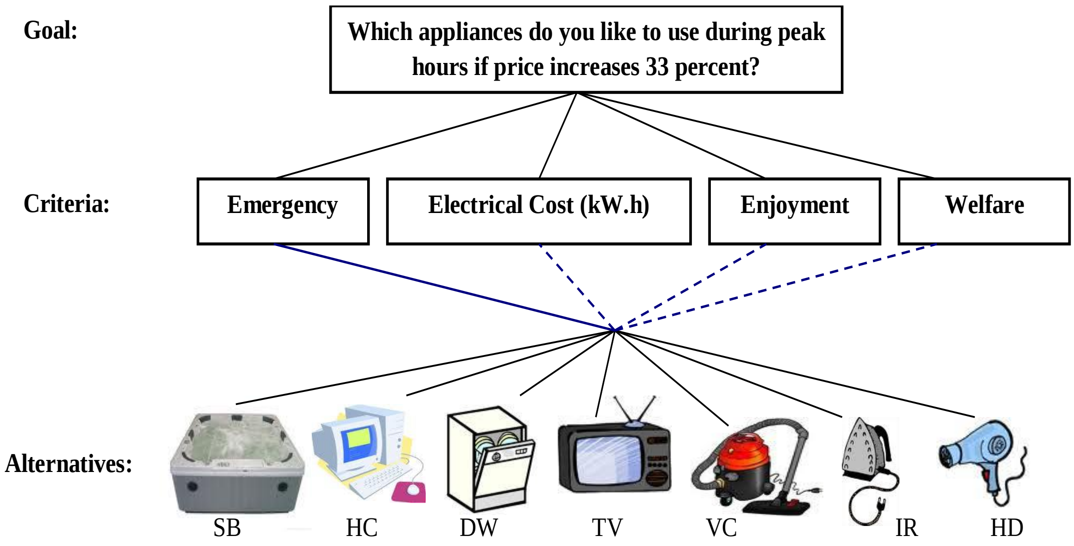
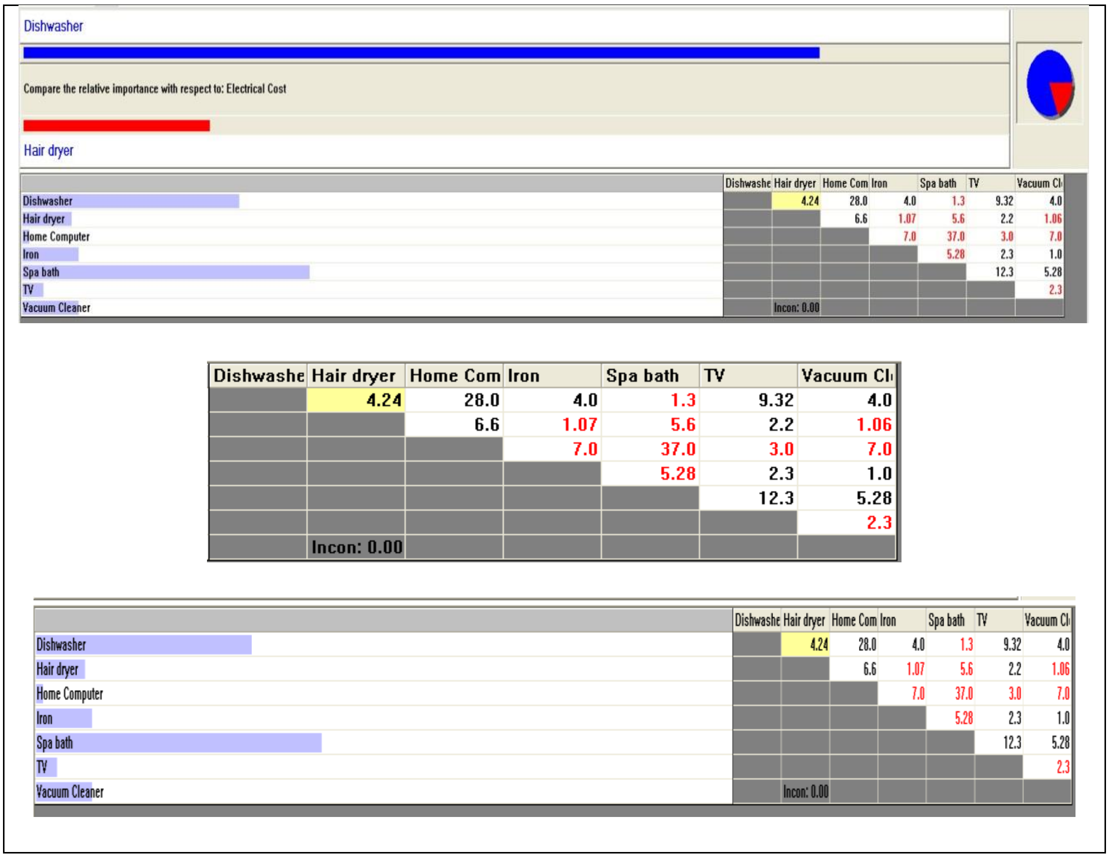


Figure 3.6. AHP Hierarchy in the Given Scenario



Dishwashe	Hair dryer	Home Com	Iron	Spa bath	TV	Vacuum Cl
	4.24	28.0	4.0	1.3	9.32	4.0
		6.6	1.07	5.6	2.2	1.06
			7.0	37.0	3.0	7.0
				5.28	2.3	1.0
					12.3	5.28
						2.3
	Incon: 0.00					

Figure 3.7. Inputting Data by User for Appliances Pairwise Comparison based on Electrical Cost in Expert Choice Software

Priorities with respect to:
Goal: Which electrical devices do you like to use during peak hours?
>Electrical Cost

Spa bath	.412
Dishwasher	.313
Iron	.078
Vacuum Cleaner	.078
Hair dryer	.074
TV	.034
Home Computer	.011

Inconsistency = 0.00001
with 0 missing judgments.

Priorities with respect to:
Goal: Which electrical devices do you like to use during peak hours?
>Emergency

Home Computer	.324
Dishwasher	.190
Spa bath	.152
Vacuum Cleaner	.125
Hair dryer	.098
TV	.062
Iron	.048

Inconsistency = 0.00028
with 0 missing judgments.

Priorities with respect to:
Goal: Which electrical devices do you like to use during peak hours?
>Welfare and comfort

Dishwasher	.262
TV	.188
Spa bath	.169
Vacuum Cleaner	.167
Home Computer	.159
Iron	.033
Hair dryer	.021

Inconsistency = 0.00017
with 0 missing judgments.

Priorities with respect to:
Goal: Which electrical devices do you like to use during peak hours?
>Joy

Spa bath	.331
TV	.282
Home Computer	.169
Dishwasher	.093
Hair dryer	.053
Vacuum Cleaner	.043
Iron	.029

Inconsistency = 0.00031
with 0 missing judgments.

Figure 3.8. Result of Appliances Ranking Based on Each Criterion

Priorities with respect to:
Goal: Which electrical devices do you like to use during peak hours?

Emergency	.358
Electrical Cost	.313
Welfare and comfort	.247
Joyness	.082

Inconsistency = 0.00046
with 0 missing judgments.

Figure 3.9. Final Result of Criteria Ranking in Proposed Scenario

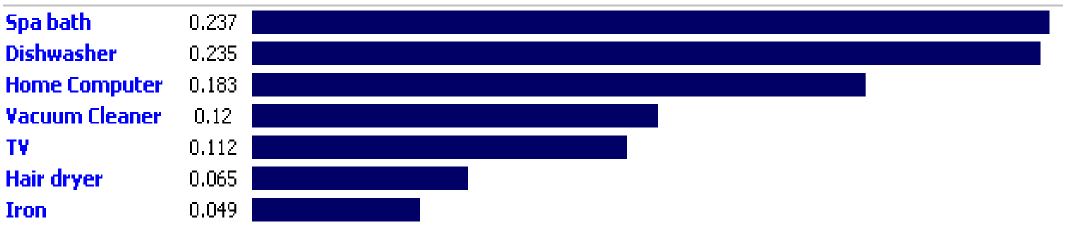


Figure 3.10. Final Appliances Ranking by AHP Method

Table 3.8. Summary of Final Decision-making

Goal: Which electrical devices do you prefer to use during peak hours when the price of electricity increases by 33 percent?	
Appliance ranking	***Numerical priority***
1- Spa Bath	0.237
2- Dishwasher	0.235
3- Home Computer	0.183
4- Vacuum Cleaner	0.120
5- TV	0.112
6- Hair Dryer	0.065
7- Iron	0.049

3.5.2. Fuzzy TOPSIS Methodology for Home Energy Management System

In Chapter 2, I stated that householders have different characteristics in terms of cultural background, gender, income, level of education and social status. Moreover, they may have to deal with different energy policies, subsidies and energy supply, all of which mean that they may use appliances differently.

This difference may be due to the different criteria that are shown in Tables 3.5. Criteria such as cost and budget are based on householders' income [264]; and energy demand urgency and comfort level are associated with the consumers' lifestyle [20, 47, 115].

In Chapter 1, I explained that the smart grid concept is intended to support "green" sources [21], and the emission trading scheme and carbon tax policy are designed to impact on the energy demand [265]. Moreover, several criteria have been identified by consumer's attitudes and behavior towards the green electricity market [266, 267] such as green gas emission, carbon tax and energy efficiency score. Two types of criteria are presented in Table 3.9. The criteria with higher values produce profit (positive) or adversely produce more cost (negative). Therefore, I try to decrease cost and increase profit when making decisions.

In section 3.3.4, a scenario is presented to demonstrate the application of fuzzy TOPSIS methodology in facilitating energy management in the smart grid. In this scenario, the conversion scale is applied to transform the linguistic terms for determining the rating of alternatives and criteria into fuzzy numbers as shown by the fuzzy triangular membership function in Fig 3.11.

In this scenario, there are two users in a house with different incomes and cultural backgrounds. I refer to the comfort management section in Chapter 2, section 2.6. to measure the comfort parameters for these users. The primary data about users and environment are presented in Tables 3.10-17.

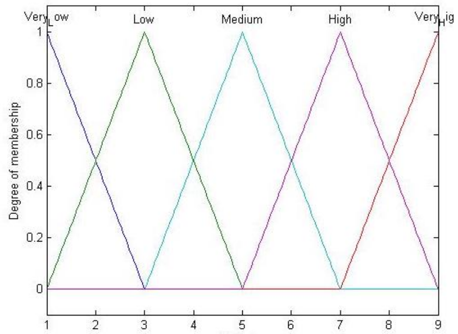


Figure 3.11. Fuzzy Triangular Membership

Table 3.9. Criteria Applicable for Decision-making by Fuzzy TOPSIS Methodology

	Criterion	Definition	Type
c_1	Energy Cost	Energy consumption cost of all electrical devices in area A_i in time slot t_1	-
c_2	Budget	The amount of budget that users are prepared to expend on utilizing the appliances in area A_i	-
c_3	Urgency	Energy demand urgency for each area in time slot t_1	-
c_4	Thermal Comfort level	The level of thermal comfort level for each area in time slot t_1	+
c_5	Visual Comfort level	The level of visual comfort for each area in time slot t_1	+
c_6	IAQ Comfort level	The level of indoor air quality for each area in time slot t_1	+
c_7	GHG emission	Greenhouse gas emissions that are produced by consumption in areas	-
c_8	Energy efficiency score	Energy efficiency rate provided for users that can be compared with data for neighbors and other households (in social network or in a region)	+
c_9	Carbon tax	The amount of carbon tax allocated to areas by consumed energy	-
c_{10}	Occupancy level	Amount of time that a dwelling is occupied.	+

- User 1 does not care about cost and wants a high level of comfort by utilizing energy. This user is engaged in an activity that requires more light.
- User 2 is concerned about environmental issues and is a green consumer.

Table 3.10. User 1's Characteristics for Calculating PMV

Parameter	***Value***
M=Metabolic energy production ((W/m^2)	180
W= Rate of mechanical work (W/m^2)	0
I_{cl} = Basic clothing insulation (clo)	1

Table 3.11. User 2's Characteristics for Calculating PMV

Parameter	***Value***
M=Metabolic energy production ((W/m^2)	80
W= Rate of mechanical work (W/m^2)	0
I_{cl} = Basic clothing insulation (clo)	2

Formulas 2.1-4 are used for calculating the PMV index by using the users' characteristics shown in Tables 3.10,11 and the environmental parameters for each zone is shown in Table 3.12. After PMV calculation, a seven-point ASHRE thermal sensation scale is used and as shown in Table 3.13, these scales have been converted to fuzzy numbers, respectively. Moreover, values in Tables 3.14 and 15 were used for converting the visual and indoor air quality criteria to fuzzy numbers. So, by measuring the value of these parameters presented in Tables 3.16 and 17, I reached the final linguistic assessment shown in Table 3.19.

Table 3.12. Environmental Parameters in each Home Area for Calculating the PMV

	A_1 = Kitchen	**A_2= Bedrooms**	**A_3= Living room**	**A_4= Laundry**
t_a =Ambient air temperature (°C)	28	29	22	28
$\bar{t}_r$ = Mean radiant temperature (°C)	27	28	21	26
v_{ar} = Relative air velocity (m/s)	0.2	0.3	0.4	0.1
Relative humidity [rh (%)]	30	55	10	70

Table 3.13. Converting Thermal Comfort Criteria (PMV) to Linguistic Terms

Linguistic terms for thermal comfort criteria rating	PMV	Seven-point ASHRE Thermal Sensation Scale
very low=(1,1,3)	-3	Cold
Low=(1,3,5)	-2	Cool
Medium=(3,5,7)	-1	Slightly cool
High=(5,7,9)	-0.5	Slightly cool
Very high=(7,9,9)	0	Neutral
High=(5,7,9)	0.5	Slightly warm
Medium=(3,5,7)	1	Slightly warm
Low=(1,3,5)	2	Warm
very low=(1,1,3)	3	Hot

Table 3.14. Converting Visual Comfort Criteria to Linguistic Terms

Linguistic terms for visual comfort criteria rating from User 1	Linguistic terms for visual comfort criteria rating from User 2	Illuminance(Lux)
Very Low=(1,1,3)	Very Low=(1,1,3)	I>20,000
Low=(1,3,5)	Very Low=(1,1,3)	3001<I<10,000
Medium=(3,5,7)	Low=(1,3,5)	2001<I<3,000
High=(5,7,9)	Medium=(3,5,7)	601<I<2000
Very High= (7,9,9)	High=(5,7,9)	501<I<600
High=(5,7,9)	Very High= (7,9,9)	401<I<500
Medium=(3,5,7)	Medium=(3,5,7)	201<I<400
Low=(1,3,5)	Low=(1,3,5)	51<I<200
Very Low=(1,1,3)	Very Low=(1,1,3)	I<50

Table 3.15. Converting IAQ Comfort Criteria to Linguistic Terms

Linguistic terms for indoor air quality comfort criteria rating for User 1	Linguistic terms for indoor air quality comfort criteria rating for User 2	Co_2 Concentration (PPMV: parts per million by volume)
Very Low=(1,1,3)	Very Low=(1,1,3)	$3001<Co_2<5000$
Low=(1,3,5)	Low=(1,3,5)	$1501<Co_2<3000$
Medium=(3,5,7)	Low=(1,3,5)	$1201<Co_2<1500$
High=(5,7,9)	Medium=(3,5,7)	$1001<Co_2<1200$
High=(5,7,9)	High=(5,7,9)	$501<Co_2<1000$
Very High=(7,9,9)	Very High=(7,9,9)	$Co_2<500$

Table 3.16. Illuminance and Co_2 Concentration Measured in Each Zone

	Illuminance (Lux)	Co_2 Concentration (PPMV: parts per million by volume)
A_1 =Kitchen	1400	500
A_2=Bedrooms	300	650
A_3 =Living room	500	700
A_4 =Laundry	800	1200

Table 3.17. Calculated PMV and PPT for Thermal Comfort

	User 1			User 2		
	PPT	PMV	PMV Fuzzy Number	PPT	PMV	PMV Fuzzy Number
A_1 =Kitchen	94.6	2.56	L	57.9	1.63	M
A_2=Bedrooms	98.4	2.87	VL	74.7	1.96	L
A_3 =Living room	56.6	1.6	M	15.2	0.7	H
A_4 =Laundry	97.6	2.7	VL	71.5	1.89	L

The information about the cost of energy, carbon tax and GHG emission in the home areas of A_1 = Kitchen, A_2 = Bedrooms, $A_3 =$ Living room and $A_4 =$ Laundry is used to compare the efficiency of their consumption with that of their neighbors, and is provided for users as shown in Table 3.18.

So, a decision on energy allocation should be made when the unit price of electrical energy increases from the slot time of t_{i} to t_{i+1}. The users use linguistic assessment to rate the criteria (Table 3.18). For example, user 1 believes that the importance of energy cost is high, but user 2 believes that it is very high; or the importance of carbon tax for user 1 is at medium, but it is high for user 2 and so forth.

Table 3.18. Linguistic assessment for criteria

Criteria		Users		Aggregated fuzzy weight
		User 1	User 2	
c_1	Energy Cost	H	VH	(5,8,9)
c_2	Budget	M	H	(3,6,9)
c_3	Urgency	H	M	(3,6,9)
c_4	Thermal Comfort level	VH	M	(3,7,9)
c_5	Visual Comfort level	VH	M	(3,7,9)
c_6	IAQ Comfort level	H	M	(3,6,9)
c_7	GHG emission	VL	VH	(1,5,9)
c_8	Energy efficiency score	L	VH	(1,6,9)
c_9	Carbon tax	M	H	(3,6,9)
c_{10}	Occupancy level	H	H	(5,7,9)

To construct the fuzzy TOPSIS model, the first step is the linguistic assessment of criteria and alternatives and the computation of the aggregated fuzzy value using Eq. 3.25 the results of which are presented in Tables 3.18, 3.19 and 3.20. For example, in Table 3.18 for criterion c_2, “budget”, user 1 is satisfied to allocate a medium amount of budget (M) for energy for fuzzy triangular number that is (3, 5, 7), but user 2 prefers to spend a great deal (H) on energy according to the fuzzy triangular number of (5, 7, 9), so the aggregated fuzzy weight IS given by $\widetilde{w}_2 = (w_{21}, w_{22}, w_{23})$ where: $\mathrm{W}_{21} = \mathrm{MIN}_2(3,5) = 3$; $\mathrm{W}_{22} = \frac{1}{2}(5+7) = 6$; $w_{23} = max_2\,(7,9) = 9$; $\widetilde{w}_2 = (3, 6, 9)$.

Table 3.19. Linguistic Assessment for Alternatives

Criteria	Home Areas							
	A1		A2		A3		A4	
	U1	U2	U1	U2	U1	U2	U1	U2
c_1	H	M	M	H	M	VH	L	H
c_2	L	VH	M	L	H	L	H	L
c_3	M	H	M	L	M	L	VH	M
c_4	L	M	VL	L	M	H	VL	L
c_5	H	M	M	M	L	VH	H	M
c_6	VH	VH	H	H	H	H	H	M
c_7	L	H	M	H	L	VH	VL	VH
c_8	L	M	H	H	L	VH	VL	H
c_9	M	M	M	VH	L	VL	M	H
c_{10}	VH	M	L	VL	VL	M	L	M

Table 3.20. Aggregate Fuzzy Decision Matrix

Criteria	***A1***	***A2***	***A3***	***A4***
c_1	(3,6,9)	(3,6,9)	(3,7,9)	(1,5,9)
c_2	(1,6,9)	(1,4,7)	(1,4,7)	(1,4,7)
c_3	(3,6,9)	(1,4,7)	(1,4,7)	(3,7,9)
c_4	(1,4,7)	(1,2,5)	(3,6,9)	(1,2,5)

Table 3.20. Continue. Aggregate Fuzzy Decision Matrix

Criteria	*A1*	*A2*	*A3*	*A4*
c_5	(3,6,9)	(3,5,7)	(1,6,9)	(3,6,9)
c_6	(7,9,9)	(5,7,9)	(5,7,9)	(3,6,9)
c_7	(1,5,9)	(3,6,9)	(1,6,9)	(1,5,9)
c_8	(1,4,7)	(7,9,9)	(1,6,9)	(1,4,9)
C_9	(3,5,7)	(3,7,9)	(1,2,5)	(3,6,9)
C_{10}	(3,7,9)	(1,2,5)	(1,3,7)	(1,4,7)

In Step 4, I normalize the fuzzy decision matrix of alternative using Eq.3.39 and the result is shown in Table 3.21. The weighted decision matrix in step 5 is obtained by Eq. 3.38 .The result is shown in Table 3.22 below.

Table 3.21. Normalized Fuzzy Decision Matrix for Alternatives

Criteria	*A1*	*A2*	*A3*	*A4*
c_1	(0.11,0.17,033)	(0.11,0.17,033)	(0.11,0.14,0.33)	(0.11,0.2,1.00)
c_2	(0.11,0.17,1.00)	(0.14,0.25,1.00)	(0.14,0.25,1.00)	(0.14,0.25,1.00)
c_3	(0.11,0.17,033)	(0.14,0.25,1.00)	(0.14,0.25,1.00)	(0.11,0.14,0.33)
c_4	(0.11,0.44,0.78)	(0.11,0.22,0.56)	(0.33,0.67,1.00)	(0.11,0.22,0.56)
c_5	(0.33,0.67,1.00)	(0.33,0.56,0.78)	(0.11,0.67,1.00)	(0.33,0.67,1.00)
c_6	(0.78,1.00,1.00)	(0.56,0.78,1.00)	(0.56,0.78,1.00)	(0.33,0.67,1.00)
c_7	(0.11,0.20,1.00)	(0.11,0.17,033)	(0.11,0.17,1.00)	(0.11,0.20,1.00)
c_8	(0.11,0.44,0.78)	(0.78,1.00,1.00)	(0.11,0.67,1.00)	(0.11,0.44,0.100)
C_9	(0.14,0.20,0.33)	(0.11,0.14,0.33)	(0.20,0.50,1.00)	(0.11,0.17,033)
C_{10}	(0.33,0.78,1.00)	(0.11,0.22,0.56)	(0.11,0.33,0.78)	(0.11,0.44,0.78)

The fuzzy positive ideal solution (FPIS) and fuzzy negative ideal solution (FNIS) are obtained by Eq. 3.41 and 3.43 and then the distance of each alternative from FPIS and FNIS are obtained by using Eq. 3.45 and 3.46 as shown in Table 3.23.

Table 3.22. Weighted Normalized Fuzzy Decision Matrix

C	***A1***	***A2***	***A3***	***A4***
c_1	(0.56,1.33,3)	(0.56,1.33,3)	(0.56,1.14,3)	(0.56,1.6,9)
c_2	(0.33,1.00,9.00)	(0.43,1.5,9.00)	(0.43,0.15,9.0)	(0.43,1.6,9)
c_3	(0.33,1.00,3.00)	(0.43,1.5,9.00)	(0.43,0.15,9.00)	(0.33,0.86,3)
c_4	(0.33,3.11,7.00)	(0.33,1.56,5.00)	(1.,4.67,9.00)	(0.33,1.56,5)
c_5	(1,4.67,9.00)	(1,3.89,7.00)	(0.33,4.67,9.00)	(1,4.67,9)
c_6	(2.33,6.00,9.00)	(1.67,4.67,9.00)	(1.67,4.67,9.00)	(1,4.00,9)
c_7	(0.11,1.00,9.00)	(0.11,0.83,3.00)	(0.11,0.83,9.00)	(0.11,1.00,9)
c_8	(0.11,2.67,7.00)	(0.78,6.00,9.00)	(0.11,4.00,9.00)	(0.11,2.67,9)
c_9	(0.43,1.20,3.00)	(0.33,0.86,3.00)	(0.60,3.00,9.00)	(0.33,1.00,3)
c_{10}	(1.67,5.44,9.00)	(0.56,1.56,5.00)	(0.56,2.33,7.00)	(0.56,3.11,7)

The closeness coefficient of each alternative is calculated by Eq. 3.47 and is represented in Table 3.24. The alternative that has a higher value is preferred. Hence, the ranking of alternatives is 1- Laundry, 2-Bedrooms, 3- Kitchen, 4- Living room. This ranking shows the users' preferences for energy distribution flow to the home areas or group of appliances in accordance with the increase in energy unit price. The main purpose of presenting this scenario is to propose a methodology to cater for the preferences of householders in order to prioritize the utilization of the groups of appliances when the function of users' utility is significant in load curtailment in demand response programs. Economic, social, cultural and environmental factors influence users' consumption behavior [268, 269] and users with different backgrounds choose different linguistic terms to evaluate and to judge about their consumption. Hence, a proposed fuzzy TOPSIS methodology is a tool that can assist a group of household members to assess their consumption and to make decisions about the energy flow distribution.

Table 3.23. Distance of Each Alternative from FPIS and FNIS

C	d_i^-				d_i^+			
	A1	***A2***	***A3***	***A4***	***A1***	***A2***	***A3***	***A4***
c_1	1.48	1.48	1.45	4.91	7.44	7.44	7.50	6.48
c_2	5.01	5.04	5.04	5.04	6.81	6.57	6.57	6.57
c_3	1.58	5.04	5.04	1.56	7.64	6.57	6.57	7.69
c_4	4.17	2.94	5.60	2.78	6.15	6.98	5.25	6.98
c_5	5.60	4.5	5.59	5.60	5.25	5.60	5.59	5.25
c_6	5.5	5.64	5.09	4.93	4.22	4.91	4.91	5.44
c_7	5.15	1.71	5.14	5.15	6.90	7.78	6.96	6.90
c_8	4.24	5.98	5.60	5.34	6.40	5.05	5.88	6.30
c_9	1.62	1.42	5.23	1.58	7.53	7.69	5.96	7.64
c_{10}	5.67	3.04	3.86	4.00	4.70	6.89	6.31	6.05
Σ	30.59	29.92	37.21	30.40	52.49	53.07	50.85	54.64

Table 3.24. Ranking According to the Closeness Coefficient

	A1 ***Kitchen***	***A2*** ***Bedrooms***	***A3*** ***Living room***	***A4*** ***Laundry***
$\mathbf{CC_i}$	0.3523	0.3546	0.3491	0.3627
Ranking	3	2	4	1

3.5.2.1. A Multi-agent Intelligent Decision Making Support System for Home Energy Management in Smart Grid by a Fuzzy TOPSIS Method

From some of the literature reviewed in Chapter 2, I identified that householders' decision-making in regards to energy consumption is dependent on factors that influence the end-user's energy consumption behavior; hence, several surveys have been conducted to investigate these factors [47, 264, 270, 271]. For instance, Stern [272] demonstrated that the contextual domain of this behavior comprises: attributes that an individual has at birth, the immediate situation, public policy and economic variables. Kowsari et al. [264] presented a conceptual framework as a basis for formulating a household consumption behavior strategy and they proposed an integrated approach to determine the economic characteristics of a household. On the other hand, in many load scheduling and planning approaches such as those of [114, 115, 273], the researchers included the consumers' preferences and utility function in their optimization models. For instance, in the approaches suggested by Lampropoulos et al. [270] and Wang [115], the importance of including the behavior of householders in power system planning is demonstrated but there is no methodology for obtaining and ranking these preferences.

The measurement and inclusion of these factors would be more complex when there is a conflict of preferences among several consumers in a home. This issue is demonstrated by [274] when there is "*analysis talk*" among household members to identify how energy savings might be made. Therefore, in the proposed approach, the aggregated fuzzy rating of criteria for more than one consumer was computed.

Following a survey of the literature [115, 264, 270, 272, 275-279], I identified that the householders with different cultural backgrounds, gender, income, education and social status who are located in different geographic locations with different climates and dealing with different energy policies, subsidies and energy supply, will utilize appliances in accordance with the various criteria that were presented in Tables 3.5.

A multi-agent system is a combination of several agents working in collaboration to perform assigned tasks to achieve the overall goal of the system [280]. There are many publications which demonstrate the utilization of agents to produce solutions for specific smart grid applications. Researchers are currently developing agent-based methods to address demand response in a dynamic pricing scheme [281].

Reference [282] argued that a multi-agent system is not synonymous with an EMS. Rather, it is only one possible control method that can be applied to an EMS. Furthermore, the authors discussed that the individual characteristics of inhabitants in a smart grid can be adapted by agent-based systems and thus have the potential to raise subjective comfort. Thus, this may create a positive evaluation of the technology. That is, the systems' adaptability to occupants' needs and changes in preferences or behaviour over time may be crucial for the success of the systems and their related technologies. In order to respond to the householder's requirements while integrating new sources of energy, reference [281] proposed an agent-based approach for optimizing energy consumption. In their approaches, these agents are the generators, prosumer agents and consumer agents, while the goal of each agent is to maximize its profits in terms of energy unit price paid per day. Three levels of agents including grid agent, control agent and residential agent are proposed by [280]. These agents communicate with each other in order to make decisions about shifting loads to off-peak hours based on the dynamic price of electricity. In their approach, the residential agent makes the decision to change scenarios.

The application of multi-agent systems for studying comfort management of householder behaviour in the context of home energy management is proposed by [110]. This approach proposed a new distributed comfort evaluation that, when compared with the traditional method of Predicted Mean Vote (PMV) index [198], reveals the need for a more robust comfort standard that allows for the input of actual occupant preferences when available.

According to the above discussion, the architecture of a multi-agent intelligent decision-making support system for a smart home is proposed in Figure 3.12. In this proposal, HEMS is a multi-agent system that consists of agents dedicated to measuring the decision-making criteria. The intelligent decision support agent will receive dynamic price signals from the utility provider by means of smart meters and it will act according to the proposed fuzzy TOPSIS method for including the occupants' preferences during load energy management under a demand response program. In this proposed model, the comfort level controller agent may use Eq. 2.6 presented in Chapter 2.

In a research review of the modelling and complexity of home energy management systems by Beaudin et al. [283], the proposed multi-agent intelligent decision-making support system has been reviewed and considered as a unique research with objectives that pertain to the cost, well-being, emissions, and consumption. Furthermore, the fuzzy TOPSIS methodology proposed and applied in the above scenario has been reviewed and included as one of the techniques used for addressing multi-objective optimization problems in HEMS.

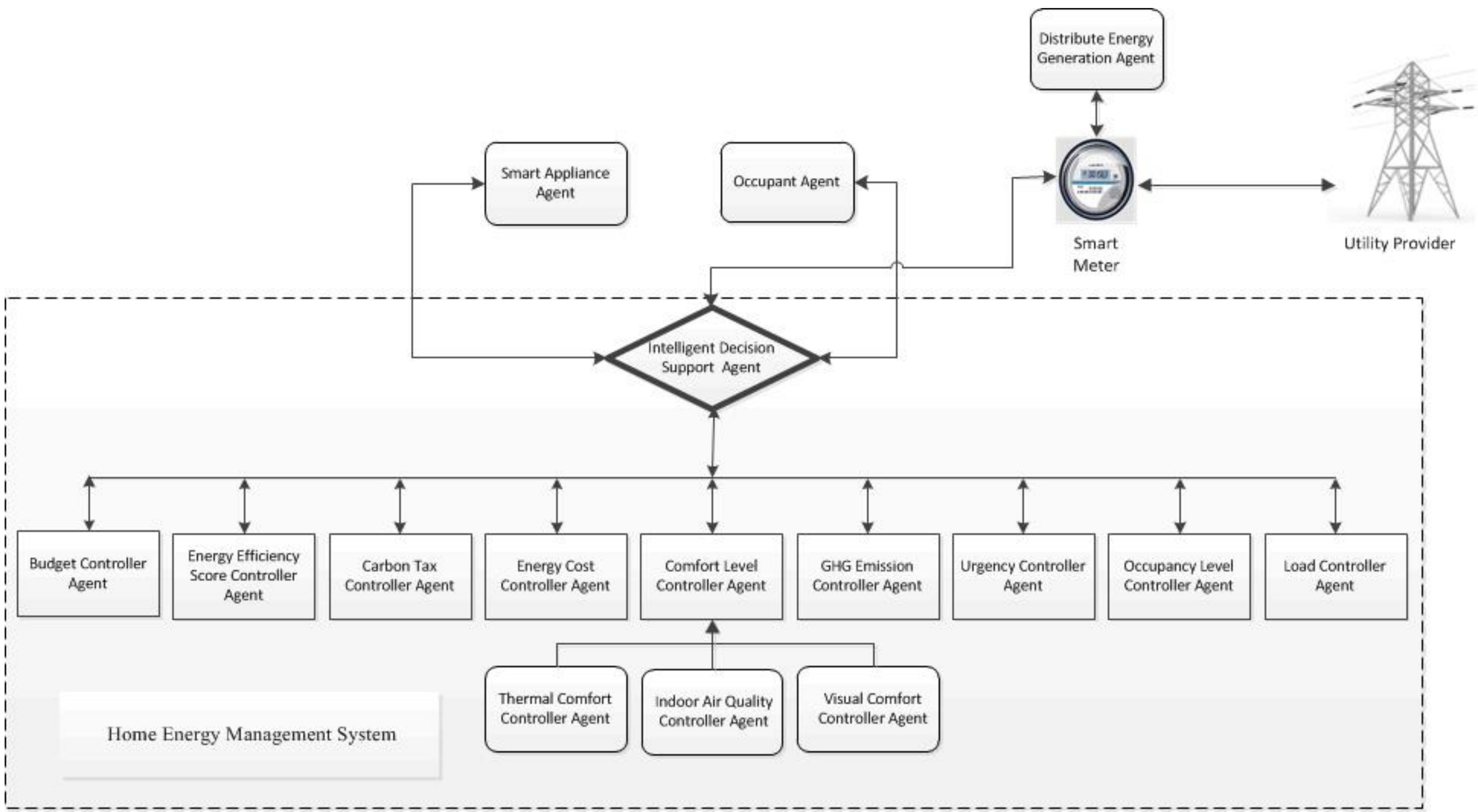


Figure 3.12. Intelligent Decision Support Agent for HEMS

3.5.3. A Scenario for Application of TOPSIS and ELECTRE Methods for HEMS

The proposed scenario in this section demonstrates an application of the TOPSIS and ELECTRE methods in a day-ahead demand response program presented in Fig 3.13 by mapping consumer preferences during a 24-hour time frame.

3.5.3.1. Application of TOPSIS in Scenario

In this scenario, a consumer (householder or energy manager) wants to decide which appliances to use during the day, taking his preferences into consideration. The preference for using a particular electrical appliance is not constant and it changes over time. For example, the use of a computer depends on the purpose and it is variable during the course of a day. There may be times during the day when the user needs the computer to check the business email, so the need to use the computer is more urgent than when the user wants to use the computer to watch a movie on YouTube for entertainment. Hence, the user is asked to map his preference by considering each criterion for utilising each appliance during a time planning horizon that has been divided into 24 timeslots, each of which is equal to one hour.

The criteria selected in this scenario are similar to those in the first scenario presented in this Chapter. They include

- $c_1 =$ Energy cost, Negative criterion
- $c_2 =$ Urgency (the degree of importance or emergent of use), Positive criterion
- $c_3 =$ Enjoyment (entertainment), Positive criterion
- $c_4 =$ Comfort and welfare, Positive criterion

In terms of the above criteria, the preferences of consumers when using nine appliances are shown in Figures 3.17, 3.18, 3.20, 3.21. The energy cost presented in Figure 3.17 has been calculated by considering the operating time, power, and demanded energy of each appliance, and energy unit price imposed by DRP. The appliances used in this scenario are shown in Table 3.25.

The objective of this decision-making is: if during demand response, the user decides to curtail the consumption (energy), which appliances are most important for him?

The number of decision-making matrices is equal to the time slot numbers; in this scenario, there are 24 decision-making matrices. For example, Table 3.25 shows the decision matrix constructed for timeslot 20. In this matrix, I allocate a very small number (0.001) to criteria that are equal to zero because of validity of calculation.

The Euclidean distance (formulae 3.18 and 3.19) of each alternative (appliance) from PIS and NIS, and the closeness coefficient of each appliance are shown in Tables 3.27 and 3.28. The result of our simulation for this scenario is presented in Table 3.29. The average elapsed time of TOPSIS performance in a computer with processor Intel Core i7 CPU@3.10GHz with 16B RAM is 4.01 seconds for each run. Table 3.28 shows the classification of each appliance. The first class of appliances are those which during demand response must run and never be switched off, so the appliances with higher class are in more demand compared with the appliances with lower class. As a result, if during DRP an appliance which belongs to the first class is curtailed, then the lifestyle of the user is compromised.

Table 3.25. Appliances Used in a Scenario for TOPSIS Method

	Appliance
A1	Iron (0.93 kw)
A2	Television (0.2 kw)
A3	Spa bath with 5 kW heater
A4	Vacuum cleaner (0.93 kw)
A5	Dishwasher (1.87 kw)
A6	Hair dryer (1.47 kw)
A7	Home computer (0.1 kw)
A8	Washing Machine (0.6 kw)
A9	Air Conditioner (3.5 kw)

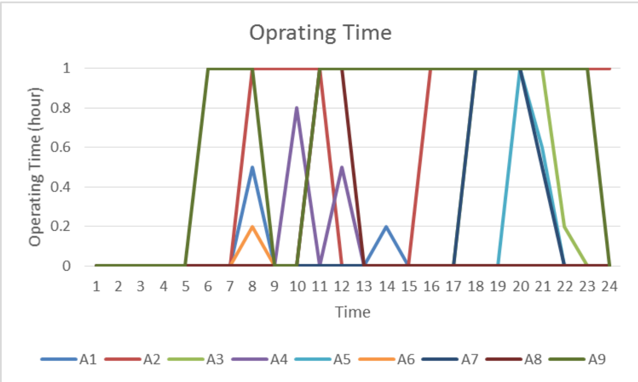


Figure 3.13. Operating Time of Nine Appliances during a Day

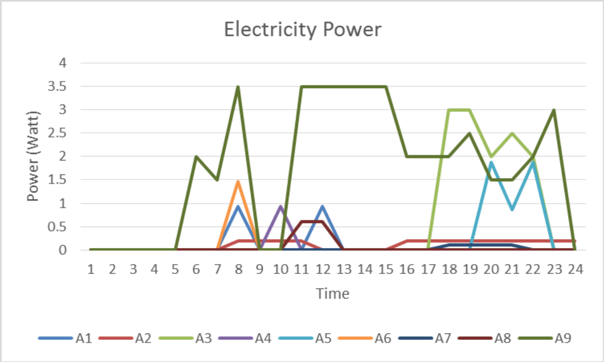


Figure 3.14. Power Consumption by Nine Appliances during a Day

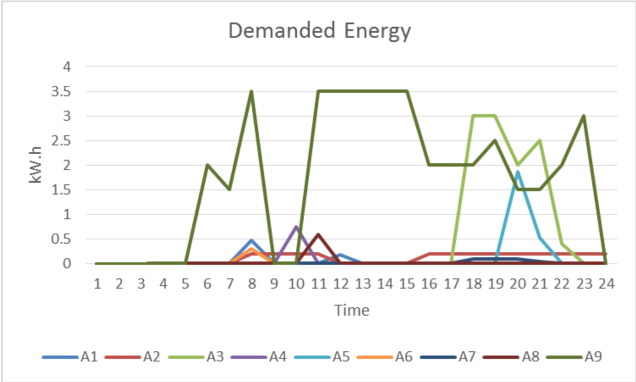


Figure 3.15. Energy Demanded by Nine Appliances during a Day

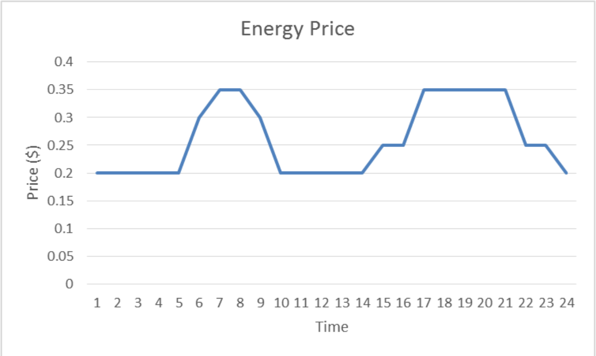


Figure 3.16. A Day-ahead Demand Response Program

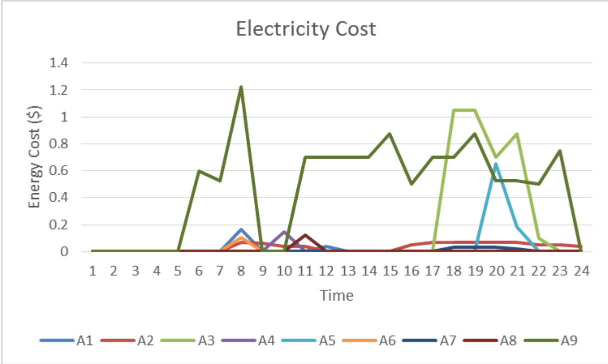


Figure 3.17. Electricity Cost of Nine Appliances during a Day (C_1)

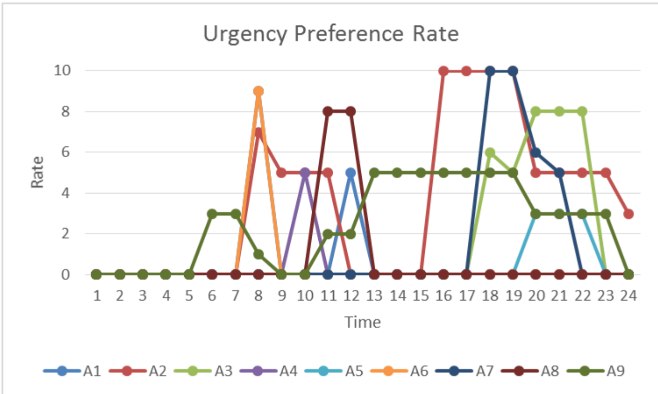


Figure 3.18. Urgency usage of Nine Appliances during a Day (C_2)

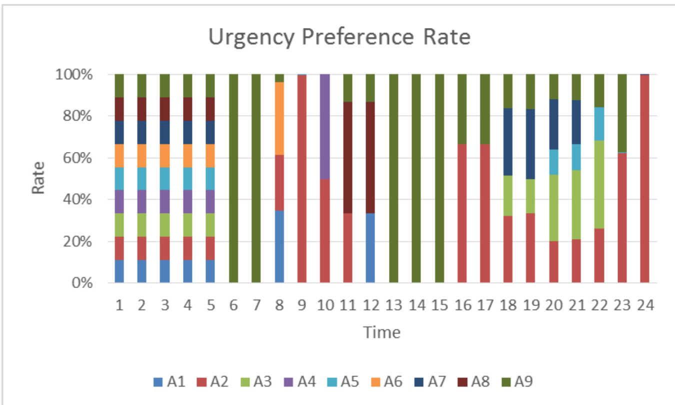


Figure 3.19. Urgency usage of Nine Appliances during a Day (C_2)

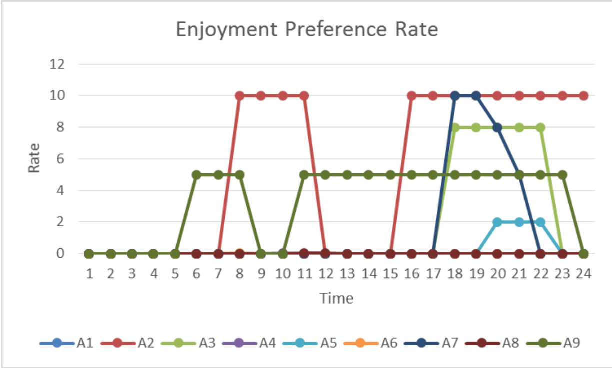


Figure 3.20. Enjoyment Preferences of Nine Appliances during a Day (C_3)

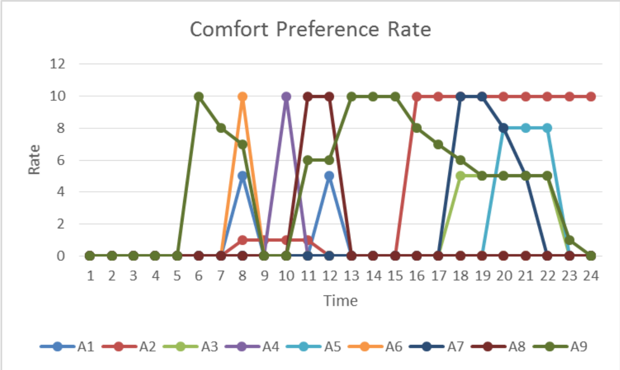


Figure 3.21. Comfort Preference of Nine Appliances during a Day (C_4)

Table 3.26. Decision-Making Matrix Constructed for Decision Making at Timeslot 20m

	C1	**C2**	**C3**	**C4**
A1	0.001	0.001	0.001	0.001
A2	0.07	5	10	10
A3	0.7	8	8	5
A4	0.001	0.001	0.001	0.001
A5	0.65	3	2	8
A6	0.001	0.001	0.001	0.001
A7	0.035	6	8	8
A8	0.001	0.001	0.001	0.001
A9	0.525	3	5	5

Table 3.27. Distance of Each Appliance from PIS and NIS

		A1	A2	A3	A4	A5	A6	A7	A8	A9
t6	d+	0.437012	0.437012	0.437012	0.437012	0.437012	0.437012	0.437012	0.437012	0.242509
	d-	0.242509	0.242509	0.242509	0.242509	0.242509	0.242509	0.242509	0.242509	0.437012
t7	d+	0.437572	0.437572	0.437572	0.437572	0.437572	0.437572	0.437572	0.437572	0.241475
	d-	0.241475	0.241475	0.241475	0.241475	0.241475	0.241475	0.241475	0.241475	0.437572
t8	d+	0.292124	0.140976	0.341115	0.341115	0.341115	0.280218	0.341115	0.341115	0.337397
	d-	0.285175	0.398706	0.283539	0.283539	0.283539	0.325299	0.283539	0.283539	0.176422
t9	d+	0.463766	0.192954	0.463766	0.463766	0.463766	0.463766	0.463766	0.463766	0.463766
	d-	0.192954	0.463766	0.192954	0.192954	0.192954	0.192954	0.192954	0.192954	0.192954
t10	d+	0.435504	0.245686	0.435504	0.369112	0.435504	0.435504	0.435504	0.435504	0.435504
	d-	0.200975	0.3758	0.200975	0.306003	0.200975	0.200975	0.200975	0.200975	0.200975
t11	d+	0.363926	0.194737	0.363926	0.363926	0.363926	0.363926	0.363926	0.248182	0.335157
	d-	0.270085	0.370772	0.270085	0.270085	0.270085	0.270085	0.270085	0.350824	0.177878
t12	d+	0.347795	0.395408	0.395408	0.395408	0.395408	0.395408	0.395408	0.334684	0.325734
	d-	0.307292	0.298271	0.298271	0.298271	0.298271	0.298271	0.298271	0.364828	0.347725
t13	d+	0.436565	0.436565	0.436565	0.436565	0.436565	0.436565	0.436565	0.436565	0.243372
	d-	0.243372	0.243372	0.243372	0.243372	0.243372	0.243372	0.243372	0.243372	0.436565
t14	d+	0.436565	0.436565	0.436565	0.436565	0.436565	0.436565	0.436565	0.436565	0.243372
	d-	0.243372	0.243372	0.243372	0.243372	0.243372	0.243372	0.243372	0.243372	0.436565
t15	d+	0.435815	0.435815	0.435815	0.435815	0.435815	0.435815	0.435815	0.435815	0.24474
	d-	0.24474	0.24474	0.24474	0.24474	0.24474	0.24474	0.24474	0.24474	0.435815
t16	d+	0.356961	0.027395	0.356961	0.356961	0.356961	0.356961	0.356961	0.356961	0.320393
	d-	0.278986	0.436713	0.278986	0.278986	0.278986	0.278986	0.278986	0.278986	0.211959
t17	d+	0.360536	0.027755	0.360536	0.360536	0.360536	0.360536	0.360536	0.360536	0.325025
	d-	0.281175	0.44069	0.281175	0.281175	0.281175	0.281175	0.281175	0.281175	0.203398
t18	d+	0.2336	0.018317	0.293235	0.2336	0.2336	0.2336	0.009026	0.2336	0.215345
	d-	0.278479	0.349647	0.149091	0.278479	0.278479	0.278479	0.356614	0.278479	0.156067
t19	d+	0.23802	0.01681	0.275719	0.23802	0.23802	0.23802	0.008283	0.23802	0.243936
	d-	0.255564	0.33713	0.143462	0.255564	0.255564	0.255564	0.343222	0.255564	0.126405
t20	d+	0.250164	0.060629	0.213465	0.250164	0.243916	0.250164	0.055898	0.250164	0.204124
	d-	0.201143	0.285006	0.204646	0.201143	0.122992	0.201143	0.273606	0.201143	0.125005
t21	d+	0.254672	0.060812	0.300759	0.254672	0.169438	0.254672	0.117404	0.254672	0.223441
	d-	0.29148	0.351005	0.206296	0.29148	0.262726	0.29148	0.31806	0.29148	0.165445
t22	d+	0.27296	0.071301	0.103315	0.27296	0.169689	0.27296	0.27296	0.27296	0.373392
	d-	0.341478	0.390242	0.353459	0.341478	0.366836	0.341478	0.341478	0.341478	0.124752
t23	d+	0.389943	0.018021	0.389943	0.389943	0.389943	0.389943	0.389943	0.389943	0.39044
	d-	0.275461	0.467259	0.275461	0.275461	0.275461	0.275461	0.275461	0.275461	0.155206
t24	d+	0.475609	0.17125	0.475609	0.475609	0.475609	0.475609	0.475609	0.475609	0.475609
	d-	0.17125	0.475609	0.17125	0.17125	0.17125	0.17125	0.17125	0.17125	0.17125

Table 3.28. Closeness Coefficient (cc) of Each Appliance during 24 Timeslot

	A1	A2	A3	A4	A5	A6	A7	A8	A9
cc_t6	0.356882	0.356882	0.356882	0.356882	0.356882	0.356882	0.356882	0.356882	0.643118
cc_t7	0.355609	0.355609	0.355609	0.355609	0.355609	0.355609	0.355609	0.355609	0.644391
cc_t8	0.493981	0.73878	0.453914	0.453914	0.453914	0.537225	0.453914	0.453914	0.343355
cc_t9	0.293815	0.706185	0.293815	0.293815	0.293815	0.293815	0.293815	0.293815	0.293815
cct_10	0.315761	0.604679	0.315761	0.45326	0.315761	0.315761	0.315761	0.315761	0.315761
cc_t11	0.425994	0.655643	0.425994	0.425994	0.425994	0.425994	0.425994	0.585676	0.346716
cc_t12	0.469086	0.429984	0.429984	0.429984	0.429984	0.429984	0.429984	0.521547	0.516327
cc_t13	0.357933	0.357933	0.357933	0.357933	0.357933	0.357933	0.357933	0.357933	0.642067
cc_t14	0.357933	0.357933	0.357933	0.357933	0.357933	0.357933	0.357933	0.357933	0.642067
cc_t15	0.359618	0.359618	0.359618	0.359618	0.359618	0.359618	0.359618	0.359618	0.640382
cc_t16	0.438694	0.940972	0.438694	0.438694	0.438694	0.438694	0.438694	0.438694	0.398156
cc_t17	0.438165	0.94075	0.438165	0.438165	0.438165	0.438165	0.438165	0.438165	0.384915
cc_t18	0.54382	0.950219	0.33706	0.54382	0.54382	0.54382	0.975315	0.54382	0.420199
cc_t19	0.517772	0.952506	0.342244	0.517772	0.517772	0.517772	0.976435	0.517772	0.34132
cc_t20	0.44569	0.824586	0.489454	0.44569	0.335213	0.44569	0.830357	0.44569	0.379805
cc_t21	0.533698	0.852333	0.406851	0.533698	0.607931	0.533698	0.730392	0.533698	0.425433
cc_t22	0.555756	0.845515	0.773817	0.555756	0.683725	0.555756	0.555756	0.555756	0.250434
cc_t23	0.413976	0.962865	0.413976	0.413976	0.413976	0.413976	0.413976	0.413976	0.284444
cc_t24	0.26474	0.73526	0.26474	0.26474	0.26474	0.26474	0.26474	0.26474	0.26474

Table 3.29. Classification of Appliances

	Rank					
Timeslot	***1***	***2***	***3***	***4***	***5***	***6***
T6	A9	A1- A8				
T7	A9	A1- A8				
T8	A2	A6	A1,A3-A5,A7-A9			
T9	A2	A1,A3-A9				
T10	A2	A4	A1,A3, A5-A9			
T11	A2	A8	A1,A3-A7, A9	A9		
T12	A8	A9	A1	A2-A7		
T13- T15	A9	A1-A8				
T16	A2	A1,A3-A8	A9			
T17	A2	A1,A3-A8	A9			
T18	A7	A2	A1,A4-A6,A8	A9	A3	
T19	A7	A2	A1,A4-A8	A3	A9	
T20	A7	A2	A3	A1,A4,A6,A8	A9	A5
T21	A2	A7	A5	A1,A4,A6,A8	A9	A3
T22	A2	A3	A5	A1,A4,A6,A7,A8	A9	
T23	A2	A1,A3-A8	A9			
T24	A2	A1,A3-A9				

3.5.3.2. Application of ELECTRE Method in Scenario

In the previous scenario, I demonstrated the application of the TOPSIS method to assist consumers to map their preferences regarding appliance usage when they have decided to participate in a day-ahead DRP. In this section, I simulate the same scenario but apply the ELECTRE method, and I will demonstrate how a user is able to outrank the appliances during DRP.

By executing the ELECTRE program in MATLAB verR2014b presented in Table 3.4, the total outranking relation matrix $H = [h_{lk}]_{9\times9}$ for each timeslot is measurable. To avoid complexity, the intermediate calculations and steps are not presented and I have calculated the outranking relation matrix just for timeslots T18 to T22 in order to compare them with the TOPSIS method. The results of these simulation are presented in Tables 3.30 – 34.

Table 3.30 shows the outranking of each appliance. For example, A1 in the first row is zero for A2, A3 and A7 which means that A1 is not outranked by A2, A3 and A7 but by looking at A3 in first column it is understood that A3 is not outranked to A1; also, it shows that there is no meaningful relationship between A1 and A3. The result of ELECTRE in timeslots 18 to 22 is compatible with the TOPSIS simulation result presented in Table 3.29.

The total outranking relation matrix provides us with a more meaningful and in-depth view of appliance utilization during DRP. Referring to the four possible outranking configurations explained in the ELECTRE method section in this Chapter, Table 3.30 can be explained as follows:

Outranking relations configuration in timeslot T18:

- (A_2SA_1) &- (A_1SA_2): Appliance A_2 is strictly preferred to appliance A_1: A_2PA_1
- (A_1SA_4) & (A_4SA_1): " A_1" with respect to the four criteria is indifferent to "A_4":
- A_7S$A_{1,2,3,4,5,6,8,9}$ &-($A_{1,2,3,4,5,6,8,9}$S A_7): A_7P$A_{1,2,3,4,5,6,8,9}$ (Appliance A_7 with respect to the four criteria is strictly preferred to other appliances).
- (A_2S$A_{1,3,4,5,6,8,9}$) & -($A_{1,3,4,5,6,8,9}$SA_2): A_2P$A_{1,3,4,5,6,8,9}$, it shows that appliance A_2 has dominant position in relation to other appliances except A_7 that is consistent with the TOPSIS result.
- -(A_3SA_8) &- (A_8SA_3): Appliance A_3 with respect to the four criteria is incomparable to appliance A_8.
- It is clear from A_3 that this appliance is not preferred to any other appliance as its value is zero; so I can conclude that this appliance is ranked last as has been shown (Table 3.28).when using the TOPSIS method

As can be seen, using the ELECTRE method, I are able to investigate comprehensively the outranking relations among appliances. For example, by looking at timeslot T22 in Table 3.29, in the TOPSIS methodology I found that the A2 is ranked the highest, A3 is ranked second and A5 is ranked third. However, the ELECTRE method result presented in Table 3.34 shows that appliance A2 has an incomparable relation with A3; however, appliance A2 is in a more dominant position as it is strictly preferred to other appliances. But, A3 is not preferred to A5 as these relationships are confirmed by the TOPSIS method result but the TOPSIS will not show us this relation. Similarly, the same relation exists between the A3 and A5. The TOPSIS method in the previous section specified that the A3 rank is higher than A5 but does not show any outranking relations between them. In Table 3.34, the value in A9 raw is zero for all fields which means that A9 is not outranked to any other appliances. However, when I look at values in the A9 field (column), I see that this value is 1 for A2, A3 and A5, indicating that these appliances are strictly preferred to A9 that is consistent with the TOPSIS result.

Table 3.30. Total Outranking Relation Matrix for Timeslot T18

	A1	**A2**	A3	A4	A5	A6	**A7**	A8	A9
A1	0	0	0	1	1	1	0	1	0
A2	1	0	1	1	1	1	0	1	1
A3	0	0	0	0	0	0	0	0	0
A4	1	0	0	0	1	1	0	1	0
A5	1	0	0	1	0	1	0	1	0
A6	1	0	0	1	1	0	0	1	0
A7	1	1	1	1	1	1	0	1	1
A8	1	0	0	1	1	1	0	0	0
A9	0	0	0	0	0	0	0	0	0

Table 3.31. Total Outranking Relation Matrix for Timeslot T19

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	**0**	**0**	**0**	**1**	**1**	**1**	**0**	**1**	**0**
A2	**1**	**0**	**1**	**1**	**1**	**1**	**0**	**1**	**1**
A3	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
A4	**1**	**0**	**0**	**0**	**1**	**1**	**0**	**1**	**0**
A5	**1**	**0**	**0**	**1**	**0**	**1**	**0**	**1**	**0**
A6	**1**	**0**	**0**	**1**	**1**	**0**	**0**	**1**	**0**
A7	**1**	**1**	**1**	**1**	**1**	**1**	**0**	**1**	**1**
A8	**1**	**0**	**0**	**1**	**1**	**1**	**0**	**0**	**0**
A9	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**

Table 3.32. Total Outranking Relation Matrix for Timeslot T20

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	**0**	**0**	**0**	**1**	**0**	**1**	**0**	**1**	**0**
A2	**1**	**0**	**1**	**1**	**1**	**1**	**0**	**1**	**1**
A3	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**
A4	**1**	**0**	**0**	**0**	**0**	**1**	**0**	**1**	**0**
A5	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
A6	**1**	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**0**
A7	**1**	**0**	**1**	**1**	**1**	**1**	**0**	**1**	**1**
A8	**1**	**0**	**0**	**1**	**0**	**1**	**0**	**0**	**0**
A9	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**

Table 3.33. Total Outranking Relation Matrix for Timeslot T21

	A1	**A2**	A3	A4	A5	A6	A7	A8	A9
A1	**0**	**0**	**0**	**1**	**0**	**1**	**0**	**1**	**0**
A2	**1**	**0**	**1**	**1**	**1**	**1**	**1**	**1**	**1**
A3	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**
A4	**1**	**0**	**0**	**0**	**0**	**1**	**0**	**1**	**0**
A5	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**1**
A6	**1**	**0**	**0**	**1**	**0**	**0**	**0**	**1**	**0**
A7	**1**	**0**	**0**	**1**	**0**	**1**	**0**	**1**	**1**
A8	**1**	**0**	**0**	**1**	**0**	**1**	**0**	**0**	**0**
A9	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**	**0**

Table 3.34. Total Outranking Relation Matrix for Timeslot T22

	A1	A2	A3	A4	A5	A6	A7	A8	A9
A1	0	0	0	1	0	1	1	1	0
A2	1	0	0	1	1	1	1	1	1
A3	1	0	0	1	0	1	1	1	1
A4	1	0	0	0	0	1	1	1	0
A5	1	0	0	1	0	1	1	1	1
A6	1	0	0	1	0	0	1	1	0
A7	1	0	0	1	0	1	0	1	0
A8	1	0	0	1	0	1	1	0	0
A9	0	0	0	0	0	0	0	0	0

3.6. Proposing an Intelligent Decision Support System Model for Energy Management System in Smart Grid

In the sections above, I proposed several decision-making methods to support consumers involved in demand response programs when they want to make decisions about energy curtailment. In reality and practice, there is a possibility that the consumers will not be involved efficiently and consistently, so a system is required to monitor this decision-making, elicit consumer preferences, and decisions autonomously on behalf of the consumers. In this section, I propose this system and the specifications that must be met in the SG environment.

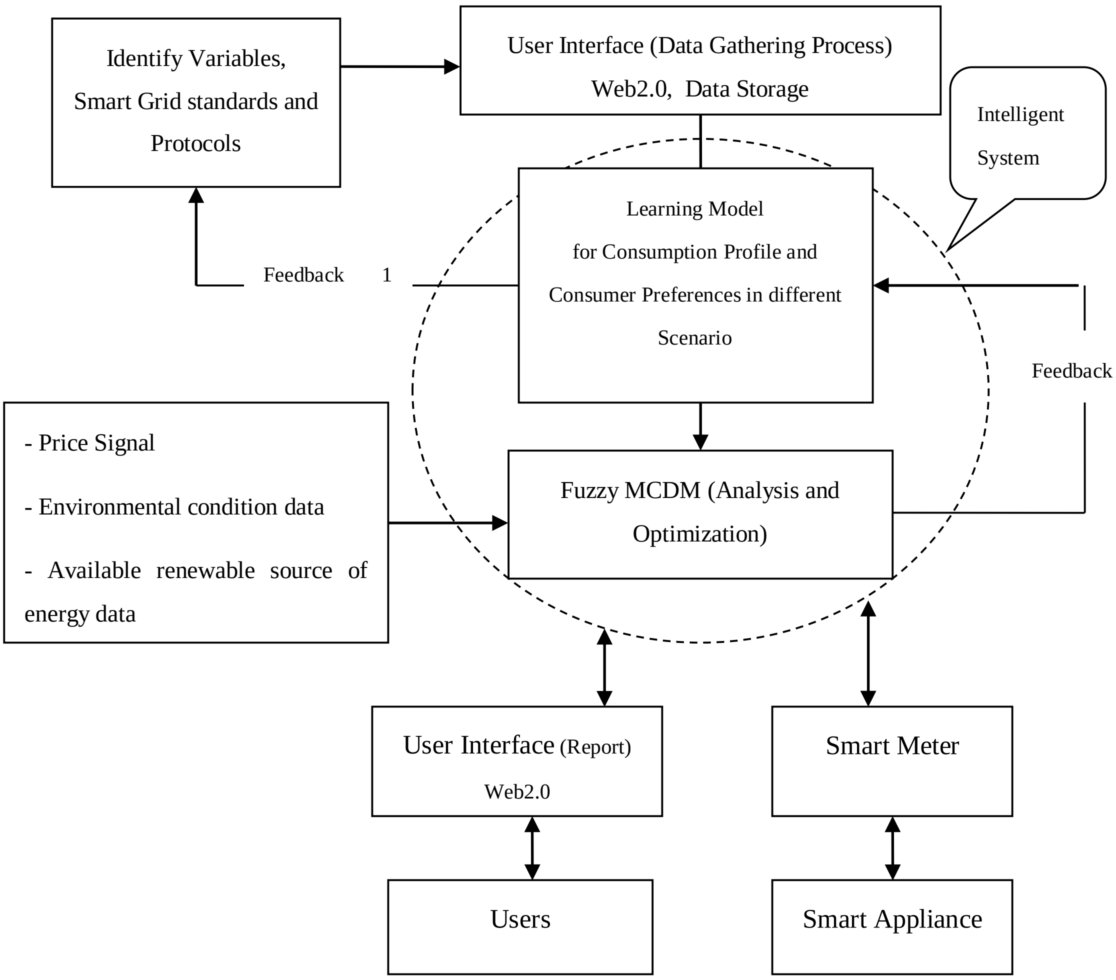


Figure 3.22. Architecture of Intelligent Decision Support System for Residential Energy Management

To achieve more effective demand response on the end-user side, I utilize the dynamic notion of price, and develop an intelligent decision support system model that will assist demand response as shown in the figure below.

This model is achievable by utilizing four steps as depicted in Figure 3.24. **The first step** is to determine the effective variables and parameters required for achieving the objectives of the next steps. As previously discussed, a wide range of data is applicable to energy management systems in a building. These data can be classified in nine categories that are shown in Figure 3.23 and listed in Table 3.35. In this classification, there are various significant parameters for the management of energy in a building. For example, there are 13 building envelope parameters which are recognised in the literature and depicted in Table 3.36. In this case because of observing the parsimonious characteristic of the model and avoiding overfitting, the effective variable identification and analyse is very significant.

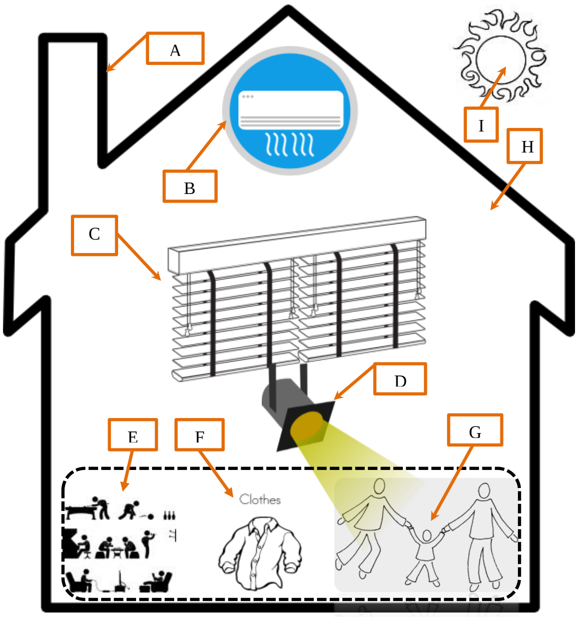


Figure 3.23. Categories of Inhabitant-oriented Parameters

By analyzing the variables, the variety of variables (qualitative, quantitative, dependent, independent, exogenous, endogenous) will be specified and then the relationships and effects of the variables on each other should be clarified. For example, when consumers prepare to use the A/C, variables such as the inside and outside temperatures or the level of humidity will influence their preferred A/C settings; another factor to consider is that there may be several occupants in a house whose preferences may be different. Residents are able to alert the system of their existence in a different way, such as using smart cards. In the second step, a user interface will capture the consumers' inputs on the identified variables and preferences in different scenarios that will provide an input to the learning phase and also inform the consumers about the result of the computed decision and let them modify the parameters according to their preferences.

Table 3.35. Categories of Inhabitant-oriented Parameters

Inhabitants Oriented Parameters	
Parameter	**Category 's name**
A	Building envelope
B	Air Conditioner
C	Window and Window blind
D	Lighting
E	Occupants' activities
F	Occupants' clothes
G	Occupants' characteristics (age, income, sex, job, health)
H	Indoor environment
I	Outdoor environment

Step 3 has a two-fold purpose. The first is to capture the outside variables like price signal from the grid, environmental conditions, and available renewable sources. Once that is done, the second is to utilize that information and develop a fuzzy rule based on the Fuzzy Multi Criteria Decision Making (MCDM) model that will assist the consumer to achieve demand response. MCDM methods include two techniques. One is a Multi Objective Decision Making (MODM) technique which will apply when the system objectives are different.

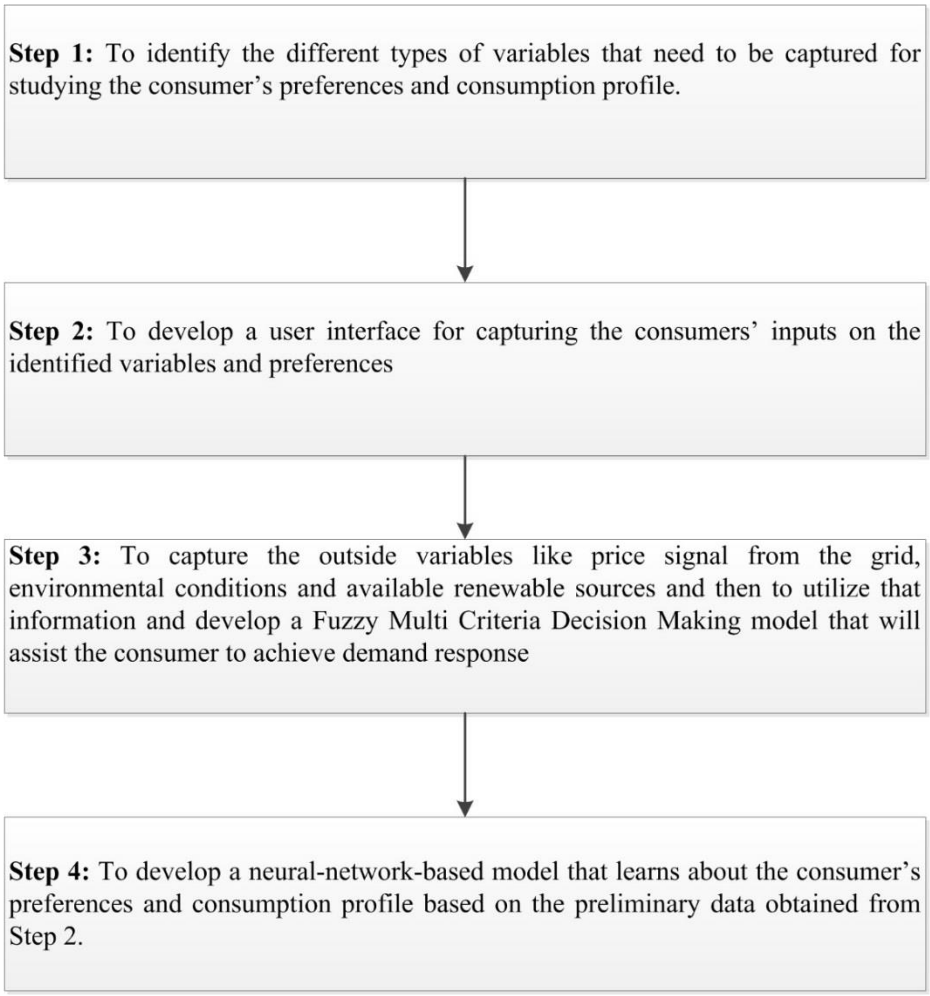


Figure 3.24. Four Steps for Model Utilization

In this case, when the objective is cost reduction, the system behavior is different, whereas the system objective is to maintain lifestyle. The second is a Multi Attribute Decision Making (MADM) technique that will apply when there are many decision-makers in the system and their decision should be considered in the decision-making process, or where there is an energy manager who wants to make a decision on energy curtailment. According to the nature of variables such as temperature, price, comfort and economical consumption etc. and also considering the core meaning of variables and accurate communication between users and system, the Fuzzy techniques will develop terms most appropriate for this model. In this step, feedback (shown as number 2 in the model) is included in terms of addressing any changes in user behavior or preferences. Moreover, any event will be recognized by the model and will create a learning model that can adapt to such events and changes.

Table 3.36. Building Envelope's Parameters that Affect on Energy Management

Building Envelope's Parameters		
	Parameter	**Ref #**
1	Radiant ceiling and panel system	[284]
2	Window opening behaviour	[285]
3	Building orientation	[286]
4	General layout and siting	[287]
5	The thermos-physical properties of the building materials (thermal penetration coefficient)	[287]
6	Location of windows and their sizes	[287]
7	Shading of windows and envelope	[287]
8	Insulation	[287]
9	Surface treatment of the enclosing envelope	[287]
10	Mass and surface area of partitions	[287]
11	Building thermal mass	[288, 289]
12	Building design characteristics (room size, height, wall thickness)	[288, 289]
13	Phase change material (PCMs)	[288, 289]

In **Step 4**, where a neural network model can be developed, I expect to learn about the fuzzy rule-based and consumption pattern based on the preliminary data obtained in Step 2 and the fuzzy MCDM in step three. This model will be responsible for acting autonomously on behalf of the user and in turn facilitates the decision-making process. Such a model will evolve continually when the users modify their preferences according to different scenarios. In order to develop a model that captures various terms of cost function for different classified consumption patterns, neural network techniques will be utilized to derive meaning from complicated or imprecise data; moreover, they can be used to capture consumption patterns and detect trends that are too complex to be recognized by computers. In neural networks, the learning scheme is divided into supervised learning and unsupervised learning [290]. At first, when the system is going to recognize patterns or features in data sets, which include the correct output for each input, supervised learning will apply and then after capturing the data, an unsupervised learning technique is applied so that the system can act on its own in a kind of self-reflection. For this purpose, a feedback (shown as number 1 in the model) is considered for identifying and capturing new emerging variables in terms of any consumer behavior modification.

The model presented in Figure 3.22 has attracted and been referenced by several researchers. For instance, research was conducted by Shahgoshtasbi et al. [291-293] in which a fuzzy system and intelligent lookup table were designed for training the system in different scenarios and conditions in order to cater for the consumers' preferences.

3.7. Conclusions

In Chapter 1, it is stated that one of the functions of a modernized electricity delivery and the use of electricity in SG, is customer electricity consumption optimization that provides information enabling consumers to make educated decisions about their electricity use. Householders should have this ability to optimize in order to achieve multiple goals such as reduced cost, reliability, comfort, and decreased environmental impact.

Energy-efficient behaviour may be encouraged by making available to consumers adequate information about energy prices and the energy consumption of appliances. I explained that energy-efficient behaviour is defined as the operation of appliances by consumers in a way that optimizes energy efficiency while reducing energy wastage. On the other hand, in a dynamic pricing demand response program in which the market-based energy price signal varies over time, it is very difficult for end-users to save on their utility budget during billing periods. I depicted this dilemma in Figure 3.1. In the smart grid, it is expected that, by receiving consumption information, consumers will change their consumption behaviour in order to mitigate cost and save on their power bill. However, this goal will not be achievable if the consumers do not engage wholeheartedly in the energy management process; in this situation, they require a decision-making system that will assist them. For this reason, this Chapter studied the multi-attribute decision-making methods in order to assist consumers to make better decisions regarding their energy consumption.

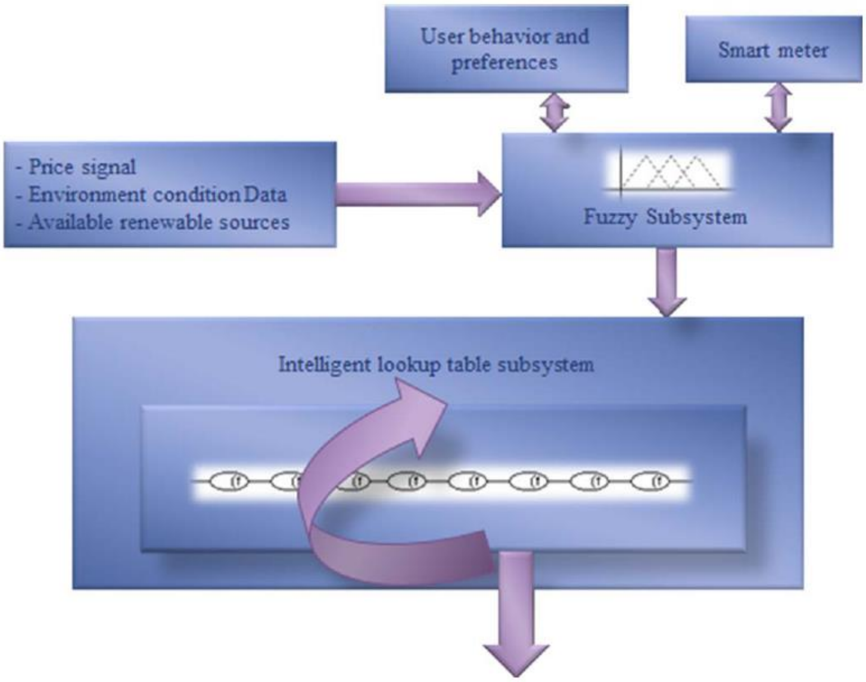


Figure 3.25. Intelligent Energy Management System Proposed by [291]

The methods which were introduced had different functions. Some methods such as AHP and ANP are based on pairwise comparison and are dependent on the decision makers' opinion and ideas, while other methods such as TOPSIS are based on measuring the alternatives to the criteria value by using Euclidean distances. In this Chapter, the ELECTRE methods were proposed in order to cater for the preferences of end-users and as tools to assist consumers to for outranking their appliances over a time horizon during demand response program engagement. Using different scenarios, I demonstrated the application of MCDM methods, and concluded that:

- Pairwise comparison techniques such as AHP and ANP require the intense and committed involvement of end-users during the decision-making process, and it is difficult to involve them whenever the value of the criteria changes over a time horizon.
- The Fuzzy TOPSIS technique can be an effective method for situations where end-users want to allocate the energy to different building zones and when users have conflicting attitudes towards energy consumption.
- The TOPSIS technique requires the minimum amount of decision-maker involvement by catering for the consumer's preferences according to specific criteria within a time scale. The importance and ranking of appliances are measurable in a dynamic pricing scheme such as a day-ahead DRP. By presenting the example of a scenario, I explained how comfort criteria can be calculated and included in decision-making.

- In this Chapter, I compared the TOPSIS method with the ELECTRE method for one scenario. I showed how the results obtained by performing these methods are in accordance with each other. I showed that the ELECTRE method is more suitable when the home energy management system is required to compare the outranking of appliances one-by-one in order to achieve a comprehensive and rigorous comparison when the decision-making objective is to curtail the consumption of energy with minimum interference with preferred lifestyle and consumption behaviour.

In the next chapter, I investigate the proposed decision-making methods and optimality. The proposed decision-making models are not intended to assist consumers to manage their utility budget, but to balance power consumption with their lifestyle. I introduce an appropriate optimization technique which will help consumers to save on power costs when the energy unit price is variable by utilizing the proposed decision-making methods presented in this Chapter.

Chapter 4

Energy Scheduling and Optimization for Home Energy Management in Smart Grid

4.1. Introduction

The future home energy management system (HEMS) in the smart grid will need to include contractual grid regulations imposed by the utility while also taking into consideration the domestic users' comfort, preferences, budget, and security. The emerging autonomous demand response (ADR) programs have initiated steps to utilize sophisticated software algorithms for the scheduling and optimization of HEMS. The aim of this Chapter is to propose a system of systems approach as a versatile energy scheduling system that takes into account the components, characteristics and methodologies required for achieving an efficient level of energy consumption in the residential sector of the smart grid.

The recent achievements and outstanding developments in information and communications technologies (ICTs) have turned the page for energy management in the smart grid (SG) and paved the way for emerging advanced metering infrastructures (AMIs) particularly for the monitoring of real-time electricity usage. As a result, the utility service providers are able to have bidirectional communications with end-users and measure the details of real-time consumption data and encourage customers to modify their consumption habit by regulating different demand response programs (DRPs)[23]. For example, an ADR program is one where there are minimal controls over load management and scheduling. In this program, each user is equipped with an energy consumption scheduling device for automatically controlling his/her load in order to reduce the energy cost.

HEMSs as a subset of the Building Automation System (BAS), can be integrated with the SG which needs a sophisticated system in order to interact with different DRPs. Furthermore, there are various parameters associated with householders' consumption behaviours including appliances, home environment, building envelope characteristics and service utility provider. These parameters need to be measured accurately and thoroughly, and monitored intelligently in order to have a robust and reliable SG [20]. Consequently, the creation of this intelligent system has greatly attracted many researchers interested in addressing different aspects of energy efficiency in the SG. On the other hand, the ICTs developments in wired networks, wireless sensor networks (WSNs) and home area networks (HANs) have made HEMS capable of consolidating information associated with those parameters to improve energy management processing. For example, the Zigbee smart energy profile 2 known as the IP-based communication standard for energy management in HANs, and similarly IEEE standard 802.15.4, are two enhancements that have improved the monitoring of networks to facilitate the interoperability of communications [21].

Although ICTs have integrated the communications into the SG components and enriched the quality of services, householders' unpredictable demands can still impinge on electricity supply. Hence, system developers are still facing the challenge of trying to balance demand and supply. This cannot be achieved unless all the parameters that affect demand under different conditions are taken into consideration. Thus, it needs ubiquitous computing apparatuses and infrastructures that not only take all the underlying factors into account, but that also require minimal configuration by the end-users in bidirectional communication to avoid undue complexity in demand response programs [21]. Hence, this Chapter presents a versatile energy management system together with its sub-systems to assist customers with their DRPs.

The remainder of this Chapter is organized as follows. The second section presents the new characteristics of HEMS compatible with SG network components described in standard [3]. In section 4.2, the energy cost and the management of the users' utility budget have been mathematically formulated. In section 4.2.1, a versatile energy scheduling system that comprises specifications will be presented. In 4.3, the characteristics of electrical appliances are presented, and an optimization technique with different scenarios is presented in section 4.4. A decision-making algorithm intended to assist householders with their budget management is proposed in section 4.5; and finally, section 4.6 concludes this Chapter.

4.2. Characteristics of HEMs in Smart Grid

The ISO/IEC 15067-3 [3] standard presents a high level energy management model which focuses on three primarily demand-response methods: direct load control (DLC), time of use (TOU) and real-time pricing (RTP). In Chapters 1 and 2 I mentioned that a DLC program is essentially proposed for the low energy consumers such as residential and small commercial users. In this program, the service provider has the authority to remotely shut down appliances such as air-conditioners, pool pumps, and water heaters at short notice. In the RTP program, changes in the wholesale energy market will be reflected, and the energy price fluctuates hourly or a day ahead. RTP is one of the most efficient DRPs that has a prices-to-devices scheme whereby smart appliances will receive the energy price signals to adjust themselves accordingly. For example, a program may be embedded in the appliances by the manufacturer to adjust the load based on the price of energy. In air-conditioners, the operation and temperature set point may be modified by changes in energy pricing. In Chapter 1, I explained that in this case, the communication can be directly done by a wide utility area network to HAN, or directly to smart appliances, or through a gateway such as HES. This can be compatible with IEC/PAS 62746-10-1 Ed. 1.0 [294] which is an OpenADR 2.0b profile specification, a systems interface between customer energy management system and the power management system [294].

Figure 4.1 depicts the Energy Management Agent (EMA) the function of which is defined by standard [3] as: “The EMA performs specialised computing functions by receiving the electricity rate data from the residential gateway and applying sophisticated software algorithms to determine which appliances and distributed energy resources (DERs) to operate and when”. The characteristics of this agent as shown in Figure 4.1 are as follows:

1. It can determine how and when appliances must operate.
2. It considers the cost of the energy.
3. The consumer inputs and the amount of distributed energy resources have to be considered in EMA operation.
4. The EMA is a controller which causes appliances to increase or decrease power consumption, or turning off or on.
5. The EMA must be capable of receiving pricing data hour-by-hour or a day in advance.
6. The EMA can be overridden by consumers.
7. Consumers might input in the control system their monthly energy budget and their preferences.
8. Consumers have the opportunity to override the EMA scheduling at any time.
9. The EMA will send signals to appliances via a home network.
10. The EMA receives the energy signal from the utility or aggregator and sends the usage data to the utility.
11. To avoid data interception and ensure consumer security and privacy, the data stream from consumer to utility must be encrypted but the data stream that is publicly published by the utility does not need encrypting.

12. Data encryption is required in the gateway rather than on the appliance side.
13. EMA software is complex for balancing budget and comfort level ([3], P.27).
14. For more effective operation, artificial intelligence may be required.
15. For a decision-making problem, the consumers are not involved in a complicated decision-making procedure, but they may make simple decisions.
16. The EMA must be capable of deferring the appliance operation for scheduling purposes.
17. The EMA utilises switching control of many circuits for smart demand control of appliances such as refrigerator and air-conditioners.
18. The appliances must have an indicator such as an LED for control purposes to signal to the consumer that energy for an appliance has been deferred and the appliance cannot be operated.
19. A display in the home or on appliances must be provided to alert users of the cost that will be incurred if consumption is overridden.

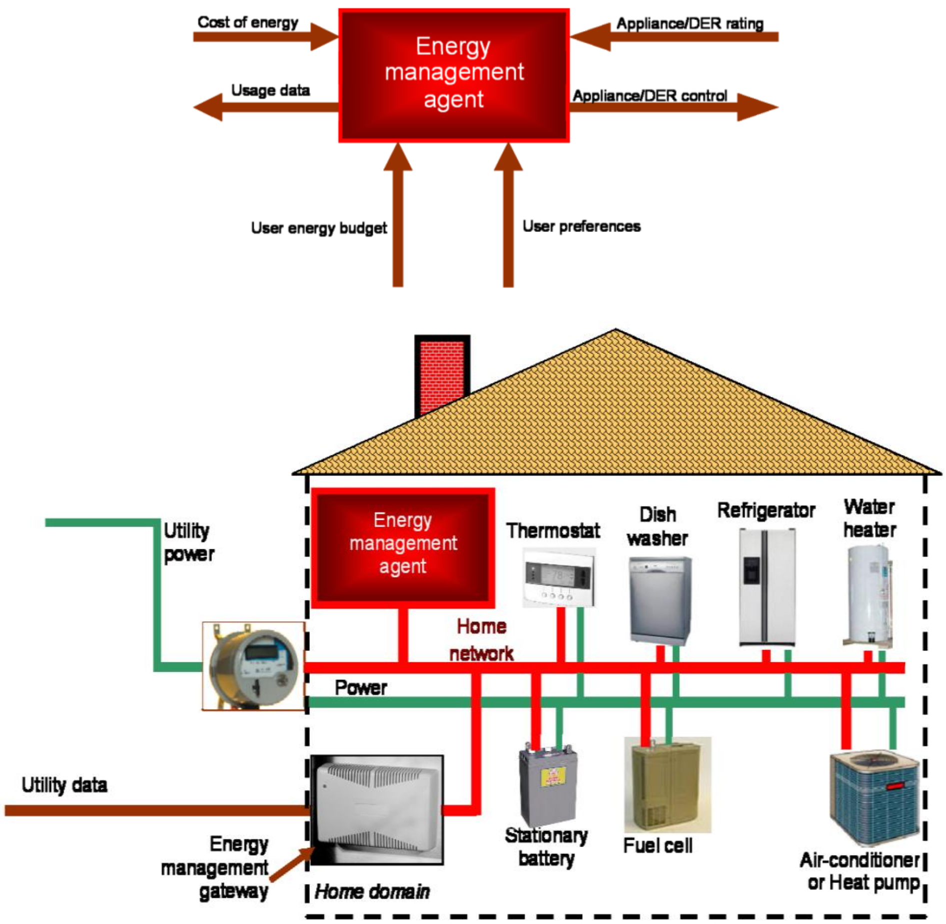


Figure 4.1. Distributed Load Control System and the EMA Proposed by ISO/IEC 15067-3 [5]

A sophisticated software algorithm for scheduling and optimization should be at the core of EMA and ADR and should take into account the above-mentioned 19 characteristics. In particular, the future HEMSs will be complex adaptive systems with self-organization, versatility, self-healing, interoperability, affordability, and cybersecurity characteristics. As a result, the design of intelligent scheduling algorithms with optimization techniques has been a major focus of research on HEMS in the SG; hence, I reviewed the most significant ones in Chapter 2. In the next sections, firstly the correlation between energy and cost in a building will be explained using an example; and secondly, I demonstrate a versatile energy scheduler system for SG-based HEMS which is compatible with ADR.

4.3. The Energy Cost and Users' Utility Budget Management

The cost of electric energy for residential customers is dependent to three variables:

- U: The price of Energy ($\$/(\mathrm{kw.h})$)
- P: The appliances 'power (kW) consumed and
- t: Length of the operation time (h)

The power rate over operation time is called energy "E" $(\mathrm{kW.h})$.

In order for households to save on the cost of energy, two of these variables, power and time, can be managed by the user, while the price of the energy is imposed by the utility.

As discussed in the literature review in Chapter 2, researchers have used a discrete time framework for the scheduling of energy by dividing the planning horizon into many timeslots. For example, in the dynamic real-time pricing scheme of a DRP, energy price fluctuates over timeslots.

Assume that E_i^t denotes the energy demanded by appliance "i" in timeslot "t" when the energy price value is equal to U^t at that timeslot. This relationship is shown mathematically by Eq.4.1. a. Eq.4.1. b shows the total energy cost when the scheduling horizon is divided into "n" timeslots for "m" appliances.

$$\mathrm{EC}_i^t = \mathrm{U}^t \times P_i \times \mathrm{t} = \mathrm{U}^t \times \mathrm{E}_i^t \qquad (4.1.a)$$

$$\mathrm{EC}_{total} = \sum_{t=1}^{t=n} U_t \left(\sum_{i=1}^{i=m} \mathrm{E}_i^t\right) \qquad (4.1.b)$$

In terms of user budget management, users allocate budget (BD) for their utility cost. This budget is easy to manage when the price of energy is constant. But when the energy price is dynamic over time, it is difficult to control the budget and balance it with the consumption cost.

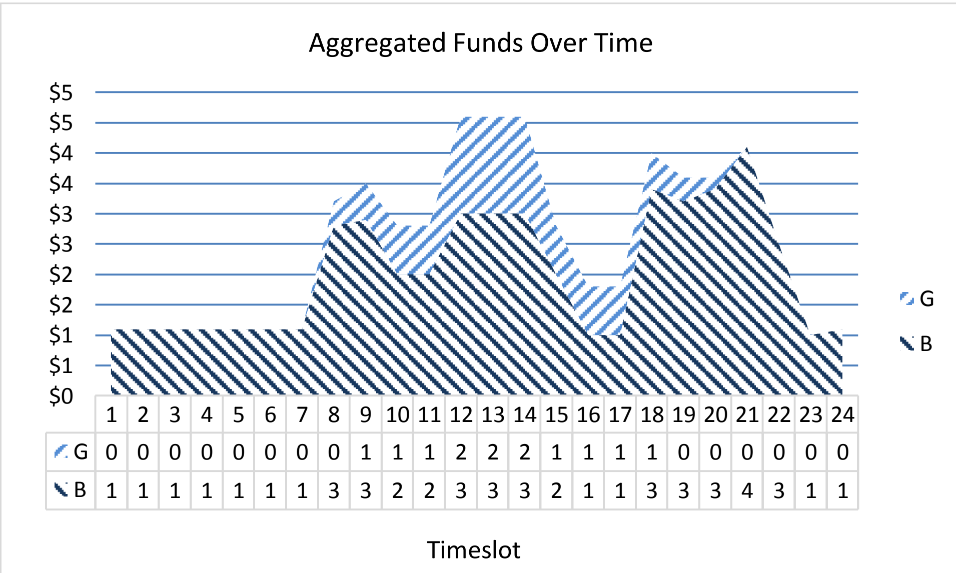
Highlighted in the second characteristic of the EMA in the smart grid, users are equipped with mechanisms for utilizing the distributed energy resources (DER) such as solar rooftop panels with a storage system; this stored energy can be either used or sold back to the grid for a profit. This supplementary source of energy reduces the cost of energy for users and decreases the load demand for utility power. The buying DER price (U_{sell}^{t}) is not essentially equal to the selling energy price (U^{t}).

After a period of consumption, the utility budget can be underestimated by less or more consumption. In this situation, the deviation from the planned budget (BD) can be positive or negative that it is favourable if the value BD is either zero or greater ($B \geq 0$) in Eq. 4.2.a.

$$BD^{t}(\$) = [B^{t}\ (\$) + \ {G_S}^{t}(\$)] - EC^{t} \tag{4.2.a}$$

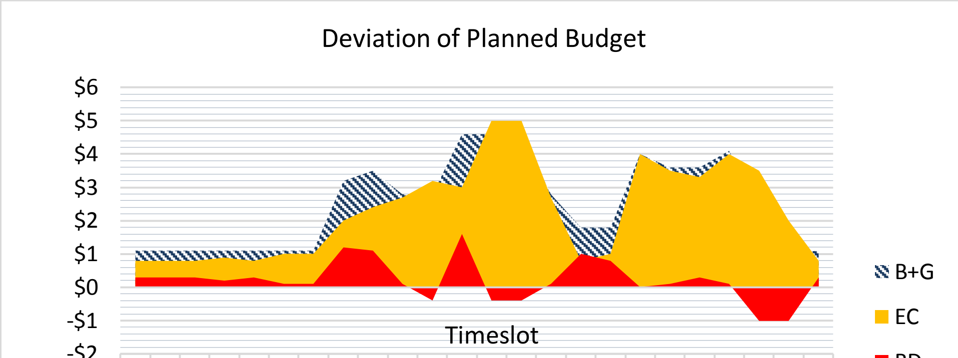
$$BD_{total} = \sum_{t=1}^{t=n} B^{t} + \sum_{t=1}^{t=n} U_{sell}^{t}\, E_S^{t} \ - \sum_{t=1}^{t=n} U^{t}\ (\sum_{i=1}^{i=m} \mathrm{E}_i^{t}) \tag{4.2. b}$$

where $BD^{t}$is the quantity of deviation from the planned budget in timeslot "t", $B^{t}$is the amount of budget allocated to timeslot "t" , and ${G_S}^{t}$ is the profit made by selling stored energy E_S^{t} or equivalently used in timeslot "t". The total available funds for energy consumption are equal to the sum of the value of stored energy and the allocated budget. The above formula has been demonstrated by the example shown in Figure 4.2.a-b. Figures show the deviation from planned budget for timeslots 11, 13, 14, 22 and 23.



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
G	0	0	0	0	0	0	0	0	1	1	1	2	2	2	1	1	1	1	0	0	0	0	0	0
B	1	1	1	1	1	1	1	3	3	2	2	3	3	3	2	1	1	3	3	3	4	3	1	1

Figure 4.2.a. Aggregated Funds for Energy Consumption



	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24
B+G	1	1	1	1	1	1	1	3	4	3	3	5	5	5	3	2	2	4	4	4	4	3	1	1
EC	1	1	1	1	1	1	1	2	2	3	3	3	5	5	3	1	1	4	4	3	4	4	2	1
BD	0	0	0	0	0	0	0	1	1	0	-0	2	-0	-0	0	1	1	0	0	0	0	-1	-1	0

Figure 4.2.b. Deviation from the Planned Budget

4.3.1. Energy Cost based on Building Subdivisions

In Chapter 3, I explained how the fuzzy TOPSIS methodology can be applied to indicate the flow of energy to building subdivisions based on various criteria and users' preferences. In order to determine the energy cost in a building based on subdivided, I divide a building into "k" zones and time planning horizon into equal timeslots in which the energy price is constant. Consequently, the minimum number of timeslots is equal to the number of times that the energy price changes or fluctuates.

The total amount of energy consumed within a building during "n" timeslots E_{total}^{n} and associated cost C_{total}^{n} is calculated by Eq.4.3-5.

$$E_{total}^{n} = \sum_{ts=1}^{ts=n} \sum_{z=1}^{z=k} E_{z}^{ts} = \sum_{ts=1}^{ts=n} \sum_{z=1}^{z=k} (P_{A_z}^{ts} \times t_{A_z}^{ts}) \qquad (4.3)$$

$$C_{total}^{n} = \sum_{ts=1}^{ts=n} \sum_{z=1}^{z=k} U^{ts} \times E_{A_z}^{ts} = \sum_{ts=1}^{ts=n} \sum_{z=1}^{z=k} U^{ts} \times (P_{A_z}^{ts} \times t_{A_z}^{ts}) \qquad (4.4.a)$$

$$C_{total}^{ts} = U^{1} \times [\,(P_{A_1}^{1} \times t_{A_1}^{1}) + \cdots + (P_{A_k}^{1} \times t_{A_k}^{1})] + \cdots + U^{n} \times [\,(P_{A_1}^{n} \times t_{A_1}^{n}) + \cdots + (P_{A_k}^{n} \times t_{A_k}^{n})] \qquad (4.4.b)$$

$$z = 1,2,3,..,k$$
$$ts = 1,2,3,..,n$$
$$ts, z \geq 1 \qquad (4.5)$$

where $E_{A_z}^{ts}$ is the amount of energy consumed by appliance "A_z" in zone "z" in timeslot "ts". "$P_{A_z}^{ts}$" is the amount of power used by appliance "A_z" in zone "z" for duration of "$t_{A_z}^{ts}$" in timeslot "ts". Also, "U^{ts}" is the price of energy in timeslot "ts". I present an example to give a better understanding of the above relationship. It is assumed the price of energy in a day-ahead DRP is provided as shown in Figure 4.2.

The building is divided into four zones (shown by different colour), $m = 4$, and the planning horizon is divided into 24 timeslots, $n = 4$.

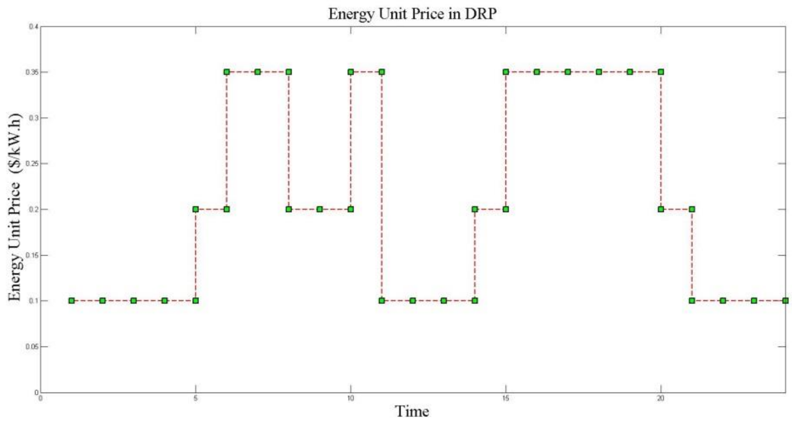


Figure 4.3. Energy Price in a Day-ahead Pricing Scheme

The equations 4.2, 3, and 4 depicted visually in Figures 4.4.1 - 4. In this example, for the sake of simplicity, the information about the amount of operation time of appliances in each zone has not been shown. Figure 4.2 shows the peak periods between 6:00 a.m. to 8:00 a.m., 10:00 a.m. to 12:00 a.m., and 16:00 to 20:00.

4.4. A Versatile Energy Scheduler System for Building Energy Management System

4.4.1. A System of Systems (SoS)

As discussed earlier, the proposed energy management agent shown in Figure 4.1 needs to provide a control mechanism for appliance usage based on users' budget and preferences.
Different policies and strategies may be chosen for scheduling in order to save cost and energy on the end-user side such as

- adjusting power and/or time,
- switching appliances on/off , or
- shifting an operation to the time when the energy price is lower (off-peak)

But, issues arise and arguments may occur concerning which one of the policies, or combination of policies, must be chosen that neither compromise the comfort and householders' lifestyle nor violate demand response. I tackled this issue in the previous chapter by proposing decision-making methods to assist end-users to decide which appliances to use based on their preferences. However, the proposed decision-making methods are not an appropriate mechanism as they do not guarantee that the users will save on their energy bill or allocated budget.

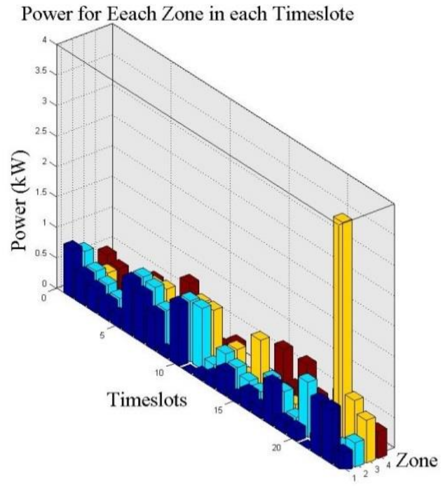


Figure 4.4.1. Power Consumed in Each Zone

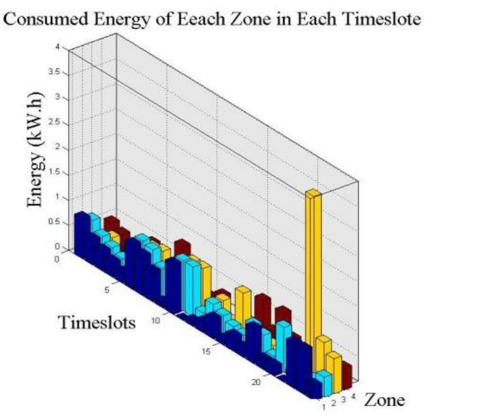


Figure 4.4.2. Energy Consumed in Each Zone

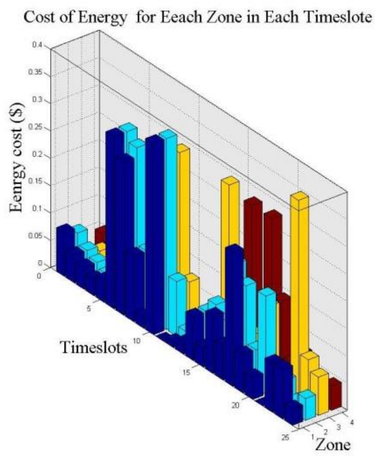


Figure 4.4.3. Cost of Energy in Each Zone

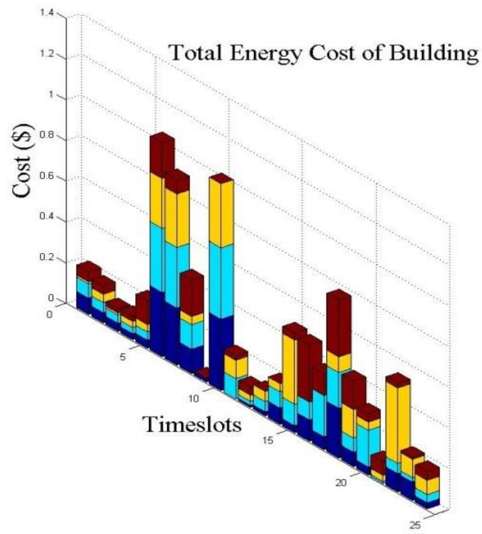


Figure 4.4.4. Total Energy Cost of Building in Each Timeslot

Figure 4.4. Building Energy and Cost Calculation

In Chapter 2, most of the significant optimization algorithms were reviewed and as Table 2.2 showed, the minimization of cost is the main objective of those optimizations. However, the aim of this Chapter is to propose a decision-making algorithm in order to control and manage the consumption of energy by appliances, taking into account the householders' budget and preferences, and the distributed energy resources and demand response.

Before proposing this algorithm, I revisit the literature which was reviewed in Chapter 2 and examine the various methodologies pertaining to this subject. In the Conclusions section of Chapter 2, I demonstrate that because the building energy management in a dynamic pricing demand response program is a complex and challenging problem, a comprehensive albeit complex system is required to resolve the issues. Moreover, by studying the literature, I discover that a combination and integration of different systems are essential for achieving a desired overall efficient, robust and reliable management and control of energy consumption.

The system of systems (SoS) is an effective approach when designing a complex system. SOS is defined as "a collection of individual, possibly heterogeneous, but functional systems integrated together to enhance the overall robustness, lower the cost of operation, and increase the reliability of the overall complex SoS system" [295]. There are many different definitions of SoS in different science fields, six of which have been enumerated by [296]. However, several of the most significant SoS characteristics can be summarized as follows:

- Integration: ability of communication among systems
- In general, SoS comprises three components including people, processes and products. The people in SoS have behaviour and attitude. The process can be considered as the collaboration among systems and the products as a component means the software and hardware of systems.
- SoS capabilities and behaviour can be effected and limited by constraints of adjoining systems.
- In the SoS environment, architectural constraints imposed by existing systems have a major effect on the system capabilities, requirements, and behaviour.
- The systems in SoS have a common goal such as increasing the performance.
- There is no difference between architecting a complex system and designing a simple system [296].

As can be seen, the SoS definition and its characteristics are similar to the characteristics of SG explained in Chapter one where many SG domains have been defined. This view to Sg is investigated by [297]. Due to the complexity of the problem and the objective of increasing the interoperability and performance, *a system of systems* modelling approach [298] is presented in this Chapter that comprise the following four sub-systems as shown in Figure 4.2.:

- Predictor system (PS).
- Monitor and allocator system (MAS).
- Identifier system (IS).
- Optimizer system (OS).

In the energy scheduler system shown in Figure 4.5, each sub-system has its own control and mathematical model with different or partially similar inputs and outputs [35]. The arrows in Figure 4.5 indicate the flow of information. Before analysing and explaining each sub-system, I define *home energy scheduling* in SG as:
an offline, semi-online, or online process of allocating energy resources to supply the energy demand of various electrical devices in a time scale of short, medium and long term in order to satisfy the regulations of demand response programs' and to optimize the householder's comfort level and energy cost savings.

However, the main issue and problem is the complexity of scheduling and optimization which depends on the size of input and the average running time of an algorithm. The methodology chosen for solving the problem can be classified from easy (polynomial-time algorithm) to strongly NP- complete (polynomially reducible) problem [299]. However, a detailed account of these algorithms is beyond the scope of this thesis. A great deal of research has been done to develop these sub-systems which are explained in Chapter 2. Some of these approaches are demonstrated in Table 4.1. The function of each sub-system is explained in the following.

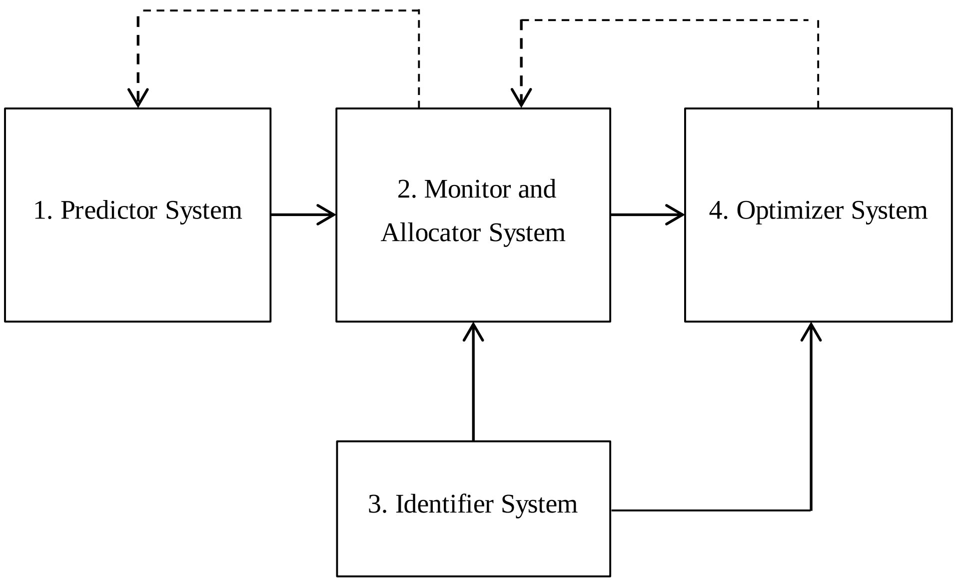


Figure 4.5. A Versatile Energy Scheduler System

A. *The Predictor System (PS)*

PS is the first sub-system that evaluates the effective variables for the forecasting of
a) the demand for energy (time and power),
b) energy price,
c) amount of available distributed renewable resources,
d) power and load constraints imposed by demand response program, and
e) energy cost associated with each task or demand.

Depending on the applied methodology, the prediction can be implemented monthly, daily, hourly, in minutes or seconds. To achieve these goals, the system needs to scrutinize the parameters reviewed in Chapter 2 such as householders' energy behaviours (income, age, employment status, etc.) [47, 300], occupancy profile, users' activities and preferences, comfort parameters (indoor air quality, thermal and visual comfort factors), environmental factors, and building envelop characteristics. According to [14], forecasting methods can be classified as "elaborate engineering", "simplified engineering", "statistical", "artificial neural networks", and "support vector machine". Note that each model may have different complexity, ease of use, running speed, inputs, and accuracy. The predicted factors will be utilized by a second sub-system, the Monitor and Allocator System.

B. *The Monitor and Allocator System (MAS)*

MAS is the second sub-system which is a knowledge-based and learning system that uses the information provided by the predictor system and the optimizer system (fourth sub-system). It will evaluate the cumulative energy cost and the demand response program regulation, as well as the household's consumed and remaining budget. This system has two interfaces, one for communicating with the utility and another for meeting inhabitants' preferences. This system will balance the occupant's budget and via its interface reports in detail their energy consumption trend to end-users.
This system has seven main functions:
a) monitoring system errors and correcting the prediction system by providing appropriate feedback;
b) balancing cost and household budget considering optimization objective function;
c) managing the DRP scheme;

d) allocating slack received from optimization phase to other time slots; e) switching on/off;
f) indicating optimization objective function; and
g) shifting a task if it is shiftable. Other duties of the MAS are mid-term and long-term scheduling.
MAS and IS subsystems are equipped with ubiquitous ICT and utilize the internet for their operation.

C. The Identifier System (IS)

The third sub-system, IS, measures the real-time and online variables. This sub-system identifies which device, and from which zone, has been connected by whom to the power line. It will also identify how much energy a device or piece of equipment requires in order to operate and how much time needs to complete its task. IS has an interface with electrical devices. These data are input for sub-system four and MAS. A non-intrusive load monitoring system may also be utilized by this system [57, 95, 278].

D. The Optimizer System (OS)

OS is the fourth subsystem in the core of the main system that executes the short-term scheduling. The primary optimization variables, objective function and constraints for time slot t_i will be provided for OS by MAS. The optimization system model may be deterministic with a convex function or stochastic with a Marko decision process [129]. OS will receive the real-time (online) data by IS and will perform the optimization for t_i. In this phase, OS indicates which electrical devices with what level of power will operate and for how long. The command of on/off switching or adjusting the power level will be performed by MAS. However, in real-time conditions, some intervening variables may be identified by IS which may affect the optimization process and would be considered as a prediction error. This system error will be calculated by MAS according to what has been predicated and what has been measured online. So the feedback is provided by MAS to IS for this purpose. The functional goal of OS is to minimize energy consumption cost or electric load dynamically and in real-time; or it can maximize the comfort level while taking into consideration the three constraints of load, operating time and energy cost. In other words, this sub-system is a decision-maker [21] for:
a) adjusting the duration and required power for fulfilling a task, and
b) allocating tasks on the time horizon.
Depending on the objective function, constraint and optimization methodology, the inputs will be provided by the MAS and IS systems.

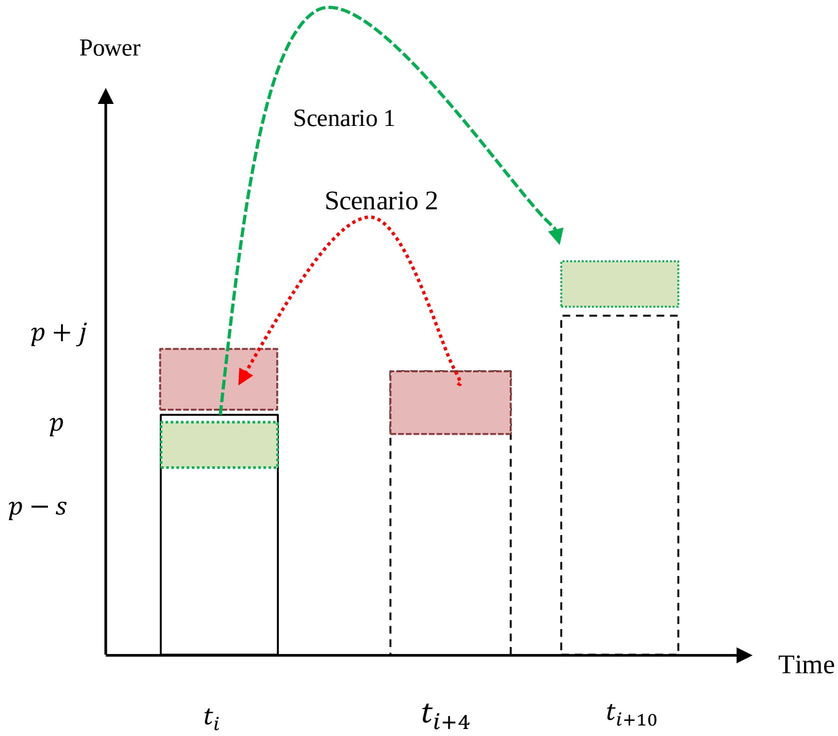


Figure 4.6. Proposed Example for Demonstrating the SoS Functions

I present an example to provide a better understanding of the interaction of sub-systems. Assume that a demand response program indicates (or will be predicted by PS) that the energy price will be $x\ \frac{\$}{kW.h}$ in timeslot t_i. The PS has predicted all variables associated with energy demand and forecasted which appliances will run during t_i . Furthermore, the time and power individually required by each electrical device to finish the task have been also predicted. This information will be sent to MAS which accordingly allocates $p\ (kW)$ power to timeslot t_i; so, the load constraint dictated for that timeslot is p in which the associated allocated budget "B" for that load would be equal to $B(\$) = p(kW) \times t(h) \times x\ \left(\frac{\$}{kW.h}\right)$ where t is the total time estimated for all tasks or power demand during t_i. In this phase, an optimization formula is established. In a real-time situation, the IS will determine the demand power individually for each device and accordingly the optimization will be implemented. Hence, there may be two scenarios. The first scenario is when the idle resources remain after optimization as the slack. For instance $p - s\ (kW)$ will be used so there is $s\ (kW)$ slack that the MAS system will allocate it to those timeslots that bring more efficiency that it has been shown in Figure 4.4 in timeslot t_{i+10}. Afterwards, the PS needs to re-organize the prediction algorithm for future periods so feedback can be sent to the PS.

The second scenario can occur when there is no optimal solution for that timeslot (it may occur in some NP- hard algorithm [299]). One reason for this is that the load demand has been underestimated. In our example, a preceding task with $j\ (kW)$ power demand has been predicted to run in t_{i+4} but starts instead at timeslot t_i. So the MAS that is operating long-term scheduling monitors the condition and allocates load $j\ (kW)$ from t_{i+4} resources to t_i or supplies it from a storage system, thereby increasing the load capacity to $p + j\ (kW)$.

Table 4.1. Proposed Methodologies for Subsystems in Literature

Subsystems	Methodology	References
1. Predictor System (PS)	a) ANFIS, ANN; b) ARIMA	a)[14], [144]; b)[159],[118]
2. Monitor and Allocator System (MAS)	a) Water-filling; b) Game theory; c) Nonintrusive method	a)[195]; b)[301]; c)[302]
3. Identifier System (IS)	a) Nonintrusive method	a)[57]
4. Optimizer System (OS)	a) Mixed integer linear programming; b)Heuristic	a)[303]; b)[304]

In order to design a system with this level of intelligence, a combination of different methodologies with complex algorithms needs to be utilized. Hence, some of the methodologies reported in the literature for each stage of the system function have been summarized. However, because the characteristics of electrical devices are inherent in the scheduling process, in the next section, their details are presented.

4.5. Electrical Equipment Characteristics

To design the versatile energy scheduling system, the electrical equipment has been classified into two groups. The first group consists of equipment which has to be connected to an outlet in order to receive power. So a building can be divided into different zones for monitoring the energy flow demand by this group. Following our comprehensive research and review of the literature, 26 characteristics of this type of equipment in Table 2 have been set out and proposed. These parameters can be used in designing a scheduling algorithm and methodology. However, there are many parameters associated specifically with the efficiency of appliances which are not within the scope of this thesis. The second group of equipment includes those devices which are embedded in buildings in a hardwired manner. This group of equipment comprises lighting (hardwired lamps), heating, ventilation, and air conditioning (HVAC) system, and hot water heaters. In the proposed example in Table 2, a washing machine has the task of washing clothes. This task is performed by five operation sequences: S1- filling, S2- agitating, S3- pump out, S4- rinsing, and S5- spin mode.

The specification of each operation is dependent on machine adjustment. In Table 4.2, an interruptible or non-interruptible task is one where the task has various sequences of operation which can be interrupted and, in this case, it can be deferrable or non-deferrable which refers to whether the task can be shifted to another time. Some of these functions are embedded in smart appliances such as General Electric H2G appliances [305]. In this example, from the end of “filling operation” to the start of “agitating operation”, there can be a delay of 10 minutes, but after agitating ends, the pump-out operation will start immediately. The washing machine is not a mobile device and always extracts power from one specific outlet. An interdependency parameter is applied for appliances which need other appliances in order to accomplish their task. For example, a vacuum cleaner needs light or a dryer that runs after washing machine. The programmability parameter is for smart appliances such as an oven or microwave which are adjustable.

Table 4.2. Electrical Equipment Characteristics

Attributes		**Parameters**	**Example: Washing Machine (LG, 54 kg)**
1	***Time Based Parameters***	Day	Sunday
2		Start time of use	10:20a.m
3		Start time of each operation sequence	S1)10:20 S2)10:30 S3)10:37 S4)10:41 S5)10:47
4		Finish time of each operation sequence	S1)10:25 S2)10:35 S3)10:40 S4)10:45 S5)10:52
5		Finish time of use	10:52 a.m.
6		Length of total operation time	22 min
7		Deferrable or non-deferrable task	Deferrable
8		Interruptible or non-interruptible task	interruptible
9		Time deadline after interruption to finish an operating sequence	S1-S2=10 min, S2 –S3=0 S4-S5= 10 min
10		Operation time of each sequence	S1)5 min S2)5 min S3)3 min S4)4 min S5)5 min
11		Usage frequency	12 times in a month

Table 4.2. Continue. Electrical Equipment Characteristics

Attributes		Parameters	Example: Washing Machine (LG, 54 kg)
12	*Operation Based Parameters*	Minimum power to finish task i (W)	36
13		Maximum power to finish task i (W)	440
14		Standby power (W)	0.75
15		Number of operation sequences to fulfil task i	S1-Filling S2-Agitating S3- Pump out, S4- Rising, S5- Spin mode
16		Power requirement in each operation sequence (W)	S1)22 S2)160 S3)60 S4) 54 S5)440
17		Energy of each operation sequence (kW.h)	S1) 0.0018 S2) 0.0133 S3)0.0030 S4)0.0036 S5)0.0366
18		Total Energy (kWh) of task i	0.0584
19		programmability (adjustable power for operation)	Programmable
20		interdependency to other equipment (preceding, concurrence and succeeding operations)	No interdependency
21		Cost($) of each operation sequence	(if E=0.2 $/kW.h) S1) 0.0004 S2)0.0026 S3)0.0006 S4)0.0007 S5)0.0073
22		Total cost of task i ($)	0.011 $
23		Location , zone or outlet that equipment connected to network	Laundry
24		ownership	Family
25		Fixed in location or mobile	Fixed equipment
26		Alternative	Without alternative

4.6. Optimization and Scheduling Algorithms for HEMs

Based on the reviewed characteristics of an energy management system and the proposed SoS, the aim of this section is to propose a decision making algorithm to optimizer the system function in a dynamic pricing demand response program in order to achieve objectives such as:

- Maximize the consumers' satisfaction while he has been forced to curtail the consumption in order to minimize the effect of DRP on his lifestyle;
- Save the consumers' utility budget in variable energy price scheme;
- Utilizing the distributed energy resources.

Therefore, as explained earlier in section 4.4.1, assume that the optimizer system is in interactive and integrated with the other three sub-systems in the proposed SoS. In this fashion, the information (data) provided for this system in a planning time horizon are:

- Input1: predicted energy price
- Input 2: budget allocated to each timeslot
- Input 3: amount of available distributed energy resources
- Input 4: characteristics of appliances (deferrable/ non-deferrable, interruptible/non-interruptible)
- Input 5: the amount of power demanded by appliances
- Input 6: the amount of time required for fulfilling the task operated by an appliance
- Input 7: the amount of time that a deferrable appliance can be shifted

Accordingly, it is expected that the OS will optimize the energy by accepting or rejecting the demand requested from an appliance. The inputs and outputs of this system are shown in Figure 4.6.

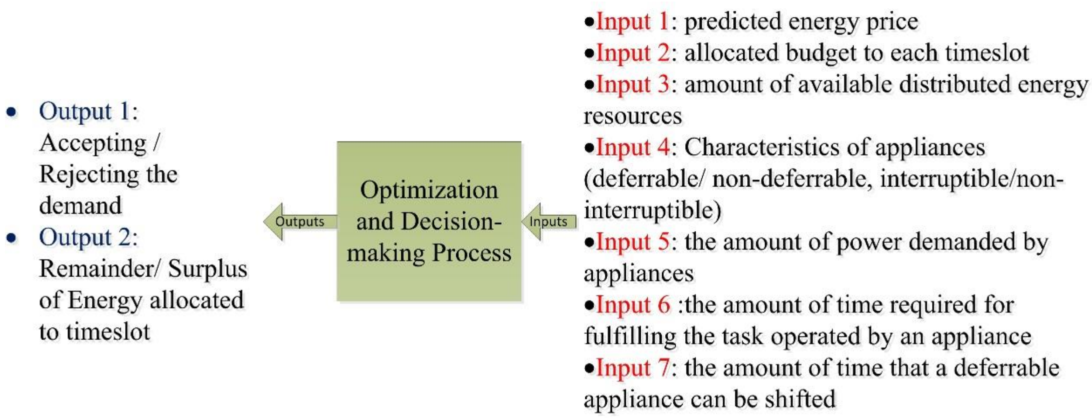


Figure 4.7. The inputs and outputs of Optimizer System

In Chapter 2, section 2.4.1, I classified optimization problems for smart homes and demand response in the context of energy management in four main categories with a total of twelve subcategories. Our proposed optimization method for this system is focused on problems 1, 2, 4, and 11. Moreover, according to the methodologies that were classified in Table 2.2, the proposed methodology in this Chapter can be categorised as shown in Table 4.3.

Table 4.3. The Proposed Optimization Classification Compared with Methods Reviewed in Literature

Optimization Objective	Optimization Method	Appliances	DRP
Maximizing the energy consumption based on the value specified by consumers in a restricted allocated cost	Combinatorial optimization (linear integer programming)	PHEV, water heater, air conditioner, dishwasher, oven , cloth dryer	Real time pricing (a day-ahead or an hour-ahead)

4.6.1. Combinatorial Optimization Methodology: Knapsack Problem (KP)

The knapsack problem is a very simple non-trivial integer programming model with binary variables and is a classic form of a maximization problem which has been studied for centuries. Although this method has only one single constraint and positive coefficient, this simple program is considered difficult problem. This problem has borrowed its name by considering a mountaineer who has decided to pack his knapsack (rucksack) to climb a mountain. The capacity of his knapsack is limited, so he needs to select items carefully according to their values and weight. I can use the analogy of a burglary to explain this problem. A burglar has decided to steal valuable items and fill his knapsack. In this case, the capacity of knapsack is limited and he needs to decide which items to take in order to fill the knapsack and maximize the total value of the objects. In our case, there is a consumer who has a restricted amount of energy that s/he can use during a specific period of time (T). S/he has many devices to use that provide different amounts of comfort and convenience. These devices require different amounts of power (Kw) when operated. The user must select a set of appliances that afford the greatest benefit and satisfaction but in such a way that the total energy consumption does not exceed the energy constraint. In other words, the user has a limited amount of budget ($) to allocate to the use of appliances during a period of time (T) and now s/he has to buy (pay for) the energy (Kw.h) to run appliances based on his limited budget; so s/ he tries to choose a set of appliances which are more convenient.

The binary KP can be formulated as linear integer programming as follows:

Maximize $\sum_{i=1}^{m} p_i x_i$ (4.6)

Subject to $\sum_{i=1}^{m} w_i x_i \leq c$ (4.7)

$x_i \in \{0,1\}, i = 1, \ldots, m$ (4.8)

[306] is one of the best and most valid references for studying the KP algorithm, methodology and solutions. There are various forms of KPs such as binary, the bounded, unbounded, multiple, multiple-choice, quadratic, multi-objective, precedence constraint, nonlinear, fractional, on-line, and semi online knapsack problems. Furthermore, there are various methodologies for solving KP such as the greedy algorithm, linear programming relaxation, dynamic programming, branch and bound, and approximation algorithms. A close examination of KP and its related algorithm is not within the scope of this thesis. I employed the dynamic programming algorithm presented in [306] and accordingly programmed the methodology in MATLAB as shown in Figure 4.13 for binary KP solution.

In the following, I aim to evaluate how MCDM methods discussed in the previous chapter can provide the profit associated with KP optimization. Using this method, I can show how the effect of decision making on energy consumption can affect the optimization.

4.6.2. Knapsack Problem and MCDM for Energy Optimization

By quantifying the consumer's preference using the AHP method described in Chapter 3 section 3.5.1, the priority level of using the appliances was achieved (Table 3.8). If the consumer would like to maintain a certain lifestyle during peak hours and not change consumption behaviour, then s/he should pay for it. But if s/he decides to not exceed budget, then s/he should alter energy consumption and turn off some appliances and shift the consumption to off-peak hours. In our scenario, the energy cost for one hour during the off-peak period was \$0.896 and it was increased to \$1.195 at peak time. The decision-making in the proposed scenario concerned the appliances that the user likes to use during the peak period if the energy price increases by 33%. Now the question is: which appliances should be turned off during peak hours in order to not exceed the total cost?

By considering the hierarchy of preferences shown in Table 3.8 when Iron, Hair dryer, Television and Vacuum cleaner are turned off, then the total cost during peak time would be $0.88 and the consumer would be able to use Spa Bath, Dishwasher and Home computer which have the highest ranking according to his preferences. It is significant that this particular decision is the preferred solution. In order to achieve the optimal choice, I will apply the knapsack problem. The scenario described in the previous section is programed in Lingo software shown in Figure 4.8.

```
Max= (0.237* SB )+( 0.235*DW) + (0.183 * HC)+ (0.12* Vc)+( 0.112* TV)+ (0.065* HD) +
(0.049* IR);
0.2*(4.93 * SB+ 1.867*DW+ 0.067*HC+ 0.933*Vc + 0.2* TV+ 1.46 *HD+ 0.933*IR )<=0.896;
IR < 0.5;
VC<0.5;
HD< 0.3;
HC <1;
TV<1;
SB<0.5;
DW<1;
```

Figure 4.8. Lingo Software Binary Knapsack Programming Code

This problem is solved by LINGO software [307] version12.0 (Figure 4.7). This is a powerful optimization software, and the results shown in Figure 4.7 reveals that if the consumer turns the Dishwasher off, then s/he saves the same amount of money during the on-peak period as he does during off-peak hours.

The optimal solution shows that the total value of preferences is 0.765; meanwhile, according to consumer's preferences achieved by AHP method, the total value was 0.655. This means that through this optimization the user is able to use more appliances. As indicated in Table 3.8, the Dishwasher was the second priority in the ranking of appliances that the consumer decided to use during peak hours, and turning it off is not in accord with this preference; but on the other hand, the total value is maximized. This consumption pattern is efficient because the demand and amount of energy is decreased. In this case, a report can be sent to the user to make the final decision. In section 3.7 of the previous chapter, I discussed the disadvantages of the AHP methodology. Pairwise comparison techniques such as AHP and ANP require the intense and committed involvement of end-users during the decision-making process that may discourage householders from engaging in energy management, or they find this method tedious.

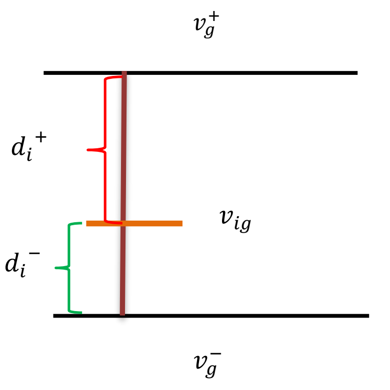
```
SETS:
ITEMS / SB, DW, HC,VC, TV, HD, IR/:
INCLUDE, WEIGHT, RATING;
ENDSETS
DATA:
WEIGHT RATING =
0.493 0.237
0.373 0.235
0.013 0.183
0.093 0.12
0.04 0.112
0.088 0.065
0.093 0.049;
KNAPSACK_CAPACITY = 0.896;
ENDDATA
MAX = @SUM( ITEMS: RATING * INCLUDE);
@SUM( ITEMS: WEIGHT * INCLUDE) <=
KNAPSACK_CAPACITY;
@FOR( ITEMS: @BIN( INCLUDE));
```

Figure 4.9. The Lingo Code for AHP and Knapsack Problem Scenario

```
Global optimal solution found.
Objective value:                              0.7660000
Objective bound:                              0.7660000
Infeasibilities:                               0.000000
Extended solver steps:                                0
Total solver iterations:                              0

Model Class:                                       PILP

Total variables:                  7
Nonlinear variables:              0
Integer variables:                7

Total constraints:                2
Nonlinear constraints:            0

Total nonzeros:                  14
Nonlinear nonzeros:               0

                              Variable           Value        Reduced Cost
                     KNAPSACK_CAPACITY       0.8960000            0.000000
                         INCLUDE( SB)         1.000000          -0.2370000
                         INCLUDE( DW)         0.000000          -0.2350000
                         INCLUDE( HC)         1.000000          -0.1830000
                         INCLUDE( VC)         1.000000          -0.1200000
                         INCLUDE( TV)         1.000000          -0.1120000
                         INCLUDE( HD)         1.000000          -0.6500000E-01
                         INCLUDE( IR)         1.000000          -0.4900000E-01
                          WEIGHT( SB)        0.4930000            0.000000
                          WEIGHT( DW)        0.3730000            0.000000
                          WEIGHT( HC)        0.1300000E-01        0.000000
                          WEIGHT( VC)        0.9300000E-01        0.000000
                          WEIGHT( TV)        0.4000000E-01        0.000000
                          WEIGHT( HD)        0.8800000E-01        0.000000
                          WEIGHT( IR)        0.9300000E-01        0.000000
                          RATING( SB)        0.2370000            0.000000
                          RATING( DW)        0.2350000            0.000000
                          RATING( HC)        0.1830000            0.000000
                          RATING( VC)        0.1200000            0.000000
                          RATING( TV)        0.1120000            0.000000
                          RATING( HD)        0.6500000E-01        0.000000
                          RATING( IR)        0.4900000E-01        0.000000

                                   Row    Slack or Surplus      Dual Price
                                     1        0.7660000            1.000000
                                     2        0.7600000E-01        0.000000
```

Figure 4.10. The result of Solving Knapsack Problem by Lingo Software

TOPSIS is a technique which requires a minimal amount of decision-maker involvement by catering for the consumer's preferences according to specific criteria within a time scale. In Chapter 3, I showed how by using TOPSIS, the importance and ranking of appliances are measurable in a dynamic pricing scheme such as a day-ahead DRP. TOPSIS is based on measuring the alternatives to the criteria value by using Euclidean metrics to compute the distance of each alternative from PIS (d_i^+) and NIS (d_i^-) as shown by Eq. 3.17 and 3.18 and in Figure 4.6. Consequently, by considering the closeness coefficient of each alternative, CC_i^+ as "the profit value" in knapsack problem objective function Eq.4.6 can reflect the user's degree of preference for each appliance.



$$d_i^+ = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^+\right)^2} \quad (3.18)$$

$$d_i^- = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^-\right)^2} \quad (3.19)$$

$$CC_i^+ = \frac{d_i^-}{(d_i^- + d_i^+)} \quad (3.20)$$

Figure 4.11. Using Euclidean Metrics Flor Computing the Distance of Each Alternative from PIS (d_i^+) and NIS (d_i^-)

Considering the above discussion and the energy and cost relationship I can re-formulate the Eqs.4.6-8 as follows:

Maximize $\sum_{i=1}^{m} v_i x_i$ (4.9)

Subject to

$$\sum_{i=1}^{m} E_i x_i \leq E_{DRP}^t \quad (4.10.a)$$

Or $\sum_{i=1}^{m} P_i . t_i . x_i \leq E_{DRP}^t$ (4.10.b)

Or $\frac{1}{U^t}\sum_{i=1}^{m} c_i x_i \leq \frac{1}{U^t} C_{DRP}^t \equiv \sum_{i=1}^{m} c_i x_i \leq C_{DRP}^t$ (4.10.c)

$$x_i \in \{0,1\}, i = 1, \dots, m \quad (4.11)$$

Where E_{DRP}^{t} and C_{DRP}^{t} are the energy limit and its associated cost imposed by DRP; and v_i is the value rank of the alternative achieved by the TOPSIS methodology. It is worth mentioning that calculating v_i by TOPSIS is proposed when there are many criteria associated with assessing the energy consumption, but when there is just one criterion for specifying the profit of using appliances, it can be directly reflected to the objective function. This can be done by demonstrating to the user a scale like the one depicted in Figure 4.12 with which they can indicate their preferences for particular appliances. I designed a scale (shown below) which allows the user to show the extent to which certain appliances are needed. For example, when the user chooses “up to the system” it means s/he has given the value of “0.5” as profit, or when s/he urgently needs an appliance, then the profit value, according to the KP methodology, is considered as 0.9.

In our proposed methodology, there are items which must remain in knapsack, because their functions is a prerequisite for other appliances functions or because the consumer insist to use them even if the system has selected them for turning-off. In this situation a big-number, M, equal to 1000 will be allocated as the value (profit) to those items. I will show this methodology in section 4.6.4 of this chapter.

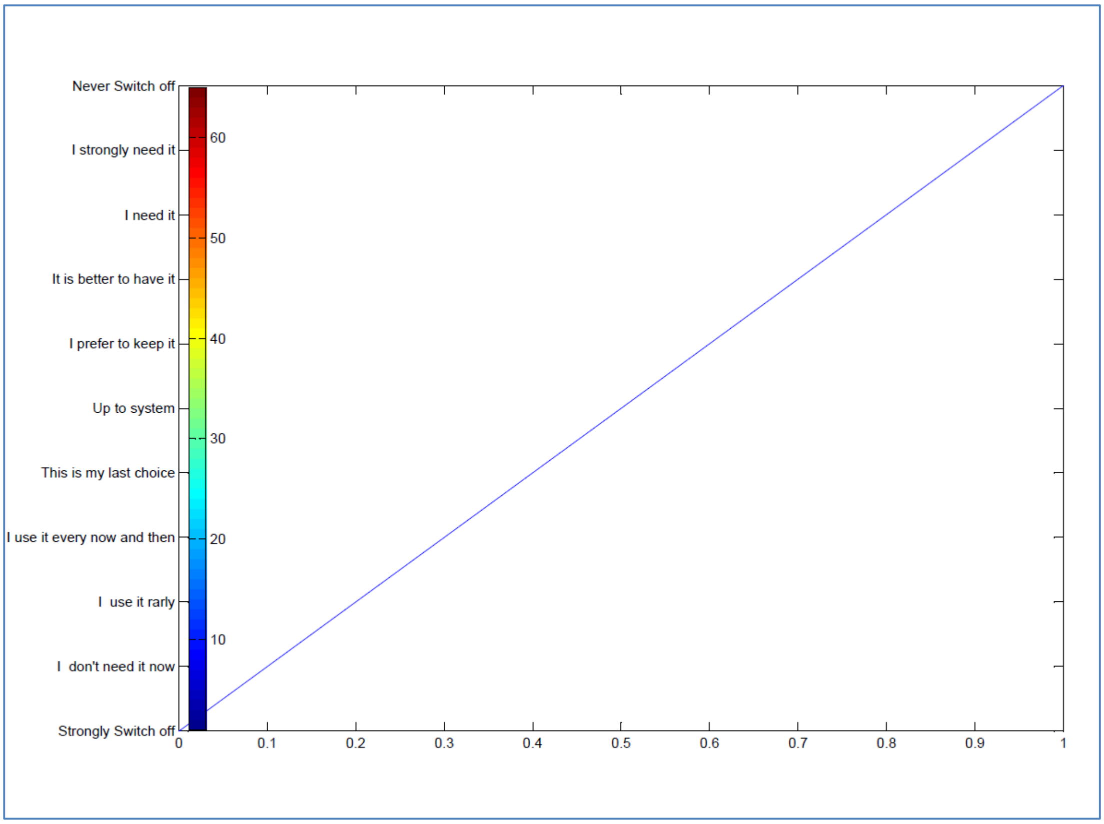


Figure 4.12. A scale for Elicitation of Consumer’s Preference for Using an Appliance

The methodology proposed above has attracted many researchers [105, 308-312]. For example, [308, 312] used our methodology for implementing a power allocation on a smart outlet shown in Figure 4.11. In their paper, [308] raise an important issue that they propose to tackle in future work how KP is capable of distinguishing the interdependencies of appliances. I attempt to address this issue by proposing a decision making algorithm in the following section.

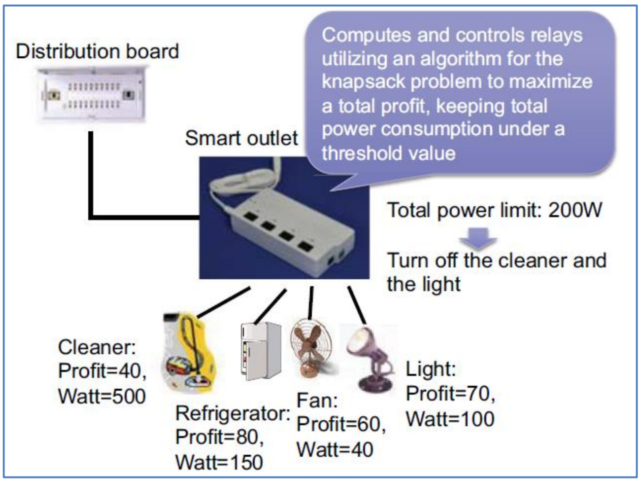


Figure 4.13. Knapsack Problem Application Implemented on a Smart Outlet by [308, 312]

4.6.3. Feasibility of Knapsack Problem Optimization by Presenting Eight Scenarios

The feasibility of Knapsack Problem Optimization can be investigated by applying this method in different scenarios. For this purpose, I have designed and created a database with 900 entries for the operations of different electrical devices I called *tasks*. These data are presented in Figure 4.12. These data are gathered from resources such as government websites [313, 314] and appliance manufacturers' catalogues.

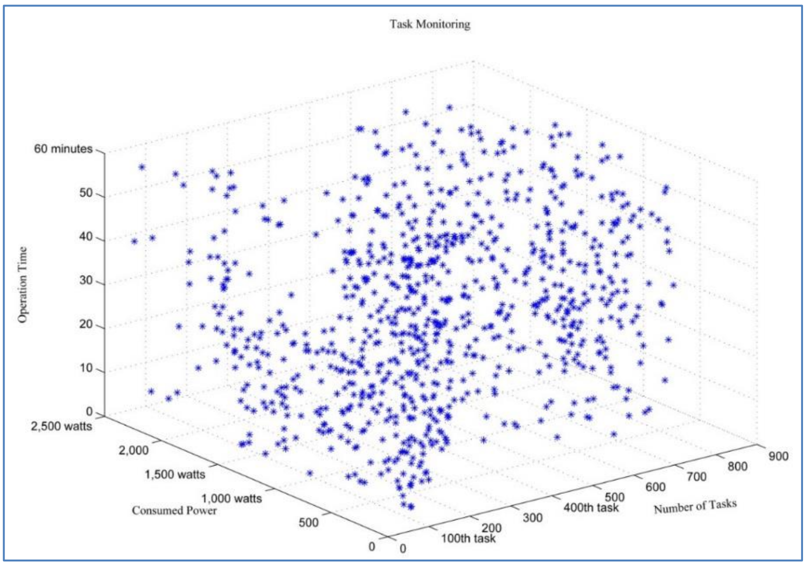


Figure 4.14. The Data of 900 Appliance Operation Tasks Used For Scenarios Simulation

I implemented the knapsack method in eight scenarios. To calculate the profit value, it is assumed that there is one criterion in decision-making and that criterion is the degree of importance that the householder gives to each appliance.

```
function [best item]= knapsack(weights, values, W)
    if ~all(positive_integer(weights)) || ...
       ~positive_integer(W)
        error('Weights must be positive integers');
    end
    [M N] = size(weights);
    weights = weights(:);
    values = values(:);
    if numel(weights) ~= numel(values)
        error('The size of weights must match the size of values');
    end
    if numel(W) > 1
        error('Only one constraint allowed');
    end
        A = zeros(length(weights)+1,W+1);
    for i = 1:length(weights)
        for K = 1:W
            if weights(i) > K
                A(i+1,K+1) = A(i,K+1);
            else
                A(i+1,K+1) = ...
                    max( A(i,K+1), values(i) + A(i,K-weights(i)+1));
            end
        end
    end
    best = A(end,end);
      item= zeros(length(weights),1);
   a = best;
   i = length(weights);
   K = W;
   while a > 0
       while A(i+1,K+1) == a
           i = i - 1;
       end
       i = i + 1;
       amount(i) = 1;
       K = K - weights(i);
       i = i - 1;
       a = A(i+1,K+1);
   end
    amount = reshape(amount,M,N);
end
 function yn = positive_integer(X)
    yn = X>0 & floor(X)==X;
end
```

Figure 4.15. Knapsack Programming MATLAB Function Code

It is assumed that in a timeslot, the amount of energy has been scheduled (allocated); then by randomly selecting appliances, a level of demanded energy will be specified. If the amount of demanded energy (DE) is higher than the scheduled energy (SE) level, the KP optimization will be performed so that I reach a new level of energy as the optimized level of energy (OE). In Tables 4.4 -14, these scenario inputs to optimization algorithm has been demonstrated that they can be discussed as follows:

1. The value index is obtained by dividing the total values in the timeslot by the total number of items. So after optimization, I can study the trend of this value index and see how KP is dealing with the total value in each simulation.
2. After KP optimization the removed items in Tables 4.4- 14 are shown with orange colour.

3. Scenarios 4 and 5 are similar with together and the only difference is the amount of scheduled energy. In scenario 5, this amount is 40 watts higher because in this case this amount has been added by battery-stored energy. So by comparing Tables 4.10 and 11, I can see the effect of distributed energy resources in optimization.

4. In scenario 8, the demanded energy is 2,426 watts while the scheduled energy is 2,200 watts. On the other hand, there is a clothes dryer with 2,100 watt power with profit value equal to “1” that means this device must not ever be switched off. The result of optimization shows this item has been removed in order to reach an optimal solution. There are seven other appliances with a total energy consumption of 325.7 watts with a value adding up to 4.3; in this case, if all of them are removed from the knapsack, then the total value index will drop dramatically. This scenario shows how KP works to maximize the profits. In this case, the user must sacrifice his need for a clothes dryer, but keeps the electric blanket and light with value one. I will show in our proposed decision-making algorithm that the system can notify the user about this kind of situation.

5. The three levels of energy, demanded energy, restricted energy by DRP as scheduled energy, and the energy level after optimization have been shown in Figure 4.17 and 18.

Table 4.4. Scenario #1 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt.hour)	Value
1	tsk1	air-conditioner	30	1640	820.00	1
2	tsk60	lighting	10	20	3.00	1
3	tsk69	lighting	35	75	44.00	1
4	tsk57	computer	45	270	203.00	0.5
5	tsk50	cooking1	30	600	300.00	1
6	tsk51	cooking2	15	1400	350.00	0.4
7	tsk83	cell phone charger	60	10	10.00	0.7
8	tsk32	refrigerator	60	750	750.00	1
9	tsk33	coffee maker	5	1200	100.00	0.2
10	tsk79	pool pump	20	1100	367.00	0.3

Table 4.5. Scenario #2 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt.hour)	Value
1	tsk59	computer	35	270	158.00	0.7
2	tsk60	lighting	10	20	3.00	1
3	tsk76	lighting	60	7	7.00	1
4	tsk770	hair dryer	5	1500	125.00	0.2
5	tsk80	iPad charge	50	20	17.00	0.8
6	tsk81	printer (laser)	5	500	42.00	0.3
7	tsk70	air-conditioner	60	1830	1830.00	0.9
8	tsk8	clothes dryer	60	2200	2200.00	1

Table 4.5. Continue. Scenario #2 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt.hour)	Value
9	tsk210	watching TV	60	400	400.00	1
10	tsk6	cooling	45	2100	1575.00	0.4
11	tsk83	cell phone charger	60	10	10.00	1
12	tsk70	lighting	25	63	26.00	1
13	tsk40	vacuum cleaner	30	1500	750.00	0.2
14	tsk65	lighting	20	52	17.00	1
15	tsk66	lighting	60	42	42.00	1
16	tsk29	cooking	25	1400	583.00	0.6

Table 4.6. Scenario #3 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt.hour)	Value
1	tsk59	computer	35	270	158.00	0.2
2	tsk16	bath water heater	20	1300	433.00	0.4
3	tsk17	TV	45	400	300.00	0.8
4	tsk63	lighting	5	26	2.00	1
5	tsk64	lighting	15	24	6.00	1
6	tsk65	lighting	20	52	17.00	1
7	tsk66	lighting	120	42	84.00	0.9
8	tsk67	lighting	5	35	3.00	0.8
9	tsk68	lighting	40	20	13.00	1
10	tsk79	pool pump	20	1100	367.00	0.5
11	tsk49	cooking	25	1600	667.00	0.8
12	tsk44	cloth washing	15	150	38.00	1
13	tsk45	cloth washing	40	2400	1600.00	1
14	tsk46	cloth washing	5	300	25.00	1

Table 4.7. Scenario #4 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Rounded Energy (watt. Hour)	Value
1	tsk59	computer	35	270	158.00	0.6
2	tsk16	bath water heater	20	1300	433.00	1
3	tsk17	TV	45	400	300.00	0.8
4	tsk63	lighting	5	26	2.00	1
5	tsk66	lighting	60	42	42.00	0.5
6	tsk67	lighting	5	35	3.00	0.4
7	tsk68	lighting	40	20	13.00	0.3
8	tsk79	pool pump	20	1100	367.00	1
9	tsk53	cooking	40	1950	1300.00	0.8
10	tsk46	cloth washing	25	300	125.00	1
11	tsk47	cloth washing	20	30	10.00	1
12	tsk48	cloth washing	5	1400	117.00	1

Table 4.8. Scenario #5 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt. Hour)	Value
1	tsk59	computer	35	270	158.00	0.6
2	tsk16	bath water heater	20	1300	433.00	1
3	tsk17	TV	45	400	300.00	0.8
4	tsk63	lighting	5	26	2.00	1
5	tsk66	lighting	60	42	42.00	0.5
6	tsk67	lighting	5	35	3.00	0.4
7	tsk68	lighting	40	20	13.00	0.3
8	tsk79	pool pump	20	1100	367.00	1
9	tsk53	cooking	40	1950	1300.00	0.8
10	tsk46	cloth washing	25	300	125.00	1
11	tsk47	cloth washing	20	30	10.00	1
12	tsk48	cloth washing	5	1400	117.00	1

Table 4.9. Scenario #6 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt. Hour)	Value
1	tsk693	lighting	5	26	2.00	0.5
2	tsk614	lighting	15	24	6.00	0.5
3	tsk765	lighting	20	52	17.00	1
4	tsk66	lighting	60	42	42.00	1
5	tsk67	lighting	5	35	3.00	0.4
6	tsk33	coffee maker	5	1200	100.00	0.4
7	tsk32	refrigerator	60	750	750.00	1
8	tsk226	TV	60	400	400.00	1
9	tsk687	video game player	60	200	200.00	1

Table 4.10. Scenario #7 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt. Hour)	Value
1	tsk3	lighting	5	26	2.00	0.5
2	tsk164	lighting	15	24	6.00	0.5
3	tsk65	lighting	20	52	17.00	0.9
4	tsk466	lighting	60	42	42.00	1
5	tsk67	lighting	5	35	3.00	1
6	tsk2	air-conditioner	20	1680	560.00	0.4
7	tsk32	refrigerator	60	750	750.00	1
8	tsk26	playing TV	60	400	400.00	0.8
9	tsk187	video game player	60	200	200.00	0.8
10	tsk34	cooking (microwave)	5	1400	117.00	1
11	tsk241	vacuum cleaner	25	1500	625.00	0.8

Table 4.11. Scenario #8 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt.hour)	Value
1	tsk64	lighting	15	24	6.00	0.5
2	tsk65	lighting	20	52	17.00	0.5
3	tsk66	lighting	60	42	42.00	0.9
4	tsk67	lighting	5	35	3.00	1
5	tsk85	electric blanket	60	100	100.00	1
6	tsk59	computer	35	270	158.00	0.4
7	tsk8	clothes dryer	60	2100	2100.00	1

Table 4.12. Scenario #9 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt.hour)	Value
1	tsk63	lighting	5	26	2.00	0.5
2	tsk64	lighting	15	24	6.00	1
3	tsk49	cooking	25	1600	667.00	0.9
4	tsk5	cooling (air-conditioner)	15	170	43.00	0.7
5	tsk32	refrigerator	60	750	750.00	1
6	tsk84	blender	10	300	50.00	1
7	tsk30	cooking	5	1400	117.00	1

Table 4.13. Scenario #10 Energy Demand Profile

#	task code	task name	operation time (minute)	power (watt)	Energy (watt.hour)	Value
1	tsk63	lighting	5	26	2.00	0.5
2	tsk64	lighting	15	24	6.00	1
3	tsk50	cooking (stove)	30	600	300.00	0.2
4	tsk5	cooling	15	170	43.00	0.7
5	tsk32	refrigerator	60	750	750.00	1
6	tsk84	blender	10	300	50.00	0.8
7	tsk30	cooking (microwave)	5	1400	117.00	0.8
8	tsk65	lighting	20	52	17.00	0.8

Table 4.14. Summary of Eight Scenarios

Scenarios	Total Number of Items	Total Number of After items	TV Before Optimization	TV After optimization	VI Before Optimization	VI After Optimization	DE	SE	OE	DE-SE	SE-OE	DE-OE	Time Elapsed (E-06)
sce-01	10	9	7.1	6.9	0.71	0.77	2947	2900	2847	47	53	100	2.81
sce-02	16	14	12.1	11.5	0.76	0.82	7785	6200	5460	1585	740	2325	1.49
sce-03	14	13	11.40	11.00	0.81	0.85	3713	3400	3280	313	120	433	1.31
sce-04	12	11	9.40	8.80	0.78	0.80	2870	2800	2712	70	88	158	1.68
sce-05	12	11	9.40	8.90	0.78	0.81	2870	2840	2828	30	12	42	1.49
sce-06	9	8	6.80	6.40	0.76	0.80	1520	1500	1420	20	80	100	1.31
sce-07	11	10	8.70	8.30	0.79	0.83	2722	2500	2162	222	338	560	1.31
sce-08	7	6	5.30	4.30	0.76	0.72	2426	2200	326	316	1874	2100	1.31
sce-09	7	6	6.10	5.40	0.87	0.90	1635	1600	1592	35	8	43	1.31
sce-10	8	6	5.8	4.8	0.73	0.8	1285	900	868	385	32	417	1.31

DE: demanded energy (watt. Hour), SE: scheduled energy (watts. Hour), OE: optimized energy (watts. Hour), TV: Total value, VI= Value index

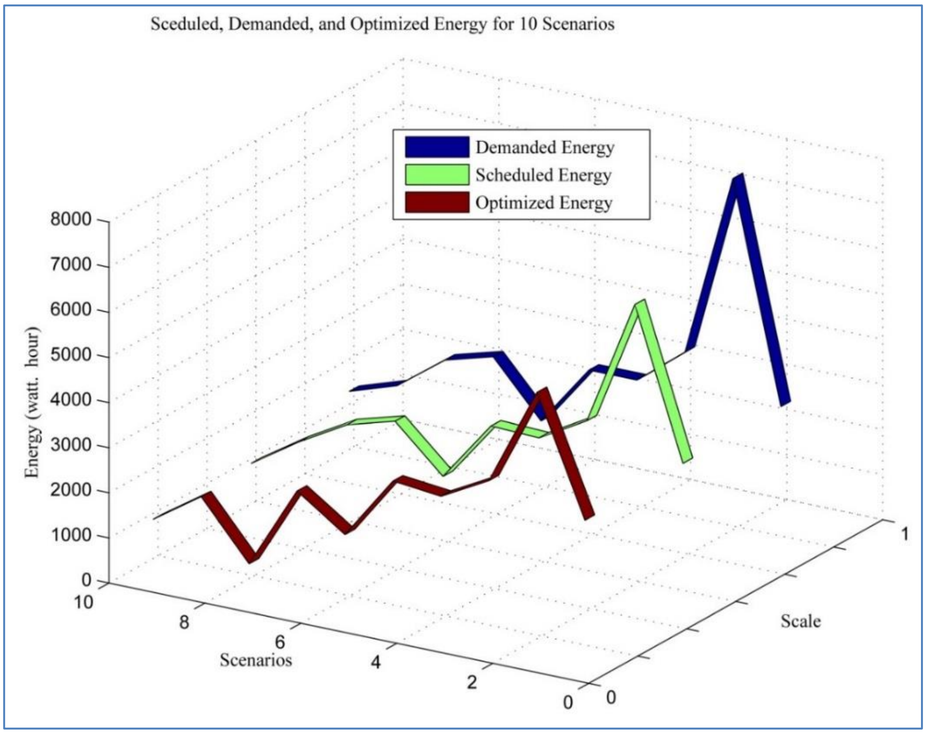


Figure 4.16. The Energy Levels Before and After Optimization (3D)

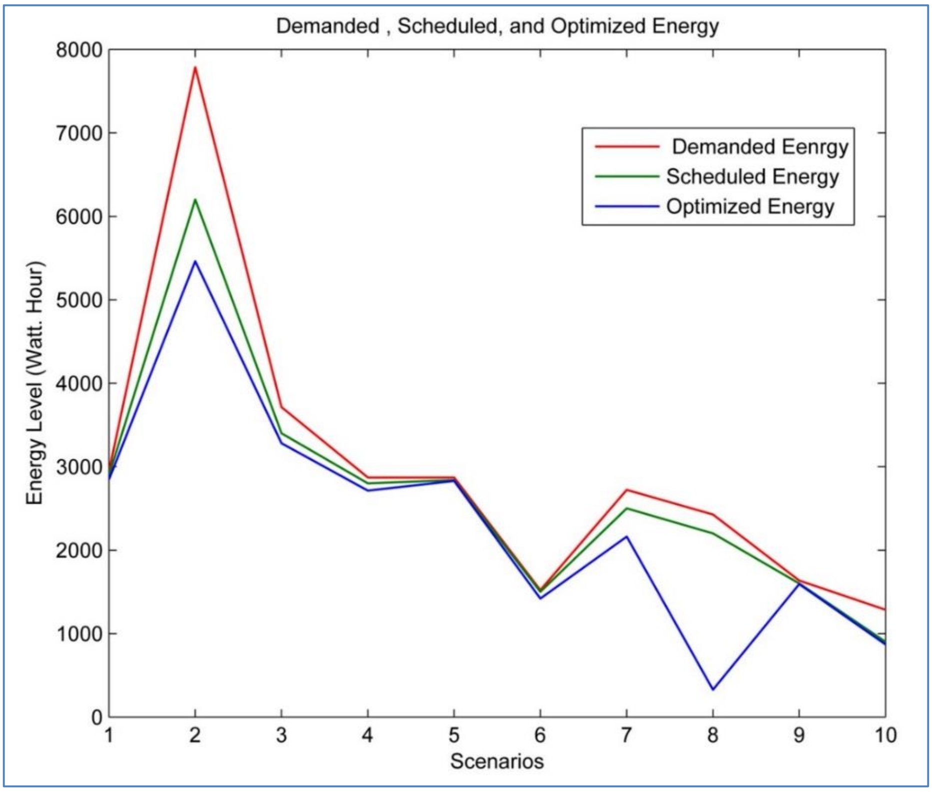


Figure 4.17. The Energy Levels Before and After Optimization (2D)

4.6.4. Decision-making Algorithm for Optimal Energy Consumption

In SoS, the proposed optimizer system interacts with the other three systems and the user. In this case, a decision-making framework is required for establishing an intelligent level of interaction. The proposed decision-making algorithm is shown in Figure 4.19.

This algorithm can be explained as follows:

1. The scheduling time horizon is divided into "n" equal timeslots.
2. The algorithm runs from the first timeslot n=1.
3. The energy demand and input data 1 to 7 explained in the section above are provided by IS, PS, and MAS systems.
4. The knapsack weight and value in steps 3 and 4 are provided for executing the KP optimization in step 5.
5. By implementing the KP optimization, the algorithm asks whether or not the optimal solution exists. If there is an optimal solution, the removed item must be investigated in step 8a and 8b but prior to this, the algorithm checks whether the removed item has a high value.
6. In step 8, the algorithm checks three attributes of the removed items. If the removed items (rejected appliances) are pre-requisites for other tasks (attributes 20 in Table 4.2, dependency on other equipment) which are already in the knapsack, then they must revert to it. Furthermore, it is very important that the removed items be interruptible or shiftable. If an item is not, then a high value, "M" which is equal to 1000 will be allocated to the item and again the KP optimization will executed.
7. After repeating the optimization, in step 7, the algorithm checks whether the item with a high value has been removed; and in this case the algorithm asks the user to override the system by allocating more budget in order to increase the knapsack capacity.
8. In step 8, if none of the situations arises, then the algorithm becomes ready for the next timeslot.
9. If the OS cannot find the optimal solution, two decisions will be taken: the system checks whether the optimization has been executed after adding the available stored energy; otherwise, if there are available resources, then the system reverts to step 4 and specifies the new size for the knapsack. However, if there are not enough resources, then the user is required to allocate more funds to meet the demand and optimization.
10. In step 12, when the user allocates more budget to meet his demand, then a new knapsack size will be specified in step 4 and the system will perform a new optimization10- In step 12 when the user allocate more budget for his demand, then a

new size of knapsack will be specified in step 4 and system will perform a new optimization.

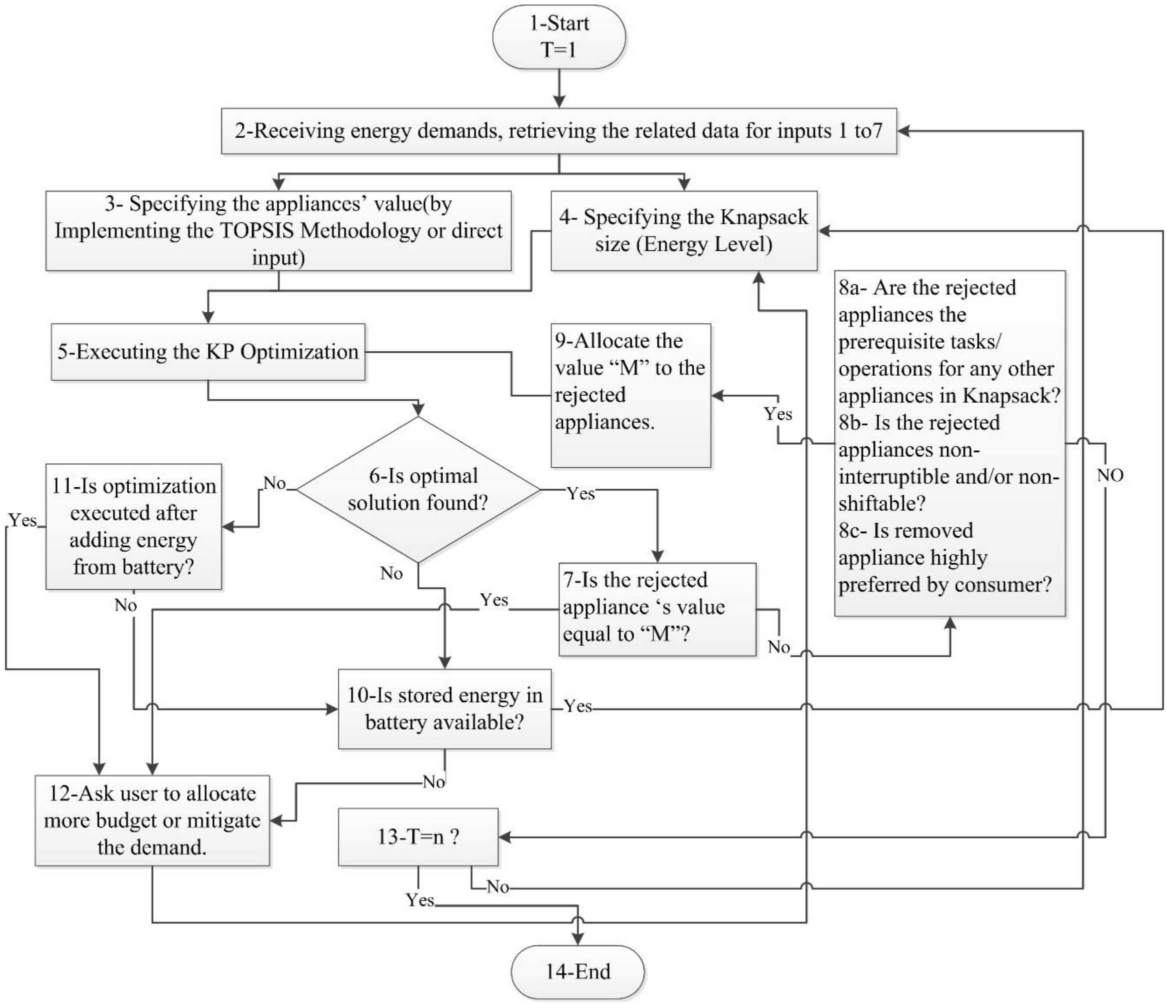


Figure 4.18. Optimizer System Decision Making Framework

I explain the function of proposed algorithm for aforementioned scenario 8 as follows:

In scenario 8, Table 4.14, there are 7 appliances that in total have a demand for 2426 watts. Hour energy for the demand response limit on this timeslot is 2200 watt-hours. After optimization, the clothes dryer with 2100 watt-hours energy will be removed. Its value is equal to 1 which means that the consumer preferred to have this appliance in that timeslot; so, in step 9 of the algorithm, a value equal to 1000 is allocated to it, and the second round of optimization is executed.

In the second round of optimization, appliances such as the electric blanket and computer with values of 1 and 0.4 respectively have been removed. However, the electric blanket is preferred, so again a value of 1000 is allocated to it and a third round of optimization executed.

In third round of optimization, electric blanket and cloth dryer with high value remained in the Knapsack and other appliances have been removed that among them a "light" with value (profit) equal to one is included. The budget deviation in this round is zero. So a value of big number "M" allocates to the light and fourth round of optimization executed. In this KP optimization, I have three items which their values (profit) are equal to the big number, M, that execution of this round will be exactly the same as the first round of the optimization in which those appliances had the value equal to "1". In this situation, the system must override by user to allocate budget or change the value of preferences (step 12). In this situation, the user allocates 100 watt.hour energy, so the level of energy increases from 2200 watt.hour to 2300 watt.hour. With this budget allocation, the "computer" appliance with a value of 0.4 removed from the knapsack and the energy surplus comes to +32 watt.hour.

Table 4.18. Implementing the Decision–making Algorithm for Scenario 8

Optimization	removed appliances (Watt.hour, Value)	Energy level after Optimization
1st round	Cloth dryer(2100,1)	326
2nd round	Elec Blanket(100,1), Computer(158,0.4)	2168
3rd round	Computer(158,0.4),light(6,0.5), light(17.33,0.5),light(42,0.9),	2200
4th round	computer(158, 0.4)	2268

4.7. Conclusions

The ISO/IEC 15067-3 standard [5] and the OpenADR 2.0b profile specification [6] which are used to enhance the functionality of HEMS compatible with SG regulations, inspired us to propose a system of systems approach for the design of a versatile home energy scheduler. The residential aspect of the SG is a complex adaptive system that needs to utilize convoluted algorithms to achieve an efficient level of energy consumption. In this Chapter, I have explained the functions of the proposed HEMS scheduler model that inherent includes event detection, resource allocation, task monitoring, and optimization.

The methodologies in the sub-system level are set out briefly in Table 4.1 As was demonstrated in sections 4.2.1 and 4.3, understanding the nature of the operation's task, the degree of concurrency, running time of scheduling algorithm execution, and satisfying residents' preferences are obstacles facing system designers in this field. The interaction of an optimizer system needs a decision-making algorithm in order to achieve an optimal level of optimization. I proposed knapsack problem optimization as a powerful combinatorial optimization to achieve an optimal level of energy when the energy level in each timeslot is limited and restricted by a DRP.

In the next Chapter, a developed methodology is presented for the industrial sector of the smart grid where an energy manager needs to make a decision about whether to participate in a DRP or use energy provided by a DER.

Chapter 5

A Decision-Making Framework for Assessing Demand Response Engagement in Industrial Sectors of Smart Grid

5.1. Introduction

In Previous Chapters, I developed a decision-making methodology for achieving the end-user's preferences and proposed an optimization technique for energy management based on those preferences in order to increase the DRP willingness for participation. Our methodologies in previous Chapters 3 and 4 focused on residential sector in SG. However, this method is deployable in industrial sector where energy manager must make decision whether to participate in DRP or accept the high peak period energy cost.

Demand response programs (DRPs) in the smart grid (SG) industrial sector should take production and operation management into consideration. Since any loss of energy will directly affect all aspects of an organization, any decision about load curtailment requires a comprehensive risk and defect assessment. In this Chapter, Delphi method is proposed for identifying the criteria required for evaluating the effects of DRP engagement on operational and production management factors. The TOPSIS technique with information entropy proposed in third Chapter is employed to compute the significant values of equipment during energy planning according to the criteria. Then the computed values are used by a linear programming (LP) model to evaluate DRPs and plan the energy required for equipment during production, taking into account all the constraints imposed by DRP and production resources. The methodology presented in this Chapter assists operation and energy managers to make better decisions regarding DRPs and to plan energy efficiently.

As discussed in Chapter 1 and 2, in smart grid (SG), demand-side management (DSM) comprises those technologies, activities and strategies used by the utility provider on the demand side of the energy network to manage load, improve energy efficiency, reduce emissions, and increase consumer participation in energy management [73]. The main aim of DSM is to balance demand with available supply instead of the conventional policy where energy is supplied to meet demand.

SG's consumers are residential, commercial, municipal, or industrial, the last being the focus of this Chapter since it has the largest share of the total energy consumption[74]. For example, in 2011-12, Australia's manufacturing sector was the largest user of electricity with 43.6% (or 67,400 GWh) of electricity consumption and 27.3% (or $5.5b) of total electricity expenditure [315]. The demand response program (DRP) is a DSM method by which electricity aggregators or utilities can manage power consumption via price-based or incentive-based regulations, benefitting participants who curtail their energy demand during peak periods or shift their demands to off-peak periods [74, 316].

In Chapter 1, I discussed that DRPs are categorized into two main groups of incentive-based and time-based programs (IBP, TBP) [16, 17, 76]. It is mentioned that in IBPs, participants are rewarded based on their consumption behaviour performance in critical conditions by receiving discount rates or credits on their bill. In TBPs, electricity tariffs are designed based on dynamic pricing rates that fluctuate according to the real time cost of electricity market [17]. The methodology proposed in this Chapter is based on real TOU, a type of real time pricing (RTP), which is the most efficient and direct program in competitive energy market [17, 76] . In such programs, participant will be informed about the energy prices which are reflected by the real cost of energy in wholesale market on a day-ahead or an hour-ahead basis [17].

In industrial sector of smart grid, offering commercial incentives to industrial consumers or shifting the demand to off-peak periods can cause a dilemma since a DRP may disrupt the production process and the organization may incur losses if its energy load is decreased. However, principally in electricity demand economics, the more electricity is consumed, the more products are produced. In *production functions*, the production output such as sales income, profit, and value-added are positively correlated with electricity consumption as an input [317]. However, most industrial consumers are equipped with on-site energy generators for emergency back-up or auxiliary power for DR[74]. Hence, industries could consider one of the following options:

a) Rejecting DRP, sustaining production during on-peak periods, and accepting high energy prices and penalties;
b) Engaging in DRP and compensating for lost production by receiving discounts on energy price rate or accepting a commercial incentive;
c) Using back-up on-site energy generators during peak-hours and/or a storage system;
d) Curtailing energy consumption during peak hours by shifting loads to off-peak periods and employing an economically and technically viable energy plan.

Apart from choosing the strategy most appropriate for production, there should be adequate information and communication technologies (ICT) and advanced metering infrastructure (AMI) to provide precise and real-time information for energy-efficient decision-making [24, 318, 319]. Although many researches have proposed solutions for decision making and energy optimization in the residential sector of smart grid [23, 320], energy-efficient manufacturing is more complicated and not limited to a cost and benefit analysis since efficacy and efficiency are priorities in all layers of operational management [321-323]. Industrial participants in DRP need to assess the risks associated with DRP in terms of financial gain and loss.

This Chapter proposes a decision support model and a methodology to assist energy experts in industrial sectors to assess the risks posed by DRP in production environments. By utilizing real-time energy consumption information, an energy optimization method is employed to schedule and allocate energy during DRP to identify any potential loss of production. Energy managers may be able to make decisions about whether or not to implement a DRP program after considering the DRP’s energy constraints and the potential loss of production whilst achieving the optimized level of energy.

The remainder of this Chapter is organized as follows. Section 5.2 presents related works and identified problems. Section 5.3 addresses decision making for evaluating equipment operation and energy management. Energy, power and cost correlations have been delineated in section 5.4; in section 5.5 DRP engagement evaluation is studied and section 5.6 an algorithm is introduced for energy optimization and a DRP engagement evaluation. Section 5.7 presents a case study simulating the proposed methodologies. Section 5.8 presents the sensitivity analysis of the proposed algorithm, and section 5.9 concludes this Chapter.

5.2. Related Studies and Identified Problems

With the emergence of SG, DRPs in the industrial sector have attracted intense research. The significances of prioritizing loads and products are presented in [321] by dividing the products into three categories A, B, and C from highest value to the lowest value to prioritize workshops for load curtailment in DRP. Daily production and inventory constraints, maintenance schedules, crew management, and characteristics of the workstations have been considered in the conceptual model designed to assess the processes for load curtailment or temporary shut-down. However, after ranking the workstation, authors did not present a methodology to determine the electricity cost-saving potential or a method to evaluate whether or not the financial benefits of DRP are attractive for incentives.

A load scheduling strategy aimed at minimizing electricity costs to the industrial users in real-time pricing DRP is presented by [322]. This research utilizes a linear programming optimization algorithm to minimize the electricity cost by harmonizing the hourly marginal rate duration curve with maximum and minimum power demand levels. Electricity cost for the end-user with and without load scheduling operation while considering the total spare energy consumption capacity and optimum load scheduling have been modelled. However, potential electricity cost savings and the cost of unserved energy for evaluating the economic value of RTP have not been considered.

The effect of unreliable and finite information on the efficiency of the operations plans in RTP scheme of DRP has been investigated by [324]and the LP mathematic model has been utilized for minimizing the average hourly operating cost under RTP scheme. Authors of [325-329] have focused on the throughput of sustainable manufacturing systems in different DRP schemes such as critical peak pricing, RTP and TOU. They mostly employed mixed integer nonlinear programming methods to achieve near-optimal solutions for minimizing the energy cost by concentrating on reservation and buffer inventory management build-up during off-peak periods to overcome the load curtailment. However, these methodologies give rise to problems when there are high verities of product in the system and the production flexibility is not responsive enough to build a buffer. Furthermore, the production and lean manufacturing paradigm such as just-in-time and pull production are in contrast with these proposed methodologies. In addition, these methods are not suitable for perishable products such as food.

On the other hand, one of the aims of SG is the development of distributed energy resources. The research of [330] focuses on this aspect of SG; it analyses the cost of purchasing and generating electricity against the revenue generated by selling electricity to the grid. The authors have established a LP model to minimize the total energy cost in hourly day-ahead DRP. Furthermore, the tasks are divided into schedulable and non-schedulable groups, making the research methodology more feasible to implement. This research deals with the flow of electricity together with other resources including flow of material, real-time processes, and the serious financial and technical problems posed by a reduction in electricity.

The attention of the aforementioned research projects are mainly focused on energy management by minimizing energy costs while considering production constraints, machine operations and maintenance, and inventory management for making throughputs as efficient as possible by utilizing linear and non-linear programming methods. But to the best of the authors' knowledge, no research has yet focused on evaluating the feasibility of DRP in terms of supporting operations managers to make a decision about DRP adoption. The existing research can be useful when manufacturers have decided to participate in DR; however, prior to making this decision, they need to investigate the potential gains and losses associated with a DRP. Furthermore, the associated risk of energy loss is not limited to production management; it is an energy efficiency and productivity matter. As mentioning [321] , ICT can help to manage and reduce energy consumption and emissions in manufacturing processes. ICT in manufacturing industries comprises different systems such as enterprise resource planning (ERP), customer relationship management (CRM), manufacturing execution system (MES), material resource planning (MRP), and product lifecycle management (LCM) [14]. For example, development in internet of things (IOT) in industrial sectors can facilitate the real-time intelligent collection of energy consumption of a product during its entire life [331] and assist numerous types of decision-making at different levels of enterprise systems[318, 319].

Figure 5.1 shows an Energy Management System (EMS) combined with ERP system to form an industrial DR information model in which our proposed methodology is embedded in EMS for evaluating the effects of DRP on operations and production management. The energy information such as price signal will be sent through wide area network (WAN) to enterprise while the energy consumption information received by EMS with local area network (LAN) will be sent back to the utility by smart meter. The next sections I explain the decision making algorithm for this expert system.

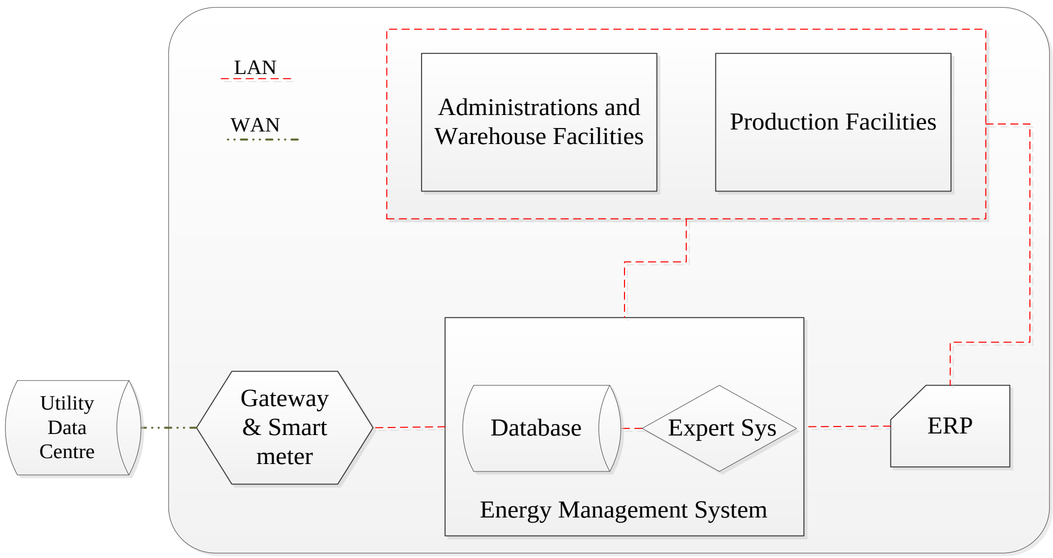


Figure 5.1. Industrial DR Information Model

5.3. Decision Making For Evaluating Equipment Operation and Energy Management

5.3.1. Multi-Criteria Decision Making for Energy Planning

As discussed in Chapter 2, Multi-Criteria Decision Making (MCDM) techniques have been increasingly employed for energy planning decisions. These methods can be classified into three main groups of a) value measurement models, b) goal and reference model, and c) outranking model [225]. Among numerous MCDM methods, as earlier pointed out, the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), originally presented by [219], has received interest from researchers as an effective tool for evaluating and selecting the energy system performance [256].

TOPSIS is a practical method for ranking and selecting a number of possible alternatives by measuring Euclidean distances. The first step in all decision-making methods is determining the criteria. The principles and methods for selecting the appropriate criteria in decision-making for energy planning are presented in[332]. For selecting the criteria, the energy expert should obey systemic, consistency, independency, measurability, and comparability principles. Furthermore, there are three main methods for selecting criteria including

- Delphi
- Least mean square (LMS)
- Min-max deviation

I have employed the Delphi method in our proposed methodology.

The TOPSIS method [219] based on information entropy is proposed as a decision support tool for an energy manager to determine the effects of DRP on productivity and energy efficiency. In this section, ‘alternative’ refers to all the equipment and ‘criteria’ indexes determined in the previous section. There are two types of criteria. Positive criteria are those that should be increased and negative ones are those which need to be decreased in order to mitigate risk.

The purpose of this methodology is to first arrive at an ideal solution and a negative ideal solution, and then find a scenario which is nearest to the ideal solution and farthest from the negative ideal solution. This methodology has been presented in Chapter 3 and it can be implemented by taking the steps summarized in Table 5.1.

The final step of TOPSIS methodology presented in below table, takes us to the ranking of equipment. This ranking indicates that the production of equipment with higher value should be maintained during DRP and any load curtailment for this equipment will constitute a high risk to the enterprise. Therefore, it is preferable to curtail the energy provided to equipment with lower ranking. I utilize these values in our optimization methodology proposed in the next section.

Table 5.1. Summarized TOPSIS Methodology Presented and Explained in Chapter 3.

TOPSIS Steps	Formulas	Equation number
Step 1: *Specify alternatives and criteria*	Equipment : $A = \{ A_1, \dots, A_m\}$	
	Criteria: $C = \{C_1, \dots, C_c\}$.	
Step 2: *Assign ratings to criteria and alternatives*	$X_{m\times c} = \begin{array}{c c} & \begin{array}{cccc} C_1 & C_2 & C_g & C_c \end{array} \\ \begin{array}{c} A_1 \\ A_i \\ \vdots \\ A_m \end{array} & \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1c} \\ . & . & x_{ig} & . \\ \vdots & \vdots & \cdots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mc} \end{bmatrix} \end{array}.$	3.6
Step 3: *Calculate weight of criteria by entropy technique*	$q_{ig} = \dfrac{x_{ig}}{(x_{1g} + \cdots + x_{mg})}$; $\forall g \in \{1, .., c\}$.	3.7
	$\Delta_g = -k \sum_{i=1}^{m} q_{ig} \,. \ln q_{ig}$; $\forall g \in \{1, .., c\}$	3.8
	$w'_g = \frac{\lambda_g . w_g}{(\lambda_1 . w_1 + \cdots + \lambda_c . w_c)}$; $w' = \{w'_1, w'_2, \dots, w'_c\}$	3.11 3.12
Step 4: *Construct a normalized decision Matrix*	$r_{ig} = \dfrac{x_{ig}}{\sqrt{(x_{1g}^2 + \cdots + x_{mg}^2)}}$	3.13
	$N_{m\times c} = [r_{ig}]_{m\times c}$, $(i = 1, \dots, m ; g = 1, \dots, c)$.	3.14
Step 5: *Construct the weighted normalized decision matrix*	$V = N_{m\times c} . w'_{c\times c} = (v_{ig})_{m\times c}$ $(i = 1, \dots, m ; \ g = 1, \dots, c)$	3.15

Table 5.1. Continue. Summarized TOPSIS Methodology Presented in Chapter 3.

TOPSIS Steps	Formulas	Equation number
***Step 6**: Compute (PIS) A^+ and (NIS) A^-*	$A^+ = \left\{\left(\max v_{ig} \mid g \in G\right); \left(\min v_{ig} \mid g \in G'\right)\right\} = (v_1{}^+, v_2{}^+, \ldots, v_c{}^+)$	3.16
	$A^- = \left\{\left(\min v_{ig} \mid g \in G\right); \left(\max v_{ig} \mid g \in G'\right)\right\} = (v_1{}^-, v_2{}^-, \ldots, v_c{}^-).$	3.17
***Step 7**: Compute the distance of each alternative from PIS ($d_i{}^+$) and NIS ($d_i{}^-$)*	$d_i{}^+ = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^+\right)^2}$	3.18
	$d_i{}^- = \sqrt{\sum_{g=1}^{c}\left(v_{ig} - v_g^-\right)^2}$	3.19
***Step 8:** Compute the closeness coefficient of each alternative*	$CC_i{}^+ = \frac{d_i{}^-}{(d_i{}^- + d_i{}^+)} \quad ; \quad i = 1, 2, \ldots, m$	3.20
***Step 9**: Rank the alternatives*	$v = \left\{v_i \mid \max_{1 \le i \le m} (CC_i{}^+)\right\}$	3.21

5.3.2. Selecting Decision-Making Criteria for Energy Planning: The Delphi Method

The Delphi technique is a systematic procedure to be used with a panel of experts for discovering a consensus of opinions about the future events or decision making on different disciplines [332, 333]. There is a variety of applications for Delphi method that details of the Delphi evaluative studies can be found in [333]. For instance, Galo et al. [334] employed this method for selecting the criteria among many variables to evaluate electrical systems in smart grid. In our approach, ten factors have been initially identified by a survey on operations management and lean manufacturing [335]. Delphi method is employed for selecting the appropriate criteria necessary for evaluating the effects of DRP participation on these factors and energy planning. A panel of experts will be constituted from different organizational departments with different expertise to forecast how the factors presented in Figure 5.2 will be affected by implementing DRP. The appropriate criteria for measuring these effects can be determined by designing a questionnaire to ask the experts' opinion about the risks associated with DRP and achieving complete consensus among panellists.

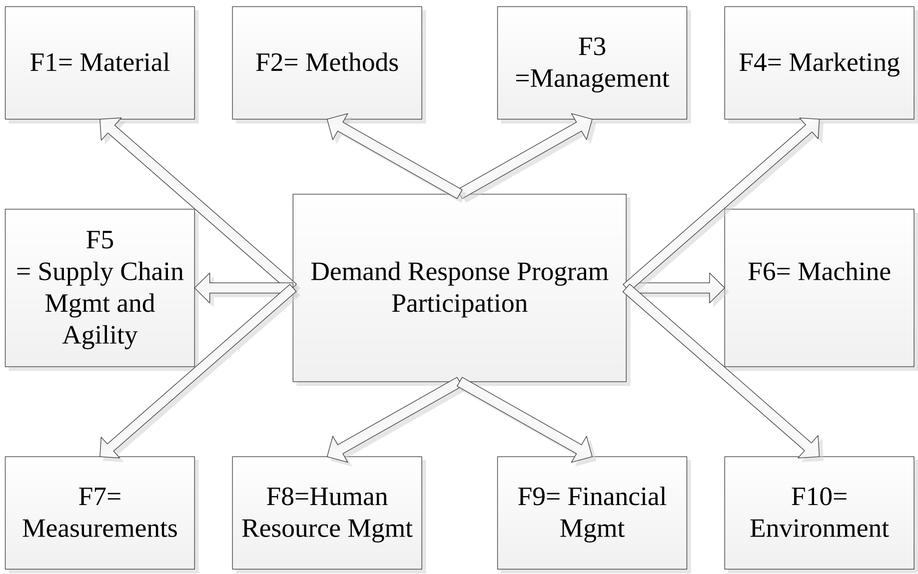


Figure 5.2. The Effected Factors by DRP Participation

The flowchart depicted in Figure 5.3 is proposed for implementing Delphi method considering the following details [333]:

a) Four key features of Delphi procedure comprise anonymity (step 1), iteration (steps 2, 3 and 4), controlled feedback (steps 4 to 2), and statistical aggregation of group responses (step 5).
b) The Delphi panel size is modest and a group of 10 to 18 members is recommended.
c) The experts may belong to the production, quality, engineering, logistics, financial, and sales departments.
d) The first round of Delphi procedure is unstructured and the number of criteria may decrease in further rounds.
e) Experts may use their own internal documents, expertise, and knowledge for assessing the effect of DRP on their operations.

f) Greater consensus amongst panellists can be determined by reduction of variance in responses.

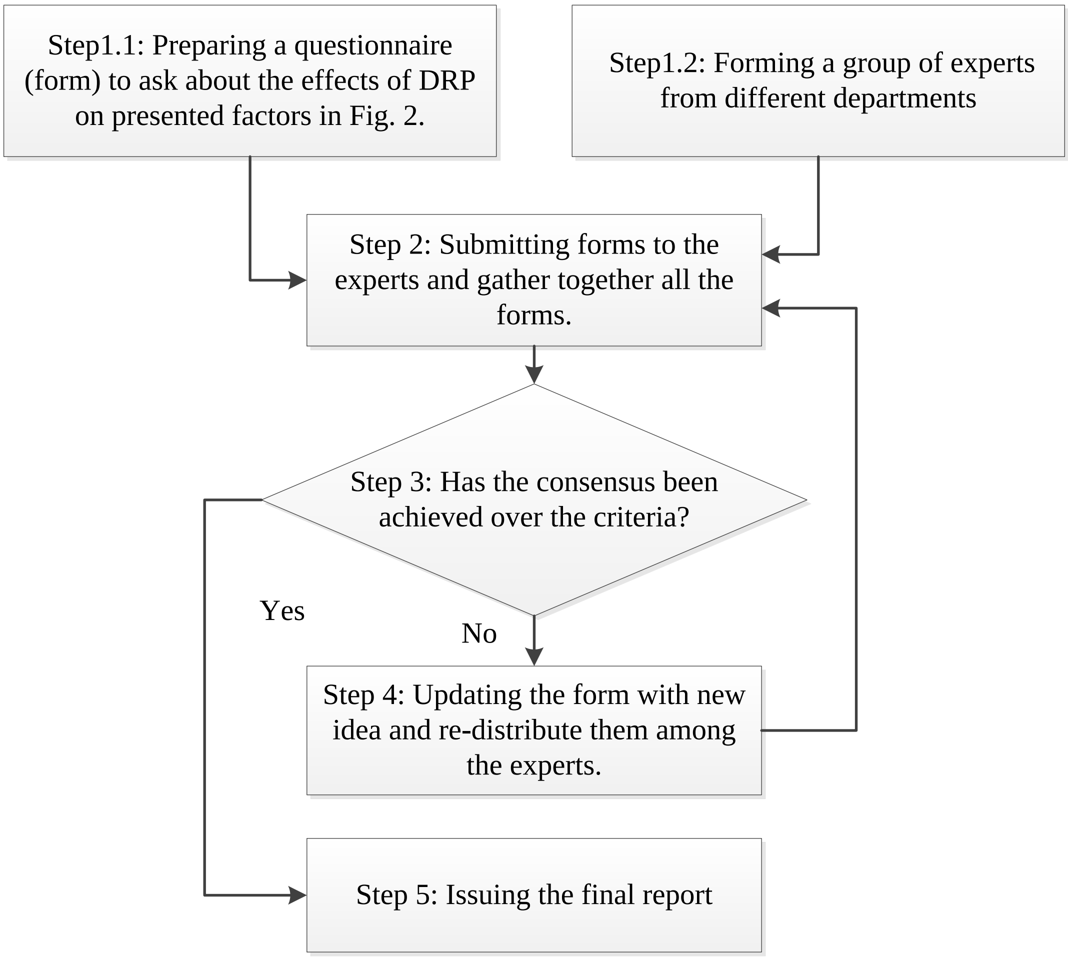


Figure 5.3. Delphi Procedure for Selecting Criteria

By achieving general consensus for decision-making criteria, TOPSIS method will be employed for prioritizing the importance of the equipment for energy planning during DRP. Afterwards I use these values in an optimization model to allocate energy to the equipment accordingly. By this methodology I have aggregated the experts' knowledge in accordance with risk mitigation in organization for participating in DRP. The summary of our proposed methodology is presented in Figure 5.4.

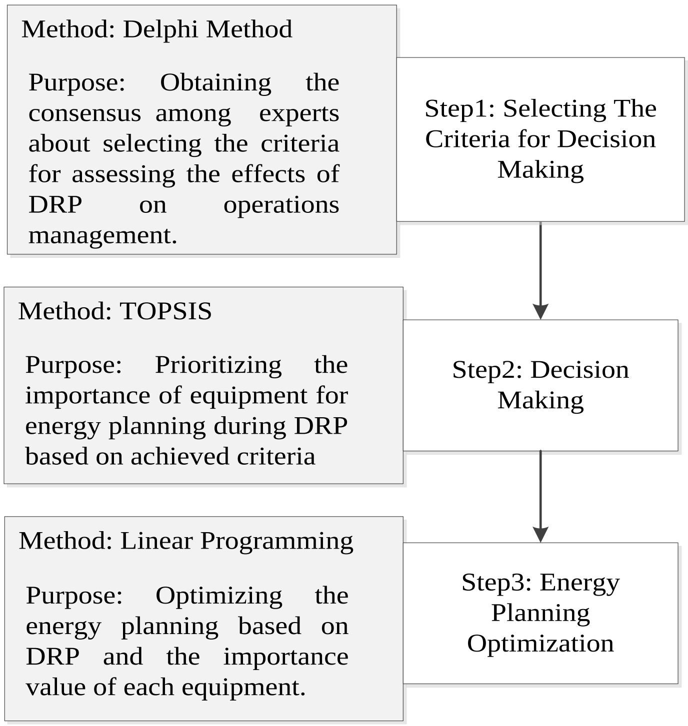


Figure 5.4. Proposed Methodology Stepwise

5.4. Energy, Cost and Power Correlations

For energy and its associated cost formulation, it is assumed that E_{ij}^{1} denotes the energy demanded by equipment i in timeslot j with energy price U_{j}^{1} where the associated energy cost C_{ij}^{1} can be calculated as [322], $C_{ij}^{1} = U_{j}^{1} \times E_{ij}^{1}$. Therefore, if the consumer allocates the same budget to timeslot j in which $EC_{j}^{2} = EC_{j}^{1}$ then the change in energy level is in contrast to the same proportion in which the energy price has been increased as shown by Eq.5.1.

Assume $C_{ij}^{1} = U_{j}^{1} \times E_{ij}^{1}$ and $C_{ij}^{2} = U_{j}^{2} \times E_{ij}^{2}$

if $C_{ij}^{2} = C_{ij}^{1}$

then $(U_{j}^{2} \times E_{ij}^{2}) = (U_{j}^{1} \times E_{ij}^{1})$

or $\frac{E_{ij}^{2}}{E_{ij}^{1}} = \frac{U_{j}^{1}}{U_{j}^{2}}$ (5.1)

Here, I divide the DRP duration by "n", the number of timeslots, to reach the unit of time for energy planning as follows:

$$\frac{Duration\ of\ DRP}{number\ of\ timeslots\ (n)} = \mathrm{T} \tag{5.2}$$

where T is "time unit of planning"; hence, the allocated operation time, energy and power are limited by this constraint. The above correlation between power, time, and energy will be used as constraints in the proposed optimization model in the next section (Eq.5.19).

Total energy and cost of m electrical equipment $\mathrm{E}^{\mathrm{n}}_{\mathrm{total\ m}}$ and $C^{n}_{total\ m}$, during n timeslots can be formulated by Eq.5.3 and Eq.5.4. It is assumed that the energy price in each timeslot is constant and each timeslot is considered as a time unit of planning.

$$E^{n}_{total,m} = \sum_{j=1}^{n}\sum_{i=1}^{m} E_{ij} = \sum_{j=1}^{n}\sum_{i=1}^{m}(P_{ij} \times t_{ij}) \tag{5.3}$$

$$C^{n}_{total,m} = \sum_{j=1}^{n}\sum_{i=1}^{m}(p_{ij} \times t_{ij}) \times U_j \tag{5.4}$$

$$i = 1,2,3,..,m\ ;\quad j = 1,2,3,..,n \tag{5.5}$$

$$t_{ij} \leq \mathrm{T} \tag{5.6}$$

where E_{ij} and P_{ij} are the amount of energy and power demanded by equipment i during timeslot j for executing an operation which takes t_{ij} in each T; and, U_j is the price of energy in timeslot j that is fixed during T. The product quantity produced can be related to its electricity consumption. This relationship is the product quantity function of electricity consumption as shown by Eqs. 5.7 and 5.8 [317]:

$$Q_{ij} = f_{Q_i}(E_{ij}) \tag{5.7}$$

$$AQ_{ij} = \frac{Q_{ij}}{E_{ij}} \tag{5.8}$$

where Q_{ij} is the production rate of equipment i by consuming energy E_{ij}, and AQ_{ij} is average production rate for each unit of energy ($Number\ of\ products/kW.h$). This formula will be used to compute the production loss derived by energy curtailment (Table 5.2).

5.5. DRP Engagement Evaluation

For evaluating DRP engagement, the load of electrical equipment can be classified in two main groups of interruptible and non-interruptible. Furthermore, the interruptible loads can be categorized in two groups of deferrable (L_D) and non-deferrable (L_{ND}) loads. The equipment with L_D can run and be scheduled at any time and their operations are not a direct input to other processes. These types of loads will not disrupt other processes which may cause delay in operation management. Conversely, L_{ND} is for unscheduled operations for DRP because due to their load scheduling, the industrial unit will face financial damage or other processes will be interrupted. Operations in chemical production such as oil refinery, plating process, and heat treatment by a furnace are in the L_{ND} category. These types of loads cannot be scheduled for DRP engagement [327]. Operations such as metal forming, stamping and cuttings in workshop press or spring manufacturing are examples of the L_D category. In this Chapter, the proposed methodology is focused on L_D; therefore, $E^n_{total,m}$ in Eq.5.3 can be formulated as:

$$E^n_{total,m} = E^n_{total,ND} + E^n_{total,D} \tag{5.9}$$

$$C^n_{total,m} = C^n_{total,ND} + C^n_{total,D} \tag{5.10}$$

$$E^n_{obj,D} = E^n_{total,D} - (E^n_{total,m} - E^n_{DR,m}) \tag{5.11}$$

$$\text{Or } E^n_{obj,D} = E^n_{DR,m} - E^n_{total,ND} \tag{5.12}$$

$$C^n_{obj,D} = \sum_{i'=1}^{D} E^n_{obj,i\ \ ,j} \times U_j; \quad \forall \text{j} \in \{1,..,\text{n}\} \tag{5.13}$$

where $\mathrm{E^n_{total,ND}}$ and $\mathrm{E^n_{total,D}}$ are the total energy of equipment which have non-deferrable and deferrable loads and their associated costs are $\mathrm{C^n_{total,ND}}$ and $\mathrm{C^n_{total,D}}$, respectively. ND and D are the number of equipment with non-deferrable deferrable loads, respectively.

By participating in demand response and accepting DR regulation and energy price U_j, the level of total required energy $\mathrm{E^n_{total,m}}$ shall be curtailed to reach to the demand response level $\mathrm{E^n_{DR,m}}$. As discussed above, this excessive amount is subtracted from deferrable energy level $\mathrm{E^n_{total,D}}$. This situation constructs the objective level of energy $\mathrm{E^n_{obj,D}}$ which is calculated by Eq.5.11 or 5.12. This limit of energy and its associated cost, $C^n_{obj,D}$ in each timeslot are the constraints in our optimization model. $\mathrm{E^n_{total,m}}$ is the level of energy that is required based on production plan. These levels of energy for our case study have been shown in Figure 5.10.

In the proposed methodology it is assumed that if $E^n_{DR,m} < E^n_{total,ND}$, the DRP will interrupt the total production process and the engagement is not feasible. I present a DRP engagement evaluation algorithm following the optimization method given in the next section.

5.6. Mathematical and Optimization Model and DRP Engagement Evaluation Algorithm

In this section, LP is presented to perform energy optimization and energy planning for DRP. I design the optimization function by maximization because of the positive and direct correlation between production and electricity consumption [317] Hence, the more products are produced, the more energy is consumed. Therefore, I include the aforementioned DRP constraints in the formula and aim to maximize the production for simulating DRP as shown in objective function by Eq.5.14. The scheduling time horizon has been divided into n timeslots to plan the energy for D amount of equipment and "i" is an index to present the equipment with deferrable loads. Considering the energy price U_j in timeslot j, the energy cost of each i will be computed. Constraints 5.15 and 5.16 will not allow these amounts to increase.

DRP imposes two constraints that are considered as inputs to our model. The first constraint is the amount of total energy allocated to each timeslot shown by δ_j in Eq.5.17 (calculated by Eq.5.12) such that the total energy of equipment E_{ij} in that timeslot will not exceed this value (constraint Eq.5.18). The second constraint is energy price, where constraint Eq.5.18 indicates that the cost of total equipment during timeslot j will not exceed the total cost allocated to that timeslot (Υ_j). In the presented model, it is assumed that the energy price in each timeslot is constant and the equipment's load is deferrable.

$$maximize \quad \sum_{i'=1}^{D}\sum_{j=1}^{n} \; v_i E_{ij} \qquad (5.14)$$

Subject to:

$$\sum_{j=1}^{n} E_{ij} \leq \; e_i \,, \qquad \forall \mathrm{i} \quad \in \{1,..,\mathrm{D}\} \qquad (5.15)$$

$$\sum_{j=1}^{n} E_{ij}.U_j \leq \; c_i \,, \quad \forall \mathrm{i} \quad \in \{1,..,\mathrm{D}\} \qquad (5.16)$$

$$\sum_{i=1}^{D} E_{ij} \leq \; \delta_j \,, \qquad \forall \mathrm{j} \in \{1,..,\mathrm{n}\} \qquad (5.17)$$

$$\sum_{i=1}^{D} E_{ij}.U_j \leq \; \Upsilon_j \,, \forall \mathrm{j} \in \{1,..,\mathrm{n}\} \qquad (5.18)$$

$$E_{ij} \; \leq \; \mathrm{T} \times p_i \quad , \qquad \forall \mathrm{i} \in \{1,..,\mathrm{D}\}, \forall \mathrm{j} \in \{1,..,\mathrm{n}\} \qquad (5.19)$$

$$e_i, \; p_i, c_i \,, U_j \geq 0 \qquad (5.20)$$

$$\mathrm{i} \in \{1,..,\mathrm{D}\} \;\; ; \mathrm{j} \in \{1,..,\mathrm{n}\} \qquad (5.21)$$

where the input variables are:

e_i : Total energy allocated to equipment i

c_i : Total energy cost allocated to equipment i

p_i : Amount of power used by equipment i

v_i : Value of importance belongs to equipment i

U_j: Price of energy in timeslot j indicated by DRP

δ_j : Total energy allocated to timeslot j

Υ_j : Total cost of energy allocated to timeslot j

T : Time unit of planning

and the output variable is :

E_{ij} : Amount of energy required for equipment i in timeslot j

The objective function maximizes the use of energy for the equipment in each timeslot along time horizon energy planning taking into account the value of each piece of equipment ($v_{i'}$) calculated by the TOPSIS approach.

In the above mathematical model, Eq.5.15 shows the constraint of energy allocation limit to the equipment i during time horizon planning while Eq.5.16 indicates its associated cost constraint.

```
/**********************************************
* OPL 12.6.0.0 Model
* Author: Omid Ameri Sianaki
* Creation Date: 06/08/2014 at 11:53:21 AM
*This file has been programed for energy allocation and optimization
to timeslots
x[i][j] = amount of energy used by equipment i during timeslot j
**********************************************/
// parameter
int n=...; //number of equipment
int m=...; //number of timeslot
range equipment=1..n;
range timeslot=1..m;
float TopsisRankingValue[equipment]=...;
float cost[equipment]=...;
float usage_time[equipment]=...;
float power[equipment]=...;
float energy[equipment]=...;
float TimeslotCostLimit[timeslot]=...;
float TimeslotEnergyLimit[timeslot]=...;
float energy_price[timeslot]=...;
// variales
dvar float+ x[equipment][timeslot];
maximize sum(i in equipment, j in timeslot) TopsisRankingValue[i]*x[i][j];
subject to {
forall(i in equipment)
Energy_limit_each_Equipment:
sum(j in timeslot) x[i][j] <= energy[i];
forall(i in equipment)
Cost_limit_each_Equipment:
sum(j in timeslot) x[i][j]*energy_price[j] <= cost[i];
forall(j in timeslot)
Timeslot_energy_capacity:
sum(i in equipment) x[i][j]<= TimeslotEnergyLimit[j];
forall(j in timeslot)
Timeslot_Cost_Capacity:
sum(i in equipment) (x[i][j]*energy_price[j]) <= TimeslotCostLimit[j];
forall(i in equipment,j in timeslot)
Max_timeslot_energy_limit_for_each_equipment:
x[i][j]<= power[i];
}
```

Figure 5.5. ILOG CPLEX Optimization Studio Programming Code

Any change to this cost limit will be projected to the product cost and profit. Eq.5.17 is the constraint of energy in each timeslot indicating that the sum of consumed energy during each timeslot should not exceed the allocated energy level dedicated to that timeslot.

Eq.5.18 is associated with the cost of energy constraint in Eq.5.17. Eq.5.19 expresses the relationship mentioned in section 5.4 indicating that the allocated power and operation time for the equipment in each timeslot will be limited to the unit of time planning T.

Figure 5.6 shows the proposed decision algorithm for engaging in DRP. In the next section, a computational experiment is presented.

5.7. A Computational Simulation for a Case Study

The proposed methodology has been assumed for implementation in a metal components manufacturer. Employing the industrial DR information model of Figure 5.1, EMS and ERP will provide information about the amount of energy and associated cost required for production plan. Accordingly, deferrable and non-deferrable loads of equipment has been identified by which ten pieces of equipment (press machines) ($D = 10$) with deferrable loads (L_D) have been identified in the press-shop factory.

In this scenario, these ten pieces of equipment produce a set of ten parts (each made by a press machine) for making an assembly (a product) such that the coefficient of each part in the bill of material for this assembly is equal to “1”. The energy, cost and power of electricity for 24 (n=24) hours production have been presented in Table 5.2. The energy price (before receiving DRP) has been considered 0.25 $/kW.h. A day-ahead demand response program has been offered with energy price presented in Figure 5.7 and energy limits are presented in Figure 5.10 for 24 hours; otherwise, without participating in DRP, the price of electricity will be 0.4 $/kW.h. Accordingly, the time unit of planning, T is calculated by Eq. 5.2 such that T=1. By this primary information, the industrial unit shall make decision, whether to accept DRP or reject it. The implementation of proposed methodology is as follows.

5.7.1. Selection Criteria

According to the first step of the proposed methodology (Figure 5.4), experts from different departments such as quality control, quality assurance, sales, engineering and production can form the Delphi expert panel. It is assumed that the experts answered the questions about the potential effects that will occur by implementing DRP in operations management factors presented in Figure 5.2. By executing the procedure presented in Figure 5.3, 26 criteria presented in Table 5.3 achieved.

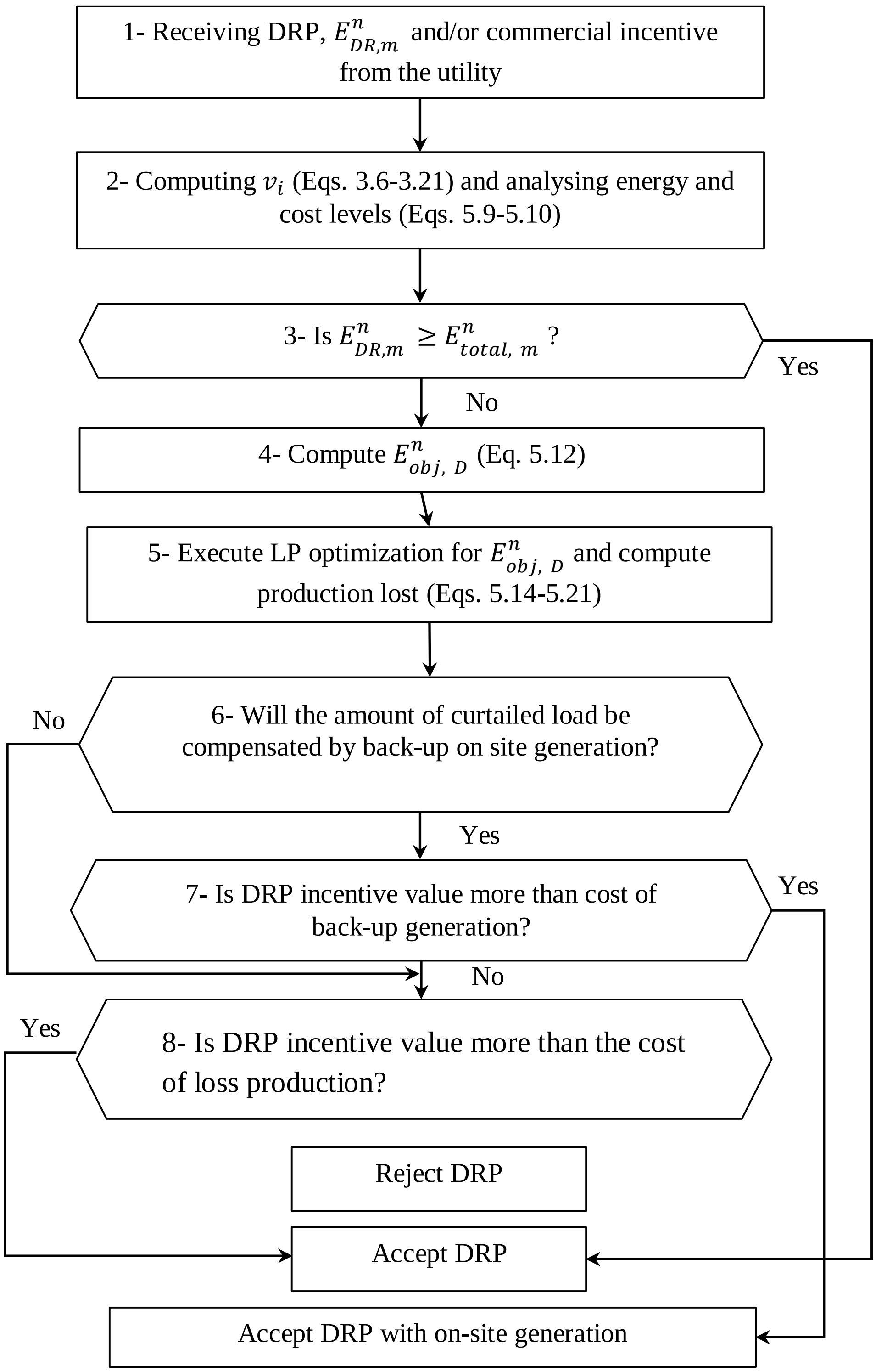


Figure 5.6. Decision-Making Algorithm for Assessing DRP Engagement

Criteria 1 to 4, availability of reserved capacity, manufacturing lead time, operation cycle time, and number of bottleneck stages have been elicited from factor 2, the method. It means that these criteria are able to evaluate the effect of participating in DRP on production method.

Similarly, loss of customers and their satisfaction are those criteria by which, the system is able to evaluate the effect of performing DRP on “F4” (Figure 5.2), marketing factor, and so forth. In this procedure, all experts believed that the DRP has no effect on factor one, material.

5.7.2. Decision Making

In this stage, the energy manager will prioritize the equipment based on the selected criteria and specify the importance of each piece of equipment if enterprise participates in DRP. As there are 26 criteria and ten pieces of equipment, the dimension of decision matrix X is 10×26. Following the second step of our proposed methodology and the algorithm presented in Figure 5.6, the TOPSIS methodology presented in Table 5.1 has been implemented in MATLAB R2014b (64bit) on an Intel Core i7-3770S CPU @3.1 Ghz computer with 16 GB memory with timing performance of three seconds.

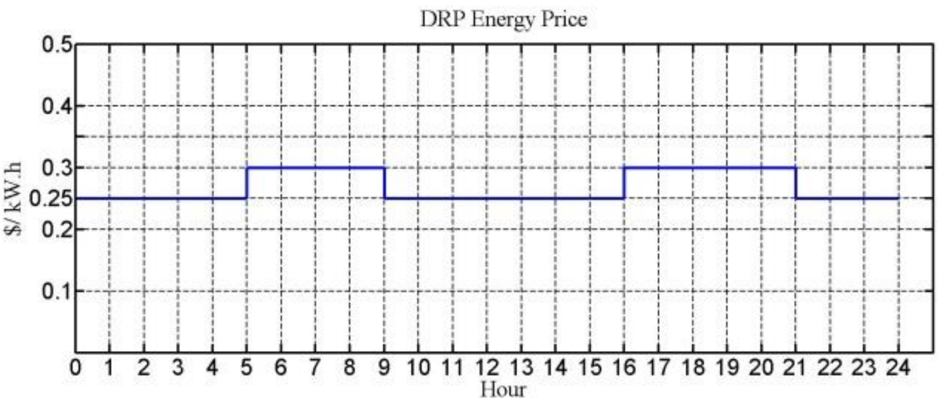


Figure 5.7. Day-Ahead DRP Scheme

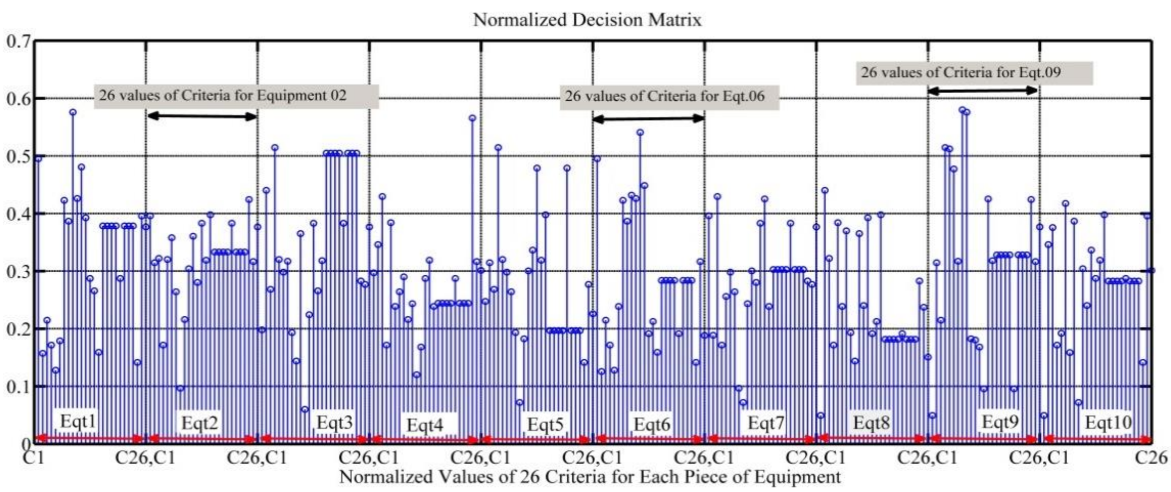


Figure 5.8. Normalized Decision Matrix ($N_{10\times26}$)

In the following, the intermediate TOPSIS calculations have been omitted for conciseness; however, the normalized matrix and the TOPSIS final result are shown in Figures5.8 and 9, respectively. Figure 5.9 shows that the equipment 1, 6, 2, and 9 have high ranking levels while the equipment 3 and 10 have the lowest rank. In this experiment, the energy manager weights of (6) are assumed to be equal for all criteria; however, the effect of this weight aggregation will be discussed in section 5.8.

Table 5.2. Energy Demand of Equipment (Eqpt) with Deferrable Load

Equipment	c_i ($)	e_i (KW.h)	Power (kW)	Operation time (h)	AQ_{ij} (Products /KW.h)
Eqt1	25.00	100	10	10	15
Eqt2	27.50	110	10	11	12
Eqt3	50.00	200	10	20	10
Eqt4	22.00	88	8	11	11
Eqt5	15.00	60	6	10	13
Eqt6	18.75	75	5	15	15
Eqt7	30.00	120	10	12	10
Eqt8	15.00	60	4	15	12
Eqt9	25.00	100	10	10	13
Eqt10	20.00	80	8	10	14
Sum:	248.25	993	81	124	

5.7.3. Optimization Steps

In this section, before performing the optimization technique, the energy and cost levels such as $(\mathrm{E}^{\mathrm{n}}_{\mathrm{total,\ D}}, \mathrm{C}^{\mathrm{n}}_{\mathrm{total,\ D}})$= (993 kW.h, $248.25), $(\mathrm{E}^{\mathrm{n}}_{\mathrm{total,\ ND}}, \mathrm{C}^{\mathrm{n}}_{\mathrm{total,\ ND}})$= (628 kW.h, $157), $(\mathrm{E}^{\mathrm{n}}_{\mathrm{total,\ m}}, \mathrm{C}^{\mathrm{n}}_{\mathrm{total,\ m}})$ = (1621 kW.h, $405.25) have been computed by (26, 27). DRP requires the total energy limit of $\mathrm{E}^{\mathrm{n}}_{\mathrm{DR,\ m}}$ = 1503 kW.h which is less than the total required energy $\mathrm{E}^{\mathrm{n}}_{\mathrm{total,\ m}}$= 1621 kW.h. According to step 4 (Figure 5.6), the $(\mathrm{E}^{\mathrm{n}}_{\mathrm{obj,\ D}}, \mathrm{C}^{\mathrm{n}}_{\mathrm{obj,\ D}})$ = (875 kW.h, $ 234.5) will be computed by (28)-(29). The amount of total objective energy and cost level for each timeslot, δ_j and Υ_j, have been presented by Figures 5.9 and 5.10.

IBM ILOG CPLEX 12.6.1 was employed to simulate the LP optimization model on the same computer with timing performance of one second. The optimization results are shown in Figures 5.11, 5.12 and 5.13. Figure 5.12 shows the amount of energy used in each unit time of planning by each piece of equipment ($\mathrm{T} = 1$).

For example, in timeslot 1, the equipment 1, 2, 6, and 10 are operating with energy levels of 10, 10, 5 and 10 kW.h, respectively. However, in the second timeslot, the equipment 1 and 9 will stop while the equipment 2 and 6 will continue their operations. Meanwhile, press machine 7 will start its operation with an energy level of 10 kW.h.

These simulation results indicate that the trend of total optimized energy profile in Figure 5.12 is exactly compatible with the energy objective level profile presented in Figure 5.10 so that $\mathrm{E}^{\mathrm{n}}_{\mathrm{obj,D}} = \mathrm{E}^{\mathrm{n}}_{\mathrm{opt,D}} = 875$ kW.h. Analysis and comparison of Figures 5.9 and 5.13 confirm that the equipment with higher priority values received the total energy while the energy for equipment with low values such as equipment 3-5, 8 and 10 were curtailed.

Furthermore, the amount of production loss associated with this energy curtailment was calculated by Eq.5.8 as shown in Table 5.4. For example, according to production plan, press machine 3 was supposed to use 127 kW.h of energy for producing 1270 parts, but by participating in DRP and after optimization, this press will only receive 54 kW.h of energy, losing 73 kW.h that it is equal to 730 parts.

5.7.4. Discussion

- By participating in this DRP, the number of assembly (product) lost can be derived from the part which has the maximum amount of production loss. In this experiment, Eqpt. 3 has the maximum amount of production loss, 730 parts meaning that 730 assemblies or products have been lost. Hence, if the unit of profit for each product is considered as one, then 730 units of profit have been lost for the company.
- Before DRP participation, $(\mathrm{E}^{\mathrm{n}}_{\mathrm{total,\ D}}, \mathrm{C}^{\mathrm{n}}_{\mathrm{total,\ D}})$ were equal to (993 kW.h, \$248.25). After implementing proposed methodology and curtailing the 118 kW.h energy (Table 5.4), the value of these parameters reached to the objective level (875 kW.h, \$234.5) that it means saving \$13.75 and losing 730 unit of benefit.
- Moreover, if the enterprise does not accept the DRP and accept the flat rate of 0.4 \$/kW.h then in this condition $(\mathrm{E}^{\mathrm{n}}_{\mathrm{total,\ m}}, \mathrm{C}^{\mathrm{n}}_{\mathrm{total,\ m}})$ will be changed from (1621 kW.h, \$405.25) to (1621 kW.h, \$648.4) that it means \$243.15 extra cost of electricity energy.
- By achieving this information, the energy manager is able to make the final decision by answering the three questions asked in steps 6, 7 and 8 of the proposed algorithm in Figure 5.6. Therefore, if the on-site generator is capable to produce 118kW.h energy and assuming that the benefit of each product is equal to \$1, then by accepting this DRP, the enterprise will lose \$730 - \$13.75=\$716.25 which is bigger than \$243.15. Moreover, if the cost of on-site generation is added, then this difference will increase and DRP will be strongly rejected.

- Assume that the benefit of each product is equal to \$0.1, then by accepting this DRP, the enterprise will lose \$59.25 (=\$73 - \$13.75). In this case if the price of onsite generation is less than \$183.9 (=\$243.15-\$59.25) and the generator is able to generate 118 kW.h energy then the DRP will be accepted.
- The cost of running generators in every industrial unit depends on the type, size, and fuel, as well as many other generators' factors that are not in the scope of this thesis.

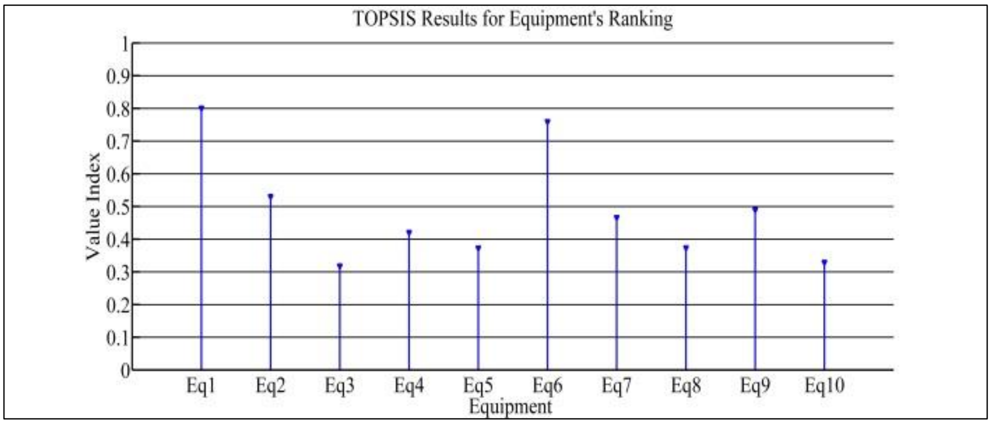


Figure 5.9. TOPSIS Output (v_i)

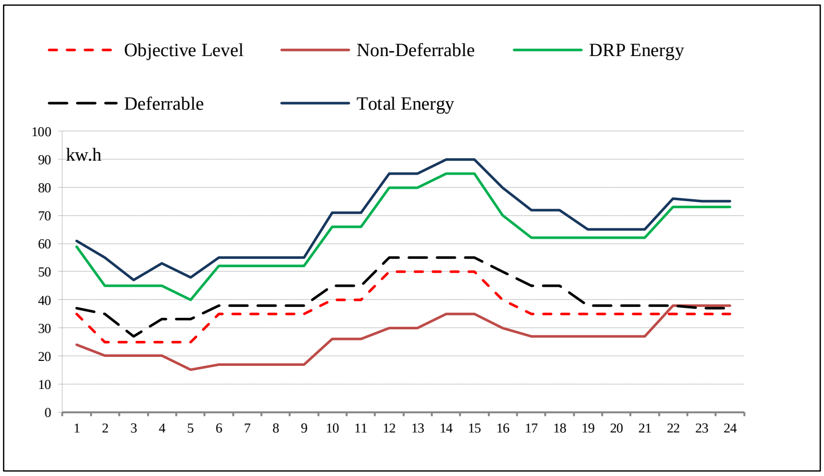


Figure 5.10. The Energy Levels δ_j, $E_{total,m}^{24}$, $E_{total,ND}^{24}$, and $E_{total,D=10}^{24}$

Table 5.3. List of Criteria for Assessing the Risk of DPR Engagement

C	Factors	Criteria	Sign
C1	F2	Availability of reserve capacity	+
C2	F2	Manufacturing lead time (hour)	-
C3	F2	Operation cycle time (second)	-
C4	F2	Number of bottleneck stages	-
C5	F3	Pressures from top management	-
C6	F4	Loss of customer	-
C7	F4	Customer satisfaction	+
C8	F5	Delivery lead time (hours)	-
C9	F5	Frequency of the deliveries	+
C10	F5	Adherence to schedule	+
C11	F5	Overall machine flexibility	+
C12	F5	Delivery priority	+
C13	F6	Re-calibration and set-up time (minutes)	-
C14	F6	Impact on equipment's safety	-
C15	F7	Effects on hazard analysis and critical control points (HACCP)	-
C16	F8	Scrap and rework cost ($)	-
C17	F8	Operating cost ($)	-
C18	F8	Maintenance cost ($)	-
C19	F8	Tooling cost ($)	-
C20	F8	Establishment and set-up cost ($)	-
C21	F8	Personnel cost ($)	-
C22	F8	Profit per product ($/Product)	+
C23	F8	Penalties due to short quantity or late delivery ($)	-
C24	F9	Number of people involving in stopping the line due to re-set up	-
C25	F9	Operators dissatisfaction	-
C26	F10	Emissions per product	-

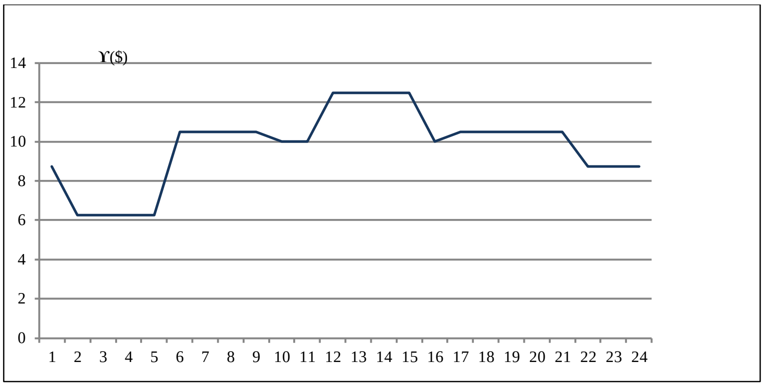


Figure 5.11. Associated Cost of Objective Energy Level in Each Timeslot (Υ_j)

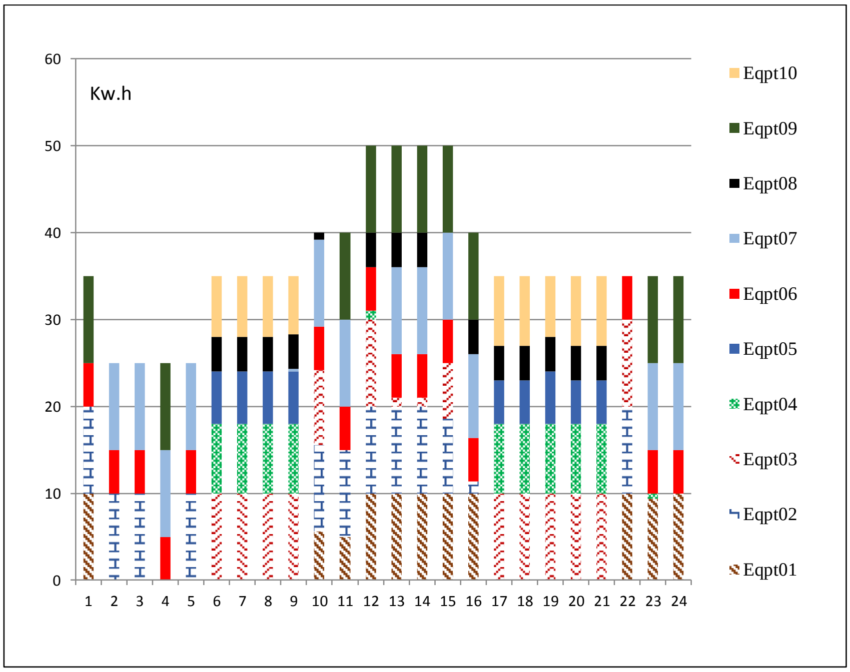


Figure 5.12. Production Energy Planning Based on DRP (E_{ij})

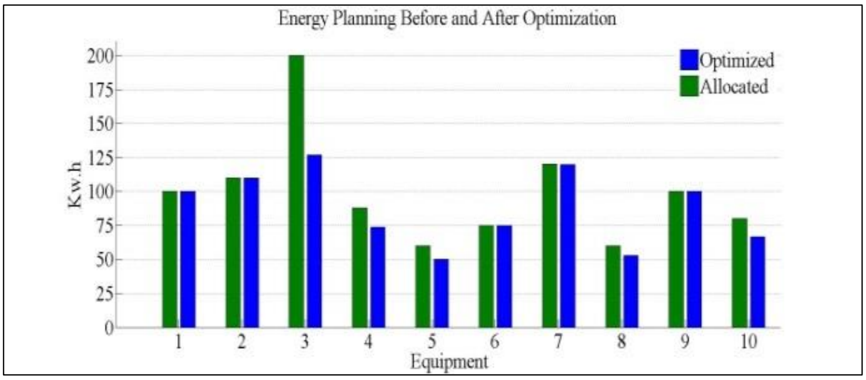


Figure 5.13. Energy Planning Before and After Optimization

Table 5.4. Summary of Energy and Production Loss

Equipment	Energy level after optimization during 24 hours (kW.h)	Energy loss (kW.h)	Product loss (parts)
Eqpt3	127	73	730
Eqpt4	73.6	14.4	158
Eqpt5	50	10	130
Eqpt8	52.8	7.2	87
Eqpt10	67	13.4	188
sum		118	

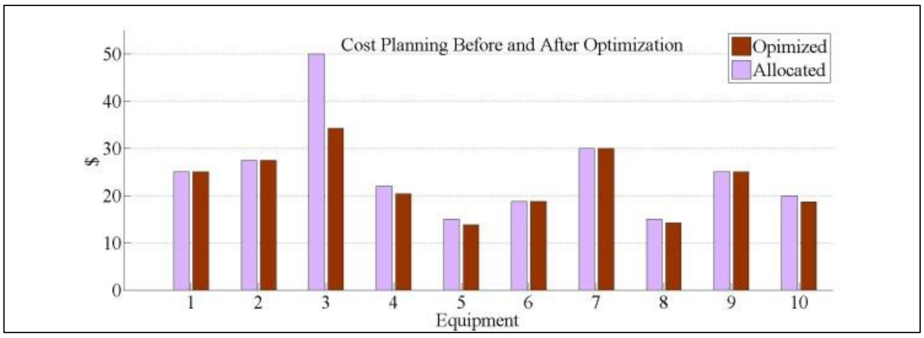


Figure 5.14. Cost Planning Before and After Optimization

5.8. Decision Making Sensitivity Analysis

In the previous section, the simulation of the proposed algorithm was executed when decision maker (DM) weight vector λ_g (Eq.3.11), was equal to one for all criteria. In the proposed methodology, the energy manager as an expert is able to increase or decrease the aggregated weight of the criteria w' by vector λ_g. In this section the sensitivity analysis for studying the effect of decision making on optimization model will be examined by comparing four scenarios as follows:

Scenario 1: I have considered the previous experiment in section 5.7 as the first scenario when the value of vector λ_g was equal to 1 for all criteria and decision maker is neutral for positive and negative criteria . λ_g and computed v_1 are shown in Figures 5.15, 5.16 for this scenario.

Scenario 2: In this scenario the energy manager gives weights to the positive criteria ten times stronger than negative criteria. In the other words it makes the effect of the negative criteria on decision making ten times lesser (weaker) than positive ones. By this, the alternatives (the pieces of the equipment) which have bigger value in positive criteria become more preferred.

Scenario 3: In this scenario the energy manager gives weights to the negative criteria ten times stronger than positive criteria in the other words, the effect of positive criteria on decision making will be ten times weaker than negative ones. By this, the alternatives with fewer values in negative criteria are more effective in ranking process.

Scenario 4: In this scenario, decision maker gives weights to the criteria 16 to 23 (Table 5.3) ten times stronger than other criteria. Referring Table 5.3, these criteria belongs to financial management factor (F8). By this DM has decided to increase the value of criteria which effect on cost.

Parameters λ_g and $v_i$are computed by TOPSIS method for these four scenario have been presented in Figures 5.15 and 5.16. Table 5.5 shows the summary of optimization result and Figure 5.17 shows the amount of energy lost in each scenario. The results achieved by considering these scenarios can be discussed as follows:

- Allocated energy after optimization in four scenarios to all equipment in Table 5.5 is equal to $E^n_{obj,D} = 875\ kW.h$ that it indicates the robustness of the proposed optimization model.

- Considering Figure 5.16, the computed value by TOPSIS method, the equipment 1 and 6 have the highest value in all scenarios meanwhile the equipment 3 has the lowest value. As a result, the equipment 1 and 6 received the total required energy and equipment 3 received the maximum energy curtailment.

- Considering scenarios 2 and 3, when the weight λ_g for positive criteria changes from maximum (in comparison to negative criteria) to minimum values, the most change in profile"v_i" in Figure 5.16 can be seen in equipment 8, 9 and 10. The effect of this variance can be interpreted in product loss for these equipment in Table 5.5.

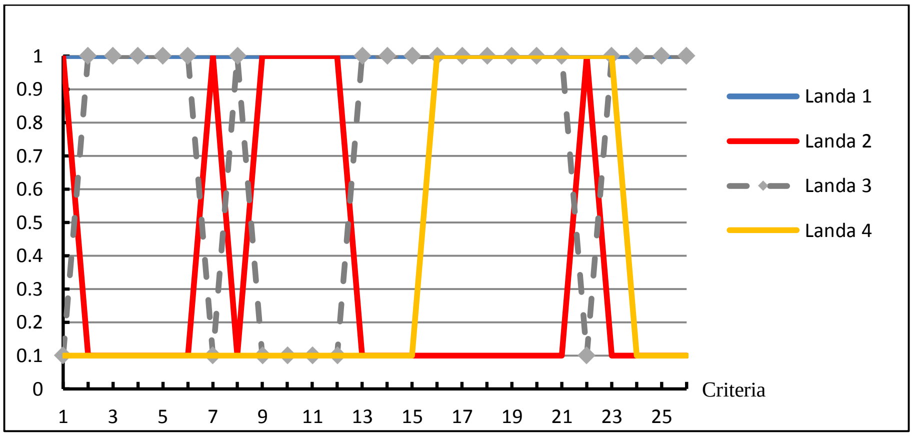


Figure 5.15. Weight Vector $\lambda_g$in Four Scenarios

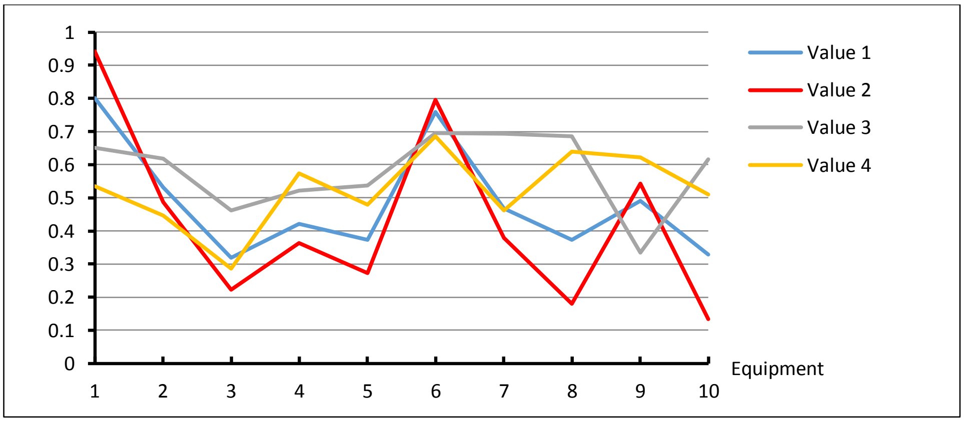


Figure 5.16. TOPSIS Result Computed for Four Scenarios

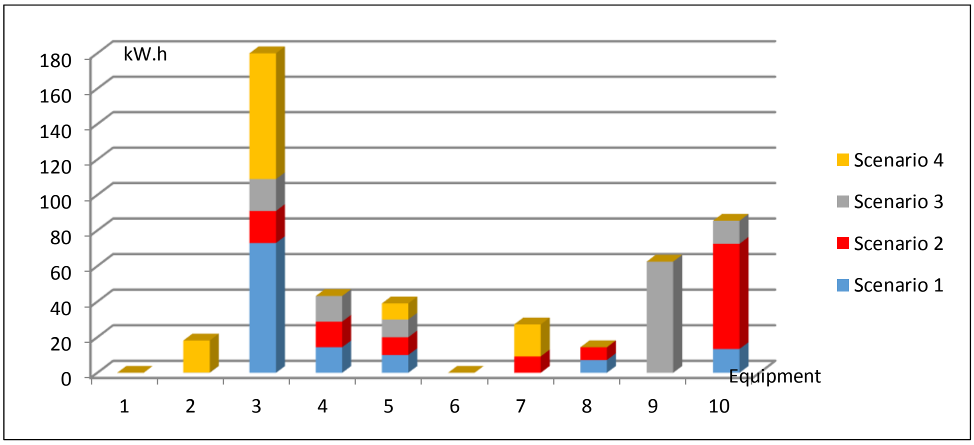


Figure 5.17 Energy Lost in Each Scenario

Table 5.5. The Optimization Result for Four Scenarios

Eqpt	Allocated Energy After Optimization (kW.h)				Product Lost (parts)			
	S1	***S2***	***S3***	***S4***	***S1***	***S2***	***S3***	***S4***
1	100	100	100	100	0	0	0	0
2	110	110	109.83	92	0	0	2	216
3	127	182	182	127	730	180	180	730
4	73.6	73.6	73.6	88	159	159	159	0
5	50	50	50	51	130	130	130	117
6	75	75	75	75	0	0	0	0
7	120	110.77	120	102	0	93	0	180
8	52.8	52.8	60	60	87	87	0	0
9	100	100	37.5	100	0	0	813	0
10	66.67	20.83	67	80	188	829	181	0
$\sum =$	875	875	875	875	1293	1476	1464	1243

5.9. Conclusions

In this Chapter, a methodology has been proposed for assessing the effects of engaging in smart grid DRP on operational and production management. The Delphi method introduced to determine the criteria for assessing the effect of energy curtailment during DRP. The TOPSIS method is employed to apply the criteria and assist the energy manager to rank the equipment according to their significance. After explaining the correlation of energy, cost and power, a LP model was proposed to utilize those ranking values to optimize energy consumption to satisfy the energy limit posed by production demands. Unlike the other research discussed in the literature which are mostly focused on minimizing cost in their optimization objective, this Chapter proposes the maximizing of the energy use in order to increase production while taking into account the utility and production constraints. An algorithm is proposed to assist energy managers to decide whether or not to participate in DRP. This methodology was implemented in a press-shop factory and the result showed that according to 26 criteria, the equipment with high priority received more energy allocation and DRP affected equipment with low priority. The sensitivity analysis carried out for four scenarios and comparing the result of each scenario indicted the robustness of optimization model. The constraints used in the proposed model were the minimum constraints required for energy planning; however, depending on the nature of the process and products, different production methods may impose more constraints on the model.

Chapter 6

Recapitulation and Future Work

6.1. Introduction

An energy management system in the context of the smart grid needs new approaches as the smart grid has added many new features in control methodologies and shifted the traditional paradigm to new and modern concepts of management. Hence, I examined the recent challenges in this field by conducting a survey in Chapter 2 which revealed that the literature to date has failed to consider all these aspects because the effective parameters in energy management systems belong to different domains of science such as science and engineering, sociology, and economics.

In this thesis which pertains to energy management, I aim to design and present methodologies which are more dependent on users' decisions or are more customer-oriented. This is an important consideration since the smart electrical network essentially has been created to benefit the end-users and they are the main customers of this provided service; so if customers are to contribute to this service management, they have to possess the facilities, technologies and methodologies enabling them to monitor the effects of the decisions they make regarding energy consumption; otherwise, they will not be motivated to engage in energy management policies or demand response programs, which are two of the most significant energy management tools in the smart grid.

In order to overcome this disadvantage, a decision support system is required to assist end-users to monitor and control their consumption in order to adapt their lifestyle to changes which have been imposed by DRPs.

The main significance of this research is that it provides benefits for a number of entities including:

- People and householders who consume electricity for their requirements and comfort.
- Utility providers and aggregators which are generating and/or selling electricity.
- Government bodies which allocate funds and invest in bulk electricity generation infrastructures.
- Environment which directly bears the impact of the negative and destructive consequences of energy generation and consumption.

- Society, which is undoubtedly one of the main stakeholders of SG development.

6.2. Recapitulation

Chapter 1 of this thesis begins with a definition of the smart grid and its architecture, and describes the system's components. Certain infrastructures are discussed for the implementation of energy management techniques at the residential level. Following this discussion, I introduce the important parameters of energy demand in the residential sector and optimization and scheduling methodologies. Finally, the research objectives and its significance along with the overall structure are presented. Chapter 1 provides the necessary background to the research motivations, its significance, and the objectives of the improved management system.

The main objectives of this thesis are to research the characteristics and functionality of a home energy management system that are generally incorporated in demand response programs of the smart grid, and to develop a set of advanced solutions to address the following issues:

1. The development of an intelligent decision support system to help users to manage their energy consumption according to their preferences and DR regulations.
2. The development of a home energy management system by proposing methodologies in which intelligence is added to this system.
3. The development of a mathematical optimization algorithm that takes into account users' preferences and comfort level, while utilizing the maximum amount of distributed energy resources.
4. The development of scheduling methodologies to encourage users to shift their consumption from on-peak period to off peak periods in demand response programs.
5. The deployment of a decision-making methodology for the industrial sector of the smart grid in order to assist the operations manager to decide whether to participate in DRP or use distributed energy resources.

In the second chapter of this thesis, I provide an overview of the literature surveyed and an evaluation of the state-of-the-art elements of an energy management system in the micro grid of the smart grid. Substantial progress has been made in providing a practical basis for a number of problems that are associated with energy optimization and scheduling methodologies in the residential sector. A number of energy efficiency tools and techniques have been documented in the literature. The works are discussed that have been previously undertaken to resolve some of the issues outlined in Chapter 1.

The research literature pertaining to the smart grid could be reviewed from an interdisciplinary perspective because this is a complex domain that involves human, socioeconomic, hardware, and software factors. However, in Chapter 2, the literature review is limited to the micro level of the smart grid since this is more relevant to the subject of this thesis. The research areas investigated in literature review can be classified into six categories:

1. Demand-side management and demand response programs
2. The role of smart meters in DR
3. Building an energy management system
    a. Energy consumption scheduling and optimization methods
    b. Prediction of building energy consumption
    c. Load demand identification
4. The effect of consumers' behaviour and their preferences on energy demand
    a. Energy consumption behaviour and activities related to energy demand
    b. The effect of consumers' consumption behaviour in optimization models
5. Comfort management
    a. Comfort management: Thermal Comfort
    b. Comfort Management: Indoor Air Quality
    c. Comfort Management: Visual Comfort
        i. Visual comfort: Electric Lighting Control by Switching Method
        ii. Visual Comfort: Electric Lighting Control by Dimming Method
6. Decision-making approaches in energy management and smart grid

In Chapter 2, I addressed the most significant elements of electrical energy management systems in terms of the end-users of the smart grid, and I examined those studies most relevant to the topic of this thesis.

Hence, the main issues identified in the literature and that addressed in this research are:

a. No approach in the literature has been proposed that measures consumers' preferences and consumption profiles in order to efficiently utilize energy.

b. Much research has been done to achieve efficiency in demand response and price. However, none has proposed a solution for studying the effectiveness of such systems when customers are not well-trained, or unwilling or passive in responding to price signals; consequently, the demand increases. To overcome this, an intelligent decision support system for energy management is required to assist customers to make decisions according to their criteria for demand response.
c. As shown in the optimization and scheduling literatures reviewed in Chapter 2, the study of the preferences of consumers has been limited to the preferred set-up time for the scheduling of appliance operations or air or water temperatures. There are no any approaches in the literature that assist the end-user to aggregate the total preferences regarding all effective parameters in energy consumption, and employ them in optimization models that demonstrate the effect of these preference changes on the optimization of energy consumption.
d. In the reviewed literature, no approach has been proposed that uses an algorithm to facilitate the decision-making process for end-users when they decide to participate in DRP and want to reduce energy consumption.

In Chapter 3, I develop decision-making models by means of which intelligence is added at each home level on a continuous basis, thereby achieving demand response. Prior to constructing our model, firstly I introduce the decision-making process and methodologies. Secondly, the appropriate criteria for decision-making in the residential sector are discussed; and thirdly, I review the multi-criteria, decision-making techniques such as AHP, ANP, TOPSIS, Fuzzy TOPSIS, and ELECTRE and by means of several scenarios, I discuss the advantages and disadvantages of each method in the context of building energy management systems in the smart grid. Fourthly, an intelligent decision support system for building energy management system proposed. I explain that this model can be utilized in four steps: identifying the effective variables, developing the user interface for capturing the consumers' preferences, developing a multi-criteria decision making model and finally developing a neural network based model for learning the consumers' preferences and consumption profile based on the obtained data.

The fourth chapter of this thesis proposes a system of systems approach for scheduling and optimizing the energy supply to buildings. It introduces the knapsack problem optimization method in order to save the householders' utility budget while the preferences of using appliances have been maximized in a dynamic pricing scheme of DRP. I proposed a methodology in which the multi-criteria decision-making approach which was proposed in Chapter 3 is combined with the knapsack problem optimization technique. In Chapter 4, I presented eight scenarios to demonstrate the methodology. Finally, Chapter 4 proposes a decision-making algorithm by which an optimization system of the proposed SoS model can perform optimization.

Chapter 5 of this dissertation utilizes the TOPSIS method and combines it with a linear programming allocation technique to support an industrial energy manager (or an operation manager) in making the decision whether to participate in a DRP, or instead use the distributed resources. Our proposed methodology in this chapter has focused on the most available equipment the operations of which can be deferred or interrupted because they are not a prerequisite for other operations. Mathematical and optimization models and a DRP engagement evaluation algorithm have been simulated using ILOG CPLEX Optimization studio programming.

The software employed for simulating and executing the proposed models and algorithms include Lingo, MATLAB, and IBM ILOG CPLEX Optimization studio.

6.3. Contribution of the Thesis

The major contribution of this thesis to the literature is that it proposes methodologies as decision-making frameworks for end-users to involve and consider the criteria which can be affected by the energy curtailment of DRP participation. In the residential sector, these criteria pertain to the users' lifestyle, and in the industrial sector they concern the loss/ benefits and risks associated with production management.

The contributions of this thesis are as follows:

1. Addressed the most significant elements and approaches of electrical energy management systems in terms of the end-users of the smart grid by reviewing the researches presented in the literature review, Chapter 2.
2. Proposed a methodology which allows users to apply the criteria to their decision-making with a solution for the wise consumption of energy. The proposed decision-making framework helps users to manage their energy consumption according to their preferences and DR regulations and balance power consumption with their lifestyle.
3. Proposed MCDM methodologies to measures consumers' preferences in order to efficiently utilize energy, and compared the advantages and disadvantages of each method.

4. Proposed an IDSS to monitor consumers' decision-making, elicit consumer preferences, and decisions make autonomously on behalf of the consumers to achieve more effective demand response.
5. Proposed an optimization methodology by utilizing MCDM methods such as AHP and TOPSIS together with the knapsack problem approach in order to reflect the consumers' preferences in the final optimal solution. The optimal solution reflects maximum consumer satisfaction.
6. Proposed a system of systems model to create a robust building energy management system that is compatible with the dynamic pricing demand response program of the SG.
7. Proposed a decision-making algorithm for implementing the optimization based on proposed KP and MCDM techniques and utilise the distributed energy resources in an efficient way. The application of this decision-making framework is essential particularly when the optimizer system interacts with other systems such as identifier, predictor and monitor systems.
8. Proposed the Delphi methodology to determine the appropriate criteria for assessing the effects of energy curtailment in the industrial sector of the SG.
9. Proposed the application of TOPSIS technique for ranking electrical equipment based on the criteria when the manufacturer decides to engage in DRP.
10. Proposed a combinatorial optimization technique for utilizing energy as much as possible when constraints are imposed by the amount of energy required to run equipment and the commitment to a particular energy level in DRP.
11. Proposed a decision-making algorithm in order to mitigate the effects of energy curtailment on operation management and assist energy managers to decide whether to engage DRP or draw from distributed energy resources.

6.4. Future Work

In this thesis, decision-making frameworks and optimization techniques are proposed as an important part of BEMS for the area of DRP in the SG. However, during the course of the approaches presented in this thesis, many significant future outlooks have emerged. The proposed methodology and framework would be strengthened further by future work that considers these directions. The following are the most significant areas which have been identified for future work.

1. Expanding the intelligent decision support system proposed in Chapter 3 for achieving a unique energy consumption profile for the family members: Comparing the electrical system

with telecommunication and media system, especially the mobile network, the users of that system receive real-time data about their consumption. The provided information will detail the usage of each application. Furthermore, the mobile network providers are able to inform their users about any overconsumption trend and offer them a more appropriate service based on the user's consumption profile. Consequently, because of the information provided, each user knows how many gigabytes of data and how many hours s/he requires during a billing period. In order to add such intelligence to the smart grid, the proposed IDSS must be able to examine the users' consumption behaviour and lifestyle.

2. Expanding the proposed knapsack method to an online stochastic knapsack: in our proposed optimization methodology, the data input to the system is done within the offline or semi-online state. But the online and stochastic method can provide an approximation of future energy consumption trends for the BEMS.

3. Expanding the proposed methodology presented in Chapter 5 to consider the Operation process chart (OPC) and adding more operation constraints to the mathematical formula. These constraints can be the concurrent and preceding operation times in scheduling.

4. Implementing the algorithm proposed in Chapter 5 for hourly real-time pricing demand response but with the addition of an energy price forecasting model.

5. Expanding the optimization algorithm proposed in Chapter 5 by considering the parameters related to the flexibility of the equipment such as the set-up time in each interruption, the minimum energy required for performing an operation, as well as appropriate correlation between power and operation time for adjusting the energy needed to operate particular equipment.

6.5. Conclusions

This chapter reviewed the significance of the thesis and recapitulated the objectives, the issues and the proposed solutions that have been presented and discussed. The contributions of the thesis have been highlighted according to the identified research issues. Finally, it gave a brief description of future research directions which could extend the proposed approaches.

The proposed methodologies and decision-making algorithms that were undertaken in this thesis have been published in peer reviewed international journal and conferences.

References

[1] EIA, "International Energy Outlook 2013," the U.S. Energy Information Administration, Washington, DC DOE/EIA-0484, 2013.

[2] A. Vojdani, "Smart Integration," *Power and Energy Magazine, IEEE,* vol. 6, pp. 71-79, 2008.

[3] ISO/IEC, "ISO/ IEC 15067-3: Information technology- Home electronic system (HES) application model - part 3: Model of a demand- response energy management system for HES," in *ISO/ IEC 15067-3,* ed. Switzerland, 2012, p. 45.

[4] P. Nabuurs, "Strategic Deployment Document For Eoroupe 's Elictricity Networks of the Future," N.V. KEMA, DraftSeptember, 2008.

[5] S. Electric. (2009). *Leading the way in energy efficiency*. Available: http://www.schneider-electric.com/sites/corporate/ en/solutions/energy_efficiency/ energy-context.page

[6] J. Torriti, M. G. Hassan, and M. Leach, "Demand response experience in Europe: Policies, programmes and implementation," *Energy,* vol. 35, pp. 1575-1583, 2010.

[7] NIST, "NIST Framework and Roadmap for Smart Grid Interoperability Standards, Release 2.0," The National Institute of Standards and Technology USA NIST SP - 1108R2, February 16, 2012.

[8] DOE, "The Smart Grid: An Introduction," DE-AC26-04NT41817, 2008.

[9] NIST, "NIST Framework and Roadmap for Smart Grid Interoperability Standards, Release 3.0," The National Institute of Standards and Technology USA NIST SP - 1108R2, May, 2014.

[10] *Title xiii- smart grid sec. 1301- 1308 statement of policy on modernization of electricity grid,* Office, 2007.

[11] H. Merz, T. Hansemann, and C. Hübner, "BACnet," in *Building Automation*, ed: Springer Berlin Heidelberg, 2009, pp. 185-273.

[12] H. K. Ozturk, O. E. Canyurt, A. Hepbasli, and Z. Utlu, "Residential-commercial energy input estimation based on genetic algorithm (GA) approaches: an application of Turkey," *Energy and Buildings,* vol. 36, pp. 175-183, 2004.

[13] I. E. Agency, "Technology roadmap energy-efficient buildings: heating and cooling equipment.," 2011.

[14] H.-x. Zhao and F. Magoulès, "A review on the prediction of building energy consumption," *Renewable and Sustainable Energy Reviews,* vol. 16, pp. 3586-3592, 2012.

[15] L. Pérez-Lombard, J. Ortiz, and C. Pout, "A review on buildings energy consumption information," *Energy and Buildings*, vol. 40, pp. 394-398, 2008.

[16] F. E. R. Commission, "Assessment of Demand Response and Advanced Metering," 2012.

[17] M. H. Albadi and E. F. El-Saadany, "A summary of demand response in electricity markets," *Electric Power Systems Research*, vol. 78, pp. 1989-1996, 2008.

[18] S. Australia, "AS4755.3.1-2008: Interaction of demand response enabling devices and electrical products—Operational instructions and connections for airconditioners," in *Demand response capabilities and supporting technologies for electrical products*, ed, 2008.

[19] SA, "AS5711-2013: Smart grid vocabulary," ed. Australia, 2013.

[20] O. A. Sianaki, O. Hussain, and A. R. Tabesh, "A Knapsack problem approach for achieving efficient energy consumption in smart grid for endusers' life style," in *Innovative Technologies for an Efficient and Reliable Electricity Supply (CITRES), 2010 IEEE Conference on*, Boston, USA, 2010, pp. 159-164.

[21] O. A. Sianaki, O. Hussain, T. Dillon, and A. R. Tabesh, "Intelligent Decision Support System for Including Consumers' Preferences in Residential Energy Consumption in Smart Grid," in *Computational Intelligence, Modelling and Simulation (CIMSiM), 2010 Second International Conference on*, Indonesia, 2010, pp. 154-159.

[22] O. A. Sianaki and M. A. S. Masoum, "A fuzzy TOPSIS approach for home energy management in smart grid with considering householders' preferences," in *Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*, Washington D.C., USA, 2013, pp. 1-6.

[23] O. A. Sianaki and M. A. S. Masoum, "A Multi-agent Intelligent Decision Making Support System for Home Energy Management in Smart Grid: A Fuzzy TOPSIS Approach," *Multiagent and Grid Systems - An International Journal*, vol. 9, pp. 181–195, 03/11/2013.

[24] R. Rashed Mohassel, A. Fung, F. Mohammadi, and K. Raahemifar, "A survey on Advanced Metering Infrastructure," *International Journal of Electrical Power & Energy Systems*, vol. 63, pp. 473-484, 2014.

[25] G. M. Huebner, J. Cooper, and K. Jones, "Domestic energy consumption—What role do comfort, habit, and knowledge about the heating system play?," *Energy and Buildings*, vol. 66, pp. 626-636, 2013.

[26] P. H. Shaikh, N. B. M. Nor, P. Nallagownden, I. Elamvazuthi, and T. Ibrahim, "A review on optimized control systems for building energy and comfort management of smart sustainable buildings," *Renewable and Sustainable Energy Reviews*, vol. 34, pp. 409-429, 2014.

[27] W. Lingfeng, W. Zhu, and Y. Rui, "Intelligent Multiagent Control System for Energy and Comfort Management in Smart and Sustainable Buildings," *Smart Grid, IEEE Transactions on,* vol. 3, pp. 605-617, 2012.

[28] S. M. Hakimi, S. M. Moghaddas-Tafreshi, and M. M. Alamuti, "Smart heating system control strategy to enhance comfort and increase renewable energy penetration," in *Intelligent Energy Systems (IWIES), 2013 IEEE International Workshop on*, 2013, pp. 191-196.

[29] R. Yang and L. Wang, "Development of multi-agent system for building energy and comfort management based on occupant behaviors," *Energy and Buildings,* vol. 56, pp. 1-7, 2013.

[30] Y. Rui and W. Lingfeng, "Multi-agent based energy and comfort management in a building environment considering behaviors of occupants," in *Power and Energy Society General Meeting, 2012 IEEE*, 2012, pp. 1-7.

[31] L. Bei, S. Gangadhar, S. Cheng, and P. K. Verma, "Predicting user comfort level using machine learning for Smart Grid environments," in *Innovative Smart Grid Technologies (ISGT), 2011 IEEE PES*, 2011, pp. 1-6.

[32] N. Saxena, A. Roy, and J. Shin, "CHASE: Context-aware heterogenous adaptive smart environments using optimal tracking for resident's comfort," *Ubiquitous Intelligence and Computing,* vol. 4611 LNCS, pp. 133-142, 2007.

[33] N. Saxena, A. Roy, and J. Shin, "Near-optimal tracking for residents' comfort in context-aware heterogeneous smart environments," *Computer Journal,* vol. 52, pp. 879-889, 2009.

[34] A. I. Dounis, M. J. Santamouris, C. C. Lefas, and A. Argiriou, "Design of a fuzzy set environment comfort system," *Energy and Buildings,* vol. 22, pp. 81-87, 1995.

[35] A. I. Dounis and C. Caraiscos, "Advanced control systems engineering for energy and comfort management in a building environment—A review," *Renewable and Sustainable Energy Reviews,* vol. 13, pp. 1246-1261, 2009.

[36] R. Yang and L. Wang, "Multi-objective optimization for decision-making of energy and comfort management in building automation and control," *Sustainable Cities and Society,* vol. 2, pp. 1-7, 2012.

[37] J. R. Villar, E. De La Cal, and J. Sedano, "Energy saving by means of fuzzy systems," in *Intelligent Data Engineering and Automated Learning-IDEAL 2007,* ed: Springer, 2007, pp. 155-167.

[38] T. A. Nguyen and M. Aiello, "Energy intelligent buildings based on user activity: A survey," *Energy and Buildings,* vol. 56, pp. 244-257, 2013.

[39] ISO, "ISO 7730:2005(E)," in *Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV*

and PPD indices and local thermal comfort criteria, ed. Switzerland: American Society of Heating, Refrigerating and Air-conditioning Engineers (ASHRAE), 2005, p. 61.

[40] ASHRAE, "ANSI/ASHRAE Standard 55-2013," in *Thermal Environmental Conditions for Human Occupancy*, ed, 2013.

[41] G. Reynders, T. Nuytten, and D. Saelens, "Potential of structural thermal mass for demand-side management in dwellings," *Building and Environment,* vol. 64, pp. 187-199, 2013.

[42] C. Chen, W. Jianhui, H. Yeonsook, and S. Kishore, "MPC-Based Appliance Scheduling for Residential Building Energy Management Controller," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 1401-1410, 2013.

[43] M. Frascarolo, S. Martorelli, and V. Vitale, "An innovative lighting system for residential applicationwhich optimize visual comfort and energy saving for different Users' needs," *Energy and Buildings,* 2014.

[44] M. Song, K. Alvehag, J. Widén, and A. Parisio, "Estimating the impacts of demand response by simulating household behaviours under price and CO2 signals," *Electric Power Systems Research,* vol. 111, pp. 103-114, 2014.

[45] C. Chen, D. J. Cook, and A. S. Crandall, "The user side of sustainability: Modeling behavior and energy usage in the home," *Pervasive and Mobile Computing,* vol. 9, pp. 161-175, 2013.

[46] DaYan and T. Hong, "EBC Annex 66 Proposal: Definition and Simulation of Occupant Behavior in Buildings," International Energy Agency, 2014.

[47] Y. G. Yohanis, "Domestic energy use and householders' energy behaviour," *Energy Policy,* vol. 41, pp. 654-665, 2012.

[48] A. Ingle, M. Moezzi, L. Lutzenhiser, and R. Diamond, "Better home energy audit modelling: incorporating inhabitant behaviours," *Building Research & Information,* pp. 1-13, 2014.

[49] C. Xiaodao, W. Tongquan, and H. Shiyan, "Uncertainty-Aware Household Appliance Scheduling Considering Dynamic Electricity Pricing in Smart Home," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 932-941, 2013.

[50] C. Zhi, W. Lei, and F. Yong, "Real-Time Price-Based Demand Response Management for Residential Appliances via Stochastic Optimization and Robust Optimization," *Smart Grid, IEEE Transactions on,* vol. 3, pp. 1822-1831, 2012.

[51] E. Mashhour and S. M. Moghaddas-Tafreshi, "Integration of distributed energy resources into low voltage grid: A market-based multiperiod optimization model," *Electric Power Systems Research,* vol. In Press, Corrected Proof, 2010.

[52] G. Chicco and P. Mancarella, "Distributed multi-generation: A comprehensive view," *Renewable and Sustainable Energy Reviews,* vol. 13, pp. 535-551, 2009.

[53] A. J. D. Rathnayaka, V. M. Potdar, T. Dillon, O. Hussain, and S. Kuruppu, "Analysis of energy behaviour profiles of prosumers," in *Industrial Informatics (INDIN), 2012 10th IEEE International Conference on*, 2012, pp. 236-241.

[54] W. Zhu and W. Lingfeng, "Negotiation agent with adaptive attitude bidding strategy for facilitating energy exchanges between smart building and utility grid," in *Transmission and Distribution Conference and Exposition (T&D), 2012 IEEE PES*, 2012, pp. 1-8.

[55] A. Agnetis, G. de Pascale, P. Detti, and A. Vicino, "Load Scheduling for Household Energy Consumption Optimization," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 2364-2373, 2013.

[56] J. Clement, J. Ploennigs, and K. Kabitzsch, "Detecting Activities of Daily Living with Smart Meters," in *Ambient Assisted Living*, ed: Springer, 2014, pp. 143-160.

[57] W. Zhenyu and Z. Guilin, "Residential Appliances Identification and Monitoring by a Nonintrusive Method," *Smart Grid, IEEE Transactions on,* vol. 3, pp. 80-92, 2012.

[58] M. Pipattanasomporn, M. Kuzlu, S. Rahman, and Y. Teklu, "Load Profiles of Selected Major Household Appliances and Their Demand Response Opportunities," *Smart Grid, IEEE Transactions on,* vol. 5, pp. 742-750, 2014.

[59] L. Xin, L. Ivanescu, K. Rui, and M. Maier, "Real-time household load priority scheduling algorithm based on prediction of renewable source availability," *Consumer Electronics, IEEE Transactions on,* vol. 58, pp. 318-326, 2012.

[60] L. Seungwoo, C. Yohan, K. Yunjong, H. Rhan, and C. Hojung, "Occupancy Prediction Algorithms for Thermostat Control Systems Using Mobile Devices," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 1332-1340, 2013.

[61] K. Basu, L. Hawarah, N. Arghira, H. Joumaa, and S. Ploix, "A prediction system for home appliance usage," *Energy and Buildings,* 2013.

[62] K. Basu, V. Debusschere, and S. Bacha, "Residential appliance identification and future usage prediction from smart meter," in *Industrial Electronics Society, IECON 2013 - 39th Annual Conference of the IEEE*, 2013, pp. 4994-4999.

[63] M. Avci, M. Erkoc, A. Rahmani, and S. Asfour, "Model predictive HVAC load control in buildings using real-time electricity pricing," *Energy and Buildings,* vol. 60, pp. 199-209, 2013.

[64] H. Dae-Man and L. Jae-Hyun, "Smart home energy management system using IEEE 802.15.4 and zigbee," *Consumer Electronics, IEEE Transactions on,* vol. 56, pp. 1403-1410, 2010.

[65] J. Monteiro, P. J. Cardoso, R. Serra, and L. Fernandes, "Evaluation of the Human Factor in the Scheduling of Smart Appliances in Smart Grids," in *Universal Access in Human-Computer Interaction. Aging and Assistive Environments*, ed: Springer, 2014, pp. 537-548.

[66] T. P. Dirienzo, N. A. Krishnan, and J. R. Santos, "Effects of smart appliances on residential consumption patterns," in *Systems and Information Engineering Design Symposium (SIEDS)*,2014, pp. 188-192.

[67] S. I. Gass and C. M. Harris, "Encyclopedia of operations research and management science," in *Journal of the Operational Research Society* vol. 48, Third ed: Springer US, 2013, p. 1641.

[68] T. D. o. Energy, "Guidebook for ARRA smart grid program metrics and benefits " 2010.

[69] H. Ibrahim, A. Ilinca, and J. Perron, "Energy storage systems—Characteristics and comparisons," *Renewable and Sustainable Energy Reviews,* vol. 12, pp. 1221-1250, 2008.

[70] C. W. Gellings and J. H. Chamberlin, "Demand-side management: concepts and methods," 1987.

[71] C. W. Gellings, "The concept of demand-side management for electric utilities," *Proceedings of the IEEE,* vol. 73, pp. 1468-1470, 1985.

[72] D. S. Loughran and J. Kulick, "Demand-side management and energy efficiency in the United States," *The Energy Journal,* pp. 19-43, 2004.

[73] P. Warren, "A review of demand-side management policy in the UK," *Renewable and Sustainable Energy Reviews,* vol. 29, pp. 941-951, 2014.

[74] P. Palensky and D. Dietrich, "Demand Side Management: Demand Response, Intelligent Energy Systems, and Smart Loads," *Industrial Informatics, IEEE Transactions on,* vol. 7, pp. 381-388, 2011.

[75] G. Strbac, "Demand side management: Benefits and challenges," *Energy Policy,* vol. 36, pp. 4419-4426, 2008.

[76] J. Aghaei and M.-I. Alizadeh, "Demand response in smart electricity grids equipped with renewable energy sources: A review," *Renewable and Sustainable Energy Reviews,* vol. 18, pp. 64-72, 2013.

[77] R. Earle, E. P. Kahn, and E. Macan, "Measuring the Capacity Impacts of Demand Response," *The Electricity Journal,* vol. 22, pp. 47-58, 2009.

[78] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "Demand response implementation in a home area network: A conceptual hardware architecture," in *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*, 2012, pp. 1-8.

[79] S. Braithwait and K. Eakin, "The role of demand response in electric power market design," *Edison Electric Institute,* 2002.

[80] J. Chinnow, K. Bsufka, A. D. Schmidt, R. Bye, A. Camtepe, and S. Albayrak, "A simulation framework for smart meter security evaluation," in *Smart Measurements for Future Grids (SMFG), 2011 IEEE International Conference on*, 2011, pp. 1-9.

[81] A. Sikora, "Implementation of Standardized Secure Smart Meter Communication," in *Telecommunications Energy Conference 'Smart Power and Efficiency' (INTELEC), Proceedings of 2013 35th International*, 2013, pp. 1-5.

[82] R. Rashedi and H. Feroze, "Optimization of process security in smart meter reading," in *Smart Grid Conference (SGC), 2013*, 2013, pp. 150-152.

[83] A. A. Mohamed and O. A. Mohammed, "Real-time load emulator for implementation of smart meter data for operational planning," in *Power and Energy Society General Meeting, 2012 IEEE*, 2012, pp. 1-6.

[84] O. Tan, D. Gunduz, and H. V. Poor, "Increasing Smart Meter Privacy Through Energy Harvesting and Storage Devices," *Selected Areas in Communications, IEEE Journal on,* vol. 31, pp. 1331-1341, 2013.

[85] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid," *Smart Grid, IEEE Transactions on,* vol. 1, pp. 320-331, 2010.

[86] C. Efthymiou and G. Kalogridis, "Smart Grid Privacy via Anonymization of Smart Metering Data," in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*, 2010, pp. 238-243.

[87] C. Barcellona, P. Cassara, G. Di Bella, J. Golic, and I. Tinnirello, "Multi-party metering: An architecture for privacy-preserving profiling schemes," in *Sustainable Internet and ICT for Sustainability (SustainIT)*, 2013, pp. 1-6.

[88] L. Sankar, S. R. Rajagopalan, S. Mohajer, and H. V. Poor, "Smart Meter Privacy: A Theoretical Framework," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 837-846, 2013.

[89] S. R. Rajagopalan, L. Sankar, S. Mohajer, and H. V. Poor, "Smart meter privacy: A utility-privacy framework," in *Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on*, 2011, pp. 190-195.

[90] M. Ghofrani, M. Hassanzadeh, M. Etezadi-Amoli, and M. S. Fadali, "Smart meter based short-term load forecasting for residential customers," in *North American Power Symposium (NAPS)*,2011, pp. 1-5.

[91] Z. Guo, Z. J. Wang, and A. Kashani, "Home Appliance Load Modeling From Aggregated Smart Meter Data," *Power Systems, IEEE Transactions on*, vol. PP, pp. 1-9, 2014.

[92] T. Bier, D. O. Abdeslam, J. Merckle, and D. Benyoucef, "Smart meter systems detection & classification using artificial neural networks," in *IECON 2012 - 38th Annual Conference on IEEE Industrial Electronics Society*, 2012, pp. 3324-3329.

[93] L. Hongfei, F. Dongping, S. Mahatma, and A. Hampapur, "Usage analysis for smart meter management," in *Emerging Technologies for a Smarter World (CEWIT), 2011 8th International Conference & Expo on*, 2011, pp. 1-6.

[94] J. Wang, Z. Hu, and K. Shen, "The Method of the Online Detection that the Accuracy of Three-phase Smart Meter," in *Computer Distributed Control and Intelligent Environmental Monitoring (CDCIEM), 2012 International Conference on*, 2012, pp. 761-763.

[95] R. S. Prasad and S. Semwal, "A simplified new procedure for identification of appliances in smart meter applications," in *Systems Conference (SysCon), 2013 IEEE International*, 2013, pp. 339-344.

[96] B. Stephen, A. J. Mutanen, S. Galloway, G. Burt, and P. Jarventausta, "Enhanced Load Profiling for Residential Network Customers," *Power Delivery, IEEE Transactions on*, vol. 29, pp. 88-96, 2014.

[97] S. Semwal, D. Joshi, R. S. Prasad, and D. Raveendhra, "The practicability of ICA in home appliances load profile separation using current signature: A preliminary study," in *Power, Energy and Control (ICPEC), 2013 International Conference on*, 2013, pp. 756-759.

[98] R. Danping, L. Hui, and J. Yuefeng, "Home energy management system for the residential load control based on the price prediction," in *Online Conference on Green Communications (GreenCom), 2011 IEEE*, 2011, pp. 1-6.

[99] D. Ming, P. C. M. Meira, X. Wilsun, and C. Y. Chung, "Non-Intrusive Signature Extraction for Major Residential Loads," *Smart Grid, IEEE Transactions on*, vol. 4, pp. 1421-1430, 2013.

[100] B. Stephen and S. J. Galloway, "Domestic Load Characterization Through Smart Meter Advance Stratification," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 1571-1572, 2012.

[101] D. Benyoucef, P. Klein, and T. Bier, "Smart Meter with non-intrusive load monitoring for use in Smart Homes," in *Energy Conference and Exhibition (EnergyCon), 2010 IEEE International*, 2010, pp. 96-101.

[102] B. Shah, A. Bose, and A. Srivastava, "Load modeling and voltage optimization using smart meter infrastructure," in *Innovative Smart Grid Technologies (ISGT), 2013 IEEE PES*, 2013, pp. 1-6.

[103] C. W. Gellings and M. Samotyj, "Smart Grid as advanced technology enabler of demand response," *Energy Efficiency,* vol. 6, pp. 685-694, 2013.

[104] D. T. Nguyen and L. Long Bao, "Joint Optimization of Electric Vehicle and Home Energy Scheduling Considering User Comfort Preference," *Smart Grid, IEEE Transactions on,* vol. 5, pp. 188-199, 2014.

[105] N. Kumaraguruparan, H. Sivaramakrishnan, and S. S. Sapatnekar, "Residential task scheduling under dynamic pricing using the multiple knapsack method," in *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*, 2012, pp. 1-6.

[106] H. P. Khomami and M. H. Javidi, "An efficient home energy management system for automated residential demand response," in *Environment and Electrical Engineering (EEEIC), 2013 13th International Conference on*, 2013, pp. 307-312.

[107] Y. Ji Hoon, R. Baldick, and A. Novoselac, "Dynamic Demand Response Controller Based on Real-Time Retail Price for Residential Buildings," *Smart Grid, IEEE Transactions on,* vol. 5, pp. 121-129, 2014.

[108] N. Hieu Trung, N. Duong, and L. Long Bao, "Home energy management with generic thermal dynamics and user temperature preference," in *Smart Grid Communications (SmartGridComm), 2013 IEEE International Conference on*, 2013, pp. 552-557.

[109] K. Wonsuk and H. Tae-Kyung, "Analysis of Consumer Preferences for Electric Vehicles," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 437-442, 2013.

[110] L. Klein, J.-y. Kwak, G. Kavulya, F. Jazizadeh, B. Becerik-Gerber, P. Varakantham, and M. Tambe, "Coordinating occupant behavior for building energy and comfort management using multi-agent systems," *Automation in Construction,* vol. 22, pp. 525-536, 2012.

[111] B. F. Mills and J. Schleich, "Profits or preferences? Assessing the adoption of residential solar thermal technologies," *Energy Policy,* vol. 37, pp. 4145-4154, 2009.

[112] P. Howley, M. Scott, and D. Redmond, "An examination of residential preferences for less sustainable housing: Exploring future mobility among Dublin central city residents," *Cities,* vol. 26, pp. 1-8, 2009.

[113] D. Diakoulaki, C. Zopounidis, G. Mavrotas, and M. Doumpos, "The use of a preference disaggregation method in energy analysis and policy making," *Energy,* vol. 24, pp. 157-166, 1999.

[114] P. Samadi, A. Mohsenian-Rad, R. Schober, V. W. S. Wong, and J. Jatskevich, "Optimal Real-Time Pricing Algorithm Based on Utility Maximization for Smart

Grid," in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*, 2010, pp. 415-420.

[115] C. Wang and M. d. Groot, "Managing end-user preferences in the smart grid," presented at the Proceedings of the 1st International Conference on Energy-Efficient Computing and Networking, Passau, Germany, 2010.

[116] I. Vassileva, F. Wallin, and E. Dahlquist, "Understanding energy consumption behavior for future demand response strategy development," *Energy,* 2012.

[117] C. Li and L. Li, "Utility-based scheduling for grid computing under constraints of energy budget and deadline," *Computer Standards & Interfaces,* vol. 31, pp. 1131-1142, 2009.

[118] A. J. Conejo, J. M. Morales, and L. Baringo, "Real-Time Demand Response Model," *Smart Grid, IEEE Transactions on,* vol. 1, pp. 236-242, 2010.

[119] M. Erol-Kantarci and H. T. Mouftah, "Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid," *Smart Grid, IEEE Transactions on,* vol. 2, pp. 314-325, 2011.

[120] R. Missaoui, H. Joumaa, S. Ploix, and S. Bacha, "Managing energy Smart Homes according to energy prices: Analysis of a Building Energy Management System," *Energy and Buildings,* vol. 71, pp. 155-167, 2014.

[121] S. D. Ramchurn, P. Vytelingum, A. Rogers, and N. R. Jennings, "Agent-based homeostatic control for green energy in the smart grid," *ACM Trans. Intell. Syst. Technol.,* vol. 2, pp. 1-28, 2011.

[122] M. J. Dolan, E. M. Davidson, G. W. Ault, K. R. W. Bell, and S. D. J. McArthur, "Distribution Power Flow Management Utilizing an Online Constraint Programming Method," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 798-805, 2013.

[123] J. Widén, A. M. Nilsson, and E. Wäckelgård, "A combined Markov-chain and bottom-up approach to modelling of domestic lighting demand," *Energy and Buildings,* vol. 41, pp. 1001-1012, 2009.

[124] T. T. Kim and H. V. Poor, "Scheduling Power Consumption With Price Uncertainty," *Smart Grid, IEEE Transactions on,* vol. 2, pp. 519-527, 2011.

[125] C. Tsung-Hui, M. Alizadeh, and A. Scaglione, "Real-Time Power Balancing Via Decentralized Coordinated Home Energy Scheduling," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 1490-1504, 2013.

[126] E. Jean-Yves Le Boudec and E. Dan-Cristian Tomozei, "Stability of a stochastic model for demand-response," *Stochastic Systems,* vol. 3, pp. 11-37, 2013.

[127] Y. Zhe, L. McLaughlin, J. Liyan, M. C. Murphy-Hoye, A. Pratt, and T. Lang, "Modeling and stochastic control for Home Energy Management," in *Power and Energy Society General Meeting, 2012 IEEE,* 2012, pp. 1-9.

[128] J. Widén and E. Wäckelgård, "A high-resolution stochastic model of domestic activity patterns and electricity demand," *Applied Energy,* vol. 87, pp. 1880-1892, 2010.

[129] G. Chen, W. Xiaodong, X. Weiqiang, and A. Tajer, "Distributed Real-Time Energy Scheduling in Smart Grid: Stochastic Model and Fast Optimization," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 1476-1489, 2013.

[130] D. Caprino, M. L. Della Vedova, and T. Facchinetti, "Peak shaving through real-time scheduling of household appliances," *Energy and Buildings,* vol. 75, pp. 133-148, 2014.

[131] A. Chaouachi, R. M. Kamel, R. Andoulsi, and K. Nagasaka, "Multiobjective intelligent energy management for a microgrid," *Industrial Electronics, IEEE Transactions on,* vol. 60, pp. 1688-1699, 2013.

[132] D. Li and S. K. Jayaweera, "Distributed smart-home decision-making in a hierarchical interactive smart grid architecture," 2015.

[133] C. Ibars, M. Navarro, and L. Giupponi, "Distributed demand management in smart grid with a congestion game," in *Smart grid communications (SmartGridComm), 2010 first IEEE international conference on*, 2010, pp. 495-500.

[134] W. Saad, Z. Han, H. V. Poor, and T. Basar, "A noncooperative game for double auction-based energy trading between PHEVs and distribution grids," in *Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on*, 2011, pp. 267-272.

[135] A.-H. Mohsenian-Rad, V. W. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous demand-side management based on game-theoretic energy consumption scheduling for the future smart grid," *Smart Grid, IEEE Transactions on,* vol. 1, pp. 320-331, 2010.

[136] H. M. Soliman and A. Leon-Garcia, "Game-theoretic demand-side management with storage devices for the future smart grid," 2014.

[137] M. A. A. Pedrasa, T. D. Spooner, and I. F. MacGill, "Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services," *Smart Grid, IEEE Transactions on,* vol. 1, pp. 134-143, 2010.

[138] M. H. Tushar, C. Assi, and M. Maier, "Distributed Real-Time Electricity Allocation Mechanism for Large Residential Microgrid," 2015.

[139] S. Caron and G. Kesidis, "Incentive-Based Energy Consumption Scheduling Algorithms for the Smart Grid," in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*, 2010, pp. 391-396.

[140] N. Gatsis and G. B. Giannakis, "Cooperative multi-residence demand response scheduling," in *Information Sciences and Systems (CISS), 2011 45th Annual Conference on*, 2011, pp. 1-6.

[141] N. Gatsis and G. B. Giannakis, "Residential load control: Distributed scheduling and convergence with lost AMI messages," *Smart Grid, IEEE Transactions on,* vol. 3, pp. 770-786, 2012.

[142] Z. Baharlouei, M. Hashemi, H. Narimani, and H. Mohsenian-Rad, "Achieving Optimality and Fairness in Autonomous Demand Response: Benchmarks and Billing Mechanisms," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 968-975, 2013.

[143] S. K. Das, N. Roy, and A. Roy, "Context-aware resource management in multi-inhabitant smart homes: A framework based on Nash H-learning," *Pervasive and Mobile Computing,* vol. 2, pp. 372-404, 2006.

[144] J. Yang, H. Rivard, and R. Zmeureanu, "On-line building energy prediction using adaptive artificial neural networks," *Energy and buildings,* vol. 37, pp. 1250-1259, 2005.

[145] R. Yokoyama, T. Wakui, and R. Satake, "Prediction of energy demands using neural network with model identification by global optimization," *Energy Conversion and Management,* vol. 50, pp. 319-327, 2009.

[146] X. Xue, S. Wang, C. Yan, and B. Cui, "A fast chiller power demand response control strategy for buildings connected to smart grid," *Applied Energy,* vol. 137, pp. 77-87, 2015.

[147] K. Basu, V. Debusschere, and S. Bacha, "Load identification from power recordings at meter panel in residential households," in *Electrical Machines (ICEM), 2012 XXth International Conference on*, 2012, pp. 2098, 2104.

[148] M. K. Haider, A. K. Ismail, and I. A. Qazi, "Markovian models for electrical load prediction in smart buildings," *Neural Information Processing,* vol. 7664 LNCS, pp. 632-639, 2012.

[149] J. L. Mathieu, D. S. Callaway, and S. Kiliccote, "Variability in automated responses of commercial buildings and industrial facilities to dynamic electricity prices," *Energy and Buildings,* vol. 43, pp. 3322-3330, 2011.

[150] R. Halvgaard, N. K. Poulsen, H. Madsen, and J. B. Jorgensen, "Economic Model Predictive Control for building climate control in a Smart Grid," in *Innovative Smart Grid Technologies (ISGT), 2012 IEEE PES*, 2012, pp. 1-6.

[151] B. Ramachandran, S. K. Srivastava, C. S. Edrington, and D. A. Cartes, "An intelligent auction scheme for smart grid market using a hybrid immune algorithm," *Industrial Electronics, IEEE Transactions on,* vol. 58, pp. 4603-4612, 2011.

[152] F. Zhong, "A Distributed Demand Response Algorithm and Its Application to PHEV Charging in Smart Grids," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 1280-1290, 2012.

[153] A.-H. Mohsenian-Rad and A. Leon-Garcia, "Optimal residential load control with price prediction in real-time electricity pricing environments," *Smart Grid, IEEE Transactions on,* vol. 1, pp. 120-133, 2010.

[154] A. Molina, A. Gabaldon, J. Fuentes, and C. Alvarez, "Implementation and assessment of physically based electrical load models: application to direct load control residential programmes," *IEE Proceedings-Generation, Transmission and Distribution,* vol. 150, pp. 61-66, 2003.

[155] A. Di Giorgio and L. Pimpinella, "An event driven Smart Home Controller enabling consumer economic saving and automated Demand Side Management," *Applied Energy,* vol. 96, pp. 92-103, 2012.

[156] D. Pengwei and L. Ning, "Appliance Commitment for Household Load Scheduling," *Smart Grid, IEEE Transactions on,* vol. 2, pp. 411-419, 2011.

[157] M. Rastegar, M. Fotuhi-Firuzabad, and F. Aminifar, "Load commitment in a smart home," *Applied Energy,* vol. 96, pp. 45-54, 2012.

[158] M. Rastegar and M. Fotuhi-Firuzabad, "Outage Management in Residential Demand Response Programs," *Smart Grid, IEEE Transactions on,* vol. 6, pp. 1453-1462, 2015.

[159] S. J. Kang, J. Park, K.-Y. Oh, J. G. Noh, and H. Park, "Scheduling-based real time energy flow control strategy for building energy management system," *Energy and Buildings,* vol. 75, pp. 239-248, 2014.

[160] C. O. Adika and W. Lingfeng, "Autonomous Appliance Scheduling for Household Energy Management," *Smart Grid, IEEE Transactions on,* vol. 5, pp. 673-682, 2014.

[161] W. Tongquan, C. Xiaodao, and H. Shiyan, "Reliability-Driven Energy-Efficient Task Scheduling for Multiprocessor Real-Time Systems," *Computer-Aided Design of Integrated Circuits and Systems, IEEE Transactions on,* vol. 30, pp. 1569-1573, 2011.

[162] M. D. McKay, R. J. Beckman, and W. J. Conover, "Comparison of three methods for selecting values of input variables in the analysis of output from a computer code," *Technometrics,* vol. 21, pp. 239-245, 1979.

[163] L. Na, C. Lijun, and S. H. Low, "Optimal demand response based on utility maximization in power networks," in *Power and Energy Society General Meeting, 2011 IEEE,* 2011, pp. 1-8.

[164] K. M. Tsui and S. C. Chan, "Demand Response Optimization for Smart Home Scheduling Under Real-Time Pricing," *Smart Grid, IEEE Transactions on,* vol. 3, pp. 1812-1821, 2012.

[165] J. Byun, I. Hong, and S. Park, "Intelligent cloud home energy management system using household appliance priority based scheduling based on prediction of renewable energy capability," *IEEE Transactions on Consumer Electronics,* vol. 58, pp. 1194-1201, 2012.

[166] N. Arghira, L. Hawarah, S. Ploix, and M. Jacomino, "Prediction of appliances energy use in smart homes," *Energy,* 2012.

[167] A. S. Ahmad, M. Y. Hassan, M. P. Abdullah, H. A. Rahman, F. Hussin, H. Abdullah, and R. Saidur, "A review on applications of ANN and SVM for building electrical energy consumption forecasting," *Renewable and Sustainable Energy Reviews,* vol. 33, pp. 102-109, 2014.

[168] F. Shu and C. Luonan, "Short-term load forecasting based on an adaptive hybrid method," *Power Systems, IEEE Transactions on,* vol. 21, pp. 392-401, 2006.

[169] H. Chitsaz, H. Shaker, H. Zareipour, D. Wood, and N. Amjady, "Short-term Electricity Load Forecasting of Buildings in Microgrids," *Energy and Buildings,* 2015.

[170] F. Pan, H.-z. CHENG, J.-f. YANG, C. Zhang, and Z.-d. PAN, "Power system short-term load forecasting based on support vector machines [J]," *Power System Technology,* vol. 21, p. 008, 2004.

[171] D.-f. ZHAO, M. Wang, J.-s. ZHANG, and X.-f. WANG, "A Support Vector Machine Approach for Short Term Load Forecasting [J]," *Proceedings of the Csee,* vol. 4, p. 004, 2002.

[172] M. Mohandes, "Support vector machines for short-term electrical load forecasting," *International Journal of Energy Research,* vol. 26, pp. 335-345, 2002.

[173] F. Sultanem, "Using appliance signatures for monitoring residential loads at meter panel level," *Power Delivery, IEEE Transactions on,* vol. 6, pp. 1380-1385, 1991.

[174] G. W. Hart, "Nonintrusive appliance load monitoring," *Proceedings of the IEEE,* vol. 80, pp. 1870-1891, 1992.

[175] K. Basu, V. Debusschere, A. Douzal-Chouakria, and S. Bacha, "Time series distance-based methods for non-intrusive load monitoring in residential buildings," *Energy and Buildings,* vol. 96, pp. 109-117, 2015.

[176] D. Rahayu, B. Narayanaswamy, S. Krishnaswamy, C. Labbé, and D. P. Seetharam, "Learning to be energy-wise: discriminative methods for load disaggregation," in *Future Energy Systems: Where Energy, Computing and Communication Meet (e-Energy), 2012 Third International Conference on*, 2012, pp. 1-4.

[177] A. Zoha, A. Gluhak, M. A. Imran, and S. Rajasegarar, "Non-intrusive load monitoring approaches for disaggregated energy sensing: A survey," *Sensors,* vol. 12, pp. 16838-16866, 2012.

[178] M. Zeifman and K. Roth, "Nonintrusive appliance load monitoring: Review and outlook," *IEEE Transactions on Consumer Electronics,* pp. 76-84, 2011.

[179] H.-G. Kwag and J.-O. Kim, "Reliability modeling of demand response considering uncertainty of customer behavior," *Applied Energy,* vol. 122, pp. 24-33, 2014.

[180] F. McLoughlin, A. Duffy, and M. Conlon, "Characterising domestic electricity consumption patterns by dwelling and occupant socio-economic variables: An Irish case study," *Energy and Buildings,* vol. 48, pp. 240-248, 2012.

[181] G. R. Newsham and B. J. Birt, "Building-level occupancy data to improve ARIMA-based electricity use forecasts," in *Proceedings of the 2nd ACM workshop on embedded sensing systems for energy-efficiency in building*, 2010, pp. 13-18.

[182] J. Lu, T. Sookoor, V. Srinivasan, G. Gao, B. Holben, J. Stankovic, E. Field, and K. Whitehouse, "The smart thermostat: using occupancy sensors to save energy in homes," in *Proceedings of the 8th ACM Conference on Embedded Networked Sensor Systems*, 2010, pp. 211-224.

[183] A. Barbato, L. Borsani, A. Capone, and S. Melzi, "Home energy saving through a user profiling system based on wireless sensors," in *Proceedings of the first ACM workshop on embedded sensing systems for energy-efficiency in buildings*, 2009, pp. 49-54.

[184] D. T. Delaney, G. M. O'Hare, and A. G. Ruzzelli, "Evaluation of energy-efficiency in lighting systems using sensor networks," in *Proceedings of the First ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Buildings*, 2009, pp. 61-66.

[185] L. Hawarah, S. Ploix, and M. Jacomino, "User behavior prediction in energy consumption in housing using Bayesian networks," in *Artificial Intelligence and Soft Computing*, 2010, pp. 372-379.

[186] M. C. Mozer, "The neural network house: An environment hat adapts to its inhabitants," in *Proc. AAAI Spring Symp. Intelligent Environments*, 1998, pp. 110-114.

[187] H. Hagras, V. Callaghan, M. Colley, G. Clarke, A. Pounds-Cornish, and H. Duman, "Creating an ambient-intelligence environment using embedded agents," *Intelligent Systems, IEEE,* vol. 19, pp. 12-20, 2004.

[188] Y. Agarwal, B. Balaji, R. Gupta, J. Lyles, M. Wei, and T. Weng, "Occupancy-driven energy management for smart building automation," in *Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, 2010, pp. 1-6.

[189] H. Chen, P. Chou, S. Duri, H. Lei, and J. Reason, "The design and implementation of a smart building control system," in *e-Business Engineering, 2009. ICEBE'09. IEEE International Conference on*, 2009, pp. 255-262.

[190] P. Davidsson and M. Boman, "Saving energy and providing value added services in intelligent buildings: A MAS approach," in *Agent Systems, Mobile Agents, and Applications*, ed: Springer, 2000, pp. 166-177.

[191] A. Marchiori and Q. Han, "Distributed wireless control for building energy management," in *Proceedings of the 2nd ACM Workshop on Embedded Sensing Systems for Energy-Efficiency in Building*, 2010, pp. 37-42.

[192] C. Harris and V. Cahill, "Exploiting user behaviour for context-aware power management," in *Wireless And Mobile Computing, Networking And Communications, 2005.(WiMob'2005), IEEE International Conference on*, 2005, pp. 122-130.

[193] Y. Kim, Z. M. Charbiwala, A. Singhania, T. Schmid, and M. B. Srivastava, "Spotlight: Personal natural resource consumption profiler," in *Proceedings of the 5th Workshop on Hot Topics in Embedded Networked Sensors*, 2008.

[194] K. C. Sou, J. Weimer, H. Sandberg, and K. H. Johansson, "Scheduling smart home appliances using mixed integer linear programming," in *Decision and Control and European Control Conference (CDC-ECC), 2011 50th IEEE Conference on*, 2011, pp. 5144-5149.

[195] M. Shinwari, A. Youssef, and W. Hamouda, "A Water-Filling Based Scheduling Algorithm for the Smart Grid," *Smart Grid, IEEE Transactions on,* vol. 3, pp. 710-719, 2012.

[196] Z. Lin and S. Deng, "A study on the thermal comfort in sleeping environments in the subtropics—developing a thermal comfort model for sleeping environments," *Building and Environment,* vol. 43, pp. 70-81, 2008.

[197] P. O. Fanger, "Thermal environment — Human requirements," *Environmentalist,* vol. 6, pp. 275-278, 1986/12/01 1986.

[198] P. O. Fanger, *Thermal comfort: analysis and applications in environmental engineering*. New York: McGraw-Hill, 1972.

[199] B. Zingano, "A discussion on thermal comfort with reference to bath water temperature to deduce a midpoint of the thermal comfort temperature zone," *Renewable energy,* vol. 23, pp. 41-47, 2001.

[200] J. A. Stolwijk, *A mathematical model of physiological temperature regulation in man* vol. 1855: National Aeronautics and Space Administration, 1971.

[201] J. L. M. Hensen, *On the thermal interaction of building structure and heating and ventilating system*: Technische Universiteitt Eindhoven, 1991.

[202] N. Djongyang, R. Tchinda, and D. Njomo, "Thermal comfort: A review paper," *Renewable and Sustainable Energy Reviews,* vol. 14, pp. 2626-2640, 2010.

[203] ISO, "Ergonomics of the thermal environment - Instruments for measuring physical quantities," in *ISO 7726:1998* ed: ISO, 1998.

[204] M. Mysen, S. Berntsen, P. Nafstad, and P. G. Schild, "Occupancy density and benefits of demand-controlled ventilation in Norwegian primary schools," *Energy and Buildings,* vol. 37, pp. 1234-1240, 12// 2005.

[205] T.-C. Yu, C.-C. Lin, C.-C. Chen, W.-L. Lee, R.-G. Lee, C.-H. Tseng, and S.-P. Liu, "Wireless sensor networks for indoor air quality monitoring," *Medical Engineering & Physics,* vol. 35, pp. 231-235, 2013.

[206] ISO, "ISO 16814:2008(E)," in *Building environment design — Indoor air quality — Methods of expressing the quality of indoor air for human occupancy*, ed. Switzerland ISO, 2008.

[207] A. E. Program, "REMP:Lighting Data Collection and Analysis," Australia2012.

[208] R. Yang and L. Wang, "Multi-zone building energy management using intelligent control and optimization," *Sustainable Cities and Society,* vol. 6, pp. 16-21, 2// 2013.

[209] S. Australia, "AS/NZS 1680.1:2006," in *Interior and workplace lighting: Geenral Principles and recommendations*, ed. NSW,Australia: Standards Australia, 2006, p. 129.

[210] E. Shen, J. Hu, and M. Patel, "Energy and visual comfort analysis of lighting and daylight control strategies," *Building and Environment,* vol. 78, pp. 155-170, 8// 2014.

[211] M. Frascarolo, S. Martorelli, and V. Vitale, "An innovative lighting system for residential application that optimizes visual comfort and conserves energy for different user needs," *Energy and Buildings,* 2014.

[212] G. Y. Yun, H. J. Kong, H. Kim, and J. T. Kim, "A field survey of visual comfort and lighting energy consumption in open plan offices," *Energy and Buildings*, vol. 46, pp. 146-151, 2012.

[213] S. Ozenc, M. Uzunoglu, and O. Guler, "Experimental evaluation of the impacts of considering inherent response characteristics for lighting technologies in building energy modeling," *Energy and Buildings,* vol. 77, pp. 432-439, 2014.

[214] L. L. Fernandes, E. S. Lee, D. L. DiBartolomeo, and A. McNeil, "Monitored lighting energy savings from dimmable lighting controls in The New York Times Headquarters Building," *Energy and Buildings,* vol. 68, Part A, pp. 498-514, 2014.

[215] A. K. Athienitis and A. Tzempelikos, "A methodology for simulation of daylight room illuminance distribution and light dimming for a room with a controlled shading device," *Solar Energy,* vol. 72, pp. 271-281, 2002.

[216] T. L. Saaty, "An eigenvalue allocation model for prioritization and planning," *Energy Management and Policy Center, University of Pennsylvania,* pp. 28-31, 1972.

[217] T. Saaty, "What is the Analytic Hierarchy Process?," in *Mathematical Models for Decision Support*. vol. 48, G. Mitra, H. Greenberg, F. Lootsma, M. Rijkaert, and H. Zimmermann, Eds., ed: Springer Berlin Heidelberg, 1988, pp. 109-121.

[218] T. L. Saaty, "Decision making with dependence and feedback: The analytic network process," *RWS publications,* vol. 4922, 1996.

[219] C. L. Hwang and K. P. Yoon, "Multiple attribute decision making: Methods and applications," *Springer-Verlag,* 1981.

[220] B. Roy, "The outranking approach and the foundations of ELECTRE methods," *Theory and Decision,* vol. 31, pp. 49-73, 1991.

[221] T. Gwo-Hshiung, "Multiple attribute decision making: methods and applications," *Multiple Attribute Decision Making: Methods and Applications,* 2010.

[222] S. Opricovic and G.-H. Tzeng, "Compromise solution by MCDM methods: A comparative analysis of VIKOR and TOPSIS," *European Journal of Operational Research,* vol. 156, pp. 445-455, 2004.

[223] J.-P. Brans, P. Vincke, and B. Mareschal, "How to select and how to rank projects: The PROMETHEE method," *European Journal of Operational Research,* vol. 24, pp. 228-238, 1986.

[224] J.-P. Brans and P. Vincke, "Note—A Preference Ranking Organisation Method: (The PROMETHEE Method for Multiple Criteria Decision-Making)," *Management science,* vol. 31, pp. 647-656, 1985.

[225] E. Løken, "Use of multicriteria decision analysis methods for energy planning problems," *Renewable and Sustainable Energy Reviews,* vol. 11, pp. 1584-1595, 2007.

[226] S. D. Pohekar and M. Ramachandran, "Application of multi-criteria decision making to sustainable energy planning—A review," *Renewable and Sustainable Energy Reviews,* vol. 8, pp. 365-381, 2004.

[227] K. Dong-Min and O. K. Jin, "Design of Emergency Demand Response Program Using Analytic Hierarchy Process," *Smart Grid, IEEE Transactions on,* vol. 3, pp. 635-644, 2012.

[228] S. Shengnan, M. Pipattanasomporn, and S. Rahman, "An approach for demand response to alleviate power system stress conditions," in *Power and Energy Society General Meeting, 2011 IEEE,* 2011, pp. 1-7.

[229] Y. Shimomura, Y. Nemoto, F. Akasaka, R. Chiba, and K. Kimita, "A method for designing customer-oriented demand response aggregation service," *CIRP Annals - Manufacturing Technology,* vol. 63, pp. 413-416, 2014.

[230] H. H. Chen and H. Gu, "A Fuzzy ANP Model Integrated with Benefits, Opportunities, Costs, and Risks to Prioritize Intelligent Power Grid Systems," *Mathematical Problems in Engineering,* vol. 2013, p. 9, 2013.

[231] H. Falsafi, A. Zakariazadeh, and S. Jadid, "The role of demand response in single and multi-objective wind-thermal generation scheduling: A stochastic programming," *Energy,* vol. 64, pp. 853-867, 2014.

[232] P. Xu, E. H. W. Chan, H. J. Visscher, X. Zhang, and Z. Wu, "Sustainable building energy efficiency retrofit for hotel buildings using EPC mechanism in China: analytic Network Process (ANP) approach," *Journal of Cleaner Production,* 2015.

[233] E. Wang, "Benchmarking whole-building energy performance with multi-criteria technique for order preference by similarity to ideal solution using a selective objective-weighting approach," *Applied Energy,* vol. 146, pp. 92-103, 2015.

[234] C. Kahraman and İ. Kaya, "A fuzzy multiple attribute utility model for intelligent building assessment," *Journal of Civil Engineering and Management,* vol. 18, pp. 811-820, 2012.

[235] İ. Kaya and C. Kahraman, "A comparison of fuzzy multicriteria decision making methods for intelligent building assessment," *Journal of Civil Engineering and Management,* vol. 20, pp. 59-69, 2014.

[236] Y. Yang, B. Li, and R. Yao, "A method of identifying and weighting indicators of energy efficiency assessment in Chinese residential buildings," *Energy Policy,* vol. 38, pp. 7687-7697, 2010.

[237] T. U. Daim, X. Li, J. Kim, and S. Simms, "Evaluation of energy storage technologies for integration with renewable electricity: Quantifying expert opinions," *Environmental Innovation and Societal Transitions,* vol. 3, pp. 29-49, 2012.

[238] Y. Zhou, J.-C. Zhang, X.-N. Bao, and J.-X. Li, "Evaluation of Energy Storage System Based on PROMETHEE-GAIA," *East China Electric Power,* vol. 40, pp. 0405-0407, 2012.

[239] P. Aragonés-Beltrán, F. Chaparro-González, J.-P. Pastor-Ferrando, and A. Pla-Rubio, "An AHP (Analytic Hierarchy Process)/ANP (Analytic Network Process)-based multi-criteria decision approach for the selection of solar-thermal power plant investment projects," *Energy,* vol. 66, pp. 222-238, 2014.

[240] T. Kaya and C. Kahraman, "Multicriteria renewable energy planning using an integrated fuzzy VIKOR & AHP methodology: The case of Istanbul," *Energy,* vol. 35, pp. 2517-2527, 2010.

[241] Ü. Şengül, M. Eren, S. Eslamian Shiraz, V. Gezder, and A. B. Şengül, "Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey," *Renewable Energy,* vol. 75, pp. 617-625, 2015.

[242] J. M. Sánchez-Lozano, M. S. García-Cascales, and M. T. Lamata, "Identification and selection of potential sites for onshore wind farms development in Region of Murcia, Spain," *Energy,* vol. 73, pp. 311-324, 2014.

[243] M. Beccali, M. Cellura, and D. Ardente, "Decision making in energy planning: the ELECTRE multicriteria analysis approach compared to a FUZZY-SETS methodology," *Energy Conversion and Management,* vol. 39, pp. 1869-1881, 1998.

[244] M. Beccali, M. Cellura, and M. Mistretta, "Decision-making in energy planning. Application of the Electre method at regional level for the diffusion of renewable energy technology," *Renewable Energy,* vol. 28, pp. 2063-2087, 2003.

[245] N. Hopper, C. Goldman, and B. Neenan, "Demand response from day-ahead hourly pricing for large customers," *The Electricity Journal,* vol. 19, pp. 52-63, 2006.

[246] R. L. Keeney and H. Raiffa, *Decisions with multiple objectives: preferences and value trade-offs*: Cambridge university press, 1993.

[247] O. Svenson, "Process descriptions of decision making," *Organizational Behavior and Human Performance,* vol. 23, pp. 86-112, 1979.

[248] D. E. Bell, H. Raiffa, and A. Tversky, *Decision making: Descriptive, normative, and prescriptive interactions*: Cambridge University Press, 1988.

[249] P. R. Kleindorfer and H. Kunreuther, *Decision sciences: an integrative perspective*: Cambridge University Press, 1993.

[250] G.-H. Tzeng and J.-J. Huang, *Multiple attribute decision making: methods and applications*: CRC Press, 2011.

[251] D. Kahneman and A. Tversky, *Choices, values, and frames*: Cambridge University Press, 2000.

[252] K. P. Yoon; and Ching-Lai Hwang, *Multiple Attribute Decision Making. Multiple Attribute Decision Making. SAGE Publications, Inc*. Thousand Oaks, CA: SAGE Publications, Inc., 1995.

[253] L. A. Zadeh, "Fuzzy sets," *Information and control,* vol. 8, pp. 338-353, 1965.

[254] G.-H. Tzeng and J.-J. Huang, *Fuzzy multiple objective decision making*: CRC Press, 2013.

[255] T. L. Saaty, "The analytic hierarchy process: planning, priority setting, resources allocation," *New York: McGraw,* 1980.

[256] M. Behzadian, S. Khanmohammadi Otaghsara, M. Yazdani, and J. Ignatius, "A state-of the-art survey of TOPSIS applications," *Expert Systems with Applications,* vol. 39, pp. 13051-13069, 2012.

[257] C. E. Shannon, "A mathematical theory of communication," *SIGMOBILE Mob. Comput. Commun. Rev.,* vol. 5, pp. 3-55, 2001.

[258] H. Zhang, C.-l. Gu, L.-w. Gu, and Y. Zhang, "The evaluation of tourism destination competitiveness by TOPSIS & information entropy – A case in the Yangtze River Delta of China," *Tourism Management,* vol. 32, pp. 443-451, 2011.

[259] R. Benayoun, B. Roy, and B. Sussman, "ELECTRE: Une méthode pour guider le choix en présence de points de vue multiples," *Note de travail,* vol. 49, 1966.

[260] J. Figueira, V. Mousseau, and B. Roy, "Electre Methods," in *Multiple Criteria Decision Analysis: State of the Art Surveys*. vol. 78, ed: Springer New York, 2005, pp. 133-153.

[261] T. Saaty, "Introduction to a modeling of social decision processes," *Mathematics and Computers in Simulation,* vol. 25, pp. 105-107, 1983.

[262] R. W. Saaty, "The analytic hierarchy process—what it is and how it is used," *Mathematical Modelling,* vol. 9, pp. 161-176, 1987.

[263] E. Choice, "Academic Products and Programs," EC11.5 ed: Expert Choice, 2010.

[264] R. Kowsari and H. Zerriffi, "Three dimensional energy profile:: A conceptual framework for assessing household energy use," *Energy Policy,* vol. 39, pp. 7505-7517, 2011.

[265] K. Mori, "Modeling the impact of a carbon tax: A trial analysis for Washington State," *Energy Policy,* vol. 48, pp. 627-639, 2012.

[266] L. Gan, G. S. Eskeland, and H. H. Kolshus, "Green electricity market development: Lessons from Europe and the US," *Energy Policy,* vol. 35, pp. 144-155, 2007.

[267] S. Salmela and V. Varho, "Consumers in the green electricity market in Finland," *Energy Policy,* vol. 34, pp. 3669-3683, 2006.

[268] F. Kelly, T. Alice, L. Winnifred, and W. Clive, "Environmental, sustainability, understanding, attitudes, behaviour, Australian, households," Australian Housing and Urban Research Institute Melbourne, Australia 1834-7223, 2010.

[269] R. J. Yang and P. X. Zou, "Households'perceptions on sustainable home behaviour and improvements in australia," in *SB 2013: Proceedings of the Sustainable Building and Construction Conference,* 2013, pp. 166-175.

[270] I. Lampropoulos, G. M. A. Vanalme, and W. L. Kling, "A methodology for modeling the behavior of electricity prosumers within the smart grid," in *Innovative Smart Grid Technologies Conference Europe (ISGT Europe), 2010 IEEE PES,* 2010, pp. 1-8.

[271] T. Hargreaves, M. Nye, and J. Burgess, "Keeping energy visible? Exploring how householders interact with feedback from smart energy monitors in the longer term," *Energy Policy,* 2013.

[272] P. C. Stern, "Information, Incentives, and Proenvironmental Consumer Behavior," *Journal of Consumer Policy,* vol. 22, pp. 461-478, 1999.

[273] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, and R. Schober, "Optimal and autonomous incentive-based energy consumption scheduling algorithm for smart grid," in *Innovative Smart Grid Technologies (ISGT), 2010,* 2010, pp. 1-6.

[274] T. Hargreaves, M. Nye, and J. Burgess, "Making energy visible: A qualitative field study of how householders interact with feedback from smart energy monitors," *Energy Policy,* vol. 38, pp. 6111-6119, 2010.

[275] S. Gottwalt, W. Ketter, C. Block, J. Collins, and C. Weinhardt, "Demand side management—A simulation of household behavior under variable prices," *Energy Policy,* vol. 39, pp. 8163-8174, 2011.

[276] T. Krishnamurti, D. Schwartz, A. Davis, B. Fischhoff, W. B. de Bruin, L. Lave, and J. Wang, "Preparing for smart grid technologies: A behavioral decision research approach to understanding consumer expectations about smart meters," *Energy Policy,* vol. 41, pp. 790-797, 2012.

[277] E. J. S. Plug and B. M. S. Van Praag, "Similarity in response behavior between household members: An application to income evaluation," *Journal of Economic Psychology,* vol. 19, pp. 497-513, 1998.

[278] G. Wood and M. Newborough, "Dynamic energy-consumption indicators for domestic appliances: environment, behaviour and design," *Energy and Buildings,* vol. 35, pp. 821-841, 2003.

[279] Y. Yamamoto, A. Suzuki, Y. Fuwa, and T. Sato, "Decision-making in electrical appliance use in the home," *Energy Policy,* vol. 36, pp. 1679-1686, 2008.

[280] R. Fazal, J. Solanki, and S. K. Solanki, "Demand response using multi-agent system," in *North American Power Symposium (NAPS), 2012*, 2012, pp. 1-6.

[281] D. Nabouch, N. Matta, R. Rahim-Amoud, and L. Merghem-Boulahia, "An Agent-Based Approach for Efficient Energy Management in the Context of Smart Houses," in *Highlights on Practical Applications of Agents and Multi-Agent Systems*. vol. 365, J. Corchado, J. Bajo, J. Kozlak, P. Pawlewski, J. Molina, V. Julian, R. Silveira, R. Unland, and S. Giroux, Eds., ed: Springer Berlin Heidelberg, 2013, pp. 375-386.

[282] G. Rohbogner, S. Fey, U. J. J. Hahnel, P. Benoit, and B. Wille-Haussmann, "What the term agent stands for in the Smart Grid definition of agents and multi-agent systems from an engineer's perspective," in *Computer Science and Information Systems (FedCSIS), 2012 Federated Conference on*, 2012, pp. 1301-1305.

[283] M. Beaudin and H. Zareipour, "Home energy management systems: A review of modelling and complexity," *Renewable and Sustainable Energy Reviews,* vol. 45, pp. 318-335, 2015.

[284] T. Imanari, T. Omori, and K. Bogaki, "Thermal comfort and energy consumption of the radiant ceiling panel system.: Comparison with the conventional all-air system," *Energy and buildings,* vol. 30, pp. 167-175, 1999.

[285] H. B. Rijal, P. Tuohy, M. A. Humphreys, J. F. Nicol, A. Samuel, and J. Clarke, "Using results from field surveys to predict the effect of open windows on thermal comfort and energy use in buildings," *Energy and Buildings,* vol. 39, pp. 823-836, 2007.

[286] M. Haase and A. Amato, "An investigation of the potential for natural ventilation and building orientation to achieve thermal comfort in warm and humid climates," *Solar Energy,* vol. 83, pp. 389-399, 2009.

[287] N. Bouchlaghem, "Optimising the design of building envelopes for thermal performance," *Automation in Construction,* vol. 10, pp. 101-112, 2000.

[288] X. Wang, Y. Zhang, W. Xiao, R. Zeng, Q. Zhang, and H. Di, "Review on thermal performance of phase change energy storage building envelope," *Chinese Science Bulletin,* vol. 54, pp. 920-928, 2009.

[289] B. Zalba, J. M. Marín, L. F. Cabeza, and H. Mehling, "Review on thermal energy storage with phase change: materials, heat transfer analysis and applications," *Applied thermal engineering,* vol. 23, pp. 251-283, 2003.

[290] A. Mellit and S. A. Kalogirou, "Artificial intelligence techniques for photovoltaic applications: A review," *Progress in energy and combustion science,* vol. 34, pp. 574-632, 2008.

[291] D. Shahgoshtasbi and M. M. Jamshidi, "A New Intelligent Neuro–Fuzzy Paradigm for Energy-Efficient Homes," *Systems Journal, IEEE,* vol. 8, pp. 664-673, 2014.

[292] D. Shahgoshtasbi and M. Jamshidi, "Modified Intelligent Energy Management system in a smart house," in *World Automation Congress (WAC), 2012,* 2012, pp. 1-6.

[293] D. Shahgoshtasbi and M. Jamshid, "Energy efficiency in a smart house with an intelligent neuro-fuzzy lookup table," in *System of Systems Engineering (SoSE), 2011 6th International Conference on*, 2011, pp. 288-292.

[294] IEC, "IEC PAS 62746-10-1:Systems interface between customer energy management system and the power management system " in *Part 10-1: Open Automated Demand Response (OpenADR 2.0b ProfileSpecification),* ed, 2014.

[295] T. Nanayakkara, F. Sahin, and M. Jamshidi, *Intelligent control systems with an introduction to system of systems engineering*: CRC Press, 2009.

[296] M. Jamshidi, *Systems of systems engineering: principles and applications*: CRC press, 2008.

[297] A. J. Lopes, R. Lezama, and R. Pineda, "Model Based Systems Engineering for Smart Grids as Systems of Systems," *Procedia Computer Science,* vol. 6, pp. 441-450, 2011.

[298] M. C. Jackson and P. Keys, "Towards a System of Systems Methodologies," *The Journal of the Operational Research Society,* vol. 35, pp. 473-486, 1984.

[299] Peter Brucker, *Complex Scheduling*: Springer Berlin Heidelberg, 2006.

[300] P. K. Narayan and R. Smyth, "The residential demand for electricity in Australia: an application of the bounds testing approach to cointegration," *Energy Policy,* vol. 33, pp. 467-474, 2005.

[301] C. Zhang, W. Wu, H. Huang, and H. Yu, "Fair energy resource allocation by minority game algorithm for smart buildings," in *Design, Automation & Test in Europe Conference & Exhibition (DATE),*2012, pp. 63-68.

[302] F. Jazizadeh and B. Becerik-Gerber, "A Novel Method for Non Intrusive Load Monitoring of Lighting Systems in Commercial Buildings," *Bridges*, vol. 10, p. 9780784412343.0066, 2014.

[303] M. Tasdighi, H. Ghasemi, and A. Rahimi-Kian, "Residential microgrid scheduling based on smart meters data and temperature dependent thermal load modeling," 2013.

[304] F. Corno and F. Razzak, "Intelligent Energy Optimization for User Intelligible Goals in Smart Home Environments," 2012.

[305] D. Najewicz, "Demand Response Enabled Appliances/Home Energy Management System," *Presentation at NREL, Golden, CO,* 2009.

[306] H. Kellerer, U. Pferschy, and D. Pisinger, *Knapsack problems*: Springer, 2010.

[307] LINDO, "Lingo, The Modeling Language and Optimizer," 2010 ed. Chicago, Illinois: Lindo Systems INC., 2010.

[308] N. Morimoto, Y. Fujita, M. Yoshida, H. Yoshimizu, M. Takiyamada, T. Akehi, and M. Tanaka, "Optimizing power allocation to electrical appliances with an algorithm for the knapsack problem," in *Consumer Electronics (ISCE), 2013 IEEE 17th International Symposium on*, 2013, pp. 155-156.

[309] M. Song, K. Alvehag, J. Widén, and A. Parisio, "Estimating the impacts of demand response by simulating household behaviours under price and CO 2 signals," *Electric Power Systems Research,* vol. 111, pp. 103-114, 2014.

[310] A. Gupta and S. Venkataraman, "Reducing price volatility of electricity consumption for a firm's energy risk management," *The Electricity Journal,* vol. 26, pp. 89-105, 2013.

[311] J. M. Lujano-Rojas, C. Monteiro, R. Dufo-López, and J. L. Bernal-Agustín, "Optimum residential load management strategy for real time pricing (RTP) demand response programs," *Energy Policy,* vol. 45, pp. 671-679, 2012.

[312] N. Morimoto, Y. Fujita, M. Yoshida, H. Yoshimizu, M. Takiyamada, T. Akehi, and M. Tanaka, "A Power Allocation Management System Using an Algorithm for the Knapsack Problem," in *Computer Software and Applications Conference Workshops (COMPSACW), 2014 IEEE 38th International*, 2014, pp. 590-595.

[313] energy.gove. *Estimating appliance and home electronic energy use*. Available: http://energy.gov/energysaver/estimating-appliance-and-home-electronic-energy-use

[314] E.-E. E. Efficiency, "Energy Rating - Search the Registration Database."

[315] ABS, "Catalogue number: 4660.0 - Energy Use, Electricity Generation and Environmental Management, Australia," Australian Bureau of Statistics2013.

[316] P. Siano, "Demand response and smart grids—A survey," *Renewable and Sustainable Energy Reviews,* vol. 30, pp. 461-478, 2014.

[317] Z. Hu and Z. Hu, *Electricity Economics: Production Functions with Electricity*: Springer, 2013.

[318] B. Zhuming, X. Li Da, and W. Chengen, "Internet of Things for Enterprise Systems of Modern Manufacturing," *Industrial Informatics, IEEE Transactions on,* vol. 10, pp. 1537-1546, 2014.

[319] M. Karlsson, "The MIND method: A decision support for optimization of industrial energy systems – Principles and case studies," *Applied Energy,* vol. 88, pp. 577-589, 2011.

[320] Y. Ozturk, D. Senthilkumar, S. Kumar, and G. Lee, "An Intelligent Home Energy Management System to Improve Demand Response," *Smart Grid, IEEE Transactions on,* vol. 4, pp. 694-701, 2013.

[321] K. Bunse, M. Vodicka, P. Schönsleben, M. Brülhart, and F. O. Ernst, "Integrating energy efficiency performance in production management – gap analysis between industrial needs and scientific literature," *Journal of Cleaner Production,* vol. 19, pp. 667-679, 2011.

[322] A. Hasanbeigi, C. Menke, and P. du Pont, "Barriers to energy efficiency improvement and decision-making behavior in Thai industry," *Energy Efficiency,* vol. 3, pp. 33-52, 2010.

[323] P. Sandberg and M. Söderström, "Industrial energy efficiency: the need for investment decision support from a manager perspective," *Energy Policy,* vol. 31, pp. 1623-1634, 2003.

[324] M. H. Karwan and M. F. Keblis, "Operations planning with real time pricing of a primary input," *Computers & operations research,* vol. 34, pp. 848-867, 2007.

[325] Z. Sun and L. Li, "Potential capability estimation for real time electricity demand response of sustainable manufacturing systems using Markov Decision Process," *Journal of Cleaner Production,* vol. 65, pp. 184-193, 2/15/ 2014.

[326] Y. Wang and L. Li, "Time-of-use based electricity demand response for sustainable manufacturing systems," *Energy,* vol. 63, pp. 233-244, 2013.

[327] A. Bego, L. Li, and Z. Sun, "Identification of reservation capacity in critical peak pricing electricity demand response program for sustainable manufacturing systems," *International Journal of Energy Research,* vol. 38, pp. 728-736, 2014.

[328] M. Fernandez, L. Li, and Z. Sun, "“Just-for-Peak” buffer inventory for peak electricity demand reduction of manufacturing systems," *International Journal of Production Economics,* vol. 146, pp. 178-184, 2013.

[329] Z. Sun, L. Li, M. Fernandez, and J. Wang, "Inventory control for peak electricity demand reduction of manufacturing systems considering the tradeoff between production loss and energy savings," *Journal of Cleaner Production,* vol. 82, pp. 84-93, 11/1/ 2014.

[330] Y. Ding, S. Hong, and X. Li, "A Demand Response Energy Management Scheme for Industrial Facilities in Smart Grid," *Industrial Informatics, IEEE Transactions on,* vol. PP, pp. 1-1, 2014.

[331] F. Tao, Y. Zuo, L. Xu, L. Lv, and L. Zhang, "Internet of Things and BOM based life cycle assessment of energy-saving and emission-reduction of product," 2014.

[332] J.-J. Wang, Y.-Y. Jing, C.-F. Zhang, and J.-H. Zhao, "Review on multi-criteria decision analysis aid in sustainable energy decision-making," *Renewable and Sustainable Energy Reviews*, vol. 13, pp. 2263-2278, 2009.

[333] G. Rowe and G. Wright, "The Delphi technique as a forecasting tool: issues and analysis," *International journal of forecasting,* vol. 15, pp. 353-375, 1999.

[334] J. J. Galo, M. N. Macedo, L. A. Almeida, and A. C. Lima, "Criteria for smart grid deployment in Brazil by applying the Delphi method," *Energy,* vol. 70, pp. 605-611, 2014.

[335] A. Gurumurthy and R. Kodali, "A multi-criteria decision-making model for the justification of lean manufacturing systems," *International Journal of Management Science and Engineering Management,* vol. 3, pp. 100-118, 2008.

[336] R.-L. Hwang, M.-J. Cheng, T.-P. Lin, and M.-C. Ho, "Thermal perceptions, general adaptation methods and occupant's idea about the trade-off between thermal comfort and energy saving in hot–humid regions," *Building and Environment,* vol. 44, pp. 1128-1134, 2009.

Appendix 01

Predicted Mean Vote (PMV) index calculation by ISO 7730:2005(E), Ergonomics of the thermal environment - Analytical determination and interpretation of thermal comfort using calculation of the PMV and PPD indices and local thermal comfort criteria

A human being's thermal sensation is mainly related to the thermal balance of his or her body as a whole. This balance is influenced by physical activity and clothing, as well as the environmental parameters such as:

a) air temperature;
b) mean radiant temperature;
c) air velocity;
d) air humidity.

When these factors have been estimated or measured, the thermal sensation for the body as a whole can be predicted by calculating the predicted mean vote (PMV).

The PMV is an index based on the heat balance of the human body that predicts the mean value of the votes of a large group of persons on the seven point thermal sensation scale shown by Table A1.1. Thermal balance is obtained when the internal heat production in the body is equal to the loss of heat to the environment. In a moderate environment, the human thermoregulatory system will automatically attempt to modify skin temperature and sweat secretion to maintain heat balance.

Table A1.1. Seven-Point Thermal Sensation Scale

+ 3	Hot
+ 2	Warm
+ 1	Slightly warm
0	Neutral
- 1	Slightly cool
- 2	Cool
- 3	Cold

Calculate the PMV using Equations as follows:

$$PMV = \left(0.303 \times e^{(-0.036 \times M)} + 0.028\right)L = \alpha L \quad \text{(A1.1)}$$

$$L = \{(M - W) - 3.05 \times 10^{-3} \times (5733 - 6.99 \times (M - V) - p_a) - 0.42 \times \big((M - V) - 58.15\big) - 1.7 \times 10^{-5} \times M \times (5867 - p_a) - 0.0014 \times M \times (34 - t_a) - 3.96 \times 10^{-8} \times f_{cl} \times ((t_{cl} + 273)^4 - (\bar{t}_r + 273)^4) - \big(f_{cl} \times h_c \times (t_{cl} - t_a)\big)\} \quad \text{(A1.2)}$$

$$t_{cl} = 35.7 - 0.028 \times (M - V) - I_{cl} \times \{3.96 \times 10^{-8} \times f_{cl} \times ((t_{cl} + 273)^4 - (\bar{t}_r + 273)^4) + \big(f_{cl} \times h_c \times (t_{cl} - t_a)\big)\} \quad \text{(A1.3)}$$

$$h_c = \begin{cases} 2.38 \times |t_{cl} + t_a|^{0.25} \; for \; 2.38 \times |t_{cl} + t_a|^{0.25} > 12.1 \times \sqrt{v_{ar}} \\ 12.1 \times \sqrt{v_{ar}} \; for \; 2.38 \times |t_{cl} + t_a|^{0.25} < 12.1 \times \sqrt{v_{ar}} \end{cases} \quad \text{(A1.4)}$$

$$f_{cl} = \begin{cases} 1.00 + 1.290 \times I_{cl} \quad for \; I_{cl} \le 0.078 \quad m^2.K/W \\ 1.05 + 0.645 \times I_{cl} \quad for \; I_{cl} > 0.078 \quad m^2.K/W \end{cases} \quad \text{(A1.5)}$$

where

L is the thermal load on the body defined as the difference between internal heat production and heat loss to the environment for a person hypothetically kept at comfort values of temperature of the skin layer and evaporative heat loss of regulatory sweeting at the activity level, and

α is the sensitivity coefficient;

M is the metabolic rate, in watts per square metre (W/m^2);

W is the effective mechanical power, in watts per square metre (W/m^2);

t_a is the air temperature, in degrees Celsius (°C);

$\bar{t}_r$ is the mean radiant temperature, in degrees Celsius (°C);

t_{cl} is the clothing surface temperature, in degrees Celsius (°C);

f_{cl} is the clothing surface area factor;

I_{cl} is the clothing insulation, in square metres kelvin per watt ($\frac{m^2.K}{W}$);

h_c is the convective heat transfer coefficient, in watts per square metre kelvin ($\frac{W}{m^2.k}$) ;

v_{ar} is the relative air velocity, in metres per second (m/s);

p_a is the water vapour partial pressure, in Pascals (Pa).

And the units' correlation is as follows:

1 metabolic unit = 1 met = 58.2 W/m^2

1 clothing unit = 1 clo = 0.155 $\frac{m^2 \times °C}{W}$

PMV may be calculated for different combinations of metabolic rate, clothing insulation, air temperature, mean radiant temperature, air velocity and air humidity. The equations for t_{cl} and h_c may be solved by iteration.

The PMV index is derived for steady-state conditions but can be applied with good approximation during minor fluctuations of one or more of the variables, provided that time-weighted averages of the variables during the previous 1 h period are applied.

The index should be used only for values of PMV between −2 and +2, and when the six main parameters are within the following intervals:

Table A1.2. The Intervals of Parameters for PMV Calculation Using Eq.A1.1

Parameter	**from**	**to**	**Unit**
M	46	232	W/m^2
I_{cl}	0	0.310	$\frac{m^2.K}{W}$
	0	2	clo
t_a	10	30	°C
$\bar{t}_r$	10	40	°C
v_{ar}	0	1	m/s
p_a	0	2700	pa

The PMV can be determined in one of the following ways:

a) Using a digital computer and programming Eq. 1. A BASIC program has been given in Annex D of standard.

b) Tables of PMV in Annex E standard ISO 7730:2005(E), give values for different combinations of activity, clothing, operative temperature and relative velocity.

c) By using an integrating sensor (equivalent and operative temperatures) and direct measurement.

The PMV can be used to check whether a given thermal environment complies with comfort criteria (see Clause 7 and Annex A in Standard ISO 7730:2005(E)), and to establish requirements for different levels of acceptability.

By setting PMV = 0, an equation is established which predicts combinations of activity, clothing and environmental parameters which on average will provide a thermally neutral sensation.

The Institute for Environmental Research of the State University of Kansas, under ASHRAE contract, has conducted extensive research on the subject of thermal comfort in sedentary regime. The purpose of this investigation was to obtain a model to express he PMV in terms of parameters easily sampled in an environment. The results have yielded to an expression of the form:

$$PMV = aT + bP_v - c \tag{A1.6}$$

where P_v is the pressure of water vapour in ambient air and T the temperature. Coefficients a, b and c are given in Table A1.3.

Table A1.3. a, b, c Coefficients for Calculating PMV

Time	**Sex**	***a***	***b***	***c***
1h	man	0.220	0.233	6.673
	woman	0.272	0.248	7.245
	both	0.245	0.248	6.475
2h	man	0.221	0.270	6.024
	woman	0.283	0.210	7.694
	both	0.252	0.240	6.859
3h	man	0.212	0.293	5.949
	woman	0.275	0.255	8.620
	both	0.243	0.278	8.802

Predicted Percentage Dissatisfied (PPD) Index

The PPD predicts the percentage of the people who felt more than slightly warm or slightly cold. The PMV predicts the mean value of the thermal votes of a large group of people exposed to the same environment. But individual votes are scattered around this mean value and it is useful to be able to predict the number of people likely to feel uncomfortably warm or cool.

The PPD is an index that establishes a quantitative prediction of the percentage of thermally dissatisfied people who feel too cool or too warm. For the purposes of this International Standard, thermally dissatisfied people are those who will vote hot, warm, cool or cold on the 7-point thermal sensation scale given in Table A1.1.

The predicted percentage dissatisfied (PPD) index provides information on thermal discomfort or thermal dissatisfaction by predicting the percentage of people likely to feel too warm or too cool in a given environment. The PPD can be obtained from the PMV.

Dissatisfaction can be caused by hot or cold discomfort for the body as a whole. Comfort limits can in this case be expressed by the PMV and PPD indices. But thermal dissatisfaction can also be caused by local thermal discomfort parameters.

With the PMV value determined by Eqs.A1.1- 4, the PPD will be calculated by using Equation

$$PPD = 100 - 95 \times e^{(-0.03353 \times PMV^4 - 0.2179 \times PMV^2)} \tag{A1.7}$$

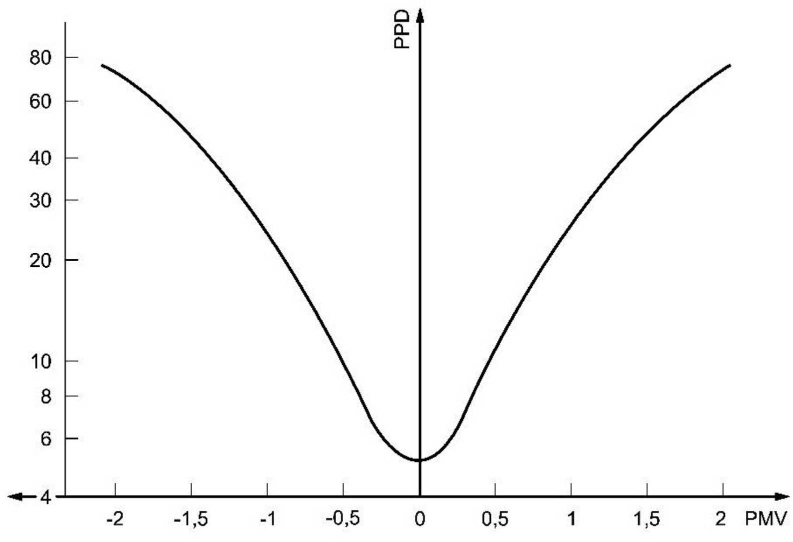


Figure A1.1. PPD as a Function of PMV

The merit of this relation is that, it reveals a perfect symmetry with respect to thermal neutrality (PMV = 0). It can be seen (Figure A1.2) that even when the PMV index is 0, there are some individual cases of dissatisfaction with the level of temperature, although all are dressed in a similar way and that the level of activity is the same. This is due to some differences of approach in the evaluation of thermal comfort from one person to another. It is shown that at PMV = 0, a minimum rate of dissatisfied of 5% exists[336].

The PPD predicts the number of thermally dissatisfied persons among a large group of people. The rest of the group will feel thermally neutral, slightly warm or slightly cool. The predicted distribution of votes achieved based on experiments involving 1300 subjects is given in Table A1.4.

Table A1.4. Distribution of Individual Thermal Sensation Votes For Different Values Of Mean Vote

PMV	PPD (%)	**Persons predicted to vote Based on experiments involving 1300 subjects (%)**		
		0	-1,0 or +1	-2, -1, 0,+1,or +2
+2	75	5	25	70
+1	25	30	75	95
+0.5	10	55	90	98
0	5	60	95	100
-0.5	10	55	90	98
-1	25	30	75	95
-2	75	5	25	70