2017

Smart home energy management: An analysis of a novel dynamic pricing and demand response aware control algorithm for households with distributed renewable energy generation and storage

Jamal Abushnaf
Edith Cowan University

Smart Home Energy Management: An Analysis of a Novel Dynamic Pricing and Demand Response Aware Control Algorithm for Households with Distributed Renewable Energy Generation and Storage

This thesis is presented for the degree of

Doctor of Philosophy

Jamal Abushnaf

Edith Cowan University

School of Engineering

2017

DECLARATION

I certify that this thesis does not, to the best of my knowledge and belief:

(i) Incorporate without acknowledgement any material previously submitted for a degree or diploma in any institution of higher education;

(ii) Contain any material previously published or written by another person except where due reference is made in the text; or

(iii) Contain any defamatory material.

I also grant permission for the Library at Edith Cowan University to make duplicate copies of my thesis as required.

Signed [redacted]

Data: 30-03-2017

ABSTRACT

Home energy management systems (HEMS) technology can provide a smart and efficient way of optimising energy usage in residential buildings. One of the main goals of the Smart Grid is to achieve Demand Response (DR) by increasing end users' participation in decision making and increasing the level of awareness that will lead them to manage their energy consumption in an efficient way. This research presents an intelligent HEMS algorithm that manages and controls a range of household appliances with different demand response (DR) limits in an automated way without requiring consumer intervention. In addition, a novel Multiple Users and Load Priority (MULP) scheme is proposed to organise and schedule the list of load priorities in advance for multiple users sharing a house and its appliances. This algorithm focuses on control strategies for controllable loads including air-conditioners, dishwashers, clothes dryers, water heaters, pool pumps and electrical vehicles. Moreover, to investigate the impact on efficiency and reliability of the proposed HEMS algorithm, small-scale renewable energy generation facilities and energy storage systems (ESSs), including batteries and electric vehicles have been incorporated. To achieve this goal, different mathematical optimisation approaches such as linear programming, heuristic methods and genetic algorithms have been applied for optimising the schedule of residential loads using different demand side management and demand response programs as well as optimising the size of a grid connected renewable energy system. Thorough incorporation of a single objective optimisation problem under different system constraints, the proposed algorithm not only reduces the residential energy usage and utility bills, but also determines an optimal scheduling for appliances to minimise any impacts on the level of consumer comfort. To verify the efficiency and robustness of the proposed algorithm a number of simulations were performed under different scenarios. The simulations for load scheduling were carried out over 24 hour periods based on real-time and day ahead electricity prices. The results obtained showed that the proposed MULP scheme resulted in a noticeable decrease in the electricity bill when compared to the other scenarios with no automated scheduling and when a renewable energy system and ESS are not incorporated. Additionally, further simulation results showed that widespread deployment of small scale fixed energy storage and electric vehicle battery storage alongside an intelligent HEMS could enable additional reductions in peak energy usage, and household energy cost. Furthermore, the results also showed that incorporating an optimally designed grid-connected renewable energy system into the proposed HEMS algorithm could significantly reduce household electricity bills, maintain comfort levels, and reduce the environmental footprint.

The results of this research are considered to be of great significance as the proposed HEMS approach may help reduce the cost of integrating renewable energy resources into the national grid, which will be reflected in more users adopting these technologies. This in turn will lead to a reduction in the dependence on traditional energy resources that can have negative impacts on the environment. In particular, if a significant proportion of households in a region were to implement the proposed HEMS with the incorporation of small scale storage, then the overall peak demand could be significantly reduced providing great benefits to the grid operator as well as the households.

ACKNOWLEDGEMENTS

Completion of this Doctoral research would not have been possible without the support of many people throughout my candidature as a student at Edith Cowan University (ECU). I would like to thank my principal supervisor, Dr Alexander Rassau, and Co-principal Dr Włodzimierz Górnisiewicz. Their support, provided to me throughout the duration of the research project has been invaluable.

The generous support awarded to me in the form of an ECU International Postgraduate Research Scholarship is acknowledged and my gratitude and appreciation is extended to the staff of ECU for their support and assistance during the development of the research project.

I would like to express my profound gratitude to mum Rokia and my wife Inas for their understanding, endless patience and encouragement when it was most required during difficult times. Also, special thanks to my daughters and sons, Riham, Rawan, Mohamed, Abdalrhman and Ruba, who have always been my motivator for success. I would also like to thank my family from Libya for their unconditional love and support specially my brother Farag and my sisters Souad, Najat, and Fatima, as well as my mother in law Touria. Finally, I am grateful to my friend Adel for his help and support during my academic journey.

LIST OF PUBLICATIONS

Published Journal Papers

- Abushnaf, Jamal, Alexander Rassau, and Włodzimierz Górnisiewicz. "Impact of dynamic energy pricing schemes on a novel multi-user home energy management system." *Electric power systems research* 125 (2015): 124-132. http://www.sciencedirect.com/science/article/pii/S037877961500108X

- Abushnaf, Jamal, Alexander Rassau, and Włodzimierz Górnisiewicz. "Impact on electricity use of introducing time- of- use pricing to a multi- user home energy management system." *International Transactions on Electrical Energy Systems* (2015). http://onlinelibrary.wiley.com/doi/10.1002/etep.2118/abstract

TABLE OF CONTENTS

LIST OF FIGURES

LIST OF TABLES

1 Chapter 1. Introduction

1.1 Background and Motivations

The ability for Energy Management Systems (EMS) to provide grid operators with effective assistance towards enhancing the performance of electric utilities, power grid transmission systems, power plants and distribution networks is well evidenced [1]. However, the new challenge created by increasingly wide scale implementation of renewable energy systems like solar and wind farms to the power grid is to maintain equilibrium between demand and supply as the renewable energy sources are intermittent in nature. Furthermore, the Distributed Network Operators (DNOs) are beginning to struggle more in handling the power flow via the aging assets of the existing electricity grid due to the increasing use of distributed energy resources (DERs), such as Electric Vehicles, Energy Storage Systems and Rooftop PV Systems. Control and automation technology has progressed much in the process of delivering the 21st century power grid known as 'Smart Grid'. It has been envisaged that Smart Grid will support large penetrations of intermittent, distributed demand-side resources coupled with system-wide Demand Response (DR) driven by economic and reliability signals [2].

Increasing numbers of utilities are looking at Demand Side Management (DSM) and DR programs to better manage their networks [2, 3]. DR programs enable payment incentives to the customers so that load can be reduced when grid conditions become critical or energy costs high. To put it another way, both customers and utilities are rewarded in DSM and DR programs because of wiser energy use. Moreover, on the basis of control techniques and modern ICT, it is assumed that the smart grid will encourage the use of ICT devices to develop smart buildings and homes and at the same time promote interaction between grid operators and customers in order to maintain the power network more proactively. Thus, EMS loses its exclusive status of being the tool solely for grid operators to link system operators with end users. Increasingly Home Energy Management Systems (HEMS) are being explored to allow for better management of residential energy usage. The common vision of HEMS is usually associated with the growth of the so-called Internet of Things (IoT), where through the use of sensors coupled with ICT, intelligent monitoring and management can be achieved via the usage of networked embedded devices. Moreover, a bigger justification for HEMS has been obtained through the increasing usage of Demand Side Management (DSM) from DR programs as part of modern electricity tariffs. DSM has created multiple value streams that offer EMS various approaches to serve the customers. HEMS can help with scheduling of the local loads, which plays the role of a ‘negotiator’ between energy suppliers or operators and the end users, attempting to maximise the benefit to both parties.

Mass adoption of renewable energy systems by householders has led to imbalances between demand and supply. One possible solution to these problems are intermediate storage mechanisms such as batteries and/or EVs, etc. The households are endowed with flexibility with the introduction of such storage systems along with floating tariffs, but capitalisation of this requires control capability and real-time communication of HEMS. The end users are then able to use inexpensive energy at off-peak time in comparison to the general tariffs. However, the HEMS is challenged with more issues after the incorporation of these new features. The responding mechanisms, data prediction and real-time control approaches of EMS are gradually grabbing all the attention of critical areas in HEMS research. The above discussion delineates the motivations of this thesis, which can be summarised as follows:

- Large and unpredictable fluctuations in power output can result from the intermittency of renewable energy sources, therefore demand management solutions are needed to mitigate the disadvantages of renewable energy adoption.
- The demand for and advantages of automatic load managers and Distributed Energy Resources (DERs) among home owners is increasing.
- There is a need to explore the best way of managing the electricity usage to respond to the emerging of DSM service.
- Significant benefits can theoretically be realised by coupling residential scale energy storage systems with rooftop solar installations and HEMS
- Consumers will only be willing to adopt such HEMS controlled approaches if they can do so without significantly impacting their personal comfort levels and routines, thus it is essential that the HEMS algorithm accounts for these factors in the optimisation function

1.2 Research Focus, Objectives and Contributions

The primary research aim of this work is to investigate the optimal control approach and efficient energy management for the DERs and loads within homes with the help of an intelligent HEMS so that the equilibrium between demand and supply can be maintained, energy costs can be decreased, and the efficiency of DERs can be optimised. The following provides an overview of the research objectives:

- Development of a novel HEMS algorithm that monitors and controls household appliances based on a combination of energy pricing models including time of use (TOU), real time pricing (RTP), and multiple inhabitants sharing a home and its appliances. This algorithm is intended to help manage and schedule usage by prioritising between multiple users with preferred usage patterns.
- The Demand Response (DR) program is an essential part of Demand Side Management (DSM) and it is gaining popularity among smart homes. However, customers are not readily able to intervene manually to control the operation of household appliances and DERs to check how the DR system responds. Therefore, this study investigates the implementation of a real-time HEMs to process the DR events without the requirement for customer intervention.
- In order to investigate the effectiveness of the proposed HEMS algorithm, a mathematical model of the residential energy system and the Smart Grids must be developed and implemented. The developed models are applied to determine the optimal operational schedules in concern of controllable loads as well as local DERs and/or energy storage systems utilising a variety of information sources relating to the external environment to enable reductions in energy demand, total cost of energy and emissions while taking into account the comfort and preferences of household occupants.
- In particular, the potential gains that can be afforded through combining an appropriately configured HEMs system with a short-term home energy storage system such as a Plug-in-Electric Vehicle (PEV) and/or standalone battery system have been explored.

The most significant contributions of this research are as follows:

- A detailed mathematical model to simulate the scheduling and optimisation of the controllable components within a typical home energy management system has been developed and validated. The model includes a set of controllable loads including a dishwasher, clothes dryer, water heater, pool pumps, heating and air-conditioning systems, and electrical vehicle, coupled with solar PV panels, and a energy storage system and allows for detailed simulations under a range of conditions and optimisation parameters.

- A novel HEMS algorithm supporting multiple users and load priority (MULP) has been developed for building a demand response strategy which can cater for several users sharing the same home and appliances so that a single load priority can be obtained. The algorithm solves the proposed optimisation model for real-time applications and incorporates a range of contextual factors including time of day, day of week and season.
- A set of realistic mathematical optimisation models for residential electric loads that cover high power consumption loads and energy storage systems has been developed using a Linear Programming (LP) approach. These Mathematical models are incorporated into an intelligent HEMS algorithm that can be used to optimise the scheduling of these loads based on pricing signals, energy availability in the storage system including standalone batteries and/or electrical vehicle battery, consumer preferences, and load priority. The proposed model attempts to minimise the customer's total energy costs and CO_2 emissions and ensure that the total power consumption is kept under the demand limit, while minimising any impacts on consumer comfort.
- The impacts of adding a low cost residential scale short term energy storage system into a household energy mix in conjunction with an appropriately aware intelligent HEMS have been investigated and quantified. Clear advantages are demonstrated through the addition of a small scale battery storage system alongside the proposed novel HEMS algorithm.
- A Genetic Algorithm approach to optimised sizing of hybrid grid-connected batteries and photovoltaic power systems has been developed. This model utilises real electricity demand and hourly solar irradiation data and accounts for system lifetime, capital cost, and ongoing cost. Significantly, with the appropriate optimisation and incorporation of the intelligent HEMS the cost of electricity bought from the grid is demonstrated to be higher than the cost from local renewable sources.
- GA based control methods are presented to optimise the efficient energy management and control approach to the loads and DERs. In this approach the impact of the percentage of energy contribution used to supply the loads from the DERs including Grid, PV and energy storage system such as batteries and EV batteries in homes through intelligent HEMS is studied.

1.3 Organisation Of The Thesis

Following the introduction and literature review, the subsequent four chapters of the thesis are comprised of journal articles, which are either published or under review in peer-reviewed journals, these are followed by a general discussion and conclusion chapter. A brief summary of the content of each of these chapters is as follows:

Chapter 1 introduces the research background and the motivation of the thesis followed by a summary of the research focus and contributions.

Chapter 2 provides a detailed literature review covering energy management systems, an overview of the smart grid, distributed energy resources, and demand side management and demand response.

Chapter 3 Describes a model for the optimisation of load scheduling incorporating hybrid renewable energy systems in a residential context using several different optimisation techniques.

Chapter 4 presents a novel HEMS model that uses a heuristic algorithm to monitor and control household appliances based on a combination of energy pricing models including time of use (TOU), real time pricing (RTP), inclining block rate (IBR) while accounting for multiple inhabitants sharing a home and its appliances. This algorithm helps to manage and schedule usage by prioritising multiple users with disparate preferred usage patterns.

Chapter 5 investigate the potential for increased efficiency and reliability of the proposed HEMS algorithm through incorporation of a short-term energy storage system.

Chapter 6 This chapter focusses on the optimal sizing of hybrid grid-connected batteries and photovoltaic power systems based on real hourly solar irradiation data and electricity demand.

Chapter 7 presents a Genetic Algorithm based control method to optimise the efficient energy management and control approach to the loads when DERs are included in the mix. The DERs including Grid, PV and energy storage system such as batteries and EV batteries are managed through an intelligent HEMS, so as to balance the demand and supply, reduce the energy costs and improve the efficiency and impact of the DERs.

Chapter 8 presents conclusions and future work.

2 Chapter 2: Energy Management Systems

2.1 Introduction

The significance of energy management systems (EMS) is rising because of the rapid advancement of technology employed in home appliances as well as the growing number of such devices as a result of increasing populations. Statistics from the World Business Council for Sustainable Development suggest that in the order of 40% of global energy consumption can be attributed to residential buildings across the world. Additionally, every year those same buildings generate 30% of the global carbon footprint [4]. Furthermore, it has been estimated that by 2035 worldwide power consumption will increase by a further 53% approximately [5]. For example, the US Energy Information Administration has informed that the growth rate of energy consumption is very fast in countries like India and China due to their large scale industrial activities and large populations [6].

As a result of growing pressure to decrease CO_2 emissions due to global warming concerns and increases in the costs of fuels, the energy suppliers have begun to offer various service and tariff options designed to motivate customers to manage and control their energy consumption efficiently. Incentivised mechanisms include installation of their own DERs or/and shifting the load to off peak periods. In addition, the overall energy mix has turned greener due to the rising use of DERs in commercial and residential buildings such as small wind turbine, solar PV systems, or small scale energy storage systems. This has, however, complicated the grid management process for utilities much more than previously. Despite many utility companies having made extensive efforts to install smart metering in distribution networks, the customers still struggle to manage energy consumption wisely because this new system requires them to change their energy usage habits. From the resident's perspective, electricity costs are rising providing increased incentives to explore mechanism by which household energy use can be more efficiently managed, provided this does not unduly impact comfort and practicality. As a result, further exploration of the development and design of suitable HEMS controllers in academic and industrial sectors needs to be carried out to discover new scopes for managing the DERs and devices in homes and workplaces.

Studies [7] have informed that in 2013 the EMS market (such as enterprise EMS, BEMS, HEMS etc.) has reached $17.4 billion and the expected amount in 2018 is $38.49 billion where the Compounded Annual Growth Rate (CAGR) will be 17.2%. EMS products have a wide range of services and features to offer to consumers. Supervising the energy consumption of installed devices and controlling the operation states of devices according to time schedules are the most common functions. Core supporting methods in order to advance the development of energy management can be provided through more functions of effective energy management such as optimisation functions and real-time monitoring with the proliferation of Demand Response (DR) programs, RTP and other advanced tariffs or power services.

2.2 Smart Grid Overview

Power demand has been increasing rapidly in last few years resulting in growing challenges for grid reliability. In the past, maintaining excess capacity on a system having unidirectional flow of electricity from a centralized hub of power distribution to the customers ensured grid reliability. As more diverse and distributed power generation systems and sub-systems are being incorporated at a growing rate into legacy grid systems maintaining reliability becomes a growing challenge. To address this challenge power grids around the world are being upgraded with increasingly sophisticated communication and autonomous monitoring and control capabilities – the so called "Smart Grid". Significant and large data (such as electric power communication) are now transferred through the Internet as it is an effective and reliable medium of communication [8, 9]. The principle motivations driving the development of a future grid identified by academia as well industry are as follows:

- Around 25% of global greenhouse gas emissions are caused by electric power consumption and utilities are increasingly being required to provide greener electric systems.
- In order to address the issue of greenhouse gas emissions, renewable and distributed power generation are becoming ever more prevalent on grid systems, requiring more sophisticated monitoring and control for effective and efficient utilisation.
- The drive to DSM to assure optimised energy efficiency levels and reduce overall electricity consumption is growing, requiring direct real-time communication between the utility and its customers.
- Real-time monitoring of grid performance has the capability of identifying concerns regarding grid reliability which will help to increase the utilisation and reliability of the grid, minimising blackouts and maximising financial returns on investment (ROI) in the grid.

A new and more advanced system is required to execute the changes in both demand and supply in order to control the rising complexity of electricity grids [10]. A smart grid functions as the basis of this change of integrating numerous ideas, Internet connectivity, and automation technologies and concepts. The different components of the smart grid are illustrated in Figure 2.1. The bidirectional communication between the utility and its customers is the significant characteristic of the smart grid and this is also the principal difference between the traditional power grid and smart grid. There are computers, controls, automation and other new equipment and technologies operating together in the smart grid.

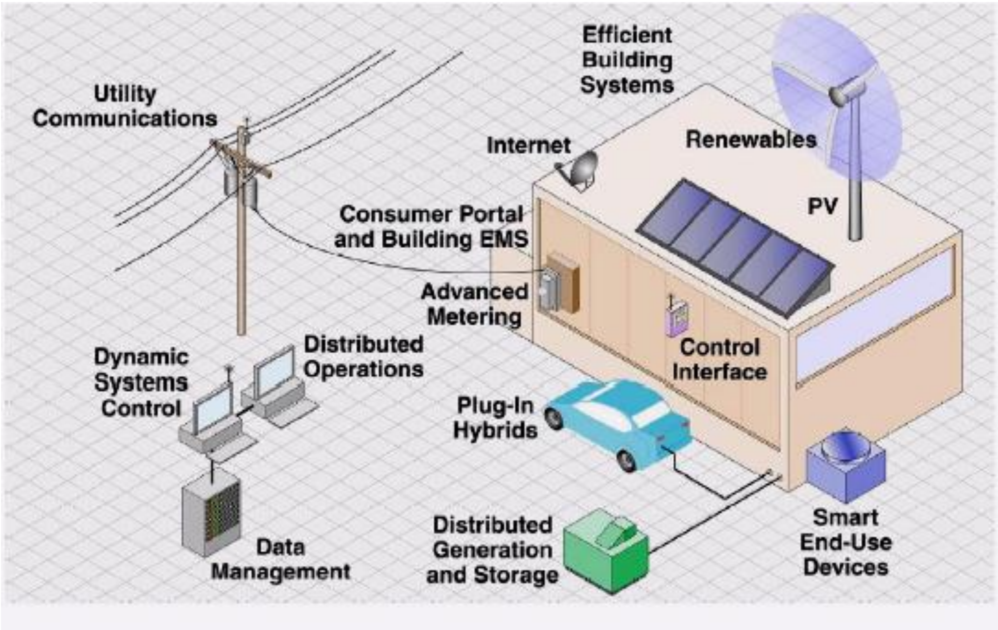


Figure 2-1: Smart Grid concept [11]

It is technology that makes the electric system smart. Utilities are empowered with the capability of managing the whole electricity system through near-real-time information to make it an integrated framework that will have the sensing and responding ability of changing cost, quality, demand, supply and emission of power throughout different locations and devices [10].

The following features should be present in an advanced smart grid system [12]:

- Cost effective
- Eco friendly
- Integrated with renewable and conventional sources of energy
- Extremely high reliability.

- Provided with simple integration for further technical advancement and research

The following aspects are defined as significant to the smart grid by the United States Department of Energy [13]:

- Intelligent - It should have the capacity of detecting system overloads and re-routing power to stop or reduce any potential outage, with the capability of making autonomous decisions where faster resolution is required compared to human response time.
- Efficient - It should have the capability of meeting growing demand without need to add new infrastructure.
- Flexible - It should have the capacity to receive energy from any source such as wind, coal, solar, natural gas etc. Moreover, it must be enabled with the capacity to support future progress and development.
- Customisable - It should enable real-time communication between the consumer and the utility to provide individual consumers the opportunity to customise their energy consumption on the basis of personal preferences regarding environmental concerns and price.
- Opportunistic – It should be able to integrate energy storage systems to support the system during peak load periods.
- Quality-focused - It should optimise clean quality power and minimise the potential for spikes, interruptions, sags or other disturbances.
- "Green"- It should support the integration of more decentralised renewable and environmentally friendly power generators in order to significantly reduce the environmental impacts,

It is widely accepted that the benefits that can be gained through implementation of the smart grid are much greater than what can be achieved just by upgrading the existing conventional power grid. The smart grid enables new avenues in the areas of demand-side management and integration of distributed energy storage that cannot be achieved on conventional power networks [14].

2.3 Distributed Energy Resources (DER)

The role of distributed energy resources (DER) is critical in the context of reliability and efficiency on the emerging smart grid. Generally, the following components can be found in DER: 1) distributed generation (DG) through micro turbines, diesel generators, photovoltaic systems or wind power generation, etc., and 2) energy storage systems like capacitors and batteries [15]. The effective operation of these kinds of energy resources can be well accommodated through the smart grid enabled infrastructure, which incorporates distributed control capability and real-time communication [16, 17]. Different types of DER affect the smart grid differently. DG can be installed by residential, commercial or industrial customers to reduce their electricity demand and return excess electricity to the grid. Generally, these types of distributed generation can be divided into renewable and conventional energy sources.

2.3.1 Conventional energy sources

Coal, nuclear power, oil and natural gas are considered as conventional sources. The materials required for generating power are generally inexpensive and almost any site is appropriate to construct the power stations to handle these resources. Nevertheless, the shortcomings of traditional energy solutions are clear. First, these are finite resources and thus the availability of these resources will eventually cease. Secondly, the surrounding environment can be affected badly by the very generation process leading to pollution and other serious environmental issues. Thus, drastic price hikes in the generating cost of this type of energy will be unavoidable due to rising scarcity of these resources and the growing political and public cognizance of the serious environmental impacts. Traditional electric grids are the medium of managing these conventional energy sources and are designed to connect a one-way and interconnected network that carries electricity from the suppliers to the customers [18]. Thus, to fully utilise alternative energy solutions that will be renewable, sustainable and with less carbon footprint, requires a redesign of electric grid infrastructure, and this is another significant driver for deployment of smart grid technologies.

2.3.2 Renewable Energy Sources (RES)

Lately, the major factors that have driven the major growth in development of hydropower, solar power and wind power generation systems in terms of distributed energy resources are the rising concerns of climate change and cost reduction. Renewable energy technologies have many benefits over conventional sources of energy, but also introduce significant complexities that must be accounted for. There are a wide range of different potential renewable energy sources, and many different types are available on the basis of geography. Many renewable energy sources also have the ability to complement each other. The key advantage are that significantly less pollutants or waste are created by systems of renewable energy and since the propensity of urban smog, acid rain, and associated health issues are minimised, the cost of waste disposal and environment clean-up are also saved.

Renewable energy systems yield no waste by-products in their operational phase, thus, if they are implemented, the global climate will be positively impacted [19, 20].

The major disadvantage of most renewable energy systems, however, is intermittent generation. To account for this, normally, a storage system and distributed intermittent generation are combined in the distribution system for renewable DERs [7]. Investment deferral, power loss reduction, peak load alleviation etc. can be realised by implementation of storage systems and distributed electricity generation [21], but significant costs can be associated with their deployment, which can be a limiting factor.

2.3.3 Hybrid energy systems

The prevalence of hybrid energy systems comprising conventional sources from the traditional main utility grid and renewable energy resources such as wind power and solar power is increasing. Furthermore, the prevalence of incorporating storage systems is also increasing to enable development of more efficient hybrid energy systems. Here, the renewable energy sources can be converted into other energy forms directly or indirectly enabling the energy to be saved in storage units or used in home appliances as shown in Figure 2.2 [22].

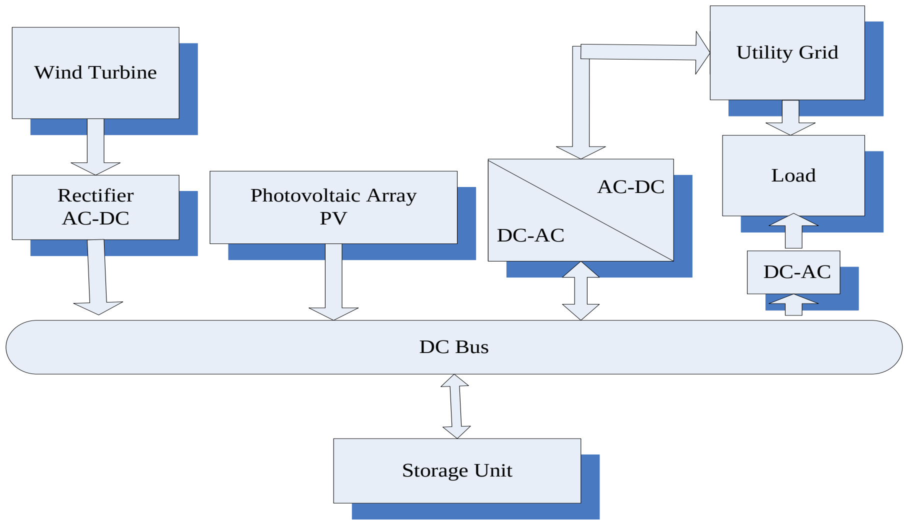


Figure 2-2: 2Hybrid energy system

The importance of energy storage technology in respect of renewable energy systems cannot be avoided due to the necessity of storing additional energy for use during periods of inadequate energy production from renewable energy sources. Different ways are available to charge these storage devices. For example, when the energy price is low then these devices are able to accommodate energy from the main grid or from the renewable resources during periods when generation exceeds demand. Subsequently, supply becomes more flexible and reliable through these devices. Deployment of such storage systems at the grid scale can be a significant challenge, but there is a growing interest in exploring the potential of distributed energy storage solutions. The most common storage device used in residential buildings is a battery bank as costs are rapidly falling and it is fast to respond and easy to install. Other storage systems are available as well to accommodate different energy forms like heat, electrochemical and electrical for optimising the energy management system through establishing equilibrium between demand and supply of energy [23-25].

2.3.4 Energy Storage System (ESS)

Energy storage is considered as a means of preserving generated energy at times when excess is available so that it can be used at a later time when demand is higher. The forms of storage are electrical, chemical, electrochemical, and mechanical. Supply and demand between end consumers and suppliers can be balanced through developing energy storage. Apart from that, effective utilisation of renewable energy in a consistent, sustainable and reliable way would be impossible without the incorporation of storage in some form [26].

2.3.4.1 Batteries

Batteries stand as one promising approach among the range of energy storage options. Batteries are defined as electrochemical storage devices. Lately, higher capability of storage has been offered by the revolutionary development on battery technology at ever cheaper cost [27]. As an energy storage technology, batteries are excellent for integration with renewable resources. Their compact size is suitable for use in distributed locations and it is possible for them to control frequency and accommodate variations in local solar or other renewable source output. In spite of current limits relating to cost and market penetration, the scalability and modularity promise to decrease the cost further in future [26, 28].

Two significant influential factors to the battery cost are capacity and technology. However, the longevity or operation of batteries is affected by several other parameters as well. The amount of battery charge/discharge per unit allowed and the energy percentage of total capacity that can be extracted while keeping the battery undamaged [11]. Moreover, the life time of the battery depends on several factors which are the depth of discharging; and the number of times have been charged and discharged; charging and discharging efficiency; as well as by the time the battery start leak some of its energy[29]. To account for these factors necessitates that a smart energy management system of some kind be installed alongside the storage system.

2.3.4.2 Electrical vehicle

The growing penetration of Electric Vehicles (EV) into vehicle populations adds both economic and social advantages. It has been stated in studies [30] that by 2020, there will be 20 million EVs worldwide. This is likely to result in significant new challenges for power grid operators in regards to grid stability, patterns of voltage profile, power flow and new peak load after connecting such significant numbers of EVs with the power system. Conversely, however, if used in conjunction with intelligent energy management systems and the smart grid, EVs can function as decentralised storage resources, which can afford significant flexibility to power grid operators, particularly when considered in conjunction with renewable energy sources. Both negative and positive scenarios require the same answer: the charging process needs to be coordinated through smart charging following the conditions of customer preferences, availability of local renewable energy resources (RES) and distribution grid constraints. Extreme overloads can be prevented and the power system can be optimised only through smart charging. The energy use can then be optimised in a smart way through shifting the charging to the electric vehicles and also other loads of electricity. The system can be further optimised and customers empowered with information through intelligent information exchange by equipping recharging points with smart meters or other such intelligent infrastructure and interlinking electric vehicles. According to studies, the majority of cars, including EVs, usually remained parked almost 90% of their lifetime.

Their large storage capacity combined with the fact that normally the battery remains at a relatively high charge state following an average journey constitutes for an effective and flexible solution for the EVs when used as distributed storage, which supports the system operation. Significant capacity remains available, which can be gathered through services of smart charging. The smart grid could empower electric vehicles to produce flexibility services in two ways for the power system. First, the charging process of load management of electric vehicle charging can be brought under control through transferring the charging duration to periods of lower demand, decreasing or increasing the charging power or disrupting the battery charge of a car in emergency situations. The schedule of charging can be adapted according to availability of RES like solar or wind, which focuses on renewable integration. Second, EVs are able to obtain higher flexibility in the long run for the system through providing power to the grid or the home in a Vehicle-to-Home (V2H) or Vehicle-to-Grid (V2G) situation.

Additional power can be stored from RES through the cars' batteries and it can be discharged when the demand becomes high. EVs can be used as decentralised storage in the long run as the growth of the number of renewable sources and EVs continue. Here, the complete integration of EVs including DERs and storage can be added [31, 32].

Electricity can be stored by distributed storage systems when additional electricity can be obtained at cheap rate and then supplied at time of deficiency. Thus, in different situations they function as both load and generation. Moreover, electricity storage systems can be utilised for smoothing the volatilities of renewable generation and potentially to transfer arbitrage electricity or peak load to a dynamic scheme of pricing [33].

In order to minimise cost and save energy, the in-house utilisation of energy storage device is accounted as the primary method. Nevertheless, if the charging process of thousands of in-house storage devices is going on simultaneously, the chance of excessive peak load on the distribution grid could become higher. Thus, power suppliers would need to construct redundant generation capacity to meet the requirement. This will increase carbon emission and can even cause power outages because of excessive demand. Thus, both consumers and suppliers will benefit from the in-house energy storage system having a managed strategy for mitigating the peak demand. A strategy is proposed in this thesis on the basis of an intelligent approach to address this challenge.

2.4 Demand Side Management and Demand Response

One of the functions made possible through the establishment of the smart grid is Demand Side Management (DSM), a technique that has high significance in respect to energy management to support future infrastructure construction, electricity grid management and market control, EV and distributed storage utilisation and decentralised energy resource management. The overall peak load demand can be decreased, the demand profile reshaped and grid reliability and sustainability increased by real-time control of energy demand, affording reductions in overall energy supply cost and levels of carbon emissions. The requirement for utilities to deploy new transmission lines, distribution networks and power plants can potentially be deferred or eliminated by effective demand side management. The smart grid enables the special capability of smart pricing [34, 35], which can be implemented through the use of smart metering devices within an automatic metering infrastructure. This enables cost-reflective pricing on the basis of the whole supply chain that delivers a particular quantity of electricity at a particular location within a particular period. Incentive schemes and real-time penalties at each level of the supply chain will affect the control over energy usage by the customer through time of use smart pricing including demand side management. Principally, promotion of overall system effectiveness, sustainability and security through leveraging the capacity of existing infrastructure while enhancing the use of low carbon technology into the generation and distribution system is the rationale for the implementation of demand side management [36, 37].

A huge number of controllable loads of multiple types must be handled by the strategies of demand side management in a smart grid. Moreover, loads can have characteristics which spread over several hours. Thus, these strategies should have the ability to manage all possible control duration of different controllable loads. Additionally, demand side management can be perceived in a new way through the transformation of standard grids into smart grids. It is assumed in smart grids that a major part of generation will comprise renewable energy resources like solar and wind [38].

The functions of power dispatch in the smart grid are hindered by the uncertainty of such renewable energy sources requiring implementation of load control methodologies. This necessitates establishment of bidirectional communication between several system elements and the central controller for the operation of the smart grid. Thus, the designed demand side management system should have the capability of managing the communication infrastructure between the controllable loads and the central controller. Consideration must also be given to the fact that wide variety can be noticed in the criteria for determining the optimal load consumption. Maximising the utilisation of renewable energy resources, the economic advantages through bidding for diminishing demand in peak periods, and reducing the amount of power imported from the local main grid to supply the loads or reducing peak load demand are some of the criteria.

As a result of these diverse factors, DSM schemes require sophisticated coordination between customers and network operators. Electrical network load shapes indicate the seasonal or daily electricity demand among residential, industrial and commercial customers for off-peak times and on-peak times and these can be reshaped through six broad techniques [39-41]: peak clipping, strategic conservation, strategic load building, valley filling, flexible load shape and load shifting. Some combination of these are expected to be implemented in future smart grid advancements as demand response (DR) programs and DSM methods become more mainstream. Figure 2.3 depicts those six DSM techniques.

- Peak Clipping: Loads are reduced at the time of peak demand periods.
- Strategic Conservation: End-use consumption is reduced through using energy efficient appliances and reducing overall usage patterns when both total power consumption and peak demand are high.
- Strategic Load Building: The overall power consumption is increased during particular time periods. As a result, both total energy consumption and peak demand are increased.
- Valley Filling: Total energy consumption is increased during off-peak periods through elevating the loads at those times.
- Flexible Load Shape: The quantity or reliability of service is varied when the utility has the option of controlling the consumer's appliances if needed.
- Load Shifting: Load is shifted from on-peak periods to off-peak periods in order to yield a reduction in peak demand without changing the total energy consumption.

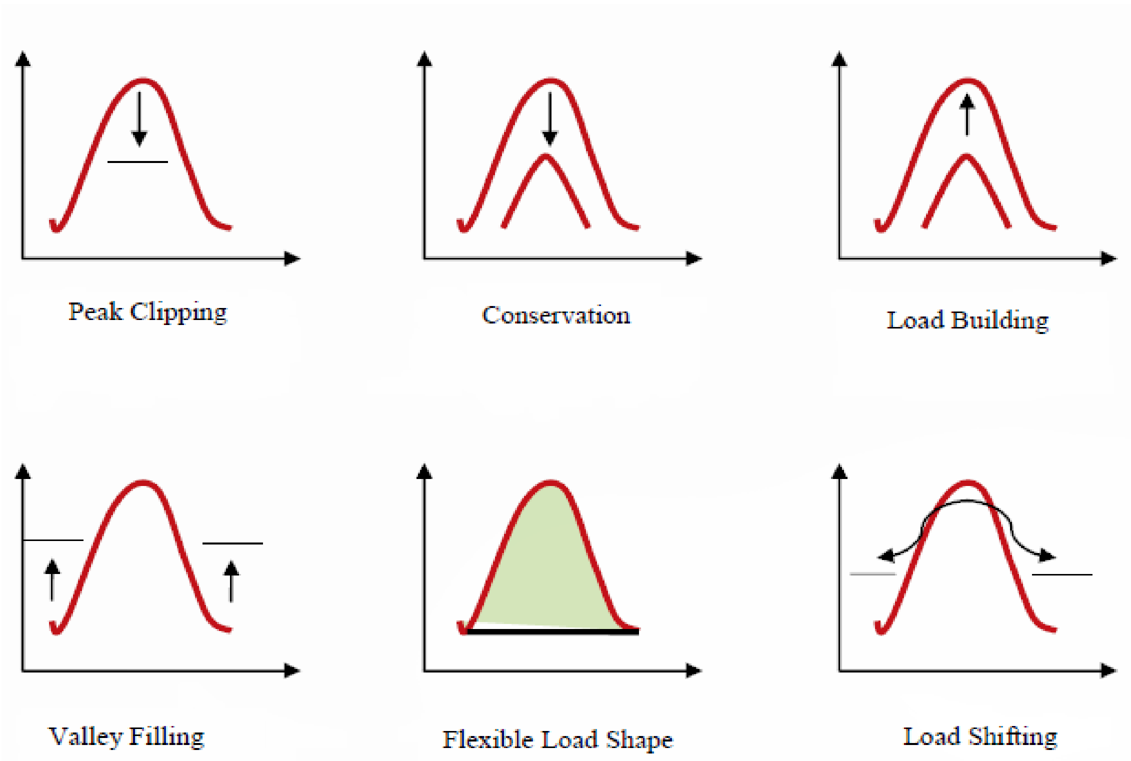


Figure 2-3: Load Shape Objectives [42]

2.5 Demand response programs

Demand Response (DR) defines the change in usage patterns of electricity as the result of variances in electricity prices. The function of DR programs is to transfer excess load to off-peak hours and to balance between demand and supply of energy in the short term [43]. DR programs are divided into two categories as found in Table 2.1. The first group consists of price based programs (PBP) where time of use (TOU) pricing and real time pricing (RTP) are included and these provide customers with time-varying rates that dictate the cost and value of electricity in different times. This proposition is based on the assumption that customers are inclined to utilise electricity less when electricity prices increase [8, 44].

Demand response programs based on incentives can be defined as programs where customers opt-in to be paid for decreasing the loads as requested by the program sponsor either because of high electricity prices or grid reliability problems. Dynamic control and monitoring of electricity usage are actively assisted by the demand response technologies that comprise services and products [8], for example, smart meters. As an effective and direct tool, real-time pricing carries out demand response programs and realises the resulting benefits [8]. The service provider (utility) declares prices on a cyclical basis in demand response programs. Therefore, prior to the beginning of the period, the energy price is decided and declared such as a day ahead or hour ahead. Smart metering technologies help these real-time price indications to be provided multiple times a day, an hour or even at intervals of seconds to the consumers.

Measurement at pre-set time intervals and the transfer of time-based pricing signals to consumers as encouragement for decreasing and shifting usage can be achieved with advanced metering infrastructure, so called ‘smart meters’. These smart meters along with other smart grid technologies make way for bidirectional communication between service providers and customers and information is generated that is useful for both electricity providers and customers. The customers usually receive this time-based information through emails, voice or text messages and in-home display devices that enable customers to monitor and comprehend their electricity consumption and implement appropriate control measures [8].

Table 2-1: Demand response programs [40]

Incentive Based Programs (IBP)	Direct Load
	Interruptible Load
	Demand Bidding
	Emergency Demand Response
	Spinning Reserves and Non-Spinning Reserves
	Capacity Market
	Ancillary Services Market
	Load as Capacity Resource
Price Based Programs (PBP)	Time Of Use, Super Peak Time of use
	Extreme Day Critical Peak Pricing, Critical Peak Pricing
	Flat rate
	Critical Peak Real Time Pricing, Real Time Pricing
	Variable Peak Pricing, Peak Time Rebate

2.6 Conclusion

In conclusion, no standard method yet exists for economical optimisation of energy supply and usage within residential buildings in the form of a home Energy Management System. This thesis focusses on implementation of the EMS to reduce energy cost, increase efficiency of usage and reduce utility load while maintaining consumer comfort. The background material reviewed in this chapter such as dynamic pricing technology with DSM, energy storage systems, and renewable energy resources form the basis for the development of appropriate models for optimal home energy management in the context of Smart Grids.

3 Chapter 3: Optimisation Methodology

Numerous mathematical optimisation techniques have been used over the years for many power systems control problems, and for operational planning. Optimisation is an essential tool for scientists and engineers who strive for better system performance, efficiency, and cost viability. Most of the development and implementation in the area of optimisation is based on mathematical optimsation algorithms, or mathematical programming. Optimisation methods such as linear programming, dynamic programming, genetic algorithm and heuristics have been generally applied in real world problems. Solving these optimisation problems provides helpful solutions and guidance for the implementation of system parameters [26, 34].

3.1 Optimisation of residential load scheduling

3.1.1 Related Works

An objective function must be defined that can be used to derive the formula of the minimisation cost for an optimal load scheduling procedure based on the application of a given energy pricing scheme. The design of an optimal load scheduling scheme that considers the attributes of every load and the particular needs of the customers such as temperature limits specified by users for thermostatically controlled appliances, is the main challenge for the optimisation determination problem. Furthermore, the computational complexity of the solution for the energy management optimisation problem is determined by the characteristics of the objective function, and the design of the optimisation problem vector, which is additionally influenced by the number of consumers, household appliances, and energy sources considered in the optimisation problem. A number of different mathematical optimisation methods for load scheduling are described in the literature [45-53]. The impact of the use of stochastic dynamic programming for scheduling loads based on varying time prices is studied in [45]. The mixed-integer linear programming approach for optimal energy scheduling and management of power consumption by electric household appliances has been proposed in [46]. Fuzzy logic combined with a dynamic programming approach has been used in [47-49] in order to determine the Direct Load Control (DLC) scheduling for the household load including customer variation in temperature resilience and load uncertainties. Further improvements have been proposed in [50], by integrating DLC with interruptible load management using a dynamic programming and fuzzy logic optimisation approach to provide instantaneous reserves for ancillary services. The authors in [51] propose a linear programming-based column generation approach to reduce the peak load through control of an electric water heater. While in [52] an objective function for optimal appliance schedules was used to minimise the aggregate cost of electricity usage at home using linear programming techniques.

An Integer Linear Programming (ILP) method is used in [53] to derive the minimum energy cost for single or multiple houses. The proposed method has the ability to maintain the consumer comfort using prediction errors approach. However, the optimal solutions can be obtained over particular scheduling window, without considering the time beyond the set window, this may lead to sub-optimal solutions. Moreover, a near optimal solution based on a greedy search heuristic method has been proposed in [54]. The results obtained using this approach is effectively flattened demand curve, even if the end user's electricity bill is not reduced. For such cases, fast and near optimal solutions can be obtained using heuristic approaches. For instance, in [55], the authors proposed a heuristic-based evolutionary approach to reduce the electricity bills of consumers in commercial, industrial and residential areas. This is acquired through a load shifting technique, for the support of a large number of different types of loads

To select optimal starting times for operation of different home appliances, the authors in [56] propose a calculation approach that also keeps the load below the limitation curve. In this work the management problem of the electrical loads is modelled using nonlinear integer programming and an evolutionary algorithm with local search is applied to reduce violations of the load limitation curve and minimise the electricity bill of the end user. Furthermore, a Genetic Algorithm (GA) has been suggested by the authors in [57], to solve the optimal load shifting problem. In [58] an Iterative Deepening GA (IDGA), has been proposed to determine the scheduling for DLC. The scheduling strategy arranged by the IDGA not only controls the load so that the load required to be shed at each sampling interval is individually satisfied, but it also minimises the shedding load to minimise the utility company's revenue loss due to DLC.

A domestic load scheduling scheme using GA has been proposed by the authors in [59], this approach aims to minimise the consumer's electricity bill taking into account the consumer preferences and keeping the power consumption in each time slot below a certain limit by imposing penalties when their usage exceeds that limit. While [60], uses a distributed agent-based control using different artificial neural networks (ANNs) located at the home appliances for demand side management. Particle Swarm Optimisation is another approach intended to optimise the utilisation of several energy services from the consumers' point of view that has been presented in [24].

Each of the aforementioned approaches has its own advantages and disadvantages. ANNs are able to model complex, non-linear processes that have unknown relationship between input and output variables [61]. However, they need a training procedure to be able to obtain optimal solutions, which requires collecting data that may not be readily available. PSO requires low computational memory capacity which makes it suitable for real-time optimisation applications [62]. However, it is less reliable for finding global optimal solutions compared to other techniques. It is also less effective in finding global solutions. Linear programming techniques are easy to code but require long computational times to solve complex optimisation problems[63]. Genetic Algorithm techniques provide the ability to find the global solutions efficiently and handle any number of optimisation variables. However, it has a complex structure that makes it challenging to code [59, 64, 65]. Heuristic techniques can be applied to many problems because they do not rely on complicated mathematical characteristics of the problem but they do not guarantee finding optimum solutions [66]. Among the available techniques, Linear programing and heuristic methods are widely used for home energy management applications [23, 67-71] and proven to achieve efficient results. Therefore, these methods will be used in this research to examine the effectiveness of a novel management and control method for household appliances to improve the user comfort level and minimise the end user electricity bill. Compared to many other well-known optimisation techniques, Genetic Algorithms have a better capability of finding global optimal solutions when many optimisation variables are involved. In addition, GA has the ability to easily jump out of local solutions[65, 72, 73]. Therefore, it is used in this research for optimising the size of a grid connected renewable energy system taking into account the charging and discharging dynamics of an electric vehicle as well as scheduling the distributed energy sources and household appliances.

3.1.2 Proposed Approach

In this research, three different mathematical optimisation approaches have been applied for optimising the schedule of residential loads using different demand side management and demand response programs. In chapters 4, and 5 a heuristic based evolutionary algorithm optimisation method will be applied that can handle a large number of devices of several types. The proposed algorithm provides an efficient and cost effective solution to the problem, that can readily adapt to different heuristics. One of the main advantages of the proposed algorithm is the flexibility in constructing and developing the optimisation approach, which cannot be afforded by other conventional approaches. The flexible nature of the evolutionary algorithm allows implementation of features that model load demand patterns based on the lifestyles of the customers so that the impact on the customers can be minimised. In chapter 6, a linear programming (LP) approach is proposed as another optimisation algorithm. The LP approach is adaptive, providing more flexibility to analyse the problems, and it has the ability to provide for a better quality of decision. This algorithm has been deployed to optimally schedule the daily loads according to the operation time for each of the home appliances and consumer preferences while incorporating the flexibility in the HEMS to consume energy from energy storage systems including batteries and PEV during peak demand and periods of high electricity prices. In chapter 7, an approach based on GAs has been proposed that aims to achieve an optimal (balanced) daily load schedule. Different energy sources have been proposed including residential solar and energy storage systems to minimise the dependency on traditional energy sources, which also allows the HEMS to be more flexible and reliable to manage and control the loads effectively. The next sections briefly introduces these heuristic optimisation, LP, and GA methods.

3.2 Heuristic Optimisation (HO)

The common features of all optimisation techniques is an attempt to provide an optimum solution to a problem. The heuristic method is an optimisation technique that attempts to yield a good solution but not necessarily an optimum one. The solution method for the heuristic optimisation problem is to start off with a more or less arbitrary initial solution, iteratively produce new solutions by some generation rule and assess these new solutions, and at the end of the search process report the best solution. In addition, if there is no further improvement or acceptable solution for the problem over a given number of iterations, the execution of the search process will be halted. There are also other reasons that may cause the search procedure to be stopped such as the allowed CPU time has been reached, when there is no valid candidate solutions, or the algorithm execution is terminated by some internal parameters [74].

3.3 Linear programming (LP)

Linear programming (LP) is one of the most common mathematical programming methods characterised by a linear objective function and a set of linear equality and inequality constraints. Thus, the general form of LP formulation is as follows:

Minimise:

$$c^T x \tag{3.1}$$

Subjected to:

$$Ax \leq b \tag{3.2}$$

Where:
x represents the variable's vector to be determined, A is the coefficient matrix, b is the known vector values, and c is the objective function coefficient vector.

Furthermore, the linear objective function optimised by the LP technique is subject to linear inequality constraints, also the inequalities define a polyhedron of feasible solutions, and the optimal solution is typically at one of the vertices.

The Simplex and Interior-point methods are the most well-known solution methods used with LP problems. The Simplex strategy is a precise system for creating and testing the vertices of the polyhedron. It begins at an arbitrary vertex as a possible candidate solution and at each iteration the candidate solution is moved to a new vertex in a direction that yields the biggest improvement in the objective function [75]. In the Interior-point technique, the candidate solution navigates through the interior of the polyhedron to arrive at the optimal solution. The number of iterations in the Simplex method are significant when applied for large LP problems; in cases like this, the Interior-point method is a better option in order to reduce the computational costs [76].

3.4 Genetic Algorithm (GA)

Genetic Algorithms are a class of search techniques that use the mechanics of natural genetics and selection to perform a global search of a solution space. This searching technique is used to find a global optimum solution to the objective optimisation problem in an efficient and effective way. The GA approach also has the ability to solve difficult optimisation problems such as problem with non-differentiable, non-continuous, and highly non-linear objective functions. The solution population is derived using five operators to produce new offspring for the next generation. These operators are selected from an initial random population generator; a fitness evaluation unit; genetic operators for selection; crossover; and mutation operations [77, 78]. Thus, the new potential solution can be obtained when the new population undergoes reproduction by means of the crossover and mutation operators. The evaluation of the population of each generation will be used to compute the solution fitness values until a convergence criterion is satisfied. Furthermore, these solutions, which are generated randomly by the GA according to the defined objective function, will be used to evaluate the solution of any optimisation problem. Therefore, the below GA flowchart displays all the execution steps used to solve the optimisation problem as shown in the Figure 3.1. While Eq. (3.3) illustrates the typical constraints of the optimisation problem that can be solved using a GA.

$$Minimise_x[\,f(x)] \tag{3.3}$$

Subject to the constraints:

$x_{min} \leq x \leq x_{max}$

To solve this kind of optimisation problem using the GA, the variable x is presented in an array structure which includes all of the optimisation variables. Additionally, the values for GA operators must be set before the GA-based optimisation process is started.[79, 80].

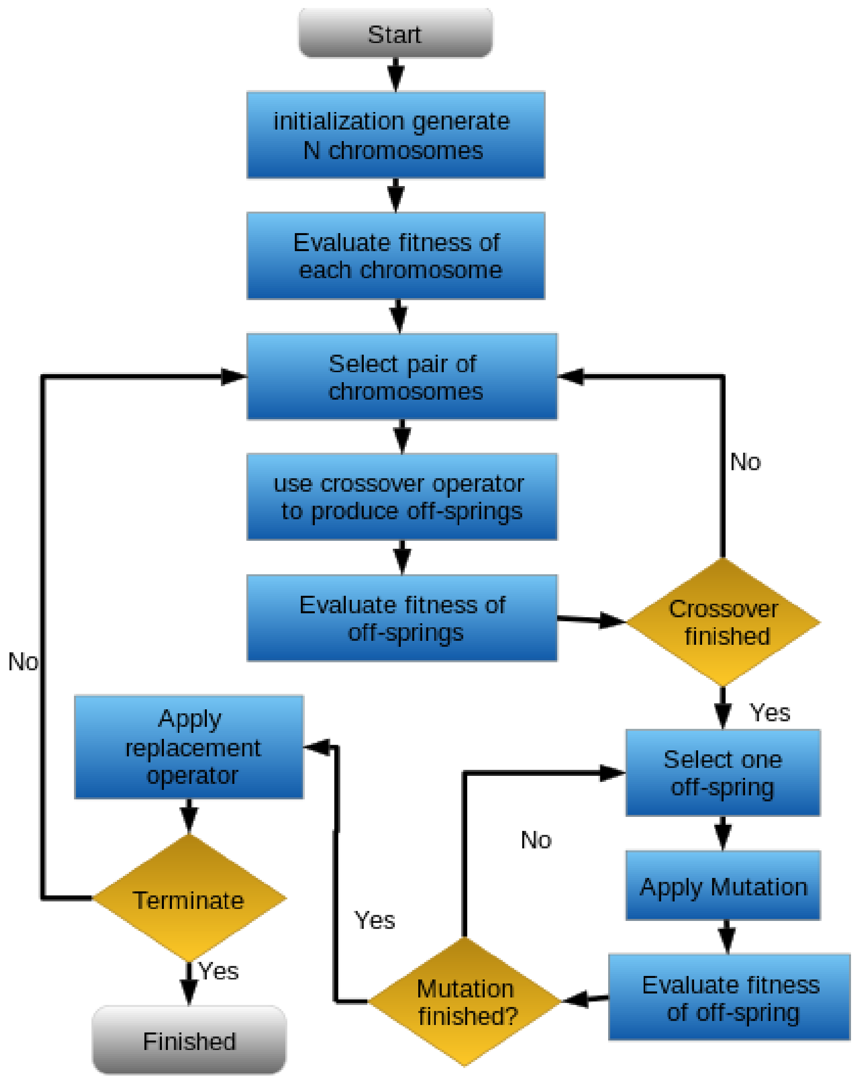


Figure 3-1: Flowchart of genetic algorithm [80]

3.5 Optimisation of Residential Hybrid Renewable Energy Systems

Optimisation methods have been used widely in several aspects of renewable energy systems. This is necessary in order to design an optimal hybrid energy system to efficiently utilise the renewable energy resources, and obtain the minimum cost with the maximum usage of all the components of the system. Recently, much research has focussed on developing several methods and techniques to optimise the sizing, forecast the availability of renewable resources, and control the operation of different characteristics of renewable energy systems. This section reviews methods and techniques used to optimise the system sizing and resources forecasting.

3.5.1 Component sizing

Many different optimisation techniques have been utilised for sizing hybrid renewable energy systems within the literature, such as probabilistic, iterative, intelligent iterative strategies and graphic construction methods [81-85]. In general, for simplicity, these methods are based around the worst case scenario or the average values of renewable energy resources (e.g. solar or wind), however, the results obtained by applying these methods to design the system tend to be oversized due to the worst case having a low occurrence probability and the average values obtained are not constant all the time [86, 87]. Better results can be obtained using a long time series of electric load profiles and weather forecasting methodologies,, where HOMER is the most common tool using this approach [88, 89]. However, using this approach increases the complexity of the system, which results in significant increases in simulation time and in the required number of simulations.

Several intelligent optimisation techniques have been used widely for sizing hybrid renewable energy systems, due to their ability to handle multi-direct or non-straight cost objectives in complex problems [90]. In general, these optimisation techniques mimic the social behaviour of species and/or their natural biological evolution. Such techniques have been developed to reach near optimal solutions for large scale optimisation problems for which conventional mathematical systems may fail. Different optimisation techniques for hybrid energy systems sizing are mentioned in the literature [91-94]. Designing a hybrid renewable energy system in a cost effective way using different optimisation techniques such as Fuzzy Logic (FL), Simulated Annealing (SA) [95, 96], Particle Swarm Optimisation [83], and Genetic Algorithms (GAs) [97], have been proposed by many researchers.

Among the aforementioned optimisation techniques, GAs have been widely utilised for optimising the size of hybrid renewable energy systems. The advantage of this technique is the ability to jump from the local optimum solution to the global optimum solution efficiently [64]. Furthermore, using a large number of parameters in coding by GAs makes them suitable for the purpose of sizing studies. Therefore, in this research a GA will be applied for optimising the component sizing of the proposed renewable energy system. The identification of research shortfalls in the sizing of renewable energy systems is deferred to Chapter 6.

3.5.2 **Renewable resources forecasting**

Time-series meteorological data are very important for the design and feasibility studies of renewable energy systems. In this regard, the global weather data could be acquired from local meteorological stations or the Internet, yet these data are not readily accessible and may not be appropriate for choosing the most feasible solution for energy systems. Furthermore, the data used for estimating renewable resources (e.g. solar radiation) can be obtained via satellite. However, these data may not be accessible particularly in developing countries. Rather, site-to-site based weather data such as temperature, hourly solar irradiance and wind, are usually required. Moreover, in many locations, measured records of meteorological data are not available. At the point when measured weather data are not available, there are two methods used to obtain these data for any location. Firstly, the vital data might be synthetically obtained from monthly-average values of the meteorological data, however, more accurate models are generally needed. The second method is making necessary adjustments on the measurement data obtained from the nearest site, which may not be useful in some locations due to rough earth topology [98]. Several estimation and analysis methods have been conducted on renewable energy sources including wind and solar energy [99, 100]. The next section briefly describes some of the methods developed for wind speed and solar irradiance forecasting.

3.5.2.1 Sun/Solar irradiance forecasting methodology

Different computational models used for solar irradiance forecasting are reported in the literature such as satellite-data-based models [55, 56], NN models [57-60], and linear regression models [53, 54]. However, the availability of information of atmospheric conditions in detail or meteorological data are required for these models. Developing or studying the accuracy of the existing models for forecasting solar irradiance are beyond the scope of this research. The ASHRAE method is a simple and well known method used for forecasting solar irradiance to estimate solar power. This method has been widely used by engineers in different research areas such as communication, control systems (e.g. to define the comfortable level for consumers in terms of heating, cooling and water heating in different zones), and power systems (e.g. renewable energy applications) [51]. It was developed by the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) [52, 53].

ASHRAE model

In this model, hourly beam irradiance in the direction of rays (I_N), the hourly diffusion radiation (I_d) on the horizontal surface of a clear sky, and the hourly global irradiance (I), are calculated by using the following formulae [101]:

$$I_N = A\, exp[-B/\cos\theta_Z] \tag{3.4}$$

$$I_d = CI_N \tag{3.5}$$

$$I = I_N \cos\theta_Z + I_d \tag{3.6}$$

where A is the apparent solar irradiance constant, B is the atmospheric extinction coefficient and C is the diffuse sky factor. The zenith angle represented by θ_Z in equations **Error! Reference source not found.** and (3.6), while its cosine is given as follows:

$$\cos\theta_Z = \sin\emptyset\ .\sin\delta + \cos\emptyset\ .\cos\delta\,.\cos\omega \tag{3.7}$$

In equation 2.7 the angle $\emptyset$ is the location latitude, ω is known as the hour angle and the solar declination is known as δ, which can be obtained by the following equation [102]:

$$\delta = 23.45\sin[360\,.(284 + n)/365] \tag{3.8}$$

The number of days in a year is represented as n. The angular measurement of time is hour angle (ω) which is equivalent to 15°h-1. This is measured by noon-based on Local Apparent Time (LAT).

$$\omega = 15.0(12.0 - LAT) \tag{3.9}$$

The following equation shows how the LAT value can be obtained from the Standard Time (ST):

$$LAT = ST + ET \mp 4.(STL - l) \tag{3.10}$$

where E is the time correction (in minutes), l is the location longitude, and STL is the standard meridian for the local time zone.

$$E = 229.2(0.000075 + 0.001868\cos B - 0.032077\sin B - 0.014615\cos 2B - 0.04089\sin 2B) \quad (3.11)$$

where, $B = \frac{(n-1)}{360}/365$ and $n = n^{th}$ day of the year.

In addition to the longitude (l) and latitude ($\emptyset$), values for the A, B and C parameters correspond to a particular location are required to obtain solar irradiance data. These parameters can be retrieved from the ASHRAE handbook [103].

3.6 Conclusion

Several optimisation techniques have been discussed in this chapter and the main focus was on using these techniques to improve the reliability and cost-effectiveness of home energy management system. To achieve this goal, three different mathematical optimisation approaches including, LP, HO, and GA have been applied for optimising the schedule of residential loads using different demand side management and demand response programs as well as optimising the size of a grid connected renewable energy system.

4 Chapter 4. Impact on Electricity Use of Introducing Time of Use Pricing to a Multi-User Home Energy Management System

4.1 Introduction

Energy management systems can play an important role in residential energy usage due to recent rapid progress in home appliance technology coupled with rising populations. According to the World Business Council for Sustainable Development, approximately 40% of global energy consumption and 30% of carbon footprint are attributable to residential and commercial buildings [4]. The world's power consumption is expected rise by approximately 53% by 2035[5]. This will likely lead to more frequent blackouts and power curtailment during peak periods as well as rises in electricity prices. To reduce these impacts, some energy suppliers now provide their customers with different demand-side management (DSM) programs to help limit the need for new power plants, transmission and distribution networks, while reducing negative environmental impacts and lowering the cost of delivering sufficient energy to customers. DSM optimises residential electricity usage and minimises costs by modifying or changing the system's load shape through load shifting techniques.

DSM can introduce different demand response (DR) programs that are essential for shifting unnecessary loads to off-peak hours and also balancing energy demand and available supply over shorter time scales [104]. The first group of DR programs comprises price-based programs (PBP) including real time (RTP) and time of use (TOU) energy pricing, which reduce power consumption during peak periods by utilizing peak and off-peak price differentials.

The second group comprises incentive based programs (IBP) and controls loads using strategies like direct load control and interruptible load control, providing consumers with financial incentives to reduce their peak demand power consumption, such as cash rewards or special peak demand prices [105]. In this chapter, DR programs will be simulated to reduce the patterns of energy usage by optimising loads while minimising inconvenience to consumers.

The proposed home energy management (HEMS) algorithm for managing and controlling the household appliances has been simulated to illustrate the performance of this algorithm. Two different scenarios are used to compare the results obtained by applying different DSM programs: in the first scenario, TOU pricing with different demand limits (DL) are applied without considering the load priority and consumer preferences; in the second scenario, TOU pricing with different demand limits (DL) are combined with the MULP model. Both scenarios involve a group of appliances that can be controlled without significant influences on consumer comfort. This comparison will allow an evaluation of which DSM program can be introduced as the most effective solution for home energy management to address environmental and economy of energy issues, taking into account issues of user acceptance. This latter point is considered to be of great significance as the overall impact of such schemes have the potential to be greatly impacted by user acceptance rates.

This chapter is organized as follows. Sections two and three present the related works and load classification, respectively. Section four introduces the proposed multi-user home energy management system (HEMS) algorithm. Section five presents the simulation tools and results, followed by conclusions in section six.

4.2 Related Work

Recently, both energy demand and energy prices have been continuously increasing due to several reasons. One of these reasons is an increasing number of electrical home appliances in the average household. As a result, there is a need to manage energy usage patterns to reduce electricity costs and demand on the grid. At present, this is achieved solely through resident self-awareness with some incentives provided through different pricing models. HEMSs provide the capability to more efficiently and proactively implement such management strategies. Most previously discussed HEMSs have been designed based on one of several pricing models to implement a robust scheduling algorithm used for optimising home energy management [106]. The use of different pricing models has been proposed in many HEMSs. In [52, 107, 108], TOU pricing was proposed, which consists of time varying electricity prices, such as on-peak, moderate-peak and off-peak times. This type of electricity pricing is provided by the utility to encourage customers to shift their loads from on-peak to less expensive moderate- or off-peak times, producing a reduction in overall peak hours load on the grid and leading to reduced greenhouse gas emissions. Another pricing scheduling scheme reported in several papers [109-111] is a real time pricing model (RTP) that is suitable for controlling home appliances directly based on changeable pricing signals provided by the utility; pricing typically varies according to the current real-time level of overall grid demand. In [112], the authors proposed a fully automated approach, called a direct load control (DLC) technique, to control the power consumption of home appliances. This DLC control technique allows the utilities to control home appliances by connecting or disconnecting the selected appliances when the prices go high or during peak demand without user interaction. In [50], Huang, et, al. suggested a HEMS that combines the DLC control load technique with interruptible load management to avoid peak load and power interruption, which may occur and cause inconvenience to the customer. Pengwei and Ning suggest using the RTP model and predictions of power consumption by appliances for the next day to meet the requirements of maintaining the level of consumer comfort while minimising the electricity bill. Peizhong et al. suggest using the RTP scheme with a random device priority and different waiting times to minimise household electricity bills. In [23, 113, 114], the authors proposed combinations between two different pricing models (i.e., the RTP and IBR pricing models), which are used to give incentives to consumers to reduce overall power consumption and minimise the cost of energy. Furthermore, there are a number of other pricing models, such as day ahead pricing (DAP) and critical-peak pricing (CPP), that are also used by utilities to motivate consumers to shift their loads to off-peak hours to reduce peak demand [113, 115]. In [116, 117] the authors proposed a framework considering forward contracts and varying electricity prices including flat, TOU and RTP pricing schemes that incorporates demand response in Distribution Companies' short and medium-term decision making to maximize the utility profit, while the same authors in [116], proposed the mathematical formulation of the system-wide demand response management model to minimise the energy monetary expense from the user side.

These works do not, however, consider a multi-user usage case and also do not really consider issues of user acceptance. In this chapter a HEMS model is presented that uses a heuristic algorithm to manage and control home appliances accounting for individual user preferences as well as external signals. The main new contributions in this chapter are 1) this chapter presents a multiple users and load priority (MULP) algorithm that is used to develop a demand response strategy that will accommodate multiple users sharing the same home and its appliances in order to generate a single load priority for all users, 2) the full influence of dynamic energy price awareness on the HEMS approach is analysed, 3) the use of TOU pricing with different demand load levels is investigated while considering multiple users and dynamic energy price awareness, 4) the impacts of the mentioned electricity price schemes is evaluated on the user side, rather than the utility's side, 5) most significantly the proposed HEMS algorithm accounts for user acceptability by seeking to control the controllable loads with least influence on the users' life styles. This final point is considered of great significance as a distributed home energy management system is only useful if it is adopted by a significant proportion of users.

4.3 Load Classification

Typical residential hourly loads profiles are available for most home appliances from the RELOAD database; these profiles are regularly used by the Electricity Module of the

National Energy Modelling System (NEMS). These data are available for various day types (i.e., weekday, weekend and peak day) over the period of one year. In this chapter, loads are categorized into two groups as shown in Figure 4.1. The first group is comprised of controllable loads that can be contextually controlled without significant impact on the consumer's life style, which include space cooling/heating, water pump, water heating, dishwashers, electric vehicles and clothes dryer. The second group is comprised of loads that either cannot be controlled (non-controllable) or very important loads (critical). These include all other loads in a house, such as lighting, refrigeration, cooking, entertainment appliances and other general loads. In addition, some of loads (i.e., EV and some entertainment appliances) are calculated based on estimation as these type of loads are not represented in the RELOAD database [118]. These comprise a small portion of, around 1.1%, of the overall load, the loads are estimated based on how many hours per day these appliances run and power usage. Table 4.1 shows an example of the load priority list including consumers' preferences, which can be significantly different from one user to another and between summer and winter. These preferences are assumed based on the possible range of comfort level settings that can be specified for each appliance.

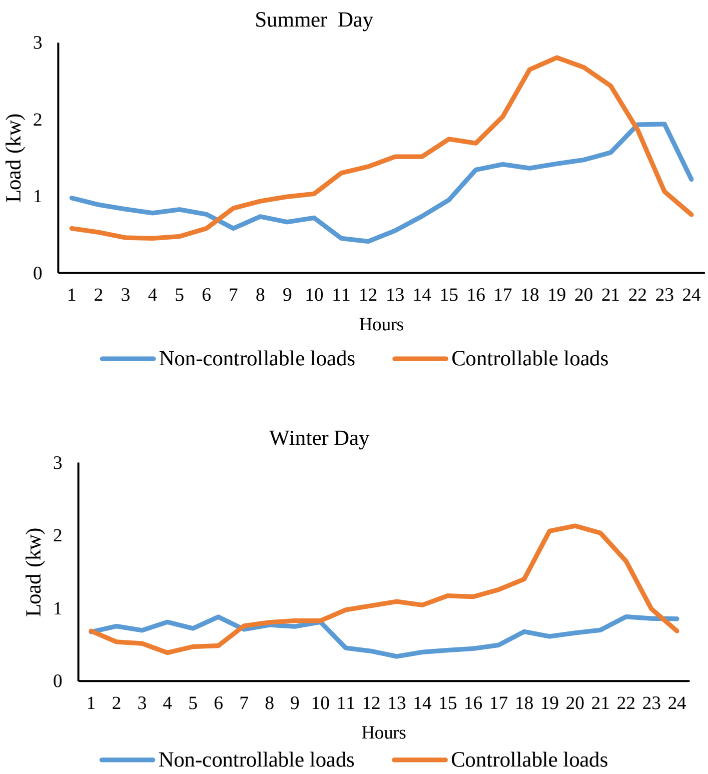


Figure 4-1: The load curve in summer and winter season.

Table 4-1: Sample of priority list

Summer season			Winter Season		
Appliance	Priority	Range of Users Preferences	Appliance	Priority	Users Preferences
Cooling	1	Room temperature: 24 - 26°C	Heating	2	Room temperature: 26 - 29°C
Dishwasher	3	Water temperature: 38- 48°C	Dishwasher	5	Water temperature: 38- 48°C
Water Pump	4	Water level: 75-100%	Water Pump	7	Water level: 75-100%
Clothes Dryer	6	Max OFF time: 30 min Min ON time: 30 min	Clothes Dryer	3	Max OFF time: 30 min Min ON time: 30 min
Electrical Vehicle	5	Max SOC 100 % Min SOC 50%	Electrical Vehicle	6	Max SOC 100 % Min SOC 50%
Water Heater	7	Water temperature: 38-43°C	Water Heater	1	Water temperature: 43- 49°C

4.4 HEMS models and architectures

The aim of the HEMS model is to minimise the cost of energy usage at home while causing the least comfort degradation for consumers. This model uses two groups of loads as described in section three. These loads accommodate consumer demands at times when electricity usage is less expensive according to different utility electricity prices and control signals or different DR programs. In this regard, one of the objectives when applying DR programs is to reduce the stress on the grid resulting from higher demand peaks and delay the necessity for investments in grid capacity. Several ways can be used to determine the demand limit levels allocated to different homes. Demand limit levels could be adaptable and can change in real time using time-variable electricity price signals, real-time electricity usage or other utility-defined factors. For this purpose, the authors developed the algorithm for home energy management and demand response presented in [43]. This algorithm aims to minimise the energy expenses of the consumers by optimising the operation and energy consumption for each appliance to less expensive hours according to the TOU tariff in conjunction with different demand limits, which are received from the utility as signals. The following subsections describe the HEM system models and problem definition.

4.4.1 Multiple Users and Load Priority (MULP)

The advent of home energy management is developed from the concept of ubiquitous computing in an indoor environment with a goal to provide consumers with sufficient comfort by running the fewest number of household appliances possible at the same time. To achieve better acceptance, performance and a sufficient level of consumers' comfort, several important factors should be considered for any home energy management system. These factors include the number of inhabitants living in a single house and the acceptable range of their preferences with regard to room temperature, water level, maximum and minimum charging of an EV battery, water temperature used by a dishwasher, preferred water temperature range produced by the water heater, and the acceptable time to turn ON/OFF a clothes dryer. These types of appliances can be controlled without significant influence on the consumer's everyday life. Table 4.1 shows an example of the default load priority list with their preferences, which can be significantly different from one user to another and between summer and winter.

The MULP scheme has been designed to be a very simple model that is used to organize and schedule the list of load priority in advance and to choose the preferred starting and ending times to run specific appliances. Used with multiple users, sharing a house and its appliances, this model can provide significant cost reductions without violating consumer comfort by avoiding conflict requests between users and can ensure that every user's request is processed within a certain time window according to the load priorities that were listed in advance. The MULP algorithm scheme works as shown in Figure 4.2. This algorithm can be divided into two main parts, the first part shows the way of creating a new priority list obtained from different users, while the second part focusses on which appliance could be shifted or switched off during peak hour based on the consumer preferences settings, if no appliances are in the range of preferred settings then the MULP algorithm will shift or switch off a certain appliance based on the priority list created in advance.

In each time interval, the MULP algorithm starts by gathering information from three different inputs. Firstly, user input includes the load priority of each user and their preferences. Secondly, control signals and demand limits are provided by the utility. Finally, the power consumption of all appliances and the controllable loads status are collected by the HEMS controller through different sensors. The MULP algorithm then creates the priority list for different situations. The first case priority allows all users U_I to accept the default priority list *DPlist*, which is done in advance, negating the need for a new priority list. Secondly, a new priority list *nPlist* will be created if the majority of users have the same requests so that if more than one user requests the same appliance a_i, then the MULP will adopt this request if it is not repeated in the last period of time; this avoids ignoring any other user's request. In the third case, if different users request different appliances, then the algorithm will check each user's request and compare it with the default priority list. For example, if three users request to run different appliances (e.g., the dishwasher, air conditioner and water pump), the algorithm will compare their requests to the default priority list to decide which one has the highest priority; once one of these requests is determined to have the highest priority, the other users' request will move to the next time request to ensure that all requests are served but not repeated. Once the MULP algorithm completes a new priority list, the HEMS can make decisions to either shift or switch off certain appliances based on different consumers' preferences whenever power consumption exceeds the demand limit. If all controllable loads are working in the consumer's preferred range when the total power consumption exceeds the demand limit, the MULP algorithm will ignore the preferred consumer range and start switching off or shifting the lowest priority appliances until the total power consumption drops below the demand limit. However, the algorithm will switch off the appliances whenever a certain appliance drops below the minimum preferred range. Therefore, The MULP algorithm will manage and control the loads dynamically in a real time.

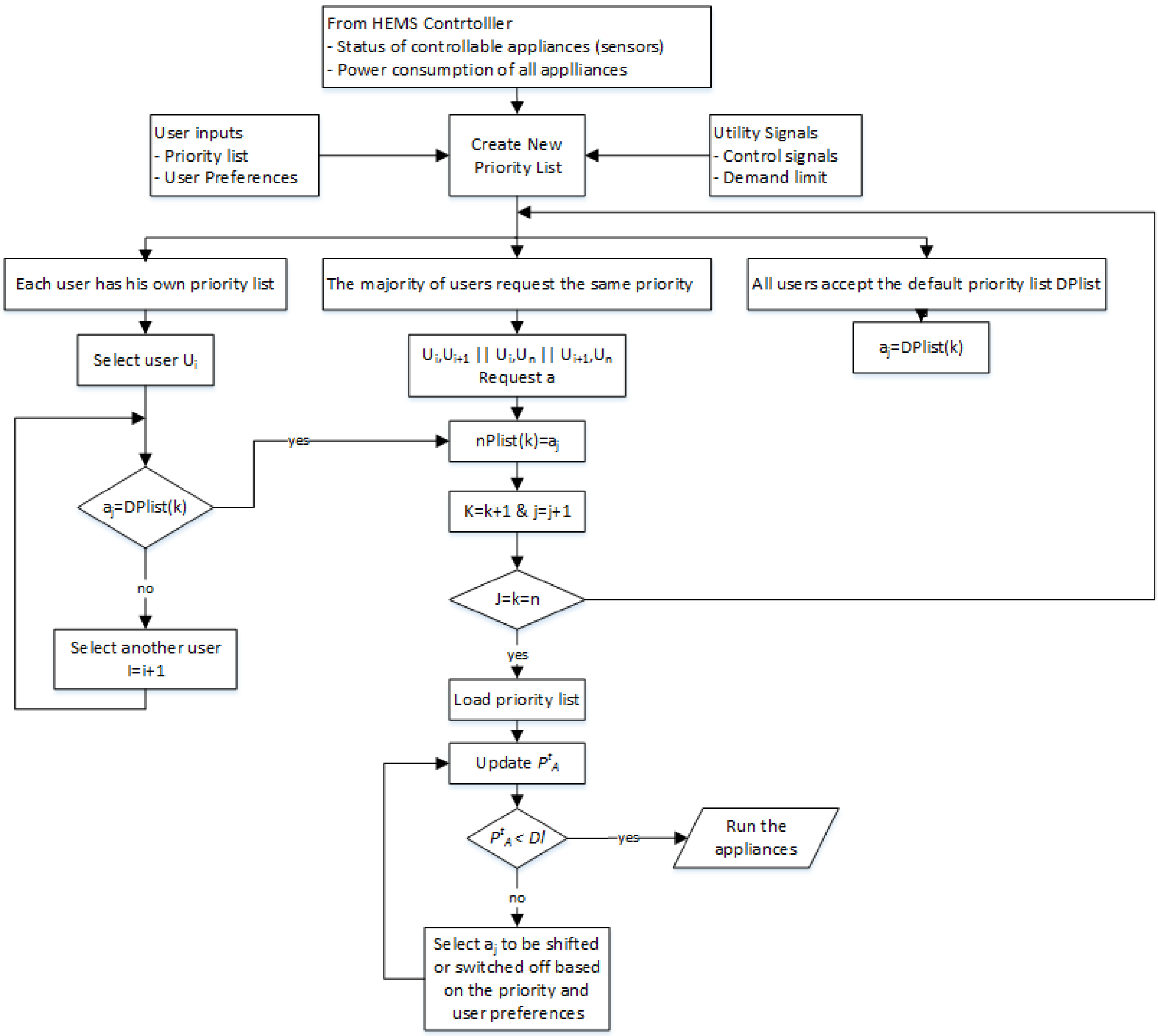


Figure 4-2: Multiple users and load priority (MULP) algorithm

4.4.2 Residential Consumers Model

As mentioned in section three, different types of home appliances can be found in most houses, including air conditioners, heaters, cooking, entertainment, washing appliances and many other appliances. Considering a, which denotes an appliance, and A, which denotes a set of appliances, the energy consumption scheduling vector P for each appliance $a \epsilon A$ can defined as follows:

$$P = [p_a^1, p_a^2, ..., p_a^T] \tag{4.1}$$

where p_a^t denotes the energy consumption scheduling of the vector P in the $t \epsilon T$ scheduling horizon. For instance, if T=12, 24 or 48 hours, then t could be any time unit between [1,...,T], which is scheduled for p_a^t. The resolution of the scheduling horizon can be hours or minutes depending on the utility signals that are received in that time; these may include electricity prices and demand limits. Considering that mxE_a, mnE_a denote the maximum and minimum energy consumptions, respectively, for *a ϵ A* in time unit *t ϵ T*, where S_t and E_t indicate the start and end operations for the specific appliance *a* in the scheduling horizon *T* and $S_t < E_t$ always, then:

$$p_a^t = 0 \quad \forall \begin{cases} t < S_t \\ t > E_t \end{cases} \tag{4.2}$$

where p_a^t is defined as the real energy consumed by the specific appliance *a*, which is always $p_a^t \le mxE_a$.

For example, a user may want to run the clothes dryer between 4 PM and 7 PM, which is referred to as the start and end times, respectively, and drying clothes using the heater in *t* time unit with maximum mxE_a or minimum mnE_a energy when the clothes dryer is switched off. Another example is when the water heater may run at a maximum energy consumption mxE_a to raise the water temperature to a desired degree, while the energy consumption may reach the minimum mnE_a in *t* when the water temperature goes above or equals the pre-set degree. Therefore, E_a denotes the actual energy consumed by appliance *a ϵ A* in time unit *t ϵ T*:

$$E_a = \sum_{t=S_t}^{E_t} p_a^t \tag{4.3}$$

In addition, the power utility usually imposes a limit on the total energy consumption in each *t* time unit for the each residential unit; this demand limit is denoted as Dl_A^t:

$$\sum_{a \in A} p_a^t \le Dl_A^t \tag{4.4}$$

Therefore, from both constraints presented equations 4.2 and 4.3, the scheduling of appliances can be defined as follows:

$$E^t = \sum_{a \in A} p_a^t \forall p_a^t \le Dl_a^t \qquad p_a^t = 0 \quad for \quad t < S_t \; and \; t > E_t \tag{4.5}$$

4.4.3 Time of use pricing model (TOU)

In the TOU pricing model, a day is divided into different time slots that have varying prices for electricity consumption. All TOU tariffs will be used in different days and seasons. The purpose of this model is to minimise the total cost of electricity usage at home. Although home appliances consume the same amount of energy regardless of the time the appliances are switched on, the hours when appliances are used affect the cost of energy due to TOU tariffs; this contrasts to a flat rate pricing model where electricity prices are fixed. Therefore, the function of hourly cost of the energy consumption for all home appliances $C_A^t(p_A^t)$ relies on different parameters as presented in equations 4.6 and 4.7.

$$C_A^t(p_A^t) = \begin{cases} b_1 \quad p_A^t \quad \forall \; on-peak \\ b_2 \quad p_A^t \quad \forall \; off-peak \\ b_3 \quad p_A^t \quad \forall \; shoulder \end{cases} \tag{4.6}$$

where *b1, b2 and b3* are the prices for the on-peak, off-peak, and shoulder time slots, respectively. However, the power utility usually imposes a limit on the total load demand for each household during peak hours. When the total energy consumption of household appliances exceeds the given load limit during peak hours, as formulated in equation 4.7, electricity tariffs are increased or the home power network cuts power, harming consumer comfort. Due to these issues, the TOU algorithm using equations 4.6 and 4.7 in conjunction with the MULP algorithm allows the users to make a decision to avoid increasing their electricity bills by shifting the lowest and unnecessary controllable loads into off-peak hours by considering all users' load priority as presented in Algorithm 1:

$$C_A^t(p_A^t) = \begin{cases} b_n \quad p_A^t \geq Dl_A^t \quad \forall \; on-peak \\ b_2 \quad p_A^t \quad \forall \; off-peak \\ b_3 \quad p_A^t \quad \forall \; shoulder \end{cases} \tag{4.7}$$

where b_n represent the new tariffs when the total energy consumption exceeds the demand limit Dl_A^t.

Algorithm 1: Scheduling for TOU with energy limit

If $(p_a^t \ is \, in \ peak \, and \ \ p_A^t \geq Dl_A^t)$
  load priority list
  While ($p_A^t \geq Dl_A^t$)
    $p_a^t \leftarrow Plist_a^t$
    If $(U_I \quad accept \, shifting \ p_a^t)$
      $p_a^t \rightarrow Shift \, to \ off\!-\!peak$
      $C_A^t(p_A^t) = (p_A^t - p_a^t) * b_1$
    Else if $(U_I \quad accept \, switching \, off \ \ p_a^t)$
      $p_a^t = mnE_a$
      $C_A^t(p_A^t) = (p_A^t - p_a^t) * b_1$
    Else
      $C_A^t(p_A^t) = p_A^t * b_1$
    End
    $i = i + 1$
  End while
Else if $(p_a^t \ is \, in \ peak \, and \ \ p_A^t < Dl_A^t)$
    $p_a^t = mxE_a$
    $C_A^t(p_A^t) = p_A^t * b_1$
    If $p_a^t = preset \ \ point$
      $p_a^t = mnE_a$
      $C_A^t(p_A^t) = (p_A^t - p_a^t) * b_1$
    Else
      $C_A^t(p_A^t) = p_A^t * b_1$
    End
Else if $(p_a^t \ is \, in \, shoulder)$
    $C_A^t(p_A^t) = p_A^t * b_3$
Else
    $C_A^t(p_A^t) = p_A^t * b_2$
End

4.5 Simulation and Results

A simulation tool has been developed in MATLAB to design the HEMS simulation platform based on different DSM programs. The HEMS simulation platform has been designed to work as a dashboard to simulate a household environment to provide customers the ability to manage, control and monitor the household appliances. For example, consumers can monitor appliance status, such as room temperature, water level, clothes dryer status and water temperature, total power consumption, create load priority list and consumer preference based on multiple inhabitants sharing a home and its appliances, demand limits and different pricing models. All facilities provided by the HEMS platform can be used to provide the consumer with the ability to compare different demand programs and select a suitable program to reduce overall power consumption and minimise costs, which will also result in the reduction of greenhouse gas emissions.

To illustrate the performance of the HEMS algorithm in terms of managing and controlling the household appliances, a case study with two different scenarios are used to compare the results that are obtained by applying different DSM programs.

4.5.1 Case study

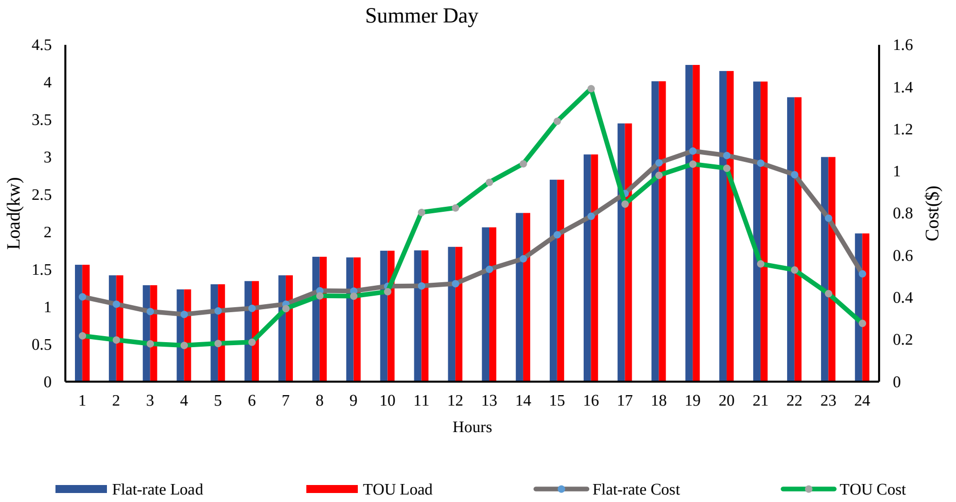
4.5.1.1 Scenario 1

In this scenario, a TOU tariff that is provided by Electricity Retail Corporation in Australia is considered. In this model, a day is divided into three time slots that have varying prices for electricity consumption based on different times during a day. These time slots include off-peak, on-peak and shoulder periods, as shown in Table 4.2. Different TOU tariffs are used in different days and seasons. There are typically two types of days (e.g., a weekday and a weekend day), while a year is considered to have two different seasons: summer, which is extended into autumn; and winter, which is extended into spring. The purpose of this model is to minimise the total cost of electricity usage at home. Figure 4.3 shows the influence of using the TOU pricing model, saving the consumer more in electricity bills than if a flat rate tariff were used; the results show that the consumer can save about $1.13 (8%) daily in the summer while only about $0.16 (1.6%) daily in the winter, while the power consumption remains the same in all time slots because no action was taken to switch off some appliances or shift unnecessary loads to a less expensive time period. However, the electricity prices during peak hours in TOU pricing are shown to be significantly higher than those when using flat rates in the same periods; this is likely caused by a need to control electricity usage during this period. Therefore, using TOU pricing with other parameters including demand limits and scheduling based on priority and consumer preferences for multiple inhabitants sharing the same house could minimise energy costs and reduce total power consumption of household appliances.

Table 4-2: Time of use rates

Weekends all Year Around		
Type	Time	Cost (c/kWh)
Shoulder	7 am to 9 pm	20.6459
Off-peak	9 pm to 7 am	13.9737

Summer weekday		
Off-peak	9 pm to 7 am	13.9737
Shoulder	(7 am to 11 am) and (5 pm to 9 pm)	24.4481
On-peak	11 am to 5 pm	45.8784
Winter weekday		
Off-peak	9 pm to 7 am	13.9737
Shoulder	11am to 5 pm	24.4481
On-peak	(7 am to 11 am) and (5 pm to 9 pm)	45.8784



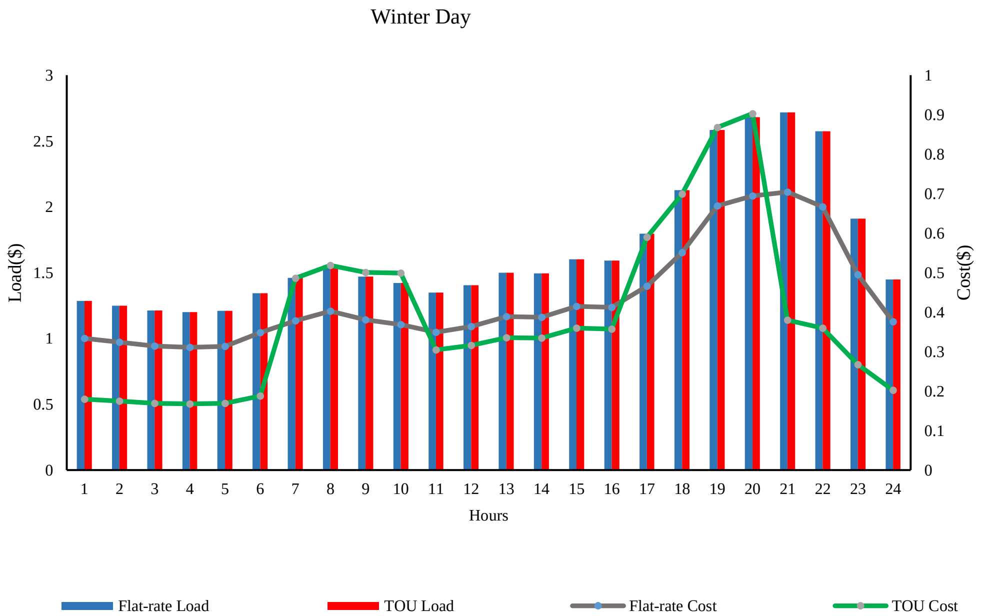


Figure 4-3: The impact of using TOU on power usage and cost reduction

4.5.1.2 Scenario 2

In this scenario, to enhance the performance of the HEMS algorithm, several actions will be considered based on different parameters added to the previous scenario. These parameters include demand limit and MULP in conjunction with the TOU pricing model, which has been described in the previous section. In this scenario, three users sharing a house and its appliances are considered while the shifting technique is used to shift unnecessary loads from on-peak to a less expensive period to minimise electricity costs. For this purpose, different demand limit levels (e.g., 1.5, 2, 2.5 and 3 kW in the summer and 0.9, 1.1, 1.3 and 1.6 kW in the winter) are assumed to be fixed during peak hours in both seasons, while there is no need to apply shifting loads during weekends because no peak period exists on weekends. The reason behind the different demand limits in the summer and winter are due to the differences in daily energy consumption in both seasons. For the same purpose, the electricity cost of 48 cents/kWh) is assumed to be a new electricity tariff when the energy consumption exceeds the energy limit during peak hours. The flexible design of the HEMS platform has the ability to provide consumers with different options to reduce daily energy consumption of their household appliances and electricity cost. For example, when the HEMS platform receives requests from the consumers to run their appliances, the HEMS algorithm begins organizing the household appliances scheduling by create the priority list. In this case, the controllable load category is considered, including a dishwasher, clothes dryer, water pump, water heater, electrical vehicle and space cooling/heating loads. In addition, users can also enter pre-set preferences, such as room temperature, water heater temperature or a water level set point. While the HEMS algorithm can read the current status of these appliances through several sensors deployed in the house or built into these appliances, a random function was created to generate different values which can be used as inputs to the system instead of sensors; the HEMS algorithm then compared these values with the consumers' preferences to decide which appliance will be switched on/off; note that shifted loads to a less expensive period. The random function is carefully designed to generate these values based on logical ranges of values. For instance, random values of room temperature will be generated between 22°C and 29°C during a day and between 18°C to 26°C during the night in the summer; the water temperature used in the winter was chosen to be between 38°C and 49°C.

Then, the HEMS algorithm calculates the total amount of energy consumed and the energy cost according to the TOU tariffs for different time periods. These calculations consider the demand limit and new electricity tariffs when the total energy consumption exceeds the selected limits during peak hours. Once all calculations are complete, the HEMS algorithm will send the consumers a message that details how much they will have to pay after shifting their energy usage to off-peak hours and how much they will have to pay if they decide to proceed to run these appliances during peak hours with a new electricity tariff. If the consumers accept shifting their loads, then the HEMS algorithm will decide which appliances should be shifted to less expensive periods to keep the total energy consumption below the demand limit. Decisions are made based on the priority list that has been created by the MULP algorithm.

By running this simulation, several comparisons between different DR programs have been conducted. The differences in the daily energy cost between the previous programs are also presented in Table 4.3. The cost when using TOU pricing with different demand limits and scheduling appliances to off-peak or shoulder hours using the MULP algorithm is shown to be lowest compared to TOU pricing without scheduling. In addition, by applying different energy demand limits, lower demand limits are shown to minimise daily energy costs. Figure 4.4 shows the influence of different demand limits on the shape of daily energy consumption after shifting loads to less expensive periods. At a 1.5 kW limit, most loads are shifted to off peak (i.e., between 17 pm and 11 pm), while at a 3 kW limit, the energy consumption is similar to the original energy consumption because the loads during on-peak hours did not exceed the demand limit. Choosing a lower demand limit may also have a negative influence on both consumer's comfort and the distribution and transformer network because consumers shifting their loads to off-peak hours when these loads exceed the demand limit may create a new on-peak period during currently off-peak hours. Conversely, choosing a higher demand limit that is either equal to or above the current energy usage may have no significant influence on the electricity usage and cost. Therefore, the demand limit should be carefully chosen.

Furthermore, to illustrate the effect of the MULP algorithm combined with switch-off and load-shift techniques on reduction of both power consumption and costs, this algorithm was examined using TOU alone and TOU with demand limit. Figure 4.5 shows that the household electricity usage over a 24 hour period remains the same when applying the TOU model with or without an imposed demand limit, while scheduling the electricity usage at home using the combination of switching-off and shifting loads in the MULP algorithm with TOU pricing reduces the overall power consumption by about 11.8% during peak hours from11am to 5pm in a summer day and about 7.8% from 7am to 11am and 5pm to 9pm in a winter day, while Figure 4.6 shows that the savings in the consumer's electricity bill in both seasons is significantly increased by about 22% and 14% in summer and winter days respectively, compared with TOU without scheduling. No significant further improvement in energy reduction is achieved when a demand limit is added in conjunction with TOU when the using MULP algorithm with DSM techniques, highlighting the degree of optimisation achieved.

Table 4-3: Daily energy cost savings in the summer and winter using TOU and TOU with DL and MULP

	TOU	TOU with DL & MULP				
		DL (kW)	1.5	2	2.5	3
Summer	Daily savings ($) = 1.135	Daily savings ($)	2.003	1.50	1.313	1.15
		DL (kW)	0.9	1.1	1.3	1.6
Winter	Daily savings ($) = 0.165	Daily savings ($)	2	1.597	1.347	0.915

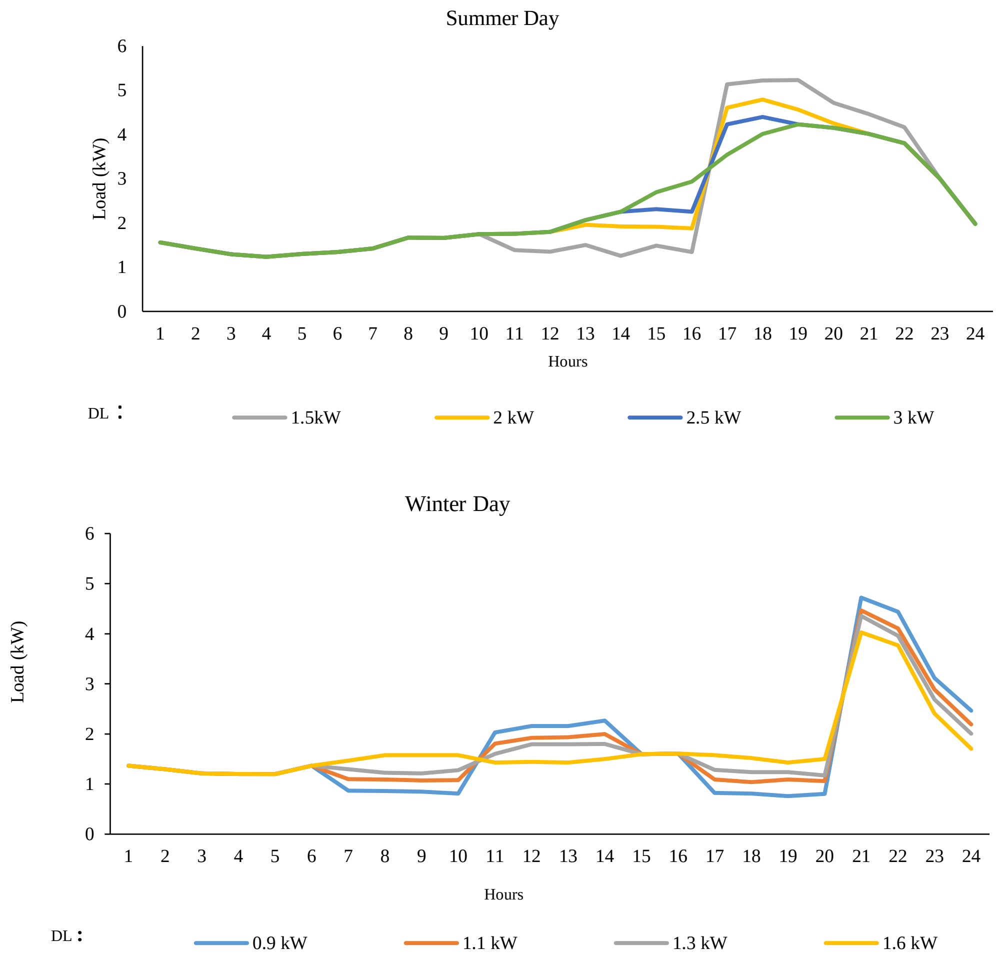
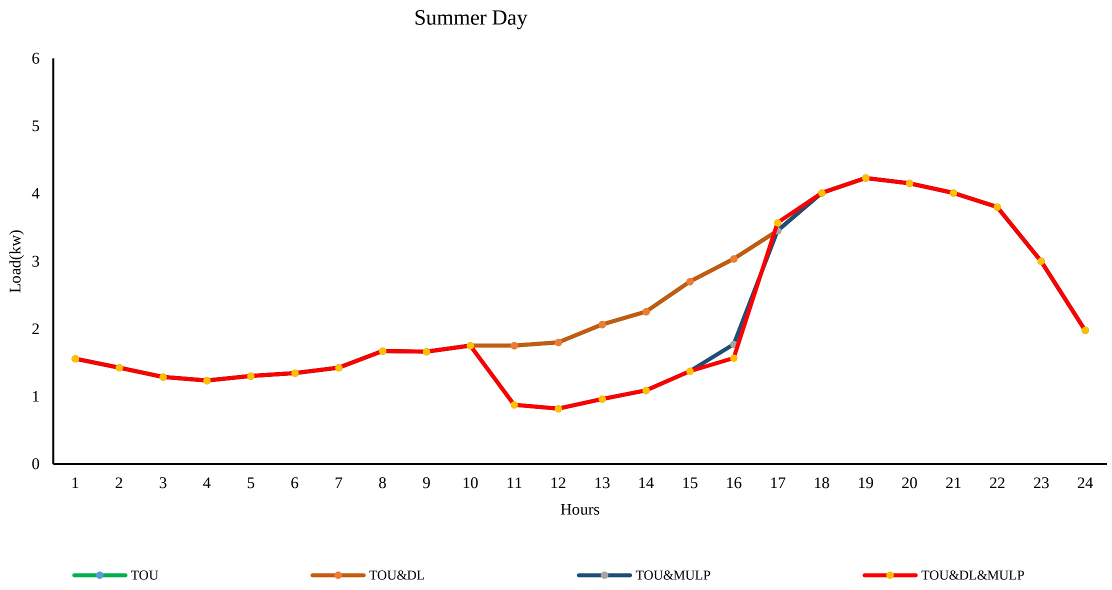


Figure 4-4: Influence of shifted loads based on DL set



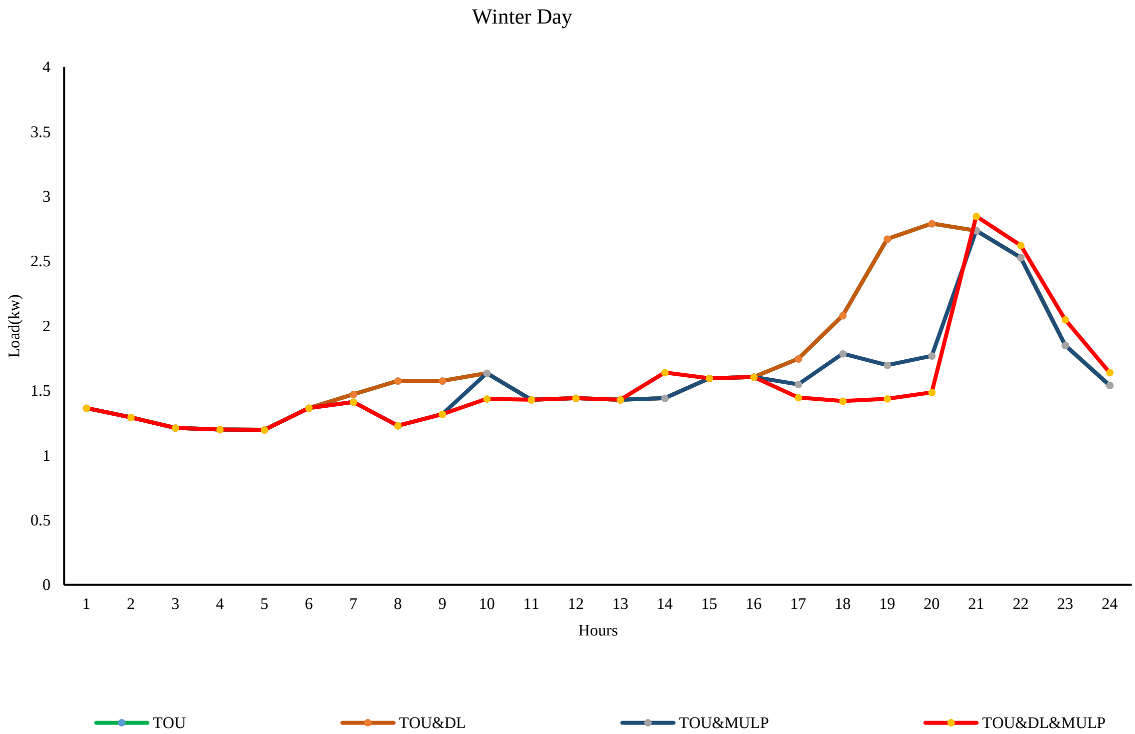
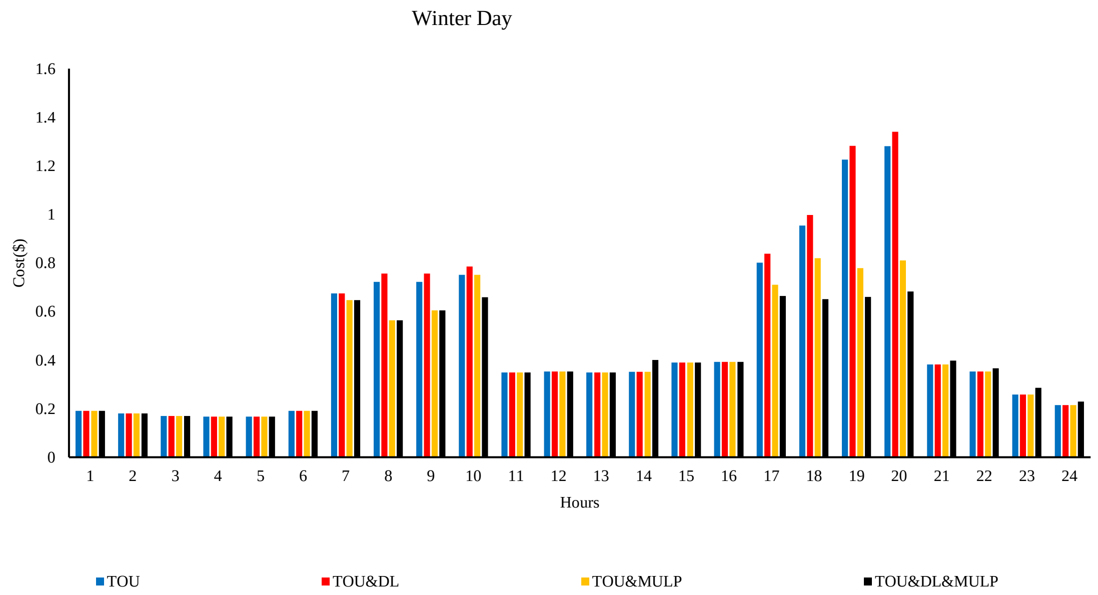


Figure 4-5: The impact on power consumption of using TOU, demand limit and MULP combined with the load shifting and switching-off management technique



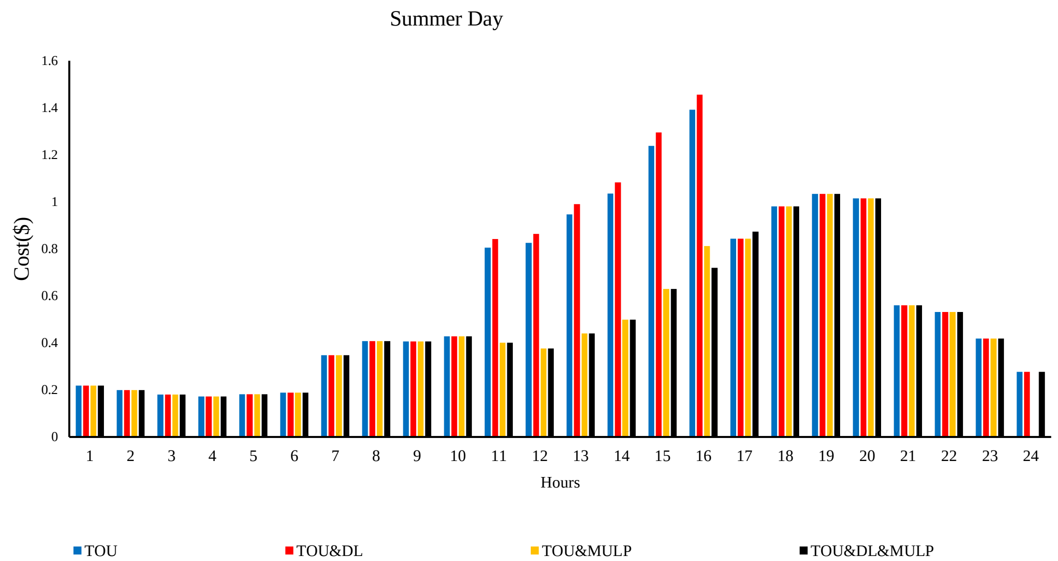


Figure 4-6: The impact on daily energy costs of using TOU, demand limit and MULP combined with the load shifting and switching-off management technique

4.6 Conclusion

In this chapter, a smart HEMS algorithm has been presented that aims to reduce overall usage and cost of energy without significantly degrading consumer comfort. This algorithm can be used in home/building energy management systems to help users automatically create more optimal load operation schedules based on TOU pricing models, different priorities and comfort settings; the system can also be used to compare the costs associated with different schedules. To evaluate the performance of the HEMS algorithm, different scenarios were examined to compare the results obtained by applying different DSM programs. This comparison evaluates which DSM program produces better results for home energy management, particularly with regard to environmental and economic issues.

Although TOU pricing has several potential advantages, the benefits of using this pricing model are currently limited due to several issues, including a lack of efficient home automation, user difficulty in manually managing power usage with time-varying prices, which reflects the lack of consumer's knowledge, and the number of inhabitants sharing a home and its appliances. Therefore, in this chapter, an automatic residential energy management system has been introduced that aims to achieve a trade-off between minimising electricity costs and the total energy consumption based on different users' load priorities and comfort settings. This study examined a scenario with TOU pricing combined with different demand limits where the HEMS algorithm controls some loads to keep the total energy consumption under the limit during peak demand; this system requires less effort from consumers, which is beneficial. The proposed algorithm effectively enables several inhabitants sharing a home to easily manage and schedule their requests in terms of priority and preferences. Simulation results show that the combination of the MULP algorithm and the TOU pricing model leads to significant reductions in user payments and total energy consumption (of the order of 10%). This achievement encourages consumers to participate in the HEM system to manage and control their energy loads in an efficient way. Furthermore, the results also show that the reduction of total energy consumption, particularly during peak demand periods, can produce incentives for power utilities to support HEM systems.

The focus of this work has been for Australian conditions, the algorithm developed can easily be adapted to suit conditions in any other context. The next chapter focusses on developing and applying the mathematical models of residential energy usage and management based on real time pricing (RTP) that can easily be integrated into automated decision making technologies, such as HEMSs, in the context of Smart Grids. These models are used to generate the optimal operational schedules for household appliances (e.g. controllable and non-controllable loads), and energy storage systems (ESSs) including batteries and plugin electric vehicles (PEV).

5 Chapter 5: An Intelligent Control Algorithm for a Home Energy Management System Incorporating Short-Term Energy Storage Based On Demand Response Constraints And Real-Time Pricing Signals

5.1 Introduction

Emerging smart grid technologies have the potential to improve the efficiency and reliability of urban power system based on information gathered regarding the dynamic status of both the end users and energy suppliers. The roll out of smart meters working in conjunction with other smart grid technologies can improve electricity supply services and support different demand response programs. Moreover, the recent rapid developments in smart home appliances and the Internet of Things (IoT) enable both utilities and consumers of energy in residential or commercial sectors to take advantage of this “smart grid”. These technologies give the end users access to real time information about their energy use. This information can induce customers to reduce their loads during periods of critical grid conditions or periods of high electricity prices. Encouraging individuals to reduce their energy footprint is becoming ever more important due to growing concerns relating to global warming. Additionally, energy costs have increased dramatically due to inefficient energy generation and growing energy demand, creating further need for households to find ways to constrain their energy usage.

Looking for alternative renewable energy resources such as solar panels or wind turbines is becoming an ever more important factor to drive reductions in greenhouse gas emissions. However, the wide scale use of renewable resources within the grid creates major challenges due to varying weather conditions, which can significantly affect solar or wind power sources and put more pressure on the grid. This is of particular concern during peak periods when the renewable resources cannot be relied on to meet demand leading to a necessity to improve the capacity of traditional power plants if power outages are to be avoided, resulting in higher carbon emissions. The high cost of installation and maintenance of power plants also puts further upward pressure on already high energy prices and can create an unaffordable situation for both customers and suppliers [113, 119].

One possible strategy to address these challenges is to incorporate short-term energy storage systems (e.g. batteries and/or plug-in electric vehicles) into households along with a sophisticated home energy management strategy to help to control the electricity demand and mitigate the pressure on the grid during periods of peak demand. Energy storage devices such as batteries are expected to start being installed in most modern houses in the near future, particularly when solar generation capacity is also present, due to rapidly falling costs and immediate benefits. However, attempting to maximise the benefits given the diversity of household loads, general lack of consumer knowledge, diversity of automation and monitoring technology, and different mixes of renewable and grid supplied energy results in a large and complex combinatorial problem. Presently, energy savings through this kind of strategy can only be achieved via resident self-awareness along with some incentive programs provided by the energy suppliers such as time dependant electricity pricing. Given this, significant improvements can potentially be realised through the implementation of a smart Home Energy Management System (HEMS) that can provide an automated decision making capacity based on data gathered through connection to appliances and the smart grid.

This chapter presents an intelligent HEMS algorithm that manages and controls a range of household appliances with different demand response (DR) by prioritising multiple users with preferred usage patterns in an automated way without the need for consumer intervention. The proposed algorithm focuses principally on control strategies for controllable loads (high power consumption loads) including space cooling/heating, dishwasher, clothes dryer, water heater, water pump and electrical vehicle, as these loads represent the highest residential energy consumption and provide the greatest opportunity for optimisation. In this work, to increase the efficiency and reliability of the proposed HEMS model, a short-term storage system including battery and/or Plug-in Electric Vehicle (PEV) battery has also been incorporated. Two different scenarios are implemented to develop and test the influence of controlling and scheduling these loads with different combinations of available energy storage on energy consumption, energy cost and carbon footprint. An emphasis is also placed on minimising impacts on consumer comfort to reduce potential barriers to widespread adoption.

5.2 Related Work

The objective of any HEMS is to provide the capability to efficiently and proactively implement energy management strategies. Previously proposed HEMSs have implemented a number of different strategies to help customers manage their electricity consumption and cost in smart and efficient ways [18, 43, 111, 120-123]. These strategies are used to achieve more optimal energy management by applying different demand response programs, distributed energy resources, and advanced hardware and communication technology. In [43, 123], the authors presented a HEM control strategy to manage the high power consumption category of household appliances according to pre-set consumer preferences and keep the household power consumption below a certain level by shifting these loads to another time slot without considering the energy prices. The authors in [121], developed an optimal dispatching model of smart HEMS with intelligent home appliances based on TOU pricing and different energy sources to minimise the energy expense while maintaining living comfort. Similarly in [111], Son et al. suggested a smart HEMS based on a historical power consumption data to control appliances, where the house is equipped with renewable energy sources alongside the grid, and information are exchanged between the HEMS controller and the utility company via power lines and a smart meter.

Another HEM system is presented to manage and control various home appliances based on gathered information through a PLC Power Controlled Outlet Module (PPCOM) [18]. To improve consumer awareness of energy management strategies, the authors suggested another approach to control their appliances based on information gathered from different customers in real-time by the utility companies. The utilities offer this information to allow customers to compare their own electricity usage to that for the same kinds of home appliances of other customers or neighbours to encourage them to minimise their energy consumption and see how efficient these appliances are [122]. The authors in [124], proposed a mathematical formulation of the system-wide demand response management model to minimise the energy cost from the user side. It is designed to generate the schedule of the daily load profile of home appliances based on the electricity price signals and the information exchanged between the home load management (HLM) and the utility. This operation is continued between the HLM and utility side until there is no further improvement and then the home load profile is generated.

In [125], the authors proposed mathematical optimisation models for residential energy hubs. These models are designed to be incorporated into automated decision making technologies in the smart grid to control the major residential loads in real time. While Hubert et al. suggested a similar work, an energy optimisation algorithm to schedule and control residential loads based on dynamic energy price signals (e.g. whenever the prices of biofuel increase above a certain level, the turbine or energy storage can be scheduled to supply the loads) [126]. A similar work has been presented by the authors in [127], this work focussed more on the development of the appliance level loads and conventional controllable loads such as space cooling/heating, water heater, clothes dryer and PEV. Scheduling these appliances by keeping these loads under a certain load level without considering the electricity prices and not exploiting the PEV as available energy storage. In [128], control strategies for some of the highest power consumption category loads have been presented by the authors. This work aimed to effectively balance between maintaining consumer comfort and minimising the energy expense by controlling the household appliances including, air-conditioner/heater and water heater in a simulated real-time pricing environment. An appliance commitment algorithm has been developed by the authors in [109], this algorithm is used to schedule the thermostatically controlled appliances (TACs), such as a water heater, based on electricity price signals and forecasted usage of hot water.

In [23, 114], the authors proposed combinations between two different pricing models (i.e. the RTP and inclining block rate pricing models), which are used to give incentives to consumers to reduce overall power consumption and minimise their cost of energy. Unpredictable wholesale energy prices and several other factors (e.g. weekend, weekday and holidays) makes controlling residential loads in a RTP environment challenging, because of that, in [113], the authors proposed a control strategy in a real time environment based on the historical electricity prices. Shahgoshtasbi et al. suggested Neuro and Fuzzy paradigm techniques to develop an intelligent energy management system (iEMS) algorithm. It was designed to find the effective and efficient energy consumption by scheduling the residential loads according to the dynamic price signals and consumers' preferences [129]. A three steps control strategy has been presented by the authors in [25], these steps are, set a plan of household operation in advance based on a prediction of load profile including different energy sources (e.g. grid, renewable and energy storage system), then control these appliances in real-time in order to reduce the demand during peak period.

All the previous related works have mostly focussed on the consumer prospective, while, in [116, 130], the authors focus more on maximising profit for the utility rather than the consumer. This is achieved by proposing a framework considering forward contracts and varying electricity prices including flat, TOU and RTP pricing schemes that incorporates demand response in distribution companies' short and medium term decision making. To maximise the net benefit, the authors proposed an energy service decision support tool. The energy service tool is used to manage and schedule the distribution energy sources to optimise the energy consumption by the end user [131]. The author in [19] presents an in-home PEV charging control algorithm. This algorithm attempts to achieve a trade-off between reducing the waiting time for the PEV to be fully charged and minimising the electricity bill taking into account the consumer comfort level. However, using the PEV as a possible storage system is not considered. In [42], the authors present a control strategy to reduce growing demand, increase the network efficiency and to achieve the benefit of demand response programs by controlling the electric water heater, air-conditioner and heating ventilation.

It is clear from a detailed review of the literature that most of the existing research studies are based around a specific category of household appliances such as thermostatically controlled or interruptible (e.g. air-conditioner, heater, water heater), or non-interruptible appliances (e.g. clothes washer/dryer, dishwasher or oven), while a few other works focus on both categories. Furthermore, most of these works are designed to optimise for one or two objectives (e.g. reducing power consumption, CO_2 emissions, peak demand, or monetary expense) without considering consumer preferences, multiple users, sharing the same home and its appliances, or maintaining a level of consumer comfort. The use of energy storage systems incorporated with renewable energy sources and the grid has been proposed by many researchers. Most of the previously mentioned works, however, rarely considered the use of a PEV's battery as energy storage/production. Different pricing models such as time of use (TOU), real-time pricing (RTP), day ahead pricing (DAP) and inclining block rate (IBR), or combinations of these models have been proposed in some of the previously mentioned works, while the wide range of works have adopted a RTP model. However, controlling and managing household appliances based on real time pricing signals is very complicated due to unpredictable energy prices where the end user cannot distinguish whether this is a high electricity price signal or not in order to avoid running their appliances in an expensive time slot. Because of this problem, some of these researchers suggested using historical data to predict the electricity price of the next time slot.

The main contribution of the work presented here focusses on developing and applying mathematical models of residential energy usage and management that can easily be integrated into automated decision making technologies, such as HEMSs, in the context of Smart Grids while attempting to tackle the key shortcomings that have been previously identified in this section. In this regard an intelligent HEMS algorithm using the proposed mathematical models to generate the optimal operational schedules for household appliances (e.g. controllable and non-controllable loads), and energy storage systems (ESSs) including batteries and plugin electric vehicle (PEV), has been proposed as shown in Figure 5.1. This algorithm uses a variety of information from the external environment including, RTP pricing incorporated with DAP signals to predict the pricing in the next time slot, weather forecast to moderate the indoor temperature setting, and the network imposed demand limit during peak periods.

In this chapter, the main objective of the proposed intelligent HEMS is to minimise the electricity bill and greenhouse gas emissions over the next 24 hours subject to constraints on keeping the total power consumption below a certain limit during peak periods, while attempting to maintain an acceptable level of consumer comfort. The comfort constraints are used to generate a single load priority for all users sharing the same home and its appliances reflecting the range of the hot water temperature, indoor temperature, running operation time of the household appliances including the pool pump, dishwasher and clothes dryer, and charging and discharging of the electric vehicle.

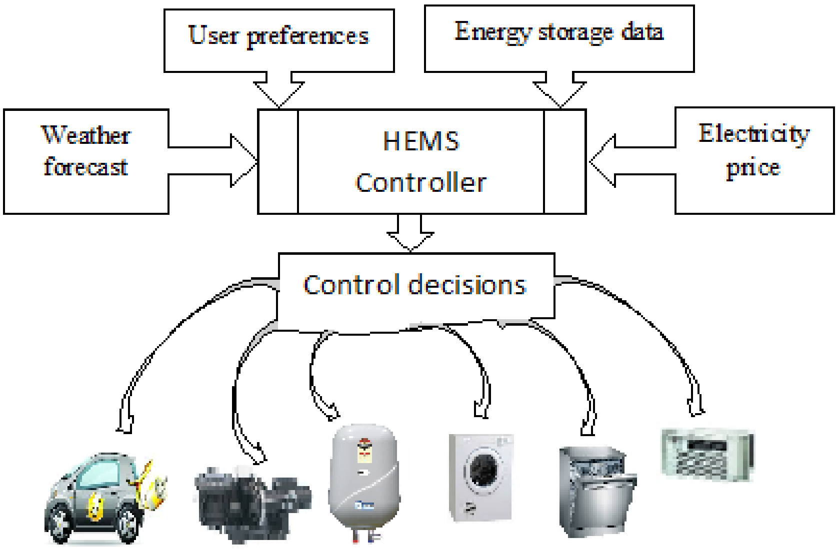


Figure 5-1: HEMS load modelling and control strategy

5.3 Pricing Models

The energy pricing model is the most important factor for an intelligent load controller. Nowadays, most of the electricity consumers, particularly householders, act as price takers with flat rates. Due to the lack of consumer knowledge about the differences in electricity pricing models, and automation and monitoring technology, they have no incentives to manage their power consumption patterns. Moreover, unpredictable energy prices and lack of ability to distinguish whether the current electricity price signal is high or low makes control operations for household appliances complicated, resulting in sub-optimal energy usage patterns. The use of day ahead pricing (DAP) may help to solve this problem by providing the end user with 24 hours of electricity prices in advance as shown in Figure 5.2.

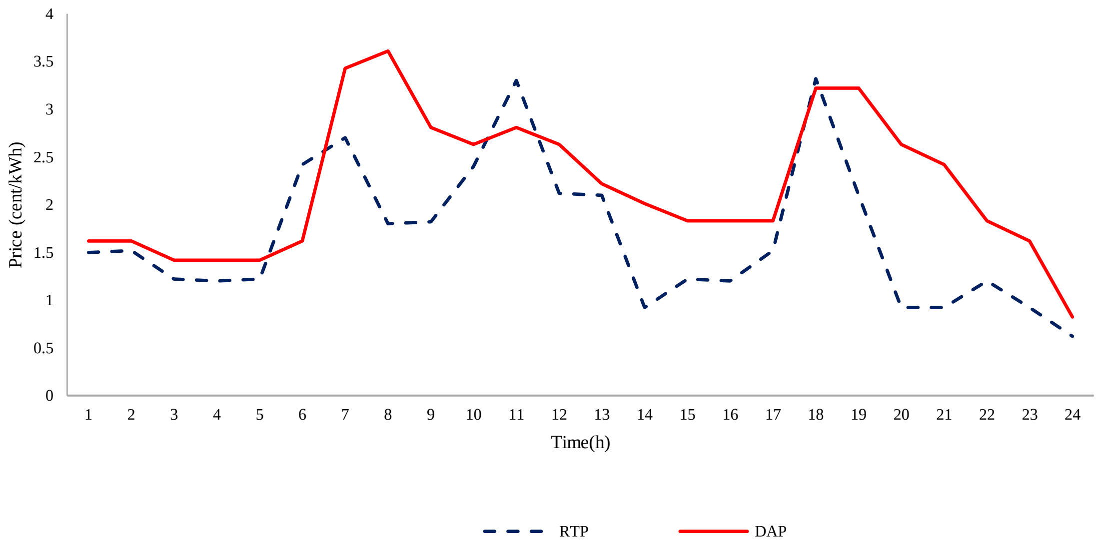


Figure 5-2: Real-Time hourly prices for January 6th, 2015 (RTP &DAP)

This information, which is provided by the utility based on the wholesale energy market, can be used to predict whether the current RTP signal is high or low as described in Equations (5.1) and (5.2). The incorporation of the RTP with DAP pricing will provide an incentive to the consumer to modify their load profile in order to reduce their power bills.

$$Pr_t^s = \frac{1}{T}\sum_t^T DAP_t \qquad t \in \{1,2,..,T\} \tag{5.1}$$

$$_{status}Pr_t = \begin{cases} 1 & electricity\ price\ is\ low \\ 0 & otherwise \end{cases} \tag{5.2}$$

where

Pr_t^s Real time electricity price signal.

$_{status}Pr_t$ Status of the current price signal.

DAP_t Day ahead pricing at time t

5.3.1 Intelligent Decision-Making in a Home Energy Management System

The proposed modelling approach is used to incorporate demand response coupled with an energy storage system in home energy management decision making. However, it is impractical to request a customer, who is neither an economist nor an experienced network operator, to optimally schedule their loads according to different scenarios. Thus, it is necessary to develop an autonomous decision-making system to assist in minimising the overall energy cost (benefit to consumer) and keep the total household power consumption below a certain demand limit during peak periods (benefit to utility), in a way that does not conflict unduly with consumer requirements and convenience. Therefore, a control strategy model at the appliance-level in home energy management decision making has been implemented for controllable loads including, cooling/heating, water heater, pool pump, dishwasher, clothes dryer and energy storage system (e.g. battery and/or electrical vehicle battery). The proposed control strategy is implemented based on several conditions including, real-time energy prices and energy availability in the storage system, while the other conditions have been discussed in detail in the previous work [132], including multiple inhabitants in one dwelling sharing the same appliances, and consumer preferences as well as the load priority and seasonal changes and day type.

5.3.1.1 Mathematical models

The model of the HEMS including the operation of different types of household appliances needs to be effectively managed and controlled within a household to minimise the total electricity bill under the RTP environment and incorporating the energy storage system. Therefore, the minimisation problem is formulated as a Linear Programming (LP) model. The 24-hour time horizon T is divided into t time slots, which have varying electricity prices. Our objective function is to minimise the total energy expense by scheduling the household appliances activities represented by the set A, the status of each appliances $a \in A$, represented by the binary variable $P_t^{s,a}$, is equal to 1 if the appliance a is "ON" in each time slot $t \in T$, 0 otherwise.

$$min\, C = \sum_{t,a}^{T,A} TP_t \ . \ Pr_t \tag{5.3}$$

where $a \in \{ac, wh, dw, cd, pp\}$, $d \in \{pev, b\}$

This objective function is intended to minimise the total energy cost, which can be calculated using Equation (5.4), the total power consumption at a given time, TP_t, is equal to the summation of the controlled and critical loads, ${}_{ctr}P_t^a$, ${}_{cr}P_t$ respectively, and the summation of power consumption used by the energy devices ES_t^d including, battery and PEV.

$$TP_t = \sum_{\mathrm{t,a}}^{\mathrm{T,A}} {}_{ctr}P_t^a + {}_{cr}P_t + \sum_{\mathrm{t,d}}^{\mathrm{T,D}} {}_{chg}ES_t^d \quad d \in \{pev, b\} \tag{5.4}$$

$$TP_t \leq Dl_t \tag{5.5}$$

$${}_{status}TP_t = \begin{cases} 1 & if \;\; TP_t > Dl_t \\ 0 & otherwise \end{cases} \tag{5.6}$$

Where:

${}_{ctr}P_t^a$ Controllable loads in time interval t

${}_{cr}P_t$ ${}_{cr}P_t^a$ Critical loads in time interval t

${}_{chg}ES_t^d$ Amount of energy charged in energy storage devices in time interval t

Equations (5.5) and (5.6) are used to ensure that the total power consumption at a given time TP_t including ${}_{ctr}P_t^a$, ${}_{cr}P_t$ loads and charging of energy storage devices ES_t^d does not exceed the specified demand limit level, while the binary variable ${}_{status}TP_t$ represents the status of the current total power consumption according to the demand limit at a given time *t*. The operational time for each appliance, *a*, will be pre-specified by users, the constraints (5.7) show that no operation is allowed outside the operation window $(St \;\&\; Et)$ of each household appliance.

$${}_{ctr}P_t^a = 0 \;\forall \begin{cases} t < St \\ t > Et \end{cases} \tag{5.7}$$

where:

St Start operation time

Et End operation time

The operational constraints of individual appliances and energy storage systems will be described in the next section.

5.3.2 The Control Strategy at Appliance Level with Demand Response

In this research study, the HEMS control strategy is used to manage the controllable loads including interruptible loads that can be switched off for small portions of time during periods of peak demand or high energy prices without undue effect on consumer comfort (e.g. space cooling/heating, water heater, and pool pump), and non-interruptible loads, which are the kinds of appliances that cannot be interrupted before the end time slot of the required operation window, but that can have their start times deferred or scheduled (e.g. dish washer, clothes dryer, etc.). By controlling these loads alongside intelligent use of energy storage devices, the HEMS controller model will help householders to minimise their electricity bills and improve energy efficiency (and, if deployed at scale, reduce peak demand on the grid). Note that in this model the critical loads such as lighting, microwave, coffee machine, communication, entertainment, etc. are not controlled by the HEMS. The operation of these loads therefore needs to be effectively managed within a household, which may require education to encourage behaviour that will benefit both the end user and the utility.

5.3.2.1 Air-conditioning (AC) and heating (HT) model

Oftentimes, most of the residential consumers adjust the indoor temperature by setting the thermostat of the air conditioner/heater at a constant setting-point, regardless of whether electricity prices are currently high or low, which results in high energy consumption and cost Equation (5.8), represents a simulation model for the indoor temperature over the next time slot, which is based on the model and parameters presented in [133-135].

$$ {}_{in}T_{t+1} = \varepsilon \, {}_{in}T_t + (1-\varepsilon)\left({}_{out}T_t \pm \frac{\eta \, P_{ah}^{max}}{A} \right) \tag{5.8} $$

where:

t Index of time slot

${}_{out}T_t$ Outdoor temperature of the current time slot

P_{ah}^{max} Maximum power level of ah where $ah \in \{ac, ht\}$

${}_{in}T_t$ Indoor temperature of the current time slot

${}_{in}T_{t+1}$	Indoor temperature of the next time slot
ε	System inertia
A	Thermal conductivity (Kw/F)

To minimise the discomfort of the consumer, the air-conditioner/heater are operated within the ASHRAE comfort zones [8], which reflects the maximum and minimum allowable temperatures that the customer is willing to tolerate. The control strategy of the air-conditioner/heater are then subject to the following constraints:

$$ {}_{min}T \leq {}_{in}T_t \leq {}_{max}T \tag{5.9} $$

$$ P_{ah}^{min} \cdot P_t^{s,ah} \leq P_t^{ah} \leq P_t^{s,ah} \cdot P_{ah}^{max} \tag{5.10} $$

$$ AC_t^s + HT_t^s \leq 1 \tag{5.11} $$

where

$$ {}_{min}T = {}_{des}T - \Delta T $$

$$ {}_{max}T = {}_{des}T - \Delta T $$

P_t^{ah}	Power consumption for appliance *ah* in time interval t, $ah \in \{ac, ht\}$
$P_t^{s,ah}$	State s of appliance a in time interval t, $P_t^{s,ah} \in \{AC_t^s, HT_t^s\}$
ΔT	Allowed deviation
${}_{min}T$	Minimum temperature
${}_{max}T$	Maximum temperature
${}_{des}T$	Desired temperature
AC_t^s	Status of air-condition in time interval t
HT_t^s	Status of heater in time interval t

Equation (5.9) ensures that indoor temperature always remains within the ASHRAE temperature. The power consumption of the air conditioner/heater should be in the allowable range between maximum power consumption P_{ah}^{max} and minimum stand-by power consumption P_{ah}^{min} as described in Equation (5.10), while Equation (5.11) is used to ensure that *AC* and *HT* cannot be ON at the same time. From the previous equations and constraints, the proposed approach is to control the air conditioner/heater according to the available real time data including RTP signal as presented in Figure 5.2, and real-time outdoor temperature. The operation of the air conditioner/heater can be controlled by the HEMS controller based on the electricity price signal, whenever the electricity price is low, the air conditioner remains on until the indoor temperature reaches the $_{min}T$, or conversely the air-conditioner/heater is switched off whenever the indoor temperature reaches the $_{max}T$.

5.3.2.2 5.3.2.2 Electric water heater model

Thermal appliances, such as electric water heaters, need to account for a number of factors to optimise their schedule over a set time horizon including the electricity price forecast, a range of thermostat settings based on a pre-set comfort range, and the characteristics of the appliances themselves. The electric water heater (EWH) is one of the main residential thermostatically controlled and high energy consumption loads used to heat and store hot water. The load model applied for water heaters is based on the load model introduced by [109, 128]. The proposed control strategy used with the EWH is similar to the control approach used with the air-conditioner/heater. This strategy is applied based on the thermal dynamic model that explains heat change with the environment and cold-water flows. The energy used by the EWH is calculated based on the average daily hot water consumption as follows:

$$LPD = 81.00782 + 0.0254 \times \mathrm{CFA} \tag{5.12}$$

where:

LDP Average daily hot water consumption

CFA Conditioned floor area

where the average daily hot water consumed in litres per day (LPD) for a residence is equal to 81 plus 25.4 LPD for each 93 m^2 of conditioned floor area (CFA). The hourly hot water consumption LPH (Litres per Hour) is calculated using the hourly water consumption schedule profile presented in Figure 5.3, which is normalised as a fraction Fsc_t of daily total hot water consumption [136], times the average daily hot water consumption (LPD) as shown in Equation (5.13). Finally, equation (5.14) is used to calculate the hourly water-heating load in (watts).

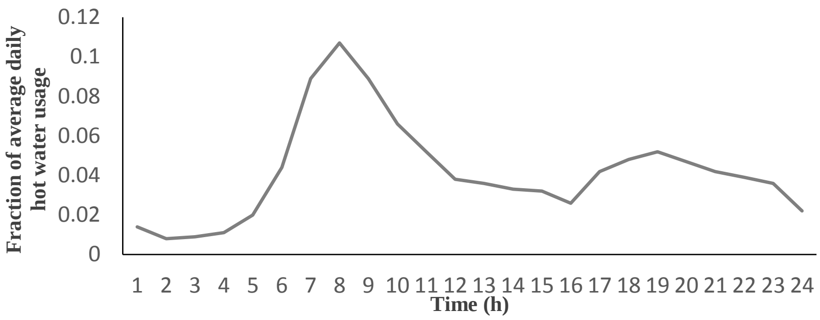


Figure 5-3: Hourly hot water use profile [136]

$$LPH_t = LPD \times Fsc_t \tag{5.13}$$

where:

LPH Hourly hot water consumption (Litres per hour)

Fsc_t Fraction of daily total hot water consumption

$$P_t^{wh} = \frac{4.184 \times LPH_t \times \Delta T^w}{3.412 \times EF} \quad (Watt) \tag{5.14}$$

where:

P_t^{wh} Hourly water-heating load

EF Efficiency of water heaters

The energy factor, *EF* is generally between 0.7 and 0.95, and ΔT^w is the difference between the cold water inlet temperature and the hot water supply temperature as expressed in Equation (5.15), times the hourly hot water consumption, and the heat required to raise a litre of water by one degree (the 4.184 kJ/kgC constant).

$$\Delta T^w = T_{out}{}^w - T_{in_t}{}^w \tag{5.15}$$

where:

$T_{out}{}^{w}$ Outlet water temperature

$T_{int}{}^{w}$ Inlet water temperature

Developing a control strategy for the EWH over 24 hour intervals in order to minimise the electricity bill over the same period is one of our objectives for the proposed HEMS algorithm. This approach specifies a varying temperature range to reflect consumer preferences on EWH thermostat settings, and varying electricity prices. Equation (5.16), represents the lower and upper range of the $T_{out}{}^{w}$ according to the thermal coefficients from ASHRAE. One of the main tasks of the HEMS controller is to control the thermostat WH_t^s of the EWH by switching it (ON/OFF) based on several conditions. The HEMS controller will keep $T_{out}{}^{w}$ at the maximum level by switching the heater ON whenever the electricity price ${}_{status}Pr_t$ is low and the water temperature drops below that level, while switching it OFF whenever water temperature exceeds the maximum level. On the other hand, when the price signal is high switching it ON to keep the $T_{out}{}^{w}$ at the minimum temperature level, and switching it OFF otherwise as shown in Equation (5.17).

$$ {}_{min}T^{w} \leq {}_{out}T^{w} \leq {}_{max}T^{w} \tag{5.16}$$

$$ {}_{max}T^{w} = {}_{des}T^{w} $$

$$ {}_{min}T^{w} = {}_{des}T^{w} - temperature\ tolerance $$

$$ EWH_t^s = \begin{cases} ON\ and\ {}_{out}T^{W} = {}_{max}T^{W} \quad if\ \ {}_{status}Pr_t = 1 \\ \quad or \\ ON\ and\ {}_{out}T^{W} = {}_{min}T^{W} \quad if\ \ {}_{status}Pr_t = 0 \\ Off \quad otherwise \end{cases} \tag{5.17}$$

where:

${}_{min}T^{w}$ Minimum temperature level

${}_{max}T^{w}$ Maximum temperature level

${}_{des}T^{w}$ Desired temperature level

WH_t^s Status of electric water heater thermostat

5.3.2.3 Pool pump model

Nowadays, many residential buildings in Australia have swimming pools. The increasing number of residential swimming pools requires more energy that leads to increases in electricity bills, greenhouse gas emissions, and more pressure on energy suppliers. Therefore, there is a need to control the usage of swimming pool pumps, which generally need to be operated for several hours per day in order to maintain the water quality. The pool pump needs to run for a certain amount of time subject to the following time constraints:

$$Rt \le St_{pp} \le T - NT_{pp} \tag{5.18}$$

$$Rt + NT_{pp} \le Et_{pp} \le T \tag{5.19}$$

where:

St_{pp} Starting operation time for pool pump

Et_{pp} Ending operation time for pool pump

NT_{pp} Length of pool pump operation time

Rt Pool pump running time

Equations (5.18) and (5.19) are used to ensure that the pool pump operation could be run anytime between the lower and upper bound constraints St_{pp} and Et_{pp}, however, it cannot be run beyond Rt hours due to noise considerations. This will allow the pool pump to complete the length of its operation time NT_{pp} when the electricity prices are low, as described in Equations (5.20) and (5.21). The minimum and the maximum bounds of power consumption for P_t^{pp} are described in Equation (5.10).

$$PP_t^s = \begin{cases} 1, & when \ {}_{status}Pr_t = 1 \\ 0 & otherwise \end{cases} \tag{5.20}$$

$$\sum_{t=St}^{Et} PP_t^s = NT_{pp} \tag{5.21}$$

$$P_{pp}^{min} \cdot PP_t^s \leq P_t^{pp} \leq PP_t^s \cdot P_{pp}^{max} \tag{5.10}$$

where:

PP_t^s Pool pump status

P_{pp}^{min} Minimum pool pump power consumption

P_{pp}^{max} Maximum pool pump power consumption

P_t^{pp} Power consumption of pool pump at time slot *t*

5.3.2.4 Dishwasher and clothes dryer control strategy model

Another high consumption category of home appliances are clothes dryers and dishwashers. For these types of controllable appliances, the start operation time can be flexible, meaning that the time when it is switched on is usually not critical. Householders are more concerned about the finish operation time. The desired finish time and duration of operation thus needs to be pre-set by the householder. These characteristics can be classified under the following timing constraints:

$$St_t^{s,ad} - Et_t^{s,ad} = P_t^{s,ad} - P_{t-1}^{s,ad} \qquad ad \in \{dw, cd\} \tag{5.22}$$

$$St_t^{s,ad} + Et_t^{s,ad} \leq 1 \tag{5.23}$$

$$NT_{ad}^j = \sum_{t=St^j}^{Et^j} P_t^{s,ad} \tag{5.24}$$

$$\sum_{j=1}^{n} NT_{ad}^j = NT_{ad} \tag{5.25}$$

$${}_{start}Mn_{ad}^j \leq St_{ad}^j \leq {}_{end}Mx_{ad}^j - NT_{ad}^j \tag{5.26}$$

$${}_{start}Mn_{ad}^j + NT_{ad}^j \leq Et_{ad}^j \leq Mx_{ad}^j \tag{5.27}$$

$$P_{ad}^{min} \cdot P_t^{s,ad} \leq P_t^{ad} \leq P_t^{s,ad} \cdot P_{ad}^{max} \tag{5.28}$$

$St_t^{s,ad}$ Status of appliance *a* at time *t* where 1 is start-up, 0 otherwise

$Et_t^{s,ad}$ Status of appliance *a* at time *t* where 1 is shut-down, 0 otherwise

$P_t^{s,ad}$ State of appliance a at time t, state of appliance a ON/OFF

${}_{start}Mn_{ad}^{j}$ Minimum operation start time for task *j* and appliance *ad* and $j \in \{1...n\}$.

${}_{end}Mx_{ad}^{j}$ Maximum operation end time for task *j* and appliance *ad*.

$P_{ad}^{min}, P_{ad}^{max}$ Minimun and maximum power consumption for dishwasher and clothes dryer

NT_{ad} Length of dishwasher and clothes dryer operation time

Constraints (22 and 23) are used to ensure the state of the appliance is currently started or stopped, while all tasks of the appliance should be completed within NT_{ad} as described in (5.24-27), which also guarantees that the next task NT_{ad}^{j+1} will not be started up until the first task NT_{ad}^{j} has been completed. Equation (5.24) are used to calculate the operation time for each task, while equation (5.25) is used to calculate the operation time for all tasks. Furthermore, equations (5.26, and 5.27) are used to ensure that the operation time for each task to be completed within the total operation time for that task. Equation (5.28) describes the minimum and maximum bounds of power consumption for P_t^{ad} as previously explained in Equation (5.10).

5.4 Energy storage systems

In the near future, Energy Storage Systems (ESSs) will play a very important role in the transition from traditional power systems to the smart grid. ESS will become an indispensable technology, which can be utilised as an effective resource to improve the efficiency of the electric power system, as well as adding flexibility, stability and balancing capability to the grid. Historically, the use of storage technologies has been limited due to a lack of cost-effective options compared with cheap energy sources such as fossil fuels. Recently, however, ESSs are beginning to become a more attractive option due to rapidly lowering cost and the increasing importance placed on the reduction of greenhouse gas emissions [21, 33]. In conjunction with energy management systems, the use of ESS can lead to reduced electricity costs and develop a low carbon electricity system by storing energy from the grid during off-peak times at lower prices and then supplying this energy during peak times when rates are higher. As the costs of ESSs fall, it is expected that most modern houses will start to be equipped with some form of energy storage device such as batteries, or PEVs. In this chapter, batteries and PEVs are considered as available residential ESSs as described in Equation (5.29). The availability of energy in the ESS at any time slot is the summation of the energy available in the battery E_t^B and PEV E_t^{pev}. However, the battery energy is always available (on grid) to use, while the electrical vehicle battery is unavailable when the vehicle is away from the house (off grid).

$$ES_t^d = E_t^B + E_t^{pev} \quad d \in \{pev, b\} \tag{5.29}$$

where:

E_t^B Energy available in the fixed battery

E_t^{pev} Energy available in the PEV's battery

5.4.1 Storage battery model

Modelling of the battery and its constraints is an important aspect of our formulation. The following constraints show that the energy level of the battery capacity E_t^B is bounded between the maximum energy level for the battery $_{max}E^B$ and the minimum energy level required for the battery $_{min}E^B$ as described in Equation (5.30). Charging or discharging a battery beyond these levels can reduce battery lifetime or even damage the battery's capacity to hold a charge. Therefore, these limitations are usually imposed by its manufacturer.

$$_{min}E^b \leq E_t^b \leq {}_{max}E^b \qquad \forall t \in T \tag{5.30}$$

$_{min}E^b$ Minimum energy level required for the battery

$_{max}E^b$ Maximum energy level required for the battery

Equation (5.31) controls charging and discharging of the battery in each time interval to prevent concurrency. The binary variables for charging $_{chg}G_t^b$ and discharging $_{dsc}G_t^b$ the battery are equal to 1 if the battery is charging or discharging in time slot *t* and 0 otherwise. Furthermore, Equations (5.32) and (5.33), illustrate that the binary variables for charging and discharging

${}_{chg}G_t^b$, ${}_{dsc}G_t^b$ respectively will be equal to 1 based on whether the pricing signal is low or high, and whether the total power consumption is below or above the demand limit.

$$ {}_{chg}G_t^b + {}_{dsc}G_t^b \leq 1 \qquad \forall t \in T \tag{5.31}$$

$$ {}_{chg}G_t^b = \begin{cases} 1, & if\ {}_{status}TP_t \cdot\ {}_{status}Pr_t\ > 0 \\ 0, & otherwise \end{cases} \tag{5.32}$$

$$ {}_{dsc}G_t^b = \begin{cases} 1, & if\ E_t^b\ > {}_{min}E^b\ \ and\ {}_{status}Pr_t\ \leq 0 \\ 0, & otherwise \end{cases} \tag{5.33}$$

where:

${}_{chg}G_t^b$, ${}_{dsc}G_t^b$ Charging and discharging battery status.

The amount of energy that can be charged/discharged during time slot *t*, ${}_{chg}E_t^b$, ${}_{dsc}E_t^b$ respectively are bounded according to the below constraints, where the minimum M_{chg}^b, M_{dsc}^b and maximum X_{chg}^b, X_{dsc}^b represent the charge and discharge rates respectively.

$$ M_{chg}^b \cdot {}_{chg}G_t^b \leq {}_{chg}E_t^b\ \leq\ X_{chg}^b \cdot {}_{chg}G_t^b \qquad \forall t \in T \tag{5.34}$$

$$ M_{dsc}^b \cdot {}_{dsc}G_t^b \leq {}_{dsc}E_t^b\ \leq\ X_{dsc}^b \cdot {}_{dsc}G_t^b \qquad \forall t \in T \tag{5.35}$$

where:

${}_{chg}E_t^b$ The amount of energy charged at time slot *t*

${}_{dsc}E_t^b$ The amount of energy discharged at time slot *t*

M_{chg}^b The minimum battery charging rate

M_{dsc}^b The minimum battery discharging rate

X_{chg}^b The Maximum battery charging rate

X_{dsc}^b The Maximum battery discharging rate

The battery energy state E_t^b fluctuates over time due to battery charging and discharging. The following equation is used to calculate the energy level at the end of the current time slot *t* by adding the energy level of the previous time slot *t-1* and the change in energy during period *t*, this change is due to the charging or discharging rates.

$$E_t^b = E_{t-1}^b + \eta ._{chg} E_t^b - \frac{1}{\eta} ._{dsc} E_t^b \quad \forall\, t \in T,\ t \geq 2 \tag{5.36}$$

where η denotes the charge and discharge efficiency.

5.4.2 The PEV model

A PEV model has similar characteristics to the fixed battery constraints as presented in the preceding section. However, the PEV model is considered the time of plug-in/out as described in the next equations. According to Equation (5.37), the state of charge for the PEV in each period should not be less than the minimum desired number of electricity units for the PEV, ${}_{min}E^{pev}$, and the maximum state of charge for the PEV in each period should not be more than its battery capacity ${}_{max}E^{pev}$. Charging and discharging the PEV battery is limited to these bounds to avoid reducing the battery's lifetime or damaging it.

$${}_{min}E^{pev} \leq E_t^{pev} \leq {}_{max}E^{pev} \tag{5.37}$$

where:

${}_{min}E^{pev}$ Minimum energy level required for the PEV's battery

${}_{max}E^{pev}$ Maximum energy level required for the PEV's battery

Equation (5.38) models the state of energy level for a PEV battery at every time slot *t* as equal to the summation of the PEV battery energy of the previous time slot *t-1* and the charge and discharge rates, when the PEV is connected to the grid.

$$E_t^{pev} = E_{t-1}^{pev} + \eta ._{chg} E_t^{pev} - \frac{1}{\eta} ._{dsc} E_t^{pev} \tag{5.38}$$

The following constraints are used to control the charging and discharging operation of PEVs in the system. Equations (5.39) and (5.40) ensure that energy cannot be charged to or discharged from the PEV unless it is connected to the grid at a given time *t*, where O_t^{pev} is equal to 1 if the PEV is connected to the grid. Additionally, the PEV's battery can be charged ${}_{chg}E_t^{pev}$ or discharged ${}_{dsc}E_t^{pev}$ up to the maximum energy capacity of PEV X_{chg}^{pev} or X_{dsc}^{pev} that can be transferred from or to the PEV's battery respectively within any time slot.

$$ {}_{chg}E_t^{pev} \leq \; X_{chg}^{pev} \cdot {}_{chg}G_t^{pev} . O_t^{pev} \tag{5.39}$$

$$ {}_{dsc}E_t^{pev} \leq \; X_{dsc}^{pev} \cdot {}_{dsc}G_t^{pev} . O_t^{pev} \tag{5.40}$$

When a PEV is connected to the grid, certain information is required for the HEMS controller. The time of the next trip S_{trip} provided by the user, the time needed for charging the PEV to be ready for the next trip NT_{chg}^{pev}, which can be calculated by the controller based on the battery specifications, the status of the current total power and the current electricity price signal ${}_{status}TP_t$ and ${}_{status}Pr_t$ respectively, and the amount of energy remaining in the PEV's battery which must be greater than the minimum state of charge as described in Equation (5.37). The start time of charging the PEV SR_{chg}^{pev} can then be determined based on the previous information. These conditions will affect the status of charging or discharging as described in Equations (5.41) and (5.42), if the binary variable for charging ${}_{chg}G_t^{pev}$ or discharging ${}_{dsc}G_t^{pev}$ is equal to 1. However, no action will be taken when the O_t^{pev} is equal to 0, which means that the PEV is off grid.

$$ {}_{chg}G_t^{pev} = \begin{cases} 1, \; if \;\; S_{trip} - NT_{chg}^{pev} \leq {}_{chg}SR_t^{pev} \leq S_{trip} \\ \quad or \;\; {}_{chg}SR_t^{pev} \cdot {}_{status}TP_t \cdot {}_{status}Pr_t > 0 \\ 0, \;\; otherwise \end{cases} \tag{5.41}$$

$$ {}_{dsc}G_t^{pev} = \begin{cases} 1, \; if \;\; E_t^{pev} > minE^{pev} \; and \;\; {}_{status}Pr_t \leq 0 \\ 0, \;\; otherwise \end{cases} \tag{5.42}$$

where:

O_t^{pev} Status of whether the PEV is connected to the grid or not

SR_{chg}^{pev} Starting charging time for the PEV

S_{trip} Starting time of the next trip

NT_{chg}^{pev} The time needed for the PEV to be fully charged before next trip

${}_{chg}G_t^{pev}$, ${}_{dsc}G_t^{pev}$ Charging and discharging battery status.

5.5 Simulation Results

This section explains the application of the developed simulation tool to quantify the realisable benefits to utilities and consumers in managing and controlling high power consumption residential appliances when on-grid energy storage is available. The proposed HEMS model has been implemented in MATLAB and solved using linear programming (LP). Six typical residential appliances, including air conditioner (AC), electric water heater (EWH), clothes dryer (CD), dishwasher (DW), plug-in electric vehicle (PEV), and pool pump (PP), are considered to study the effectiveness of the proposed approach presented in section 3 with different available energy sources, including energy storage devices (battery, and PEV battery), and the grid. The assumptions for most of the appliances and storage systems are made in relation to the operation of the proposed HEMS model as presented in Table 5.1, which was simulated under different cases.

Table 5-1: The assumptions for high power consumption appliances and storage systems

Appliances	Preferences	Rated Power
Air-conditioner (AC)	Room temperature 73-79°F, (22-26°C)	2kw
Electric water heater(EWH)	Water temperature between 110-120°F, (43-49°C)	4kw per day
	Conditioned floor area (square meter) capped at 230 m2.	
Clothes Dryer (CD)	Maximum ON time= 120 min, two times first job between (9:00am – 5:00pm), the second job between (9:00pm – 5:00am),	2.795kw
Dishwasher (DW)	Maximum ON time= 120 min, between (9:00am – 5:00am)	1.455kw
Pool pump (PP)	Maximum operation run time is 5 hours	1.2kw

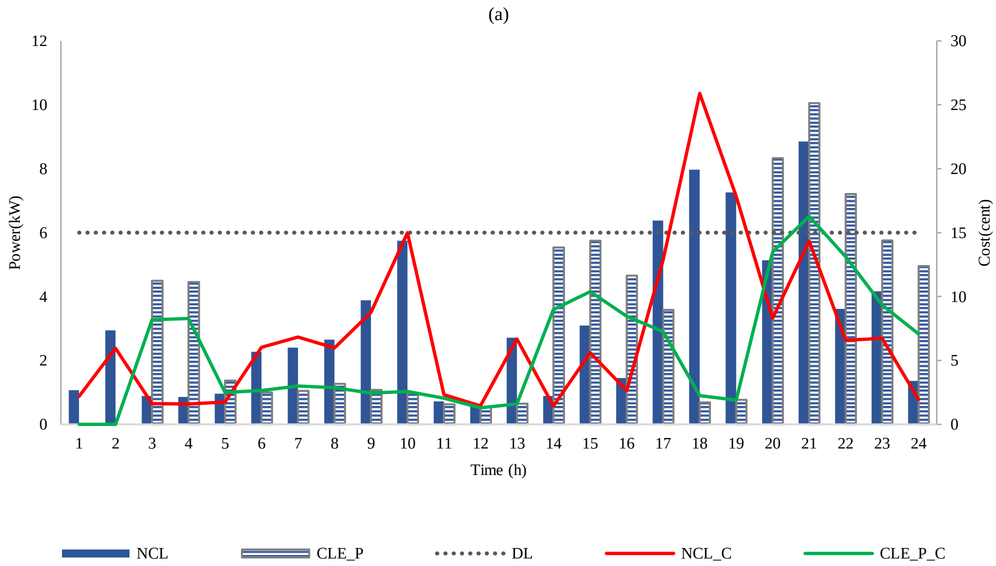
Storage system ESS	Capacity	Charging and discharging rate
Plug-in Electric Vehicle(PEV)	On grid at 6:00am with (40%*24kw) and fully charge before the next trip at 6:am, and minimum SOC is (10%*24kw) and the maximum SOC (24kw)	Maximum rate is 3.6kw/h
Battery Module (1.5 kWh)	The maximum SOC (1.5kw) and the minimum SOC is (10%*1.5kw)	Maximum rate is 0.3375

The proposed HEMS control scheme has been simulated over a 24 hour scheduling horizon with time intervals of one hour based on real-time pricing signals (RTP) and a day ahead pricing (DAP) model, which is used to predict whether the current electricity pricing signal is high or low. A number of scenarios are used to investigate the impact of adding residential energy storage to the proposed HEMS model in terms of stability, effectiveness and energy cost minimisation. In the first scenario, the RTP and DAP signals that are provided by the ComEd utility company in the USA as shown in Figure 5.2 are used (no equivalent data is currently available for Australia, so US data is taken as broadly representative). This scenario shows the influence of using these pricing signals and demand limit on minimisation of consumers' energy expense by scheduling and controlling the running operation time of the high power consumption appliances at a residence that is not equipped with any ESS (in this case the PEV was not considered an available energy storage device). The first case in this scenario presents a controlling approach that relies on the price signals only. Figure 5.4(a) shows that controlling and scheduling these appliances results in a significant reduction on the end users' electricity bill by 18.6% compared with the case where loads are not controlled. In the second case, a demand limit (DL) is imposed to minimise the likelihood that total peak load on the grid will exceed the maximum supply levels that the power plant can generate, as adding more generation capacity can lead to significant increases in CO_2 emissions. The specified 6kW demand limit has been considered based on the average power consumption during the time period (4:00pm to 12:00am) where most of the residents are at home. As can be seen from the Figure 5.4(b) the HEMS algorithm guarantees the total power consumption to be below the DL during the period 4:00pm to 10:00pm where the electricity usage during this period is high. Smoothing out these peaks in energy demand, and rescheduling the usage of the controllable loads based on the RTP pricing signals and the consumer preferences leads to a reduction in the electricity bill of 18.2% during this period compared to the cost with non-controlled loads (NCL).

Figure 5-4: The impact of managing controllable loads on the cost and power consumption based on: a) RTP, b) RTP & DL

In the second scenario, a PEV is utilised not only as a new load for electricity consumption, but also as a possible storage device when it is connected to the grid (at 6:00pm). The remaining energy in the battery, which is assumed to be 40% of the EV battery's capacity

(24kWh), can then be used to supply the loads during high pricing signals and thus reduce the peak demand, taking into account that the state of charge should not drop below mnESOC (10%). The addition of the PEV battery as storage under the control of the HEMS results in an energy cost reduction of 20.1% based on the price signal only as shown in Figure 5.5(a), and 19% when the system accounts for both the price signal and a demand limit, as shown in Figure 5.5(b). The additional energy cost savings achieved through using the PEV battery as storage relative to using the PEV purely as an appliance are 1.5% for the RTP case, and 0.8% for the RTP with DL case, which is a relatively modest improvement.



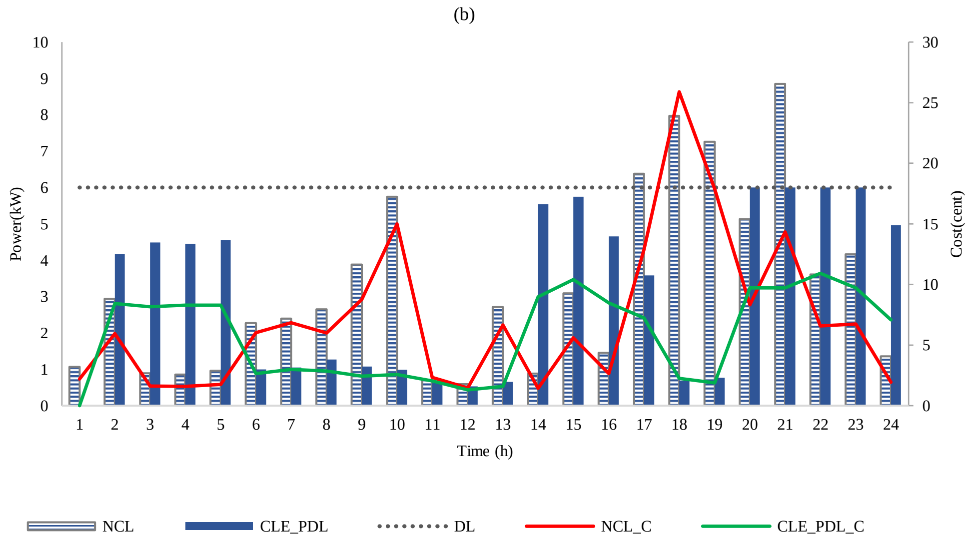


Figure 5-5: The impact of using EV as storage on cost and power consumption based on: a) RTP, b) RTP &DL

In the third scenario, a fixed 1.5kWh battery has been added to improve the reliability and efficiency of the HEMS. This battery storage is connected to the grid at all times and is able to supply the loads during periods of high demand and high energy prices with/without PEV. The charging/discharging operation and the battery state of charge based on the RTP signal with/without imposing a DL is shown in Figure 5.6 (a and b). This figure shows that the battery will be fully charged between (11:00pm and 12:00am) and (4:00am to 5:00am) due to RTP and DL constraints, while the HEMS controller will charge the battery whenever the price signal is low without considering the DL at the time (9:00pm to 12:00am) and (1:00am, 3:00am and 4:00am). On the other hand, the HEMS controller will supply the loads during periods of high electricity price signal based on the energy availability represented by the state of charge, ensuring that this does not fall below the minimum state of charge (10%).

The 1.5kWh capacity has been selected based on an analysis within the constraints of the demand limit and electricity price signals. A larger capacity battery could only be fully charged within the available time by increasing the overall electricity bill and/or exceeding the demand limit, while also incurring significant additional capital cost for additional energy that would rarely be used. On the other hand, using a smaller battery capacity than 1.5kWh does not provide a noticeable reduction on the end user’s electricity bill. A 1.5kWh battery system is also becoming ever more affordable, with systems available for as little as $240 with expected lifetimes of up to 4.3 years at 80% capacity.

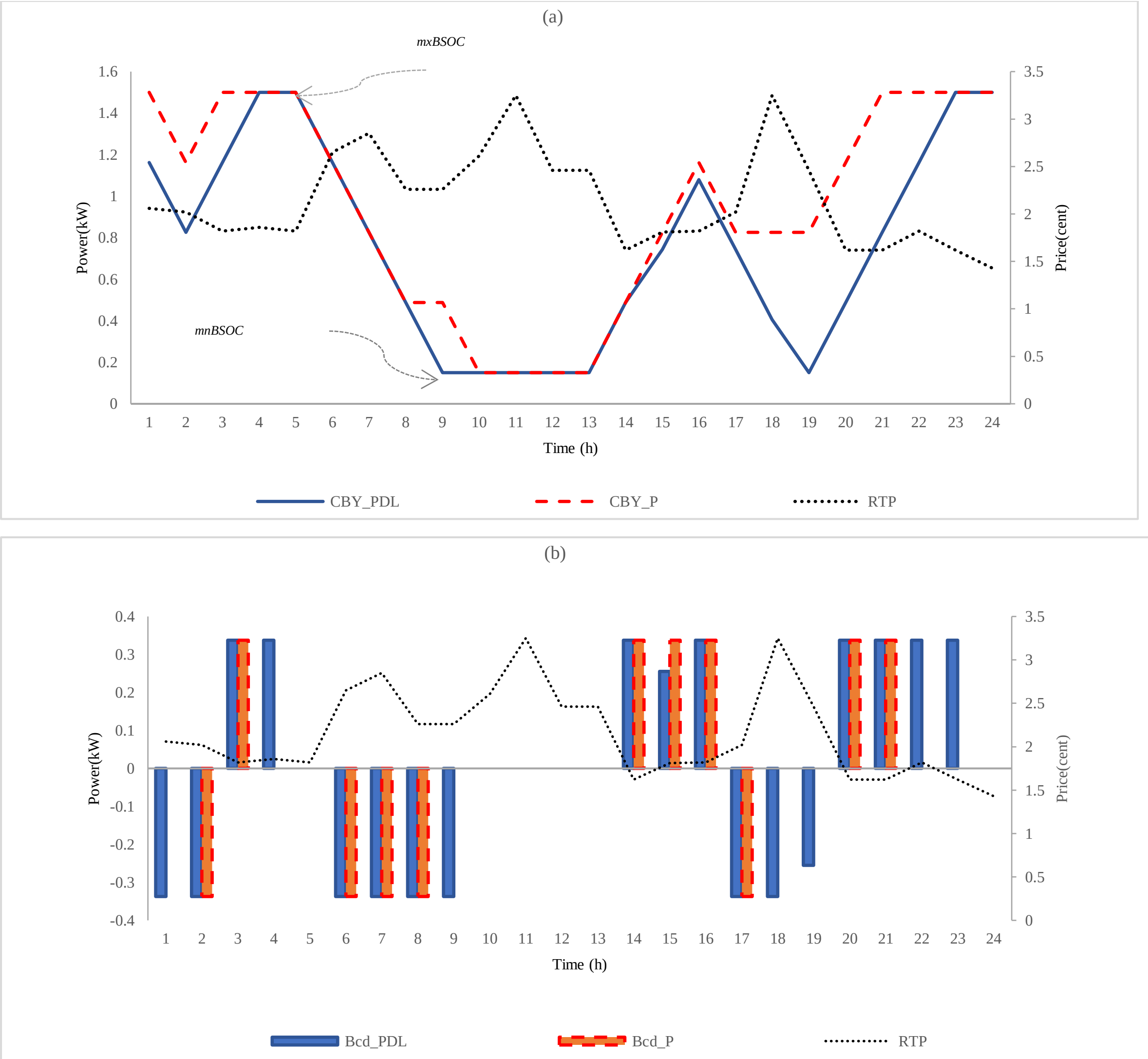
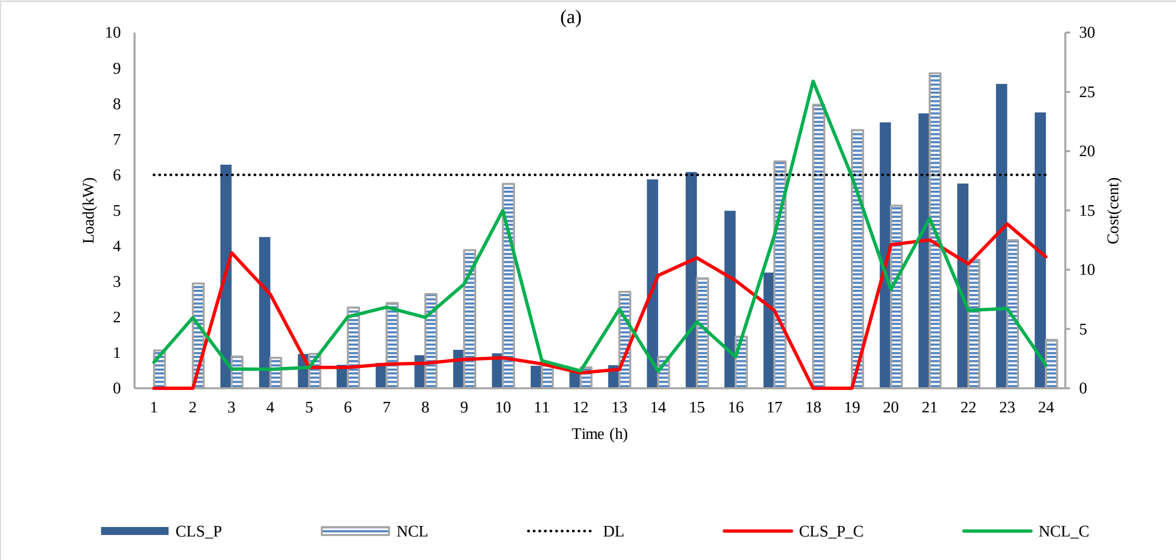


Figure 5-6: Controlling operation of battery as storage based on RTP & DL: a) Hourly battery state of charge, b) Charging and discharging battery rate.

In this scenario, two different cases have been simulated. Firstly, the daily loads profile associated with a PEV charging/discharging has been considered. Figure 5.7 (a) shows the case of using the 1.5kWh battery as storage with just the RTP signal to control the loads without considering the peak demand. The reduction of the end user energy bill was 21.8% compared with the energy cost without controlling loads, about a 3.5% further improvement over using the PEV battery as storage despite the fact that the energy remaining in the PEV's battery when it is first connected to the grid at 6:00pm is greater than the capacity of the dedicated battery storage. This is because the PEV battery is not available at all times and so cannot be used optimally throughout the day, and additionally the charging time needed to ensure that the PEV's battery is fully charged before the next trip at 6:00am is a minimum of six hours due to the maximum charge rate of the battery (C/6), which further restricts its availability. However, when the DL is imposed, the consumer's bill is reduced by about 20.5% compared to the bill with non-controlled loads as shown in Figure 5.7(b), and it is about 1.8% better than using only the PEV's battery as storage without any other storage devices.



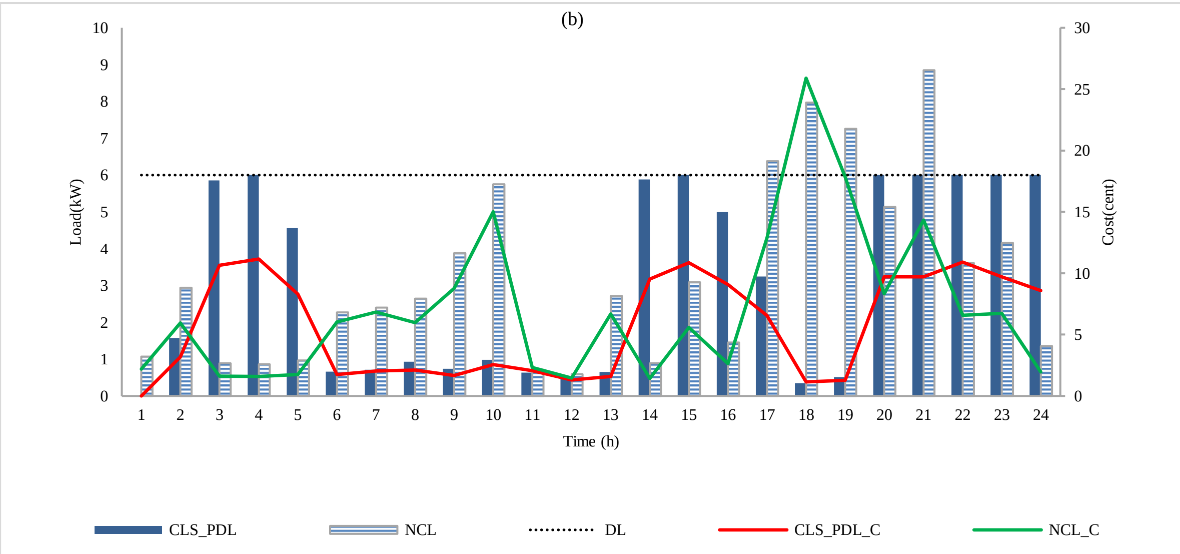


Figure 5-7: The impact of using a fixed battery and PEV battery on cost and power consumption based on: a) RTP, and b) RTP & DL

Figure 5.8(a and b) shows the impact of including the dedicated energy storage without a PEV results in a much more significant reduction on the end user's electricity bill which is about 33.4% and 33.7% in case of using RTP with/without imposing a demand limit respectively, which is 17.8% and 17% better compared with the previous case where the PEV load is associated with the residential loads. Therefore, including a relatively small storage system alongside an appropriate HEMS can be of significant benefit both to the consumer and to the electricity supplier as it can have a significant impact on reducing greenhouse gas emissions during peak periods in a scenario where the HEMS is applied to a large group of houses.

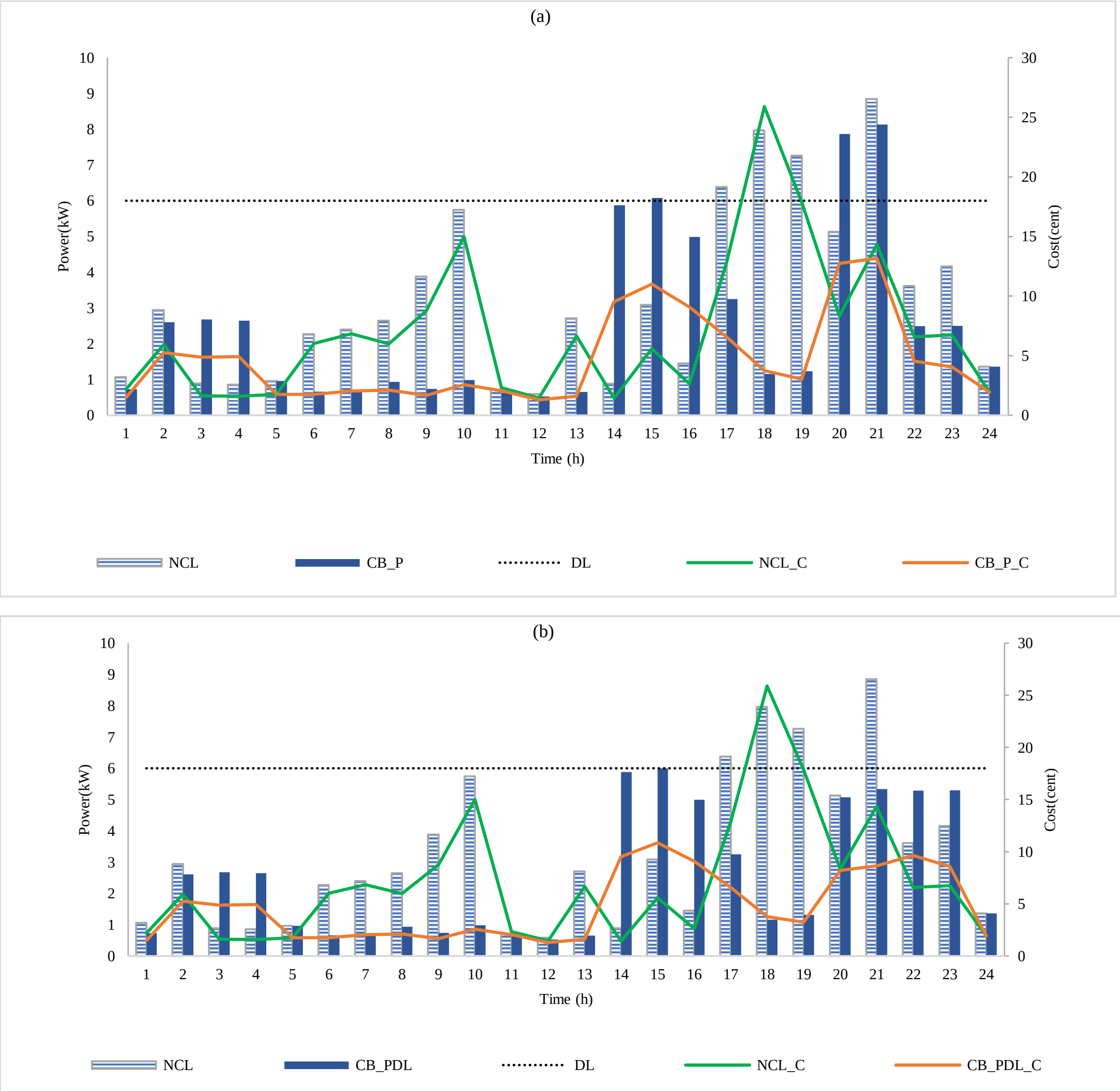


Figure 5-8: The impact of using a fixed battery without PEV battery on cost and power consumption based on: a) RTP, and b) RTP & DL

All the results that have been presented in Table 5.2 with/without the ESSs are associated with a control strategy used by the HEMS to manage the running time for the high power consumption appliances based on RTP, DL and energy available in the ESSs. Some of these appliances have been controlled thermostatically including, air-conditioner and electric water heater. For these appliances, whenever the total power consumption exceeds the DL or the electricity price signal is high, the thermostat set point is adjusted up to the maximum or minimum allowable temperature level that the consumer can reasonably comfortably accept according to the ASHRAE standard. In the case of AC, the acceptable indoor temperature range that is accepted by the consumer is between 73°F to 79°F (~23 to 26°C). As can be seen from Figure 6.9 (a and b), the air conditioner (AC) remains on whenever the electricity price signal is low unless the indoor temperature drops below the minimum set point 73°F (~23°C), while it remains off when the price signal is high unless the indoor temperature exceeds the maximum set point of 79°F (~26°C).

Table 5-2: The cost reduction achieved through energy minimisation of controllable loads in different scenarios

Type of control	Pricing	Scenario	Demand limit	PEV's battery	Battery	Cost reduction (%)
Non-controllable loads	RTP		No limit	As an appliance	None	
Controllable loads	RTP & DAP	First	No limit	As an appliance	None	18.6%
			DL<= 6	As an appliance	None	18.2%
		Second	No limit	As storage	None	20.1%
			DL<= 6	As storage	None	19%
		Third	No limit	As storage	Yes	21.8%
			DL<= 6	As storage	Yes	20.5%
		Fourth	No limit	None	Yes	33.4%
			DL<= 6	None	Yes	33.7%

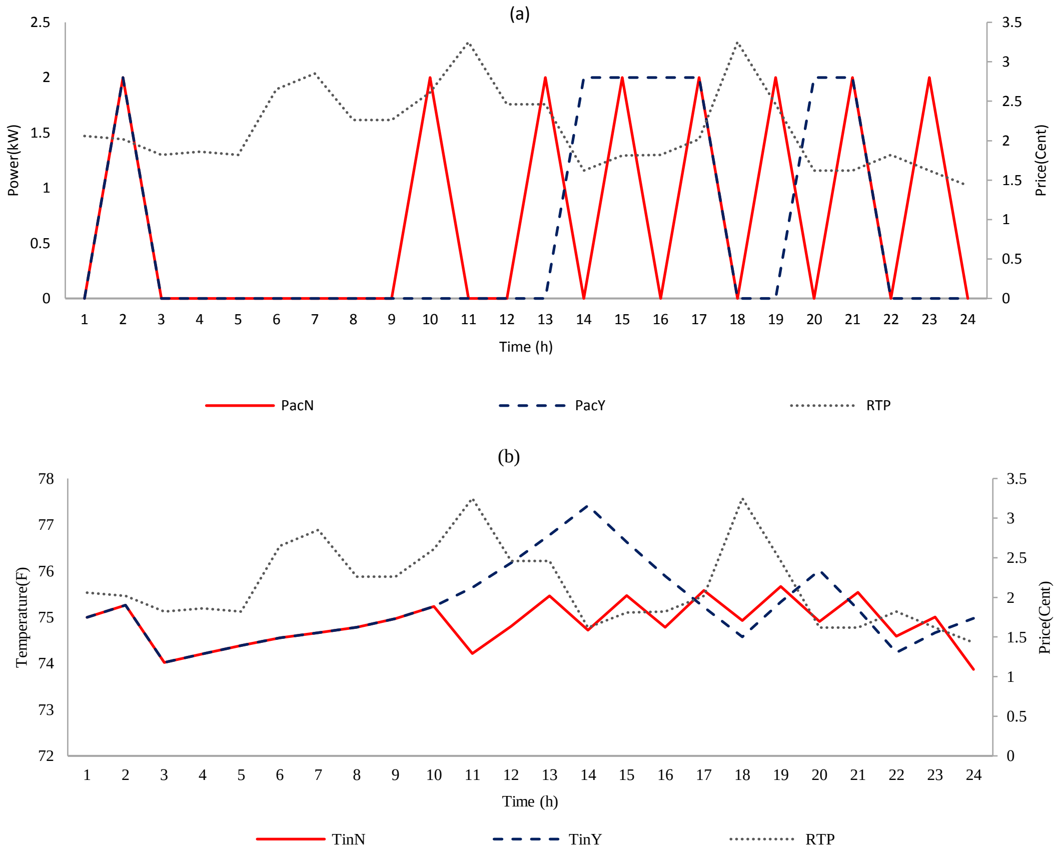


Figure 5-9: a) The controllable operation time of the AC based on RTP and DL, b) the controllable indoor temperature compared with outdoor temperature

Figure 5.10 (a) shows the thermostat set point of the EWH is set at 120°F(~49°C) while the price signal is low, when the electricity price increases the HEMS controller adjusts the set point of EWH thermostat to the minimum degree which the consumer can tolerate 110°F (~43°C), which result in reducing the power consumed by the EWH, as shown in Figure 5.10 (b).

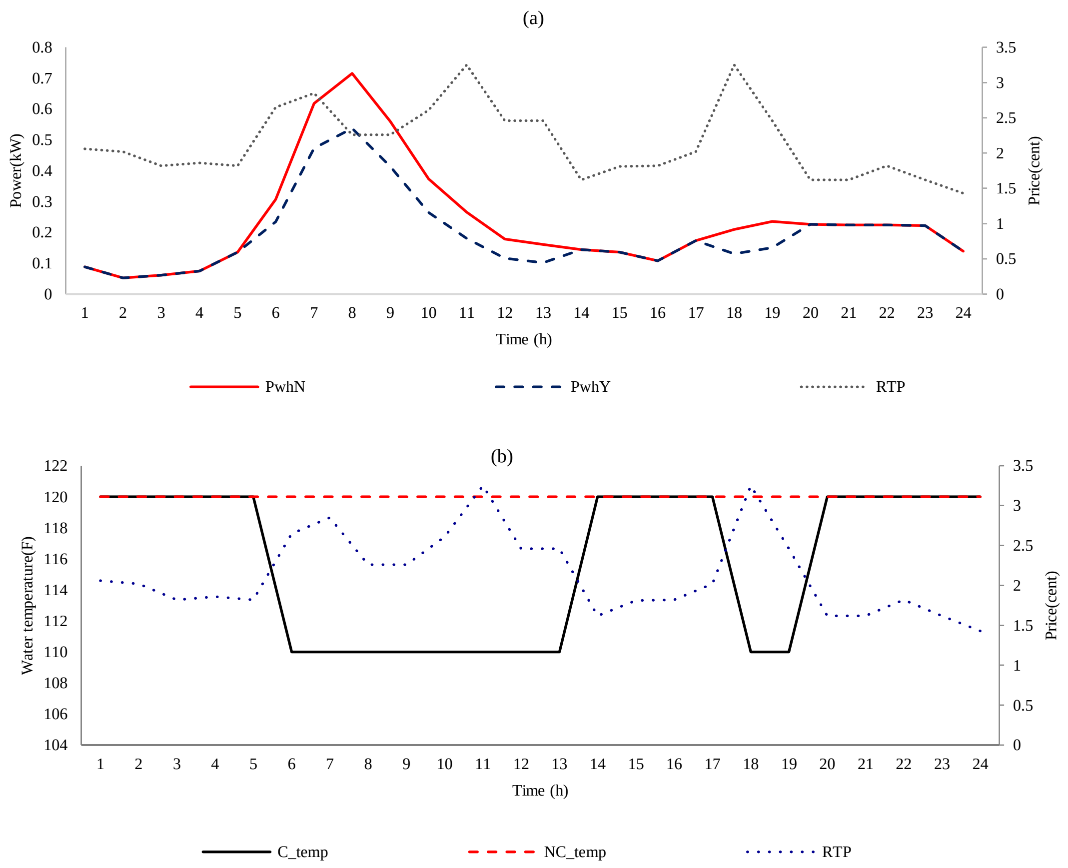


Figure 5-10: a) The controllable operation time of the EWH based on RTP and DL compared with non-controllable operation, b) the controllable water heater temperature compared with non-controllable water temperature

Some of controllable loads used in this simulation including PP and PEV are able to perform their function in a flexible time frame. The operation time of the PP is assumed to be 5 hours daily at any time between 6:00am and 12:00am, this time is different from one scenario to another, however, it cannot be run beyond midnight up to early morning (12:00am to 6:00am) due to noise considerations. For instance, Figure 5.11 shows that the PP is running between 5:00am to 10:00am, when it is not controlled, while the operation time of the PP is controlled by rescheduling it to (2:00, 4:00, 8:00, and 9:00pm), when the price signal is low, and 5:00pm, when the price signal is high, or when it can be supplied by the energy available in the ESS.

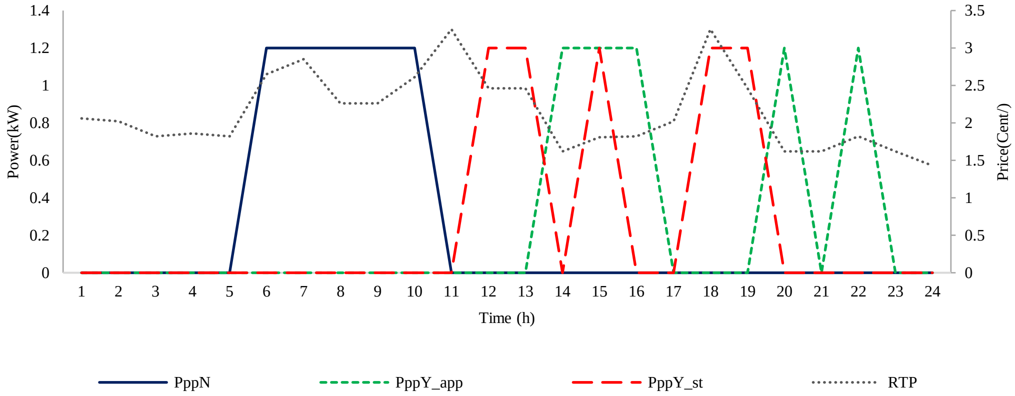


Figure 5-11: Rescheduling the operation time for the PP based on RTP, DL and energy availability in the ESS

Figure 5.12(a) shows the PEV is off grid in the period from 6:00am to 6:00pm, while the energy available in the PEV at 6:00pm when it has connected to the grid is 40% (9.6kW). Figure 5.12 (b) shows the non-controllable charging operation for PEV will started immediately once it is on grid, based on the charging/discharging rate presented in Table 5.1. The charging operation takes four hours from 6:00pm to 10:00pm without considering the energy cost or peak demand period. On the other hand, the controlled operation of the PEV, when it is considered as available energy storage, means that the charging/discharging operation for the PEV is controlled based on the RTP and the DL signal. In the period from 6:00pm to 7:00pm and at 2:00am, when the price signal is high, the HEMS controller starts using the energy available from the PEV to supply the loads unless the remaining energy in the PEV will drop below the minimum state of charge 10% (2.4kW). To ensure that the PEV is fully charged before the next trip at 6:00am, the charging operation is started whenever the RTP is low and the total power consumption is below the DL. An additional benefit to utilising a HEMS type controller with a PEV is that uncontrolled charging/discharging of PEVs will theoretically significantly increases the stress on the grid, if we consider that numerous PEV owners will arrive home from work within a narrow time period and immediately plug-in their vehicles to charge during a time of already high peak demand.

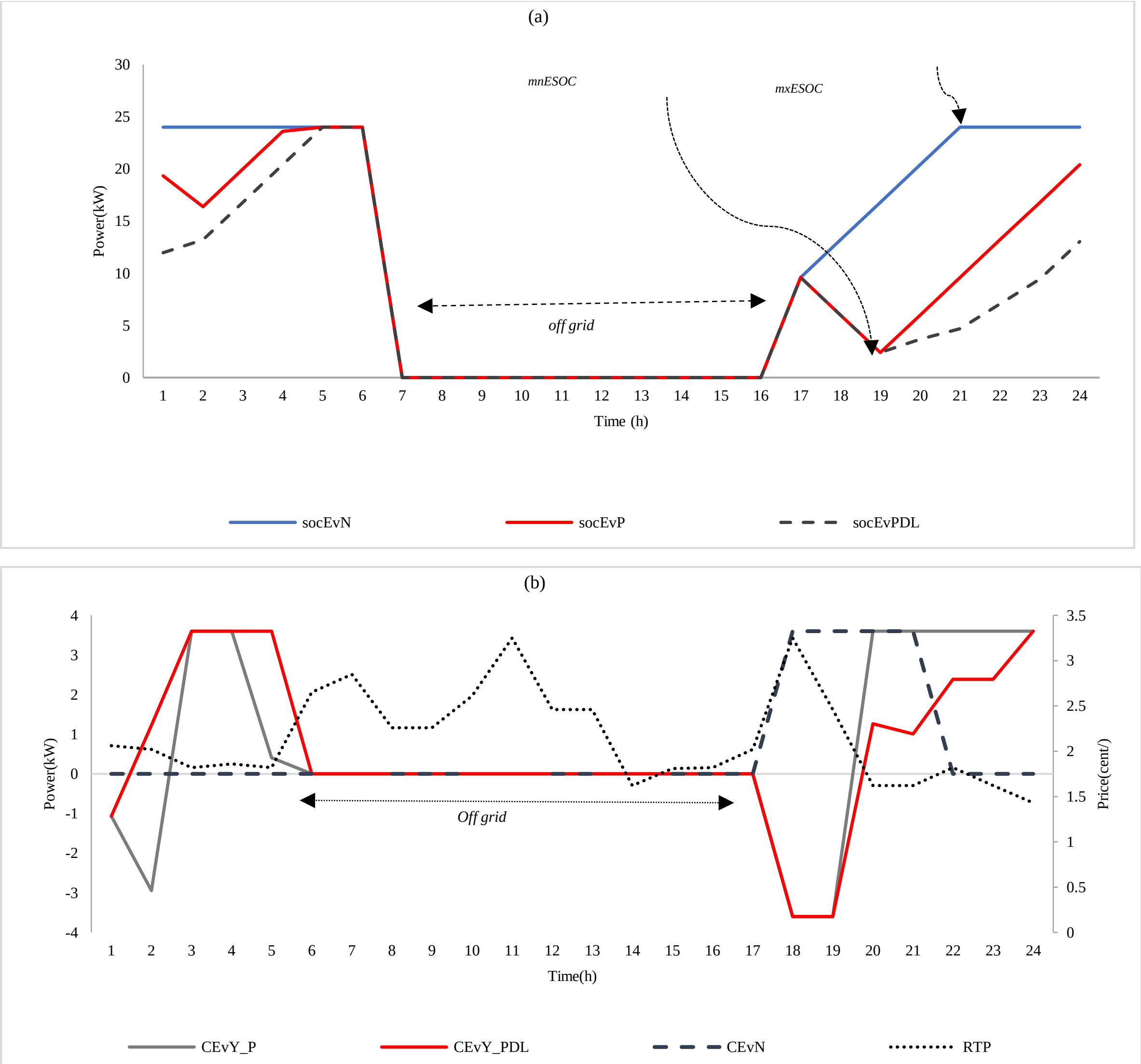


Figure 5-12: Controlling operation of the PEV as storage based on RTP & DL: a) Hourly PEV's battery state of charge, b) Charging and discharging PEV's battery rates

The proposed HEMS also manages another type of controllable appliances including DW and CD, which have different features to the PEV and the PP as the operation of theses appliances is uninterruptible. As soon as these appliances start operation they should continue till completion. The DW is assumed to have two tasks in different time periods, the first task should be turned ON at any time between 9:00pm to 5:00am and the second task from 9:00am to 5:00pm, both should be run for a 120 minute interval until the job is completed as shown in Figure 5.13.

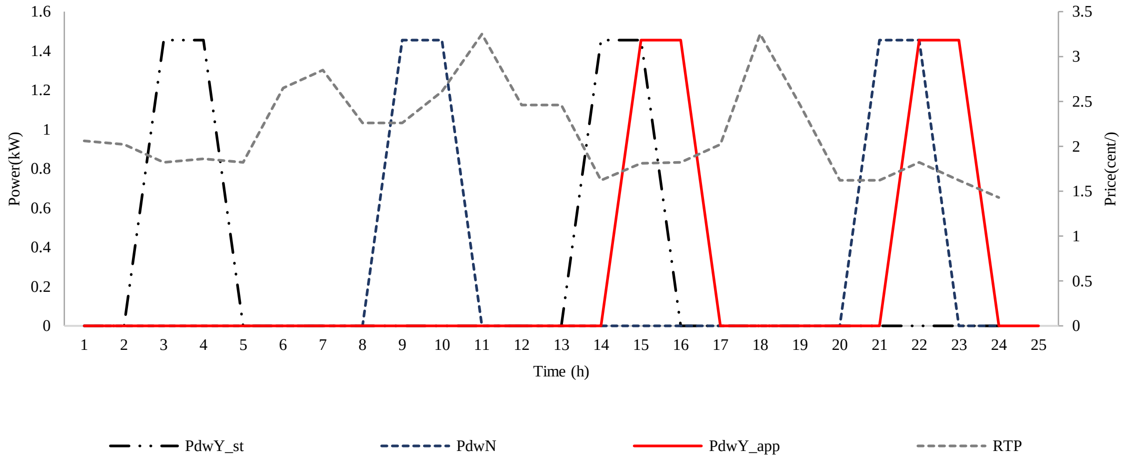


Figure 5-13: Rescheduling the operation time for the DW based on RTP, DL and energy availability in the ESS

The CD can be started any time between 5:00pm and 5:00am and it needs 120 minutes to finish its function as shown in Figure 5.14. Thus, the HEMS controller manages and determines the schedule to operate these appliances based on the electricity price, energy availability in the ESS and ensuring the total power consumption does not exceed the DL, as well as the managing consumer preferences and load priority as described in our previous work [132].

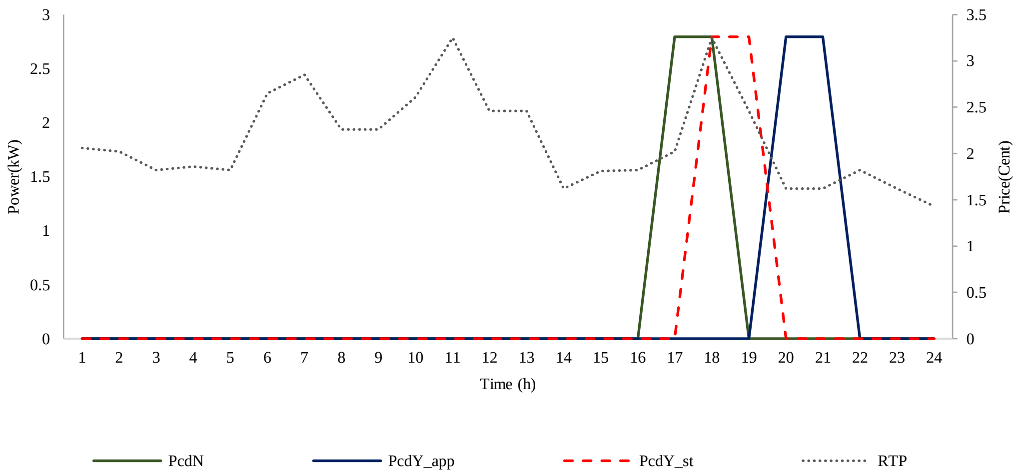


Figure 5-14: Rescheduling the operation time for the CD based on RTP, DL and energy availability in the ESS

5.6 Conclusion

This chapter presented an intelligent HEMS algorithm and optimisation models for controllable household loads with incorporation of an integrated energy storage system. Mathematical models of the high power consumption loads including air-conditioner, electric water heater, dishwasher, clothes dryer and pool pump for a typical home along with energy storage system models including fixed battery and plug-in electric vehicle have been developed. These models are used to control and schedule the operation time of the high power consumption loads based on pricing signals, energy availability, and consumer preferences and load priority to achieve reductions in energy cost and CO_2 emissions and to keep the total power consumption under the demand limit, while minimising any impacts on consumer comfort. The results obtained from the simulations show that controlling the household appliances based on the RTP without energy storage and with DL is up to 18% better than the same scenario with no HEMS control. The scenario where the loads are controlled based on the RTP without DL can achieve a slightly greater benefit to the household, however, without DL the energy demand created by consumers during low energy price periods may exceed the maximum supply levels that the power plant can generate requiring more power plants to be brought online increasing CO_2 emissions. To evaluate the potential increase in efficiency and reliability of the proposed HEMS model when energy storage is available, a short-term storage system including a fixed battery and/or Plugin Electric Vehicle (PEV) battery were also simulated. The results indicated that using a fixed battery for energy storage was considerably better than just using a PEV's battery, even if the capacity of the PEV's battery is much larger than the fixed battery. This is because the time when the PEV battery is available on grid is limited and most of the time when it is available must be utilised to charge it. The results show that installing a small additional battery storage of only 1.5kWh without a PEV present enables a significant cost reduction to a household of around a further 17% lower than the scenario where both a fixed battery and a PEV are included. This demonstrates that widespread deployment of small scale fixed energy storage alongside an intelligent HEMS could enable significant reductions in peak energy usage, and household energy cost. Different PEV usage patterns could also significantly increase the benefits possible through incorporation of a PEV battery as an available energy storage device within the system. In summary, this chapter has shown that incorporation of an intelligent HEMS algorithm with access to short term energy storage alongside a real-time pricing strategy can provide significant benefits to both consumers and utilities and more work to explore how such HEMS systems could be deployed in the context of Smart Grid rollouts is recommended, which can benefit both consumer and utility company.

Although the proposed model in this chapter has resulted in an important cost reduction, however, choosing an arbitrary capacity of the fixed battery may not only be considered subjective, it also do not guarantee that selected battery capacity is optimal. Therefore, this work has considerable scope for further development including exploration of the optimisation of residential renewable energy sources to increase the reliability and the efficiency of the proposed HEMS algorithm. A Photovoltaic (PV) systems that use solar energy to produce electricity are developing increasingly fast compared to other renewable energy options, and show great potential to offset non-renewable energy sources. Such systems can be either stand-alone or connected to the utility grid. However, a big disadvantage of such systems is that PV generation is highly dependent on weather conditions. Thus, some form of energy storage is necessary to help produce a stable and reliable output from PV generation systems to maintain power quality to loads and to improve both the steady state and dynamic behaviours of the entire generation system. The optimal sizing of a grid-connected hybrid photovoltaic/battery energy system is presented in the next chapter.

6 Chapter 6: Impact of Energy Management System on the Sizing of a Grid-connected PV/Battery system

6.1 Introduction

Rapid population growth and modern industrial developments have increased the world's demand for energy, which has traditionally been met by fossil fuels. However, these fuels are finite and not evenly distributed around the world. As a result, the prices of these resources fluctuate a great deal as they are depleted, and this also causes coincidental geopolitical factors that can also affect the long-term energy security of many nations. Moreover, the use of fossil fuels for power generation is associated with emissions that have a negative impact on the environment. Renewable resources such as solar energy are recognised as an effective and environmentally friendly alternative for electricity generation. This is supported by the fact that photovoltaic energy is available almost everywhere around the world.

Hybrid renewable energy systems that use solar energy as a primary source are assuming increased importance because of distinctive advantages such as simplicity of allocation, high dependability, absence of fuel cost, low maintenance and lack of noise and wear due to the absence of moving parts [137]. Recent deceases in the prices of modern power electronics and solar panel modules indicate good promise for an increase in installations of solar power systems [138]. However, disadvantages such as intermittency and dependence upon weather conditions, which impact on the power generation reliability of the system, need to be considered. Hybridisation with energy storage and operating in a grid-connected mode are proven to help avoid the aforementioned drawbacks [139-141]. Because of their low cost and high efficiency, batteries are widely used as an energy storage means for renewable energy systems [142-144], but the required battery capacity has to be carefully sized to ensure the highest possible reliability and lowest cost of energy of the system. Furthermore, recent developments in Electric Vehicles has encouraged may researchers to study the possibility of using their batteries as power source which may benefit the grid and consumers in terms of cost and environmental footprint [145, 146].

In order to reliably and economically design a hybrid renewable energy system, an optimal sizing method is necessary. The sizing method can help guarantee the lowest capital cost with maximised use of the renewable resources and battery bank so that the system can work at optimum capacity. Various methods have been proposed for sizing hybrid renewable energy systems such as graphic construction methods, probabilistic methods, iterative methods and intelligent methods [81-85, 147, 148]. These methodologies are used by many researchers to design several stand-alone [149, 150] and grid-connected [151, 152] configurations of hybrid renewable energy systems

In addition to location specific energy resource profiles, ‘typical’ load demand profiles are used in many studies to represent the dynamic power consumption of a household [153]. These profiles consider the consumption when no energy management system is applied to control the operation of the household appliances. Although Plug-in Electrical Vehicles (PEV) are becoming more popular, no study that the authors are aware of has investigated the impact of incorporating an PEV dynamics on the sizing of grid-connected hybrid renewable energy systems. Therefore, in this research a GA will be applied for optimising the component sizing of a grid-connected photovoltaic/battery renewable energy system when different charging/discharging scenarios of an PEV are considered.

The rest of this chapter is organised as follows. Section 2 describes the modelling of the system components; Section 3 presents the system’s operational strategy and Section 4 formulates the optimisation problem. Section 5 briefly describe the optimisation method while the results are presented and discussed in Section 6. Finally, the conclusions are summarised in Section 7.

6.2 Modelling the system components

Figure 6.1 illustrates the structure of the grid-connected renewable energy system. Beside the solar panels, the proposed system is equipped with batteries, controller, DC/DC converter and a main fuse to connect with the public grid. In addition, an electric vehicle is used as an extra energy storage when it is available.

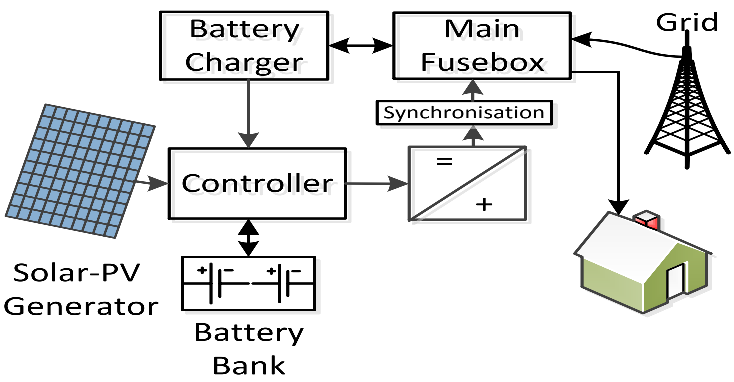


Figure 6-1: Schematic diagram of a grid-connected hybrid photovoltaic/battery power system.

The models for the battery' charging/discharging dynamics, electric vehicles and their efficiencies as well as electric grid are already presented in Chapter 5. The following subsections present the other component details including PV panel, converter, and the load.

6.2.1 PV panels model

The direct conversion of the solar energy into electrical power is obtained by solar panels. A solar PV panel consists of several serially connected solar cells, in order to provide the desired values of output voltage and current. Figure 6.2 shows the equivalent circuit of a single solar cell, from which the nonlinear I–V characteristic can be deduced.

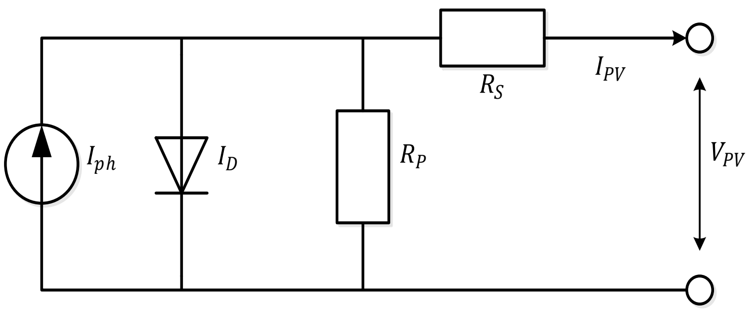


Figure **6-2** Single-diode model of practical solar-PV cell [154].

Each cell can be modelled based on a single diode equivalent circuit as follows[154]:

$$I_{PV} = I_{ph} - I_{sat}\left[exp^{\frac{V_{PV}+R_S I_{PV}}{V_t}} - 1\right] - (V_{PV} + R_S I_{PV})/R_P \tag{6.1}$$

where, I_{ph} is the photon current, I_{sat} is the diode reverse saturation current, $V_t = KT_{op}/q$ is the thermal voltage (Boltzmann constant, K; Operating temperature, T_{op}; Electron charge, q). The values of the series resistance (R_s) and shunt resistance R_P can be estimated from the characteristic curve provided by the module's manufacturer [62]. A time-series of the solar power conversion is established by feeding a solar irradiance profile, corresponding to a Western Australian site (latitude: -31.75^0, longitude: 115.8^0), into the model. The solar irradiance profile used in this study is predicted using the well-known ASHRAE clear sky model [101].

The overall output power of each PV system (P_{PV}) at time t can be obtained from the solar radiation by the following formula:

$$P_{PV}(t) = N_{PV} \times I_{PV} \times V_{PV} \times \mu_{PV} \tag{6.2}$$

where, N_{PV} is the number of panels in the system and μ_{PV} is the overall efficiency of the DC/DC converter. It is assumed that the converter has a maximum power point tracking (MPPT) system and the temperature effects are ignored. The variable N_{PV} represents the number of solar panels.

6.2.2 Inverter

The inverter has been modelled according to its efficiency as a function of the input normalised power, where losses are assumed to be a quadratic function, according to the following experimental equation [141]. The conversion efficiency formulation in the next equation is carried out from a quadratic interpolation of an experimental curve generated at the INES institute.

$$\mu_{cnv} = 1 - \frac{1}{Norm} \times (0.0094 + 0.043 \times Norm + 0.04 \times Norm^2) \tag{6.3}$$

where $Norm$ is the normalised input power of the inverter. Equation (6.3) is applied to the PV converter, the batteries' converter, and the DC/AC converter.

6.3 Load Model

A typical load demand profile is used to guide the sizing process. This profile is a result of applying a specific energy management system for controlling the operation of the household appliances as previously published by the authors [132], where no scheduling for the household appliances is applied. This load profile is shown in Figure 6.3.

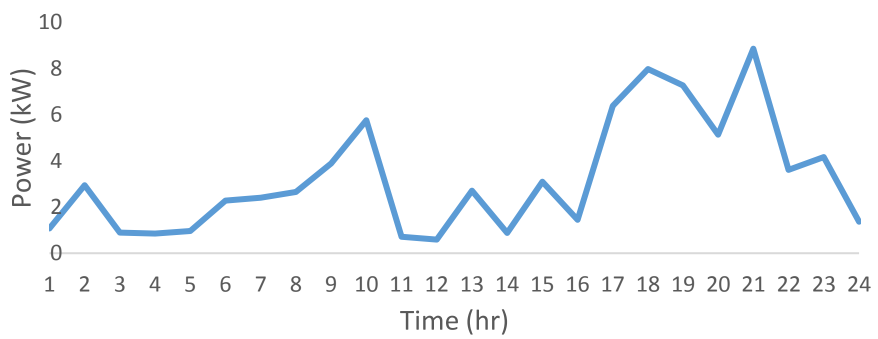


Figure 6-3: Load demand profiles when no scheduling is applied for the household appliances.

6.4 System Operation Strategy

The system's operation strategy is developed based on the energy balance between generation and demand. Figure 6.4 shows a flow chart of the strategy employed to operate the proposed grid connected renewable energy system. After selecting the size of components, the power generated by the solar panels (P_{solar}) is compared with the load demand (P_{Load}) to determine the flow of energy between PEV and the battery storage system. Based on the net power (P_{net}), either the grid mode, the battery storage system, or the electric vehicle battery will be used to offset the deficit/surplus of energy. If $P_{net} < 0$, the grid mode will be activated to compensate the power deficit. On the other hand, when $P_{net} > 0$, the surplus will be used to charge either the battery storage system, the electric vehicle or both depending on their state of charge.

The chosen components are then assessed to ensure that the power they generate satisfies the Renewable Energy System Contribution ($RESC$) limit, which represents the contribution of the renewable energy system to the total demand. It is set to ensure that the system can provide a reasonable amount of energy to residential load. In the calculation mode, the total cost of energy (COE) of the system which includes the cost of energy generated by the renewable system (solar panels and battery storage system) and the cost of energy drawn from the grid, is calculated. Based on the value of the COE, the GA will evaluate whether the chosen components acquire the best possible minimum cost or another combination of component sizes will provide better COE.

When the grid mode, Figure 6.5, is activated, the cost of energy from the grid is firstly assessed. If the energy price is higher than a predefined limit, the cost of energy from the grid is considered 'High'. In this case, the deficit is drawn from the electric vehicle if it is on grid and has available power and/or the battery storage system. The rest of the deficit (if any) is drawn from the grid. When the cost of energy from the grid is 'Low', the load will be satisfied from the grid in addition to charging the electric vehicle (if it is on grid) as well as charging the battery storage system.

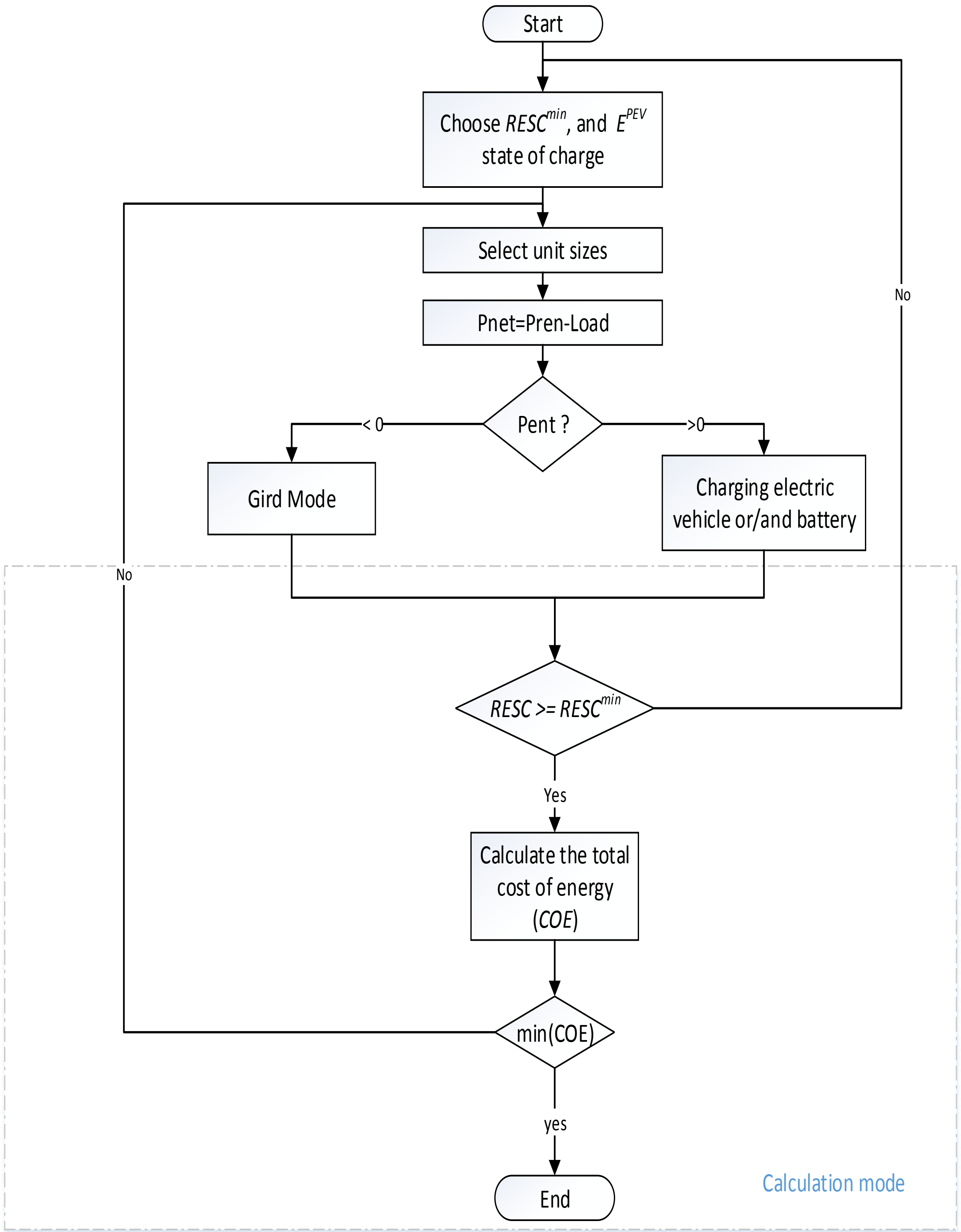


Figure 6-4:The flowchart of the system's operation strategy “Calculation mode”

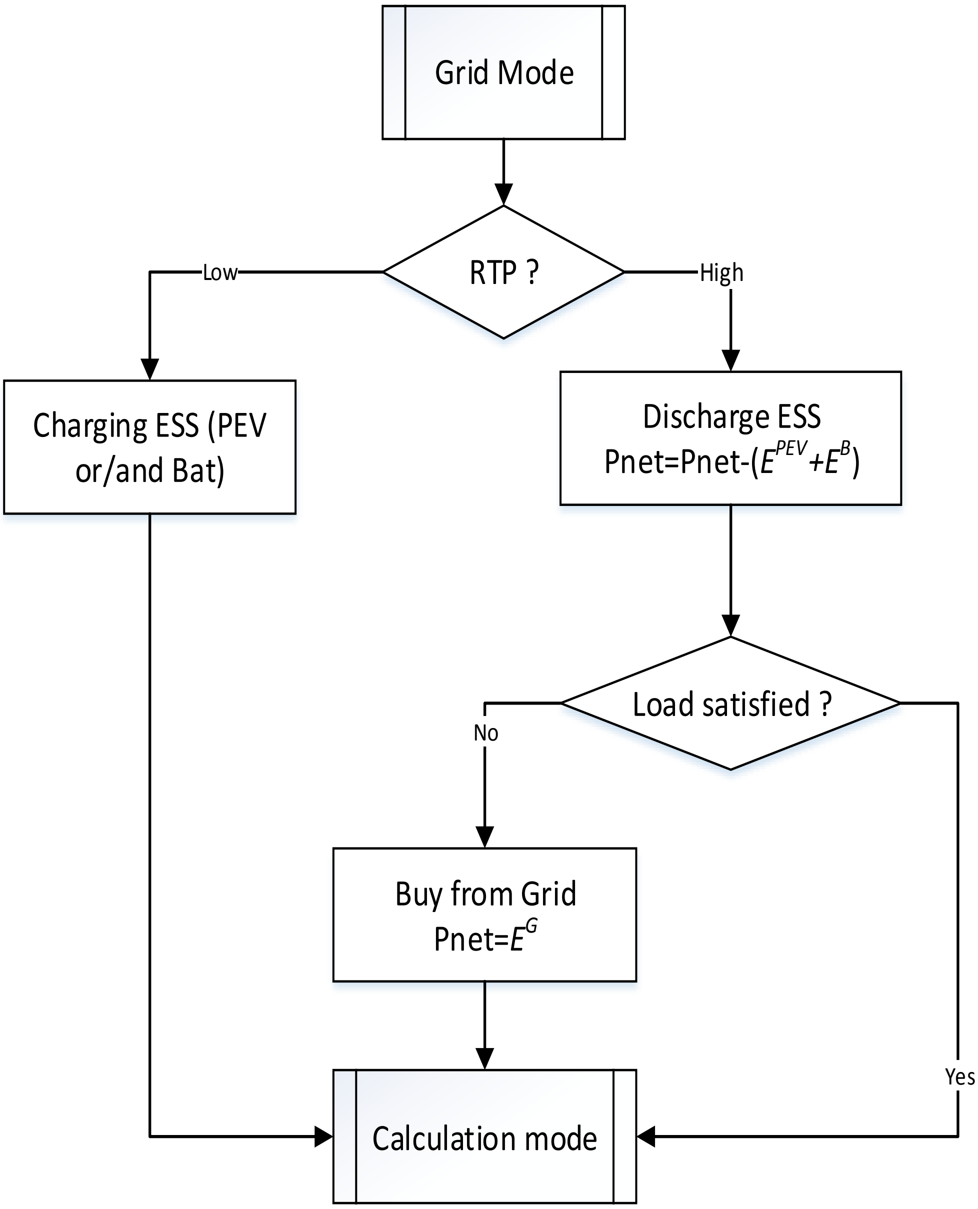


Figure 6-5: The flowchart of the system's operation strategy “Grid mode”

6.5 Sizing problem formulation

6.5.1 Problem statement

The aim is to optimally design a grid-connected solar system with battery storage to supply renewable power for a residential building. Optimisation variables are the number of solar panels N_{PV}, number of batteries N_B, and number of inverters N_{inv}. The sizing is formulated as a single objective function designed to optimise (minimise) the Cost of Energy (COE) as follows:

$$F(N_{PV}, N_B, N_{inv}, RESC) = \min(COE) \tag{6.4}$$

The COE ($/kWhr) for a renewable energy system can be calculated by considering either the useful power only (power consumed by the load) and ignoring the dumped power, or by considering the total power generated by the system. For this study, the second concept is used to calculate the system's COE and it may be expressed as [155]:

$$COE = C_{annual}/E_{annual} \tag{6.5}$$

Here, C_{annual} is the total annual cost ($) and E_{annual} is the total annual energy (kWhr) generated by the renewable energy system. The annual cost of component i is defined as:

$$AC_{i=}N_i\{[CC_i + RC_i \times K_i(ir, L_i, y_i)] \times CRF(ir, R) + OMC_i\} \tag{6.6}$$

where, CC_i is the annual capital cost, RC_i is the replacement cost, OMC_i is the operation and maintenance cost, ir is the monetary interest rate, and R is the project lifetime of the entire system (in this research this is taken to be equal to the lifetime of the solar-PV module), L_i is the component's lifetime and y_i is the number of component replacements required during the project lifetime ($L_i, y_i \leq R$). The installation and balance of system costs are set to 10% percent of the system's capital cost [29]. The parameters CRF, and K_i, which help define the salvage worth of the system at its end of lifetime, are the Capital Recovery Factor and single payment present worth, respectively, and they are defined as follows:

$$CRF(ir, R) = ir\,(1 + ir)^R/((1 + ir)^R - 1) \tag{6.7}$$

$$K_i(ir, L_i, y_i) = \sum_{n=1}^{y_i} 1/(1 + ir)^{n\,L_i} \tag{6.8}$$

The costs, lifetime and size for the components used in the sizing process are presented in Table 6.1 and derived from values in the literature [156-158]. The operation and maintenance costs of the components are taken as a percentage of the capital cost as referred by Li et. al. [81]

Table 6-1: Data for the hardware parameters used in the optimisation: Costs and component lifetimes.

Component	**Unit size**	**Capital/Replacement ($/unit)**	**O&M ($/year)**	**Lifetime (year)**
Solar panel	250W	245	0	25
Lead-acid Battery	1.5kWhr	615	7	5
Inverter	3kW	722	7	10

6.5.2 Constraints

For the renewable energy system considered, the following constraints must be satisfied:

$$N_{PV} = Integer, \qquad 1 \leq N_{PV} \leq N_{PV}^{Max} \tag{6.9}$$

$$N_B = Integer, \qquad 1 \leq N_B \leq N_B^{Max} \tag{6.10}$$

$$RESC \geq RESC^{Min} \tag{6.11}$$

where N_{PV}^{Max} and N_B^{Max} are the maximum available number of solar panels and batteries, respectively, and $RESC^{Min}$ is the minimum limit of the contribution of the renewable energy system to the total load demand. The last constraint is designed to ensure that the renewable energy system provides a reasonable contribution to the overall demand of the building.

6.6 Optimisation Method

An integer single objective Genetic Algorithm is implemented using the MATLAB optimisation toolbox. For the sizing problems considered in this chapter, the GA searches for the optimal number of the system components, i.e. selects the optimal number of solar panels, batteries, and the rating of the DC/AC converter. The primary objective is to minimise the system's overall cost of energy over its entire lifetime. In order to use the optimisation toolbox, a MATLAB code representing the fitness function, which calculates the values of the total cost of energy (fitness value), has been written as an M-file. To account for the $RESC$ constraint presented in Equation (6.11), the algorithm is adopted to eliminate all solutions that do not satisfy this constraint. The constraints related to the bounds on the number of components (Equations (6.9) and (6.10)) are entered directly into the optimisation toolbox. The settings used in the optimisation toolbox are as follows: four subpopulations with 100 individuals; scattered crossover function with 0.8 crossover fraction; the elite count is 2; rank and constraint dependent function are used for the scaling and mutation, respectively; the number of generations is set to 100.

6.7 Results and Discussion

In order to evaluate the impact of imposing a limit on the contribution of the renewable energy system to load demand and controlling the operation of charging/discharging of PEV on the sizing of a grid-connected hybrid PV/Battery system, the performance of the entire system is simulated using the models presented in Chapter 5. The parameters of the component modules used in this study are listed in Table 6.1. The solar radiation data used to estimate the power generated by the solar panels belongs to a Western Australian location (latitude: -31.75^0, longitude: 115.8^0) and simulated using the ASHRAE model which is already mentioned in Chapter 3. MATLAB software is used for simulating the system components as well as executing the Genetic Algorithm optimisation. The algorithm attempts to find the optimum number of solar panels and batteries. The minimum number of each component is set to 1 and the maximum allowable number of solar panels is limited to the roof area available for the household and in this study, is set to 20 panels. Ten battery units are chosen as the maximum number of batteries that can be installed and 10kW is set as the maximum allowable capacity of the DC/AC converter. Three values of $RESC^{Min}$ presented in Equation 6.11 are considered in this study which are 20%, 50% and 70%, which means that the hybrid system must at least supply 20%, 50% and 70%, respectively, of the household demand. For each value of $RESC^{Min}$, different electric vehicle state of charge (40%, 60%, 70%) at the arrival time.

Table 6.2 summarizes the sizing results when a real-time price signals and several scenarios of electric vehicle state of charge (E^{PEV}) at the arrival time are used. In this table, the optimum numbers of the solar panels and batteries as well as the corresponding COE have been indicated. As for the inverter the optimisation algorithm has chosen the optimal capacity three times more than unit size which is presented in Table 6.1. Two observations can be made from Table 6.2.

Table 6-2: Summary of the results obtained by the sizing algorithm when several scenarios of electric vehicle state of charge and Renewable Energy System Contribution.

$RESC^{Min}$ (%)	E^{PEV} (%)	PV panel (units)	Battery (units)	COE ($/day)		
				Renewable	Grid	total
20	40	5	1	2.19	12.036	14.230
	60	5	1	2.19	11.80	13.993
	70	5	1	2.19	11.36	13.553
50	40	14	1	2.47	8.93	11.411
	60	14	1	2.47	8.48	10.95
	70	14	1	2.47	8.26	10.744
70	40	17	4	4.57	7.41	11.98
	60	17	4	4.57	7.08	11.66
	70	17	4	4.57	7.08	11.66

Table 6-3: Renewable energy cost.

PV panel (units)	Battery (units)	Cost of energy from renewable system (cent/kWh)
5	1	17.0529
14	1	7.7320
17	4	10.328

The first observation is that increasing the $RESC$ limit has reduced the overall cost of energy (COE, $/day) of the grid-connected renewable energy system. When the E^{PEV} initially has a 40% state of charge; the system sized with $RESC^{Min}$ is 50% or 70%, the COE is 20% and 16%, respectively, less than when $RESC^{Min}$ is 20%. For the optimal solutions that achieved when the $RESC^{Min}$ is increased from 20% to 50% and to 70%, the required number of PV panels has changed from 5 to 14 to 17, respectively. At the same time, the required battery capacity remains the same (one battery) when $RESC^{Min}$ is 50% while the optimal number of batteries increases to four batteries when $RESC^{Min}$is 70%. These trends can also be seen when values of 60% and 70% for E^{PEV}state of charge are used.

The reason behind the total cost reduction is because the cost of energy from the renewable system tends to decrease when more solar panels are installed as can be seen from Table 6.3. For a system with only 5 solar panels, the cost of energy is 120% and 65% higher compared to a system with 14 and 17 panels, respectively. However, when more battery units are installed, the cost per kWh is slightly increased but the total trend is not affected. The reason for this is with a higher contribution limit (Equation 6.11) more renewable energy needs to be stored in order to satisfy the load during high electricity prices from the grid.

The second observation is that the state of charge of the PEV at arrival time (E^{PEV}) does not affect the optimal size of the grid-connected renewable energy system. The optimal number of solar panels and batteries remain the same when $RESC^{Min}$is 20%, 50% or 70% for all the examined PEV state of charges at arrival time (40%, 60% and 70%). Nevertheless, the total daily cost is decreased as can be seen from Table 6.2 when more energy is available from the PEV battery.

To investigate the reason behind the previous observation, further analysis for the daily power profiles of the system components is undertaken. Figures 6.6, 6.7 and 6.8 show the daily power profile of the solar panels, battery, PEV and grid for different E^{PEV}. As can be seen in these figures, the PEV has contributed to the load demand for a short period (two hours early in the morning and three late afternoon) and these hours are outside the daytime period. This means that the PEV cannot substitute the power generated by the renewable source (solar panels) because there is no solar radiation outside daylight hours. As a result, the size of solar panels required to satisfy the load demand during daytime remains the same regardless of the presence of the PEV.

As for the reason, why the total daily cost is slightly reduced when the PEV arrives with a higher state of charge, this is due to the fact that the PEV can be used to supply power instead of the grid during periods when the price is considered 'High' (hours 1, 2, 17, 18) as can be seen in these figures. These values of grid energy prices are higher than the price limit defined by the operation strategy described in Section 3. The majority of the generation deficit at these hours is augmented by the PEV, which helped to avoid buying costly power from the grid. As a result, the cost of power drawn from the grid and in turn the total daily cost are reduced.

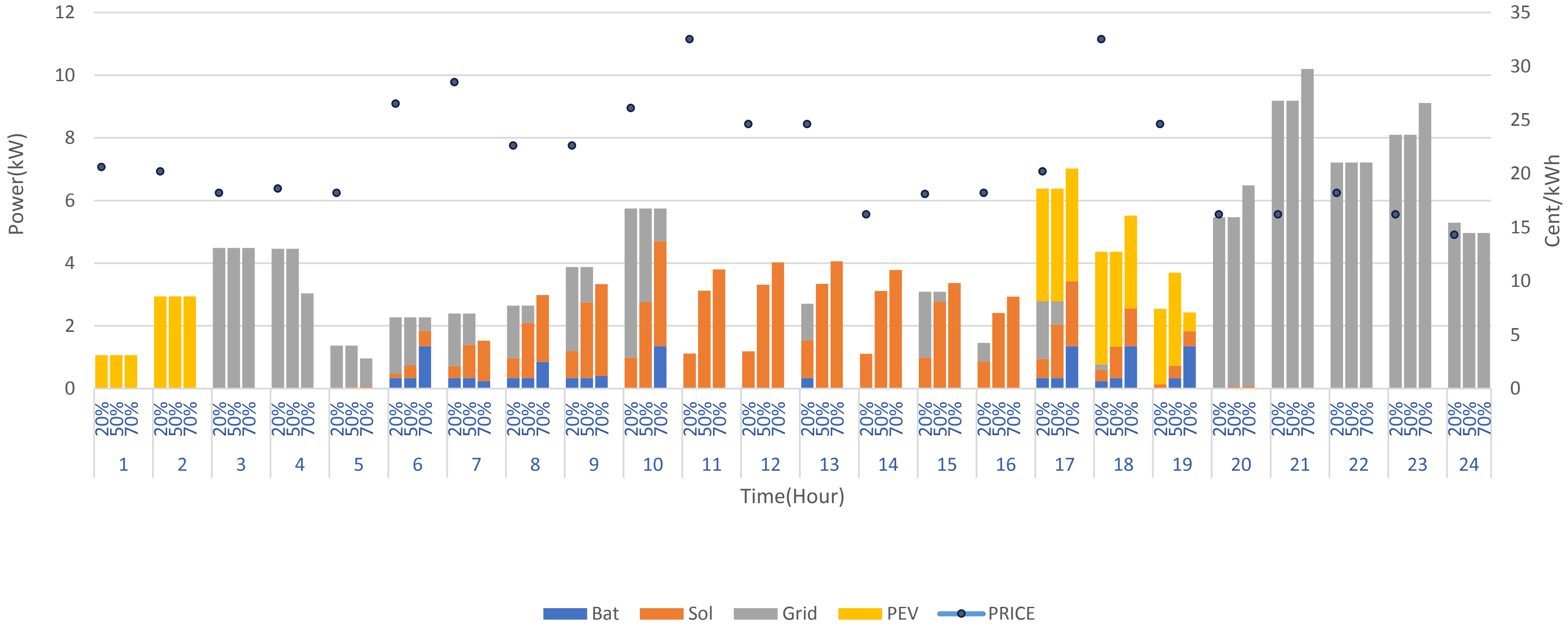


Figure 6-6: The daily power profile of the solar panels, battery, PEV and grid where PEV state of charge is 40%.

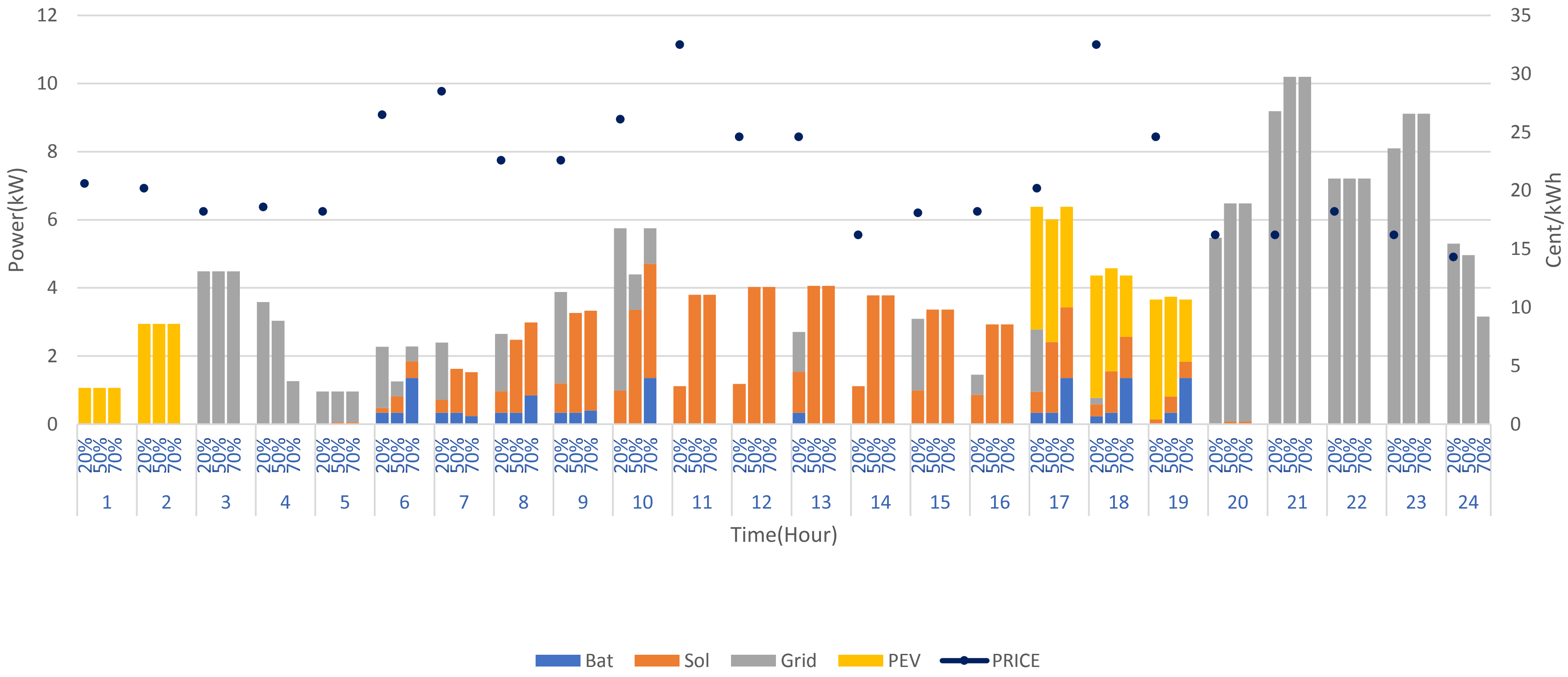


Figure 6-7: The daily power profile of the solar panels, battery, PEV and grid where PEV sate of charge is 60%

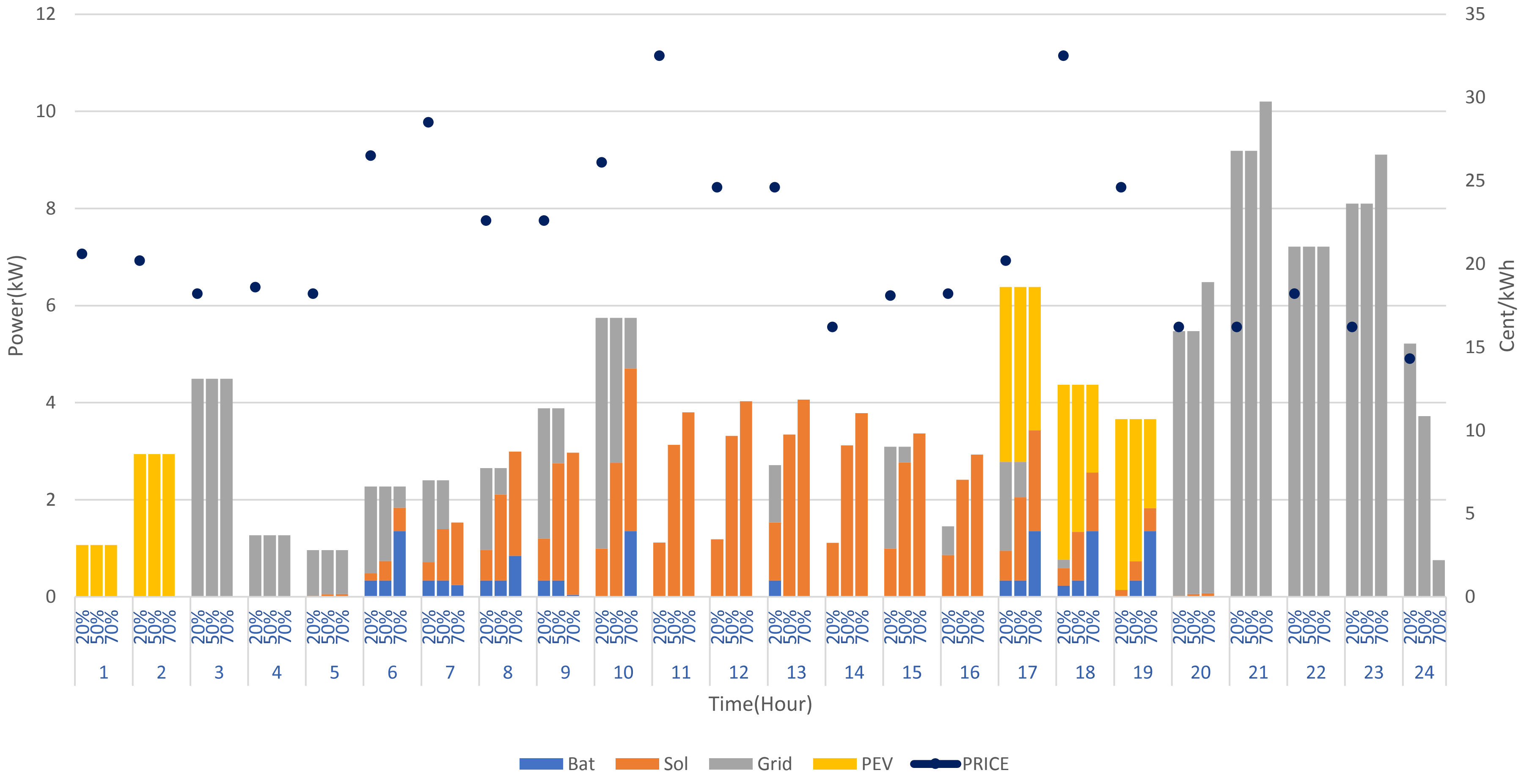


Figure 6-8: The daily power profile of the solar panels, battery, PEV and grid where PEV sate of charge is 70%

6.8 Conclusion

This chapter studied the sizing of a grid-connected hybrid renewable energy system supplying electric power to a household that employs an energy management system to control the operation of its appliances. The system evaluated consists of solar panels, a battery storage system and power converter. The solar panels are considered as a primary source while the battery storage system is used to supply the deficit power during periods the primary source cannot meet the whole load demand. An integer Genetic Algorithm (GA) is used to optimally size the system components and the Renewable Energy System Contribution parameter is adopted to ensure that the designed system reasonably contributes to the total load demand.

The results showed that the level at which the system is required to contribute to the total annual demand affects the optimal size of a grid-connected renewable energy system. However, the PEV cannot substitute the power generated by the renewable source (solar panels) because there is no solar radiation outside daylight hours. As a result, the size of solar panels required to satisfy the load demand during daytime remains the same regardless of the presence of the PEV. Nevertheless, the total daily cost is reduced when the PEV arrives with higher state of charge, this is due to the fact that the PEV is used to supply power instead of the grid during periods of high electricity prices.

The next chapter proposes an efficient scheme for residential load scheduling integrated with a DR program using the optimum size of the system components and renewable contribution that have been obtained from this simulation. It is a comprehensive solution, which is capable of automatically managing and controlling small-scale renewable energy generation facilities and energy storage system (ESSs) including batteries and PEVs, and household smart appliances based on real-time pricing signals.

7 Chapter 7: An Efficient Scheme for Residential Load Scheduling Integrated With Demand Side Programs and Small-scale Renewable Energy Generation and Storage

7.1 Introduction

Increasing numbers of countries have recently been investing heavily to upgrade their electrical power grids with smart grid capabilities. For instance, the Smart Grid, Smart City (SGSC) project has been deployed in Australia as the first commercial-scale smart grid. Economic studies predict that the outcomes of the SGSC project will encourage adoption of smart grid technologies across the National Electricity Market. Such a move will both result in an estimated overall financial benefit of $9.5-$28.5 billion over 20 years and lower network prices [159]. Transformation towards smart grids has been encouraged by the following essential factors. 1) Conditions of the infrastructure of the existing electric grid is deteriorating due to both age and overuse. This deterioration is associated with the ongoing rise in demand without a matching investment in the overworked power transmission and distribution infrastructure and 2) concerns about relying on fossil fuels available in politically unstable regions along with negative impacts on the environment and eventual depletion, which drives efforts for diversification of energy sources. In this context, renewable sources of energy are an attractive option to reduce reliability on depleting resources while also decreasing the environmental burden associated with the use of fossil fuels [121]. However, renewable sources of energy may be associated with fluctuation of energy generation, a problem that needs to be addressed if these sources are to be effectively integrated with the supply system [160, 161].

Furthermore, new loads such as Plugin Hybrid Electric Vehicles (PHEV) are likely to significantly increase the burden on aging power systems and infrastructure [162-164]. With the adoption of smart grids, electric power can become more reliably and efficiently generated, transmitted, and consumed compared to traditional electricity systems [13]. Through the two-way flow of information (embedded into the smart grid system) between suppliers and consumers, the grids can also adapt more readily to the increased utilisation of distributed renewable energy sources, which can help to address the adverse impact of a large number of electric vehicles, reduce dependence on peak power plants, and encourage users' participation in energy saving through demand response (DR) programs. These DR programs enable consumers to effectively participate in the operation of the electric grid by adjusting their consumption profile according to the available generation, grid requests and their preferences, while simultaneously helping to compensate for the intermittency of renewably generated power [165, 166]. In addition to the traditional power grid capabilities, the design of smart grids would include integration of renewable energy generation, energy storage, demand side management and demand response programs.

7.1.1 Renewable energy generation

Renewable energy sources such as wind and solar are perceived to become critical for energy security and sustainability for many nations. To stimulate investments in solar and wind energy technology development and integration, the Australian government introduced the Small-scale Renewable Energy Scheme (SRES) which creates a financial incentive for households, small businesses and community groups. In addition, a target for large-scale renewable energy generation has been set that aims to supply 23.5 percent of Australia's electricity demand from renewable sources by 2020 [167]**.** However, the intermittency and seasonal dependency of renewables such as wind and solar impose a significant challenge to achieving this ambitious target [168]**.**

7.1.2 Energy storage

Energy storage technologies can be used to store surplus energy during high renewable energy generation periods. The stored power can be used to alleviate the need to generate power at low or no renewable generation times. This will help mitigate generation intermittency and demand uncertainty. For residential applications, batteries are increasingly widely being used for temporarily storing electric energy. Due to recent developments of PEVs, the batteries in them may also be used as temporary energy storage when they are connected to the grid [145, 146, 169].

7.1.3 Demand Side Management and Demand Response programs

A key difference between traditional and smart grids is the capacity to incorporate advanced demand response and management capability. Demand Side Management (DSM) approaches use highly controllable power generation to supply a largely uncontrollable and uncertain demand, while Demand Response (DR) programs use a new energy balancing paradigm to facilitate more penetration of intermittent energy sources along with an unpredictable demand. Home appliances such as water heaters, air conditioners, cloth dryers, and dish washers, which are known as controllable loads and consume around 25 percent of Australia's generated electric energy [170], have features that make them suitable for ‘smart’ control. The key features being that the operation of these appliances is elastic and delay tolerant. Another group of home appliances such as lighting, ovens and TV, which are known as critical loads, have unpredictable operation modes and should be powered whenever needed. DSM and DR strategies allow consumers to determine which load to control according to their own preferences. In smart grids, consumer comfort indices are introduced to quantify the impact of the smart operation strategies on the consumers’ lifestyle. User preferences and comfort constraints have already been discussed in detail in the previous chapters. The flexibility of smart grids can help in realising several often conflicting objectives such as minimising the electricity bill, reducing peak demand periods, maintaining consumer comfort and minimising greenhouse gas emissions, if appropriate incentive programs (such as real-time pricing) are effectively utilised.

7.2 Related work

For a smart grid, advanced dynamic control is required to simultaneously manage hybrid energy generation, which may include solar and wind power generation technologies, and several means of energy storage such as electric vehicles and batteries, as well as flexible load and real-time pricing of imported energy [171]. Many strategies have been put in place to increase consumer participation in DR programs. In this regard, Time of Use pricing (TOU), Inclining Block Rate (IBR), Day Ahead Pricing (DAP), and Real-Time Pricing (RTP) are the most common strategies [172, 173].

Home Energy Management Systems (HEMS) can play a vital role in the smart grid through coordinating the operating schedule of smart appliances. The energy management controller (EMC) acquires the DR signal through a smart meter and uses it along with price information and user inputs to generate operation schedules for the home appliances [52, 174]. In response to the dynamic price signals, the customers can shift their demands either automatically or manually, with the help of a home energy management system (HEMS), to the off-peak hours to minimise their electricity bill. Accordingly, the HEMS plays the important role of automatically coordinating the operating schedule of smart appliances with the consent of the customers, who have the option to monitor and directly control their own primary appliances [175]. The HEMS can be used to make the best decisions when scheduling the loads to be managed according to input signals and the end-user's preferences The challenge, which has received considerable attention recently [1, 24, 65, 113, 132, 176-178] is how to develop an efficient and optimal DR model of home electrical appliances taking into account conflicting objectives. Several studies on smart grid scenarios focused on optimising the scheduling of residential loads [56, 113]. In [113], an optimisation framework is developed to find the optimal trade-off between the electricity bill and waiting time of each home appliance taken into account real-time and forecasted energy prices. An approach for defining the optimal starting point of different home appliances while some constraints are put on the load limitation curve, is depicted in [56]. In this study, an evolutionary algorithm with local search is used to solve a nonlinear integer problem that minimises the energy cost and the violation of the load limitation curve. The optimisation variables were the demand response of electric vehicles, washing machines, dryers and dishwashers.

Several studies have recently focused on the role of decision support tools in helping domestic end-users to optimise different energy resources. The algorithm developed in [179] schedules the operation of home appliances, namely shiftable loads (e.g., dishwasher, laundry machine, and electric vehicle), controllable loads (e.g., lighting and heating, ventilation and air conditioning system), and a storage system. An exponential smoothing model is used in the aforementioned study to predict the power demand of managed loads. In addition, a Bayes theorem is used to estimate the likelihood of using a given load. Thermostatically controlled loads have also attracted the attention of some researchers. In [109] an appliance commitment algorithm is described that takes into account the user’s comfort, price and consumption forecasts, for scheduling thermostatically controlled appliances. Another optimal residential appliances scheduling scheme that uses RTP is depicted in [180]. The objective was to minimise the cost and the unconventional usage of the thermal load. However, the proposed scheme does not incorporate any optimisation approach which makes the achieved results not optimal. Adika et al [181] adopted a Linear programming strategy that focuses on cost minimisation but no distributed generation is incorporated in the proposed approach. Instead, the energy is purchased during off-peak periods and saved for reuse when energy from the grid is expensive.

Optimisation approaches that have been explored for this problem include Binary Particle Swarm Optimisation (BPSO) [182], [24] [183] and Greedy Iterative Algorithm [184]. The optimisation objectives span minimising the end-use energy consumption and/or maximising comfort level. Cooperative game theory has been used to realise an HEM strategy that considers minimising consumption cost in a smart home energy system [185]. Game theory has also been employed by Gao et al. [186] to implement an HEM strategy that takes advantage of favourable pricing tariffs adopted by utility companies and sells them back surplus energy from plug-in vehicle batteries. The Neural Networks' ability to accurately forecast future load demand has been employed by Ahmed et al. to manage conventional and renewable power sources within a smart grid [187]. This study revealed that research done on smart grid should not focus on the customer only but also try to tackle the problem from the point of view of the utilities.

Research has also been undertaken to develop optimisation models of smart grids [186, 188]. The outcomes indicate that the optimal control of smart grid in grid-connected and isolated mode is affected by many parameters including the availability of renewable resources, the load distribution and the changes to electricity prices. These parameters are central and must be sensibly considered in order to formulate an effective and optimal scheduling mechanism of electricity supply and demand in micro grids. The optimisation problem to reduce the electricity bill for different types of household appliances using Mixed Integer Programming Linear programming (MILP), was proposed in [189]. The optimal load schedule of a smart energy system that incorporates renewable energy sources and storage devices is modelled as a mixed integer programming optimisation problem in [190]. Another optimal scheduling of residential load using a MILP model is presented in [191] wherein the operation of the consumer's appliances and the distributed energy generators are optimised to minimise the total one-day ahead energy cost for a residential load.

This chapter extends the abovementioned studies and the work presented in the previous chapters, by proposing an efficient scheme for Residential Load Scheduling (RLS) integrated with a DR program wherein a small-scale grid-connected solar power generation facility, energy storage system (ESSs), plug-in vehicles, and household smart appliances are automatically controlled to maximise the consumer's comfort, minimise the daily electricity cost and minimise the CO_2 emissions. The proposed scheme uses Advanced Metering Infrastructure (AMI) to acquire time-based price messages from utilities to residences. The optimisation problem is formulated as a multi-variable single-objective problem that aims to reshape the end-user's consumption profile according to the available generation, grid requests and consumer's preferences, while simultaneously helping to compensate for the unpredictability of the renewable energy source. In addition to its ability to solve optimisation problems with infinite numbers of variables, GA has the advantage over other techniques of being able to easily jump out of a local minimum and find the global optimum efficiently [64]. Therefore, GA has been applied to solve the aforesaid optimisation problem.

7.3 System architecture and models

This section proposes an efficient scheme for Residential Load Scheduling (RLS) integrated with DR program**,** renewable energy generation, and an energy storage system to develop an autonomous decision-making system. Both the information flow (e.g., electricity price signals, weather forecast) and the power flow from the different power generations (e.g., power grid, solar power) and energy storage systems can be controlled and managed for an optimal performance by the HEM controller, as depicted in Figure 7-1. The proposed scheme is used to assist in minimising the overall energy cost and keeping the total household power consumption below a certain demand limit during peak periods, without compromising the comfort of the customers or undermining their needs. To evaluate the impact of DR on consumers' daily life, comfort indices are needed to measure the consumer's comfort level.

Two different types of energy demand are considered in the proposed system controllable loads and critical loads, which have been explained in the previous chapters. The mathematical models for renewable energy generation, energy storage systems (including battery and PEV), dynamic electricity prices and residential energy demand are described in the next sub-sections.

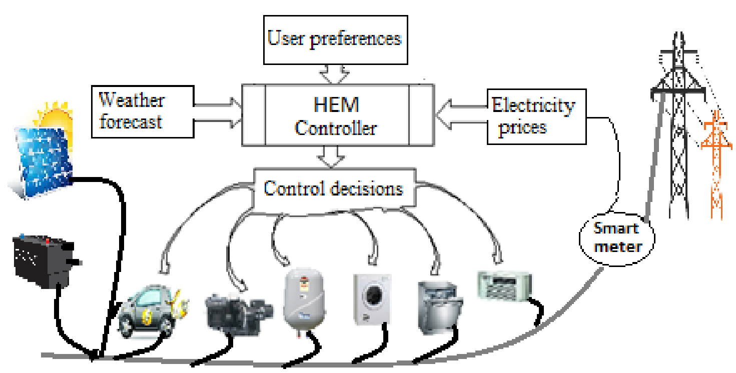


Figure 7-1 HEMS load modelling and control strategy

7.3.1 Renewable Energy Generation model

Let E_t^{sol} denotes the amount of solar energy generated in time slot t and assume that the energy is first supplied to meet the critical load before it can be used to supply the controllable load based on load priorities and consumer preferences, E_t^{sol} would then store the remaining amount of energy generated by local solar system in the battery at every time slot *t*, unless the battery is full; in this case, this amount of energy can be spilled or sold to the smart grid (not considered in this study). A controller variable y_t is used to regulate the remaining portion of $E_t^{sol}$of the generated energy provided to the critical load first to maintain the consumer comfort (as this load is more important to the consumer) to serve immediately without delay than the other loads.

$$0 \leq y_t \leq 1 \tag{7.1}$$

Note that the amount or energy generated by the solar system E_t^{sol} is limited by a maximum value E_{max}^{sol} as follows:

$$0 \leq E_t^{sol} \leq E_{max}^{sol} \tag{7.2}$$

7.3.2 Energy Storage model

Generally, there are several physical factors that compromise both the efficiency and life of a battery, since these parameters depend on the frequency at which the battery undergoes charging/discharging cycles plus the depth of discharging, as well as energy conversion loss during these cycles. These factors have been discussed in chapters two and five. For simplicity, an ideal battery model is assumed, without any inefficiency in charging or discharging. It is also assumed that the battery does not leak, rendering any reduction in the stored energy level exclusively associated with actual discharge. A battery storage system is used at the consumer side to store the energy generated by local solar generation${}_{chg}E_t^{sol,b}$; it uses the stored energy at any particular time of energy requirement. Moreover, it is assumed that, in each time slot t, an energy amount ${}_{chg}E_t^{g,b}$can be drawn from the traditional power grid (or simply power grid) to recharge the battery to utilise the time diversity of electricity prices. The intuition is that if we recharge the battery when the electricity price is low, the overall electricity cost may be reduced with a proper controller design. This approach can also be applied to the PEV battery. The state of charge (SOC) level for both batteries (fixed battery and PEV battery), E_t^b and E_t^{pev} are defined according to the following formulae:

$$E_{t+1}^b = E_t^b + {}_{chg}E_t^{sol,b} + {}_{chg}E_t^{g,b} - {}_{dsc}E_t^b \tag{7.3}$$

$$E_{t+1}^{pev} = E_t^{pev} + {}_{chg}E_t^{g,pev} - {}_{dsc}E_t^{pev} \tag{7.4}$$

where ${}_{dsc}E_t^b$, ${}_{dsc}E_t^{pev}$ are the amount of energy discharged from the battery and PEV to supply the demand in a time slot t respectively, which are limited by the maximum discharge rate X_{dsc}^b, X_{dsc}^{pev} as presented in equations (7.5 and 7.6).

$${}_{dsc}E_t^b \leq X_{dsc}^b \tag{7.5}$$

$${}_{dsc}E_t^{pev} \leq X_{dsc}^{pev} \tag{7.6}$$

The amount of energy drawn from the power grid ${}_{chg}E_t^{g,b}$ and solar energy generation ${}_{chg}E_t^{sol,b}$ to charge the battery at each time slot is limited by the maximum battery charging rate, and a similar limitation exists when charging the PEV battery ${}_{chg}E_t^{g,pev}$ from the grid each time slot t as presented in equations (7.7) and (7.8).

$${}_{chg}E_t^{g,b} + {}_{chg}E_t^{sol,b} \leq X_{chg}^b \tag{7.7}$$

$${}_{chg}E_t^{g,pev} \leq X_{chg}^{pev} \tag{7.8}$$

The battery is assumed to have a finite capacity ${}_{max}E^b$ so that $E_t^b \leq {}_{max}E^b$ for all values of t. Further, for the purpose of reliability, it may be needed to maintain a minimum energy level ${}_{min}E^b \geq 0$ at all times. The detailed equations used in computing the charging operations from the grid and discharging level for the next time step have been discussed in Chapter 5.

7.3.3 Pricing model

In the context of a smart grid, different electricity pricing models such as RTP, TOU and DAP have been presented and studied in this research. These models are used in home energy management systems to schedule household appliances based on time-varying electricity prices to minimise the energy cost in an efficient and smart way. However, the cost of power consumption becomes more complicated when the residential home is equipped with local renewable energy generation. In this section, the evaluation of the electricity consumption cost at residential homes depends on the cost rate of the total power generated by local renewable sources E_t^{ren} presented in equation (7.9) including the power generated by solar $E_t^{sol,l}$ and discharging from battery ${}_{dsc}E_t^{b,l}$ to supply the critical and controllable load; and the power drawn from the grid E_t^g (equation 7.10) well as the level of consumer comfort as will be described in the next section.

$$E_t^{ren} = E_t^{sol,l} + {}_{dsc}E_t^{b,l} \tag{7.9}$$

$$E_t^g = E_t^{g,l} + {}_{chg}E_t^{g,b} \tag{7.10}$$

The hourly cost of the power generated by renewable sources, COE, has been obtained from the previous simulation in chapter six. The real-time electricity pricing signal is sent by the utility company at each time slot via the end user's smart meter and it is known as Pr_t, as has been discussed in detail in the previous chapters. $E_t^{g,l}$ is the total power drawn from the grid at time slot *t* to supply the load including PEV battery, while ${}_{chg}E_t^{g,b}$ is the amount of power drawn from the grid to recharge the battery in each time *t*. Moreover, E_t^{ren} ($E_t^{sol,l}$, ${}_{dsc}E_t^{b,l}$) is the total power generated by the solar system generation and battery to supply the load (critical, controllable load and charging PEV battery). On the other hand, the power generated by the solar system may be used to charge the battery after the critical and controllable loads are satisfied. The total energy cost TC_t for each time slot *t* is calculated as follows:

$$TC_t = \left(E_t^g \times Pr_t\right) + \left(E_t^{ren}.COE\right) \tag{7.11}$$

7.3.4 Residential energy demand model

In the smart grid, some residential energy demands are critical, such as ovens, TVs, lighting, entertainment appliances and other general on demand loads. These kinds of loads either cannot be controlled or are very important loads that must be operated at the time *t* when needed. The total power consumption for these kinds of loads at time slot *t* is denoted as ${}_{cr}P_t$. Conversely, the household appliances such as air conditioner (AC), clothes dryer (CD), dish washer (DW), electric water heater (EWH), pool pump (PP), and plug-in electric vehicle (PEV) are defined as controllable loads, which can be controlled without significant impact on the consumer's lifestyle.

All mathematical models and constraints of theses appliances have been discussed in detail in Chapter 5. The ${}_{ctr}P_t^A$ variable represents the total power consumption at time slot *t* for controllable loads, where *A* denotes a set of appliance *a*, where $a \epsilon A$, as shown in the following equation.

$$ {}_{ctr}P_t^A = \sum_{a}^{A} {}_{ctr}P_t^a \quad \forall\, t \in T \tag{7.12} $$

where

$a \in (AC, EWH, DW, CD, PP, PEV)$

The start time of any appliance cannot be fixed due to the varying of electricity prices in each hour during the scheduling horizon. Therefore, adjusting the starting time of these appliances by the scheduling algorithm will result in maximising the cost saving but can eventually harm the consumer comfort. On the other hand, the scheduling algorithm strategy can be designed to increase the level of consumer comfort but with the penalty of increasing the electricity cost. These two objectives are contradictory and difficult to achieve at the same time. Therefore, operating the household appliances in a smart way according to the optimal schedules generated by the RLS controller algorithm is very significant to reduce the end user's electricity bill and maintain consumer comfort. Several factors that will increase the reliability, flexibility and cost efficiency for the proposed controller algorithm are incorporating alternative energy sources such as residential solar and an energy storage system into the energy mix, and DR programs including real time electricity price signals sent by the utility company, and a utility defined demand limit as explained in the next formulas. Equation (7.13) presented the total power consumption of the critical loads TE_t^{cr} for each time slot *t*, which is the summation of the power drawn from the grid ${}_{cr}P_t^g$ and renewable generation E_t^{ren} including the solar power and battery (${}_{cr}P_t^{sol}$, ${}_{cr}P_t^b$) respectively. In equation (7.14), the total power provided to the controllable load from the grid ${}_{cnt}P_t^{g,A}$ and renewable generation are ${}_{cnt}P_t^{A,sol}$, ${}_{cnt}P_t^{A,b}$, in each time slot *t*, while y_t is the controller variable used to ensure that the loads are supplied by the renewable energy generation after the critical load has been satisfied and taking into account the load priority of the controllable load. For instance, the critical loads are supplied first then the controllable load, if the amount of power generated from the renewable source is not enough to supply the load then the controller algorithm will apply the priority list of these appliances. Equations (7.15) is used to guarantee that the total power drawn from the grid should not exceed the demand limit. Equation (7.16) describes the total power provided to the load by renewable generation TE_t^{ren}each time slot *t*.

$$TE_t^{cr} = {}_{cr}P_t^{g} + {}_{cr}P_t^{sol} + {}_{cr}P_t^{b} \tag{7.13}$$

$$TE_t^{cnt} = {}_{cnt}P_t^{g,A} + \left({}_{cr}P_t^{sol} + {}_{cr}P_t^{b}\right).y_t \tag{7.14}$$

$$TE_t^{g} = {}_{cr}P_t^{g} + \sum_{a\in A} {}_{cnt}P_t^{a,g} \tag{7.15}$$

$$TE_t^{ren} = {}_{cr}P_t^{sol} + {}_{cr}P_t^{b} + \sum_{a\in A} y_t.\,{}_{cnt}P_t^{a,sol} + {}_{cnt}P_t^{a,b} \tag{7.16}$$

Additionally, to evaluate the potential impact of DR programs on a consumer's lifestyle, the measurement of the maximum and minimum level of consumer comfort were added to the proposed algorithm. The RLS controller algorithm is designed to solve this issue for those customers who are aware about wanting to minimise their electricity bill and carbon footprint and can compromise a small amount on comfort without this having an unduly negative impact on their lifestyle.

7.4 Consumer comfort level model

To evaluate the impact of the proposed algorithm on the consumer's daily life, two comfort indices are required to measure the level of consumer's comfort based on the control strategies which have been presented in chapter five. These indices are duration of convenience violation and violation level for controllable appliances.

7.4.1 Violation level index

The tolerance comfort level Cmf_t as presented in equation (7.17) is used to measure to what extent the levels of consumer comfort are violated based on the percentage deviation of the current settings ${}_{crr}S_t$ each time slot t from the original settings ${}_{pre}S_t$.

$$Cmf_t = \left|\frac{{}_{crr}S_t - {}_{pre}S_t}{{}_{pre}S_t}\right| \times 100 \tag{7.17}$$

Two levels of tolerance deviation of consumer comfort including the preferred and allowable comfort level as shown in Figure (7-2).

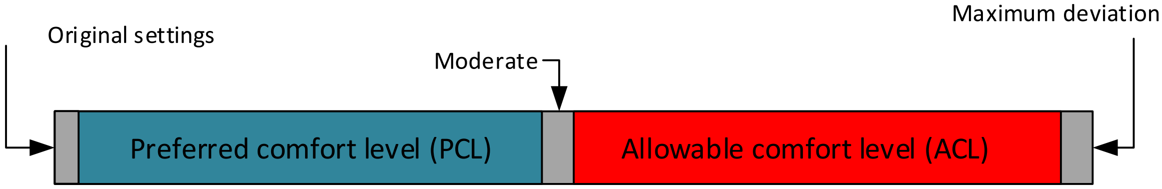


Figure 7-2 Tolerance level of convenience violation for each appliance

The Preferred Comfort Level (*PCL*) and Allowable Comfort Level (*ACL*) are described in equations (7.18) and (7.19), where the percentage of the comfort level Cmf_t is considered as the allowable deviation, if it is confined between the moderate and the maximum level of convenience violation for each controllable appliance, while the preferred is confined between the original setting and the moderate point.

$$PCL = \begin{cases} 1 & if \;\; {}_{min}Cmf \leq Cmf_t \leq {}_{mod}Cmf \\ 0 & otherwise \end{cases} \tag{7.18}$$

$$ACL = \begin{cases} 1 & if \;\; {}_{mod}Cmf < Cmf_t \leq {}_{max}Cmf \\ 0 & otherwise \end{cases} \tag{7.19}$$

7.4.2 Duration index

The length of the inconvenience period for running the controllable appliances is known as the duration index. Equation (7.20) and (7.21), describes the duration of the PCL and ACL for each appliance.

$$PCL_{duration} = \sum_{t}^{T} PCL \qquad t \in T \tag{7.20}$$

$$ACL_{duration} = \sum_{t}^{T} ACL \qquad t \in T \tag{7.21}$$

The status of comfort level for controllable appliances, represented by the variable Cmf_t^s, is set based on the electricity price signal, and energy availability in renewable energy resources including solar power and energy storage systems. The Cmf_t^s is set to the original settings mode when the electricity price is low, the *PCL* mode when the electricity price is high and the load is partially supplied by the renewable generation, otherwise the comfort level mode will be set to *ACL* as described in the next formula.

$$Cmf_t^s = \begin{cases} Cmf_t = original\ settings\ \ if\ E_t^{ren} \geq P_a^{max}\ or\ {}_{status}Pr_t^s\ is\ low \\ Cmf_t = PCL\ \ if\ P_a^{min} \leq E_t^{ren} \geq P_a^{max}\ or\ {}_{status}Pr_t^s\ is\ high \\ Cmf_t = ACL\ \ if\ P_a^{min} > E_t^{ren}\ or\ {}_{status}Pr_t^s\ is\ high \end{cases} \tag{7.22}$$

7.5 Control objective and optimisation algorithm

The HEMS model including the operation of different types of household appliances needs to be effectively managed and controlled within a household to minimise the total electricity bill under the RTP environment. Furthermore, incorporating the renewable energy resources, and energy storage system will make the system more reliable and cost effective without adversely affecting the consumer comfort. Recently, the stochastic and deterministic methods are the most common used in such optimisation problems. In deterministic models the output is always the same when the set of inputs are under identical conditions, while the output in the stochastic model may fluctuate even with the same inputs due to using the probabilistic translation rules. The GA is a stochastic model used for global search, and optimisation for different applications, which have been discussed in chapter three. The optimisation problem considered in the study involves selection of running time and duration of the controllable load that produce minimum cost, and is subject to the consumer comfort level, renewable energy availability and electric vehicle state of charge constraints. The objective function intends to minimise the total energy cost is presented in the next equation.

$$min\,TC = \sum_{t \in T} \left(TE_t^g \times Pr_t\right) + \left(TE_t^{ren}.COE\right) \tag{7.23}$$

Subject to the following constraints:

$$0 \leq y_t \leq 1$$

$$0 \leq E_t^{sol} \leq E_{max}^{sol}$$

$$E_{t+1}^b = E_t^b + {}_{chg}E_t^{sol,b} + {}_{chg}E_t^{g,b} - {}_{dsc}E_t^b$$

$$ {}_{dsc}E_t^b \le X_{dsc}^b $$

$$ {}_{chg}E_t^{g,b} + {}_{chg}E_t^{sol,b} \le X_{chg}^b $$

$$ E_{t+1}^{pev} = E_t^{pev} + {}_{chg}E_t^{g,pev} - {}_{dsc}E_t^{pev} $$

$$ {}_{dsc}E_t^{pev} \le X_{dsc}^{pev} $$

$$ {}_{chg}E_t^{g,pev} \le X_{chg}^{pev} $$

$$ TE_t^g = {}_{cr}P_t^g + \sum_{a\in A} {}_{cnt}P_t^{a,g} $$

$$ TE_t^{ren} = {}_{cr}P_t^{sol} + {}_{cr}P_t^b + \sum_{a\in A} y_t \cdot {}_{cnt}P_t^{a,sol} + {}_{cnt}P_t^{a,b} $$

$$ Cmf_t^s = \begin{cases} Cmf_t = original\ settings\ \ if\ E_t^{ren} \ge P_a^{max}\ or\ {}_{status}Pr_t^s\ is\ low \\ Cmf_t = PCL\ \ if\ P_a^{min} \le E_t^{ren} \ge P_a^{max}\ or\ {}_{status}Pr_t^s\ is\ high \\ Cmf_t = ACL\ \ if\ P_a^{min} > E_t^{ren}\ or\ {}_{status}Pr_t^s\ is\ high \end{cases} $$

7.6 Simulation Results

The simulation results of our proposed GA based RLS are represented in this section. The utility power supply is assumed to be available day and night to support the consumer's load. The advanced information and communication technologies (ICTs) integrated with the smart grid will enable real-time communication between the consumer and the utility to provide the end users all information signals that may be needed to optimise power usage on the basis of personal preferences regarding environmental concerns and price. The utility signals used in our proposed RLS algorithm are RTP pricing signal and forecast outdoor temperature. In addition, users can also enter pre-set preferences, such as room temperature, water heater temperature and running operation time for any appliances. These preferences are assumed based on the possible range of comfort level settings that can be specified for each appliance. In this study, the solar irradiance profile used to estimate the available solar power is predicted using the well-known ASHRAE clear sky model.

To evaluate the performance of the proposed algorithm, different scenarios have been examined to compare the results obtained by applying different energy resources (solar, battery and PEV battery), and DR programs as well as different consumer comfort levels. This comparison evaluates which scenario produces better results for home energy management, in terms of minimising the energy cost, keeping the demand below a certain limit particularity during peak periods, and reduction in greenhouse gas emissions. An emphasis is also placed on minimising impacts on consumer comfort to reduce potential barriers to widespread adoption.

The first scenario examined the impact of the electric vehicle when it is connected to the grid on the power consumption, total cost of the electricity usage, and the behaviour of the household appliances which affect consumer comfort level both with and without imposing a demand limit. Figures (7-3, and 7-4) show that the reduction in the total power consumption (17.1%, and 21%), and the total energy cost (5.5%, and 8.4%) when the PEV state of charge(E_t^{pev}) is (40% and 60%) respectively, compared to the case when the PEV is not considered as energy storage and no demand limit was applied. Thus, the total amount of power consumption and cost are decreased by 0.5% and 6% when the E_t^{pev} is changed from 40% to 60%, respectively as shown in Figure (7-5). In addition, the level of consumer comfort model for each controllable load is presented in section 7.4. As described previously the proposed RLS is implemented to ensure the consumer comfort level is maintained in the original settings comfort range based on the minimum and maximum percentage deviation from the original settings. The violation level and duration of the consumer comfort being violated for each controllable load are described in Table (7-1 and 7-2).

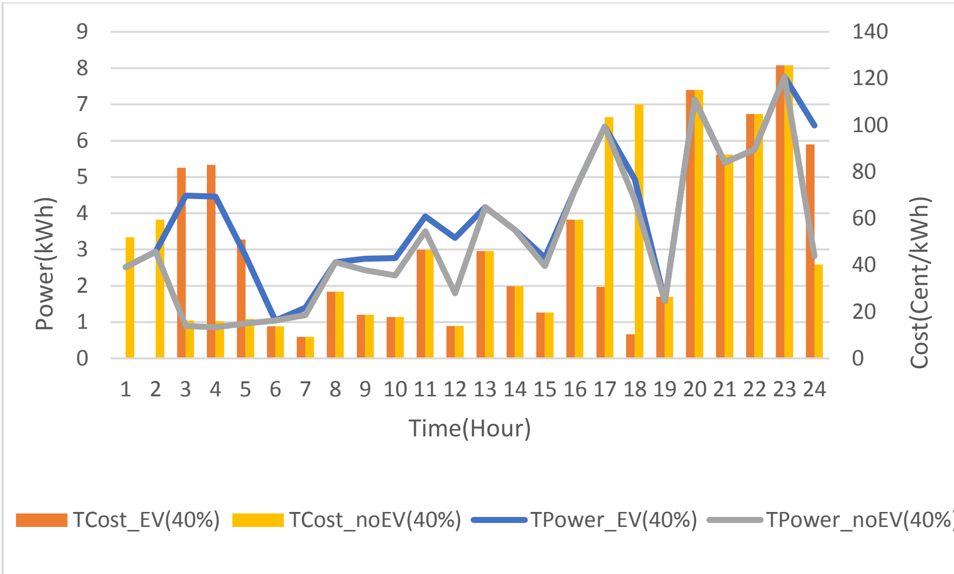


Figure 7-3 The impact of PEV(SOC is 40% and no *Dl*) on the total power consumption, cost.

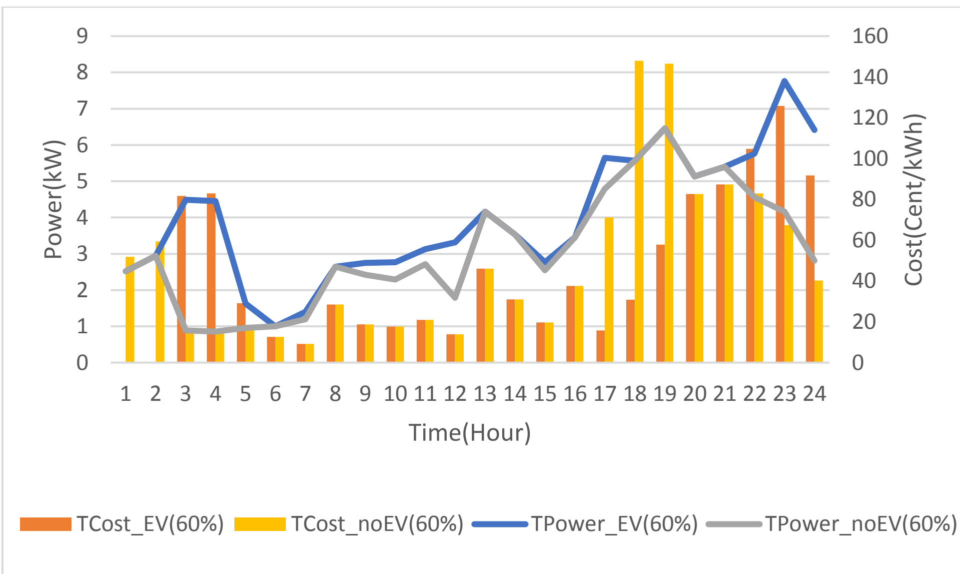


Figure 7-4 The impact of PEV(SOC is 60% and no Dl) on the total power consumption, cost.

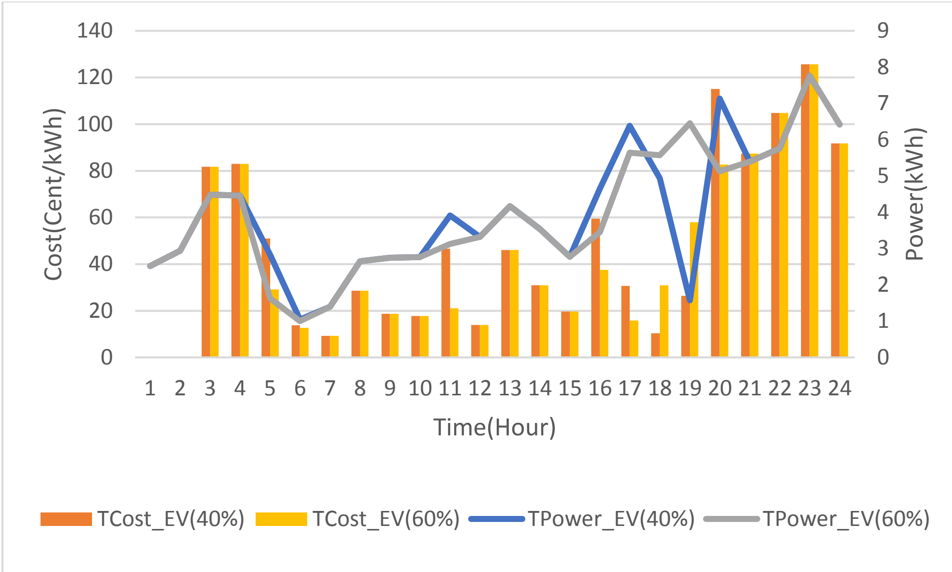


Figure 7-5 The influence of demand limits on the shape of daily energy consumption when PEV state of charge (40% and 60%).

Table 7-1 where the demand limit is not imposed, the impact of using the PEV as storage beside the local power generation and battery are examined, where a running operation time for each controllable appliance is in the range of the *PCL*, which indicates that the level of convenience violation is close to the original settings. For instance, in case of the *AC* the violation level of indoor temperature is 1.6% and 1.7% and the duration of convenience violations is three hours in the PCL range and two hours in the *ACL* range, when the PEV state of charge is 40% and 60 % respectively.

Table 7-1 Level of Consumer Comfort for controllable appliances, when no demand limit *Dl* is imposed.

Appliance	Consumer comfort level Cmf	SOC PEV (40%)		SOC PEV 60%	
		PCL	ACL	PCL	ACL
AC	*Violate Set point*	1.6%	-	1.7%	-
	Duration	3 hrs	-	2 hrs	-
EWH	*Violate Set point*	3.3%	8.3%	-	8.3%
	Duration	1hr	1hr	-	1hr

PP	*Violate Set point*	1.25%	-	1.25%	-
	Duration	1hr		3hr	-
DW	*Violate Set point*	0.2%	-	0.2%	-
	Duration	1hr	-	1hr	-
CD	*Violate Set point*	0.28%	-	0.14%	-
	Duration	2hrs	-	1hr	-

Table 7-2 Level of Consumer Comfort for controllable appliances, when the demand limit *Dl* is imposed.

Appliance	Consumer comfort level Cmf	SOC PEV (40%)		SOC PEV 60%	
		PCL	ACL	PCL	ACL
AC	*Violate Set point*	2.5%	3.5%	2.5%	3.5%
	Duration	5 hrs	3hrs	5 hrs	3hrs
EWH	*Violate Set point*	-	8.3%	-	8.3%
	Duration	-	3hrs	-	3hrs
PP	*Violate Set point*	1.25%	1.25%	1.25%	-
	Duration	2hrs	1hr	3hrs	-
DW	*Violate Set point*	0.2%	-	0.2%	-
	Duration	2hrs	-	2hrs	-
CD	*Violate Set point*	0.28%	-	0.14%	-
	Duration	2hrs	-	1hr	-

In the second scenario, the positive impact of using the PEV battery as energy storage when it is on grid alongside with a fixed battery will continue, particularly when the total power consumption exceeds the demand limits which have been imposed by the utility company to reduce the pressure on the grid during the peak period. Therefore, the RLS algorithm will reshape the end user’s power consumption profile according to the available generation, demand limit and consumer's preferences. Figures (7-6 and 7-7) show that, the total energy cost reduced by (11.3%, and 5.3%), and the total power consumption by (7.3%, and 16.6%) when the E_t^{pev} state of charge is 40% and 60 % respectively, compared to the case when the demand limit is applied and the PEV is not considered as energy storage.

Lastly, Figure (7-8, and 7-9) show the reduction of the total energy cost is (2.8%, and 7.3%) and total power consumption is (10.6%, and 10.8%) when the demand limit is applied and the PEV state of charge is (40% and 60%) respectively, compared to the case when no demand limit is imposed. This result explains why the comfort level of the AC, EWH, and PP appliances presented in Table 7-2 including the violate set point and the duration of violation is higher than the previous scenario, which is still acceptable and remains in the allowable comfort level ACL range. Moreover, the total amount of power consumption and energy cost are decreased by 0.65% and 9.3% when the E_t^{pev} is changed from 40% to 60%, respectively as shown in Figure (7-10), where the overall power consumption does not exceed a certain limit.

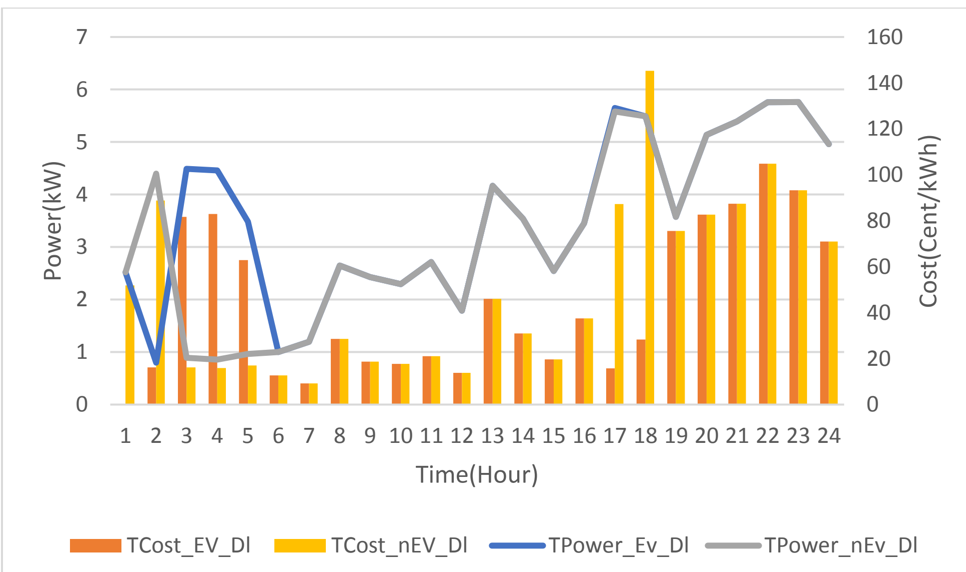


Figure 7-6 The influence of demand limits on the shape of daily energy consumption when PEV state of charge (40%) is on/off grid.

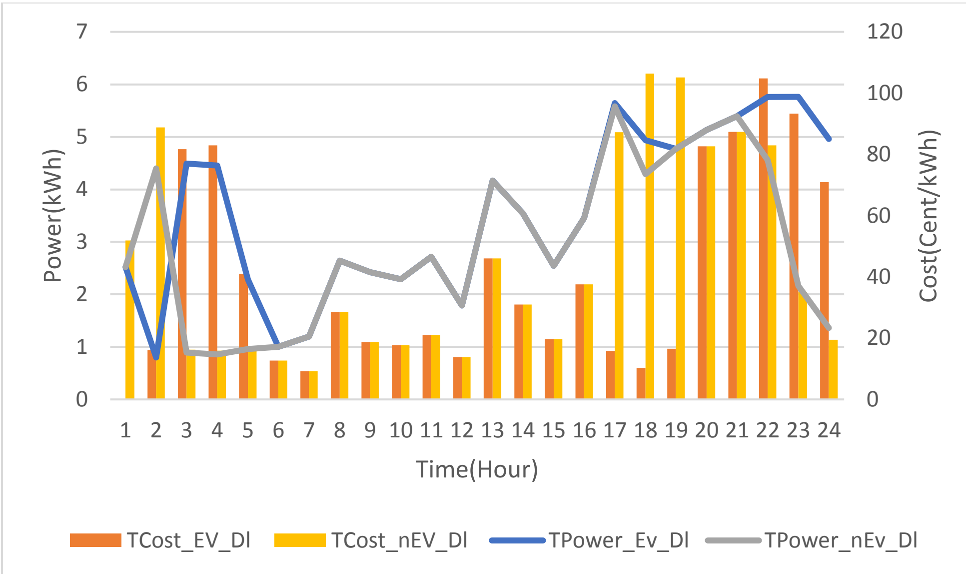


Figure 7-7 The influence of demand limits on the shape of daily energy consumption when PEV state of charge (60%) is on/off grid.

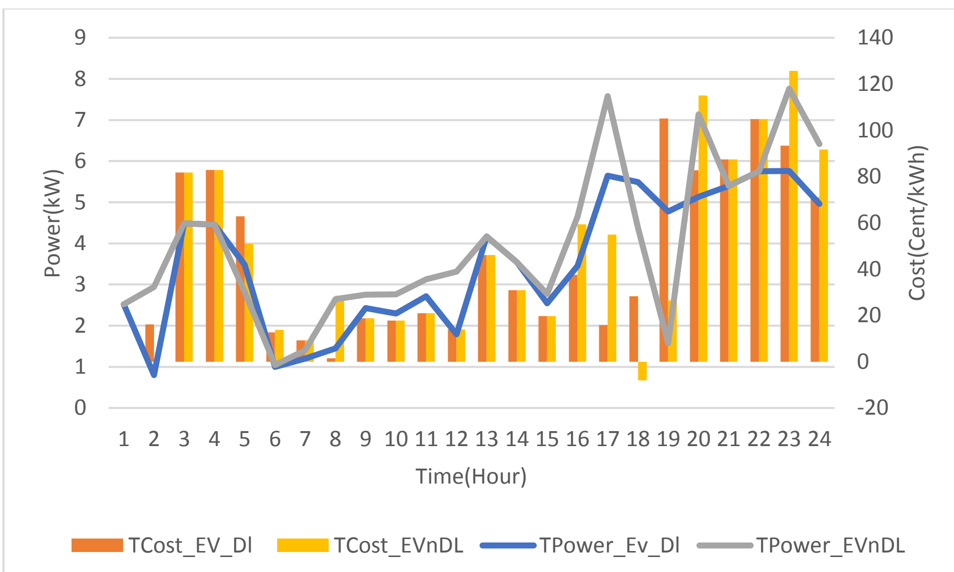


Figure 7-8 The influence of demand limits on the shape of daily energy consumption when PEV state of charge (40%).

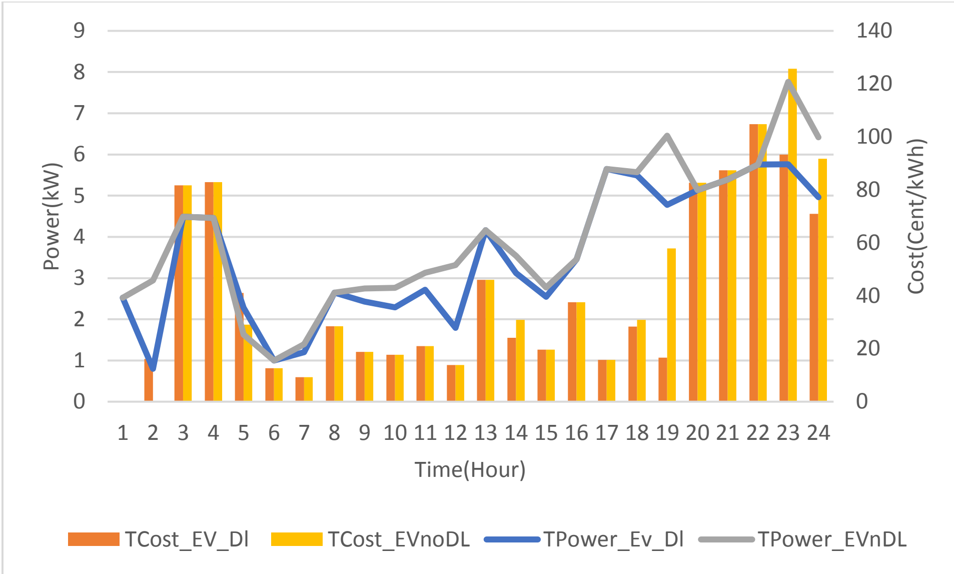


Figure 7-9 The impact of demand limit (PEV SOC =60%) on the total power consumption, cost and consumer comfort level.

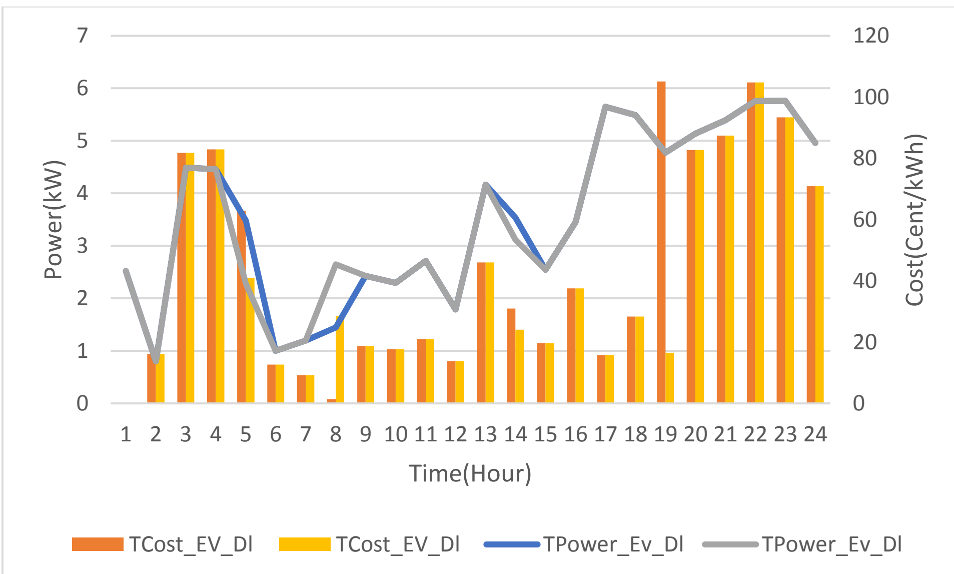


Figure 7-10 The impact of different PEV state of charge (*SOC PEV* is 40%, 60% and *Dl*) on the total power consumption, cost and consumer comfort level.

7.7 Conclusion

In this chapter, an efficient scheme for Residential Load Scheduling (RLS) integrated with a grid DR program was proposed. This algorithm can manage and control household appliances, small-scale renewable energy resources and energy storage including battery and PEV battery within a household based on real time pricing without harming the level of consumer comfort. The performance of the proposed algorithm is assessed by investigating its effect on the total cost of power consumption and the level of consumer comfort. In this context, two factors were considered, which are the presence of hybrid energy storage (battery and electric vehicle) and a demand limit. Results showed that the proposed RLS is more effective in terms of electricity bill reduction and consumer comfort improvement when a hybrid energy storage is integrated with the household. To evaluate the performance of the proposed algorithm, different scenarios were examined to compare the results obtained by applying different DR programs. Thus, the results obtained from the simulation showed that the reduction in the total energy cost is higher by about (11.3%) when the PEV initial state of charge is 60% and the demand limit is imposed compared to the case when no demand limit is applied.

The proposed smart HEMS is also proven to be more effective in optimising the consumer comfort level by maximising the operation of the household appliances within the PCL and minimising their operation in the ACL. Therefore, the results show that when the energy storage system includes the electric vehicle as storage the level of violation is reduced close to the original settings compared with when the PEV battery is not used as energy storage. On the other hand, when no demand limit is imposed the level of convenience violation is close to the original settings. In contrast, the level of convenience violation for some appliances such as AC and EWH is increased when the demand limit is applied, while the level of comfort for the other appliances remains in the ACL. In summary, this chapter has shown that incorporation of an RLS algorithm with access to an energy storage system (including battery and electric vehicle battery) alongside a real-time pricing strategy can provide a significant benefit to both consumers and utilities.

8 Conclusion and Future Work

8.1 Conclusion

The research conducted in this thesis focuses on home energy management systems in the context of optimally managing and controlling household appliances based on real-time pricing signals. The motivations and objectives of this research were presented in Chapter 1. Moreover, the main concepts related to the research area are comprehensively reviewed in chapter 2. In the context of the smart grid, mathematical models of dynamic pricing technology with demand side management, renewable energy resources, and energy storage devices (battery and electric vehicle) have been developed in the subsequent chapters to optimally simulate and evaluate the proposed HEMS algorithm.

General discussion of the optimisation techniques used in this research is presented in Chapter 3. The main focus was on using these techniques to improve the reliability and cost-effectiveness of home energy management systems. The first objective of this thesis was addressed by developing a smart HEMS algorithm to reduce overall usage and cost of energy without significantly degrading consumer comfort. Therefore, in Chapter 4, an automatic residential energy management system has been introduced that aims to achieve a trade-off between minimising electricity costs and the total energy consumption based on different users' load priorities and comfort settings. The proposed algorithm effectively enables several inhabitants sharing a home to easily manage and schedule their requests in terms of priority and preferences. When a TOU pricing model is combined with different demand limits, the HEMS algorithm controls some loads to keep the total energy consumption under the limit during peak demand. Simulation results show that the combination of the MULP algorithm and the TOU pricing model leads to significant reductions in household energy costs and total energy consumption. This system requires less effort from consumers, which is beneficial. Furthermore, the results also show that the reduction of total energy consumption, particularly during peak demand periods, can produce incentives for power utilities to support HEM systems.

The fifth chapter focusses on developing and applying the mathematical models of residential energy usage and management based on real time pricing (RTP) that can easily be integrated into automated decision making technologies, such as HEMSs. These models are used to generate the optimal operational schedules for household appliances (e.g. controllable and non-controllable loads), and energy storage systems (ESSs) including batteries and plugin electric vehicles (PEV). The goal is to achieve reductions in energy cost and CO_2 emissions and to keep the total power consumption under the demand limit, while minimising any impacts on consumer comfort. The simulation results achieved in this chapter show that controlling the household appliances based on the RTP without energy storage and with DL is up to 18% better than the same scenario with no HEMS control. The scenario where the loads are controlled based on the RTP without DL can achieve a slightly greater benefit to the household, however, without DL the energy demand created by consumers during low energy price periods may exceed the maximum supply levels that the power plant can generate requiring more power capacity to be brought online increasing CO_2 emissions.

The results achieved when a fixed battery and PEV are added to the previous model (RTP with/without DL) were considerably better than just using a PEV's battery, even if the capacity of the PEV's battery is much larger than the fixed battery. This is because the time when the PEV battery is available on grid is limited and most of the time when it is available must be utilised to charge it. Moreover, the results show that installing a small additional battery storage of only 1.5kWh without a PEV present enables a significant cost reduction to a household of around a further 20.3% compared to the scenario where both a fixed battery and a PEV are not included. Although the previously discussed model has resulted in an important cost reduction, choosing an arbitrary capacity for the fixed storage battery, as well as being considered subjective, also does not guarantee that the selected battery capacity is optimal. Therefore, Chapter 6 introduces a sizing methodology that allows identification of the optimal number and capacity of solar panels and batteries.

The methodology used employed an integer GA to optimally size the grid-connected PV system that includes a dedicated battery and PEV battery, and a Renewable Energy System Contribution (RESC) index to ensure that the designed system reasonably contributes to the total load demand. The results showed that two factors can impact the optimal size of the grid-connected renewable energy system components. These are the level at which the system is required to contribute to the total annual demand and the RTP model. Furthermore, the PEV does not affect the optimal size of the system because it is almost always plugged-in during periods where there is very low or no solar irradiance. The results obtained from the sizing methodology reveals that the best solution in terms of energy cost is a solar system consisting of 14 solar panels and a 1.5kWh battery which has the lowest energy cost and contributes 50% of the total load demand. Therefore, this optimal system is used to assess the effectiveness of the proposed HEMS when the household is equipped with a small-scale hybrid renewable energy system.

A comprehensive smart HEMS that controls the appliances of a household equipped with an optimally sized renewable energy system is proposed in Chapter 7. The performance of the proposed HEMS is assessed by investigating its effect on the total cost of power consumption and the level of consumer comfort. In this context, two factors were considered, the presence of a hybrid energy storage system (battery and electric vehicle) and enforcing a demand limit. Results showed that the proposed HEMS is more effective in terms of electricity bill reduction and consumer comfort improvement when a hybrid energy storage system is integrated with the household. While it has not had any impact on the sizing of the renewable energy system, the integration of a PEV has allowed more flexibility to the smart HEMS to optimally schedule the operation of the household appliances, which has led to further energy cost savings. The proposed smart HEMS is also proven to be more effective in optimising the consumer comfort level by maximising the operation of the household appliances within the PCL and minimising their operation in the ACL. Overall, DSM optimises the residential electricity usage.

As described in the Research focus, objectives and contributions section, one of the aims of this research has been to develop a comprehensive model for a HEMS that can be used to optimise the electricity usage at home. A smart HEMS model has been developed in this research study to manage and control critical and controllable household appliances. The modelling considers the consumer comfort level, constraints on the total demand, and the power consumption cost from both a renewable power system and utility grid. The developed HEMS involves optimising residential load scheduling as well as maximising the consumer level of comfort and minimising the cost. The novelty of this smart HEMS is introducing a demand response strategy that accommodates multi users and load priorities (MULP) sharing the same home and its appliances to generate a single load priority for all users.

The findings of this research showed that the cost reduction benefits gained from applying a smart HEMS with MULP are affected by smart residential load scheduling using dynamic electricity pricing. The average cost reduction when TOU pricing model is used for scheduling household appliances using the proposed smart HEMS with MULP is 18% compared with no load scheduling. The employment of an RTP model slightly increased the cost reduction in case of with or without imposing a limit on the household demand (0.6% and 0.2% respectively). However, this improvement in total energy cost is at the expense of the consumer comfort level.

The findings of this research have also shown that the benefits of the proposed smart HEMS with MULP can be maximised by incorporating energy storage systems including fixed battery and PEV battery. In the case of with or without limiting the household demand, the total consumption cost is further reduced by 2.1% and 1.4%, respectively, when a PEV battery is considered as available for temporary energy storage. If a fixed battery is included alongside with the PEV, the improvement in total consumption cost reached 3.2% and 2.3%, respectively. These benefits are achieved without deteriorating the consumer comfort level.

Extra benefits can be gained if the proposed smart HEMS with MULP is used to manage the appliances of a household equipped with an optimally designed small-scale renewable energy system as proven by the results of this research. The results showed that the minimisation of energy consumption cost is almost doubled compared to the same scenario with no load scheduling. Furthermore, the incorporation of the small-scale renewable energy system has allowed the smart HEMS to simultaneously enhance the consumer comfort level.

A novel smart HEMS that considers multi users and load priorities (MULP) is proposed in this research and examined with different practical household scenarios. The system is proven to be able to reduce the electricity bill without impacting the consumer quality of life by maintaining comfortable climate in the household and ensuring reliable operation of the appliances. The benefits of adopting this smart HEMS can be maximised if a small-scale renewable power system with hybrid energy storage (battery and electric vehicle) is incorporated into the household which may maximise the benefits for both end-user and utility grid companies. In this scenario, the dependence on conventional power sources can be significantly reduced, which in turn will reduce greenhouse gas emissions, as well as affording substantial reductions in energy costs for the user. These benefits may encourage wide adoption of this type of smart HEMS.

8.2 Future Work

- In addition to the controllable loads considered in this research, an optimal operation of other types of household appliances such as fridge, TV, and lighting can be investigated to reduce the monatery expense without a negative impact on the consumer lifstyle.

- The developed mathematical model presented in this research focusses on the energy consumption and cost reduction from the end user prospective. However, a considerable benefit may be achieved both from the side of the customers and from the utility's point of view. Expanding the modelling to grid scale and considering wide scale coordination between smart HEMS systems in multiple households could lead to further significant benefits.
- The recent rapid developments in smart home appliances and the Internet of Things (IoT) and the advantages of smart grid technologies may be used to further develop the proposed HEMS in this research for other sectors such as industrial, commercial or agriculture sectors.
- Further development on the proposed smart HEMS could further increase the level of consumer comfort, which may lead to a reduction in the potential barriers to widespread adoption of the smart HEMS.

References

1. Bayod-Rujula, A.A., *Future development of the electricity systems with distributed generation.* Energy, 2009. **34**(3): p. 377-383.
2. Rahimi, F. and A. Ipakchi, *Demand response as a market resource under the smart grid paradigm.* IEEE Transactions on Smart Grid, 2010. **1**(1): p. 82-88.
3. Ipakchi, A. *Smart grid of the future with large scale DR/DER penetration*. in *Power Systems Conference and Exposition, 2009. PSCE'09. IEEE/PES*. 2009. IEEE.
4. SBCI, U., *Buildings & Climate Change–A Summary for Decision-Makers*, 2009, UNEP DTIE, Paris, December.
5. Birol, F., *World Energy Outlook 2012.* International Energy Agency (IEA), Paris, 2012.
6. Gruenspecht, H., *International Energy Outlook 2011.* Center for Strategic and International Studies, 2010.
7. Atwa, Y., et al., *Optimal renewable resources mix for distribution system energy loss minimization.* IEEE Transactions on Power Systems, 2010. **25**(1): p. 360-370.
8. Gudi, N., L. Wang, and V. Devabhaktuni. *A simulation tool to demonstrate active demand-side management for household appliances,‖*. in *IEEE Power and Energy Society General Meeting*. 2010.
9. Energy, O.T.
10. Feisst, C., D. Schlesinger, and W. Frye, *Smart grid: The role of electricity infrastructure in reducing greenhouse gas emissions.* Cisco Internet Business Solution Group (IBSG): San Jose, CA, USA, 2008.
11. Schoenung, S., *Energy storage systems cost update.* SAND2011-2730, 2011.
12. Heydt, G.T., et al. *Professional resources to implement the smart grid*. in *Proc. of North American Power Symposium*. 2009.
13. Zahedi, A. *Proposing a smart electricity pricing model for future smart grid*. in *Power Engineering Conference (AUPEC), 2014 Australasian Universities*. 2014. IEEE.
14. Glanzer, G., et al. *Cost-efficient integration of electric vehicles with the power grid by means of smart charging strategies and integrated on-board chargers*. in *Environment and Electrical Engineering (EEEIC), 2011 10th International Conference on*. 2011. IEEE.
15. Asano, H., et al., *Microgrids: an overview of ongoing research, development, and demonstration projects.* IEEE Power Energy Magazine, 2007: p. 78-94.
16. Society, I.C.S., *The Impact of Control Technology: Control for Renewable Energy and Smart Grids*, 2011.
17. Eid, B.M., et al., *Control methods and objectives for electronically coupled distributed energy resources in microgrids: A review.* IEEE Systems Journal, 2016. **10**(2): p. 446-458.
18. Gupta, A., et al. *Smart home device and energy management systems*. in *India Conference (INDICON), 2011 Annual IEEE*. 2011.
19. Bull, S.R., *Renewable energy today and tomorrow.* Proceedings of the IEEE, 2001. **89**(8): p. 1216-1226.
20. Quaschning, V., *Understanding renewable energy systems*. 2016: Routledge.
21. Alba Rios, J., et al., *Decentralised storage: impact on future distribution grids.* Brussels, Belgium: Union of the Electricity Industry, 2012.
22. Brown, R.E. *Impact of smart grid on distribution system design*. in *Power and Energy Society General Meeting-Conversion and Delivery of Electrical Energy in the 21st Century, 2008 IEEE*. 2008. IEEE.

23. Chen, X., T. Wei, and S. Hu, *Uncertainty-Aware Household Appliance Scheduling Considering Dynamic Electricity Pricing in Smart Home.* Smart Grid, IEEE Transactions on, 2013. **PP**(99): p. 1-10.
24. Pedrasa, M.A.A., 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, 2010. **1**(2): p. 134-143.
25. Molderink, A., et al., *Management and Control of Domestic Smart Grid Technology*. Smart Grid, IEEE Transactions on, 2010. **1**(2): p. 109-119.
26. Dunn, B., H. Kamath, and J.-M. Tarascon, *Electrical energy storage for the grid: a battery of choices.* Science, 2011. **334**(6058): p. 928-935.
27. Wald, M.L., *Wind drives growing use of batteries.* New York Times. Published 28th July, 2010.
28. Wu, X., et al., *Stochastic control of smart home energy management with plug-in electric vehicle battery energy storage and photovoltaic array*. Journal of Power Sources, 2016. **333**: p. 203-212.
29. Kannan, R., et al., *Life cycle assessment study of solar PV systems: an example of a 2.7 kW p distributed solar PV system in Singapore.* Solar energy, 2006. **80**(5): p. 555-563.
30. Tokuda, K., *A proposal for next generation ITS wireless communications system in EV generation.* IEICE TRANSACTIONS on Fundamentals of Electronics, Communications and Computer Sciences, 2012. **95**(1): p. 271-277.
31. A EURELECTRIC paper, *smart charging: steering the charge, driving the change*, 2015.
32. Wu, X., et al., *Stochastic Optimal Energy Management of Smart Home with PEV Energy Storage.* IEEE Transactions on Smart Grid, 2016.
33. Nourai, A., *Installation of the first distributed energy storage system (DESS) at American Electric Power (AEP).* Sandia Report SAND2007-3580, 2007.
34. Ng, K.-H. and G.B. Sheble, *Direct load control-A profit-based load management using linear programming.* IEEE Transactions on Power Systems, 1998. **13**(2): p. 688-694.
35. Schweppe, F., B. Daryanian, and R. Tabors, *Algorithms for a spot price responding residential load controller.* IEEE Transactions on Power Systems, 1989. **4**(2): p. 507-516.
36. Rahman, S., *An efficient load model for analyzing demand side management impacts.* IEEE Transactions on Power Systems, 1993. **8**(3): p. 1219-1226.
37. Cohen, A.I. and C.C. Wang, *An optimization method for load management scheduling.* IEEE Trans. Power Syst.;(United States), 1988. **3**(2).
38. Logenthiran, T., D. Srinivasan, and A.M. Khambadkone, *Multi-agent system for energy resource scheduling of integrated microgrids in a distributed system.* Electric Power Systems Research, 2011. **81**(1): p. 138-148.
39. Maharjan, I.K., *Demand side management: load management, load profiling, load shifting, residential and industrial consumer, energy audit, reliability, urban, semi-urban and rural setting*. 2010: LAP Lambert Academic Publ.
40. Kothari, D.P. and I. Nagrath, *Modern power system analysis*. 2003: Tata McGraw-Hill Education.
41. Gellings, C.W. and J. Chamberlin, *Demand-side management.* 1988.
42. Gellings, C.W., *The concept of demand-side management for electric utilities.* Proceedings of the IEEE, 1985. **73**(10): p. 1468-1470.

43. Pipattanasomporn, M., M. Kuzlu, and S. Rahman, *An Algorithm for Intelligent Home Energy Management and Demand Response Analysis.* Smart Grid, IEEE Transactions on, 2012. **3**(4): p. 2166-2173.
44. Mojtahedzadeh, S., M. Tavakoli, and A.R. Milani, *Review of dynamic pricing programs and evaluating their effect on demand response.* International Journal on Technical and Physical Problems of Engineering (IJTPE), 2011. **3**(8): p. 100-105.
45. Kim, T.T. and H.V. Poor, *Scheduling power consumption with price uncertainty.* IEEE Transactions on Smart Grid, 2011. **2**(3): p. 519-527.
46. De Angelis, F., et al., *Optimal home energy management under dynamic electrical and thermal constraints.* IEEE Transactions on Industrial Informatics, 2013. **9**(3): p. 1518-1527.
47. Bhattacharyya, K. and M. Crow, *A fuzzy logic based approach to direct load control.* IEEE Transactions on Power Systems, 1996. **11**(2): p. 708-714.
48. Salehfar, H., et al. *Fuzzy logic-based direct load control of residential electric water heaters and air conditioners recognizing customer preferences in a deregulated environment*. in *Power Engineering Society Summer Meeting, 1999. IEEE*. 1999. IEEE.
49. Yang, H.-T. and K.-Y. Huang, *Direct load control using fuzzy dynamic programming.* IEE Proceedings-Generation, Transmission and Distribution, 1999. **146**(3): p. 294-300.
50. Huang, K.-Y. and Y.-C. Huang, *Integrating direct load control with interruptible load management to provide instantaneous reserves for ancillary services.* IEEE Transactions on power systems, 2004. **19**(3): p. 1626-1634.
51. Laurent, J.-C., et al., *A column generation method for optimal load management via control of electric water heaters.* IEEE Transactions on Power Systems, 1995. **10**(3): p. 1389-1400.
52. Erol-Kantarci, M. and H.T. Mouftah, *Wireless Sensor Networks for Cost-Efficient Residential Energy Management in the Smart Grid.* Smart Grid, IEEE Transactions on, 2011. **2**(2): p. 314-325.
53. Molderink, A., et al. *Domestic energy management methodology for optimizing efficiency in smart grids*. in *PowerTech, 2009 IEEE Bucharest*. 2009. IEEE.
54. Xiao, J., et al. *Near optimal demand-side energy management under real-time demand-response pricing*. in *2010 International Conference on Network and Service Management*. 2010. IEEE.
55. Logenthiran, T., D. Srinivasan, and T.Z. Shun, *Demand side management in smart grid using heuristic optimization.* IEEE Transactions on Smart Grid, 2012. **3**(3): p. 1244-1252.
56. Allerding, F., et al. *Electrical load management in smart homes using evolutionary algorithms*. in *European Conference on Evolutionary Computation in Combinatorial Optimization*. 2012. Springer.
57. AboGaleela, M., M. El-Sobki, and M. El-Marsafawy. *A two level optimal DSM load shifting formulation using genetics algorithm case study: Residential loads*. in *Power Engineering Society Conference and Exposition in Africa (PowerAfrica), 2012 IEEE*. 2012. IEEE.
58. Yao, L., W.-C. Chang, and R.-L. Yen, *An iterative deepening genetic algorithm for scheduling of direct load control.* IEEE Transactions on Power Systems, 2005. **20**(3): p. 1414-1421.
59. Soares, A., et al. *Domestic load scheduling using genetic algorithms*. in *European Conference on the Applications of Evolutionary Computation*. 2013. Springer.

60. Matallanas, E., et al., *Neural network controller for active demand-side management with PV energy in the residential sector.* Applied Energy, 2012. **91**(1): p. 90-97.
61. Brka, A., Y.M. Al-Abdeli, and G. Kothapalli, *Influence of neural network training parameters on short-term wind forecasting.* International Journal of Sustainable Energy, 2016. **35**(2): p. 115-131.
62. Brka, A., G. Kothapalli, and Y.M. Al-Abdeli, *Predictive power management strategies for stand-alone hydrogen systems: Lab-scale validation.* International Journal of Hydrogen Energy, 2015. **40**(32): p. 9907-9916.
63. Stott, B. and J. Marinho, *Linear programming for power-system network security applications.* IEEE Transactions on Power Apparatus and Systems, 1979(3): p. 837-848.
64. Erdinc, O. and M. Uzunoglu, *Optimum design of hybrid renewable energy systems: Overview of different approaches.* Renewable and Sustainable Energy Reviews, 2012. **16**(3): p. 1412-1425.
65. Soares, A., et al., *A multi-objective genetic approach to domestic load scheduling in an energy management system.* Energy, 2014. **77**: p. 144-152.
66. Possingham, H., I. Ball, and S. Andelman, *Mathematical methods for identifying representative reserve networks*, in *Quantitative methods for conservation biology*. 2000, Springer. p. 291-306.
67. Rasheed, M.B., et al., *An efficient power scheduling scheme for residential load management in smart homes.* Applied Sciences, 2015. **5**(4): p. 1134-1163.
68. Graditi, G., et al., *Heuristic-based shiftable loads optimal management in smart micro-grids.* IEEE Transactions on Industrial Informatics, 2015. **11**(1): p. 271-280.
69. Imamura, A., et al. *Distributed demand scheduling method to reduce energy cost in smart grid*. in *Humanitarian Technology Conference (R10-HTC), 2013 IEEE Region 10*. 2013. IEEE.
70. Potts, C.N., *Analysis of a linear programming heuristic for scheduling unrelated parallel machines.* Discrete Applied Mathematics, 1985. **10**(2): p. 155-164.
71. Fotuhi-Firuzabad, M., S. Shafiee, and M. Rastegar, *Optimal In-Home Charge Scheduling of Plug-in Electric Vehicles Incorporating Customer's Payment and Inconvenience Costs*, in *Plug In Electric Vehicles in Smart Grids*. 2015, Springer. p. 301-326.
72. Mary, G.A. and R. Rajarajeswari, *SMART GRID COST OPTIMIZATION USING GENETIC ALGORITHM.* International Journal of Research in Engineering and Technology, 2014. **3**(07): p. 282-287.
73. Rao, K.U., et al. *Time priority based optimal load shedding using genetic algorithm*. in *Communication and Computing (ARTCom 2013), Fifth International Conference on Advances in Recent Technologies in*. 2013. IET.
74. Maringer, D., *Heuristic optimization.* Portfolio Management with Heuristic Optimization, 2005: p. 38-76.
75. Rao, S.S. and S. Rao, *Engineering optimization: theory and practice*. 2009: John Wiley & Sons.
76. Terlaky, T., *Interior point methods of mathematical programming*. Vol. 5. 2013: Springer Science & Business Media.
77. SM, A.R., F. Kamran, and M. Akbar. *Dynamic and scenario based elicitation of genetic algorithms of agents for control of distributed power system networks and renewable energy resources*. in *Microelectronics, 2005. ICM 2005. The 17th International Conference on*. 2005. IEEE.

78. Michalewicz, Z., *GAs: What are they?*, in *Genetic algorithms+ data structures= evolution programs*. 1994, Springer. p. 13-30.
79. Ulyanenkov, A., K. Omote, and J. Harada, *The genetic algorithm: refinement of X-ray reflectivity data from multilayers and thin films.* Physica B: Condensed Matter, 2000. **283**(1): p. 237-241.
80. Yang, C., *Development of intelligent energy management system using natural computing*, 2012, University of Toledo.
81. Dehghan, S., et al. *Optimal sizing of a hydrogen-based wind/PV plant considering reliability indices*. in *Electric Power and Energy Conversion Systems, 2009. EPECS'09. International Conference on*. 2009. IEEE.
82. Tina, G. and S. Gagliano, *Probabilistic analysis of weather data for a hybrid solar/wind energy system.* International Journal of Energy Research, 2011. **35**(3): p. 221-232.
83. Sharafi, M. and T.Y. ELMekkawy, *Multi-objective optimal design of hybrid renewable energy systems using PSO-simulation based approach.* Renewable Energy, 2014. **68**: p. 67-79.
84. Dufo-López, R., J.L. Bernal-Agustín, and F. Mendoza, *Design and economical analysis of hybrid PV–wind systems connected to the grid for the intermittent production of hydrogen.* Energy Policy, 2009. **37**(8): p. 3082-3095.
85. Yang, H., L. Lu, and J. Burnett, *Weather data and probability analysis of hybrid photovoltaic–wind power generation systems in Hong Kong.* Renewable Energy, 2003. **28**(11): p. 1813-1824.
86. Celik, A.N., *Techno-economic analysis of autonomous PV-wind hybrid energy systems using different sizing methods.* Energy Conversion and Management, 2003. **44**(12): p. 1951-1968.
87. Morgan, T.R., *The performance and optimisation of autonomous renewable energy systems*, 1996, University of Wales. Cardiff.
88. Khare, V., S. Nema, and P. Baredar, *Optimisation of the hybrid renewable energy system by HOMER, PSO and CPSO for the study area.* International Journal of Sustainable Energy, 2015: p. 1-18.
89. bin Othman, M.M. and I. Musirin. *Optimal sizing and operational strategy of hybrid renewable energy system using homer*. in *Power Engineering and Optimization Conference (PEOCO), 2010 4th International*. 2010. IEEE.
90. Bourouni, K., T.B. M'Barek, and A. Al Taee, *Design and optimization of desalination reverse osmosis plants driven by renewable energies using genetic algorithms.* Renewable Energy, 2011. **36**(3): p. 936-950.
91. Erdinc, O., B. Vural, and M. Uzunoglu, *A wavelet-fuzzy logic based energy management strategy for a fuel cell/battery/ultra-capacitor hybrid vehicular power system.* Journal of Power sources, 2009. **194**(1): p. 369-380.
92. Jeong, K.-S., W.-Y. Lee, and C.-S. Kim, *Energy management strategies of a fuel cell/battery hybrid system using fuzzy logics.* Journal of power sources, 2005. **145**(2): p. 319-326.
93. Karabacak, K. and N. Cetin, *Artificial neural networks for controlling wind–PV power systems: A review.* Renewable and Sustainable Energy Reviews, 2014. **29**: p. 804-827.
94. Safari, M. and M. Sarvi, *Optimal load sharing strategy for a wind/diesel/battery hybrid power system based on imperialist competitive neural network algorithm.* IET Renewable Power Generation, 2014. **8**(8): p. 937-946.

95. Ekren, O. and B.Y. Ekren, *Size optimization of a PV/wind hybrid energy conversion system with battery storage using simulated annealing.* Applied Energy, 2010. **87**(2): p. 592-598.
96. Katsigiannis, Y.A., P.S. Georgilakis, and E.S. Karapidakis, *Hybrid simulated annealing–tabu search method for optimal sizing of autonomous power systems with renewables.* IEEE Transactions on Sustainable Energy, 2012. **3**(3): p. 330-338.
97. Koutroulis, E., et al., *Methodology for optimal sizing of stand-alone photovoltaic/wind-generator systems using genetic algorithms.* Solar energy, 2006. **80**(9): p. 1072-1088.
98. Wahab, M.A. and K. Essa, *Extrapolation of solar irradiation measurements: case study over Egypt.* Renewable energy, 1998. **14**(1-4): p. 229-239.
99. Beyer, H.G. and C. Langer, *A method for the identification of configurations of PV/wind hybrid systems for the reliable supply of small loads.* Solar energy, 1996. **57**(5): p. 381-391.
100. Seeling-Hochmuth, G., *A combined optimisation concet for the design and operation strategy of hybrid-PV energy systems.* Solar energy, 1997. **61**(2): p. 77-87.
101. Ahmad, M.J. and G. Tiwari, *Solar radiation models—A review.* International Journal of Energy Research, 2011. **35**(4): p. 271-290.
102. Howell, J.R., R.B. Bannerot, and G.C. Vliet, *Solar-thermal energy systems: analysis and design*. 1982: Mcgraw-Hill College.
103. Handbook, A., *HVAC applications.* ASHRAE Handbook, Fundamentals, 2007(2003).
104. AboGaleela, M., M. El-Marsafawy, and M. El-Sobki, *Optimal scheme with load forecasting for demand side management (DSM) in residential areas.* Energy and Power Engineering, 2013. **5**(04): p. 889.
105. Albadi, M.H. and E. El-Saadany, *A summary of demand response in electricity markets.* Electric power systems research, 2008. **78**(11): p. 1989-1996.
106. Breukers, S., R. Mourik, and B. DuneWorks, *The end-users as starting point for designing dynamic pricing approaches to change household energy consumption behaviours.* Report for Netbeheer Nederland, Projectgroep Smart Grids (Pg SG). DuneWorks, 2013.
107. Erol-Kantarci, M. and H.T. Mouftah. *Tou-aware energy management and wireless sensor networks for reducing peak load in smart grids*. in *Vehicular Technology Conference Fall (VTC 2010-Fall), 2010 IEEE 72nd*. 2010. IEEE.
108. Han, P., et al. *Novel WSN-based residential energy management scheme in smart grid*. in *Information Science and Technology (ICIST), 2012 International Conference on*. 2012. IEEE.
109. Pengwei, D. and L. Ning, *Appliance Commitment for Household Load Scheduling.* Smart Grid, IEEE Transactions on, 2011. **2**(2): p. 411-419.
110. Peizhong, Y., et al., *Real-Time Opportunistic Scheduling for Residential Demand Response.* Smart Grid, IEEE Transactions on, 2013. **4**(1): p. 227-234.
111. Son, Y.-S., et al., *Home energy management system based on power line communication.* Consumer Electronics, IEEE Transactions on, 2010. **56**(3): p. 1380-1386.
112. Johnston, M.M., *Direct Load Control and Smart Grid–Customer issues for South Australia*, 2010, St Vincent de Paul Society National Council.
113. Mohsenian-Rad, A.H. and A. Leon-Garcia, *Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments.* Smart Grid, IEEE Transactions on, 2010. **1**(2): p. 120-133.
114. Samadi, P., et al., *Tackling the Load Uncertainty Challenges for Energy Consumption Scheduling in Smart Grid.* IEEE Transactions on, 2013. **4**(2): p. 1007-1015.

115. Joo, J.-Y., et al. *Option valuation applied to implementing demand response via critical peak pricing*. in *Power Engineering Society General Meeting, 2007. IEEE*. 2007. IEEE.
116. Safdarian, A., M. Fotuhi-Firuzabad, and M. Lehtonen, *Integration of price-based demand response in DisCos' short-term decision model.* Smart Grid, IEEE Transactions on, 2014. **5**(5): p. 2235-2245.
117. Safdarian, A., et al., *Domestic EWH and HVAC management in smart grids: Potential benefits and realization.* Electric Power Systems Research, 2016. **134**: p. 38-46.
118. Institute, E.P.R., *RELOD Database Documantation and Evaluation and Use in NEMS [Online]*.
119. Bryce, R., *The High Cost of Renewable Electricity Mandates*. 2012: Center for Energy Policy and the Environment, Manhattan Institute.
120. Hillen, H.C., *Beyond Smart Meters Legal compliance of Home Energy Management Systems.* 2013.
121. Wang, J., et al. *Optimal dispatching model of Smart Home Energy Management System*. in *Innovative Smart Grid Technologies-Asia (ISGT Asia), 2012 IEEE*. 2012. IEEE.
122. Jinsoo, H., et al. *Green Home Energy Management System through comparison of energy usage between the same kinds of home appliances*. in *Consumer Electronics (ISCE), 2011 IEEE 15th International Symposium on*. 2011.
123. Kuzlu, M., M. Pipattanasomporn, and S. Rahman, *Hardware Demonstration of a Home Energy Management System for Demand Response Applications.* Smart Grid, IEEE Transactions on, 2012. **3**(4): p. 1704-1711.
124. Safdarian, A., M. Fotuhi-Firuzabad, and M. Lehtonen, *A distributed algorithm for managing residential demand response in smart grids.* Industrial Informatics, IEEE Transactions on, 2014. **10**(4): p. 2385-2393.
125. Bozchalui, M.C., et al., *Optimal operation of residential energy hubs in smart grids.* Smart Grid, IEEE Transactions on, 2012. **3**(4): p. 1755-1766.
126. Hubert, T. and S. Grijalva. *Realizing smart grid benefits requires energy optimization algorithms at residential level*. in *Innovative Smart Grid Technologies (ISGT), 2011 IEEE PES*. 2011.
127. Shao, S., M. Pipattanasomporn, and S. Rahman, *Development of Physical-Based Demand Response-Enabled Residential Load Models.* Power Systems, IEEE Transactions on, 2013. **28**(2): p. 607-614.
128. Tiptipakorn, S. and W.-J. Lee. *A residential consumer-centered load control strategy in real-time electricity pricing environment*. in *Power Symposium, 2007. NAPS'07. 39th North American*. 2007. IEEE.
129. Shahgoshtasbi, D. and M.M. Jamshidi, *A New Intelligent Neuro–Fuzzy Paradigm for Energy-Efficient Homes.* Systems Journal, IEEE, 2014. **8**(2): p. 664-673.
130. Safdarian, A., M. Fotuhi-Firuzabad, and M. Lehtonen, *A Medium-Term Decision Model for DisCos: Forward Contracting and TOU Pricing.* 2015.
131. Pedrasa, M., T. Spooner, and I. MacGill, *An energy service decisionsupport tool for optimal energy services acquisition.* University of New South Wales, Sydney, NSW, 2010.
132. Abushnaf, J., A. Rassau, and W. Górnisiewicz, *Impact on electricity use of introducing time‐of‐use pricing to a multi‐user home energy management system.* International Transactions on Electrical Energy Systems, 2015.
133. Ilic, M., J.W. Black, and J.L. Watz. *Potential benefits of implementing load control*. in *Power Engineering Society Winter Meeting, 2002. IEEE*. 2002. IEEE.

134. Constantopoulos, P., F.C. Schweppe, and R.C. Larson, *ESTIA: A real-time consumer control scheme for space conditioning usage under spot electricity pricing.* Computers & operations research, 1991. **18**(8): p. 751-765.
135. Black, J.W., *Integrating demand into the US electric power system: technical, economic, and regulatory frameworks for responsive load*, 2005, Carnegie Mellon University.
136. Hendron, R., et al., *Development of an energy savings benchmark for all residential end-uses.* Proceedings of SimBuild, 2004: p. 4-6.
137. Makhlouf, M., F. Messai, and H. Benalla, *Modeling and simulation of grid-connected hybrid photovoltaic/battery distributed generation system.* Canadian Journal on Electrical and Electronics Engineering, 2012. **3**(1): p. 1-10.
138. Sharma, A.K., *PERFORMANCE ANALYSIS OF MAXIMUM POWER POINT TRACKING (MPPT) ALGORITHM FOR A SINGLE-PHASE FIVE-LEVEL PWM INVERTER CONNECTED PV SYSTEM.* International Journal of Engineering Sciences & Research Technology. **1**(5): p. 251-260.
139. Bilal, B.O., et al., *Optimal design of a hybrid solar–wind-battery system using the minimization of the annualized cost system and the minimization of the loss of power supply probability (LPSP).* Renewable Energy, 2010. **35**(10): p. 2388-2390.
140. Weniger, J., T. Tjaden, and V. Quaschning, *Sizing of residential PV battery systems.* Energy Procedia, 2014. **46**: p. 78-87.
141. Riffonneau, Y., et al., *Optimal power flow management for grid connected PV systems with batteries.* IEEE Transactions on Sustainable Energy, 2011. **2**(3): p. 309-320.
142. Castañeda, M., et al., *Sizing optimization, dynamic modeling and energy management strategies of a stand-alone PV/hydrogen/battery-based hybrid system.* International journal of hydrogen energy, 2013. **38**(10): p. 3830-3845.
143. García, P., et al., *Improving long-term operation of power sources in off-grid hybrid systems based on renewable energy, hydrogen and battery.* Journal of Power Sources, 2014. **265**: p. 149-159.
144. Prasad, A.R. and E. Natarajan, *Optimization of integrated photovoltaic–wind power generation systems with battery storage.* Energy, 2006. **31**(12): p. 1943-1954.
145. Zhang, S., R. Xiong, and J. Cao, *Battery durability and longevity based power management for plug-in hybrid electric vehicle with hybrid energy storage system.* Applied Energy, 2016. **179**: p. 316-328.
146. Cao, J. and A. Emadi, *A new battery/ultracapacitor hybrid energy storage system for electric, hybrid, and plug-in hybrid electric vehicles.* IEEE Transactions on power electronics, 2012. **27**(1): p. 122-132.
147. Tina, G., S. Gagliano, and S. Raiti, *Hybrid solar/wind power system probabilistic modelling for long-term performance assessment.* Solar energy, 2006. **80**(5): p. 578-588.
148. Khatod, D.K., V. Pant, and J. Sharma, *Analytical approach for well-being assessment of small autonomous power systems with solar and wind energy sources.* IEEE Transactions on Energy Conversion, 2010. **25**(2): p. 535-545.
149. Nelson, D., M. Nehrir, and C. Wang, *Unit sizing and cost analysis of stand-alone hybrid wind/PV/fuel cell power generation systems.* Renewable energy, 2006. **31**(10): p. 1641-1656.
150. Nafeh, A.E.-S.A., *Optimal economical sizing of a PV-wind hybrid energy system using genetic algorithm.* International Journal of Green Energy, 2011. **8**(1): p. 25-43.

151. Ru, Y., J. Kleissl, and S. Martinez, *Storage size determination for grid-connected photovoltaic systems.* IEEE Transactions on Sustainable Energy, 2013. **4**(1): p. 68-81.
152. Notton, G., V. Lazarov, and L. Stoyanov, *Optimal sizing of a grid-connected PV system for various PV module technologies and inclinations, inverter efficiency characteristics and locations.* Renewable Energy, 2010. **35**(2): p. 541-554.
153. Kamjoo, A., et al. *Optimal sizing of grid-connected hybrid wind-PV systems with battery bank storage*. in *Proc. World Renewable Energy Forum*. 2012.
154. Villalva, M.G., J.R. Gazoli, and E. Ruppert Filho. *Modeling and circuit-based simulation of photovoltaic arrays*. in *Power Electronics Conference, 2009. COBEP'09. Brazilian*. 2009. IEEE.
155. Katsigiannis, Y., P. Georgilakis, and E. Karapidakis, *Multiobjective genetic algorithm solution to the optimum economic and environmental performance problem of small autonomous hybrid power systems with renewables.* IET Renewable Power Generation, 2010. **4**(5): p. 404-419.
156. Developments., l.E. 2016; Available from: http://www.lowenergydevelopments.com.au/Solar-Panel-250W-Monoycrystalline.
157. Solar., A.B. 2016; Available from: http://www.aussiebatteries.com.au/batteries/.
158. Co., L.Y.R.E., 2016.
159. Australian Government Department of Industry, I.a.S., *Smart Grid, Smart City.*
160. Pina, A., C. Silva, and P. Ferrão, *The impact of demand side management strategies in the penetration of renewable electricity.* Energy, 2012. **41**(1): p. 128-137.
161. Yilmaz, M. and P.T. Krein, *Review of the impact of vehicle-to-grid technologies on distribution systems and utility interfaces.* IEEE Transactions on power electronics, 2013. **28**(12): p. 5673-5689.
162. Verbong, G.P., S. Beemsterboer, and F. Sengers, *Smart grids or smart users? Involving users in developing a low carbon electricity economy.* Energy Policy, 2013. **52**: p. 117-125.
163. Sousa, T., et al., *A hybrid simulated annealing approach to handle energy resource management considering an intensive use of electric vehicles.* Energy, 2014. **67**: p. 81-96.
164. Finn, P., C. Fitzpatrick, and D. Connolly, *Demand side management of electric car charging: Benefits for consumer and grid.* Energy, 2012. **42**(1): p. 358-363.
165. Oliveira, P., et al. *Load control timescales simulation in a multi-agent smart grid platform*. in *Innovative Smart Grid Technologies Europe (ISGT EUROPE), 2013 4th IEEE/PES*. 2013. IEEE.
166. Gils, H.C., *Assessment of the theoretical demand response potential in Europe.* Energy, 2014. **67**: p. 1-18.
167. Energy, A.G.D.o.t.E.a. *The Renewable Energy Target (RET) scheme.*; Available from: https://www.environment.gov.au/climate-change/renewable-energy-target-scheme.
168. Vittal, V., *The impact of renewable resources on the performance and reliability of the electricity grid.* The bridge, 2010. **40**(1): p. 5-12.
169. Aghaei, J., et al., *Contribution of Plug-in Hybrid Electric Vehicles in power system uncertainty management.* Renewable and Sustainable Energy Reviews, 2016. **59**: p. 450-458.
170. 2013, A.B.o.s. *Energy Account Australia 2011-2012*. 2012; Available from: http://www.abs.gov.au/ausstats/abs@.nsf/Lookup/4604.0main+features42011-12.

171. Anderson, R.N., et al., *Adaptive stochastic control for the smart grid.* Proceedings of the IEEE, 2011. **99**(6): p. 1098-1115.
172. Ghatikar, G., *Open automated demand response technologies for dynamic pricing and smart grid.* Lawrence Berkeley National Laboratory, 2010.
173. Oren, S., *Demand response: A historical perspective and business models for load control aggregation.* Power Systems Engineering Research Center Public Webinar, 2011.
174. Xiong, G., et al. *Smart (in-home) power scheduling for demand response on the smart grid*. in *Innovative smart grid technologies (ISGT), 2011 IEEE PES*. 2011. IEEE.
175. Energy, U.S.D.o., *SmartGrid*.
176. Conejo, A.J., J.M. Morales, and L. Baringo, *Real-time demand response model.* IEEE Transactions on Smart Grid, 2010. **1**(3): p. 236-242.
177. Li, N., L. Chen, and S.H. Low. *Optimal demand response based on utility maximization in power networks*. in *Power and Energy Society General Meeting, 2011 IEEE*. 2011. IEEE.
178. Sane, H. and M. Guay. *Minmax dynamic optimization over a finite-time horizon for building demand control*. in *American Control Conference, 2008*. 2008. IEEE.
179. Li, X.H. and S.H. Hong, *User-expected price-based demand response algorithm for a home-to-grid system.* Energy, 2014. **64**: p. 437-449.
180. Shirazi, E. and S. Jadid, *Optimal residential appliance scheduling under dynamic pricing scheme via HEMDAS.* Energy and Buildings, 2015. **93**: p. 40-49.
181. Adika, C.O. and L. Wang, *Smart charging and appliance scheduling approaches to demand side management.* International Journal of Electrical Power & Energy Systems, 2014. **57**: p. 232-240.
182. Pedrasa, M.A.A., T.D. Spooner, and I.F. MacGill, *Scheduling of demand side resources using binary particle swarm optimization.* IEEE Transactions on Power Systems, 2009. **24**(3): p. 1173-1181.
183. Rabiee, A., et al., *Optimal operation of microgrids through simultaneous scheduling of electrical vehicles and responsive loads considering wind and PV units uncertainties.* Renewable and Sustainable Energy Reviews, 2016. **57**: p. 721-739.
184. Chavali, P., P. Yang, and A. Nehorai, *A distributed algorithm of appliance scheduling for home energy management system.* IEEE Transactions on Smart Grid, 2014. **5**(1): p. 282-290.
185. Gao, B., et al., *Autonomous household energy management based on a double cooperative game approach in the smart grid.* Energies, 2015. **8**(7): p. 7326-7343.
186. Gao, B., et al., *Game-theoretic energy management for residential users with dischargeable plug-in electric vehicles.* Energies, 2014. **7**(11): p. 7499-7518.
187. Ahmad, A., et al., *A modified feature selection and artificial neural network-based day-ahead load forecasting model for a smart grid.* Applied Sciences, 2015. **5**(4): p. 1756-1772.
188. Jiang, B. and Y. Fei, *Dynamic residential demand response and distributed generation management in smart microgrid with hierarchical agents.* Energy Procedia, 2011. **12**: p. 76-90.
189. inverter, S.g.t.; Available from: https://www.google.com.au/search?q=solar+system+batteries&oq=solar+&aqs=chrome.0.69i59l2j69i57j69i59j0l2.12853j0j8&sourceid=chrome&ie=UTF-8#tbm=shop&q=3000w+grid+tied+solar+inverter&*&spd=5702118249120083812.

190. Choi, S., et al. *A microgrid energy management system for inducing optimal demand response*. in *Smart Grid Communications (SmartGridComm), 2011 IEEE International Conference on*. 2011. IEEE.
191. Di Zhanga, N.J.S., N. Shahb, and G.P. Lazaros, *Optimal scheduling of smart homes energy consumption with microgrid.* Energy, 2011: p. 70-75.