Behavioural Demand Response for Future Smart Homes

Investigation of Demand Response Strategies for Future Smart Homes that Account for Consumer Comfort, Behaviour and Cybersecurity

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Keywords

Base Loads, Demand Response, Discomfort, Essential Loads, Fuzzy Logic, Genetic Algorithm, Load Profiles and Schedules, Optimisation, Smart Homes, Smart Metering, User Participation Index.

Abstract

Smart metering and precise measurement of energy consumption levels have brought more detailed information and interest on the actual load profile of a house which continues to improve consumer-retailer relationships. Participation in demand response (DR) programs is one of these relationships but studies have shown that there are considerable impacts resulting to some level of discomfort on consumers as they aim to follow a suggested load profile. This research therefore investigates the impact on consumers while participating in DR programs by evaluating various perspectives that includes:

- Modelling the causes discomfort during participation in DR programs;
- Evaluation of user participation capabilities in DR programs;
- Identification of schedulable and non-schedulable loads and opportunities;
- Application of load scheduling mechanism which caters for specific user concerns.
- Investigation towards ensuring a secure and robust system design.

The key source of information that enhances this work is obtained from data on historical user behavior which can be stored within a smart controller installed in the home and optimised using genetic algorithm implemented on MATLAB. Results show that user participation in DR programs can be improved and effectively managed if the challenges facing home owners are adequately understood. This is the key contribution of this work whereby load schedules created are specifically tailored to meet the need of the users hence minimizing the impact of discomfort experienced due to participation in DR programs.

Finally as part of the test for robustness of the system design in order to prevent or minimize the impact of any event of a successful cyber-attack on the load or price profiles, this work includes means to managing any such attacks thereby mitigating the impact of such attacks on users who participate in demand response programs. Solutions to these attacks are also proffered with the aim of increasing robustness of the grid by being sufficiently proactive.

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Dedication

To all self-sponsored students who made similar though decisions to pursue their dreams despite all odds towards achieving their respective goals.

To my Dad Mr. Ben Ogbogu Anuebunwa of the blessed memory,

And finally

To The Most High whose grace is perfected in my weakness.

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List of Acronyms

AI	Artificial Intelligence
AMI	Advanced metering infrastructure
AMR	Automated Meter Readers
ANN	Artificial Neural Network
ARRA	American Recovery and Reinvestment Act
BB	Branch and Bound
BCVTB	Building Controls Virtual Test Bed
C-TCA	Controllable Thermostatically Controlled Appliances
DDRC	Dynamic Demand Response Controller
DER	Distributed Energy Resources
D-LAA	Dynamic Load Altering Attacks
DoE	Department of Energy
DR	Demand Response
DSI	Demand-Side Integration
EM	Energy Management
EMC	Energy Management Controller
EV	Electric Vehicles
EWH	Electrical Water Heater
FFT	Fast Fourier Transform
GA	Genetic Algorithm
GAMS	General Algebraic Modelling Systems

GBC	Generalized Branch-and-Cut
GREEN HOME	Grid Responsive Energy Efficient Networked HOME
HEMS	Home Energy Management Systems
HVAC	Heating, Ventilation and Air Conditioning
ICT	Information and Communication Technology
IOT	Internet of Things
IP	Integer Programming
ISO	Independent System Operator
MILP	Mixed Integer Linear Programming
MINLP	Mixed Integer Non-Linear Programming
PLC	Programmable Logic Controller
PSO	Particle Swarm Optimisation
PV	Photo Voltaic
RTP	Real Time Price
SCADA	Supervisory Control and Data Acquisition
(S-LAA)	Static Load Altering Attacks
TOU	Time of Use
TP	Traversal-and-Pruning
TURN	The Utility Reform Network
UC	Unit Commitment
UPI	User Participation Index
V2G	Vehicle-to-Grid
W-FFT	Windowed-FFT

List of Symbols

A	Overall Change in Energy ($\Delta\mathcal{E}$ * Occupancy)
$\boldsymbol{A_{new_{t,i}}}$	New Overall Change in Energy
A1	Sample 1 of Randomly generated Load profile
A2	Sample 2 of Randomly generated Load profile
$\boldsymbol{\alpha}$	Deviations from Actual savings
$\forall \boldsymbol{t}$	$\in \{1, 2, \ldots \ldots T\}$ Hours
$\forall \boldsymbol{n}$	$\in \{1, 2, \ldots \ldots N\}$ Sample Generations
B	Cost (Optimized Load * Price)
$\boldsymbol{\beta_t}$	Shuffled price profiles
C	Discomfort ($\Delta\mathcal{E}$ / STD of Load Profiles)
$\boldsymbol{C_{new_{t,i}}}$	New Discomfort
$\mathbf{Cns}$	Energy cost for any converged sample of non-optimised of load
$\mathbf{Cs}$	Energy cost for optimised load
$\boldsymbol{C_t}$	Price at time t
$\boldsymbol{C_{th}}$	Price threshold
C1	Crossed-over energy samples of A1
C2	Crossed-over energy samples of A2
D	Optimisation Factor (Optimized Load / Forecast Load)
$\boldsymbol{D_{new_{t,i}}}$	New Optimisation Factor
$\mathbf{D}_{\boldsymbol{P_{t,1}}}$	Dynamic Pricing

$\boldsymbol{D_t}$	Discomfort D, at time t
$\boldsymbol{D_{th}}$	Discomfort threshold.
e, $\mathcal{E}_{f_{t,n}}$, LP	Forecast load profile
$\mathcal{E}_{\boldsymbol{H}}$	Historical Load Profile
$\mathcal{E}_{\boldsymbol{H_0}}$	First Day of Historical Load Profile Data
$\mathcal{E}_{\boldsymbol{H_{-n}}}$	Last Day of Historical Load Profile Data
e_{max}	Maximum value of forecasted load profile
e_{min}	Minimum value of forecasted load profile
$\mathcal{E}_{\boldsymbol{P_{t,n}}}$	Optimized Load Profile
$\mathcal{E}_{\boldsymbol{R_{t,n}}}$	Randomly-Generated Load profile
$\Delta\boldsymbol{\mathcal{E}}$	Abs (Forecast Load – Optimized Load)
f	Frequency of samples taken
$\boldsymbol{f(C_t)}$	Price activation function
$\boldsymbol{f(D_t)}$	Discomfort threshold activation function
$\boldsymbol{f(L_i)_t}$	Appliance Status
$\boldsymbol{f(P_i)_t}$	Probability threshold activation function
$\boldsymbol{f(S_c)}$	Shifting coefficient
$\boldsymbol{f(\sigma_t)}$	Standard deviation activation function
$\boldsymbol{H_c}$	Household Occupancy
i	Iteration count
j	hourly time interval in a day
n	Number of data-days available
N	1000 Sample Generations

η_t	False data attack on price profile
$\boldsymbol{\theta}$	Actual percent profit without attack
$\boldsymbol{\sigma}$	Standard deviation
$\boldsymbol{\sigma_t}$	Standard deviation at time t
$(\boldsymbol{P_i})_t$	Probability of use for loads i, at time t.
$\boldsymbol{P_{th}}$	Probability threshold
$\boldsymbol{q_t}$	False data attack on Load profile
$\mathbf{R_t}$	Price profile with false data
$\boldsymbol{SD_{th}}$	Standard deviation threshold
SP	Percent Savings
T	24 Hours in a Day
μ	Mean Energy Samples
$\boldsymbol{\vartheta}$	False Profit with constant-pricing attack
w	Weighting factor
x	Optimized Load (Originally randomly generated)
Υ_t	Constant Price factor

Chapter 1: Introducing the Research Problem

1.1 Introduction

Human behaviour is usually complex to model or manage and one does not necessarily need to be a sociologist or an academic researcher to appreciate this. Daily interaction with other people clearly exemplifies this complex nature of humans whose behaviour at one time may differ remarkably from what was previously known or believed to be beyond the bounds of the individual's character, based on their known antecedent behaviour. For instance, a middle-class citizen who was known over the years for his conservative beliefs and had campaigned vigorously towards reduction of CO_2 emission as well as improved environmental protection, may suddenly be found driving an expensive petrol-powered car.

Such a drastic reversal in belief may be considered irrational by some people, but it obviously shows how complex human behaviour can be which is usually based on a variety of variables that may affect the individual at any given instant. While most human behaviours can be predicted to a reasonable degree of accuracy assuming sufficient historical data about previous behaviours are available, spontaneous behaviours are usually non-predictable [2]. This work is based on understanding, predicting and investigating behavioural attributes of energy consumers who participate in Demand Response (DR) programs with the aim of improving grid performance. DR generally refers to all activities initiated by the utility, or from the user which is aimed at improving energy management by promoting reduction in energy cost or consumption [3]. The problems associated with DR participation are solved by modelling future smart homes whereby the users are capable of interacting with the grid effectively while also, not compromising their comfort and benefits.

Smart grid can be defined as an intelligent grid network system applied in modern electrical grid technology whereby the integration of renewable and alternative energy sources to the main-stream grid, utilization of information and communications technology (ICT), application of efficient Energy Management System (EMS) as well as the integration of storage systems, are of primary essence [3] [4]. These four key players interacts with one another such that all important data used for this integration are processed through automated control in order to obtain, process and manage information about the provision, supply and energy consumption by various consumers thereby improving the efficiency of the grid network. It also improves the sustainability and reliability of power generation, transmission, distribution as well as improved management of energy demand, while reducing consumption costs. Provision of sustainable energy is usually discussed under two broad areas of research namely:

- Development of Renewable energy resources
- Development of mechanisms which provide high energy efficiency for consumers as well as the utility supplier.

Renewable energy resources include all energy sources that are not obtained from hydrocarbon or nuclear source which are also inexhaustible and can be replenished within a short period of time such as: wind, solar, biomass, tidal and hydroelectric energy. Demand for electricity is always on the increase principally due to increase in population across the globe and this continuous increase has brought about the need to reduce CO_2 emission from fossil fuel sources. As a result of this, research and investments in renewable sources has been a key objective in energy policies of several governments and countries whereby the introduction of solar and wind sources are increasingly popular.

Energy efficiency on the other hand, can be defined as the ability to manage and restrain the growth in energy consumption by using less energy to provide the same or similar services [4]. In other words, it can be described as using cheaper energy to achieve the same services. As a result, several contributions and applications that aim to improve EMS and techniques is investigated by researchers. One of such applications is by encouraging active participation in DR programs thereby ensuring a reduction of CO_2 emission. Hence, the need to apply efficient EMS creates little appetite to building new power plants where possible since an efficient re-distribution of energy consumption tends to reduce peak demand while upholding consumer satisfaction.

A significant amount of world’s energy consumption can be attributed to residential buildings hence policies made to optimise energy utilization naturally affects home users [5]. This is the key aspect of this research which aims to reduce the strain on energy demand especially during peak demand by encouraging consumers to shift their non-essential loads when it is required to other times of the day when demand for energy is reduced. There are usually some financial savings available as well as other incentives attached to such changes in energy consumption behaviour which is facilitated by the implementation of dynamic pricing as observed in some energy markets such as in the US and UK. This therefore implies that determining appropriate energy price which changes with time, for a market with dynamic pricing, is not a very easy thing to do but if properly done, it will be of increased benefit to the grid.

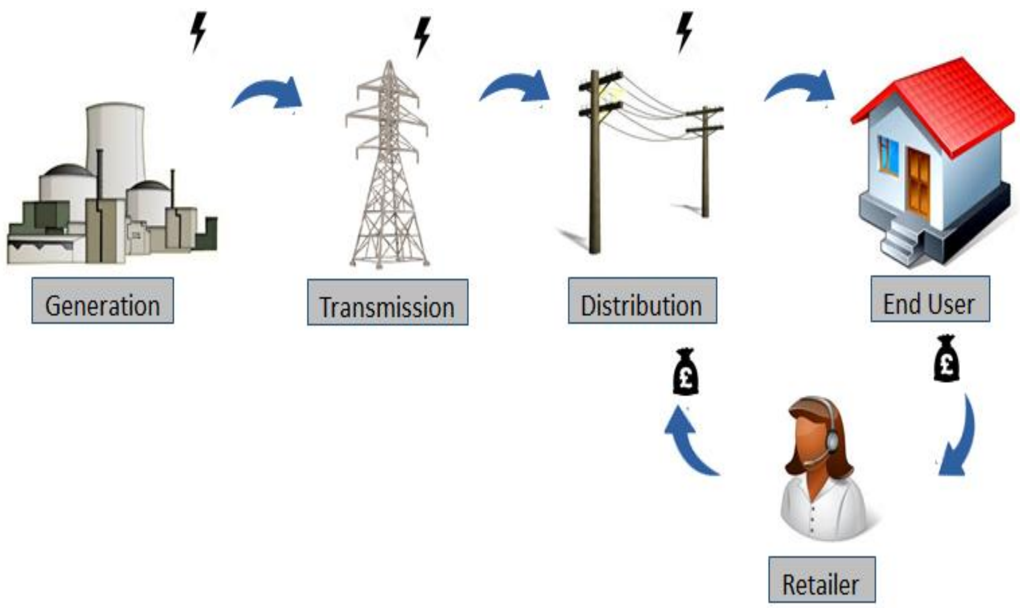

Figure 1.1: Grid Network System in an Unbundled Energy Market [3]

The grid network is traditionally made up of the Generation: which includes various renewable and non-renewable sources, Transmission: which includes high voltage power line transfer from generation sources to designated substations, Distribution: which includes lower voltage power transfer within the cities and User which may also be connected with the retail in an unbundled energy market system as shown in Figure 1.1. The area of interest is at user locations with the aim to improving EMS, assuming those are Smart Homes.

A smart home is basically a residence whose electrically powered devices can be controlled by a means of advanced automation techniques and monitored remotely via the internet, using smart phones or computer devices. Energy supplied to such homes can be managed effectively by the means of interaction between the consumers and the retailers, owing to the communication network established between these two parties, as well as data processing unit embedded in the advanced automated controller installed in the home. In this way, the consumer is required to have minimal manual involvement in the complicated interaction with the retailers but achieve the capacity to obtain the most desired energy management routine that takes into account their peculiar behavioural attributes and energy consumption choices. Taking behavioural attributes into account while designing EMS is important because it reduces the dissatisfaction of participants in DR programs and this work is as a result of the desire to minimise this dissatisfaction amongst users.

1.2 Aim and Objectives of Research

Although application of DR programs within the smart grid is still not very common amongst several energy market in most parts of the world, an observation from US energy market shows that several consumers who originally signed up to such programs ended up withdrawing [2]. Most of the cited reasons as detailed in the literature review chapter are based on dissatisfaction experienced with such schemes, which are cumbersome to follow and not to their preferred load scheduling requirements. This therefore inspires the aim of the research which is given as:

An investigation of the impact of demand response programs on energy consumers which includes evaluation of participation capabilities as well as providing means to encouraging change in behaviour for improved participation in such programs.

This is investigated using available historical data applied in order to understand user behaviour, thereby identifying what causes the discomfort associated with participation in DR programs. This therefore enables a proposal for a novel load scheduling technique which considers several aspects of these factors such that an efficient EMS what generates optimal load schedule, and also caters for the user comfort is achieved. The objectives of the research are as follows:

- To investigate techniques whereby identification of schedulable loads can be empirically deduced while differentiating them from non-schedulable loads. This therefore enhances the application of appropriate scheduling algorithms whose priority is to shift loads from times of the day when the conditions are not so favourable to other times when they become better.
- To investigate the causative to the discomfort experienced by users who participate in DR programs. This variable is a measurable and a manageable quantity which can only enhance user participation in DR programs if properly utilised.

- To investigate user participation capabilities within a community that can be used to map various participation levels amongst the users. This is capable of assisting energy providers to understand the engagement levels of their customers thereby helping to improve their participation in DR programs.
- To develop robust recovery mechanisms from defects as well as from possible cyber-attacks within the smart home thereby promoting pre-emptive approach and corrective means of securing the system design.

1.3 Assumptions and Limitations of Research

With respect to the proposed testbed activity charts for a smart home system as given in Figure 3.5, the following assumptions and limitations are derived:

Assumptions:

1. Dynamic pricing used has price data that varies at least on hourly basis. However, shorter time intervals are expected to produce better results.
2. Pricing data are received early enough before the time stipulated for load scheduling. This is to avoid issues of speed of optimisation which allows GA techniques enough time to complete. This is typically at midnight.
3. Sufficient data on historical load profile is made available.
4. Energy measurements of all the household appliances are measurable individually with the help of smart plugs, and are collated on the HEMS.
5. The user accepts the load profiles suggested without overrides such that results obtained are directly used for further computations such as measurements of discomfort and user participation capabilities.

6. At the end of the day when all energy measurements are completed, all the necessary input data are instantly updated and computed, while the load scheduling is also performed instantaneously.

Limitations:

1. This application is not convenient for a real time scenario. Although such a scenario is achievable by having to run the algorithm at intervals shorter than the hourly time intervals of pricing data coming in, it is however not applied in this work.
2. The computer used in the simulation was not very fast thereby discouraged an attempt on real time scenarios.
3. It is not possible for any computing device to perform scheduling instantaneously therefore some error are introduced whose margin increases for as long as it takes for the computing device to complete the load scheduling process.

1.4 Key Aspects of Smart Home Applications

Four key aspects of a smart home application are identified to play key roles in ensuring an overall efficient system performance. These include: The Metering, Communication, Control (Decision Making), Metering and Actuator Systems. Figure 1.2 shows this outlook and it may also be linked to other external entities such as Virtual Power Plants, Distribution Network Operators (DNOs) and micro-grid operators, in order to provide for load balancing services, renewable energy integration and ultimately financial benefit to the consumer.

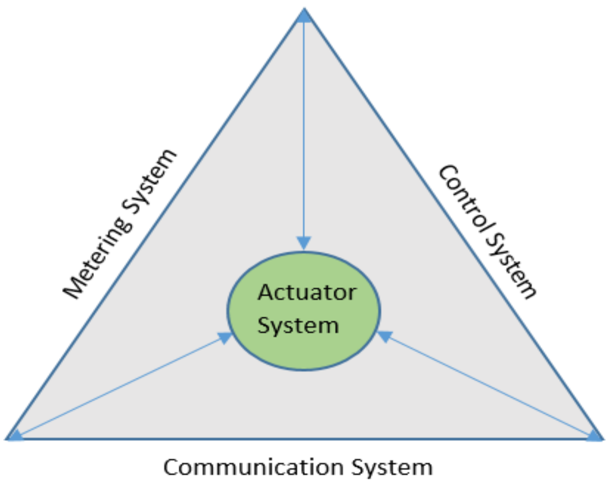

Figure 1.2: Key aspects of smart grid application within the smart home

The Communication System is key to ensuring information delivery from one point to the other which is enhanced by feedback and a two-way communication system [6]. Various communication protocols are possible and the availability of Wi-Fi communication systems has made it the obvious choice since various other associated devices such as the smart meter and smart plugs/sockets are usually WIFI enabled.

The Metering System is based on the services provided by the smart meter which enables energy measurement within specified intervals of time to be obtained and sent to the HEMS for computation. The retailer also receives this information for billing purposes using approved communication network.

The Controller System is the HEMS which also comprises of the algorithm installed, and determines the suggested load schedule for each appliance. This system is central to all the systems installed and coordinates every activity that takes place within the home. User override capabilities are also part of the control system within the home whereby the user has the ability to override any undesired schedule in order to ensure that undesired load schedules are not allowed especially at critical times of need.

The Actuator System is the smart sockets which respond to the control signals to either switch ON or OFF an appliance as required. Figure 1.2 also shows the relationship between these key aspects whereby the eventual aim is to affect the load control through the actuator responses by a combination of the effects of the metering, control and communication systems.

1.5 Scope of Investigation

In this research, understanding the importance as well as the impact of DR programs on consumers requires categorization of the scope of investigation under five themes. Each of these is individually investigated while the impact associated with each scope identified is evaluated with respect to the overall possible consumer experiences which may affect user participation in DR programs. The purpose is to present a reasonable analysis of these effects and proffer means of improving user engagement in DR programs. The themes under consideration are as presented:

- Identification of schedulable and non-schedulable loads within a household
- Developing appropriate algorithm for load scheduling purposes
- Analyzing the effect of participation in DR programs on user comfort
- Evaluation of user participation capabilities in DR programs
- Analyzing the effect of cyber-attack on the household load and price profile.

All experimental procedures undertaken are established under these themes which summarizes the scope of the research investigation. They are carefully chosen in order to fill the gaps in research as identified in the literature review thereby ensuring consumer satisfaction and improved user participation. They are also derived from expected needs of the grid as a result of a successful implementation of a robust, interactive and reliable DR application for a future smart home which serves to the benefit of both the users and the grid.

1.6 Gaps in Research Identified

While acknowledging several previous works done by various researchers especially in scheduling of appliances for optimal performance, as well as proposals to encourage energy consumers to become active participants in DR programs, there still exists gaps in this research area which has affected implementation of DR programs in the grid.

Difficulties in Implementing the Virtues of Demand Response Program: Active participation in DR programs aims to bring about a more balanced energy consumption as well as reductions in peak demands due to shifting of demands from peak to off-peak times in the day. This activity has the capacity to reduce the need for marginal cost of generation as identified in several European grid networks [7]. However, it is nearly impractical to fully implement the virtues of DR since the consumers usually do not respond appropriately to these schedules [8]. Some of these hindrances are recognised to be as a result of inelasticity of demand and low level of customer participation due to asymmetries in information, whereby consumers oftentimes consider demand schedule information as complex to monitor and time consuming to apply [3]. An example of this scenario was the experience of Real-Time Pricing (RTP) program in Chicago whereby, in as much as the price values of energy consumption with time of day was made available online and via telephone, households rarely actively checked hourly price changes to adjust their load in response to these messages [3, 9]. A similar example was experienced in San Francisco, US according to the study of The Utility Reform Network (TURN) whereby users were not able to pursue their best interests as it applies to real-time-pricing mainly due to lack of knowledge of how best to respond, or due to failure to devote adequate time to study the daily price variations and respond appropriately [3, 10]. The inability to integrate this information in an automated way for load scheduling applications which should cater for the specific needs of each user therefore, acts as a hindrance to an effective DR implementation.

Inadequate Monitoring of User Experiences: User experiences in form of feedbacks are usually not monitored in most DR programs which might at some point, become discomforting to the users. The need to minimize the effect of discomfort experienced by consumers especially when scheduling is performed by retailers which usually leads to reduced user participation has usually been underestimated or ignored. Retailer-induced load scheduling is usually performed as a bulk control of various appliances of customers who signed up for scheduling at times of the day as decided by the retailers. The consequence of this type of load scheduling program is an increased chance of operating the appliances involved at times of the day much outside the preferred comfort zones of the customer [3, 7]. This is one of the gaps in this research area that has contributed to diminished participation in DR programs.

Lack of Concise Benefits of Participation: Lastly, financial savings available for various choices of scheduling control requires a clearer investigation. It is desirable for consumers to be acquainted with estimated savings available in any given day to enable them to make informed decision about whether they should be interested in participating in DR program or not. This has the capacity to motivate customers to engage more actively especially because they will be able to observe the benefits of their behavioural changes within the day and possibly an estimated financial savings over the month and year.

1.7 Research Contributions

The proposed solutions to the problems already identified can be considered to represent the key contributions of this research area. The materials accessed in the literature played important roles to understanding the state-of-the-art research, thus helped in finding appropriate solutions towards solving the problems. These contributions are therefore summarised as thus:

Empirical Deduction from Load Characteristics of availability: One of the contributions in this work provides means to identifying schedulable and non-schedulable loads based on the standard deviation of the historical load profiles. Previous research and implementations of demand response are based on predication of appliance usage and changing behaviour. In this work, identifying opportunities for scheduling and what loads are schedulable based on the load profiles is proposed. An example of such a scenario is in the use of washing machine which is generally believed to be a schedulable load, but real-life experiences show that on certain occasions, this might not be the case. For instance, a user who goes to work at night might prefer to do laundry at home during the day. So, if peak demand falls within the day and the user happens to be engaged in group load scheduling initiated from the utility, then such a user will be forced to schedule their washing machine to be used at night time when they are away working. This has been shown to be a contributing factor to withdrawal to DR programs which this research took in consideration by preventing such schedule from occurring. Of course, the user would have saved more money but if they prefer their convenience more than the financial benefits, then such a decision should be respected. Results from this work therefore ensures that users are treated according to their preferences because any load is capable of being schedulable or non-schedulable depending on the user's behaviour.

Measurement of User Comfort: A key contribution is the measure of discomfort variable which is deduced from the relationship between the standard deviation of the load profile and the change in energy consumption, as it affects every household. This is a unique approach towards measuring the impact of load scheduling on consumers and it offers substantive means of either increasing the discomfort to yield higher monetary savings or to reducing it which invariably produces reduced financial savings. The comfort is guaranteed because the user has substantial control over the outcome thereby eliminating unexpected or undesirable outcomes. Previous research work has focused mainly on monetary or energy savings but a method for evaluating performance of DR programmes for the user is provided here for the first time.

Evaluation of User Participation Capabilities: Evaluation of participation levels amongst the users is another contribution to this work. This is a unique approach in measuring user participation levels because it offers a numeric value to this measurement thereby enabling a self-assessment by the user. It also gives the retailer an opportunity to critically measure participation levels which can help them map a community with regards to their level of engagements. This is key as it offers the retailers the ability to see how their customers respond to proposed DR programs to be able to evaluate their performance. They can therefore reach out to poor participants for increased participation levels thereby forestalling chances of sudden withdrawals from such programs which may arise due to user dissatisfaction.

Dynamic Load Scheduling Algorithm: Another contribution of this work includes the development of the fitness function used to optimise the scheduling that includes a number of factors including the comfort factor. In this work GA has been used to do the optimisation. The choice of GA is based on its ability to satisfy the basic requirements of searching for optimal results while ensuring that the search does not get stuck within a local minima or fail to converge. However, the novelty here involves the way the fitness function was formulated which provides a means to append variables in such a convenient way that makes it easy to execute. Obviously GA just as every other type of optimisation tool have their respective limitations but those limitations did not impede on the results. Hence the research focus is not finding the best of optimisation methods but to solving some important problems of which GA is a tool.

Cyber-Attack Identification and Attack Mitigation: Evaluation of the modes and the impact of cyber-attacks on domestic DR programmes as well as devising means to preventing such attacks is important in the smart home. Here the contribution is based on identifying the various attacks that could occur, and the impact that these attacks can have on the overall demand response within proposed market. In this way, any design of such a system should be able to incorporate these mechanisms in their original design.

1.8 Research Justification

Certain factors are considered important in this work and they justify the essence and the methodology applied towards attaining the goal of the research. These are considered not only from the user's perspective, but from the retailer, grid and the environment as well. These factors are therefore discussed in this sub-section as thus:

Awareness: Lack of adequate information about the impact of DR programs on users despite a widely acknowledged possible interference caused on the way of lives of those who participate in such programs, makes this research relevant. This is because having information about the cause of an event provides means to effectively managing such an event. As a result, critical issues such as discomfort, active participation measurements and a robust load schedule, can be achieved thereby improving the HEMS efficiency and provide more efficient means of interaction between the grid and the user.

Care for the Environment: This research is primarily based on the need to reduce CO_2 emissions which causes significant air pollution in cities around the world. The popularity of renewable sources is quite commendable which goes a long way to enhancing this reduction but more is needed to be done towards adequate management of energy use especially peak load reduction to minimise waste. Implementing real time pricing of electricity where possible, is therefore considered appropriate to enhance an optimal management and application of this technique at the consumer locations so that users can be able to respond appropriately to DR programs [11].

User Control Capabilities: This research acknowledges the need to carry the user along effectively before making decisions to modify their load use. User control and override capabilities are included so that users would not feel compelled or forced to a scheme that they have little or no control of, thereby minimising occasions of withdrawals with time. This is available in form of a feedback mechanism whereby the user could see on a display unit, a possible load profile for the day. Further measurements such as discomfort and user participation levels are computed and made available to the user so that they are happy to approve the proposed schedule as well as retaining the capability to override any unwanted schedule at any given time.

Government Support: Let us consider the energy sector from a business point of view whose primary aim is to make profit. This is a reasonable consideration since energy demand and supply follow similar rules just as in any other business routine. It is therefore, in the best interest of such businesses to sell as much energy as they could, depending on the availability of the resource as well as the availability of customers willing to buy. This means that naturally, energy retailers may not actually be interested in encouraging energy reduction despite the adverse effects on the environment. The government may therefore find it necessary to enact laws that compel retailers to move towards effective DR provision irrespective of whether they are happy about it or not.

Automated Load Control: Lastly, assume forecasted Real Time Price (RTP) tariff is adopted as the acceptable tariff system then, for customers who wish to minimise cost, the problem of scheduling of load will become obvious. This is because they should identify at what times of the day when prices are low within an acceptable level and then schedule to operate their non-vital loads at those times of the day. Different price changes are expected to occur at regular time intervals of the day, week, and so on whereby the consumers are expected to track these changes and respond accordingly. This can be a very tedious task for the customers to follow hence; the need to introduce automated scheduling process which is capable of not only following the optimal scheduled load, but also recognises discomfort inherent in participating in DR, and therefore apply ways to minimizing it so that user participation can be maximized.

1.9 Chapter Summary

This chapter has been a presentation of the problem statement which specifies the scope of research, while placing it in context with the state-of-the-art research and advancements in smart grid development especially within the home. The gap in the study of automated scheduling was also identified which is based on identifying the impact on user behaviour as they participate in DR programs with the aim of being able to find means to mitigating such impacts. Also identified is the need for energy retailers to understand the behaviour of their target market to assist in the planning of energy market transactions as well as acknowledging the need for a robust scheduling algorithm which can coordinate the operations within the home. A need to investigate possible security challenges was also introduced and all these aspects of the work enhances the ability to present a justification for the research which aims to providing a robust EMS for a future smart home.

The next chapter will be a review of relevant literature which has helped to structure and understanding the proposed area of research. It is a summarised account of various contributions as well as on-going research from several writers, including participations from various governments across the globe.

Chapter 2: Research Background

2.1 Introduction

An introduction of the research area as well as the scope of the work was presented in previous chapter, whereby the role of each of the key players in providing efficient energy system was discussed. This chapter is a review of state-of-the-art developments within the smart grid and most importantly, about smart home EMS which includes developing scheduling algorithms for efficient load consumption optimisation. Previous related work done by various writers within this area of study is thoroughly reviewed as well as reviews of pilot projects which are under planning or those already executed by various governments in several countries across the world. This is in view of the effect of how much advancement in technology is sought for, especially where it is economically important and capable of adding value to human life.

Researchers are keen on developing new technologies, as well as managing the infrastructures and resources that coordinates these improvements for better living because the world today thrives on energy generation, distribution, utilization and most importantly, conservation and management. Provision of improved EMS especially in smart homes is desirable because energy demand is always increasing due to growing economies of various countries around the world. Apart from growing economies, population growth as well as introduction of new loads that relies on electricity for operation such as Electric Vehicles

(EVs), are other factors that contribute to increase in energy demand, thereby increasing carbon emission especially if the source of energy for their operation was obtained from non-renewable sources. This leads to the desire to as much as possible, ensure that energy generation matches energy demand always so that marginal cost of energy generation can be reduced.

The grid as we know is getting smarter and providing it with intelligence enables it to undertake certain essential automated decisions at certain essential times to achieve certain goals aimed at energy conservation, efficiency improvement and optimisation applications, thereby encouraging researchers to seek means to actualizing this objective. An evaluation of various contributions attributable to this research area from various research teams is evaluated in this review which is based on several research topics that fall within the broader scope in developing a sustainable smart grid that cares about the environment by encouraging reduction of CO_2 emission. This review therefore reflects the four key aspects of smart grid application for smart homes, discussed in section 1.3.

2.2 Feedback as a Prerequisite in Smart Grid Systems

Feedback is important towards developing efficient optimisation techniques for energy consumption and scheduling using either manual, semi-automated or fully automated technology for DR program implementation [6]. This is in addition to its importance in coordinating system performance within the smart home by ensuring adequate information sharing amongst the four Key aspects of smart home application shown in Fig 1.2. Information can also be shared between the retailers and the users in form of signals via telephone lines, e-mail messaging system, cell phone SMS and Advanced metering infrastructure (AMI) technology [3, 12]. In this way, the user can be informed about the need to either reduce consumption or to use appliances at different times of the day. Some typical examples of data required for instant use include energy meter readings, pricing information and various types of control signals.

AMI is the aggregation of the grid, the two-way communications infrastructure and the supporting information infrastructure with IP address where security requirements and implementation guidance is the primary motivation for its development [13]. It is a very popular means of actualizing adequate feedback communication as it enables a 2-way communication network between the utility and consumers, although the major disadvantage of implementing an AMI is the problem of latency whereby prolonged response delays in data transmission could render it inefficient [14]. To obtain a reliable and readily available data, online data accessibility is promoted. Therefore, IP communication can be employed to ensure a secured online data transfer devoid of interference and interception.

The effect of feedback on electricity consumption offers one of the most important techniques and means to actualize an effective domestic or industrial energy management. This optimisation is usually aimed around heating, refrigerating, cooking and lighting energy requirements. In a research carried out in Northern Ireland using data available over a period of 20 years (1990 - 2009) and assisted by the office of the Northern Ireland Statistics and Research

Agency; the publication in 2013 shown in statistical form that the average yearly energy consumption was observed to reduce by 17-18% between 2002 and 2009 when feedback about electricity consumption was made available to the consumers as compared to energy consumption between 1990 till 2009 [5].

The viewing of real-time energy consumption levels and corresponding pricing details were facilitated using AMIs which includes smart meters and advanced meters installed at homes. Automated Meter Readers (AMR) or simply; Advanced Meters are a one-way-communication data acquisition, data retention and data transmission devices that communicates with the utility at regular intervals from the user. This enables the utility to monitor and bill customers appropriately and remotely without having to read the meter physically. On the other hand, smart meters are more complex in function as they provide a two-way communication with utility while performing the same functions as already stated for advanced meters [15]. The added exclusive feature for the smart meter is its ability to convey real-time tariff changes and peak-load information from utility to customers at varying times of the day. The AMRs are replacing the traditional analogue meter and enables households to understand their energy consumption patterns better.

The implementation of the use of feedback on energy consumption level that involves the use of cell phone SMS and e-mail messaging to alert customers when usage levels are exceptionally high, can be helpful. A study to this effect, as carried out in Denmark, was found to reduce consumption by 3% [12]. A similar research shows that in Japan, availability of feedback information on residential energy consumption using a visual display has encouraged consumers to manage their energy usage more efficiently such that a reduced energy usage of 1% was achieved regardless of the fact that no monetary incentive was offered and the display was not connected per appliance but it was for the entire household appliances [16] . The display included a graphical display of energy consumption levels with time. Although 1% is very minimal, with more education and probably with the introduction of various incentive schemes, consumers might find DR program more interesting and will improve their participation. This can therefore influence the 1% figure to have a significant increase. These results show the importance of feedback in optimisation of energy consumption, and an attempt to automate DR programs can improve cost reduction and improve the efficiency of energy usage.

2.3 Benefits of Energy Management Systems in Smart Homes

Energy management system is a set of computer-based tools or equipment which aids the operation of the electric utility to be able to monitor, control and enhance the overall performance of the grid. In the smart home for instance, automatic meter readers (AMRs) is one of the means which can be used to enhance the development of an efficient HEMS. Management of appliance use can be enhanced with the assistance of AMRs, by introducing the application of standby power on domestic appliances such that these appliances can go into standby mode when they are not in active use. This is viewed as a means of implementing energy conservation within the home rather than using a continuous active power when appliances plugged on power sources are not in active use [17]. Additionally, the benefits of applying energy conservation in the home can be further improved by:

- **Remote Control Application:** This includes the use of applications that are controllable from smart phones, laptops and also timers [17].
- **Application of Technical Solution:** This involves developing smarter energy systems and algorithms that includes optimisation of load profile for more efficient energy use.
- **Political Regulation:** Here, certain high power consumption devices are abolished and energy saving ones are preferred. A typical example is the abolition of the use of incandescent lamp in the EU which has been replaced by a more favoured energy-saving florescent lamps [18].
- **User Encouragement:** Encouraging customers to engage in DR applications includes direct marketing strategies from the retailers whereby users are made aware of the benefits of participating in load scheduling programs, thereby encouraging them to turn certain appliances ON or OFF when required.

The first step towards achieving an efficient EMS involves devising a technique towards effective load identification methodologies whereby acknowledging which load to schedule, or to switch ON or OFF at any given time, must be made. Authors in [19] implemented a scheme known as the Grid Responsive Energy Efficient Networked home (GREEN HOME) using feedback and load identification techniques as a framework for private households. The authors suggested the use of smart plugs or any other non-intrusive identification algorithms and devices based on smart meter data, and can be used for the load identification and feedback process. Hence, householders could then identify and control specific loads as required.

In [20] the authors elaborated the benefits of developing sustainable EMS whereby an appropriate balance between customer satisfaction and reduction of electricity costs is established. The paper emphasised that such state of art design must be achieved using some form of intelligent automated decision making process and actuation because, the dynamics of electricity price changes cannot be critically followed manually by anyone since consumers often lack a deep understanding of electrical systems as well as having a limited time to make energy-related decisions [21]. Such system was expected to reduce the burden on consumers to directly control all appliances at all times [22]. Finally, the paper mentioned some state-of-the art technologies in EMS which included a mobile-based feedback system and a mobile application that provides information about energy use that compares with other individuals [20].

2.4 Energy Demand Integration from New Types of Loads

With increasing demand for electricity supply in several countries mainly due to population growth and also due to introduction of new loads such as EVs and heat pumps, there has been an increasing appetite to satisfy these new demands, but from renewable sources. This appetite and preference is mainly driven by the desire to reduce carbon footprint in the environment. An expensive and therefore very difficult means of satisfying this demand is by constructing very large storage facilities on the grid to be able to satisfy peak power demand. The difficulty in implementing this is mainly due to cost and technical limitations, although research on storage facilities using battery banks and storage capacitors are ongoing [23].

Vehicle-to-Grid (V2G) Storage Capabilities: These type of storage facilities under research are exemplified by utilizing the battery storage in cars to facilitate vehicle-to-grid (V2G) storage capabilities. Incidentally, its effect on the grid is significant and it is being considered because it is capable of disrupting the grid frequency stability [24, 25]. In order to manage this effect appropriately, various V2G models are being proposed and developed to model the electric distribution system in order to precisely study the behaviour of the network where there is high involvement of V2G in the grid as proposed by authors in [26]. Here, V2G was modelled to behave as a load (when in charging mode) and as a current source component (when discharging/injecting electric power to the grid). The paper therefore describes a mathematical formulation for incorporating V2G into the distribution network with analysis on the power flow analysis. Results shows that V2G causes a decrease in bus voltages when in charging mode, while it improves the voltage profile when discharging.

Demand Side Management Interventions: A way of satisfying the increasing demand for energy consumption apart from building new power stations or storage facilities, is by implementing the virtues of demand side management. This can produce enhanced integration of large amount of renewable energy sources such as V2G technologies as well as solar panels installed on roof tops of energy consumers using adequate load management techniques, thereby increasing the participation in demand side response for customers in who may also be involved in load scheduling programs [23]. Demand-Side Integration (DSI) programs refer to all aspects of electric power system which involves the energy generation, energy supply and the end-user load consumption. Although not fully developed, it is a potentially important means of providing more reliable access to electricity in many countries [23, 27]. Its effective implementation must involve integration of advanced Information and Communication Technology (ICT) and a good knowledge of system loads. These technologies are therefore becoming popular and important aspects of the grid setup which enables systematic interruptible load scheduling [3]. This new technological approach also involves the use of smart plugs capable of communicating with one another and with a central processing unit which is integrated with the smart meter. It therefore becomes the window through which a domestic algorithm designed to understand localised energy consumption patterns and requirements can be developed. This will eventually eliminate the complexity associated with the ever-changing load schedule programs hence, will contribute immensely to DR success by increasing customer participation and in the larger sense, improve elasticity of demand.

2.5 Demand Side Management of Energy Resources

The future of efficient EMS lies in improved demand side management which is largely influenced by DR programs. Demand response is envisaged as one of the most strategic solutions for the 21st century power system already battered by limited resources, increased environmental threats as well as price-spike power demands [28]. According to Federal Energy Regulatory Commission (FERC) in the US, it is defined as deliberate modifications of electric usage by end-use customers in response to price changes of electricity with time, in order to receive associated incentive payments due to reduced energy use during high wholesale market prices or during jeopardized system reliability [29]. Due to the acknowledgement about how strategic DR is, several governments have continued to encourage and support programs and schemes that encourage improved and active participation in DR programs. Several writers have also contributed in developing methodologies that enhance improved DR programs for improved participation by users.

In [30] the authors designed a Dynamic Demand Response Controller (DDRC) which was implemented in MATLAB/SIMULINK and connected to EnergyPlus model via building controls virtual test bed (BCVTB) so that one can control Heating, Ventilation and Air Conditioning (HVAC) loads using RTP information and ambient temperature values. The justification for the research was the need to participate more actively and more economically to DR programs via RTP information rather than relying on dynamic-controlled thermostats supplied by Austin Energy in Texas USA, which were capable of switching HVAC loads on/off depending on ambient indoor temperature. This DDRC control was achieved by designating a customer-specific threshold retail price, which was to be compared with the real-time-price of electricity. If the RTP is above the threshold, DDRC changes the set-point temperature of the thermostat in line with the prevailing price difference. With a hypothetical RTP data estimated every 15 minutes, DDRC result showed a reduction of 12% and 21% in price of electricity for heating and cooling, in the months of January and August which represented the coldest and warmest months of the year, respectively.

The authors In [31] proposed a methodology for management of Distributed Energy Resources (DER) within the Supervisory Control And Data Acquisition (SCADA) systems by scheduling of the generation units in order to maximize the performance of the energy supply. The optimal operation of the variables which are: distributed generation, DR and storage resources, was formulated as a Generalized Branch-and-Cut (GBC) Mixed Integer Linear Programming (MILP) model and solved in general algebraic modelling systems (GAMS) platform using CPLEX optimizer. In a case study presented, the objective function of the MILP is the total cost for a given period (T) and was minimized [31]. Result showed that using an intelligent and flexible SCADA, existing resources are utilized by agents that require them in a robust and efficient way. Although the work as presented by the authors focused on distributed generation, this thesis is based on effective home energy management systems so these methods are not used here. However, it is important to highlight what other researchers are doing in this area since some energy consumers are also producers hence, information about applications of distributed generation becomes relevant.

In [32] the paper discussed the response to electricity spot prices (or RTP) for storage-type customers who are capable of participating actively in demand-side response programs as prosumers. This means that as well as being a consumer, such customers also have the capacity to become energy producers. The responses were classified into three categories given as:

- Curtailment: Switch off when price goes higher than a certain threshold.
- Substitution: Switch to alternative supply whenever it is cheaper to do so.
- Storage: Load scheduling to times of the day when energy costs are lower and this includes charging energy-storage facilities within such times.

The justification for the research was to establish the advantages of implementing spot pricing of electricity with data available 7 days in advance for every one hour interval, and finding the optimal times to operate domestic appliances in order to achieve optimal energy and cost savings. The cost minimization problem was presented as a linear programming formulation, written in APL*PLUS/PC programming language on an IBM PC and solved using a non-simplex algorithm as proposed by Daryanian [32]. Result from a case study showed savings obtained as a result of the difference between the avoided costs of using electricity at higher price-hours minus additional cost at the substituted lower price- hours.

Interestingly, the authors in [33] argued that the efficiency achievable while implementing DR programs is largely affected by the reserve requirement of the system with respect to whether curtailment (peak price clipping) is required, or whether supply from storage is applied. This is because at lower load levels within the load profile, price curtailment is difficult to attain since energy supply is at off-peak demand. This is unlike if the supply during this period is from storage facilities whereby there is no observed effect in obtaining supply from such storage. Hence the dynamic pricing at any given time will be the factor at any given time to determine when best it is to obtain supply from the storage and it is up to the participating consumers to either tolerate probable power curtailment or to provide actual curtailment for demand reduction. The problem was formulated as a Unit Commitment (UC) problem under a mixed integer problem framework whereby the objective function is a minimization of system total cost which comprised of three components given as: operation cost, reserve cost and expected load-not-supplied cost [33]. Results showed that the technique which is a function of several parameters like load reliability requirements, available DR resource, bidding price of services such as spinning reserve as well as peak clipping can enhance reliability of the system and also improve its economic value.

Finally, the incentives offered in DR programs are usually the motivation for end-user participation and for it to be optimally implemented, adequate awareness is required to enable customers understand how to participate. Also an appropriate application platform is required such that the end-users can easily be integrated into such programs at a minimal cost.

2.6 Government's Role in Advancing Grid Infrastructure

Oftentimes, governments play major roles in initiating and encouraging CO_2 reduction usually by legislation, offering incentives or by investing in renewable sources. Data from UK energy generation sources for instance, indicates that the average energy generation from renewable sources stands at 25% of the national electricity generation [34]. But on 8th June 2017 the UK national grid reported that at lunchtime and for the first time, energy generation from renewable sources surpassed supply from non-renewable sources such that power generated from wind, solar, hydro and wood pellet burning supplied 50.7% of UK energy [35]. This is a major step towards improving green energy production for the country. Other countries around the globe have various investments in renewable sources. An example of government legislation that enforces reduction of CO_2 emission include the ban on diesel and petrol-powered vehicles within the next 13 years by, France Spain, Greece, Mexico, UK and several others. Hence, electric and hybrid cars whose energy source is obtainable from cleaner and renewable sources are favoured [36]. Therefore governments have a role to play towards making substantial investments in smart grid infrastructure and smart meters.

The European Commission's Directive 2009/72/EC in 2009, requires that member states should implement intelligent metering systems so that consumers can participate actively in electricity and gas supply markets. The overall investment target in the EU on smart grid projects by the end of 2030 is expected to cost at least €100 billion, while the estimated cost of installing smart meters alone is €51 billion [37]. But due to the provision of dynamic pricing, peak demand is expected to be reduced thereby reducing the need for building and running new expensive peaking power plants hence; an operational savings worth between €26 and €41 billion can be provided [38].

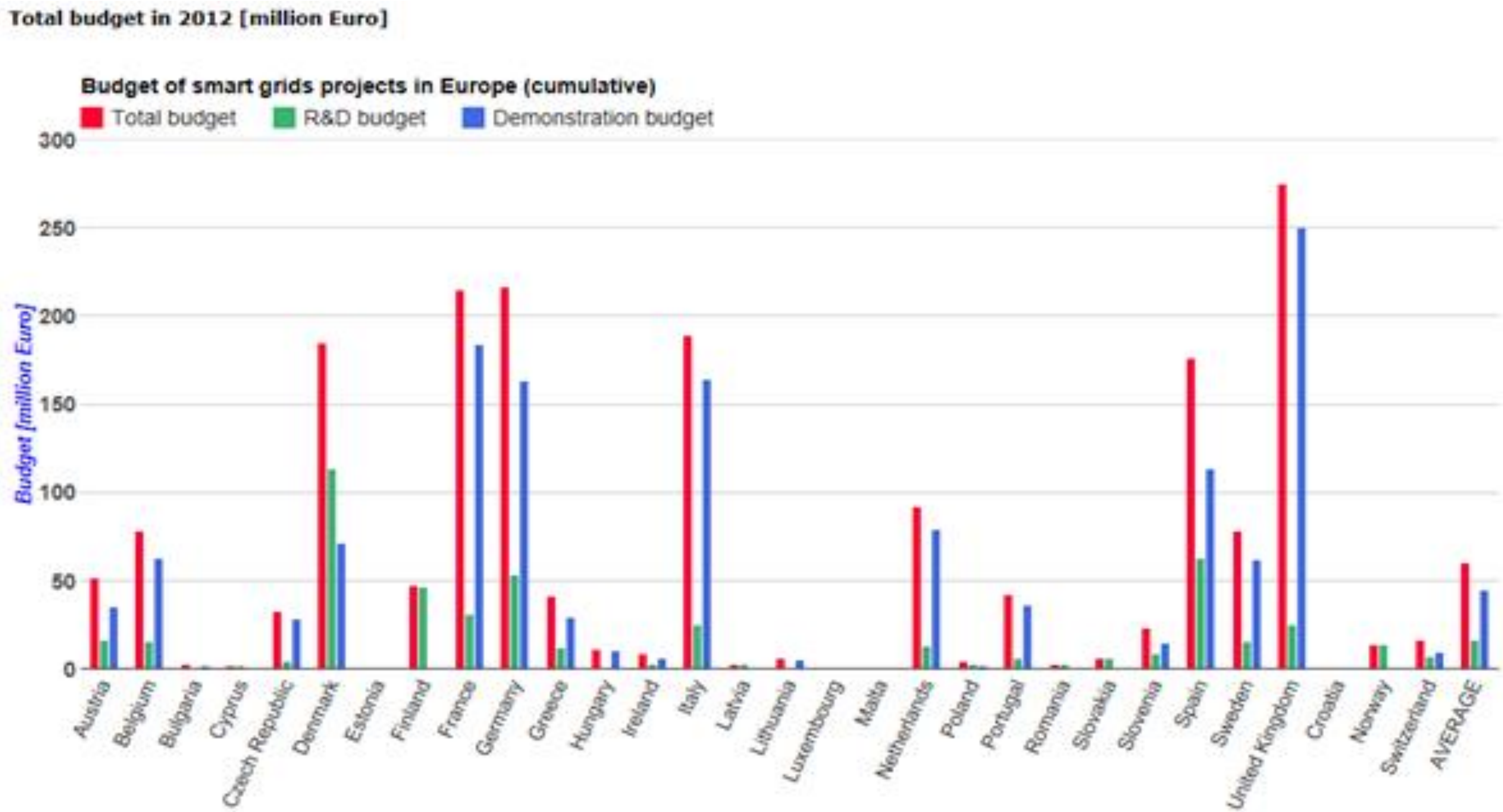

Figure 2.1: Budget of smart grids projects in 30 EU countries in 2012 [1]

Figure 2.1 shows the cumulative budget of smart grid and smart metering projects in 30 European countries for 2012: which includes 281 smart grid projects and about 90 smart metering pilots and rollouts. In December 2009, the UK department for Energy and Climate announced its intention to introduce ‘Smart Meters’ to all UK households by 2020 which should be accompanied by free standing real-time displays [6]. This budget has been sustained and by 2012, it has allocated the highest budget when compared with the rest of EU countries as shown in Figure 2.1 [1].

In other parts of the world, similar budget proposals and implementations are being applied. The U.S. government in 2009, awarded US$4.5 billion to projects aimed at building a smart grid across the country. These projects and programs are already underway in 33 states and includes the already financed 54 projects by the Department of Energy (DoE) to a cost of US$100 million in American Recovery and Reinvestment Act of 2009 (ARRA) [39]. China is also one of the big investors in the sector with an expected budget of US$596 billion while Japan, Australia and Canada are also involved in active research and development programs to achieve a smarter grid [39] [40].

Developing countries are also not left out. With several countries usually described as emerging economies such as: Nigeria, India, Brazil, also investing and researching ways to improve energy services through the adoption of smart grid and are at various stages towards developing the grid in their respective countries [40]. With the depth of funds and special allocations to installation of Smart meters, as well as intensive research by various governments, it can be implied that the future of a successful optimisation and reduction of peak power consumption can be enhanced by providing feedback about usage brought about by the communication offered using smart meters; which can thereafter act as the foundation to any further development the grid might experience towards achieving an effective DR program implementation.

2.7 Optimisation Techniques for Load Scheduling

Several techniques are available which schedules energy consumption to maximise profits by reallocating certain loads whose usage can be moved from high energy times, to times of the day when energy prices are lower [41-48]. Hence, load scheduling is a load management application aimed at balancing energy consumption which varies between peaks and crests depending on the user, on a daily basis [49]. It is important that a viable producer-consumer partnership is established in order to realize the full potentials of DR applications for load scheduling. These potentials are in terms of sacrifices made to reduce costs at certain times of the day, both by the energy supplier and the customer who participates in load scheduling programs. Pricing models contribute immensely to user participation capabilities towards engaging in load scheduling programs, while acknowledging that the factors that determine energy prices at any given time can be complex to evaluate based on various variables. This section is a discussion of various load scheduling methods implemented by various authors which are usually dependent on the type of pricing model adopted, although detailed investigation of pricing models and their derivations is out of the scope of this work.

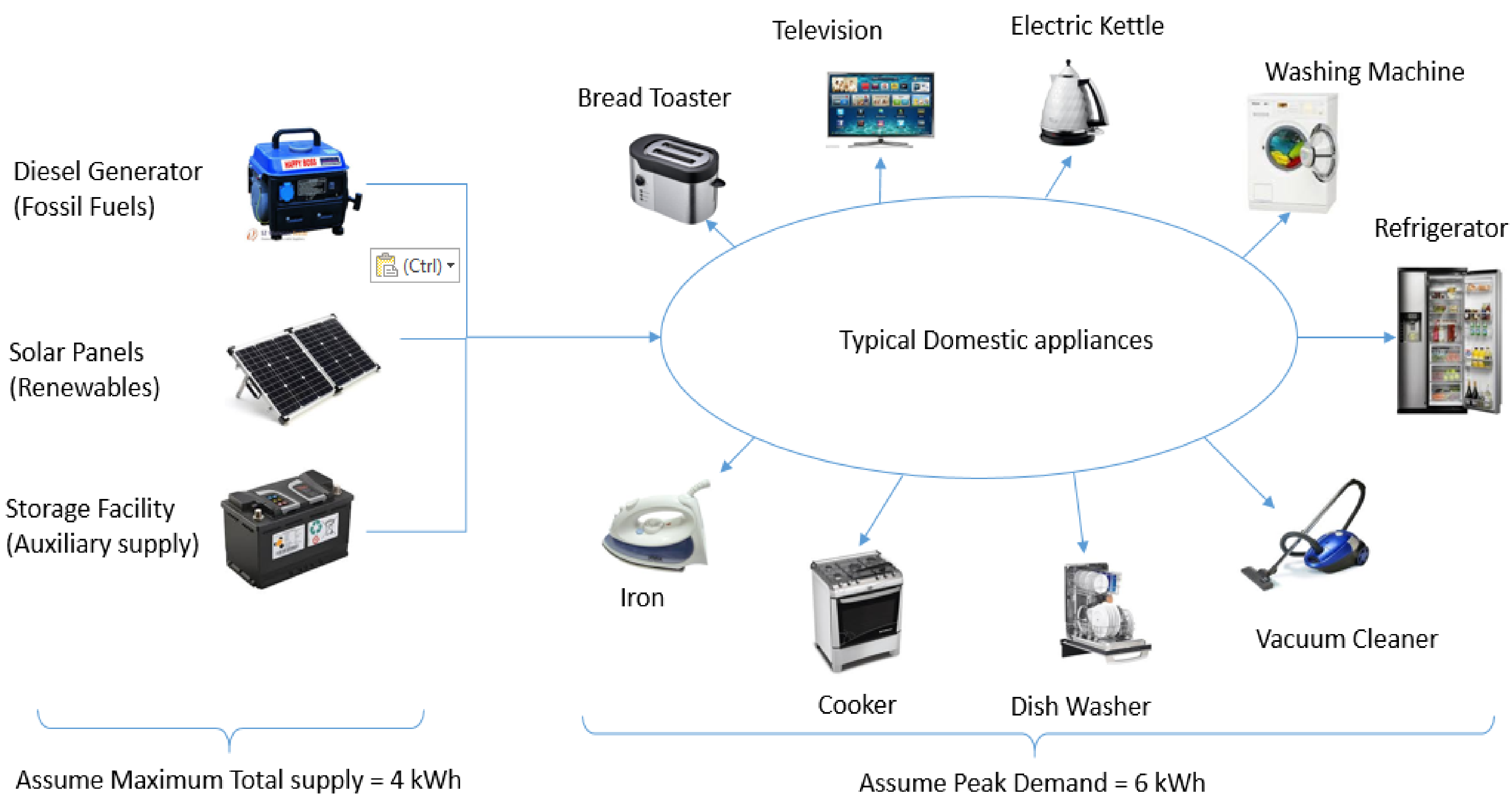

Figure 2.2: Model for Requirement of Load Scheduling in Everyday Life

Assume you supply your own energy, the reality to schedule your own load usage becomes a practical reality. Figure 2.2 shows an example of a householder who is able to produce a maximum energy supply of 4kWh at a given instant, whereas the total energy consumption at that time is given as 6kWh. From the figure, it is obvious that such a user is not capable of using all the load at the same time otherwise the energy system supply will shut down. This illustration shows a realistic requirement to perform load scheduling at an individual scale but when extrapolated to cover a community or a micro grid for instance, its application as presented in this work becomes more practical. Here, users might feel some discomfort if they cannot use all load at same time and this aspect of this work is one of the key contributions of this work.

Load scheduling implementation can be automated or manually done. An example of a scheme that implements a non-automated scheduling is the availability of the dual tariff system in the UK electricity market which provides a certain energy price to consumers during the day, and a different but usually lower energy price during night time. This is aimed at encouraging consumers to manually defer the use of any loads that they can afford to use at night time so that energy demand during the day can be reduced. This tariff system is known as “economy 7” which simply means that consumers can use energy at cheaper rates for a total of 7 hours in a day. This lower tariff times usually occur between 10:00 pm and 8:30 am depending on the energy provider as well as the geographic location of the customer within the UK [50]. To this end, consumers whose lower tariff time starts from 10:00pm will end by 5:00 am next day. Every other start and end times lies in-between these stated times.

Accordingly, a detailed work as presented by authors in [51] examined the implementation of the tariff system by investigating the impact of other different tariffs schemes on domestic electricity consumption on the load profile. The authors identified certain loads which were considered to be schedulable, and their use was implemented at night, during the reduced tariff times, in order to evaluate the benefits available. Result showed that when compared with the fixed-pricing tariff system, savings of about 13%-15% on energy bill is possible when such loads are shifted. Energy price for the fixed-tariff system usually lies between the higher and lower energy prices for the economy 7 tariff, and does not inspire load scheduling due to unavailability of incentives to participate.

Conversely, automated load scheduling scheme is usually implemented based on the execution of some computer programs that runs dedicated algorithms which determines the best times to implement specific load usage due to some predefined initial settings. This can be adopted using two approaches of load control and they include: Individually based scheduling and group scheduling.

2.7.1 Individually-Based Load Scheduling

An individually-based load scheduling is a system that possesses a localised decision-making algorithm that controls only the load of a specific domestic load and allocates time schedules for appliance use within the household. The schedules proposed are solely designed to accommodate the interest of household without any interaction or assessment of the impact on the comparative load profiles of the community. Such approach is best situated where it is difficult to encourage a community-based load scheduling program due to privacy issues, diverging interests amongst various householders within the community, or when it is not cost effective to do so.

An example is based on the work of authors in [52, 53] who analysed the results of a pilot scheme that was launched by the end of 2010, to evaluate washing machine load potential for integration in smart grid. The aim of this individually-based scheduling was to encourage certain consumers to schedule their laundry only when their photovoltaic panels were supplying electricity for over a period of more than 15 weeks. The results showed a possible peak load reduction of 5% using a coincidence factor based on average weekly washing machine load profiles. Although it was not clear if the reduction was exclusively attributed to the washing machine scheduling, the results were encouraging. A consequence of the result was pivotal in the design of a new smart grid pilot known as ‘Your energy moment’, launched in December 2012 in Netherlands and it covered more than 250 households.

In other instances as presented in [41-48, 54-65] where individually-based scheduling was applied, the authors discussed the merits of identifying specific loads also known as schedulable loads and then engaging them specifically for load scheduling purposes. In [41] the authors presented an appliance commitment algorithm that schedules thermostatically-controlled loads based on price and consumption prediction while prioritising customer comfort. Only controllable thermostatically controlled appliances (C-TCAs) such as HVACs and water heaters were scheduled using consumer level DR programs. Controllable non-thermostatically controlled loads (non-TCAs) such as washing machine and dryers are considered straightforward to schedule, unlike non-controllable appliances which the authors considered non-schedulable. Result shows the generation of day-ahead consumption schedule using forecasted day-ahead energy price forecast [41]. Although the algorithm used is fast and robust, it did not include analysis using probability of appliance use nor did it consider analysis based on historical load profile. A consequence is the non-availability of intelligent decision making capabilities which helps to reduce user involvement in the operations thereby improving user comfort.

The authors in [43] scheduled Electrical Water Heater (EWH) using a novel Traversal-and-Pruning (TP) algorithm. The problem was presented as a Mixed Integer Non-Linear Programming (MINLP) problem which can be solves in a variety of ways such as: PSO [44], Genetic Algorithm (GA) [66] and Simulated Annealing (SA) [45]. However, the authors resolved that these methods are for solving general MINLPs but on a special occasion that requires removal (pruning) of unlikely outcomes, the need for TP algorithm for solving specific appliance commitment problem becomes important. Results are a solution-tree analysis of varying temperature settings whereby branches that deviates from ambient temperature specifications were pruned and avoided in subsequent iterations. An optimal path was determined which coincides with the cheaper heating costs during the day.

The authors in [57] simulated an effective autonomous appliance scheduling for households who are both producers as well as consumers of electricity. The domestic smart scheduler, embedded in the smart meter, is based on each device’s time of use (TOU) probabilities and RTP of energy. Results showed that the schedulable appliances requests were altered by systematically switching them on and off avoiding peak or high cost durations of electricity during the day. But the methodology did not include re-distributing the appliances at other convenient times in the day when such high energy prices are encountered. Rather is it only a single on/off mechanism whenever the price of energy exceeds a certain predefined threshold.

In [58] the authors demonstrated how coordinated scheduling of residential DER could be achieved using PSO [59-65]. The user would first assign values such as hourly consumption and discharging times with which the scheduler operates. Thereafter, the desired energy services such as: electric vehicle, space heater, water heater, pool pump and photo voltaic (PV) system; which are considered random particle trajectories, are optimised by the scheduler to achieve maximum benefits using PSO. The optimal benefit was obtained by increasing repulsion among the particles which added more randomness to the particle trajectory, in order to prevent premature convergence.

In summary, individually-based load scheduling pertains to a household’s requirements and can be useful when it is difficult to accommodate events on the larger community. Since not everyone will be happy to permit sharing of the details of their load profiles to a third party, this type of load scheduling will be ideal for such customers. But if such data is free from abuse and with increased security, group-based load scheduling will be ideal as there are more advantages when scheduling is performed based on the events on the larger community than when it is individually-based because the load profile of the community will have a more reduced peak load when scheduling is considered on a micro-grid scale than when scheduling is considered on individual bases.

2.7.2 Group-Based Load Scheduling: Micro Grids

Group-based scheduling is a method applied when schedulable loads in several households within a community are controlled simultaneously based on prevailing energy demand and the requirements to shed load usually during peak demand. The household would usually receive a request or command to suspend the use of such appliances if the grid is under pressure and all householders who signed up to such schedule would have any identified load for such scheme temporarily disconnected from use. There are incentives to encourage users to participate and this section will discuss various applications of such methods in load scheduling.

Instances where group-based scheduling was implemented are presented in [67-72]. In [67] large groups of electrical loads with similar control characteristics can be controlled as a single entity. Thermostatically-controlled loads such as air conditioners, fridges and heaters are very good candidates for this exercise. According to the paper, the aim was to develop a mathematical model based on feedback control strategy whereby the aggregate power response of a population of a particular set of loads such as air conditioners, were characterised by a simultaneous step change in temperature set points and the off-set changes were then broadcast. These approximations are thereafter used to simulate the dynamics of 10,000 air conditioners over a range of parameter values and then analysed. Result showed that aggregate power output of the loads can be controlled to reduce demand over a period of time.

Group-based load scheduling can also be of practical application within a community whose load network operates as a Micro Grid. In [68] the authors developed an online adaptive electricity scheduling algorithm for a community using Lyapunov optimisation method where residents were able to classify electricity demand into basic usage and quality usage, for load scheduling purposes. Customers were also allowed to set their load priority and preference according to their choices and while basic usage supply is uninterrupted, there will be permitted outages of loads classified as quality usage loads [69]. The micro grid control centre aimed to minimise operation cost by upholding outage-probability-of-quality-usage in order to reduce peak demand and evaluate savings available. This technique is described as quality-of-service in electricity [68]. With localised cluster of distributed renewable energy sources (DRERs) provided by the micro grid, the aim is to obtain a balance of electricity demand and supply, which is essential in micro grid management [70, 71].

The authors in [46] applied appliance scheduling for home EMS using distributed algorithm, whereby each user requires only the knowledge of the price of electricity to participate. This price depends on the aggregated loads of other users and not the load profiles of individual users. With the knowledge of the price of electricity in advance (day-ahead pricing strategy), consumers can adjust their load schedule according to the prices with the help of Energy

Management Controller (EMC) and Programmable Logic Controller (PLC) [47, 48, 54-56]. In this scenario, the EMC and PLC are able to identify the times when energy costs are lower based on the price forecast, and if the energy demand within the community is higher than a chosen threshold, dedicated loads as identified by the consumers cannot be turned ON is they are scheduled to be in use. Result showed a convergence with the help of a penalty term that penalised large changes in the user schedule between iterations.

Finally, the authors in [72] described the possibility of achieving a joint scheduling for home appliances, EVs as well as DERs such as wind turbines and photovoltaic cells within in a smart micro grid. They proposed a centralised scheduling method to control electricity consumption of all the EVs within the community and other household appliances depending on the amount of energy available for supply at various times in the day. Addition of storage facilities usually helps to sustain the grid especially at night times when the EVs are not able to supply energy thereby supporting energy supply from wind turbine. The problem was formulated as an MILP problem and the result showed a better management of electricity consumption by shifting loads from high demand periods to low demand periods thereby maintaining both load consumption and energy supply regulation.

In conclusion, several methods of load scheduling have been discussed in this section. In some instances, a third party was responsible for initiating a group-based control signal dissemination which thereafter, affects every appliance connected under the scheme designed for scheduling purposes. One obvious disadvantage of group-based scheduling is an increased discomfort to consumers because the primary decision making about appliance use and scheduling is made by a third party and the timing of the scheduling events may not be favourable to all the customers who signed up for this events, at all times. This therefore casts a shadow over the long-time application of group-based scheduling while proposing that the future of scheduling of domestic appliances in smart grid is expected to be developed around implementation of scheduling programs using localized appliance control per household.

On the other hand, the major advantage of group-based scheduling over individually-based control is the relative ease of implementation since the burden of decision making lies with an Independent System Operator (ISO) who acts as a third party, and can be more easily deployed rather than trusting the participation and responses from individual householders. The next section is a review of various authors' contributions on the various algorithms used in performing load scheduling for more active participation in DR programs.

2.8 Design Algorithms for Performance Synthesis

This section deals with several algorithms developed by several authors who have written papers on how to implement and optimise various problems using different algorithmic techniques. Some of these algorithms are based on ways to implement effective demand-side management, while others are based on similar applications where specific algorithm methods are found to be useful. The mathematical analysis applied include: Branch and Bound Algorithm, simplex method, GA, particle swarm optimisation (PSO) and Simulated Annealing. These are available for solving various scheduling problems designated as an MILP problem in smart grid and these algorithms are discussed in more details in this section.

2.8.1 Algorithms Involving Energy Management Systems

Authors in [73] applied GA in demand side management scheme whereby the aim was to minimize the peak-to-average ratio of the load profile in order to increase the need for the utilization of spinning reserves, thereby increasing the efficiency of the smart grid. Residential, commercial and industrial loads were considered and result showed that GA can be used to minimize these loads so that the use of the spinning reserve was made feasible, which reduces cost.

Similarly, the authors in [74] applied GA in appliance scheduling in order to effect an active DR participation. The experiment was conducted based on the Nigerian energy market with the aim of obtaining scheduled hourly energy consumption values for each load whereby the total energy cost is minimal. In order words, loads will be shifted based on the factor of price, whereby more loads will be drafted to times of the day when energy costs are minimal. Results showed a reduced energy cost for an hourly-based energy price profile.

The authors in [75] implemented a hybrid algorithm for energy management in smart grid using a combination of GA and PSO. A need for this hybrid is to enable the scheduler to harness the positive attributes of both methods of load scheduling such as: not having to worry much about explicit definitions or getting stuck in local optima for GA, and ease of implementation and convergence for PSO. The result is an enhanced performance which showed reduced energy consumption as well as reduced energy cost. A major drawback in using GA and several other optimisation techniques in search problems is speed. This is why it may not be the best methods to use in real time applications. However, apart from the work done by the authors in [76], the authors in [77] also demonstrated how a unit commitment (UC) problem can be solved using fuzzy logic which improved the speed of convergence.

The authors in [76] simulated a multi-criteria scheduling in the grid, based on Accelerated GA. The need to improve and accelerate the computational and convergence speed of GA optimisation was the aim in order to be able to solve large search space problems such as job scheduling in the grid. Due to the improved speed of convergence, such search problems can be implemented online. This was achieved by pruning the initial search space such that only realistic solutions were included at the initial random population. This pruning was achieved by adding heuristic algorithms to form chromosomes of the initial population and as the phase starts, a Minimum-Minimum, Maximum–Minimum and a Shortest Queue chromosome are created. Result obtained showed that convergence was faster while using Accelerated GA than conventional GA.

In [78], the authors implemented hourly peak load shaving for domestic application using linear programming technique. An Energy storage device was utilized to offset peak demand at certain times of the day to reduce peak load at those times. Result showed a reduction of the hourly peak load by 38%.

In [79], [80] the authors investigated the impact of MINLP and Artificial Neural Network (ANN) on ancillary services such as regulation up, regulation down, spin reserve and non-spin reserve in a grid with competitive electricity markets. This is towards ensuring power system security and reliability enhanced by extra energy generation in order to cater for any contingencies. These services are provided by energy producers, with the aim of maximizing profits but managed by ISO with the aim of minimizing costs. The use of decision-supporting tools such as MASCEM, a multi-agent based electricity market simulator, was utilized to solve ancillary services dispatch where the energy producers bid in order to remain active participants. A comparison of results obtained when the method was implemented in view of: (1) without complex bids (linear programming problem) and (2) with complex bids (MINLP problem) showed that an informed decision can be made using this method, as demonstrated in a case study with real data from California ISO.

The authors in [77] demonstrated how a UC problem can be solved using fuzzy logic. The paper described a unit UC as an optimisation problem for determining the ON/OFF states of generating units that minimize the operating costs, subject to a set of constraints hence; it is commonly formulated as a MINLP optimisation problem. The most important feature of this method is in computational speed whereby results from dynamic programming techniques such as: GA and several other types of Evolutionary Programming, Tabu Search as well as Simulated Annealing are considered to take longer computational time, as well as in situations where the mathematical model is not explicitly known. The result from a case study in a four-generating unit thermal power plant based in Turkey showed the provision of a valid and a feasible solution to the UC problem which satisfied all constraints represented in membership functions, while minimizing the cost of production.

2.8.2 Algorithms not Involving Energy Management Systems

This section is a discussion about other applications of various design algorithms which are not directly implemented in energy management systems, but are used in other feasible applications. They are considered important so that the mathematical applications of these algorithms can enhance further understanding of the various algorithms available. Two common terminologies used in this section are Convex Functions and Nonconvex Functions. Convex functions or convex optimization problems refer to problems with only one optimal solution which is globally optimal such as a quadratic function. On the other hand, nonconvex functions have more than one optimal solution and a typical example is a sine function.

In [81], the authors described an improved branch and bound algorithm for a ZERO-to-ONE MINLP optimisation with convex objective functions and constraints. The two novelties of the design included:

- Deriving a method for obtaining lower bounds of a non-linear programming sub-problem without solving it to optimality.
- Obtaining an early branching procedure thereby avoiding to solving sub-problems to optimality in some cases.

Computed results showed that these improvements effectively reduced processing time needed to solve MINLPs although for relatively small problems, no significant time change was recorded hence, the technique is best for computing increasing number of Sequential Quadratic Programming iterations.
In [82], the authors proposed a generalised branch and cut (GBC) framework for solving MINLP optimisation problems which acts as a unifying framework for comparing branch and bound (BB) algorithms and decomposition algorithms. According to the authors, BB is the primary deterministic approach that can be used to successfully solve MINLP problems in which the participating functions are nonconvex. But with recent availability of decomposition algorithm in solving nonconvex MINLP problems, the authors proposed GBC as a means of comparing both methods for evaluation purposes. They came to a conclusion that BB and decomposition algorithms are the two classes of deterministic exponential time algorithms available to solve MINLPs in which the participating functions are non-convex, whereas deterministic polynomial algorithms were not known to solve MINLPs [83].

T. Yokota et.al in [66] were able to identify the shortcomings of the BB method which is the most widely used algorithm for solving Integer Programming (IP) problems, while proposing solving MINLP problems using GA and its applications. The major drawback as suggested by Taha is the inability of the BB in solving non-linear IP problem, mainly because the validity of the branching rules; as originally proposed in Land-Doig method, was based on an assumption of linearity [66]. There has been several modification of the original design with the aim of overcoming the deficiencies prevalent in it and one of such was Dakin's modification. This modification ensured that the branching rule is interdependent of the linearity condition. It was also observed that when the objective function and each constraint function with respect to decision variables are concave and convex respectively, a local optimum results to a global optimum. Further modification as proposed in the paper includes the use of GA for solving MINLP problems. It begins by selecting an initial set of random potential solutions and uses a process similar to biological evolution to improve upon them. It uses a special penalty multiplier of the evaluation function to modify infeasible solutions (chromosomes) in order to search the best solution more efficiently. Results showed that better solutions are available only within a constrained region, but due to the penalty multiplier involved, the population is forced to converge to the feasible region.

The authors in [84] described Simulated Annealing as a controlled-randomization process whereby the objective function to be minimized is gradually lowered by a series of improving moves to achieve optimal solution. This is analogous to annealing process involving gradual temperature reduction of a molten material in order to ensure better binding of the molecules. The authors aimed to develop optimal synthesis of a distillation column with intermediate heat exchangers using Simulated Annealing as the appropriate algorithm. Events in each column is scheduled and used as a learning strategy necessary for the development of artificial intelligence (AI) whereby probabilities were assigned to various decision rules at certain stages of the solution process. This causes the generation of various solutions to a particular problem and the best solution would be adopted depending on the quality of the results.

Furthermore in [85], the process of Simulated Annealing was used in the optimal synthesis of multi-component distillation systems aimed at minimizing cost for best investment results. Simulated Annealing was a preferred algorithmic process because the authors cited two reasons based on:

- The difficulty of solving the non-convexity of the non-linear (MINLP) formulation.
- The difficulty in solving problems with large size due to the combinatorial feature of such problems.

Branch and bound method could not be used on this instant because it is only very useful for solving small or moderate size problems [86]. Results showed the ability of the method in solving larger-scale MINLP optimisation problem without eliminating non-convexities and decompositions of the original problem into sub-problem, thereby improving efficiency.

Finally, the authors in [87] reviewed the future paths for integer programming (IP) whereby the contribution of BB approaches in the development of IP was considered more useful in practical applications due to the presence of integer variable constraints to satisfy the upper and lower bound conditions. The paper also discussed the futuristic impact of IP in solution strategies for diverse areas such as: Number Theory, Logics, Group Theory, Non-linear Functions, Convex Analysis, and Matroid Theory. Integer programming is also found to have links to Artificial Intelligence and as a result, the ability to solve a significantly increased number of IP problems effectively in the future was seen as a possibility. In all cases, near-optimal solutions are readily obtainable with minimal computational iterations which is enhanced by the union of two disciplines which are: operations research and artificial intelligence. The paper also discussed four heuristic classifications capable of enhancing the development of AI and IP which includes: Controlled Randomization, Learning Strategies, Induced Decomposition and Tabu Search.

In summary, the lists or types of algorithms available for mathematical and engineering applications are numerous and in most cases, they are designed specifically to perform designated functions. In load scheduling applications the future lies on how intelligent these algorithms could be because there are a lot of dynamics and variables involved which could make it too tedious for humans to follow in an active and accurate manner. The next section is a review of the impacts of DR participation on various households and steps taken towards minimizing those impacts.

2.9 Impact of Demand Response Programs on Users and Grid

Participating in DR programs in an ordinary term, entail users to abandon their preferred and natural times for appliance use to a time suggested by energy suppliers for the purpose of improved EMS. This means that there is a considerable impact on users who participate in DR programs as well as on the grid, and this impact can affect the long-term interest towards continued DR participation as acknowledged by various researchers in this review section.

A withdrawal from an earlier desire to participate in DR programs is an indication of dissatisfaction among the users [3]. Related literature around this cause is based on an observed failure to successfully continue to engage consumers to participate in DR programs due to discomfort experienced while participating in such programs. One of the reasons for these inadequacies is based on the difficulties experienced by the consumers in having to follow price changes which occurs on a daily basis [88]. This results to consumers having to check manually online on a daily basis to ascertain times of the day when prices are high in order to avoid using appliances at those times. A study carried out in Chicago showed that several consumers who initially signed up to dynamic pricing scheme ended up withdrawing from it as a result of a further increase in electricity bill, rather than having a reduction when compared to the original fixed flat rate [3]. The solution they proposed was to introduce an effective home automation system which should help in making those decisions, thereby improving user participation.

The authors in [89] investigated the possibilities of disruptions on the aggregate demand profile of a community who participates in DR programs, when such programs are implemented on individual households, unless those schedules are properly coordinated. The authors envisaged that a random distribution of energy requests could disrupt energy balance within the neighbourhood. This imbalance is perceived as being capable of creating new peaks which was not originally in the community load profile, thereby causing discomfort to the user. The paper proposed the formulation of coordinated HEMS which should care not just the households, but the grid in order to minimize user discomfort.

Similarly, transformers are not spared from encountering some operational stress occasioned by application of DR programs. The authors in [90] acknowledged the importance of DR in supporting the integration of renewables into the grid, and the impact of such integration on the transformer lifetime. The investigation on the effect of ageing was carried out using two models:

- By ascertaining the ageing based on the load of certain customers who operated without DR application,
- By ascertaining the ageing based on the load of those customers if they operated with DR application.

Result showed that operating the transformer at the rated load is critical in preserving the life of the transformer. This goes to suggest that DR applications can cause the transformer to operate outside the rated load, but if they were to operate within the rated load, up to 75% reductions in ageing was achieved.

Finally, authors in [91] developed an algorithm whereby certain loads such as water heater and battery storage systems were used in contingency conditions to restore grid frequency during peak demands. Apart from shedding these loads during these critical times, the battery storage systems can also be used as ancillary services to support the grid [92]. This shows that DR programs have the capacity to support the grid if managed properly. The incentive for this participation lies on the profit that the users can make by selling power to the grid, while the proposed market model includes several aggregators competing for active participation in DR programs.

Each of the instances discussed shows the consequence of applications of DR programs on the user as well as on the grid. The user being the key subject for investigation is readily affected by changes in the grid operation, while changes in the grid can also affect the user. The next section is a review of related work in the area of cybersecurity and the need to protect the HEMS from attack.

2.10 Security Issues in Smart Grid Applications

The last section of this review series is based on an investigation about security concerns which may become an issue in a fully automated and active DR programs within the smart grid. Due to the fact that we are all connected via the internet, the risk of invasion of householders' privacy from remote locations in order to steal vital information or to disrupt system operations is a cause for worry. This attack could be evident on any of the data sources and this includes the load profile data as well as the pricing data within the household.

An evidence of cyber-attack on the grid manifested on December 23 2015, whereby there was a recorded incident of attack on the Ukrainian reginal electricity distribution company where seven 110kV and twenty three 35 kV substations were disconnected for three hours [93]. This attack was attributed to foreign government-sponsored cyber-criminals who remotely controlled the SCADA distribution management system and caused blackout on approximately 225,000 customers. Such is an example of the numerous threats which cyber criminals oftentimes pose to the grid network, the vulnerabilities and the disturbing disadvantages of being all connected via the internet. Protection of vulnerable loads and other related components of the smart grid from such attack keeps attracting interests from researchers around the globe due to the numerous challenges facing the internet world. In this section, the review is based on several authors' contributions towards improved security of the grid network by highlighting the possible impacts that may be caused, as well as possible solutions available.

The authors in [94] [95] discussed the importance of detecting cyber-attacks in energy consumption data of power systems as provided by smart meters, and suggested schemes for adequate protection. Such attacks on dynamic loads known as: Dynamic Load Altering Attacks (D-LAA), was considered because the possibility to control loads dynamically implies also, the possibility to attack loads dynamically [95]. The paper suggested optimisation problem formulation, solution method and protection system design under uncertainty as approaches towards applying adequate protection schemes to hinder successful attacks on the load data. In contrast, Static Load Altering Attacks (S-LAA) is more common and is based on changing the volume of certain vulnerable loads, usually in an abrupt fashion. The paper suggested that the detection D-LAAs is possible by applying frequency domain analysis of the load profile using spectral analysis of the Fast Fourier Transform (FFT) of the original load profiles.

Another detection technique includes Real-time detection in frequency domain using Windowed-FFT (W-FFT), and detection based on both load and frequency signals [96], [97]. The paper suggested optimisation problem formulation, solution method and protection system design under uncertainty as approaches towards applying adequate protection schemes to hinder successful attacks on the load data.

Authors in [98] investigated the impact of price modification attack in smart grid and possible protection scheme capable of mitigating such attack. This attack was visualized based on the online reliance of pricing information by users who may be interested in reducing energy costs and possibly participating in DR programs. The attack model was based on false price injection on the actual pricing data which may trigger potential load altering attacks, thereby exposing the automated residential load control and increasing peak demand. The attacking scheme was formulated by failing as many transmission lines as possible due to the modified price and then a comparison is made about the effect of considering the impact of the attack when there is a cascading failure as well as when there is no cascading failure. In the cascading mode, the authors in [99] showed that the failure of a single node within the system is capable of causing load redistribution to the other nodes, which could lead to large global power failures. Nevertheless, several efficient protection scheme are successfully implemented which included the allocation of load protection resources to demand nodes in order to make such attacks unattractive.

The authors in [100] investigated the attack vectors on smart home systems analysed on a DigitalSTORM installation using solution-based analysis. This was done by identifying and ranking of possible attack vectors or entry points into a smart home system and suggested ways of thwarting such attacks. Those entry points included: the server, communication bus, smart control device (e.g. smartphone or control station) and remote third party services which provides monitoring and control services. Two theoretical attack scenarios were described and in both cases, a malicious app was surreptitiously installed on the home owner’s android smart-phone and was used as entry vector which either turns appliances ON and OFF without the home owners’ consent, or collects vital information from the household such as the load profile . For burglars, such information could be used to determine when to burgle such households. The authors recognized the merits of ensuring a secured smart home system which should include requesting some form of authentication from authorized users before obtaining access to perform any activity within the home.

Finally, the authors in [101] improved mesh network security used within various smart grid domains against cyber-attack by introducing a dynamically updating key distribution strategy on network protocols. The proposed method was mainly designed against Denial of Service (DoS) attack by utilizing a 4-way Merkle-tree based handshaking scheme. The reliability of the model was verified using Proverif and they were able to demonstrate the effectiveness of key refreshment strategy in thwarting DoS attack on the smart grid network.

Several other forms of cyber-attack are possible and may include communication system failure which could originate from the utility or from the localized HEMS [3]. For any type of attack that is capable of forcing all the consumer’s appliances to turn on at the same time portrays a potential to cause the grid to become congested which can also force it to a collapse. This type of attack or virtually any type of cyber-attack poses an immense security threat since potential terrorists can congest the grid to such a level that it succumbs and fails thereby giving these nefarious groups the appropriate environment to execute their terrorism intent. Therefore an analysis of the impact of the various types of cyber-attack could have on a household, as well as on the grid is included in this thesis. Proposals to the possible ways to identifying these treats are made and means to mitigate their effect when detected also suggested.

2.11 Juxtaposition with Other Relevant Methods

Before the completion of the literature review chapter, it is important to make comparisons with other relevant methods from various related sources. This is because such comparisons will be able to highlight the context of the work with other methods available. It will also show the contributions of the work to knowledge more clearly. Here, two broad comparisons are made and they are:

- Comparisons made based on the solution techniques used.
- Comparisons of results obtained with those from previous work.

2.11.1 Comparison of Work with Other Solution Techniques

Several other optimisation techniques can be used to solve the problem stated in this work depending on the key factors being sought. In time-critical systems, optimisation time would be important but in terms of accuracy, there might be some impact which might be of some reasonable significance. In this application, accuracy is not a critical issue since user-behaviour changes will have greater impact due to the override capabilities available to the user. Speed of convergence is also not a critical issue since all data including the day ahead price is available several hours before the time required for load scheduling. However, convergence can be an issue but this is addressed here by the GA using a large number of 1000 sample population which also reduces the chances of the search mechanism getting stuck in a local minima, but enhances global optimal attainment. Effectively, this implies that various optimisation techniques will generally lead to similar answers unless the problem itself cannot converge. In order to solve the possibility of non-convergence of the results, metaheuristic approach was chosen which also involves stochastic optimization methods whereby the solution found is dependent on some set of random variables generated. This was where the choice of GA was useful.

Other evolutionary-based optimization problems such as ant colony or particle swarm optimization (PSO) are expected to provide similar results expect for the speed of convergence which is expected to be higher for PSO. The key reason for higher convergence speed for PSO is due to fewer variables used which includes velocity and position of the variables in its algorithm. But as already stated, convergence speed is not a critical factor here unless an application that requires a real-time load scheduling is desired over very short time intervals [102]. However just as in GA and several other metaheuristics, there is no guarantee of an optimal solution although the chances of obtaining this is increased by increasing the number of the original random samples, while mutation as applied in GA enhances that the search does not get stuck in a local optimal solution. So in this regard, it can be stated that GA is more suited in this application that PSO.

2.11.2 Comparison of Results Obtained with Previous Work

Finally, Table 2.1 shows a summary of the comparison of results from proposed method with results from previous work. It is observable that the measured impact on consumers who participate in demand response is not available in other related work which is the key outcome of this research.

Table 2.1: Comparison of proposed work with related work

Ref.	Feedback Considered	Response Mechanism		Noted Impact (on User)	Scheduling Type		Measured Impact on Users
		Manual	Automated		Single	Group	
2	✓	✓	×	✓	✓	×	×
29,31	✓	×	✓	×	×	✓	×
40-47	✓	×	✓	×	✓	×	×
51-52	✓	×	✓	×	✓	×	×
66-71	✓	×	✓	×	×	✓	×
88-91	✓	×	✓	✓	×	✓	×
Prop.	✓	✓	✓	✓	✓	×	✓

2.12 Chapter Summary

This chapter presented a review of various contributions from different researchers', as well as several projects and activities engaged by various governments across the world towards improving the activities of the power grid system. The areas that are considered of greater interest include reviews which aimed at improving domestic EMS whereby householders are able to engage more effectively in DR programs with retailers. While identifying with most of the techniques proposed, there remains a number of issues that still needs to be investigated in this area. These issues are primarily observed from the literature review which confirms the research gap and can be classified into five different categories which are:

1. There is an impact on consumers who participate in DR programs with respect to the difficulties in having to check varying RTP changes because they are unable to constantly monitor and react to the price changes given other activities that they might be engaged in.

2. There is also an impact on consumers whereby appliance scheduling might deny users some preferred appliance time-of-use which might cause them some amount of discomfort. This discomfort is based on undesired schedules which can render demand scheduling programs inconvenient.

3. These difficulties has discouraged customers from investing strategically in such tariff systems, thereby making investments in smart appliances or other smart grid- related accessories such as smart plugs, unattractive.

4. As a result of the above, the number of customers who originally signed up to real-time-price tariff in several cities in the USA, have been known to decline over time. This is because those customers who fail to modify their consumption behaviour may end up paying more than they would have paid in standard tariff system [3]. So there is a strong likelihood of increased cost rather than cost reduction which can eventually drive customers back to fixed tariff pattern.

5. Similarly, customers in the UK who participate in DR programs such as Economy-7 have the challenge about not being able to discern which pricing model that is best for them. That was why a 2011 OFGEM report suggested that the addition of price comparison guide will help such customers to compare tariffs and make better decisions [103].

6. In the event of wide acceptability of the technique, the issue of security will most likely surface. Therefore, appropriate security design is required in order to ensure secure data transfer within a particular load area in order to ensure user confidence while participating.

Finally, the literature review has highlighted different optimisation techniques that are used in demand response programmes. There is room to investigate further the best method by comparing different techniques given a particular case. However in this research, the optimisation method is not a key objective nor a contribution and so Genetic Algorithm was chosen. The reasons for using GA were based more on the interest of the author and its prior use as shown in the literature [104] [105] . Moreover, load scheduling is done well in advance so there is no requirement for high speed in solving the optimisation problem. The next chapter will therefore present the architecture for a proposed model built which aims to co-ordinate the events taking place at the domestic areas. This design responds to event variables from the utility as well as customer behaviour attributes to control different household appliances by promoting behavioural modification for optimal results.

Chapter 3: Testbed Development

3.1 Introduction

In the previous chapter, a review of the related literature was carried out which discussed the state-of-the-art research by various writers as well as support from governments across the world towards enhancing grid performance. This chapter is a presentation of the testbed development that specifically describes the structure of a practical Smart Home Energy System, which satisfies the aim and objectives of the research. A description of the various aspects of the testbed highlights the approaches undertaken towards solving the research question. These are shown in various block diagrams that represents the different stages considered; starting from understanding the schematic of smart home energy system, to the proposed testbed activity chart. It therefore gives the perspective of the design structure that describes information gathering, data processing, data transfer and result display, to all the relevant aspects of system design thereby making it easier to connect with the remainder of the chapters that include the methodology, results and discussion.

3.2 Schematic for Smart Home Energy Management System

The key aspects of the smart home include: the customers, utility, retailers, load, smart meter and HEMS. This is the main system structure as shown in Figure 3.1 and their various interactions are shown by different arrow colours.

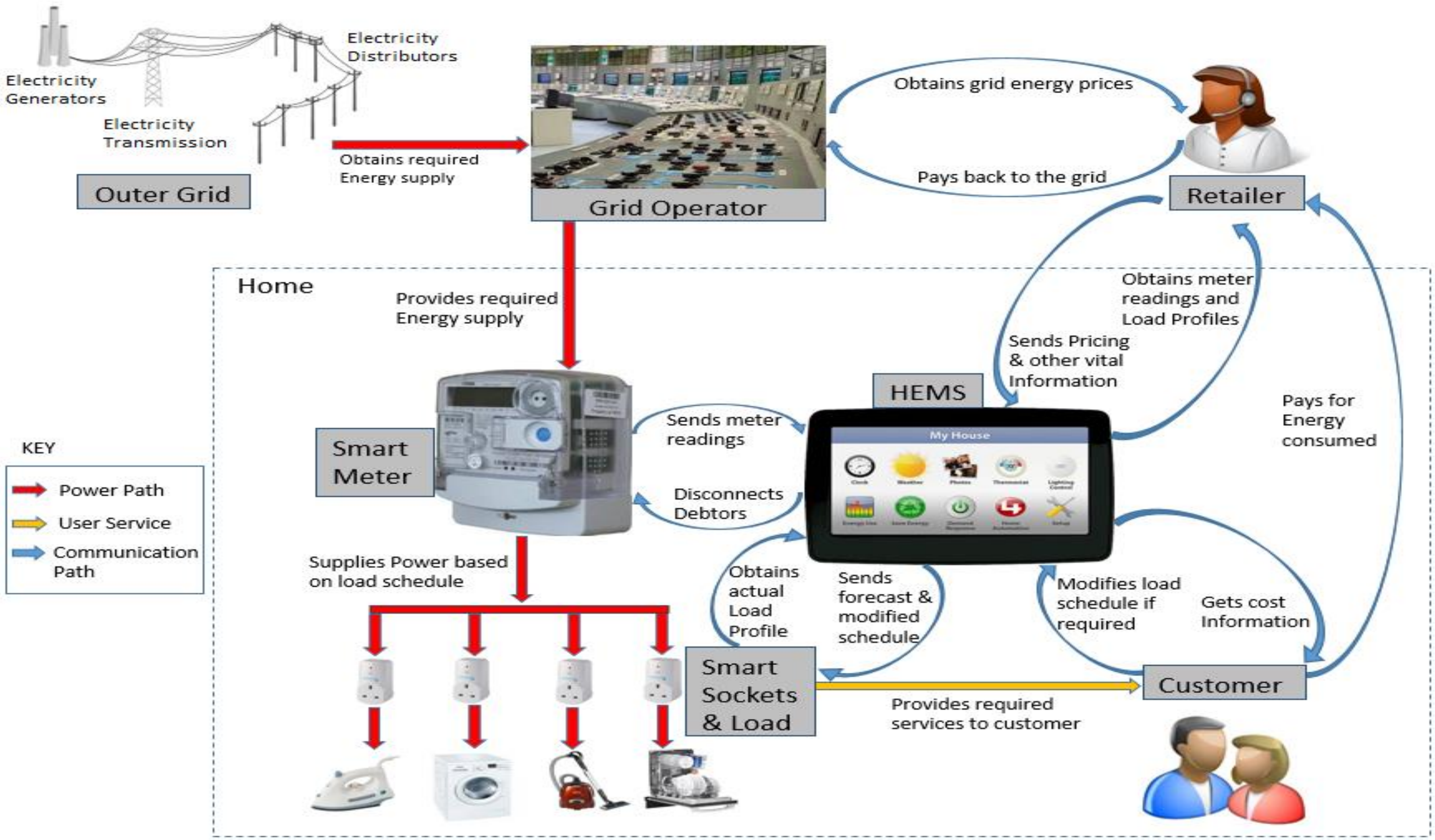

Figure 3.1 Schematic for Smart Home Energy System

The Power Path: This is the live power infrastructure that emanates from the utility down to the consumer household. The smart meter and the smart plugs effectively controls the electrical power reaching the load which is in response to any specified load schedule.

The User Service: This service is basically the human interaction between the user and the load. It is what provides satisfaction to the user as they interact with the automated home device while participating in DR programs.

The Communication Path: Adequate load control depends on effective communication of commands that connects not only the HEMS to the smart meter and smart plugs, but also the retailer as well as the user. The HEMS has control over the key Internet of Things (IOT)-enabled appliances, which supplies a schedule to the appliances and also provides the customer with required services. Two approaches towards controlled appliances are noted in the industry. The first is the rise of smart appliances themselves that are connected to the internet or are able to be controlled by a remote device [4]. This technology is fast developing particularly for thermostatically controlled loads such as fridges heaters and air conditioners. The other approach is the development of smart sockets. Consumers can buy smart sockets which can be plugged into conventional sockets between the appliance and the socket, allowing the user to switch the appliance ON or OFF as required. These new devices can be installed permanently in new buildings and they are very trendy, unnoticeable, and permit the quick adoption of smart technologies which means that it is likely that advancement in this area will develop rapidly.

Figure 3.1 also shows that the retailer can communicate with the smart meter by sending pricing information to the HEMS for load scheduling as well as obtaining meter readings through the HEMS assuming the retailer cannot establish a direct communication with the meter. The retailer also communicates with the customer by informing them of the day-ahead price as well as the energy bills, while also receiving payment.

In addition, the consumers can modify the schedule depending on their needs or based on the cost of electricity at the time of use (TOU) for which they would receive some information from the HEMS on the prices. The HEMS connects with a retailer who could be buying and selling electricity on behalf of the grid or a supplier or a load management operator working in the DNOs. Here we term this third agent as a retailer which can also be considered as a virtual power plant. The retailer receives prices for each half hour from the grid operator. In this work we assume that the prices are known a day before but they could be more real time depending on the type of market available. The retailer therefore sets prices that are passed on to the consumers and also pays the grid.

Furthermore, the HEMS interacts with the customer by sending energy costs as well as proposed impacts on modified behavioural choices while also receiving instructions from the user about any modifications preferred. The HEMS may also advice the customers on how to modify their behaviour in addition to informing them of any planned schedule.

Finally, the HEMS supplies the optimized load schedule to the various appliances, and obtains actual load usage in real time which will minimize consumer discomfort and cost [104-106]. It is assumed that the appliances are IOT enabled, and are capable of collecting and transmitting data.

3.3 Design Architecture

The proposed design architecture for automated domestic EMS consists of some set of input data usually generated from the home area as well as data from energy retailers which are thereafter processed to produce some desired output. The goal is for an enhanced interaction among the key players in assisting consumers to participate more effectively in DR programs whereby the key outcomes that are effectively managed include the discomfort associated with participation in DR programs. Other output data generated includes forecast financial savings available as well as the generated load profile based on the load scheduler results in order to achieve maximum benefits.

Figure 3.2 is the proposed design architecture of a smart home whereby the key components are clearly identified as: Input Data, Output Data, Peripherals, Central Controller, Retailers, Smart Meter and Grid Supply. The Input data set is made up of demand load profile which is user-behaviour based; pricing information which is generated by the retailer as well as customer’s interaction which is conveyed via a keyboard system. The customer’s interaction contains a user-override capabilities as well as the household occupancy profile which must be keyed in manually over all intervals required during the day. Alternatively data such as the occupancy profile can be derived by the use of sensors within the house especially at the entrance or exit point, which are capable of counting the number of people within the house at regular intervals.

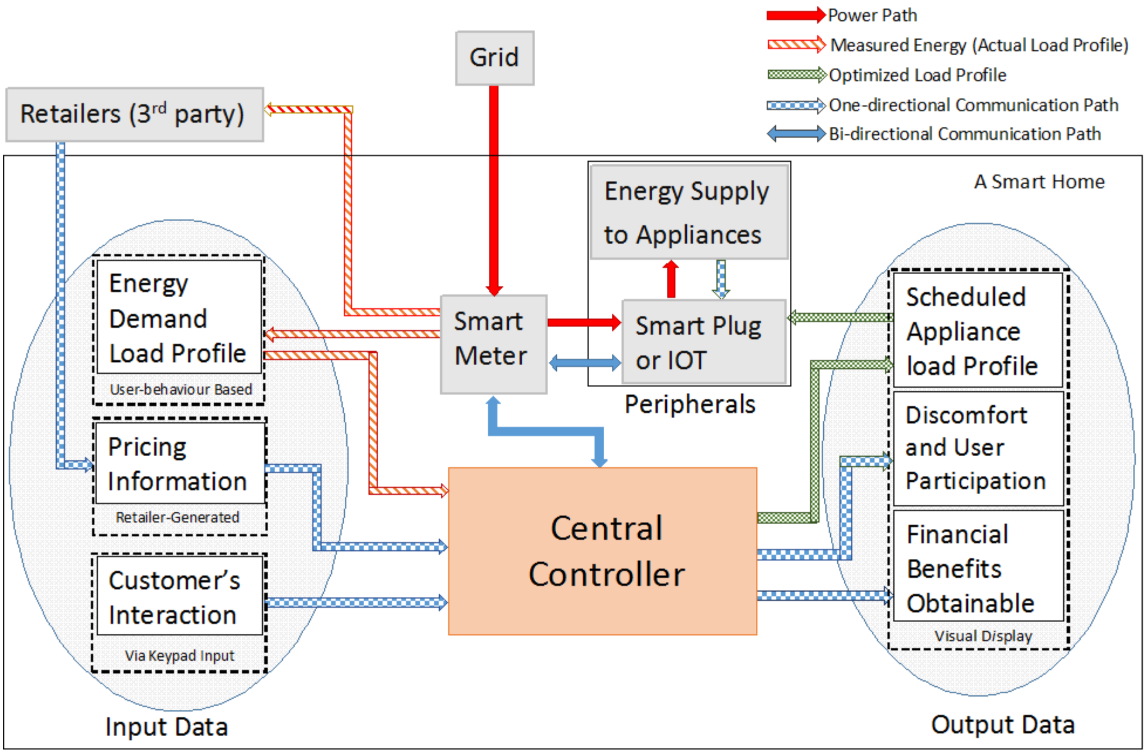

Figure 3.2: Design Architecture

The energy demand load profile information is obtained using data extraction devices such as smart plugs or appliances and connected to the smart meter, all connected as IOT. The meter measures the energy consumed at regular intervals thereby generating the user's energy demand load profile which is passed on as one of the inputs to the central controller. User interaction data can be supplied using a localized keypad or maybe from a mobile device while the pricing information can be acquired from the retailer's database.

Central Controller: This is the heart of the system design that runs the algorithm which performs the required load scheduling. Microcontrollers are the ideal possible device to be used to achieve this control although the actual application was not implemented. Other popular controllers used in the industry includes Proportional Integral (PI) and Proportional Integral Derivative (PID), but they are more suited in process-type applications hence not used here.

The central controller block also contains storage and forecasting capabilities necessary for assimilation of input data, decision making and task execution via necessary communication protocol. Several independent algorithms can be designed and installed on this unit, and they should be able to coordinate the events occurring within the smart home by synchronising their individual activities with one another to achieve a particular aim. The highlight of this design is based on developing the functional algorithm for the controller. Stored data consists of recent pricing details as well as load profile data and the primary essence for this storage is to enhance load profile and price forecasting capabilities. Although there are various forecasting techniques available, in this work moving average forecasting technique was exclusively used whereby adequate priority is given to the most recent data available for the respective quantities being forecasted. During the load scheduling process, the algorithm ensures that the user's specific characteristics and requests are met especially with regards to their accepted discomfort levels. In theory, consumers who accept higher discomfort levels tends to save more money than those that accept minimal discomfort levels. A no-discomfort means that the consumers are not participants in any form of DR activities hence, no financial savings available to them. Finally, the central controller also computes the user participation levels which can be forwarded via the bi-directional communication link to the smart meter and then, to the retailers.

Controller Output: This consists of the operating times for the scheduled load which is then fed to the smart plug as a programmed time-of-day energy consumption. The schedule is also visible to the user who may decide to override schedules that they are not comfortable with. The accepted schedules then controls the loads as connected to the smart plugs while the actual real-time energy consumption details can be made available to the central controller for comparison with the forecasted load profile which may be applied to update the original schedule as a real-time scheduling algorithm. Although real-time load scheduling, is not covered here, but can be an interesting future work. Other output data includes forecast financial savings available, the discomfort level accepted per schedule as well as user participation or engagement levels and these are made accessible to the user via visual displays. The other key structures of the design and their respective functions are summarized further.

Smart Meter: This is the window to an enhanced interaction between the utility, the retailers as well as the smart home. Details of the daily load profile data measured by the smart meter is passed down to the central controller as well as to the retailer for billing purposes, while also allowing actual power supply to be made available to the rest of the domestic appliances via the distribution board and smart plugs.

Smart Plugs: This is the interface between the energy supplied and the respective loads. These plugs determine the switching patterns of respective loads in response to any scheduling command sent from the central controller to effect the load usage. It is essentially an effector whose basic functions include switching appliances ON and OFF while at the same time, being used to send vital load information based on consumption behaviour to the controller.

Communication Network: This is Important because the availability of adequate information is required in order to be able to co-ordinate the events happening both at the appliance side and the utility side. The network topology implemented could be star or mesh network and the devices that engage in these communications oftentimes talk to each other as much as they talk to the device directly above them in the communications hierarchy.

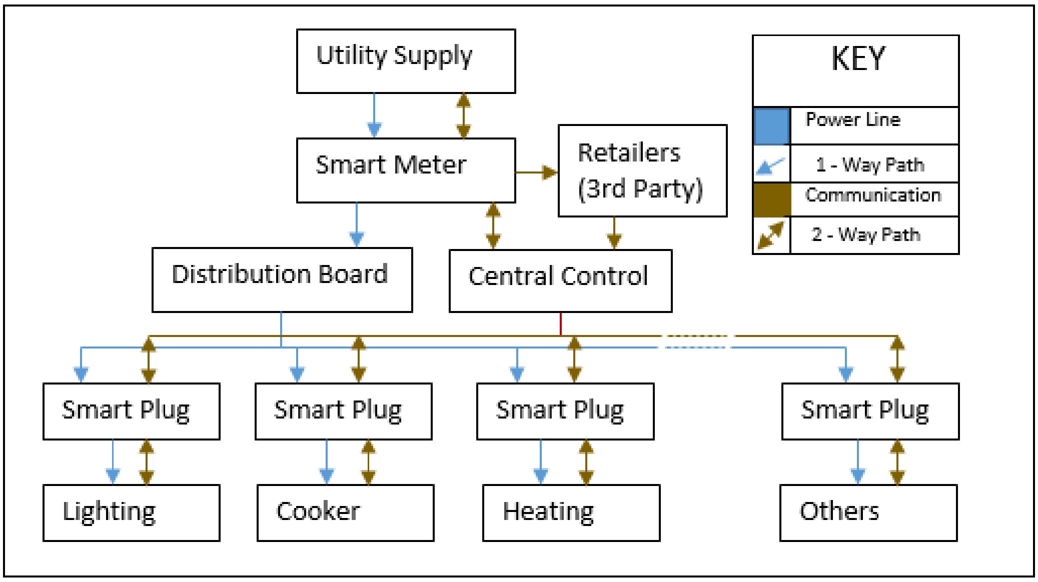

Figure 3.3: Structure of Information Transfer of Design Architecture

Figure 3.3 is basically a communication structure within the design architecture of Figure 3.2 and has been elaborated to show a hierarchical structure of the relationship between power supply routes and data transfer routes, in a vertical top-down format. In this design, the use of smart plug as data extraction devices was adopted per appliance because, apart from acting as a switching device to the appliances, it also offers a communication link between the appliances and the smart meter via Wi-Fi connection.

3.4 Controller Specifications

The central controller shown in Figure 3.2, is the heart of the proposed smart home model. Execution of several tasks and algorithms from various input sources as well as providing computational results for future use are the key functions of the central controller thereby making it by far, the busiest component that makes up the smart home. The activities executed within this unit can be given as follows:

- Execution of forecast load profile using any forecasting technique adopted.
- Execution of optimisation algorithm to obtain best schedule for appliances.
- Execution of algorithm that sends control signals to the actuators such as smart plugs.
- A computation and analysis of User Participation Index (UPI) in order to evaluate user engagement levels.
- An events coordinator that receives composite information and relays them to the appropriate unit.

- Ability to inform the customer as well as the utility of any key information available such as estimated savings possible with every scheduling pattern chosen via a visual display unit.

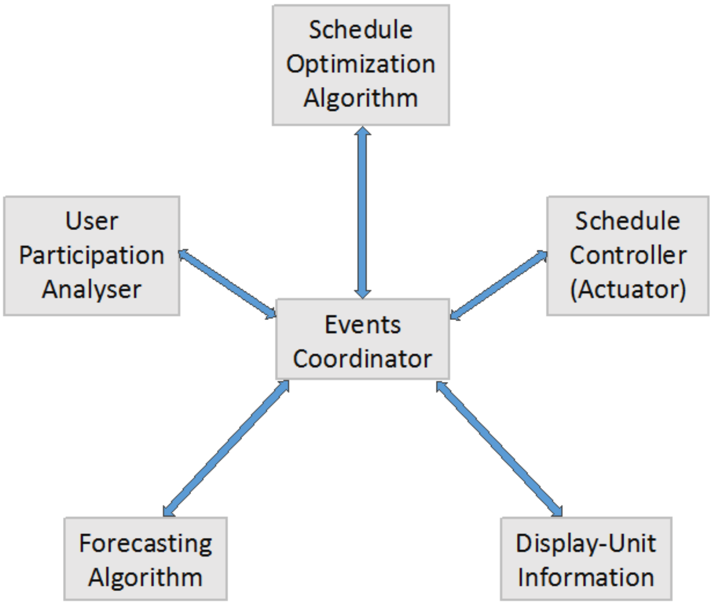

Figure 3.4: Central Controller Components Chart

A model of the major units within the controller is as shown in Figure 3.4. These represent the aspects of the HEMS where investigations are carried out in this work with the exception of the actuator schedule controller which is considered a future work. Investigation about the impact of cyber-attack on the central controller is also included which focuses on protecting the HEMS from possible cyber-attacks. Further future work may also include the inclusion of learning algorithm and AI in Figure 3.4 whereby the system will learn from historical data especially from user-related behaviour in order to predict likely consumer behaviour thereby improving the system reliability.

3.5 Design of Proposed Test-bed

Using the research aim and objectives as presented in section 1.2 while recognising the relationship amongst the component sections of the design as shown in Figure 3.2, a test-bed chart is proposed in order to serve as a model for the research experiment. Although Figure 3.2 shows the component aspects of the HEMS design, Figure 3.5 is an expansion of Figure 3.2 to show the time and sequence of event occurrences that takes place within the smart home. These events are divided into two phases and in as much as there are two phases to the events, naturally both events occur at the same time of midnight whereby they consist of:

- Phase 1: These are activities performed at the end of the day.
- Phase 2: These are activities performed at the beginning of the next day.

Phase 1: As the day progresses, the actual load consumption utilised by the consumer is measured by the smart meter and at the end of the day, the actual load profile is obtained. This information can be stored in a memory device within the HEMS and assuming historical data of previous load profiles are available, a forecast load profile is obtainable for use for the next day. Therefore, the actual and the forecast load profiles can also be computed.

Phase 2: Given a three-input supply to the “Load scheduling block and computing unit” at the beginning of the next day shown in Figure 3.5 as I/P1, I/P2 and I/P3, the scheduling process produces a visual display of the scheduled load profile as well as a display of the cost for the scheduled load.

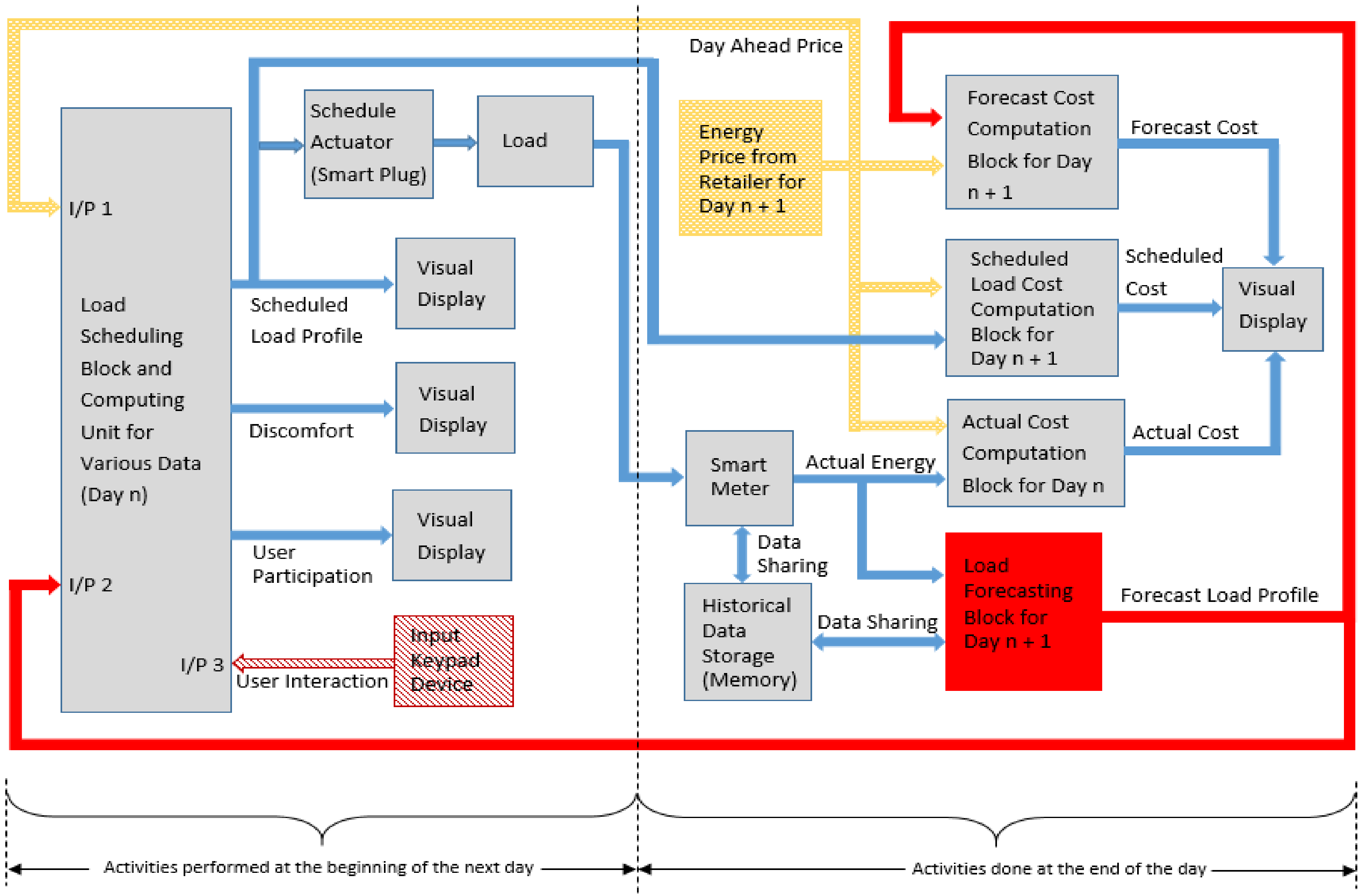

Figure 3.5 Proposed testbed activity charts for a smart home system

It also sends the appropriate scheduling signals to the smart plugs which directly controls the load switching patterns. A visual display of the discomfort level imposed on the consumer if they accept the proposed load schedule is shown, while a computation of participation level of the consumer is also evaluated. The user on the other hand, is capable of accepting, rejecting or modifying the impact on them by altering or specifying a discomfort level acceptable. For every modification affected, there is a corresponding re-calculation of the events using the input variables supplied in order to visualise the proposed new results which is also subject to the user accepting the outcome. The occupancy profile is also part of the user interaction inputs already keyed in by the user.

Furthermore, the user can more actively interact with the controller by setting a threshold that limits the discomfort because discomfort level is directly related to the amount of scheduling that is permitted for the scheduler to execute, as will be shown in the next chapter. Hence a low discomfort is expected to return a minimal load scheduling and deviation of the scheduled load from the forecast load profile, while a high discomfort is expected to return a high deviation from the forecast load profile due to load scheduling. Likewise, it is expected that the consumer will achieve minimal savings when operated in a low discomfort zone than in a high discomfort zone. The estimated savings available is calculated by finding the numerical difference between the actual cost and forecast cost.

It is also worth noting that scheduling as applied in this research is only a modification of the time of the energy use and not necessarily a reduction of average energy usage in a day. This shift is expected to yield financial savings when schedulable loads are operated at times of lower energy costs in a market that permits dynamic pricing system. The use of “User Interaction” is an enhanced feature which increases DR participation by helping the user to make an informed decision while the visual display enables the user to see the impacts of the choices they make.

Finally, due to increased cyber-threats in most computerised systems especially about data shared via the internet, the awareness of incorporating security mechanisms in original system designs has inspired the need to investigate the impact of cyber-attack on the HEMS. This investigation is based on an envisaged attack modelled on the price profile as well as the forecast load profile data given as inputs 1 and 2 respectively, in figure 3.5. The result of this investigation is expected to identify any section of the test-bed as given in Figure 3.5 that may require an application of extra security feature which is expected to increase the robustness of the design. In this way, any such attack can be countered thereby providing a more secure, robust, efficient and reliable HEMS design.

3.6 Chapter Summary

This chapter has been a presentation of the testbed that provides the design architecture of the research which makes it easier to appreciate the scope and keep track of all event activities from one event to the other, thereby making it easy to follow the rest of the work. A design of the physical components of the future smart home which includes the vital input and output information required, as well as data routing from one segment of the home design to the other is also presented. Majority of the investigation and analysis as presented in this work takes place in the “Load scheduling block and computation unit” as shown in Figure 3.5. The primary input data which includes the forecast load profile, pricing data and user interaction are processed in the central controller of the HEMS while the output data includes the scheduled load profile, financial benefits achievable, user-comfort considerations as well as user participation indices.

The communication routes involved are also discussed whereby each data processed is conveyed via dedicated paths and in specified routine. The use of Wi-Fi is supported due to compatibility with other IOT devices within the home which includes the smart plug, smart meter and HEMS.

The next chapter is therefore, a detailed description of the research methodology applied in achieving a model future smart home. This is designed within the context of the testbed proposed and in consideration to the impact of user participation in DR as well as behavioural attitude of participating customers.

Chapter 4: Research Methodology on Behavioural Demand Response

4.1 Introduction

The previous chapter was a presentation of the design architecture which defined the context of the research which is based within the home area. It also showed the communication routes, the controller specifications, as well as a presentation of the activity chart for the testbed. This chapter is a presentation of the methodology applied which includes all assumptions made, mathematical equations derived and applied, as well as the algorithm adopted for the implementation of the solution proposed. It is therefore, broadly divided into the following sections:

- A detailed description of the key input variables applied.
- A description of the GA application which includes:
  - Fitness function description.
  - Chromosome generation, selection and mutation.
  - Pseudo code application of the algorithm
- Development of the optimisation criteria which includes:
  - Change in energy
  - Cost
  - Discomfort
  - Optimisation factor

- Design of load scheduling technique which includes:
  - Identification of load scheduling opportunities
  - Identification of schedulable and non-schedulable loads
- Evaluation of user participation capabilities which includes:
  - Evaluation based on Fuzzy-logic analysis
  - Evaluation based on Boolean-logic analysis

These are the sequence of the outline of this chapter with detailed description of each sub-section. Also included is the justification for their application, while the conclusion indicated the context of application which is based on understanding and managing user behaviour in demand response applications.

4.2 Input Variables

With reference to Figures 3.2 and 3.5 as discussed in chapter 3, three primary input variables are applied in the experiments presented and they include: the forecast load profile, dynamic pricing as well as household occupancy profile. Additionally given the forecast load profile, two secondary input variables are also calculated within the computing unit of the 'Load Forecasting Block" of Figure 3.5. They include: the standard deviation of the load profile as well as a randomly-generated load profile. This therefore results to five input variables used throughout the entire experiments.

The dynamic pricing is supplied by the energy retailer while the occupancy profile can be keyed in manually by the householder or via other means of tracking the number of individuals in the home such as door and movement sensors. Although only five variables are considered of primary importance in this work, more input variables can be appended if they are found to be of relevance in determining the output. The next section is a more detailed description of each of the input variables already defined. Load forecasting techniques are discussed as well, and the respective relevancies in the experiment are also outlined.

4.2.1 Load Profile Forecasting

Forecast load profile is the framework upon which any proposed load schedule can be built. Its major function is based on providing a model load profile for the optimisation process thereby providing the constraints applicable. It is also used for result analysis by providing a reference baseline which is used for comparison of the system performance. Forecast load is derived using a consumer's historical load profile data stored in the HEMS and then an estimate of the user's load profile for the next day can thereafter be proposed [107].

Forecasting techniques can be divided into Qualitative and Quantitative forecasting techniques. While qualitative forecasting techniques are based on intuition and are therefore subject to the researcher's opinion and judgement, this work applies the use of quantitative methods and specifically; Simple Moving Average (SMA) whereby the ability to generate a future data is a function of past data.

Moving average methods are in the family of Time Series methods which include: Weighted Moving Average, Exponential Smoothing, Autoregressive Moving Average and Extrapolation, amongst other methods. The choice of SMA is because it provides a satisfactory forecast data which is assumed to be sufficient enough to obtain simulated results. This reason is acceptable since this work is not based on developing the best of forecasting techniques which may require the use of more sophisticated forecasting methods but it simply demonstrates the role played by applying load forecasting in load scheduling. Other external factors that may affect load forecasting includes weather, bank holidays, school calendar, etc. Given a series of daily historical load profile data over a period of n-days such that at the end of the most recent day up till n-days ago, the load profile can be represented as:

$$\mathcal{E}_{H_0}, \mathcal{E}_{H_{-1}}, \mathcal{E}_{H_{-2}}, \ldots., \mathcal{E}_{H_{-(n-1)}} \tag{1}$$

Therefore, the mathematical expression for SMA is therefore given as:

$$\mathcal{E}_H = \frac{\mathcal{E}_{H_0} + \mathcal{E}_{H_{-1}} + \mathcal{E}_{H_{-2}} + \cdots + \mathcal{E}_{H_{-(n-1)}}}{n} \Rightarrow \frac{1}{n}\sum_{i=0}^{n-1} \mathcal{E}_{H_{-i}} \tag{2}$$

Where:

$\mathcal{E}_H$ = Forecast load profile

$\mathcal{E}_{H_0}$ = Load profile data for n-days ago

$\mathcal{E}_{H_{-n}}$ = Load profile data for previous day

n = Number of data-days available

i = Iteration count

Given that when calculating an updated successive load profile values, a new value comes into the sum while that old value drops out. Equation 1 should therefore be updated regularly in order to reflect this addition. This is given in Equation 3.

$$\mathcal{E}_H = \frac{1}{n}\sum_{i=0}^{n-1} \mathcal{E}_{H_{-i}} + \frac{\mathcal{E}_{H_0} - \mathcal{E}_{H_{-n}}}{n} \tag{3}$$

4.2.2 Household Occupancy Profile

A household hourly-occupancy profile can be defined as the number of individuals within a household for hourly intervals of time in a day. This is calculated in a rounding-off format whereby availability within the first 29 minutes is rounded down while availability at home for 30 minutes or more is rounded up as an additional hour spent at home. According to the records of Office for National Statistics, the population of residents in the UK as at 2017 is 66.18 million. This consists of 27.2 million households whereby 7.7 million people live alone, 9.45 million households comprise of 2 people, while 9.85 million household comprise of more than 2 occupants [108].

Occupancy is considered important because the fewer there are people within the household; the easier it is to reach a consensus about decision to accept appliance scheduling. This is unlike when there are a lot of people in the house whereby it will be more difficult to convince everyone to follow a specific load scheduling pattern. Furthermore, due to different lifestyles of each inhabitant which may include working, schooling or leisure activities, different occupancy profiles can be derived for a household within a week, month or year. The exactness of this data may not be very critical as it is practically impossible to extract a perfect occupancy profile at all times, but approximate values can be acceptable.

4.2.3 Dynamic Pricing in Electricity Markets

The price of a commodity is an important factor in marketing not just in energy market but in every other market scenario. It is usually not very easy to determine the best price for a commodity in order to meet the actual objectives of the business especially in response to market forces. Some of these forces may include: demand and supply, impacts from competitors, costs of running the business, the bargaining power of the customers, as well as the state of the economy. These factors often-times causes variations in pricing which can vary not only on hourly bases but also instantaneously, thereby making such pricing models dynamic. Dynamic pricing in electricity markets can therefore be defined as a pricing strategy with substantial price variation over time, usually within a day, whereby prices are set based on the current market demands [9].

A typical example of this pricing system is found in transport services such as train and bus services whereby fares are usually higher during peak or rush hours of the morning and evening times in the day, but cheaper in the afternoon. This therefore becomes the most efficient way to discourage commuters who do not necessarily have to travel during peak hours from congesting the public service system so that people who go to work may not need to stand while on transit. Unfortunately, dynamic pricing algorithm can be manipulated in order to create a false peak demand in order to cause transporters to charge commuters higher prices. An example is based on a research as reported by “The Independent” news media which found that some “Uber” drivers collude to deliberately go offline at the same time, thereby creating an artificial scarcity of drivers which will cause price surge. This will enable them to charge commuters more travel fares when they log back into the “Uber App” [109]. This therefore shows that although dynamic pricing is favourable, it can also be subject to manipulation.

In load scheduling application as proposed in this work, the use of dynamic pricing in energy billing is used in order to encourage more active user participation so that they can defer the use of their non-essential loads when energy demand is high to other times of the day when demand is lower. This is of significant importance because consumers are still interested in lowering their energy bills whenever is it possible so if they are capable of following the price changes, it is very likely that only essential loads that will be used during peak demand and others will be used when prices are lower. Hence, it is reasonable to suggest that DR is practically unrealistic in a fixed tariff system unless there are other specific incentives to consumers who reduce their load usage on request. This is why dynamic pricing is considered one of the sources of input variables to the system design as described in chapter 3.

Implementing dynamic pricing in energy market is therefore one of the key strategies applicable in assisting to ensure a reduction of peak demand thereby reducing $C0_2$ emission. In this work, an hourly day-ahead dynamic pricing strategy is applied which encourages sufficient dynamic load scheduling. Fixed flat rates do not offer any financial interest, while dual tariff plan (known as economy 7 in the UK) do not offer as much interest as the day ahead or real time pricing strategies which changes on hourly basis. Economy 7 has been around in the UK for some time, and can be considered not sufficient enough to be able to bring about the desired change in consumers demand pattern.

4.2.4 Standard Deviation of Load Profiles

The ability to understand and model a user’s behaviour can be derived from standard deviation of the user’s load profile. Other statistical parameters such as mean, median, etc. are not suitable for this purpose. This is because, mean for instance shows the average performance and does not reveal individual behaviour. However, variance is the square of Standard deviation so can also be used.

Using the smart plug to monitor electricity consumption per appliance and recorded by the smart meter, regular intervals of energy measurements can be captured and the load profile of energy use can be built for the day. A historical data of the household which is stored in the HEMS can be made available as required and from where the forecast load profile as well as the standard deviation of the load profiles of the customer can be calculated and segregated according to what day of the week, month and season when each reading is taken. For instance, this can be done for over a period of time, say 28 days and the profiles corresponding to the same day in a week (for example, profiles for all Mondays are grouped together and so on) can be used to obtain seven different standard deviations (STDs) representing each day of the week. Figure 4.1 shows two load profile samples and the resultant standard deviation calculated from the mean load profile value as obtained from [110].

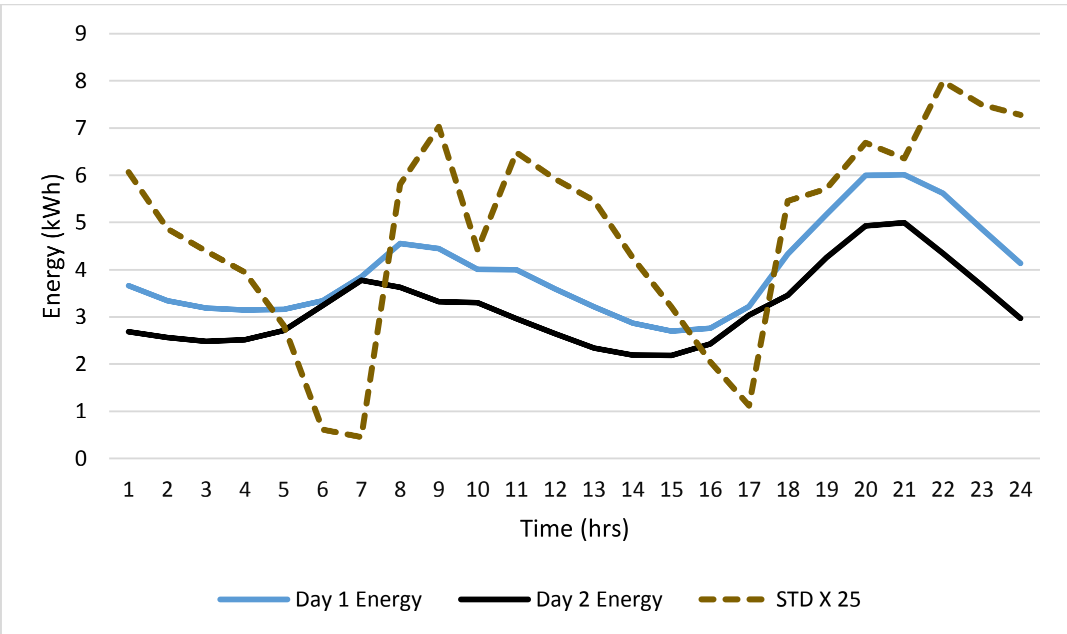

Figure 4.1: Standard deviation of 2 samples of Load profiles.

The need for the use of standard deviation in modelling user behaviour is based on the information available when a user is observed to use certain appliances constantly in a dedicated manner. This is applied such that energy consumption within any given time interval say 4:00pm daily, can be observed and if the user has a particular reason for using specific loads at that time, the standard deviation of the energy consumed will reflect the consistency of the appliances used at that time. Computed results show that the standard deviation of the load profiles at time intervals when dedicated appliances are used are very low when compared to times of the day when energy use within the home are more disperse. Therefore in this way, the user behavioural pattern can be evaluated using the information that is available in the standard deviation of their respective load profiles.

The significance of standard deviation profile in a day is the role it plays in determining the user's behaviour whereby higher values shows that the user is flexible in modifying their appliance time of use, thereby capable of participating in DR programs. On the other hand, lower standard deviation values shows that the user is rigid at those times and not particularly interested in participating in DR programs. Failure to recognize these dynamics in various users' consumption patterns as well as their respective behaviours which is also unique from one user to another has been identified in this work as an important factor for the observed withdrawal of energy consumers who initially signed up to DR programs but ended up withdrawing. Therefore, load scheduling if carried out from the utility as a bulk control on consumer loads at times pre-determined by the energy providers, creates a scenario whereby there is a very high chance for the consumers not to be satisfied with the scheduling pattern. This is therefore identified as a major cause among others; why there is a gradual withdrawal of customers who initially signed up to DR programs but became dissatisfied after a while due to inconvenient scheduling programs experienced.

4.3 Load Scheduling Application using Genetic Algorithm

In this work, the use of GA in searching for the optimal load profile that offers the maximum profit available and at optimal times of the day, is studied. Accepting the optimized load profile is at the customer's discretion since they also have the ability to override any undesired allocation offered by the scheduler. Genetic algorithm is a search algorithm based on Darwin's mechanics of natural genetics and natural selection, and was developed by John Holland and his team [111] [112]. It is in the class of evolutionary algorithm which uses mechanisms inspired by biological evolution such as selection, mutation, crossover (mating) and reproduction to produce optimal (superior) outcomes from an initial random processes [111]. Its application can be found in several fields, and can provide one of the best scheduling techniques for finding optimal solutions to search problems [112].

The choice of GA is primarily based on the ease of adding controlling variables to the objective function which offers mathematical convenience to the application. Genetic algorithm is also a very powerful optimisation technique which has the capability to converge at the true maxima thereby providing more reliable results. The major drawback of using GA is its slow convergence speed as well as the possibility of the objective function not to converge at the global optimal value, but they are still one of the most widely used type of evolutionary algorithm. In this research, the convergence speed is not an issue since all data required, especially the day-ahead pricing data, are available early enough (up to 8 hours in advance) to perform the required operation. Problems with GA can only become very obvious if more instant computations are required, almost in real time scenario. This therefore means that a preference for faster convergence of the GA optimisation which may include a search for other types of optimisation techniques may become inevitable.

4.3.1 Generating Random Load profiles for GA Application

Various optimisation techniques require the creation of initial populations of randomly-generated samples of the forecast load profile which is bound within certain constraints as determined by the forecast load profile. A thousand initial populations are generated and each load profile is referred to as a chromosome. It comprises of the energy consumption capacities per time interval taken over a 24 hour period in a day. This means that for time slots taken hourly, the chromosomes will comprise of a 24-data value, just as chromosomes with 48 and 96 data values are available for time slots taken every half-hourly and quarter-hourly time intervals, respectively.

The fitness of each chromosome is evaluated by considering all the factors that affect appliance use in any given time. These factors comprise of the input variables which relates to one another in a specified way on the load profile, thereby producing a finite numeric value that represents the strength and relevance of each chromosome to the desired goal which is to optimize the fitness value. A weak fitness value reduces the chances of accepting the proposed load profile for the day which invariably leads the optimizer to search for better optimal values, while stronger fitness values remain strong contenders for final acceptance. Two constraints which are determined by the forecast load profile data are considered while generating the original random load profile samples as well as during the optimisation process. They include:

- **Margin control**: This is given as the maximum and minimum energy values of the forecasted load profile within the day that the randomly-generated load profiles (chromosome) must not exceed. This is to ensure that the optimized load profile generated does not exceed the maximum load that the household would normally use, as given in Equation 5.

- **Energy conservation**: This is given as a rule to ensure that the sum of energy consumption for each chromosome generated is equivalent to the total energy consumption of the forecast load profile. This is reasonable since total possible energy consumption within a household is constant, and this is as given in Equation 6.

At the end of the computation, a new load profile is obtained given the fitness function which is either minimized or maximized, while the forecast load profile is computed from historical energy data and made available at the beginning of a new day. Although some incentives are available which is mainly financial, but the choice to follow any suggested load pattern depends on the user. This means that the actual load profile is only obtainable at the end of the day after the users have either adopted, modified or rejected the suggested load profiles.

4.3.2 Derivation of Fitness Function

Derivation of fitness function is based on mathematical relationships of the input variables which can also be assigned specific weights depending on their impact levels on the overall outcome. Equation 4 of Table 4.1 shows the formulated fitness function with various weightings attached to the input variables while Equations 5 and 6 shows the constraints applied. Table 4.1 also shows four independent variables whose relationships with one another are carefully considered in order to produce the most appropriate output which is a minimised function. They are combined such that results which aim to promote the best interests of the consumer are generated. In order to minimise the output, the fitness value at any given time interval for each chromosome is calculated from the fitness function and the chromosome with the highest fitness value is substituted with the chromosome with the smallest fitness value. The crossover point before mating and the choice of partner to be chosen are both randomly selected while mutant energy values whose maximum value is

1% of the maximum load profile value are randomly added or subtracted from each hourly load data. The weightings are all initially set at the same value of 1, which means they all have the same impact before being varied one after the other in order to evaluate the response of the outcome.

Table 4.1: Fitness Function Application

Input/output Variables used

$$\text{Minimize Function } F_i = (w_a * \sum A_{j,i} + w_b * \sum B_{j,i}) - (w_c * \sum C_{j,i} + w_d * \sum D_{j,i}) \quad (4)$$

Constraints used and Applications

1. $e_{min} \leq x \leq e_{max}$ (5a)
2. $\sum_{j=1}^{24} e_j = \sum_{j=1}^{24} x_j$ (5b)

Let $\Delta\mathcal{E}$ = Abs (Forecast Load – Optimized Load) per iteration. (6)

Where:

Notation	Mathematical Formulation	Inference
A	$\Delta\mathcal{E}$ * Occupancy	Overall Change in Energy
B	Optimized Load * Price	Cost
C	$\Delta\mathcal{E}$ / STD of Load Profiles	Discomfort
D	Optimized Load / Forecast Load	Optimisation Factor

e = Forecast load profile.

e_{max} = Maximum value of forecasted load profile

e_{min} = Minimum value of forecasted load profile

i = Iteration count

j = hourly time interval in a day.

w = Weighting factor

x = Optimized Load (Originally randomly generated).

Table 4.2 shows a sample of a pair (A1 and A2) of randomly generated load profiles. The pair were randomly selected just as the crossover points are also randomly selected. B1 and B2 are the crossed pair while C1 and C2 shows the mutation events. The forecast load profile from which all samples of the randomly generated load profiles is also shown and the energy data chosen is only for the first 8 hours in a day. A mutation is represented by randomly adding or subtracting 1% of the energy data per time interval. It can also be observed that the randomly generated load profiles follows the constraints as given in Equations 5a and 5b.

Table 4.2: Application of GA in Load Scheduling

Time	LP		A1	A2		B1	B2		C1	C2
1	3.50		4.64	4.77		4.64	4.77		4.69	4.72
2	3.15		4.89	5.01		4.89	5.01		4.84	5.06
3	3.00		2.72	4.97		2.72	4.97		2.69	4.92
4	2.92		4.92	3.87		4.92	3.87		4.97	3.83
5	2.93		4.13	4.70		4.13	4.70		4.17	4.75
6	3.11		2.65	3.12		3.12	2.65		3.15	2.68
7	3.74		3.15	4.85		4.85	3.15		4.80	3.12
8	4.54		4.85	2.75		2.75	4.85		2.72	4.90
LP = Forecast Load Profile										
A1 = Sample 1 of Randomly generated Load profile										
A2 = Sample 2 of Randomly generated Load profile										
B1 = Crossed-over energy samples of A1										
B2 = Crossed-over energy samples of A2										
C1 = Mutant B1										
C2 = Mutant B2										

Furthermore, the experiments are conducted such that all input variables are originally evaluated independently to observe their response before combining all variables on the fitness function for overall observation of the results. The fitness function shown in Equation 4 is a combination of the minimization and maximization of the controlling variables whereby variables A and B are minimized mathematically with the positive notation assigned while C and D are maximized with the negative notation assigned. The physical translations of the input variables are as discussed in the next subsections.

4.3.3 Description of Overall Change in Energy Variable

Change in energy ($\Delta\mathcal{E}$) is the absolute difference between the forecasted load profile and the optimized load profile for a day. This variable is derived from the fact that load scheduling which entails shifting of appliance use from one time of the day to the other, creates a change in energy consumption at any given time slot. This change gives the impact of the actual change in load consumption schedule for each household, and this impact exacerbates as the number of occupants increases. Absolute change $|\Delta\mathcal{E}|$ for this variable is shown in Figure 4.2 but as defined by Equation 7. The absolute change in energy $|\Delta\mathcal{E}|$ is considered rather than simply, the energy change $\Delta\mathcal{E}$ because irrespective of whether the load is used earlier than intended or delayed to a future time, it gives the same impact to the user since they have to use these loads outside their originally preferred times. Hence $|\Delta\mathcal{E}|$ is expected to give a more accurate representation of the events.

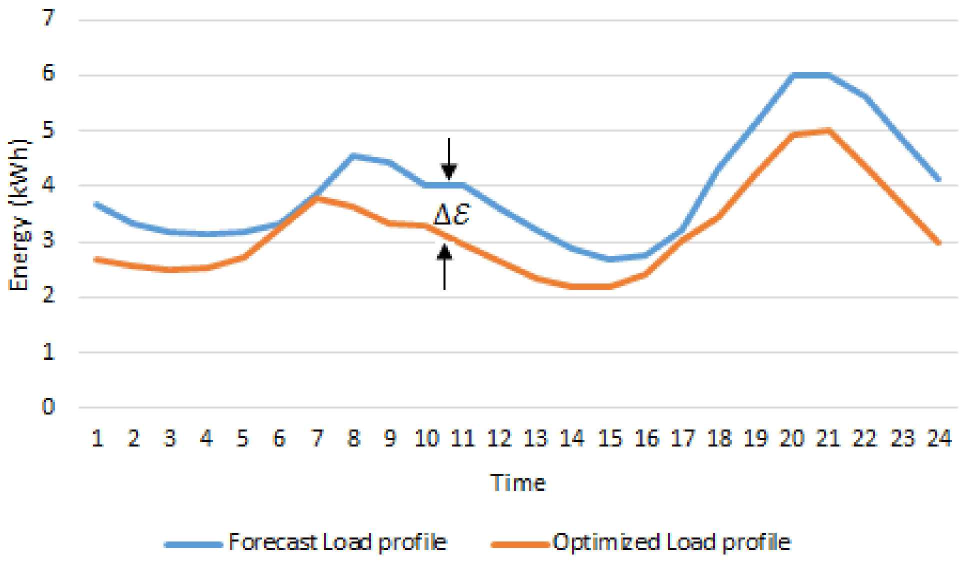

Figure 4.2: Change in Forecast Load Profile and Optimized Load Profile.

Furthermore, the effect of $|\Delta\mathcal{E}|$ depends on the number of occupants in the house. If there is nobody in house, then the change has no effect on the residents. But if there are more than one occupant in the household, then in order to account for the impact of the change on the residents, it is proposed that $|\Delta\mathcal{E}|$ is multiplied by the occupancy which produces a better measure of the impact of change in energy use on consumers. This is given as "A" in Table 4.1 and if this impact on the occupants is minimized, then this change will be more favourable to them. Mathematically from Equation 6,

$$\Delta\mathcal{E} = |\ \mathcal{E}_{f_{t,n}} - \mathcal{E}_{P_{t,n}}\ | \tag{7}$$

Where

$\mathcal{E}_{f_{t,n}}$ = Forecast Load profile

$\mathcal{E}_{P_{t,n}}$ = Optimized Load Profile (per iteration)

At the initial state of the optimisation process which is at the first iteration, the optimized load profile is not generated yet. Each randomly-generated load profile $\varepsilon_{R_{t,n}}$ can therefore substitute $\varepsilon_{P_{t,n}}$ as the initial population, before subsequent computations whereby optimised load profiles can thereafter be generated. Hence, they become better as the iteration increases until convergence. This means that Equation 7 can be rewritten as:

$$\Delta\mathcal{E} = |\ \varepsilon_{f_{t,n}} - \varepsilon_{R_{t,n}}\ | \tag{8}$$

Hence:

$$A = H_c\ \cdot (|\ \sum_{t=1}^{T} \varepsilon_{f_{t,n}} - \sum_{n=1}^{N}\sum_{t=1}^{T} \varepsilon_{R_{t,n}}\ |) \tag{9}$$

And:

$\forall t\ \in \{1, 2, \ldots\ldots T\}$; $\forall n\ \in \{1, 2, \ldots\ldots N\}$

Where:

A = Impact of Change in Energy on all Occupants

$\varepsilon_{R_{t,n}}$ = Randomly-Generated Load profile

H_c = Household Occupancy

T = 24 Hours in a Day

N = 1000 Sample Generations

4.3.4 Description of Cost Variable

Whilst the impact of energy change on householders is critical, cost has been found to be a major incentive to adoption of DR programs and as such, calculated energy cost is given as B [3]. The cost is a product of load profile and forecast price profile data whose unit is presented in the local currency of the tariff. Costs derived from forecast load profiles are referred to as forecast costs, whilst costs derived from optimized load profile are referred to as optimized or scheduled cost. The actual cost which is derived at the end of the day is a product of the actual load profile and the actual price. Lower energy costs are considered favourable to the user hence it is minimized and also positive-valued in the fitness function equation.

Mathematically:

$$B_t = \mathcal{E}_{P_{t,n}} \, . \, \mathrm{D}_{P_{t,1}} \tag{10}$$

Hence:

$$B_t = \sum_{n=1}^{N} \sum_{t=1}^{T} \mathcal{E}_{P_{t,n}} \; . \; \sum_{t=1}^{T} \mathrm{D}_{P_{t,1}} \tag{11}$$

Where:

$\mathcal{E}_{P_{t,n}}$ = Optimized Load Profile

$\mathrm{D}_{P_{t,1}}$ = Dynamic Pricing

$\forall t \in \{1, 2, \ldots\ldots 24\}$Hours; $\forall n \in \{1, 2, \ldots\ldots 1000\}$Sample Generations.

4.3.5 Description of Discomfort Variable

The discomfort experienced due to scheduling is represented by C and can either be minimized or maximized depending on the user's preferences. This is because there is a trade-off between user comfort and energy cost whereby reduced discomfort leads to higher energy price due to lower savings available, unlike increased discomfort which leads to lower energy price as a result of higher savings available. In other words, it can be stated theoretically that unscheduled load profiles implies zero discomfort considerations while load scheduling introduces some amount of discomfort up to a level depending on how much of load redistribution that was encountered. On the other hand, minimal savings are expected if operated at lower discomfort mode that at higher ones. Therefore, discomfort in this context means having to endure the impact of load scheduling by giving up a preferred time-of-use of an appliance to a proposed scheduled time.

A key contribution of this work is the measure of this discomfort function which is critical to automated real systems. Although standard deviation is considered an input variable to the central controller as shown in Figure 3.1, the actual input to the algorithm processor is the quotient of the absolute change in energy ($\Delta\mathcal{E}$) and the standard deviation of the load profile (σ). The discomfort variable is maximized according to Equation 4 of Table 4.1 which means that the deviation of the optimised load profile from the forecast load profile will be high, but with the benefit of having more financial savings available. Although maximizing discomfort may not be an ideal approach towards encouraging user participation in DR programs, the user can be empowered to be able to manage discomfort to acceptable levels so that reduced interest in DR participation amongst users will be discouraged. Details of discomfort management is discussed in more details in section 4.4.

Mathematically:

$$C = \Delta\mathcal{E}/\sigma \tag{12}$$

Where

$$\sigma = \sum_{n=1}^{1}\sum_{t=1}^{T} \mathrm{D}_{P_{t,1}}$$

$$\Delta\mathcal{E} = |\ \mathcal{E}_{f_{t,n}} - \mathcal{E}_{R_{t,n}}\ |$$

Then Equation 12 becomes:

$$C = \frac{\sum_{t=1}^{T} \mathcal{E}_{f_{t,n}} - \sum_{n=1}^{N}\sum_{t=1}^{T} \mathcal{E}_{R_{t,n}}}{\sum_{t=1}^{T} \mathrm{D}_{P_{t,1}}} \tag{13}$$

4.3.6 Description of Optimisation Factor Variable

The optimisation factor is used to scale the optimized load to the magnitude of the forecasted load. It is a dimensionless quantity used to determine how effectively a forecasted load profile should be used to create an optimized load profile with minimal discomfort. It is the quotient of the optimized load profile and the forecast load profile which can be expressed mathematically as:

$$D = \frac{\sum_{n=1}^{N}\sum_{t=1}^{T} \mathcal{E}_{P_{t,n}}}{\sum_{t=1}^{T} \mathcal{E}_{f_{t,n}}} \qquad (14)$$

Furthermore, since each sample of the sum of optimised load profile in a day which is the numerator in Equation 14, is usually not greater than the sum of forecast load profile which is the denominator in Equation 14, as a result of the constraints of Equation 5b, D is therefore a sort of a feedback system to the algorithm. It ensures stability of the optimisation process such that results that are so divergent were not obtained. In this way, the optimisation is enhanced by encouraging more loads to be moved from region of peak loads to regions of lesser load magnitude. A high value of this feedback system is considered favourable to the consumer. Mathematically, this feedback relationship can be presented as:

$$\mathcal{E}_{f_{t,n}} > \mathcal{E}_{P_{t,n}} \qquad (15)$$

Figure 4.3 shows the flow chart for the proposed testbed activity charts as given in Figure 3.5. It also shows the points of user interaction which can be modified assuming the results obtained are not accepted. A threshold for discomfort is introduced and this is discussed in more details in section 4.4.

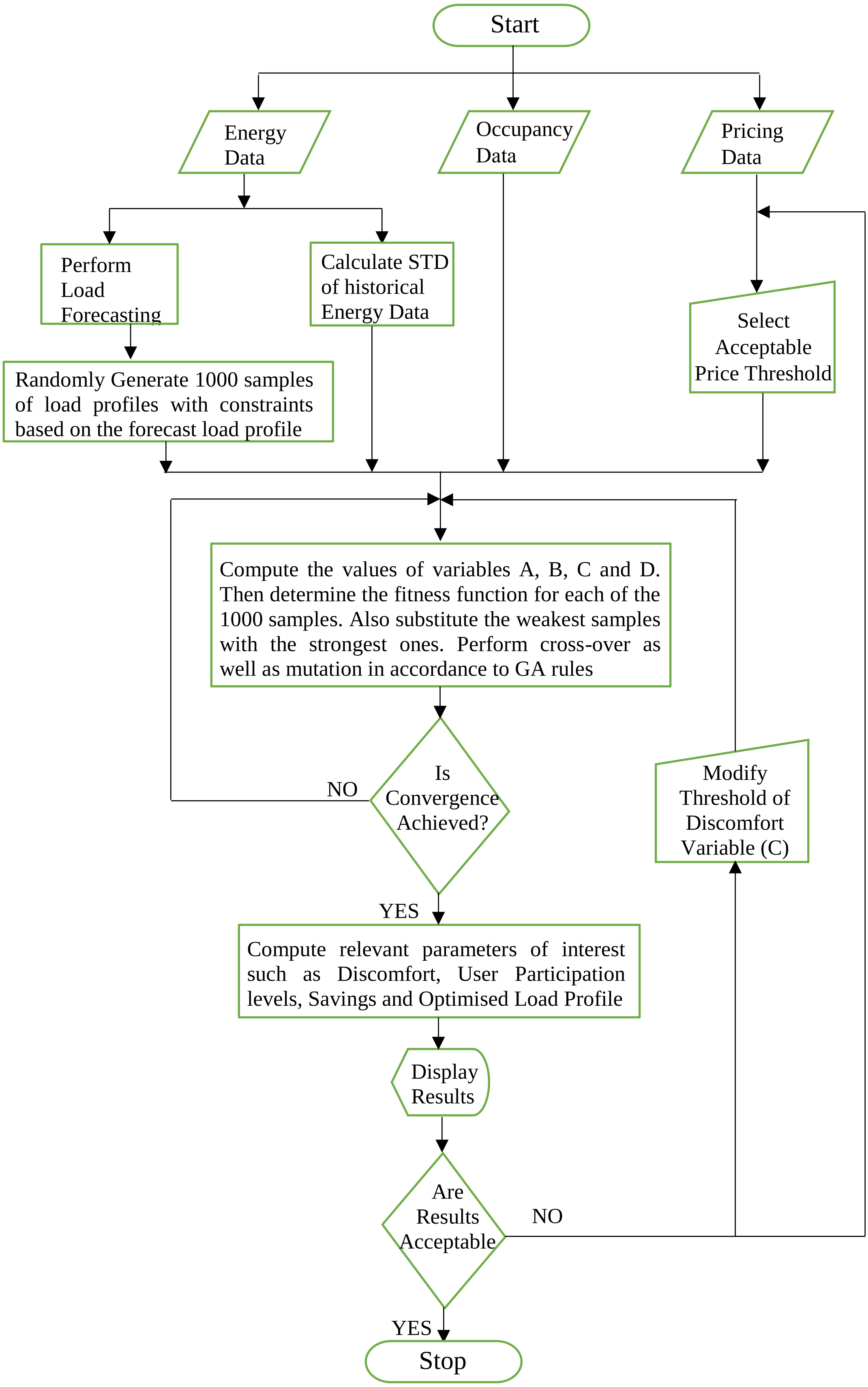

Figure 4.3: Flow Chart for the Proposed Testbed Activity chart

Table 4.3 shows the pseudo codes for the GA applied while simulating the convergence of the fitness function. These events takes place in the block that computes the values of the variables A, B, C and D as given in Figure 4.3.

Table 4.3: Pseudo codes for Genetic Algorithm Procedure

1. // Initialization;
2. **for** i = 1000 (initial population of samples)
3.   **for** j = 24 (hourly load profile interval)
4.   Randomly generate $x_{j,i}$ in the range ($E_{min,}$ E_{max});
5.   Scale the sum of $x_{j,i}$ to the sum of E ;
6.   **end for;**
7.   **end for;**
8. **for** iteration = 2000 (enough for convergence)
9.   Evaluate fitness $F_{j,i,A}$ for variable A;
10.   Evaluate sum of fitness G = $\sum F_j$ for all i ;
11.   Swap $G_{i\ min}$ for $G_{i\ max}$;
12.   Randomly set chromosomes in pairs for mating ;
13.   Randomly select crossover site ;
14.   Apply mutation, then result = $x_{j,i}$;
15.   Repeat 9 – 14 for fitness $F_{j,i,B}$ for variable B
16.   Repeat 9 – 14 for fitness $F_{j,i,C}$ for variable C
17.   Repeat 9 – 14 for fitness $F_{j,i,D}$ for variable D
18. $F_{j,i} = F_{j,i,A} \pm F_{j,i,B} \pm F_{j,i,C} \pm F_{j,i,D}$
19.   Update results after iteration
20. **End for** ;

Steps 15-18 of Table 4.3 show how the variables are effectively added or subtracted from one another depending on whether the operation carried out is a minimisation or maximisation function, respectively. 1000 samples were chosen to ensure that the accuracy of the convergence is high. Although similar results were obtainable if fewer number of samples in their hundreds were chosen, but anything less than a hundred initial samples are discouraged because the optimized load profiles changes significantly if the initial population is too low. Hourly load profile was chosen because the pricing data from [12] and energy data from [11] are both from the same country, which happens to be hourly based. More accurate results are expected if data with shorter time intervals are available. It is also worth noting that at the completion of the optimisation process, it is expected that:

$$\mathcal{E}_{P_{t,1}} = \mathcal{E}_{P_{t,2}} = \mathcal{E}_{P_{t,3}} = \cdots = \mathcal{E}_{P_{t,n}}; \quad (16)$$

Where:

$\mathcal{E}_{P_{t,n}} =$ Optimised Load Profile

$\forall t \in \{1, 2, \ldots\ldots 24\}$

$\forall n \in \{1, 2, \ldots\ldots 1000\}$

4.3.7 Percent Gain Computations on Scheduled Loads

The incentive to participating in DR programs majorly lies on financial savings obtainable because the users are expected to be keen to receiving a benefit towards such participation. This is only applicable for dynamic pricing tariff strategies since the choice of what to use schedulable loads offers the user some savings if they utilise the period of low energy costs as much as they can. Savings obtainable can be computed by finding the numerical difference between the costs of energy consumption if load scheduling is adopted, versus when it is not adopted. This is done on hourly basis and then summed up for all intervals of time in the day. Given the hourly cost of energy in a day for non-scheduling of load as the product of the forecast load profile and the energy price for the day given as:

$$C_{ns} = \sum_{n=1}^{T} \sum_{t=1}^{T} \mathcal{E}_{f_{t,n}} \, . \, \mathrm{D}_{P_{t,1}}$$

Similarly, energy cost for optimised load is the product of the optimised load profile and the energy price for the day given as:

$$C_{s} = \sum_{n=1}^{T} \sum_{t=1}^{T} \mathcal{E}_{P_{t,n}} \, . \, \mathrm{D}_{P_{t,1}}$$

Therefore, the percent savings is given as:

$$\mathrm{SP} = \frac{\mathrm{Cns} - \mathrm{Cs}}{\mathrm{Cns}} \tag{17}$$

Where:

Cns = Energy cost for any converged sample of non-optimised of load

Cs = Energy cost for optimised load

4.4 Discomfort Evaluation in Demand Response Programs

Discomfort can be described as an unpleasant feeling of being disturbed which can result to a state of physical unease, pain and constraint. It can also be a burden a customer that has accepted to participate in DR program is expected to bear to follow a load scheduling program. This burden is one of the leading causes as to why several consumers of electricity end up withdrawing from an earlier signed-up intention to participate in DR programs as indicated by [3]. Discomfort is usually occasioned by a request from the utility or localized scheduling algorithm to the consumers to adjust and modify their energy consumption pattern in order to aid grid performance which incidentally, may not be so desirable to the consumers.

A positive response to a request to implement a change in consumption behaviour gives rise to user discomfort. A typical example could be how uncomfortable a customer could feel if requested to ignore making a cup of tea at any given time and perhaps delay the activity to another futuristic time. In this scenario, if the customer had wanted the drink due to thirst, they might be required to fetch another type of drink. Or if they wanted to feel warmer inside, they might have to put up with the cold for much longer. But certain customers who feel slightly discomforted may heed to the advice and respond positively, while some other customers who may not accept such prescribed change due to high impact discomfort caused, will ignore the schedule. Hence, scheduling algorithms should have override capabilities and user comfort considerations in order to ensure active user participation [41]. Nevertheless, several new methods and algorithms are being proposed to increase DR participation by encouraging peak load reduction in order to ensure grid sustenance [43]. This is usually enhanced by the means of offering financial incentives to consumers or may include the inclusion of a penalty term in the cost function in order to discourage having large changes in scheduling programs [46]. Also the use of dynamic pricing is becoming a common practice in several countries whereby avoiding energy use during high energy cost oftentimes translates to reduced cost of energy use on the user’s energy bill [48].

4.4.1 Mathematical Modelling of Discomfort Function

Two variables are considered relevant in analysing what causes discomfort in participating in DR programs. As already discussed in section 4.3.5, it is proposed that a measure of discomfort can be obtained from the relationship between the change in energy consumption and standard deviation of the historical load profiles. This relationship is investigated by considering that change in energy as a result of load scheduling creates the scenario for discomfort. This is because, deciding to abide by a suggested schedule whereby users are required to forgo the desire to use energy at more convenient times is a sacrifice to make and the absolute magnitude of this change in energy use contains the component for measuring the discomfort inherent in responding to such change requests. Similarly, the standard deviation as discussed in section 4.2.1 expresses the likelihood of the user to respond either in a positive or negative way towards requests to change their behaviours with respect to in energy consumption schedules. This therefore implies that these two factors can be used for determining the comfort level of a user participation in DR programs. Using the two principal variables that affects the comfort level of users, a model of how these relates with each other is investigated as presented on a truth table.

Table 4.4: Truth table for comfort relationships in load scheduling

Standard Deviation	**Energy Change**	**Output State**
Low	Low	Fairly Comfortable
Low	High	Very Uncomfortable
High	Low	Very Comfortable
High	High	Fairly Uncomfortable

Table 4.4 shows all four possible combinations with regards to high and low values of the input variables, as well as all possible outcomes. It can be observed that a high standard deviation of energy use and a low change in energy consumption is desirable to achieve an optimum comfort state. This is because a high standard deviation means that load usage at those time intervals are not very routine to the customer and the user is happy to change the load hence, load scheduling is encouraged. On the other hand, a low energy change is desirable for the consumer who may not be very happy to move a lot of their loads if requested by the scheduling algorithm. However, there may not be much gain in not being able to shift loads. A combination of

both variables as shown in Equation 12 produces an output that represents "Very Comfortable" state.

An opposite relationship which encourages a minimal standard deviation and a maximum change in energy produces a "Very Uncomfortable" state. This relationship as derivable from Table 4.3 is presented mathematically as a dimensionless quantity as given in Equation 12. The "Fairly Comfortable" state indicates that although it is comforting to have a low change in energy, a low standard deviation will make it difficult to apply scheduling, just as the state of "Fairly Uncomfortable" indicates that a high standard deviation is desirable but a high energy change is not desired. Effectively, both states are considered equivalent to each other. Therefore, the method proposed here shows that the difference between the optimized and forecasted load profiles indicates discomfort, but when it relates to the standard deviation, gives a better understanding about the realistic discomfort the customer can experience.

4.4.2 Minimizing and Limiting Discomfort in Load Scheduling

Discomfort experienced can be calculated per iteration during the computational process of the optimisation. In order to minimise its impact on the optimised load profile, the discomfort variable "C" on the fitness function of Equation 4 can be modified by changing its operational sign from negative (which implies maximization) to a positive sign (which implies minimization). This modified version of Equation 4 is as shown in Equation 18, while the variables are as discussed in Table 1.

$$\text{Min } F_{j,i} = w_a * \sum A_{j,i} + w_b * \sum B_{j,i} + w_c * \sum C_{j,i} - w_d * \sum D_{j,i} \tag{18}$$

Equation 18 only relates to minimising the optimisation but further steps can be taken to restrict its numeric value from going lower than any specific value as determined by the user. Here, it is proposed that, a threshold is chosen in order to limit the differential between the optimized and forecasted load profiles thereby clipping the discomfort level experienced by the user. The expression for the discomfort threshold activation function $f(D_t)$ is given as:

$$f(D_t) = \begin{cases} D_{th}, & D_t > D_{th} \\ D_t, & D_t < D_{th} \end{cases} \tag{19}$$

Where:

$\forall t \in \{1, 2, \ldots 24\}$.

D_t = Discomfort D, at time t.

D_{th}= Discomfort threshold.

The discomfort threshold is therefore set by the user and at their discretion, but this threshold depends on their load consumption behaviour and participation capabilities in DR programs.

4.5 Schedulable and Non-Schedulable Load Identification

One of the key requirements to applying appliance scheduling lies on the identification and differentiation of schedulable from non-schedulable loads. The burden of making this identification is expected to reside with the scheduler. This can be considered a difficult task because different customers can prioritize the use of certain appliances over others in different ways thereby creating an ambiguous means of making this decision. Some researchers have therefore consigned making this identification to be based on experience and observation of load patterns, leading to an empirical identification of what is considered to constitute such loads. This method is usually subjective as it relates to the user’s perception of what such loads within the household should consist of. In this work a novel and analytical means of making such decisions about identifying which appliances are considered schedulable and which ones are not, using available historical data is applied. This is based on the use of standard deviation of historical load profiles in order to make this distinction.

In a household, the energy consumption at any time interval is the sum of energy use from all appliances used within the house at any given time. So a large deviation in amount of energy consumed for all appliances means that there will be an increased dispersion in appliance use at those times. But if the deviation is minimal, then there is more dedicated appliance use at those specific times. A measure of this dispersion can therefore be obtained by calculating the standard deviation of energy consumption at any given time interval using various load profiles available for different days. For example, the use of electrical kettle as an appliance can be dependent on a person's behaviour and if the kettle happens to be switched ON at a specific time interval over a period of time as observable in days and weeks ahead, the recorded standard deviation will be very minimal. But if the same appliance is observed to be in use at multiple times in a day as observable in subsequent days and weeks ahead, it will cause a significant increment in the recorded standard deviation. Hence, the latter will result in creation of schedulable loads while the former description will result in the creation of non-schedulable loads.

Two other variables that help in the identification of appliance status with respect to whether they are schedulable or not, are: dynamic pricing data and probability of appliance use (PAU). PAU is a measure of the likelihood of using a particular load at any given time interval in order to determine whether they can be shifted to other times within the day or not. Various probability functions exist but the calculations presented in this work are based on normal distribution function, given as:

$$P = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma}} \tag{20}$$

Each of the calculated probabilities is considered for every time interval and the effect of this combining this with the dynamic pricing helps in determining when scheduling opportunities occurs. Hence, the rest of the subsection describes the method applied in determining the state of the appliances, which is simplified by the help of threshold settings considered for each variable.

4.5.1 Identifying Load Scheduling Opportunities

The first step towards identifying schedulable loads, also known as base loads, lies on identification of load scheduling opportunities. This is evaluated for every interval of time considered, such that only the identified loads are isolated and then passed onto the algorithm provided for scheduling purposes.

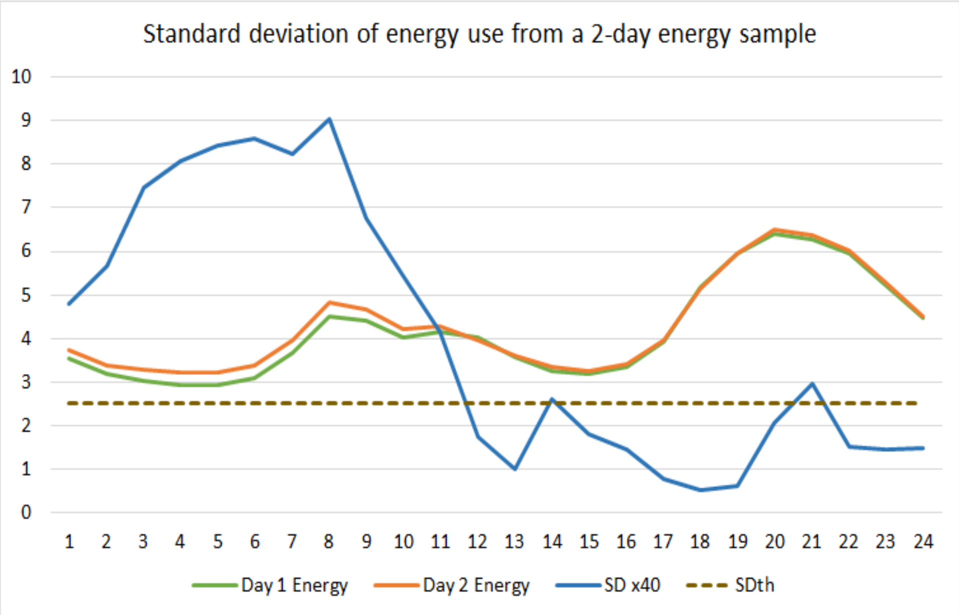

Figure 4.4: Standard deviation of Load profile samples with threshold line

Figure 4.4 shows a sample of the historical load profiles of energy consumed by all appliances in a household for a 2-day period as obtained from [110]. It also shows the standard deviation generated as well as threshold line SD_{th} chosen to determine when the standard deviation is HIGH or LOW. Regions above a threshold line are considered time intervals where schedulable loads can possibly exists while regions below the threshold line are considered time intervals where schedulable loads cannot exists

The threshold is used to trigger a standard deviation activation function $f(\sigma_t)$ given by:

$$f(\sigma_t) = \begin{cases} 1, & \sigma > SD_{th} \\ 0, & \sigma < SD_{th} \end{cases} \tag{21}$$

Where:

$\forall t \in \{1, 2, \ldots \ldots 24\}$

σ_t = Standard deviation at time t

SD_{th} = Standard deviation threshold

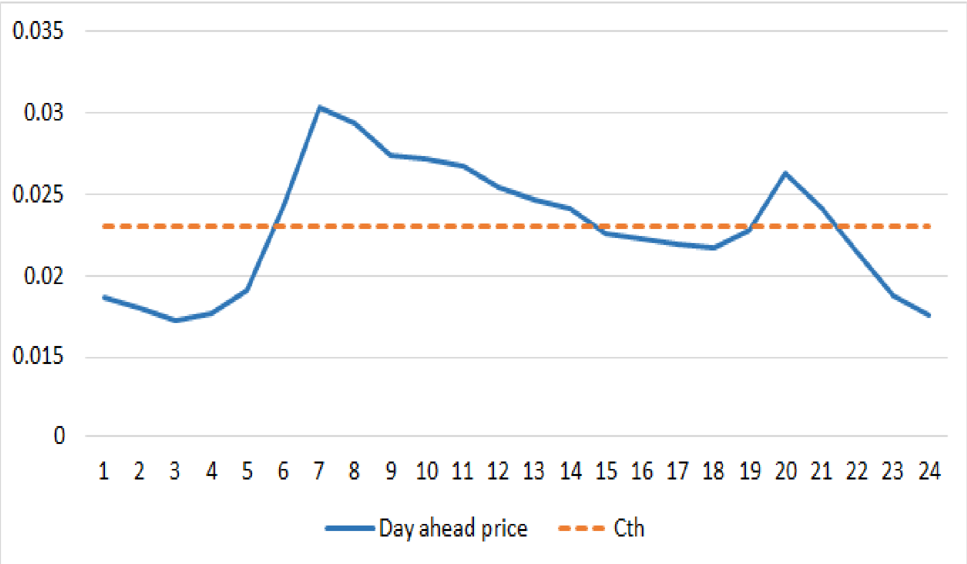

Figure 4.5: Day-ahead sample of price profile with threshold line

Similarly, Figure 4.5 shows a sample price profile as supplied by the energy provider Ameren, US and obtained from [113], while the threshold line C_{th} for the day ahead pricing profile P, as chosen by the user. This line is based on the price the user is willing to pay which should be reasonable, realistic and must be within the range of the provided price profile. Although optimisation techniques can be used to identify where the optimal threshold lies in order to maximize savings, however this aspect is not covered in this work.

Applying a similar methodology in the implementation of thresholds as described with the standard deviation, the price threshold is effectively used to trigger a price activation function $f(C_t)$ given by:

$$f(C_t) = \begin{cases} 1, & C > C_{th} \\ 0, & C < C_{th} \end{cases} \tag{22}$$

Where:

$\forall t \in \{1, 2, \ldots\ldots 24\}$

C_t = Price at time t.

C_{th}= Price threshold.

A combination of both input variables are used to determine the time intervals when scheduling opportunities are feasible in order to help to identify when and which appliances to schedule at any given time. Table 4.5 is a presentation of the truth table of a logical AND operation which combines the logical values of both $f(\sigma_t)$ and $f(P_t)$ to yield the shift coefficient function $f(S_c)$.

Table 4.5: Truth table for shifting coefficient $f(S_c)$ identification

$f(\sigma_t)$	$f(C_t)$	$f(S_c) = f(\sigma_t).f(C_t)$
0	0	0
0	1	0
1	0	0
1	1	1

These rules are based on the reasoning that if standard deviation at an interval is low, it means that loads at that time are very likely to be used hence, it is unlikely for them to be shifted, and also if the price is low then it will not be financially reasonable to shift the load. It is only when both cases are high that we can expect users to become really interested in shifting their loads and at such intervals do schedulable loads exists.

4.5.2 Identifying Schedulable Loads

It is not expected to have the entire load in a household within the times when scheduling is expected, to be switched OFF or ON. Some appliances are expected to be kept ON and they are considered to be non-schedulable (base) loads at those specific time intervals. For instance lightings are expected to be kept ON whenever it is dark, while devices such as a household broadband might be uninterruptible at all times. These loads are the base loads and should be identified so that the scheduler may exempt them from being involved in any form of load scheduling at those times of the day when they are usually kept ON. To solve this problem, the application of probabilities of each appliance turn ON as given by Equation 20, is introduced whereby the hourly probability profile for all appliance use can be obtained which helps in isolating of the base loads.

Base loads are expected to return a relatively higher PAU when compared to other loads that are not permanently kept ON in any given time interval. Therefore a threshold can be used to determine these loads such that they could be exempted from being involved in scheduling events. The activation function $f(P_i)_t$ that identifies the base load from a set of all household loads, given a specified time interval is given by:

$$f(P_i)_t = \begin{cases} 0, & P_i > P_{th} \\ 1, & P_i < P_{th} \end{cases} \tag{23}$$

Where:

$(P_i)_t$ = Probability of use for loads i, at time t.

P_{th} = Probability threshold.

$\forall t \in \{1, 2, \ldots\ldots 24\}$

Maximum values of the probability of appliance use (PAU) for all appliances is calculated using Equation 23, while Figure 4.6 shows the PAU for a specific electrical facility within the home such as a cooking system. A threshold of 0.85 is therefore chosen simply based on convenience.

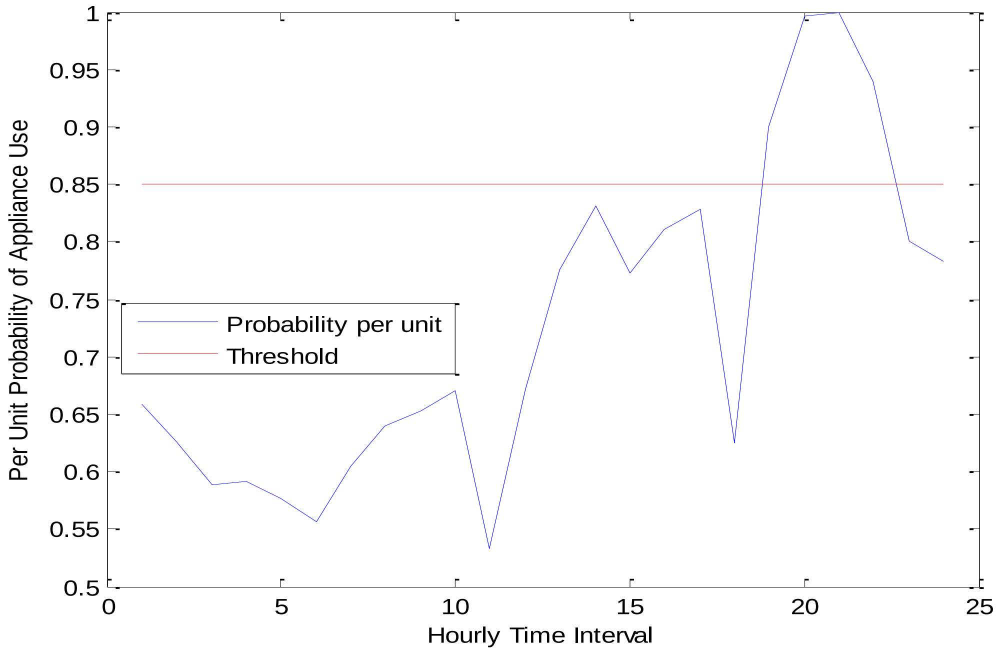

Figure 4.6: Per unit maximum probabilities of appliance use

Therefore, applying AND logic given in Table 4.5 for both price and standard deviation of load profiles, the values for the shift coefficient $f(S_c)$ is obtained throughout the day which depends on the threshold value chosen for each variable. The outcome is further combined with the PAU whose profile is given as $f(P_i)_t$ using AND logic of Table 4.6 in order to obtain the appliance status $f(L_i)_t$ which differentiates schedulable and non-schedulable loads as given in Equation 24.

Table 4.6: Truth table for appliance status identification $f(L_i)_t$

$f(S_c)$	$f(P_i)_t$	$f(L_i)_t = f(P_i)_t . f(S_c)$
0	0	0
0	1	0
1	0	0
1	1	1

Where:

$$f(L_i)_t = \begin{cases} 0, & L_i = Non - schedulable\ load \\ 1, & L_i = Schedulable\ Load \end{cases} \qquad (24)$$

In summary, classification of appliances based on their instantaneous energy behaviour pattern determines the appliance status. Although hourly time intervals are used in this report due to the data available, improved accuracy of the results are expected if energy readings are taken at shorter time intervals such as every half or quarter hourly. But the essence is to show how important it is to consider base load identification in an automated fashion rather than hand-picking these appliances based on an individual's perception.

4.6 Evaluating User Participation Levels in Demand Response

The models of evaluation of user participation in DR programs as presented in this work are carried out using two decision making techniques and they include: Boolean Logic and Fuzzy logic methods. The essence of using both approaches is mainly for comparison purposes whereby any similarities or differences between them can be observed. The primary or input data for both approaches are same and they are both based on information from the standard deviation of the load profiles as well as data from day-ahead energy prices.

In decision making techniques that involve logical assessments of variables, there is usually a specified boundary at the input which defines the region for a specific cluster to yield a definitive output. In such applications especially where human behaviour is involved, these boundaries are usually not so clearly-cut or definitive. For instance, someone might decide never to buy a certain product if the price of the item goes beyond a certain amount but if there was an unexpected increased purchasing power, he may accommodate some extra expenditure. This overlap therefore makes human behaviour quite ambiguous to model because of unexpected conditions that may influence their decisions at the last minute. This is where fuzzy logic has an advantage over Boolean logic because it gives room for an overlap in defining conditions for a particular behaviour as well as an overlap in interpreting the results [114].

This section is therefore an investigation of how actively a user can participate in DR programs. This involves the “FUZZIFICATION” of the two quantities already stated, on a daily basis as executed by the HEMS. In order to predict the possible choices a user can make when confronted with decisions about responding to a suggested DR program, computing the user’s standard deviation of historical load profiles from a mean value, can help in making this prediction [4] [6]. Price changes on the other hand influences user’s behaviour, but it is true only for energy market that uses dynamic pricing system. A day-ahead energy pricing model is assumed here and in most cases, higher energy prices are expected when energy demand is higher, but lower when energy demand are reduced. Evaluating user participation in DR programs is therefore possible with both parameters broken down as fuzzy input membership functions and processed using fuzzy logic technique.

4.6.1 Fuzzy Evaluation System

The proposed design is based on MAMDANI Fuzzy Inference System (FIS) whereby each of the input and output variables are represented in three states. Two inputs are used here although the use of more inputs is possible as shown in Figure 4.7. Input 1 is defined as the dynamic pricing profile while Input 2 is defined as the standard deviation of load profile. The three membership functions used at the input are: LOW, MEDIUM or HIGH, while the membership functions of the output being the evaluated (UPI), is represented as POOR, AVERAGE and ACTIVE.

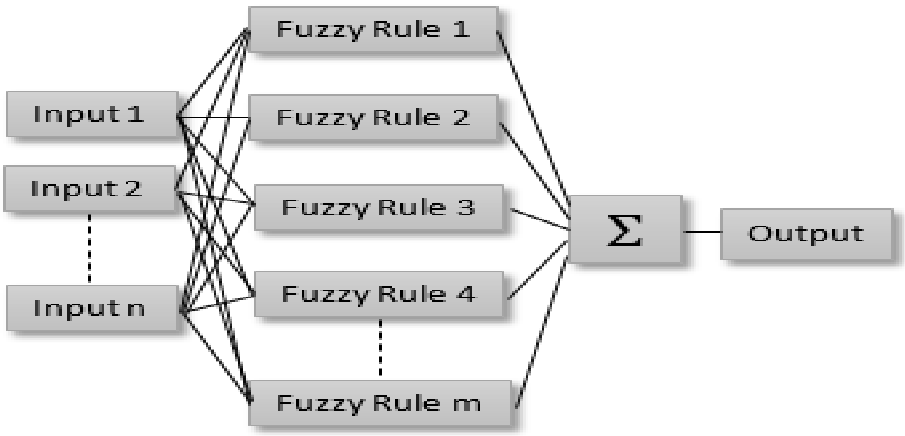

Figure 4.7: Three-State Input / Output MAMDANI FIS System

The number of fuzzy rules required is given as m and in this experiment, m is equivalent to 9. Logical AND is used as the connection amongst the input variables in order to generate the fuzzy rules used in determining the state of the output. In order to set the fuzzy rules, the state of each input variable needs to be placed into perspective since user participation is maximized when the standard deviation and price are both HIGH and it is minimal when both are variables are LOW.

Table 4.7 shows the rules table that investigates this relationship whereby the LOW, MEDIUM and HIGH states are ranked as 1, 2 and 3 respectively. On the output, a sum of 2 or 3 represents POOR participation, while a sum of 4 represents AVERAGE participation and a sum of 5 or 6 represents ACTIVE user participation. For ease of computation, all variables are converted to per-unit measurement and extrapolated to 100% before evaluation.

Table 4.7: Rules table for standard deviation and price relationship

Price	Standard Deviation (STD)	User Participation (Output)
Low (1pt)	Low (1pt)	Poor (2pt)
Low (1pt)	Medium (2pt)	Poor (3pt)
Low (1pt)	High (3pt)	Average (4pt)
Medium (2pt)	Low (1pt)	Poor (3pt)
Medium (2pt)	Medium (2pt)	Average (4pt)
Medium (2pt)	High (3pt)	Active (5pt)
High (3pt)	Low (1pt)	Average (4pt)
High (3pt)	Medium (2pt)	Active (5pt)
High (3pt)	High (3pt)	Active (6pt)

Figures 4.7a till 4.7d shows the FIS Editor for all variables and their corresponding Membership Functions. The choice of Gaussian curve as a membership function at the STD variable is because standard deviation curve is Gaussian for normal distribution.

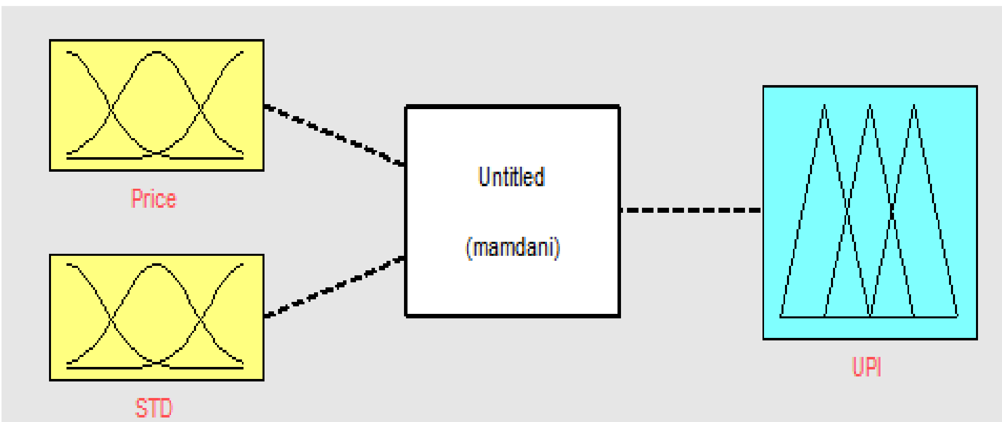

Figure 4.8a: FIS editor for a 2-input and 1-output variables

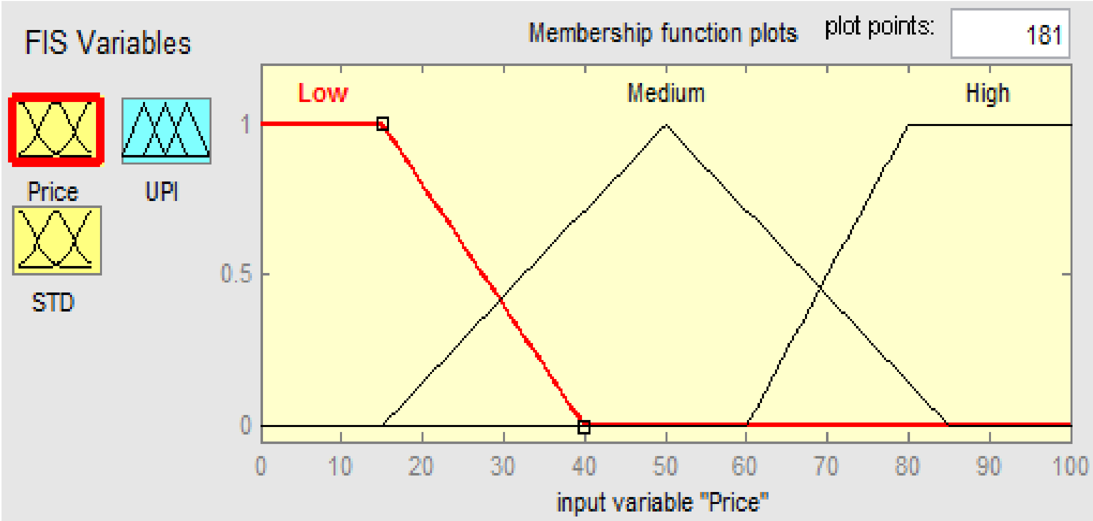

Figure 4.8b: Membership function for dynamic pricing

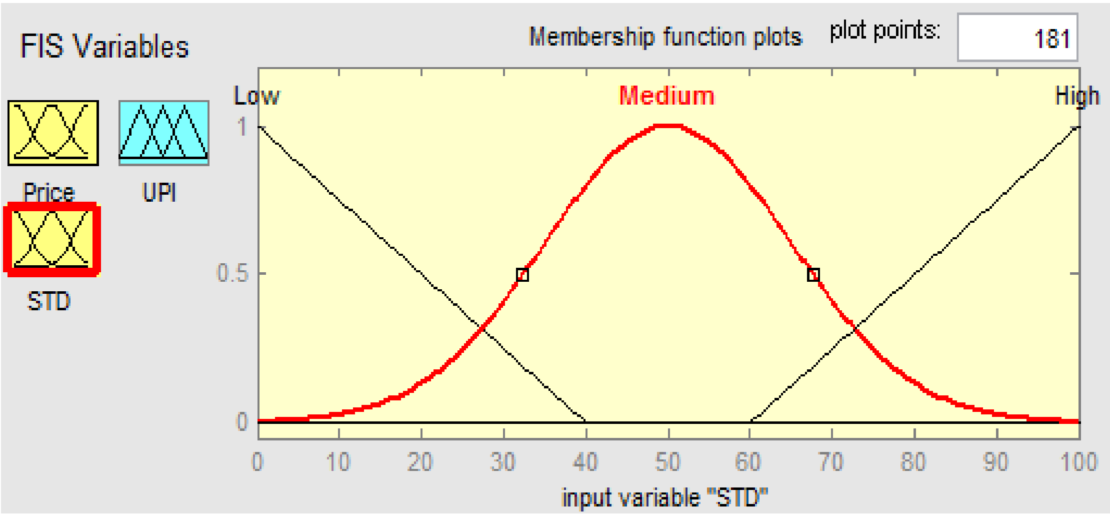

Figure 4.8c: Membership function for standard deviation of load profiles

On the other hand, the key reason for choosing trapezoidal membership function for price was because price variations for a given day are usually minimal when compared with the price for the next day. This tends to produce a more linear variation hence the preference for a trapezoidal membership function. Significant variations are usually observed depending on whether the comparison is between weekdays and weekend, or between seasons in a year.

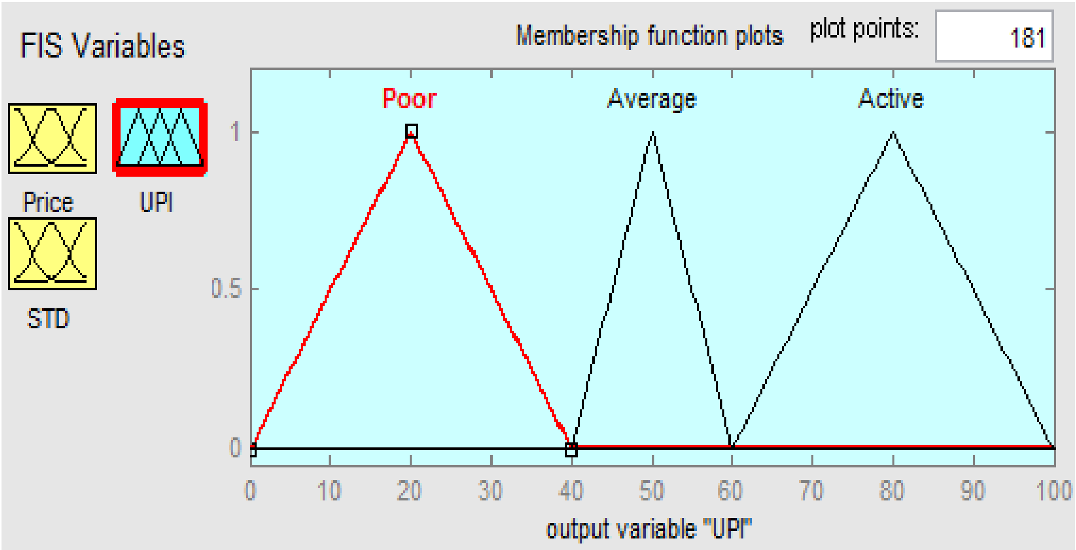

Figure 4.8d: Membership function for user participation index

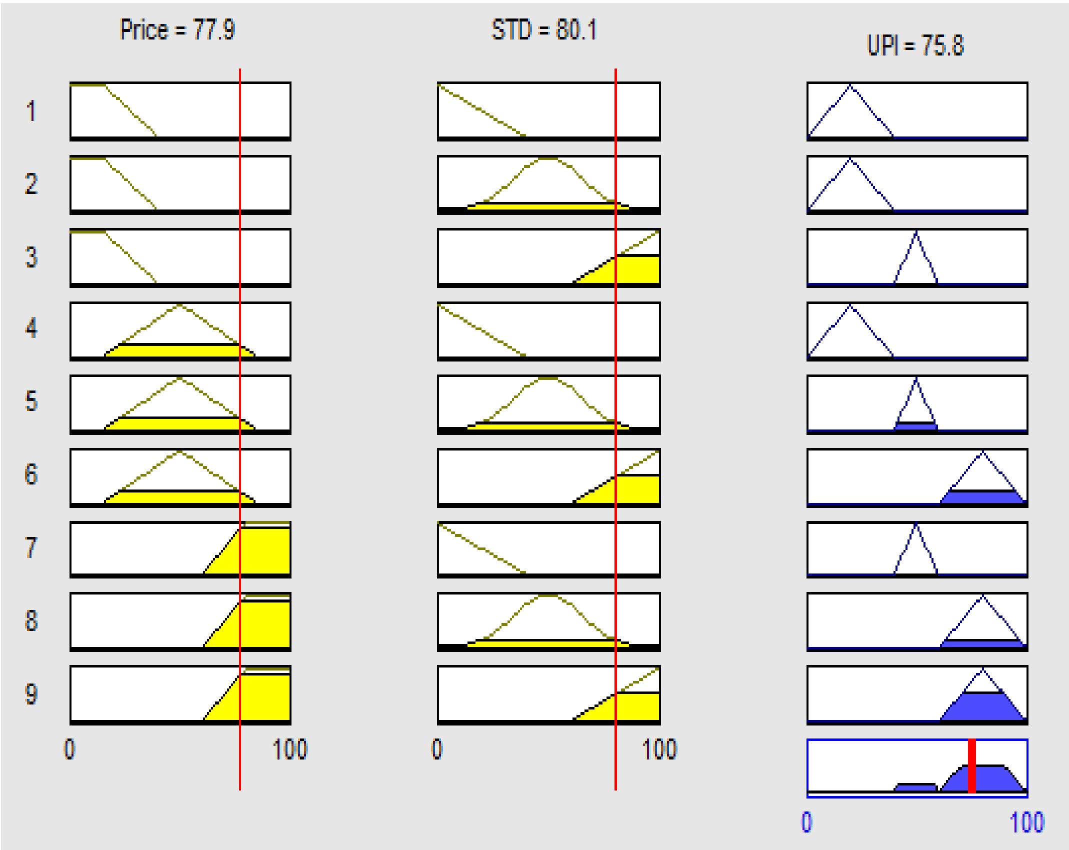

Figure 4.9: Rule viewer for all variables

For any given time interval in the day, combinations of the values of the price and STD are used to generate the UPI. Figure 4.9 shows the rule viewer whereby for a price given as 77.9% of the maximum per-unit price in a day, the associated per-unit STD value is given as 80.1% while the corresponding UPI value is evaluated to be 75.8%. So in this way, each UPI value can be calculated for any given time interval for each household. The numeric value of the UPI is therefore the centroid of the "DEFUZZIFIED" output and the various descriptions of the range of the possible outputs are presented in Figure 4.8d.

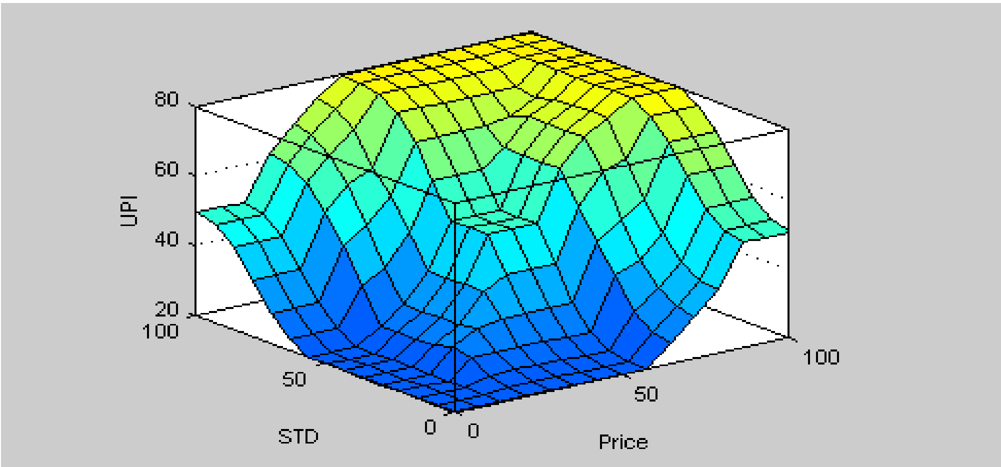

Figure 4.10: Surface viewer for all variables

The surface viewer of Figure 4.10 shows the UPI distribution for the input variables described in Figure 4.9, with respect to its relationship to the fuzzy rules given in Table 4.7. ACTIVE participants of DR programs have UPI values of 60% or more which is "coloured in yellow" and at the topmost part of Figure 4.10. On the other hand, UPI value of less than 40% represents POOR participants which is "coloured in blue" and at the lowest part of Figure 4.10. Between these values lie AVERAGE participants.

4.6.2 Model of Boolean Logic Evaluation System

The variables of the proposed model which is based on Boolean algebra are converted to logical ONE's and ZERO's. This means that thresholds will be applied to all data used in order to determine the active and non-active regions of the user participation, before being processed via a truth table. Threshold line SD_{th} as shown in Figure 4.4 is set by the user to differentiate regions of flexible and non-flexible energy use, which also depicts regions of possible active and non-active user participation. The threshold used to trigger a standard deviation activation function $\mathrm{f}(\sigma_t)$ is as given in Equation 20, just as the threshold used to trigger the price threshold activation function $\mathrm{f}(C_t)$ is as given in Equation 21. A combination of both input variables are used to deduce time intervals when participation is POOR, FAIR or GOOD. Table 4.8 is the truth table for this combination whereby the output is categorized into 3 states.

Table 4.8: Truth table for shifting coefficient identification

$f(\sigma_t)$	$f(C_t)$	$f(S_c) = f(\sigma_t).f(C_t)$
0	0	Poor
0	1	Fair
1	0	Fair
1	1	Good

Furthermore, Figure 4.11 shows an applicable logic gate assembly deducible from Table 4.7 and capable of processing the input variables. This assembly is essentially derivations of AND, EX-OR and NOR logic gates, and are used to determine the three states of the output. Each state is activated by a HIGH output which indicates the user's performance at any time. For ease of calculation, both Price and STD data are converted to the per-unit scale before computation.

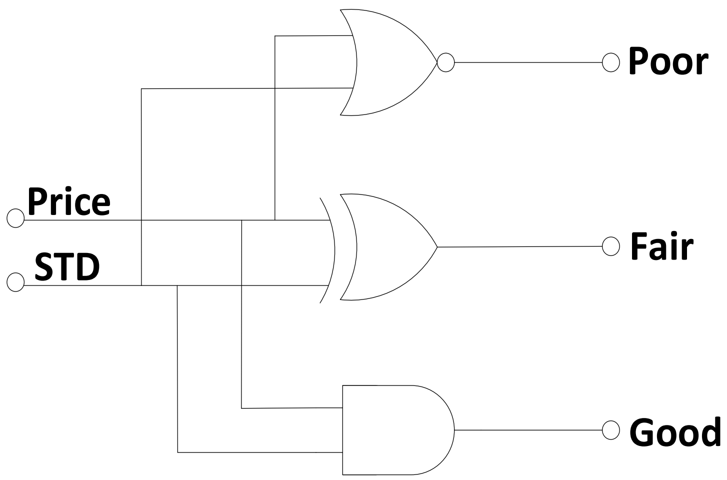

Figure 4.11: Three-State Input / Output MAMDANI FIS System

Results from both methodologies can be compared in order to check how the output relates with each other. Boolean method is presented on hourly basis and describes an estimation about the availability of schedulable or non-schedulable loads which tends to encourage GOOD or POOR user participation respectively, in DR programs. While on the other hand, fuzzy logic analysis tend to present an overall participation levels for each user throughout the entire day.

4.7 Chapter Summary

In this chapter, the approach to investigating various aspects of the research problems was evaluated and discussed. This is vital towards understanding the role of this work which includes all novelties identified and ultimately, the contributions to knowledge. It can be observed that the use of standard deviation of the historical load profiles is central to all analysis described as it was shown to have contributed immensely towards understanding human behaviour. This therefore makes it pertinent to apply its importance in the context of implementing the human behavioural aspect in DR application.

Besides the use of standard deviation, other variables which includes the pricing as well as user occupancy profile complements the input variables required to make a decision about the outcome of a forecast load profile which would be used to generate a scheduled load profile acceptable to the user. This outcome can still be over-ridden by the user in case undesired load schedule was generated and the whole optimization process started all over again. GA was used as an optimizing tool and due to the way it was construed, it has the capability to accept even more variables should there be other input variables considered in the future. The next chapter is therefore a presentation of the results obtained while investigating the outcome of an optimized load profile. This was investigated over a variety of considerations in order to ensure that relevant aspects of the research findings are obtained.

Chapter 5: Performance Evaluation of the proposed System

5.1 Introduction

The previous chapter presented a detailed description of the methodologies applied towards implementing various aspects of the design. This chapter is a presentation of the simulated results based on the methodologies applied, which therefore provides solutions to the gaps in research as discussed in section 1.5. Results of these experiments are presented in sections broadly divided into the following:

- Evaluation of individual input variables for Load scheduling
    - Impact of change in energy on optimised load
    - Impact of energy costs on optimised load
    - Impact of discomfort on optimised load
    - Impact of optimisation factor on optimised load
- Evaluation of all input variables for Load scheduling
    - GA-based Load scheduling with same weighting function
    - GA-based Load scheduling with varied weighting function.

Majority of the input data used are based on energy data available in the US market although pricing data of energy supply in the UK is used at some point.

Therefore the simulated results presented in this chapter represents a part of the methodology discussed in chapter 4 based on analysing the performance of the algorithm in order to ensure that it is working optimally.

5.2 Evaluation of Individual Input Variables for Scheduling

These experiments were carried out in order to generate results of a basic load scheduling mechanism as described in section 4.3.2. The first approach is to evaluate the scheduled load when the input variables to the fitness function of Equation 4 are independently considered. This is given as:

$$\text{Minimize Function } F_i = (w_a * \sum A_i + w_b * \sum B_i) - (w_c * \sum C_i + w_d * \sum D_i)$$

Recall also from Table 4.1 that A, B, C and D are given as: Change in Energy, Cost, Discomfort and Optimisation Factor respectively whereby on this occasion, their exclusive impact on the optimised load profile are evaluated. Although Equation 4 is a minimization function, this evaluation is done for both minimised and maximised output in order to observe broader results.

Figure 5.1 shows the basic input variables for this experiment which include: the day-ahead dynamic pricing, standard deviation of load profile, as well as the occupancy levels. Their respective relationships with the input variables in Equation 4 are also, as presented in Table 4.1

Figure 5.1: Basic Input variables used [110] [113]

5.2.1 Impact of Change in Energy on Optimised Load

The exclusive impact of change-in-energy variable on the optimised load profile, is investigated by reducing B, C and D of Equation 4 to zero while having A to be equal to the fitness function. It also implies that only the occupancy profile as given in Figure 5.1 was used on this occasion, while the others were not. Figure 5.2 shows the resultant optimised load profile when the impact of change in energy on all occupants are minimised. This shows that the load profile is equivalent to the forecast load profile. Recall also that Figure 4.2 describes this change which therefore justifies the outcome as shown in Figure 5.2 because minimising the impact of change in energy on the householders will result to the optimised load profile being equal to the forecast load profile.

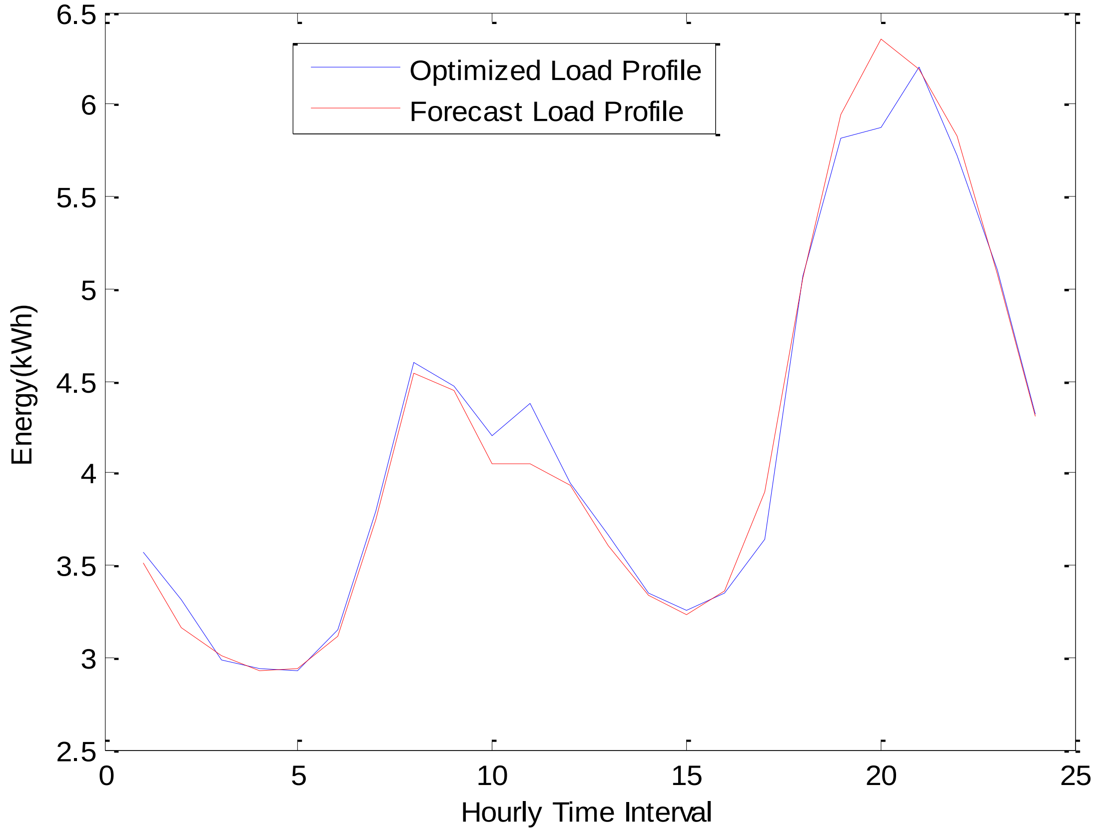

Figure 5.2: Load profiles for minimised change-in-energy

On the other hand, Figure 5.3 is a maximisation of the impact of the change in energy which effectively ensures that there is as much difference between the forecast load profile and the forecast load profile, as possible. It can therefore be concluded that the GA application for effective management of change in energy as implemented, performs efficiently as expected.

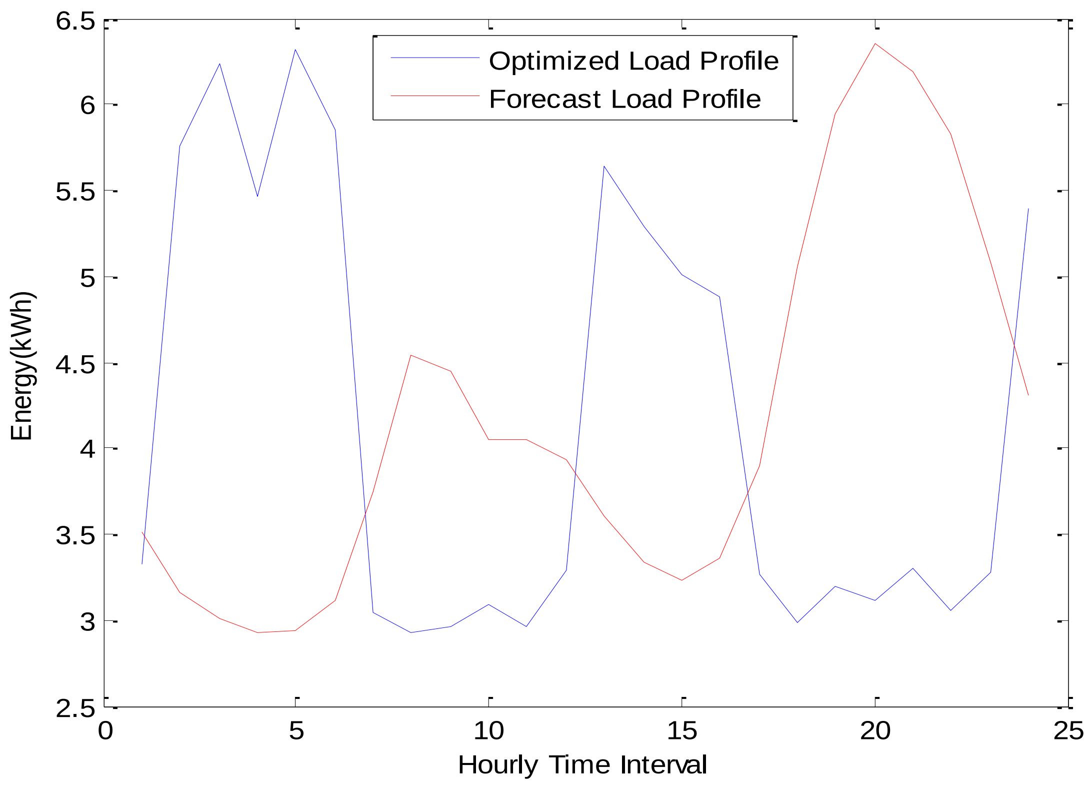

Figure 5.3: Load profiles for maximised change-in-energy

5.2.2 Impact of Cost on Optimised Load

The exclusive impact of cost variable on the optimised load profile, is investigated by reducing A, C and D of Equation 4 to zero while having B to be equal to the fitness function. It also implies that only the price profile as given in Figure 5.1 was used on this occasion, while the others were not. Setting prices for any commodity is important which usually results from balancing of the impact of market forces of demand and supply on such a commodity. In energy market, various pricing strategies are available which are designed to satisfy the local market. The pricing models which are applied in this experiment include:

- Hourly time-variant day-ahead pricing strategy.
- Fixed tariff.
- Two-part pricing model.

Hourly time-variant day-ahead pricing strategy, or simply day-ahead pricing, is expected to generate the best dynamic DR results due to the ability to shift loads at shorter intervals within the day, occasioned by hourly price changes. But rather than relying on assumptions, the other pricing models will also be tested in order to observe their absolute impacts on the results obtained.

Case 1: Day-Ahead Pricing Strategy

This pricing strategy is increasingly becoming popular and effectively used in US markets today whereby energy prices changes on hourly basis through the day depending on the prevailing market forces of demand and supply. This pricing strategy is as shown in Figure 5.1 whereby due to the hourly variations in prices published, consumers will have to identify when it is most appropriate for them to engage with the market and use their schedulable loads.

Figure 5.4 shows the resultant optimised load profile when energy costs are minimised. Time intervals with high energy costs as represented in Figure 5.1 corresponds to intervals with low energy use as shown in Figure 5.4, while time intervals with low energy costs corresponds to intervals with high energy use.

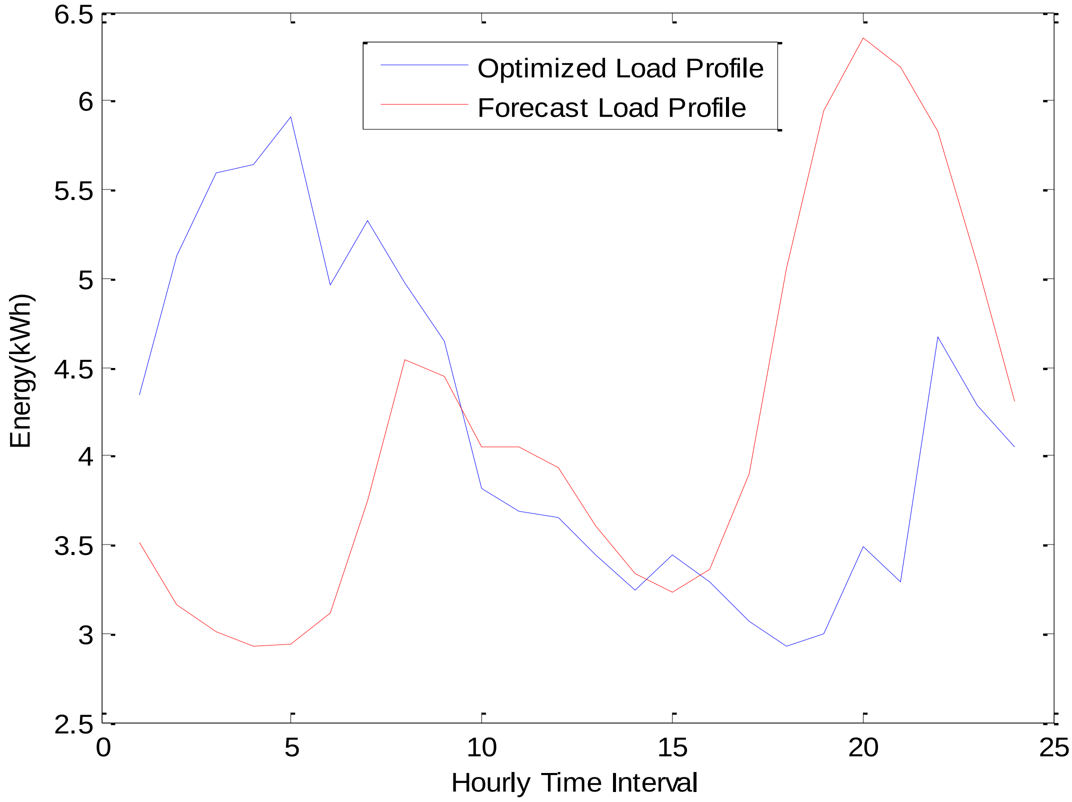

Figure 5.4: Load profiles for minimised energy costs using day-ahead tariff

Savings of 10.13% is obtainable which shows the ability to minimise costs when financial savings are exclusively maximised assuming any other factor that the user may be concerned about, are considered unimportant. However, Figure 5.4 is not expected to represent a practical choice because of the unlikelihood of users to instantly switch OFF most of their appliances when they needed to use them and then begin to use them at non-favourable times.

On the other hand, Figure 5.5 is a maximisation of energy costs which demonstrates the impact of not minimising costs. The algorithm therefore ensures that most of the energy consumption occurs when energy prices are highest, which results to a 12% loss. This shows that losses are possible if wrong choices are made towards demand response participation. Such wrong choices are also possible as a result of cyber-attack if the HEMS is not properly protected. Results from cyber-attack models are presented in Chapter 8.

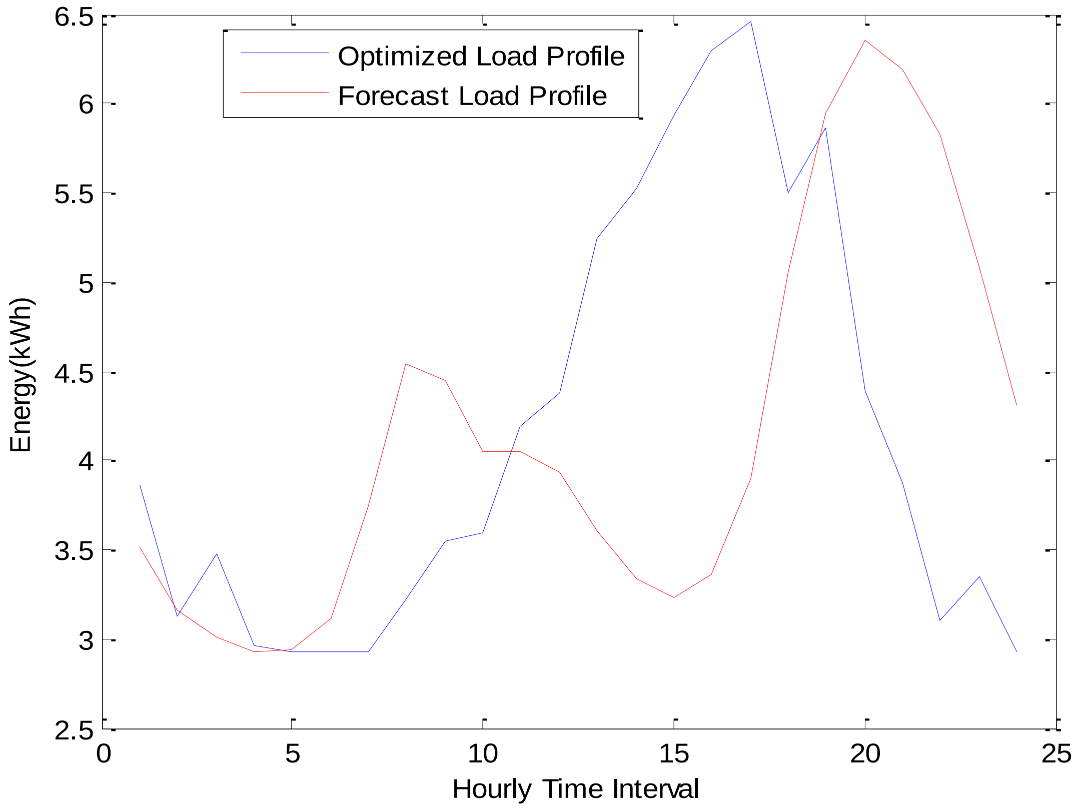

Figure 5.5: Load profiles for maximised cost using day-ahead tariff

It can be therefore be concluded that the implemented GA application for effective management of energy costs, performs efficiently as expected. The constraints are also observed to ensure that the optimised load profile remained approximately within the limits of the forecast load profile as well as maintaining the same total load as possessed by the users.

Case 2: Fixed Tariff Strategy

Fixed tariff pricing is a common pricing strategy used in several countries whereby energy prices are fixed throughout the day and year. In the UK for instance, the average fixed rate tariff for domestic customers under British Gas in 2017 till January 2019 is 11.88p/kWh in West Yorkshire [115]. Therefore in this experiment, a fixed value of 11.88p/kWh was chosen which also replaces the varied price profile given in Figure 5.1 in order to obtain Figure 5.6.

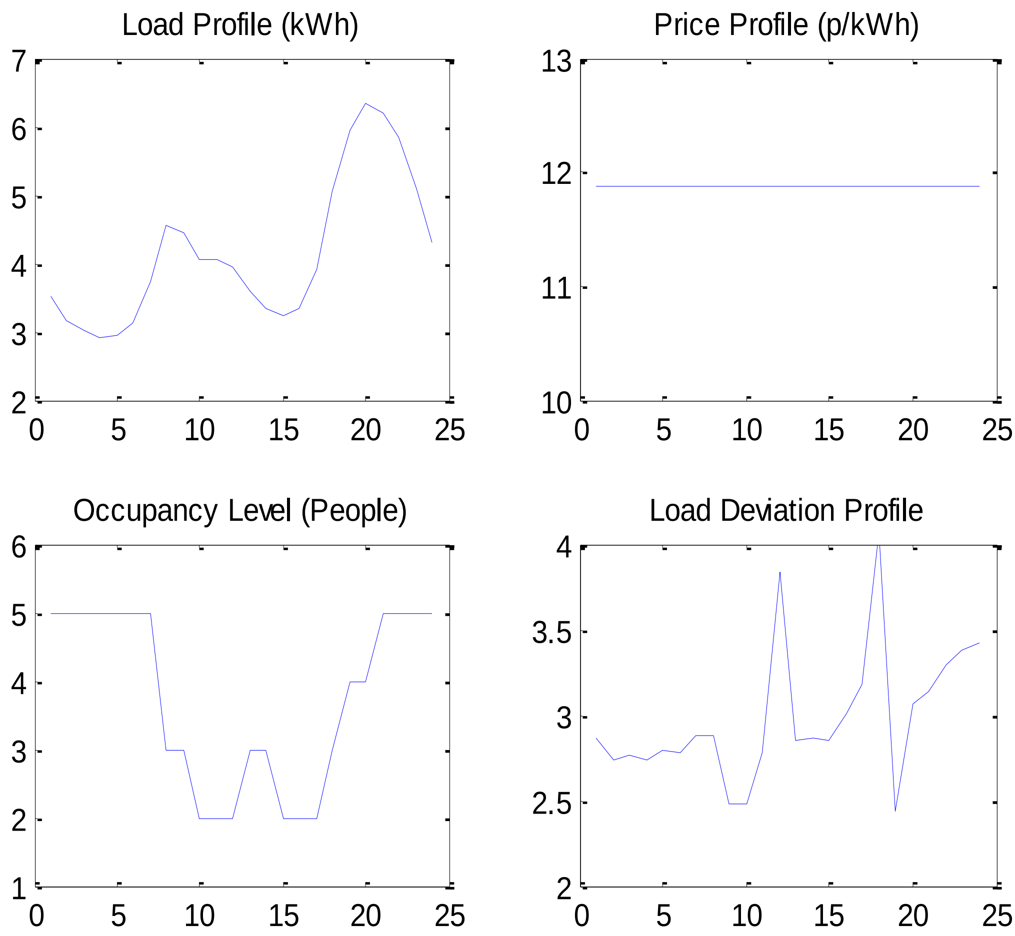

Figure 5.6: Input variables for fixed tariff strategy

Figure 5.7 shows the result of this application whereby the optimised load profile for a fixed tariff pricing is random and does not depict any particular relevance. This means that any outcome for the optimized load profile is possible, which makes sense because there is no particular need or incentive to shift the load whichever way. The optimized load profile shown in Figure 5.7 is simply a convergence of the original randomly-generated load profile and has no specific significance because it changes each time the algorithm is run. In all cases the percent financial savings computed using Equation 17, equals zero.

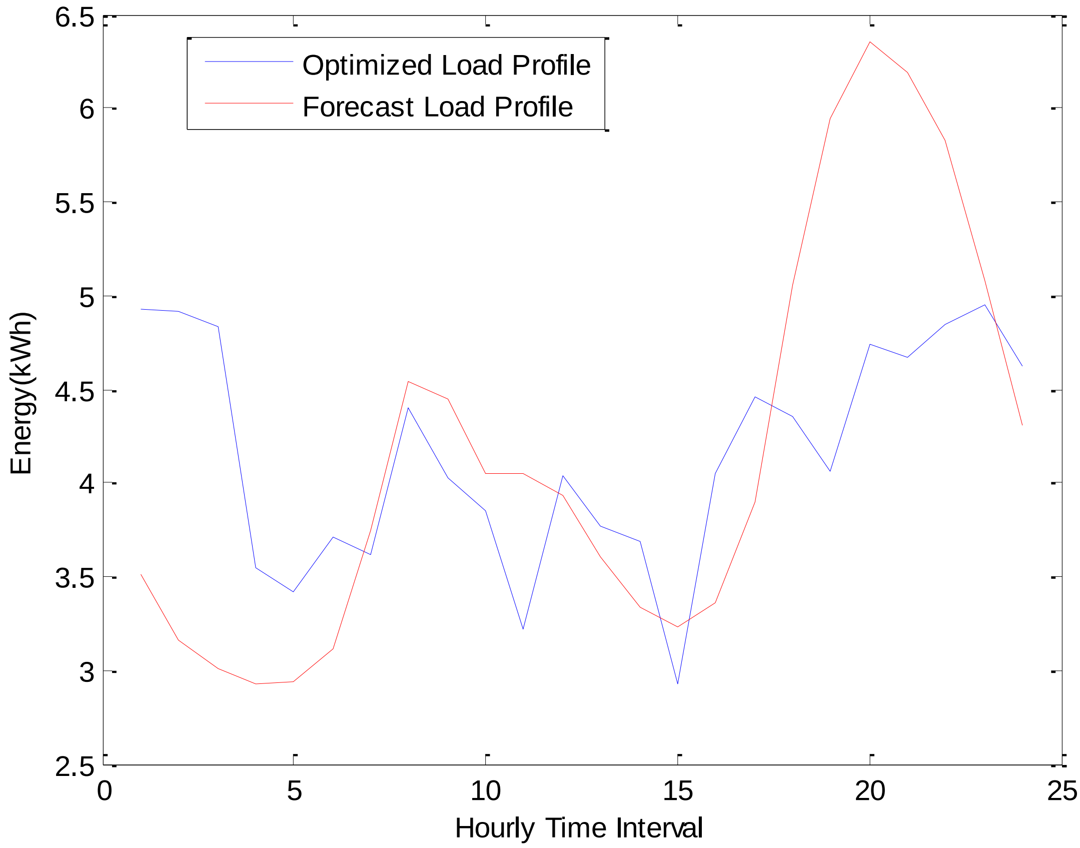

Figure 5.7: Optimized load for minimised cost using fixed tariff

Case 3: Two-part Pricing Strategy

A two-part pricing model is commonly known as economy 7 in the UK. According to British Gas tariff, the night rate which starts from 1:00 am till 8:00 am is given at 7.46 pence per kWh while the day rate continues throughout the rest of the day at 14.82 pence /kWh [115]. This two-part pricing model therefore replaces the dynamic pricing given in Figure 5.1 and this modified version of this figure is therefore given as Figure 5.8.

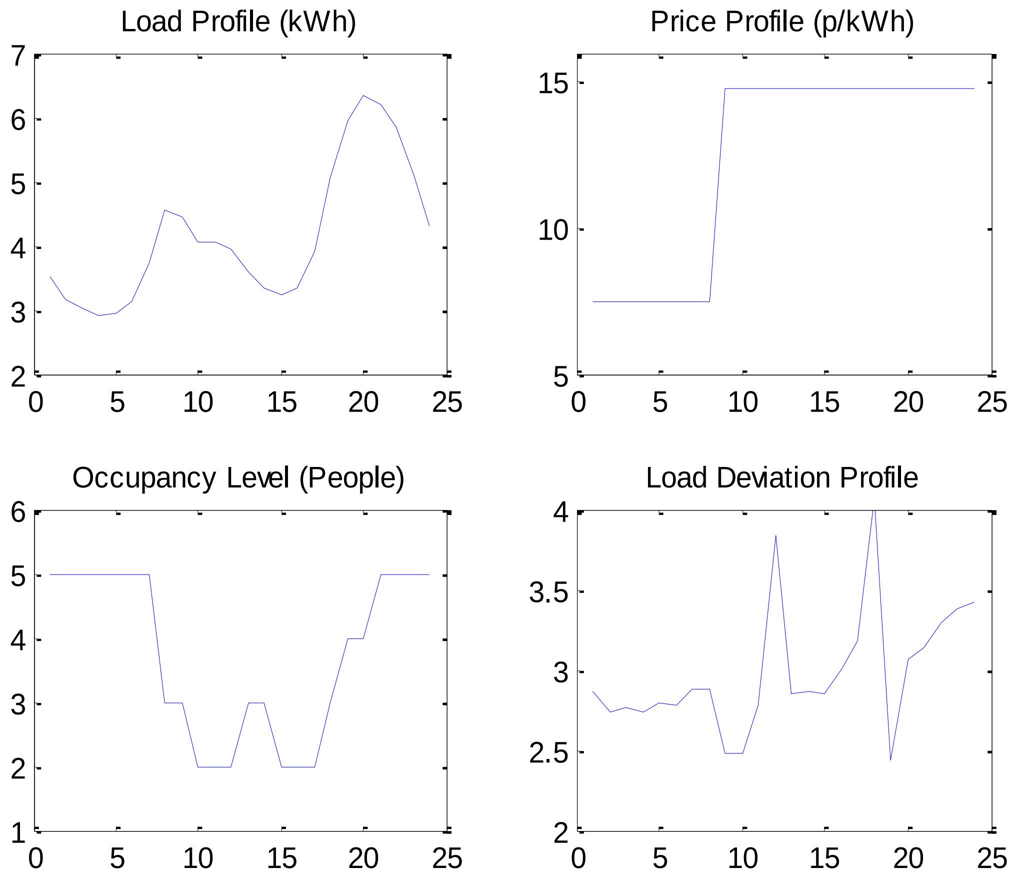

Figure 5.8: Input variables for a two-part economy 7 tariff

The resultant optimised load profile is given in Figure 5.9 whereby a significant amount of energy consumption was moved from daytime to very early in the morning representing the 8-hours of reduced energy costs. This result is only possible assuming all loads are schedulable and the users are not particularly bothered about the times of the day when their loads are scheduled.

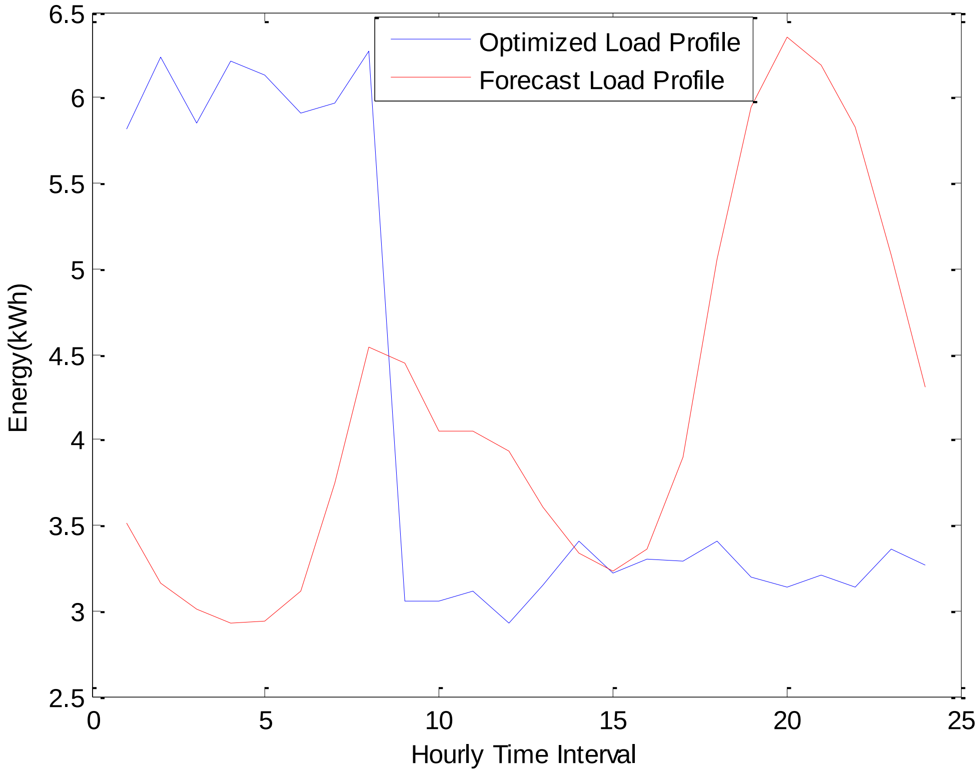

Figure 5.9: Optimised load for minimised cost using economy 7 tariffs

The percent savings obtainable using Equation 17 is found to be 17.75% although in practical application, Figure 5.9 is not expected to represent a realistic choice. This is because user comfort is largely sacrificed in order to obtain such a result. The result is also almost improbable due to nearly-flat peak demand during the early hours of the day as well as the nearly-flat minimum load demand during the later parts of the day, of which consumers will most likely not adhere to. However, the maximised version of Figure 5.9 (not shown) was observed to be an inverse of Figure 5.9 whereby a nearly-flat minimum load demand occurs during the early 8 hours of the day, while a nearly-flat maximum load demand occurs during the later hours of the day. This is relatable with Figure 5.5 but with losses of over 10%.

Case 4: Inference on the performance of the Pricing models

Section 5.2.2 gave detailed analysis of the performances of the three pricing models evaluated. Based on the results, the strengths, weakness as well as viabilities of each pricing model is clearly observable such that any realistic application of DR programs will appreciate the applicable pricing model for its application. However without any doubt, it can be observed that day-ahead pricing strategy is the only pricing model that permits constant load modification during the day which is essential for effective DR participation. This is because according to Figures 5.4 and 5.5, the optimised load profile is constantly changing depending on the prevailing pricing data. This means that if there is any need to reduce energy consumption, the utility will simply raise the price of energy at those times while reducing the prices at time intervals where they expect the users to try to use their non-essential loads. Therefore, if the incentive for DR participation is monetary, then it can be easily driven by allocating energy prices depending on the preferred and expected consumer load profile to be generated.

Conversely, the major flaw in the fixed-tariff pricing strategy is the fact that it does not encourage DR participation in any way what-so-ever as shown in Figure 5.7. This is because since all prices are the same, there is no incentive or bias towards any specified times of the day to move appliance use to. This therefore makes fixed-tariff pricing strategy in the real sense of it, a means to supress participation in DR programs. The random results obtained attests to this conclusion which means that there is no specific pattern to the use of the appliances.

On the other hand, results from the two-part pricing strategy shows that change in behaviour is possible but the major flaw is that the users cannot be effectively engaged in participating in DR programs. This is because, although non-essential loads can be moved to times when energy supply is cheaper, if there is unexpected and imminent need to further reduce load use when prices are already specified to be high, this pricing strategy cannot be applied since the higher price has already been specified. This therefore means that this pricing model cannot be effectively engaged where changes in energy consumption is prevalent which therefore defeats the aim towards applying effective user participation and behavioural changes in the ever dynamic DR programs. In the light of this, only results obtained using Day-ahead pricing model was continued with in the rest of this chapter since it is the most appropriate pricing strategy that encourages effective participation in DR programs. The next subsection investigates the impact of exclusively considering the discomfort factor when it is minimised as well as when maximised on the fitness function.

5.2.3 Impact of Discomfort on Optimised Load

The exclusive impact of discomfort variable on the optimised load profile, is investigated by reducing A, B and D of Equation 4 to zero thereby having C to be equal to the fitness function. It also implies that only the Standard deviation profile given in Figure 5.1 was used on this occasion, while others were not.

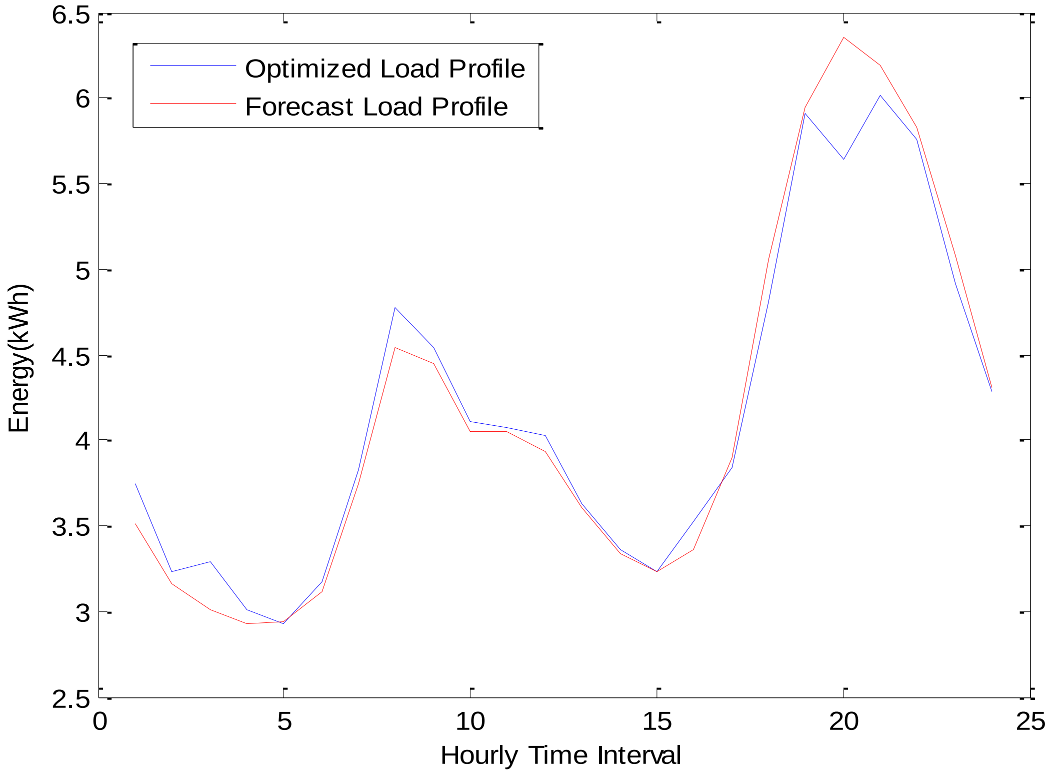

Figure 5.10: Load profiles for minimised discomfort

Figure 5.10 shows the resultant optimised load profile when discomfort experienced while participating in demand response programs was minimised. It then shows that the load profile is equivalent to the forecast load profile which is an expected outcome since experiencing zero discomfort implies non-participation in demand response programs. Recall also that discomfort function is defined as the quotient of the change in energy and standard deviation of the load profile as discussed in section 4.3.5 and section 4.4. It is therefore not surprising to observe the similarities between Figure 5.2 and Figure 5.10, as well as between Figure 5.3 and Figure 5.11.

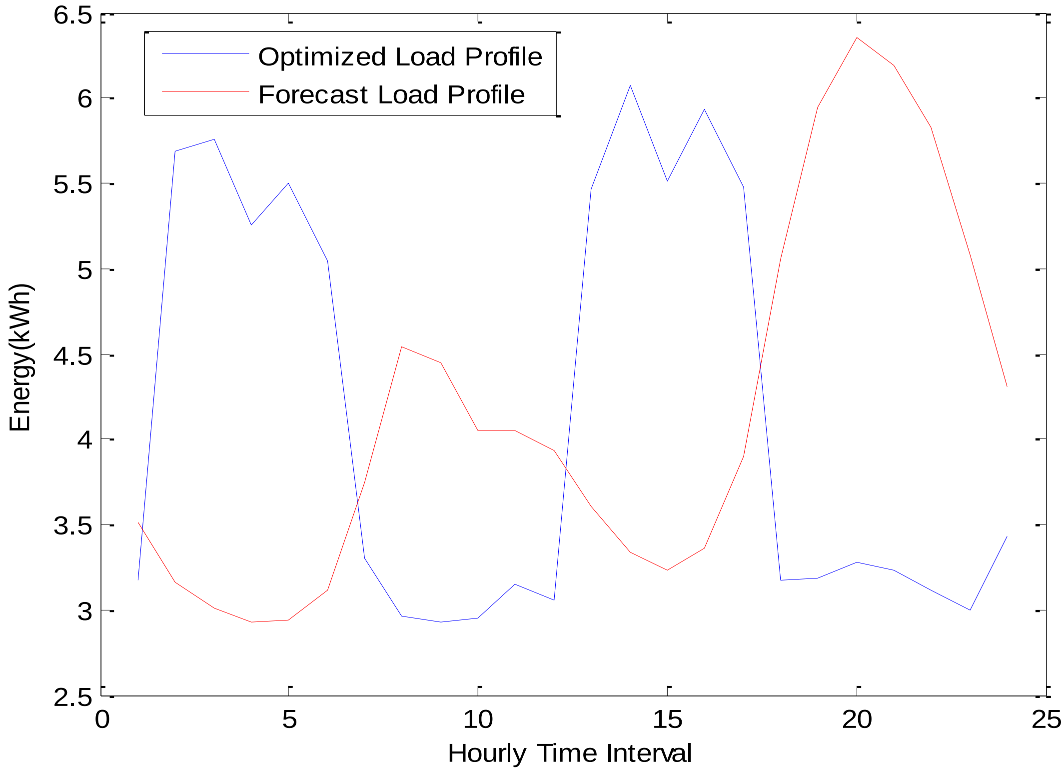

Figure 5.11: Load profiles for maximised discomfort

Figure 5.11 is therefore a maximisation of discomfort which effectively ensures that there is as much difference between the forecast load profile and the forecast load profile, as possible. Incidentally, standard deviation of the load profiles are highest at 11:00 hours and at 17:00 hours so it did not change any results. It can be concluded that the GA application for effective management of discomfort as implemented, performs optimally as expected.

5.2.4 Impact of Optimisation Factor on Optimised Load

The exclusive impact of the optimisation-factor variable on the optimised load profile, is investigated by reducing A, B and C of Equation 4 to zero thereby having D to be equal to the fitness function. Being a quotient of the relationship between the optimised load profile and the forecast load profile, it means that only the forecast load profile of Figure 5.1 was used during optimization.

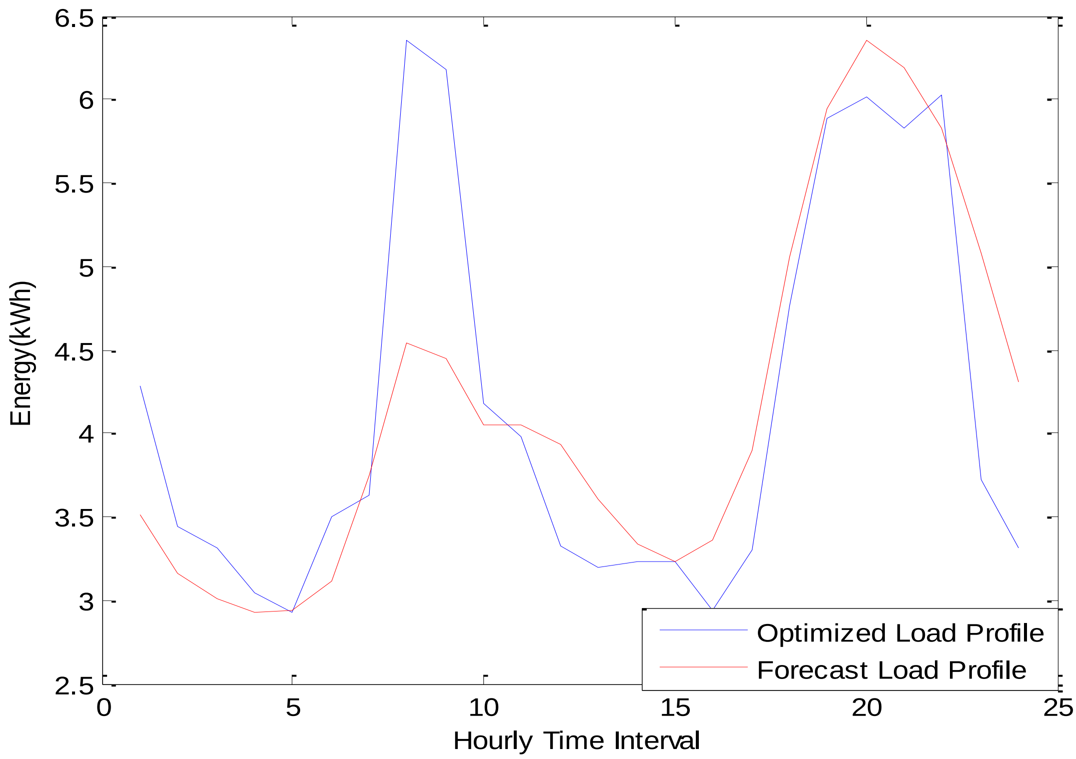

Figure 5.12: Load profiles for minimised optimisation factor

Figure 5.12 shows that minimising the optimisation factor causes the optimised load to tend towards the load profile. This shows that it does not have so much impact on the optimised load profile, hence it is dormant if minimised. On the other hand, maximising the optimisation factor creates an optimised load which is inversely related to the forecast load profile as shown in Figure 5.13.

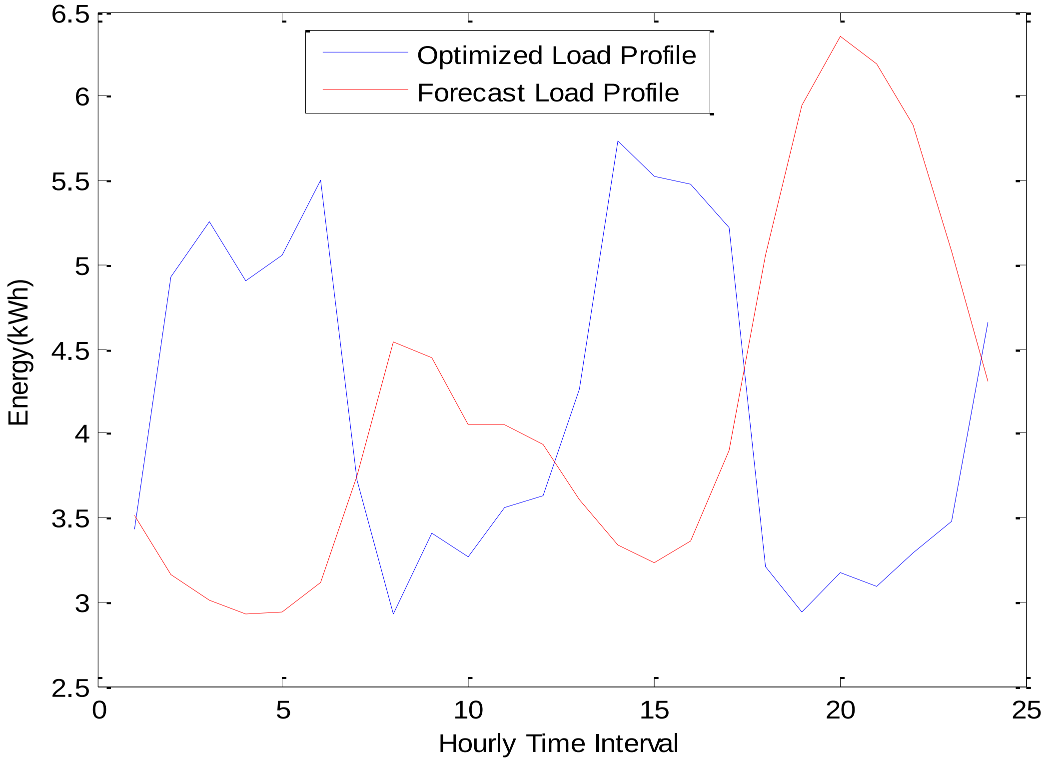

Figure 5.13: Load profiles for maximised optimisation factor

The optimisation factor is observed to assist in creating a distinct and separate optimised load from forecast load profile. The key significance of this variable as shown in Figure 5.12 and Figure 5.13 is that, it is more significant when maximised than when minimised. In other words, this variable acts as a negative feedback system that helps in stabilising the optimisation process.

5.3 Evaluation of all input variables for Load scheduling

Assigning varying weightings to controlling variables enhances the ability to project certain aspects of the results obtained, than others. They are expected to introduce more dynamics in participation in demand response programs by encouraging the creation of outputs that cater for specific requirements which represents some peculiar preferences of the user. For instance some customers may consider financial savings more desirable than comfort or vice versa, etc. Appropriate weightings are therefore crucial in generating load profiles that recognises behavioural attributes towards effective participation in demand response programs. This section will therefore evaluate the results obtained when the weightings are modified in order to bias the outcome such that specific interests which reflects the user's preferences based on their behaviour, can be achieved. The resultant optimised load profile and associated costs are thereafter compared between: when same weightings are applied and when varied weightings are applied.

5.3.1 Load Scheduling with Same Weighted Functions

In this section, all the input variables are assigned with the same weightings on the fitness function such that: $w_a = w_b = w_c = w_d$. Figure 5.14 shows the convergence of all the input as well as output variables whereby cost converged to minimum values while others converged to maximum values. Figure 5.14 also presents the average values of all variables used, as they converge after 200 iterations. Here, a fast convergence technique was applied by eliminating 100 weaker samples of the optimised load profile simultaneously so that the 200 iterations shown is also approximately equivalent to 40,000 iterations (200 multiplied by 200). Although the same weightings were applied, the numeric value of the cost variable happens to be the most dominant factor. This dominance is observable from Figure 5.14 whereby the axis that represents average values for energy costs are much higher than the others.

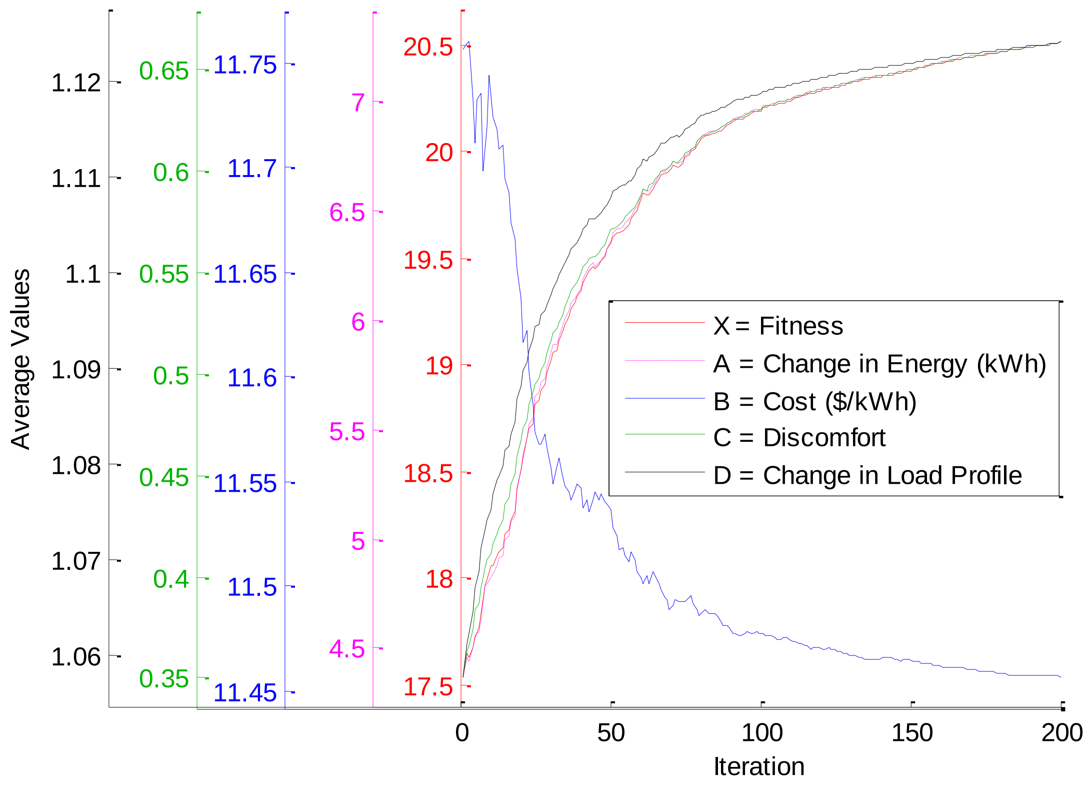

Figure 5.14: Convergence of variables with same weightings

The resultant optimised load profile generated from the forecast load profile is shown in Figure 5.15 whereby the cost variable is observed to be the dominant variable hence, the result tends towards satisfying the impact of the cost variable more than other variables. This shows that the cost variable has higher impact on the fitness function and this is evidenced on the average values of Figure 5.14. A comparison with Figure 5.4 attests to this observation whereby the highest energy prices which occurs between 16:00 and 17:00 hours has a corresponding lowest allocation for energy demand, just as the lowest energy prices outside this time interval have significantly more load usage allocation.

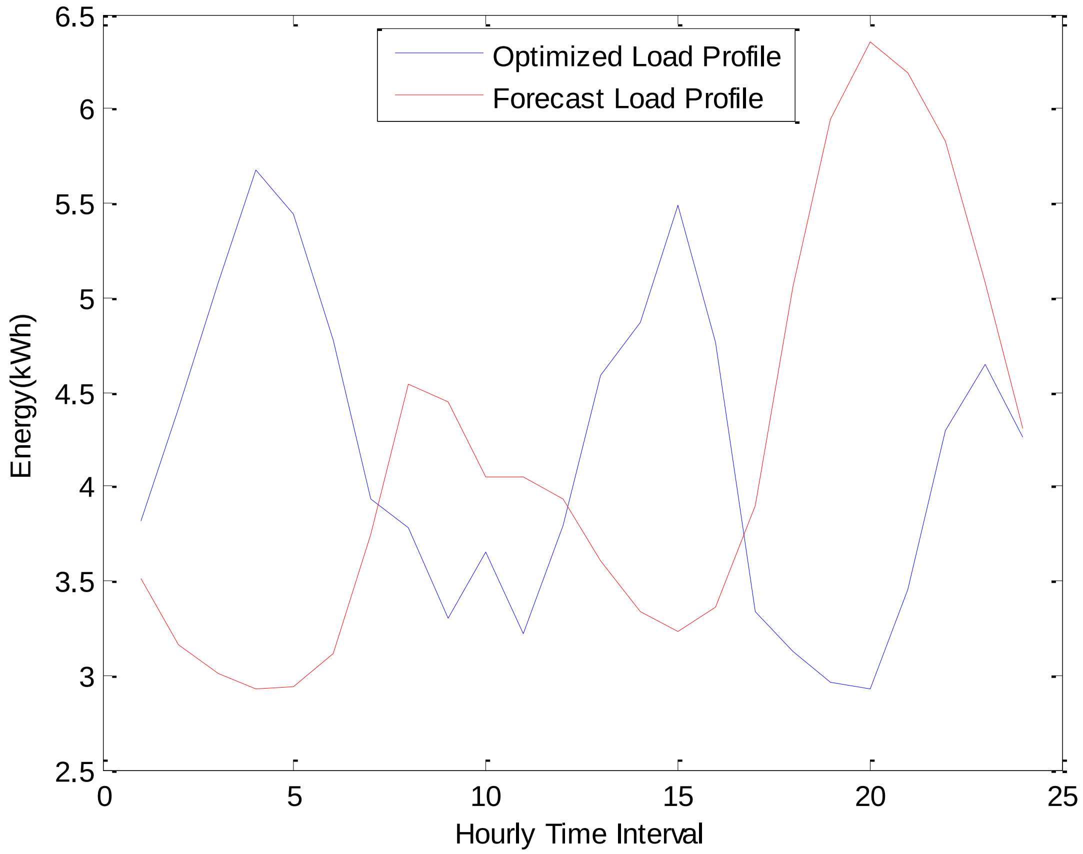

Figure 5.15: Load profiles for variables with same weightings

Figure 5.16 presents the hourly costs profiles for optimized and non-optimized load profiles whereby variations of hourly cost allocations are observable. It also shows a more flattened energy cost profile for optimised energy costs than for forecast cost profiles. Financial savings of 5.1% is also available which occurred mainly due to the shift of some loads away from times of high energy costs to times of lower energy costs in the day. Hence cost reduction and increased financial savings are usually treaded off by sacrifice of comfort.

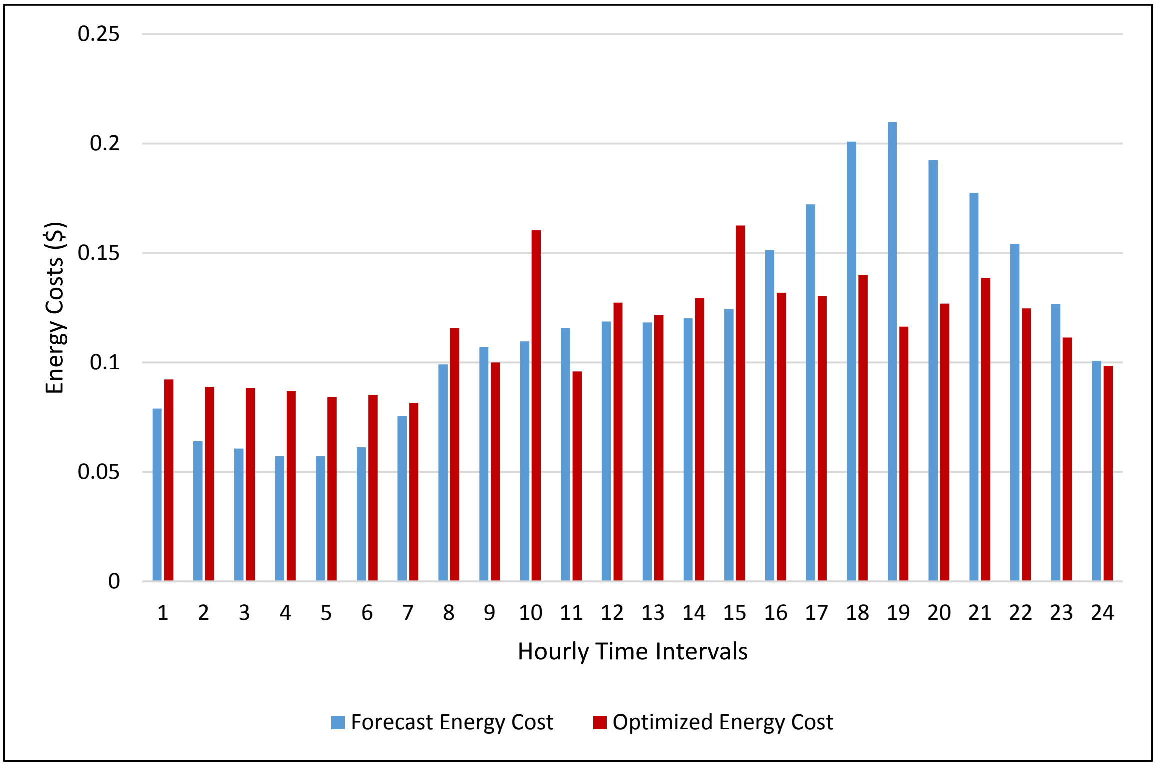

Figure 5.16: Hourly energy costs for variables with same weightings

Finally although all the weightings are the same, it is observed that the input variables are not the same. In the next section, an attempt is made in order to vary the weightings such that nearly the same numeric values of the input variables are applied in the fitness function equation and the corresponding results analysed.

5.3.2 Load Scheduling With Varied Weighted Functions

In this analysis, different weightings are attached to the input variables which enables the input variables to have approximately the same values hence, equal impacts on the fitness function. This is achieved by multiplying the inverse of the median value on the y-axis for each variable shown in Figure 5.14 such that the axis are standard unit of 1. The median values for y-axis representing A, B, C, and D as given in Figure 5.14 is as shown in Table 5.1.

Table 5.1: Weightings assigned for the respective input variables

Weighting	Input Variable	median values for y-axis	Reciprocals	Weightings to the ratio of 1
W_a	A	4.05	0.247	0.067
W_b	B	11.5	0.087	0.024
W_c	C	0.42	2.381	0.649
W_d	D	1.048	0.954	0.260

Given the weightings whose corresponding values are the reciprocals as shown in Table 5.1, Figure 5.17 is generated after 500 iterations. A significant observation shows that all the “Average Values” axis appear to be within the same range much more than in Figure 5.14 thereby giving the variables approximately the same bias within the fitness function equation. The convergence of all the input as well as output variables are also similar with that of Figure 5.14 with none of them dominating the other in a significant way.

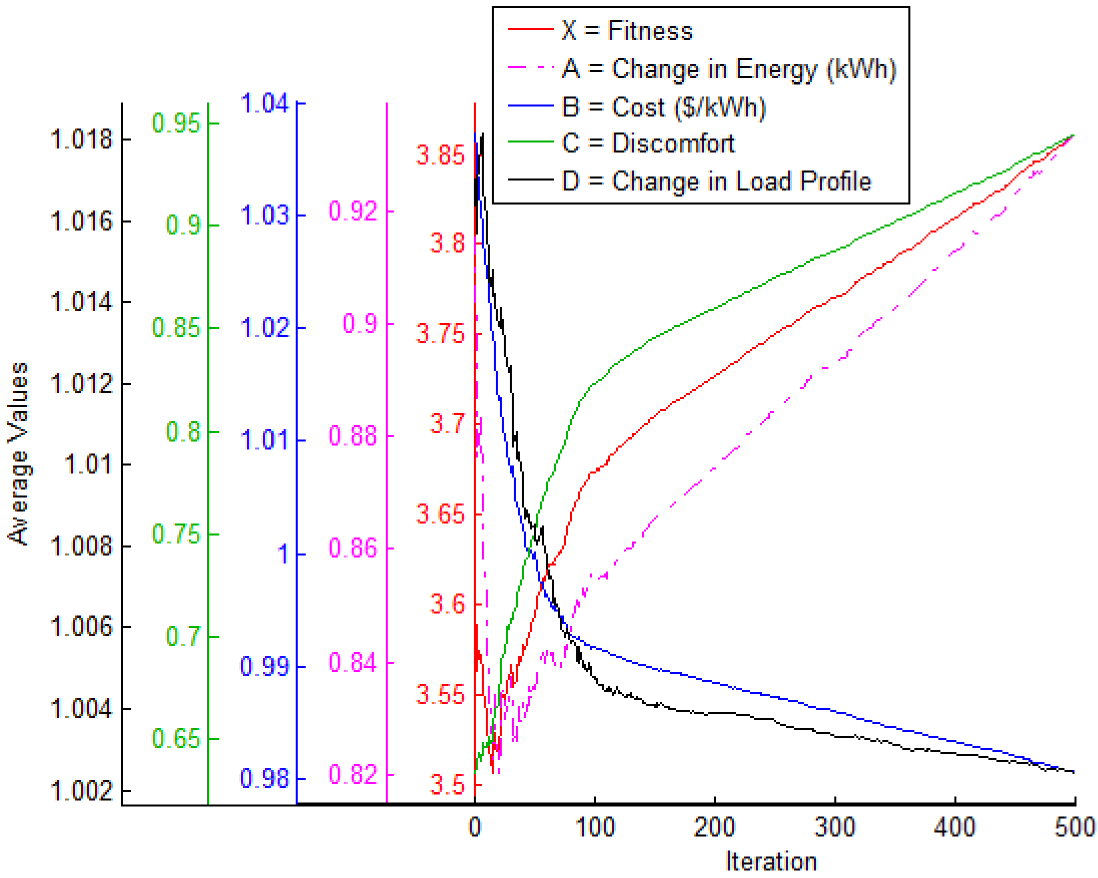

Figure 5.17: Convergence of variables with varied weightings

Figure 5.18 shows the optimised load profile generated which differs from Figure 5.15. The major differences lie between 8:00 and 17:00 hours as a result of low occupancy as shown in Figure 5.1 which permits sufficient load scheduling activity, thereby allowing the impact of the discomfort function to increase dispersion of load usage. Financial savings are also made and in this analysis whereby energy savings of 4.9% was realised. This therefore confirms that biasing the weighting for any specific variable can also tilt the outcome in favour of the quantity represented by the variable. It can be concluded that application of appropriate weightings are expected to create varied load profiles which corresponds to specific user choices. Although a limited example of investigating the impact of weightings is discussed, obtaining optimal weighting assignment for all input variables is an interesting area for future research. Choosing these variables are expected to be automated and should reflect historical behaviour of the user.

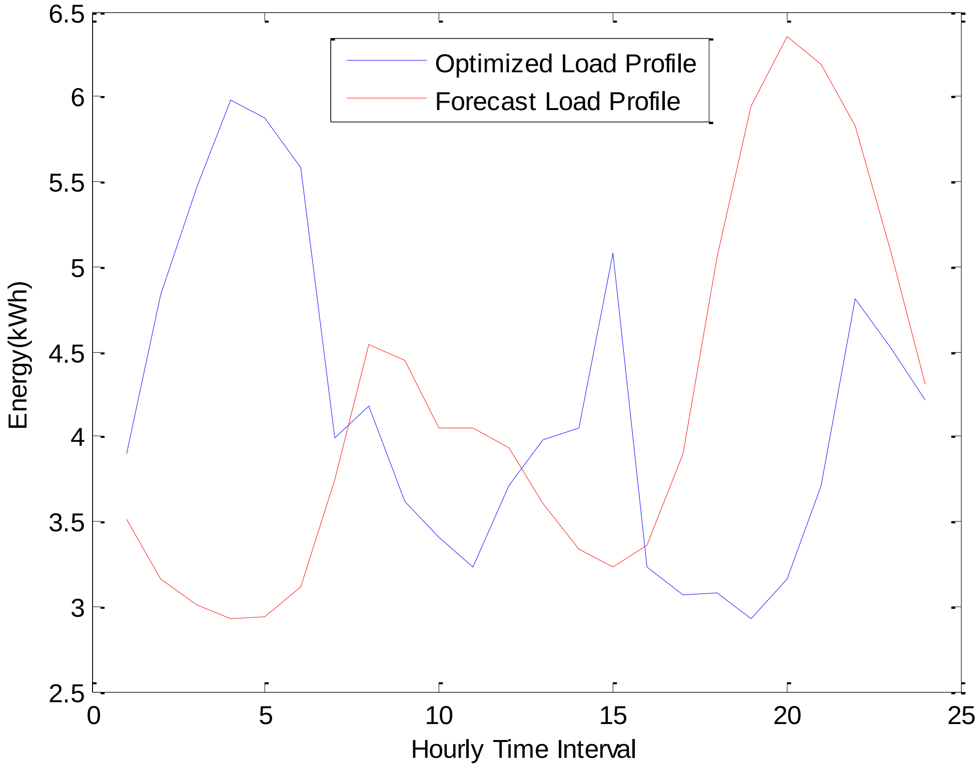

Figure 5.18: Load profiles for variables with same weightings

Finally, it is worth mentioning that the fitness function equation can be changed especially the discomfort function which is maximised on this occasion and in accordance with Equation 4, but be minimised if desired. Such a scenario has been demonstrated in section 6.3 of the next chapter whereby various methods of managing discomfort in demand response were discussed.

5.4 Chapter Summary

In this chapter, the use of GAs for load scheduling in a future smart home was demonstrated. The choice of using GA was primarily based on the ease offered in adding different controlling variables to the input source such that independent quantities identified can be appended to the fitness function in order to achieve an overall result. One of such instances of addition of very important input variables to the fitness function is the use of a variable that determines "user comfort" which is also considered one of the major contributions of the work. This is because this variable helps to ensure that scheduled loads reflect specific user behaviour, thereby encouraging user participation in DR programs. This variable was also defined as a discomfort factor whose role was to demonstrate how the quality of load scheduling can be improved. Introduction of discomfort clipping helps in limiting the dispersion of scheduled load from the forecast mean if desired by the user, thereby stabilizing the optimisation process. This can be viewed as a feedback system which is a novel idea that can be implemented in order to encourage more user participation in DR programs as well as improving their confidence to engage more actively. The next chapter therefore is a presentation of the various applications of the method presented which includes the results obtained when choosing schedulable and non-schedulable loads, results obtained when discomfort experienced in DR programs are monitored and managed to levels acceptable to the user as well as results obtained from evaluating user participation capabilities in DR programs.

Chapter 6: Application of Results

6.1 Introduction

Analysis of the system performance was carried out in the previous chapter whereby various aspects of the algorithm were tested and evaluated. This chapter is a presentation of various applications of the simulated results based on user-specific considerations of energy consumers within the future smart home. Results of these experiments are presented in sections broadly divided into the following:

- Identification of specific appliances for scheduling
- Discomfort deductions and management.
  - Impact of No Discomfort considerations
  - Impact of Discomfort considerations without clipping
  - Impact of Discomfort considerations with clipping
- Evaluation of user participation in demand response programs.

The simulated results presented in this chapter represents not only some aspects of the methodology discussed in Chapter 4 but also some aspects of the results from Chapter 5. It represents an assessment of user behaviour and participation capabilities in demand response programs for future smart homes. Most aspects of the results presented are based on GA application while others are analysis of intelligent sensor fusion of Boolean and fuzzy logic systems.

6.2 Identification of Specific Appliance for Scheduling

In most domestic applications, the use of appliances at specified times during the day is considered critical while considering what appliance to schedule and what not to schedule. With respect to section 4.5 which is a description of the methodology applied towards identifying specific appliances for scheduling, the key data required for this evaluation are: standard deviation of the load profiles, forecast load profile, price profile and probability of appliance use (PAU).

Figure 6.1 shows nine electrical appliances identified for a typical household whose individual load profiles are represented as “A to I”. These are described as: Electrical Facility, HVAC Appliance, Heating, Miscellaneous, Interior Light, Water Heater, Interior Equipment, Exterior Light and HVAC Fan respectively. They represent the forecast load profiles for each appliance in a particular day, in the month of January, for a household in Baton Rouge, Louisiana, US [110]. The data samples are obtained over a 28-day period but segregated on a weekly basis. In reference to section 4.5, the standard deviation of load profiles for each appliance is calculated within this 28 day period and a threshold of 0.25 was chosen for each appliance as given in Figures 4.4, while a threshold of 0.023$/kWh was chosen for the forecast price profile as given in Figures 4.5. A threshold of 0.85 was chosen for the PAU and Figure 4.6 represents the PAU for appliance A, which is an electrical facility represented as an electric cooker. Although the PAU for the remaining eight loads are not shown, they are individually computed and are also at the same threshold of 0.85 each.

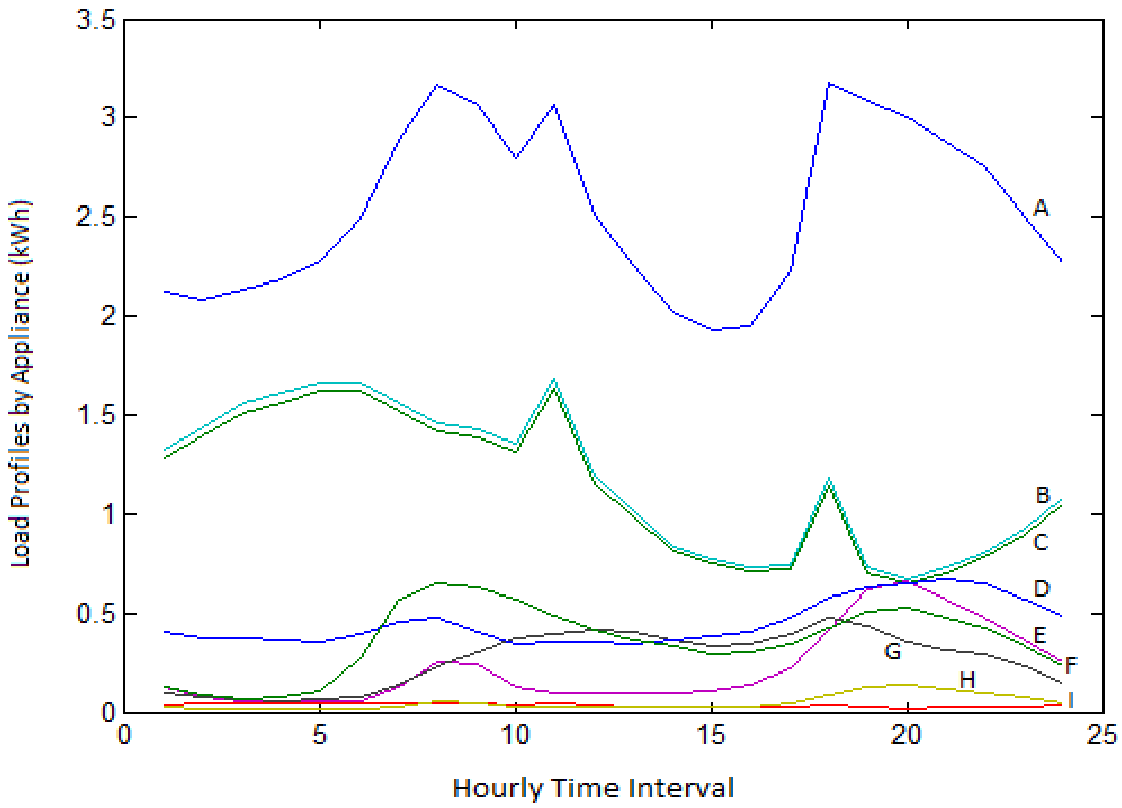

Figure 6.1: Individual load profiles of sample appliances

6.2.1 Isolating Base Loads from Scheduling

Following the algorithm for computation of all input variables as discussed in section 4.5, Table 6.1 shows the individual status of each appliance whereby the ZEROS represent intervals when the specified appliance behaved as a non-schedulable load, while the ONES represent when they are schedulable. Appliances D, E, G and H are clearly non-schedulable loads at all times, while the rest behaves as schedulable loads at certain times of the day as well as non-schedulable loads at other times.

Table 6.1: Status profile for all appliances in a day

Time	A	B	C	D	E	F	G	H	I
00:00-05:00	0	0	0	0	0	0	0	0	0
05:00-06:00	1	1	1	0	0	1	0	0	1
06:00-7:00	1	1	1	0	0	1	0	0	1
07:00-8:00	1	1	1	0	0	1	0	0	1
08:00-9:00	1	1	1	0	0	1	0	0	1
09:00-10:00	1	1	1	0	0	1	0	0	1
10:00-11:00	1	1	1	0	0	1	0	0	0
11:00-12:00	1	1	1	0	0	1	0	0	1
12:00-13:00	1	1	1	0	0	1	0	0	1
13:00-14:00	1	0	0	0	0	1	0	0	1
14:00-19:00	0	0	0	0	0	0	0	0	0
19:00-20:00	0	0	0	0	0	1	0	0	1
20:00-21:00	0	0	0	0	0	1	0	0	1
21:00-00:00	0	0	0	0	0	0	0	0	0

It is also interesting to note that inasmuch as the data presented is evaluated from 00:00 hours till 24:00 hours within the same day, Table 6.1 can also infer that from 21:00 hours of the previous night up till 5:00 hours in the new day, the use of all appliances follow a similar pattern hence, all of them are non-schedulable at these times. Times within the amber sections indicate time intervals when load scheduling is not permitted while the green sections indicate time intervals when load scheduling is possible. Table 6.2 therefore represents a summary of all the activities of the appliances whereby intervals when load scheduling is possible are indicated, as well as when there are not.

Table 6.2: Summary of activity profile for all time intervals in a day

Time Interval	$\boldsymbol{f(L_i)_t}$	**Inference**
00:00-05:00	0	Non-Schedulable (5hrs interval)
05:00-14:00	1	Schedulable (9hrs interval)
14:00-19:00	0	Non-Schedulable (5hrs interval)
19:00-21:00	1	Schedulable (2hrs interval)
21:00-00:00	0	Non-Schedulable (3hrs interval)

Figure 6.2 is obtained from Table 6.2 whereby it can be observed that all appliances used at night time and mid-afternoon are non-schedulable hence, they behave like base loads. This means that opportunities to perform load scheduling are only in the morning and late evening. It also observable from Figure 6.2 that any load scheduling technique applied by a smart scheduler should only target these intervals because the rest of the intervals will not be allowed or favourable to the user. It also shows that more appliances are available for scheduling in the morning than at late evening.

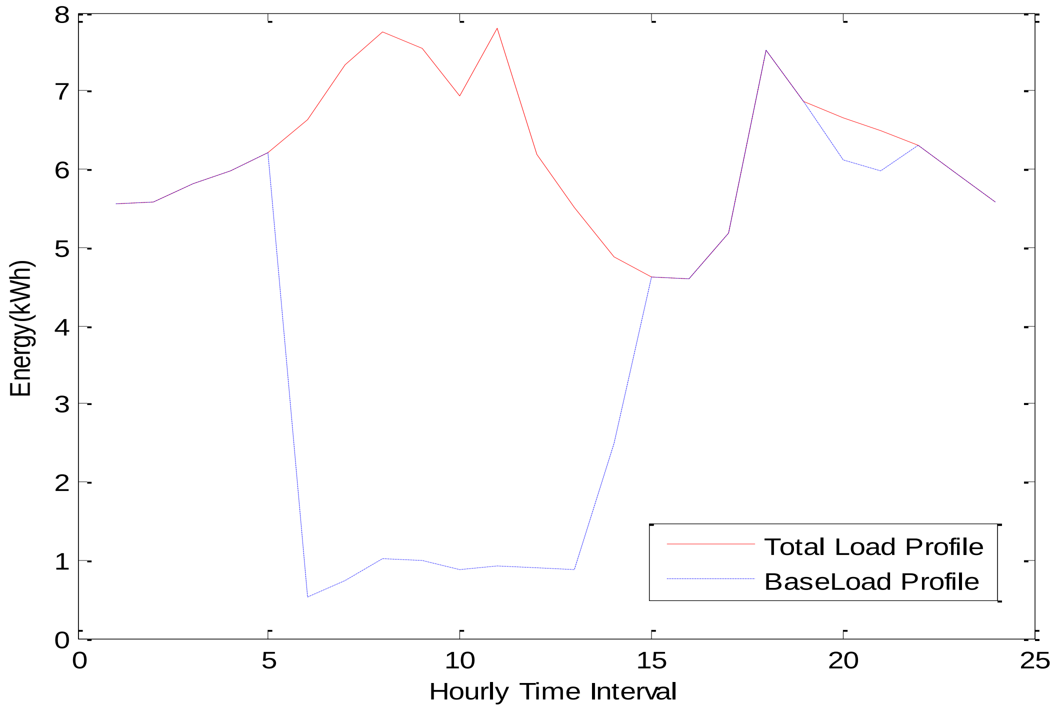

Figure 6.2: Aggregated load profile and base load

6.2.2 Eliminating Pricing Effect while Isolating Base Loads

Consider a scenario whereby the effect of price $f(C_t)$ as given in Equation 21 is excluded from the shifting coefficient $f(S_c)$ given in table 4.2. The aim is to be able to observe what happens when only the standard deviations of the load profiles are used in determining the base load during the day. Figure 6.3 shows that load scheduling can take place at all times during the day if the pricing factor is excluded. This is expected because the role of dynamic pricing in affecting the decision to schedule loads is no longer present. Although on analysing individual status of each appliance as given in Table 6.1, appliances D, E, G and H still remained base loads at all times. This is because of the very low standard deviation values which are observed to be so close to zero, although these are not shown in the report.

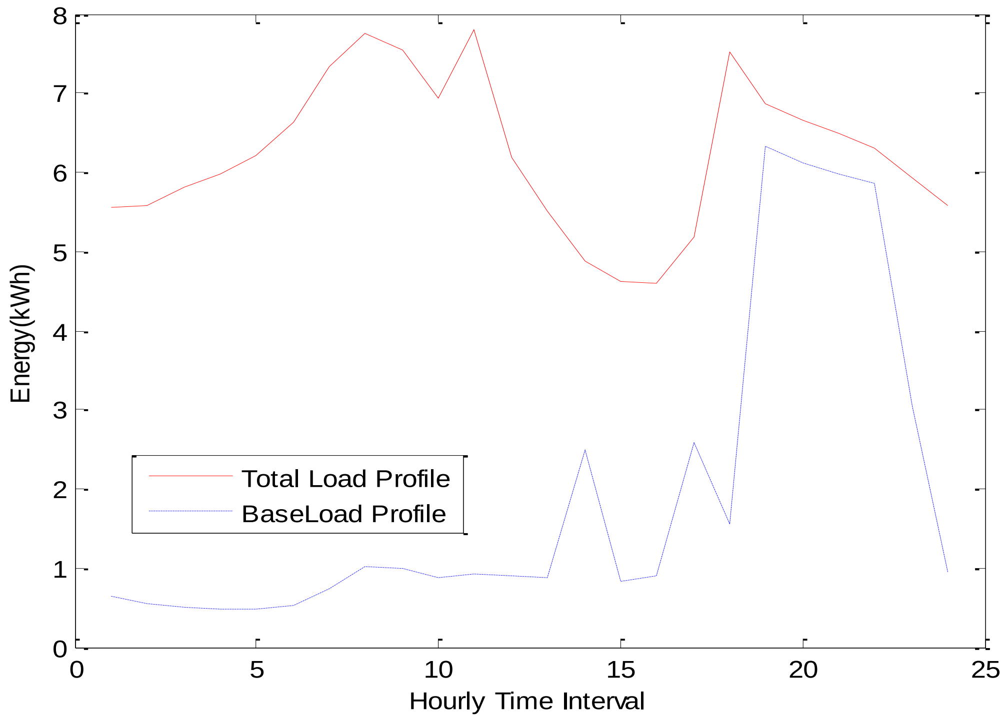

Figure 6.3: Aggregated load profile and base load without price factor

Conversely, there was never any time interval when all appliances are considered to be base loads. This is why the base load profile is completely detached from the total load profile unlike as presented in Figure 6.2 whereby at some intervals, all loads are non-schedulable thereby acting as base loads. It is therefore clear that Figure 6.2 and Figure 6.3 differ significantly depending on the number, as well as significance of the controlling variables used in making the required decisions.

In summary, identification of load characteristics with respect to user behaviour is the first step towards making a decision about what appliance to schedule if an opportunity to schedule load occurs. In this way, user preferences are placed paramount before applying load scheduling algorithms since sensitive loads used at any given time interval are identified and then prevented from the possibility of undergoing load scheduling. The next section is therefore a presentation of the results obtainable when load scheduling is applied on a load profile using GA method, using load profiles that are assumed to have been identified as schedulable loads.

6.3 Managing Discomfort Experienced in Demand Response

The problems associated with participation in DR programs on consumers as indicated by several authors and already discussed in chapter 1, are recognized to be comfort-based. This section shows the results of effective management of load scheduling routines that caters for specific needs of various users by minimizing discomfort associated with load scheduling thereby improving user participation. Profiles of the input data applied are as given in Figure 5.1 and the performance of various discomfort evaluation tests are carried out in three categories which include:

- A case of no discomfort considerations
- A case of discomfort considerations without clipping
- A case of discomfort considerations with clipping.

Figure 6.4 shows the convergence of the fitness function after 3000 iterations whereby the convergence shown is only for a case of discomfort considerations without clipping. Although this convergence is very similar for all cases presented herein, the discomfort axis is not available for the first case since it is conditioned as a case of no discomfort considerations.

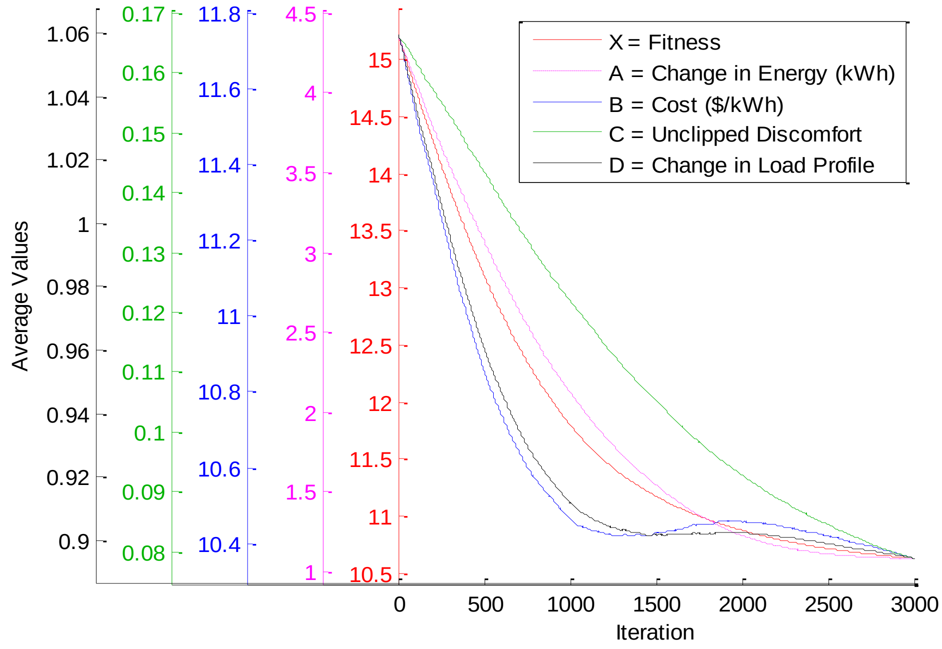

Figure 6.4: Graph of Convergence of variables for discomfort analysis

6.3.1 Case of No Discomfort Considerations

Figure 6.5 shows load profile optimisation using GA, when the discomfort variable is eliminated from the fitness function. It can be observed that at several time intervals on the graph, there exist huge differentials between the optimized and forecast load profiles. Notable among these times is at 01:00

when the difference is over 2kWh despite supposedly having a low standard deviation as given in Figure 5.1. This is because the discomfort function which contains the standard deviation factor was actually not included in the fitness function of Equation 4. This therefore permits the very low price of energy at that time to be the key decisive factor for the scheduler, thereby resulting to a shift of a significant amount of energy to 01:00 hours.

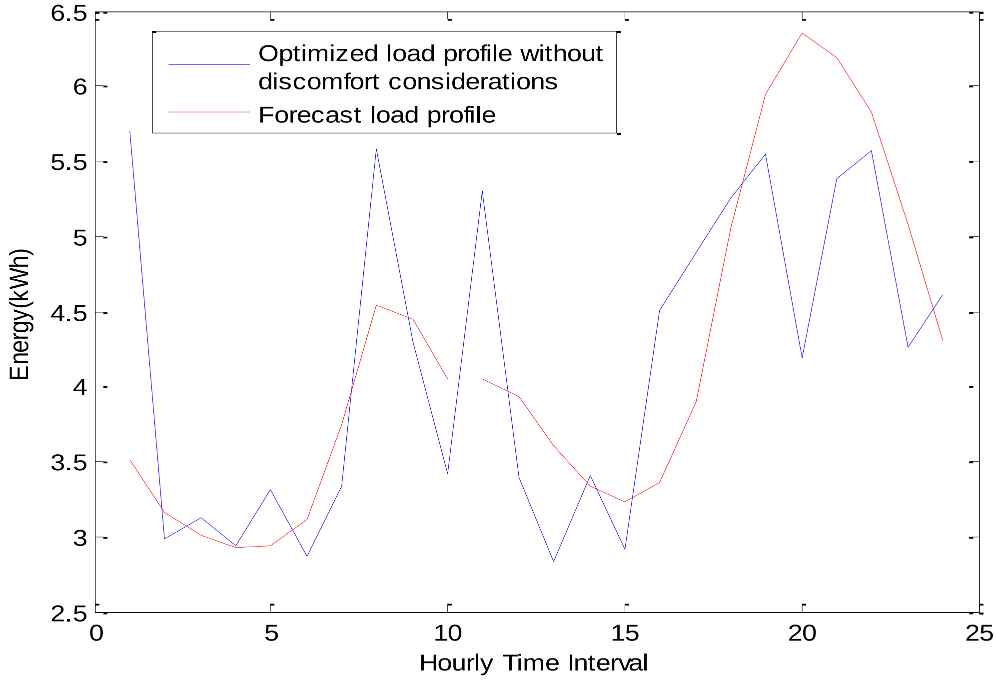

Figure 6.5: Load profiles with no discomfort consideration

This result also shows what several users will experience based on the use of conventional load scheduling algorithms that does not cater for user comfort, and are sometimes controlled from the utility side. At the end of the day, the most likely scenario would be an eventual signing off from DR programs whenever consumers are tired of enduring the huge differentials in load usage pattern, which invariably leads to high discomfort on the users.

6.3.2 Case of Discomfort Considerations without Clipping

Figure 6.6 shows unclipped optimized and forecast load profile data with the implementation of discomfort reduction considerations. Here, the discomfort function is re-introduced in the fitness function of Equation 4 but minimised as given in Equation 18, unlike in Equation 4 where it was maximised (see sign change). It can be observed that there is a significant improvement from the differentials observable between these two load profiles, than as observed in case 1. It is also observable that the large energy gap at 01:00 from case 1 is narrowed, although significant energy variations at 10:00 and 18:00 still exists which the user may or may not consider too excessive depending on their choices.

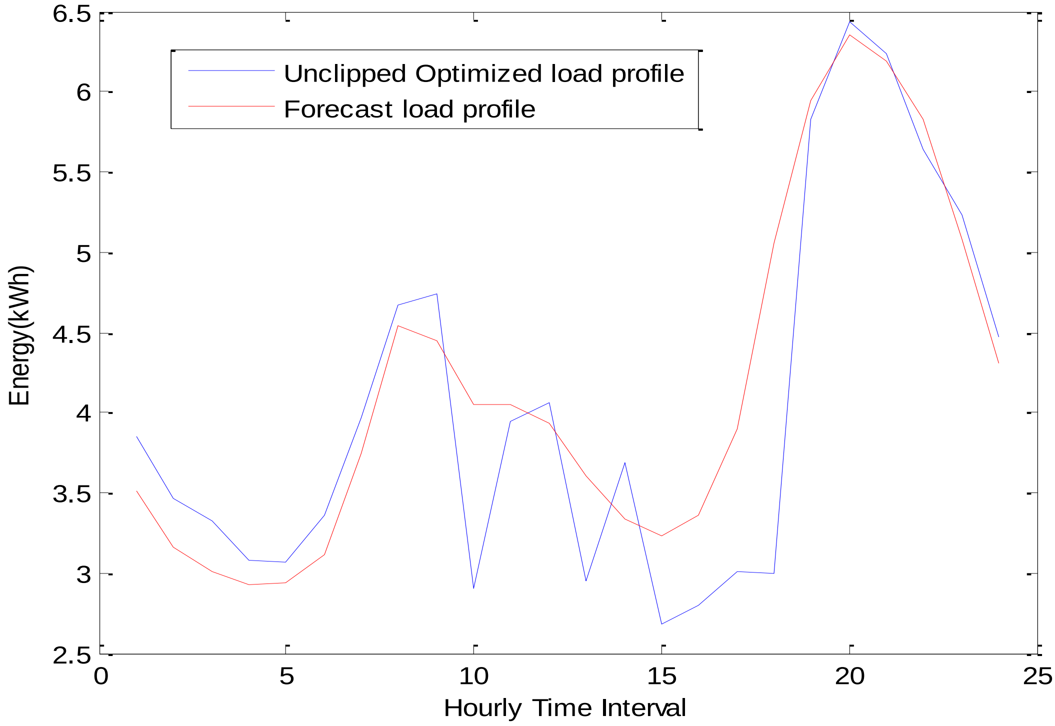

Figure 6.6: Load profiles with no limited discomfort

6.3.3 Case of Discomfort Considerations with Clipping

Figure 6.7 shows a significant narrowing of the gap between 10:00 till about 19:00 hours which is due to the limitation imposed concerning how much energy variation that is allowed due to the discomfort threshold value applied.

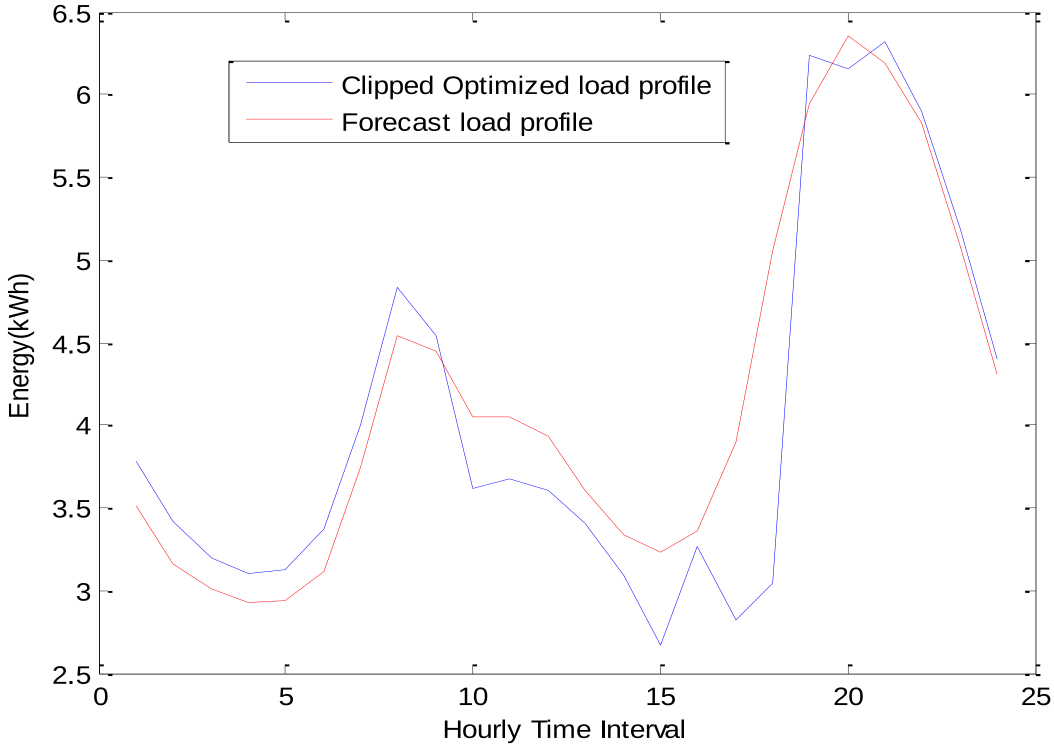

Figure 6.7: Load profiles with limited discomfort

Therefore, the very wide margins after optimisation can be reduced depending on the extent of discomfort limiting imposed. Therefore in this way, the customer can effectively manage their scheduling algorithms more appropriately, and to their specific requirements.

6.3.4 Inferences on the three cases investigated

Having observed the various results obtainable from the three cases, it will be appropriate to examine the results of the magnitudes of the discomfort caused by load scheduling, given the discomfort function of Equation 18. This is shown in Figure 6.8 whereby the graphs of the clipped and unclipped discomfort levels are compared.

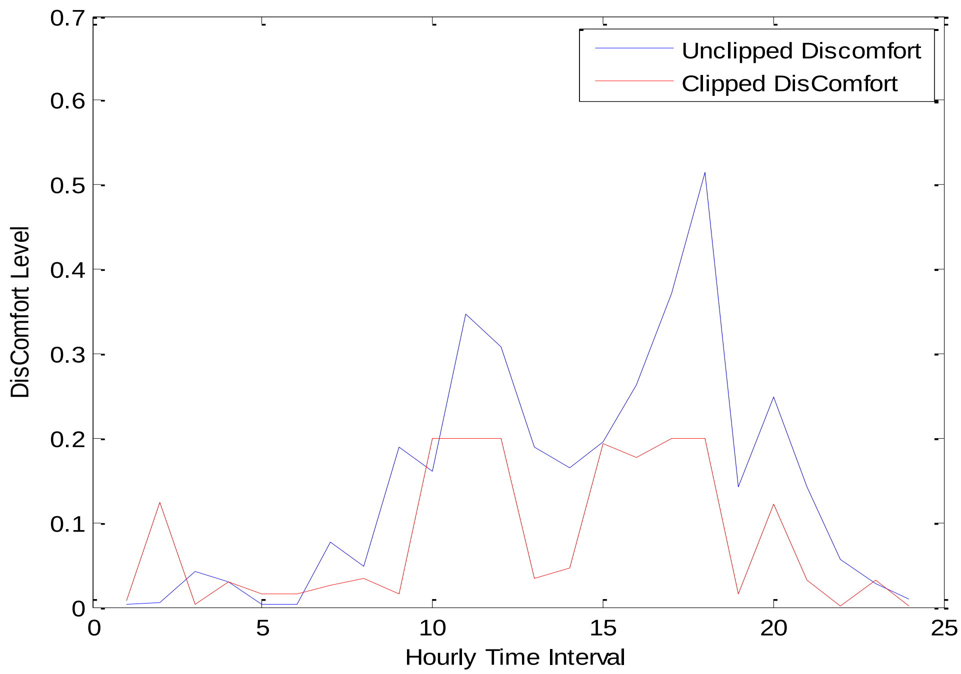

Figure 6.8: Comparison of clipped and unclipped discomfort

The magnitude of the clipped discomfort is at a threshold at 0.2 which represents about 40% of the maximum unclipped discomfort. By observation, it is clear which time intervals are prevented from generating excessive energy differentials as shown in Figure 6.6 but modified in Figure 6.7 based on the user’s choice of discomfort threshold level. The discomfort measure as used here is a novel approach towards improving customer satisfaction while implementing load scheduling, whereby Cases 1 and 2 are used as a control in order to compare with them when the discomfort is clipped.

Although GA takes a considerable amount of time depending on the computational speed of the processor (in this case, up to 3 minutes), it did not affect the system significantly as the results are required to be computed at the end of each day. Results obtained also shows that although a maximum differential of about 60% exists at various time intervals between the optimized and non-optimized load when optimisation is considered without discomfort factor, this differential could be lowered by half with the introduction of the discomfort function. Further results showed that the differential can be lowered much further depending on the user's choice. In as much as one can lower the discomfort threshold line as desired, it is also important to note that lowering this threshold reduces the savings in energy cost accruable to customers who participate actively in DR programs.

6.4 Evaluation of user participation in Demand Response

These experiments observes the causes to the inconsistencies that undermine active user participation in DR programs over a period of time. It also shows how behaviour modification can influence energy costs, while not necessarily having to alter energy consumption levels in any given time. In this section, an evaluation of user participation is achieved which shows how utility providers may be able to understand their consumer behaviours more effectively by the evaluation of UPI using fuzzy logic which can enable such energy providers to set their priorities as appropriately as desired. The method presented in this work as discussed in section 4.6 shows evaluation of consumer energy consumption behaviours whereby information obtained can be useful in designing grid network with improved active user participation in DR programs. Fuzzy logic method is a relatively straight forward approach to achieving this goal due to the ease of designing the respective membership functions. Results obtained are therefore discussed herein.

6.4.1 Comparing Two Households for Participation in DR

Two households were compared by obtaining a 2-day energy sample for each household and their corresponding standard deviations in order to evaluate their respective HPI and UPI participation. These data are as given in Figure 4.1 and Figure 4.4. A threshold of 50% of the per unit measurement is also applied while following the rest of the routine as presented in the model for Boolean evaluation system such that Figure 6.9 is obtained. The Hourly Performance Index (HPI) of each household is shown whereby Household-1 which is derived from Figure 4.4 has 22 hours of Fair HPI with 2 hours of GOOD HPI, while Household-2 which is derived from Figure 4.1 has a mixture of POOR, FAIR and GOOD HPI. Also, the day ahead dynamic pricing used is as given in Figure 5.1. at this stage, it may be difficult to ascertain which of the two households performs better than the other because, although Household-2 has several GOOD HPI's the POOR HPI's may degrade its overall performance.

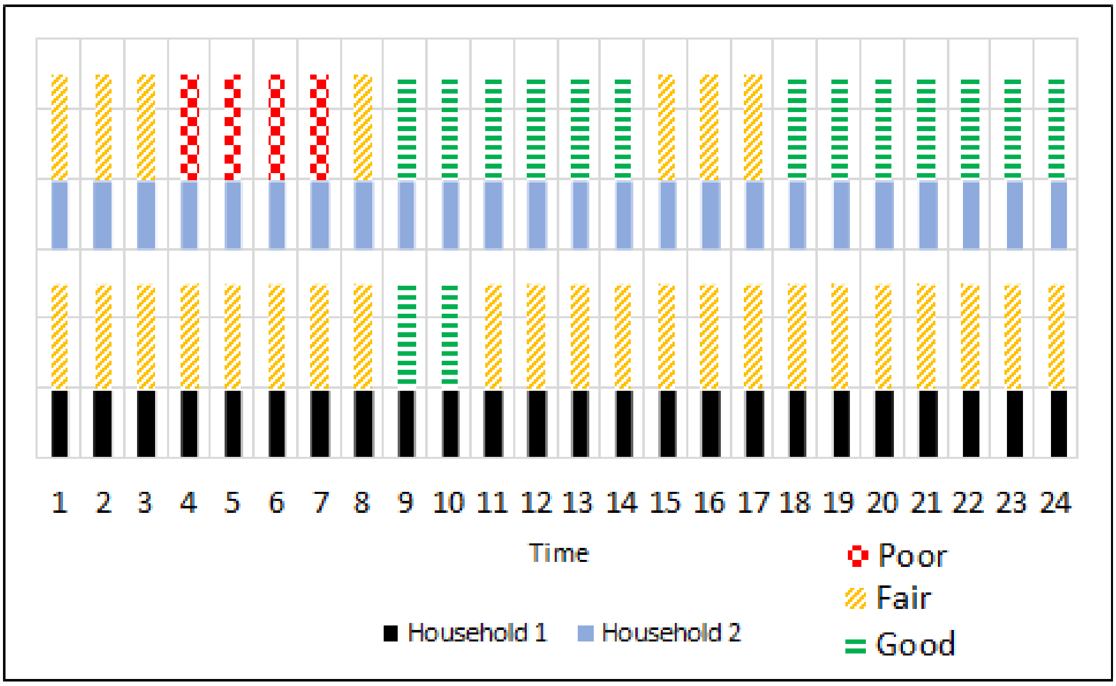

Figure 6.9: Activity profiles for 2 households over a 24-hr period

Interestingly, the next section is able to clear this ambiguity. Furthermore, it is worth noting that the threshold line plays a key role in determining the HPI values because it was observed that if the threshold line is lowered, the HPI values improve and vice versa. For instance at reduced threshold of 30% per unit threshold for both Price and STD data, Household-1 has 12 hours of Good HPI and 12 hours of Fair HPI, while Household-2 has 20 hours of Good HPI, 4 hours of Fair HPI, without any Poor HPIs (Figures not shown).

Furthermore, using the fuzzy rules as given in Table 4.8, while following the rest of the routine as presented in the model for Boolean evaluation system, the UPI profile evaluated for every hourly energy use for both households is shown in Figure 6.10. For Household 1, the average UPI value is 55.2% while the average UPI value for Household 2 is 64.6%.

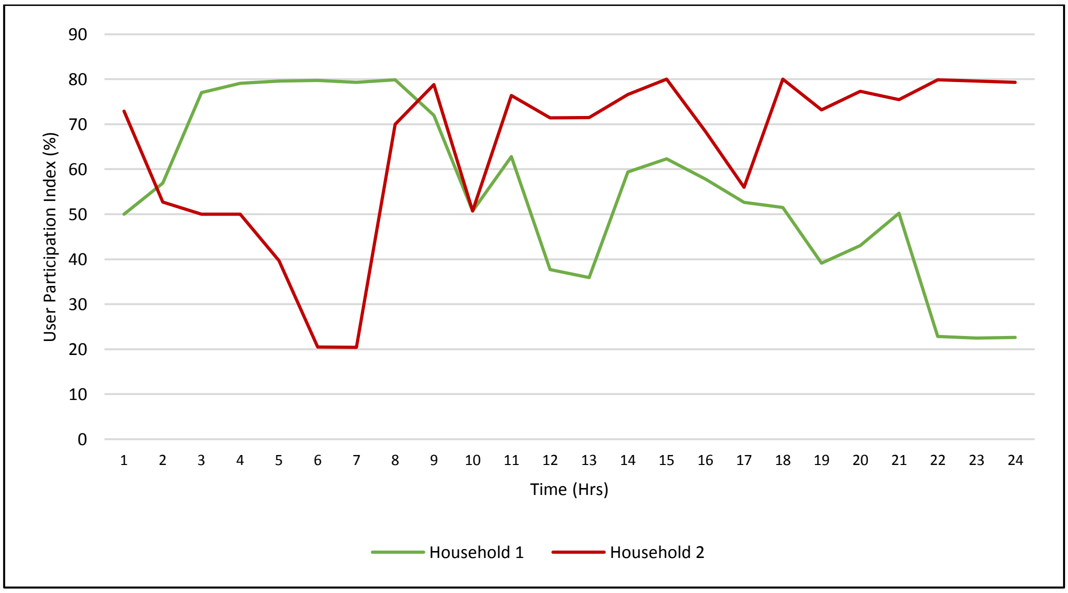

Figure 6.10: User Participation Index profiles for households 1 and 2

Theoretically, households with higher UPI values indicate more active participation in DR programs than those with lower UPI values. This is a similar result obtained in Figure 6.9 hence; occupants in Household 2 are comparatively better customers who participate in DR programs than those in Household 1. This is the key outcome of this research because it indicates clearly how any of the two techniques can be used to identify such important information which can be useful in understanding the weak link in DR participation within a community or a micro grid.

6.4.2 Verification of Results: Case studies

The results obtained and evaluated are based on non-probabilistic approach for both methods of evaluation systems applied. To be able to verify this, the results of the HPI and UPI for both households are compared against when probabilistic approach is used. The details of this approach is as already discussed in section 4.6 and the essence of this comparison is to observe the performance of each household in order to validate the theoretical suggestion that users in Household 2 are more active DR participants than users in Household 1.

Case 1: Probabilistic analysis for household 1

With reference to the methodology as discussed in section 4.6.1 which included the application of probability of appliance use (PAU) for identifying schedulable or non-schedulable loads, the input details of Household 1 was used in order to observe the proportion of time intervals when load scheduling could occur.

The resultant graph shown in Figure 6.11 comprises of the entire load profile as well as the base load profile. It can be observed that the intervals when load scheduling is possible is narrowed which is only between 9:00 hours and 10:00 hours thereby implying that fewer appliances can be scheduled under the conditions used in the experiment.

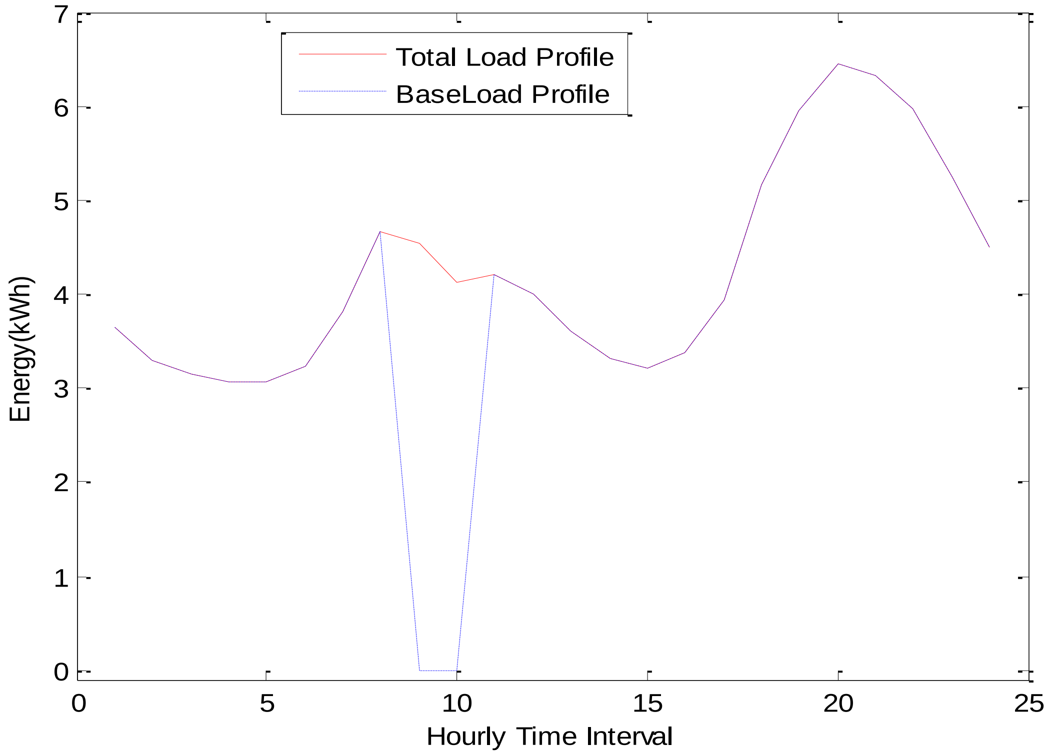

Figure 6.11: Aggregated load profile and base load for household 1

Case 2: Probabilistic analysis for household 2

On this occasion the same technique was applied, but by replacing the input data with the details of Household 2 and then generating the response graphically as shown in Figure 6.12. Here, there exists considerable interval where load scheduling can take place which is approximately between 8:00 hours and 14:00 hours, as well as 18:00 hours till midnight. This means that the intervals where scheduling could not take place are mainly in the early morning as well as in mid-afternoon. But when compared with the results from case 1, it shows that under the same pricing conditions, users in Household 2 has the tendency to engage more actively in DR programs than users in Household 1.

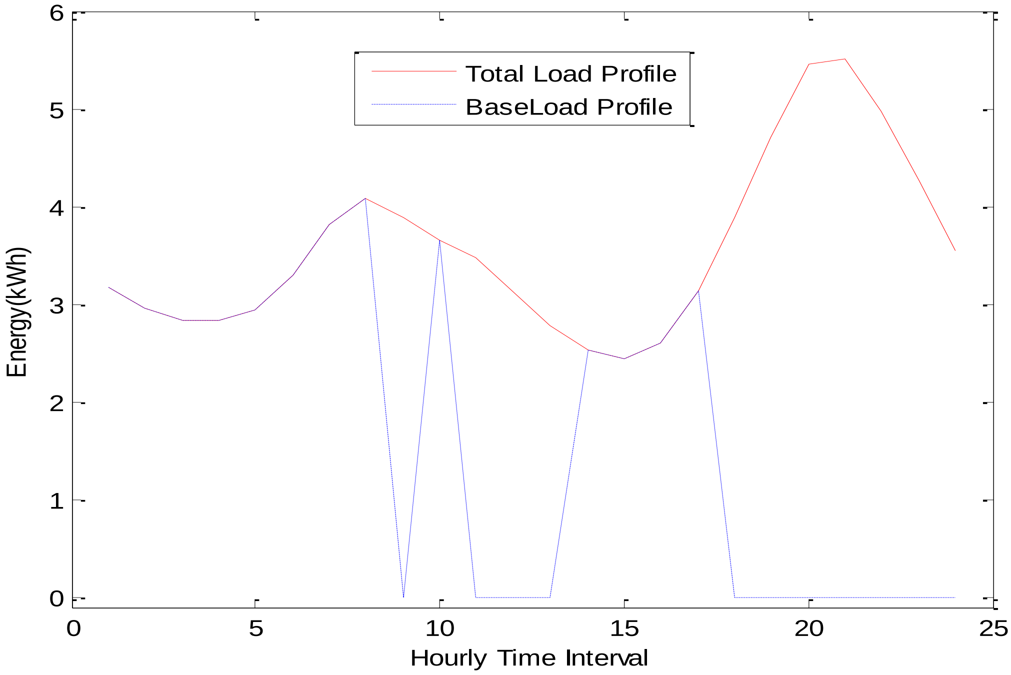

Figure 6.12: Aggregated load profile and base load for Household 2

Finally, more households within the same community are considered in order to evaluate their respective performances in DR participation. Figure 6.13 shows the performances of 10 households whereby Households 1 and 2 with UPI of 55.2% and 64.6% respectively, are the samples already discussed herein.

It is observable that participation of Household 3 in DR programs is significantly Poor (UPI < 40%) which means that the occupants may not be interested in DR participation and persuading them may not yield any reasonable result. On the other extreme lies Households 2 and 9 who are the only Active participants available (UPI > 60%). The rest of the households which constitutes of 70% of the households within the community are Average and they can be encouraged to improve their participation levels. In this way, a better energy management schedule could be designed in order to improve energy efficiency within the grid.

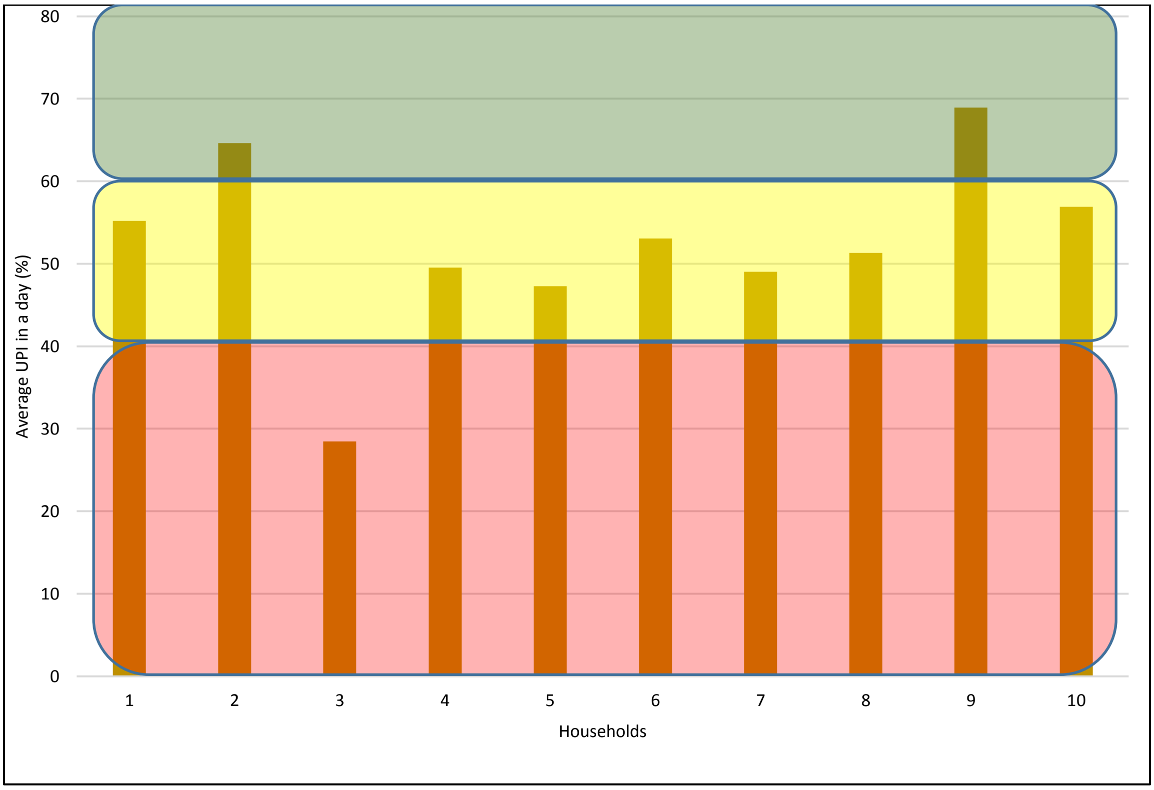

Figure 6.13 Performances of 10 Households in DR Participation

On the other hand, Figure 6.14 shows the hourly participation index of the ten households which shows that most of them are poor participants from early morning up till 8:00 hours. This is expected since fewer but dedicated appliances are usually ON at this time such as refrigerators, security lights and all loads that are usually left all through the night. Household 3 is shown to have the least activity while the best is Household 9 hence, thereby complementing Figure 6.13 results.

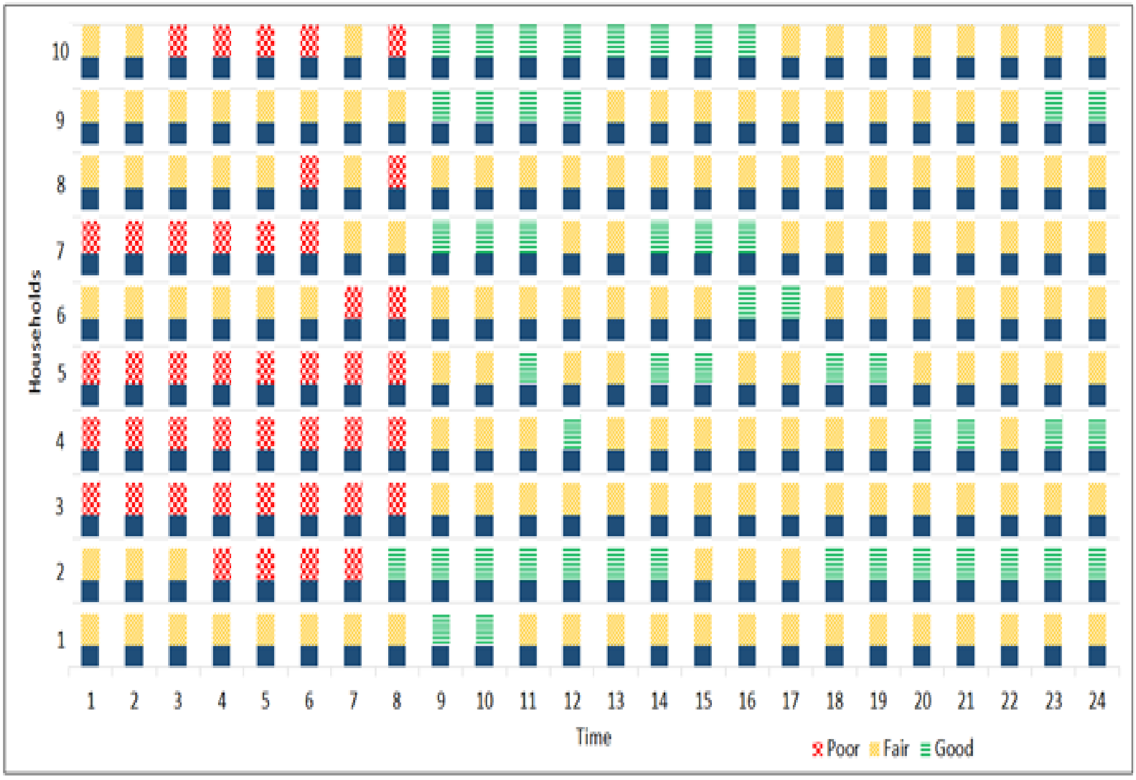

Figure 6.14: Hourly Performance of 10 Households in Demand Response

6.5 Chapter Summary

This chapter has shown the importance of using standard deviation of load profiles in various analytical applications for understanding user behaviours. This is because data with historical statistical contents tend to provide information that is useful in forecasting applications which makes it ideal for modelling user behaviour as desired in this research. The result of such usefulness as used in this work includes the application of user comfort considerations, identification of schedulable and non-schedulable loads, as well as evaluation of user participation capabilities. Understanding user behaviour is the basis of these considerations such that a design of an appropriate future smart home application can be made. Results showed that a particular appliance which behaves as a schedulable load at certain times, could become a non-schedulable load at other times, even within the same day. This relativity is important to helping load optimisation algorithm to understand the user and only apply load scheduling at the user’s convenience thereby helping to minimize discomfort. Discomfort is also reduced by directly selecting a choice threshold level as desired by the user.

Finally, this chapter shows the importance for the utility to evaluate consumers based on their potentials to participate in DR programs. Ideally, users with high UPI do not need any persuasion to participate based on the merits of their high participation levels but those with low UPI are open to being encouraged to increase their participation levels. This may be in form of increased marketing of incentive offers such as bonuses, assuming their participation levels exceed a certain threshold.

The next chapter is therefore, a detailed description of the research methodology applied in achieving various models of cyber-attacks on a future smart home. This is modelled within the context of the testbed proposed as discussed in Chapter 3 and also using the fitness function as well as the same algorithm as presented in Chapter 4. The aim is to be able to modify relevant aspects of the fitness function and then run the algorithm in order to observe the impact on the results obtained which can in turn affect user participation in DR programs assuming they received irregular load profiles due to cyber-attack.

Chapter 7: Cyber-Attack Modelling

7.1 Introduction

Cyber-attack is a familiar experience to internet users since the commercialization of internet services and operations. As in the real world, similar criminal activities are carried out by people who have capitalized on the vulnerabilities of data transferred over the internet for their own selfish needs. The realization that information transferred via the internet can be hacked, harvested and compromised, has offered intruders alternative ways to invading peoples' privacy without having to physically step into their premises. As a result, the evolution of the traditional power grid network system to a smart grid network, which fundamentally utilizes communication and data transfer infrastructure that many people have access to, has to ensure there are adequate security measures in order to deter intruders from disrupting the network and wrecking people's lives.

Several factors can encourage cyber-criminals to consider hacking into people's privacy but the commonest reasons seem to be just for fun, intending to prove a point that they can hack a new system or simply because they just want to bring down an organized system [116]. They usually find or stumble on the flaws in an existing design and then exploit these deficiencies. Sometimes information harvested from unsuspecting victims are sold to a third party for some monetary value, and this is one of the occasions whereby cyber-criminals trade directly the username, passwords, phone numbers and several other personal details of online users in the so called “dark web” [117]. Other forms of menace from cyber criminals can include but not limited to internet fraud, cyber-bullying and blackmail. This therefore leaves the energy grid itself as a matter of national security if it becomes attacked and at the end of the day, their activities turn out to be a pain not only to the users of such systems but also to the designers as well. Companies oftentimes do respond to this threats by rewarding those who help find security flaws on their own systems [118].

A case of cyber-attack in October 2016 when a Distributed Denial of Service (DDoS) attack knocks heating system offline in at least two housing bocks in the city of Lappeenranta in Finland, leaving their residents in sub-zero weather conditions. In an attempt to fight back the attack which was only short-lived, the automated systems rebooted which unfortunately got stuck in an endless loop that kept restarting and shutting down. This scenario lasted for over a week but returned to normal service by 3rd November afternoon [119]. Therefore, as much as researchers are working hard every day to improve living standards as well as efficiency of system designs, criminals are also attempting and finding ways to interfering with these systems thereby sabotaging and frustrating their operations. Cyber-attack is a persistent threat to internet users and if it is not a case of virus attack, it could be DoS or a phishing attack. In this theme, the focus of cyber-attack is on the consumer side of the smart grid within a liberalized energy market as well as within the emerging HEMS.

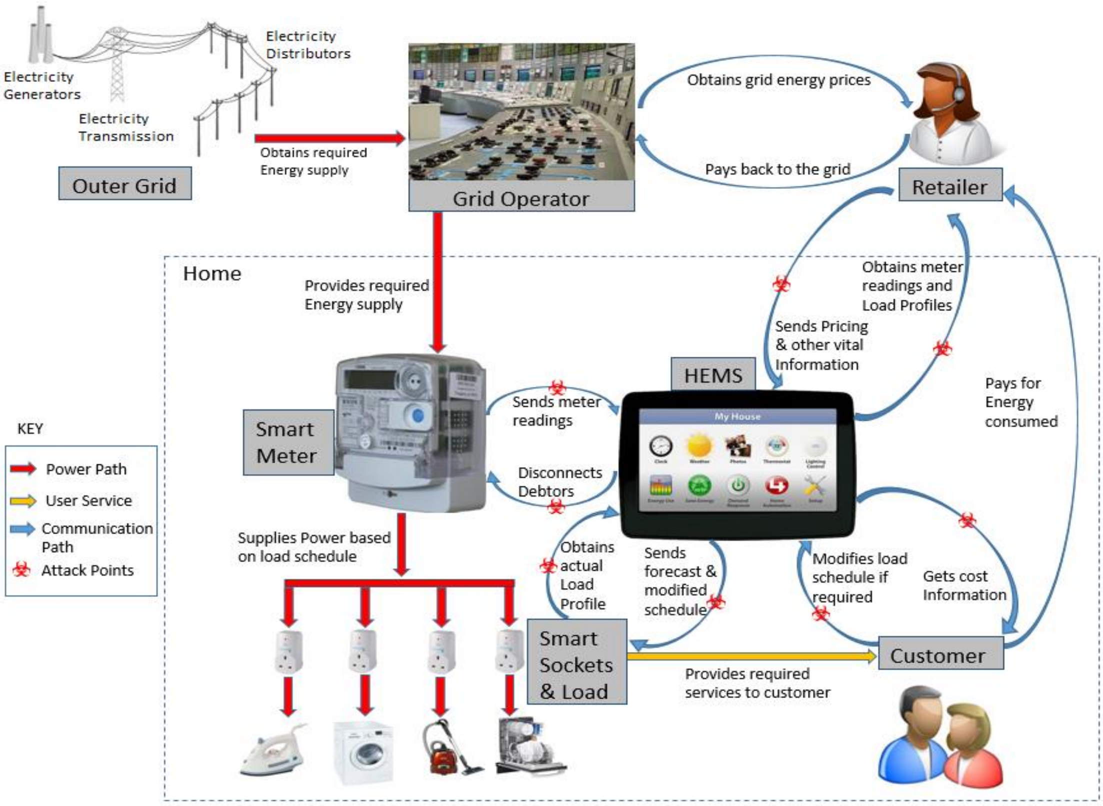

Figure 7.1: Schematic for Smart HEMS Showing Possible Attack Points

Figure 7.1 is a schematic for the HEMS that show various communication lines and various possible attack points within the architecture proposed. Attacks on the pricing data as well as on the load profile are considered, under attack scenarios such as DoS and phishing attacks. While DoS attack involves the congestion of data traffic to the HEMS thereby making it difficult for the actual data to arrive, phishing attack involves much more which includes having access to important personal details of a victim such as usernames and passwords [120]. By masking and pretending to be a trusted organization, fraudsters can get the customers to give up their login details with which they can have access to the personal information within the household.

As soon as an access is obtained onto the network, further information such as load profile, occupancy, historical data and every other personal information available to the HEMS can be accessible by the attacker and the contents of this data can be modified or replaced. If such an attacker gains access to the household, they can use sophisticated software to modify and override the entire input variables to their choice. This could lead to the generation of the worst possible load schedules which may lead to reduced profit margin or possibly losses as well, when compared to the schedule without attack.

In any smart home, the attack vector to a load profile data stored in the HEMS is via the communication network that connects the HEMS to the internet. This connection provides the connection that enables the HEMS to obtain pricing data online as they are published by the energy providers. Unfortunately, this invariably exposes the communication link to become a target for an attack of which cyber-criminals could break into. This is where appropriate security design should be enforced because as much as the load profile data is vulnerable; virtually any data on the HEMS can be attacked.

Due to the vulnerabilities of devices connected online especially as more devices are connected via IOT, the risks posed by cyber attackers is a continuous threat to users who participate in active DR programs. In as much as reactive response may become inevitable after which an attacker has left the victim counting their losses in the aftermath, proactive response to cyber-attacks is usually the best way to arrest an attack scenario. This section will analyse a simulated impact of various possible security incidents within the smart home network for users who participate actively in DR programs assuming such attacks by any means, becomes successful. The aim is to demonstrate an applicable response which is incorporated in the original smart home design thereby ensuring a proactive response to cyber-attacks. Each model of the various possible cyber-attacks is simulated in order to investigate the impact of such attacks on the localized scheduler. Pricing is an important input variable but also vulnerable because several scheduling activities are usually concerned around energy cost savings thereby making them an attacker's target [7]. Therefore, the scope for this analysis is focused on any of the numerous communication links around the HEMS as shown in Figure 7.1, whereby possible attacks on the network is investigated for pricing as well as on load profile data.

Finally in the proposed approach, a household whose inhabitants are active DR participants are presumed to have received a load schedule of which they are prepared to abide with, before a specific attack is carried out. The objective function as given by Equation 4 is optimized using GA where the input variables are as defined in Table 4.1. Various possible attacks are observed to affect specific aspects of the input variables depending on the type of attack assumed, thereby enabling a nullification or modification of the affected input variable in order to emulate the simulated attack. In this way, the impact of the respective attack on the scheduled load profile can be observed. The modelled attack scenarios are broadly divided into the following sections:

- Cyber-attack modelling and protection schemes on price profile
- Cyber-attack modelling and protection schemes on the load profile

7.2 Cyber-Attack Models on Pricing Data

The attacks on pricing data are categorized under: DoS Attack, Constant-Pricing Attack, False Data Interference as well as Data Manipulation Attack. The results from this analysis are compared with the normal scheduling operations which is used as a control to show an attack-free optimisation with secured data, in order to ascertain the impact each of these attack models could have on the household.

7.2.1 Denial of Service Attack

A typical DoS attack is initiated when an attacker deliberately generates multiple requests from his device to a target via a single protocol, thereby causing an impediment on data traffic and preventing the target from accessing their data online. Alternatively, the attacker can generate multiple requests through some master computers to the slave computers while pretending to be the victim computer as shown in Figure 7.2. The slave computers not recognizing the source of the request command presumes that all requests came from the victim computer and in an attempt to respond to those requests, they end up causing an unprecedented traffic and delays on the victim's computer.

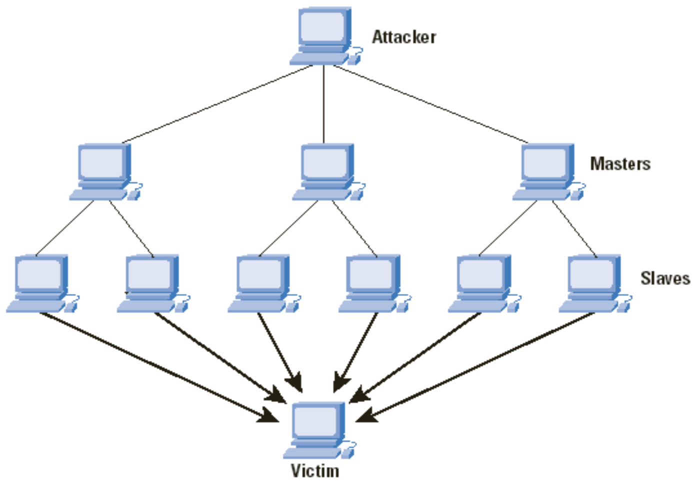

Figure 7.2: Distributed Denial of Service Attack on a Victim

Such requests are usually too massive for the server to withstand and any such attack on the pricing information is capable of preventing the load scheduling algorithm from accessing the pricing data required for load scheduling. The consequence of this attack is the unavailability of the pricing details for the fitness function and in this way, the impact on the convergence of the scheduled load profile can be observed. Mathematically from Equation 4, given the cost B, as a variable of the fitness function F, Total Energy Cost per day according to Table 4.1, is given as:

$$B = \mathrm{D}_{P_{t,1}} * \sum \mathcal{E}_{P_{t,n}} \tag{25}$$

Where:

$\mathrm{D}_{P_{t,1}}$ = Dynamic price

$\mathcal{E}_{P_{t,n}}$ = Energy Consumed

$\forall t \in \{1, 2, \ldots\ldots 24\}$ Hours.

For a DoS attack, Price = nil (Pricing data is delayed or unavailable)

Then from Equation 25,

Total Energy Cost per day = $w_b * 0 * \sum \ \mathcal{E}_{P_{t,n}}$

Therefore for a DoS attack, Equation 4 becomes:

$$F_{j,i} = w_a{}^* \sum A_{j,i} + 0 - (w_c{}^* \sum C_{j,i} + w_d{}^* \sum D_{j,i}) \tag{26}$$

7.2.2 Constant- Pricing Attack

Several domestic load scheduling models are implemented using dynamic pricing regimes which help to respond and balance the market forces of demand and supply. Higher prices are usually expected during high energy demand or during high cost of energy generation. Therefore, the domestic load scheduler requires adequate pricing model which reflects the current market scenario as accurate as possible in order to make an informed decision towards load scheduling. But if for any reason the pricing data being fed to the scheduler turns out to be a fixed pricing model, there could be consequences. Reducing a dynamic pricing regime to a fixed pricing signal could be a consequence of an unsecured network hijacked by a cyber-attacker. In order to model this attack, Let Constant Price factor = Υ_t.

Then from Equation 25,

Total Energy Cost per day, B $= \Upsilon_t * \sum \ \mathcal{E}_{P_{t,n}}$

Therefore for a fixed pricing attack, Equation 4 becomes:

$$F_{j,i} = w_a * \sum A_{j,i} + w_b * {}'\Upsilon_t * \sum \mathcal{E}_{P_{t,n}} - (w_c * \sum C_{j,i} + w_d * \sum D_{j,i}) \qquad (27)$$

7.2.3 False data Injection Attack

A cyber-attack on the dynamic pricing information can occur in form of an interference occasioned due to the injection of false data on the actual pricing signal. The aim of this sort of attack can be to cause the generation of random and unpredictable results thereby presenting a scheduled load which is not a true reflection of the market events. The unpredictability of the output is important because this type of attack could be difficult to detect since different types of results can be generated each time the algorithm is run. Let us consider an attack scenario whereby the dynamic price signal is injected with some discrete randomly generated false data η_t to create some form of distortion thereby creating a new price profile R_t. The new price profile R_t is given as:

$$R_t = D_{P_{t,1}} + \eta_t \qquad (28)$$

Where:

$\forall t \in \{1, 2, \ldots\ldots 24\}$; Hours

A variation of false data levels introduced is evaluated and a maximum false data level of up to 20% of the maximum dynamic price (signal) value is assumed. Therefore by definition, R_t is bound by a maximum allowable proportion of the actual pricing signal for only positive pricing values as given in Equation 29.

$$\mathrm{D}_{P_{t,1}\,\mathrm{min}} \leq \mathrm{R_t} \leq 1.2\mathrm{D}_{P_{t,1}\,\mathrm{max}} \tag{29}$$

The actual day-ahead pricing data was obtained from [113] and 20 iterations of increasing false data levels were incremented in a step-wise manner from zero up till 20% of the maximum price value.

Therefore, Let Price with false data $=\mathrm{R_t}$; Then from Equation 25,

Total Energy Cost per day, $B = R_t * \sum \mathcal{E}_{P_{t,n}}$

Therefore for a fixed pricing attack, Equation 4 becomes:

$$F_{j,i} = w_a * \sum A_{j,i} + w_b * R_t * \sum \mathcal{E}_{P_{t,n}} - (w_c * \sum C_{j,i} + w_d * \sum D_{j,i}) \tag{30}$$

7.2.4 Data Manipulation Attack

This attack scenario is modelled by rearranging the data of the dynamic pricing information to create new price profiles which is similar to the original pricing data but differs in their respective times of occurrence. The aim of this rearrangement is to cause the HEMS to follow a false schedule which is intended to lead to more expensive energy costs when applied by the HEMS. Four categories of this attack are presented of which the original price profile is also used, but as a control. The essence of this type of attack is based on the presumption that attackers may decide not to introduce any external data to disrupt the input variables but would rather scramble the original data with the aim of evading any security check which is capable of detecting changes in original data set, but not the scrambled original data. Manipulation of pricing data is of interest and four models are considered. These are shown in Figure 7.3 and Figure 7.4 whereby the original price profile has prices which range between $2/kWh and $4.5/kWh and the other 3 samples also have same price ranges aimed at helping in masking the true price profile. These samples are referred to as:

- Original price profile
- Flipped price profile
- Inverted price profile
- Flipped and Inverted price profile

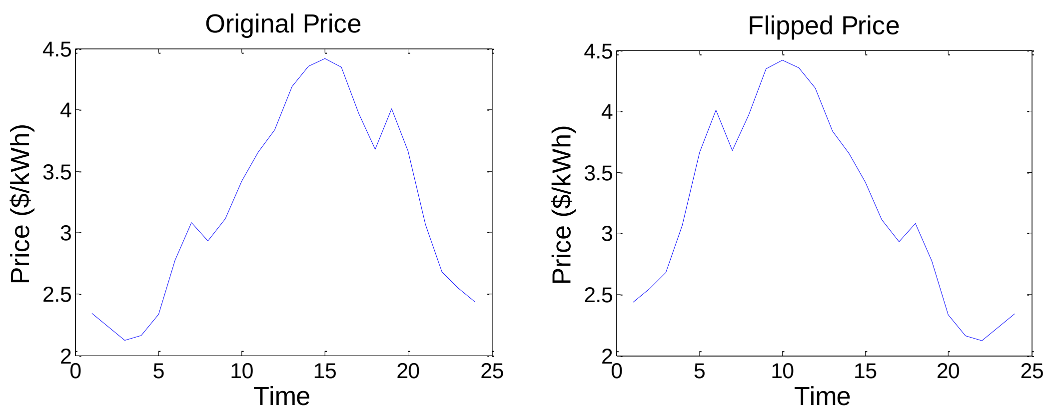

Figure 7.3: Price Profiles showing Original and Flipped price

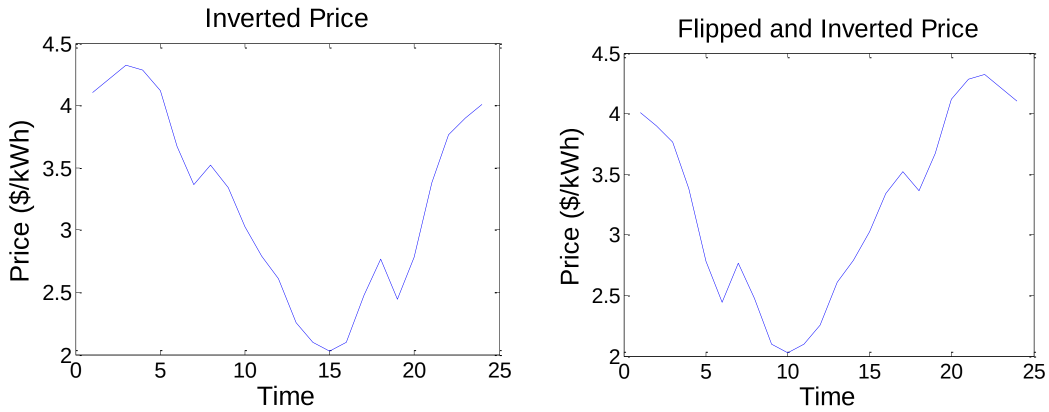

Figure 7.4: Price Profiles showing Inverted and Flipped-Inverted Price

The attacker can use any of the attack samples although it is expected that different samples are capable of generating different load schedules with varying losses, when compared to the savings accruable if the original pricing sample was used for scheduling. In order to model this attack;

Let the Imposed Price =β,

Then from Equation 25,

Total Energy Cost per day = $\beta_t * \sum\ Ɛ_{P_{t,n}}$

Therefore for an imposed pricing attack, Equation 4 becomes:

$$F_{j,i} = w_a * \sum A_{j,i} + w_b * \beta_t * \sum\ Ɛ_{P_{t,n}}\ - (w_c * \sum C_{j,i} + w_d * \sum D_{j,i}) \quad (31)$$

The lists presented herein are not exhaustive and can be directed towards any input variable on the load scheduling algorithm. Furthermore, the definitions to the variables of Equation 31 as well as Equations 26, 27 and 30 are same for Equation 4 as described in Table 1 with the exception of the cost variable which is subjected to cyber-attack. Hence the cost variable was substituted with the specific model of cyber-attack as already discussed in this section. The concluding section is based on modelling attack scenarios on load profile data on the HEMS.

7.3 Cyber-Attack Models on Load profile Data

Load profile can be described as a graph of the variation in electrical load consumption within residential, commercial and industrial consumers. It can vary with ambient temperature as well as seasons over a period of time. Some of its uses includes assistance in determining energy allocation and planning benefits depending on how much power is available for distribution as well as where the priority lies during peak and off-peak periods. A forecasted load profile is usually obtained from historical load profile data and it is very useful whenever it is required to be used for planning purposes. The emerging HEMS is an invaluable tool for use in designing load scheduling algorithms which is used to propose a futuristic scheduled load usage for consumers for improved grid balancing and reduction of consumer’s energy costs. This means that load profiles are invaluable and any successful attack can disrupt power supply and disrupt the network by producing inaccurate results as well as invalidating the outcome of the proposed load allocation and efficient energy planning schedule.

The model of attack on Load Profile is described as an injection of false data on an original load profile data with the aim to cause the creation of random and unpredictable results thereby presenting a scheduled load which is not a true reflection of the consumer's choice and the market events. By attacking the load it is expected that a direct impact will be is primarily felt on input variables A, C and D of Equation 4, because they are the variables that have load data as a component. By modifying the affected input variables as they relate to the attack on the load, the impact on the scheduled load profile is observed as the optimisation process is run. The results are thereafter compared with the normal scheduling operation which is used as the control to show an attack-free optimisation1 with secured data, in order to ascertain the impact of the attack on the household as well as the grid.

An attack scenario is considered whereby the forecast load profile $\varepsilon_{f_{t,n}}$ is injected with some discrete randomly-generated false data η_t to create some distortion which in turn results to a new forecast load profile. The new load profile q_t, over a 24 hour interval is given in Equation 32.

$$q_t = \varepsilon_{f_{t,n}} + \eta_t \tag{32}$$

The false data signal can also be a sinusoidal wave form, which may be out of phase with the original signal. Any amount of false data injection is possible although it is assumed that the maximum false data that can be introduced is up to 100% of the mean load profile value. By definition, q_t is bound by a maximum allowable proportion of the forecast load profile and for only positive load profile values given as:

$$\mathcal{E}_{f_{t,n}\min} \leq q_t \leq 2\mathcal{E}_{f_{t,n}\max} \quad (33)$$

The load profile data was obtained from [110] and 10 iterations of increasing false data levels from zero up till 100% of the mean load value was introduced. In order to derive the corresponding objective function, the new load profile q_t as it affects A, C and D is substituted in Equation 4, to produce Equation 34 as shown:

$$F_{t,i} = w_a * \sum A_{new_{t,i}} + w_b * \sum B_{t,i} - (w_c * \sum C_{new_{t,i}} + w_d * \sum D_{new_{t,i}}) \quad (34)$$

Where:

$$A_{new_{t,i}} = (q_t - x) * H_c \quad (35)$$

$$C_{new_{t,i}} = (q_t - x) / \sigma \quad (36)$$

$$D_{new_{t,i}} = x / q_t \quad (37)$$

Modifications of Equation 4 are a consequence of cyber-attack and the corresponding equations are carefully deduced to represent each attack model.

Results of the various optimized load profiles generated are presented in the subsequent chapters where each of the modified versions of Equation 4 representing specific attack is presented.

7.4 Chapter Summary

In this chapter, the means to having a secure future smart home such that any intended cyber-attack can be identified and therefore prevented, in order to achieve a more robust system design. Equations 26, 27, 30, 31 and 34 are effectively the key equations applied which substituted Equation 4 and the essence of this subsection is based on the need to be able to understand how best to prevent or minimize the impact of an attack which is only possible when detailed performance of the operations of the HEMS is carefully studied and understood. The attack methods listed are not exhaustive, which means other attack mechanisms are possible. However, the key essence of this chapter is to be able to demonstrate a means of investigating various attack models so that thwarting them can be possible.

The next chapter will be a presentation of simulated results for a robust system design which is capable of identifying, recognising and responding autonomously to possible cyber-attacks on the HEMS design for improved performance as well as sustained user participation in DR programs. This includes attack on both the pricing data as well as on the forecast load profile.

Chapter 8: Results of Cyber-Attack Impacts and Mitigation

8.1 Introduction

A robust design of the HEMS within the smart home is based on the ability of the system design to withstand cyber-attack which is capable of compromising the normal working operations of the HEMS, thereby jeopardizing the continued user participation in DR programs. With several attack models as discussed in Chapter 7, the HEMS is expected to evade being trapped as a result of any form of these attacks so that adequate response will be applied while not necessarily having to wait for the user themselves, to effect the correction. While various types of attacks on the HEMS are possible, specific attack scenarios are considered, modelled and are discussed under the following themes:

- Attack on pricing data, which include:
  - Denial of Service (DoS) Attack
  - Constant-Pricing Attack
  - Data Manipulation Attack
  - False data Injection Attack on pricing data
- Attack on forecast load profile data which includes:
  - False data injection attack on forecast load profile data

Each attack discussed can affect specific targets on the input variable as discussed in Chapter 7. Results of various simulated attacks and the corresponding means of correction are presented in this chapter which effectively shows the means of ensuring the design of a reliable system.

8.2 Cyber Security Strategies: Attack on Pricing Data

The input variables used for the simulated results are as shown in Figure 8.1 whereby the details of the pricing data, standard deviation of the load profile as well as occupancy profile are provided. This is different from the data used in the previous chapters since any data sample is capable of generating results.

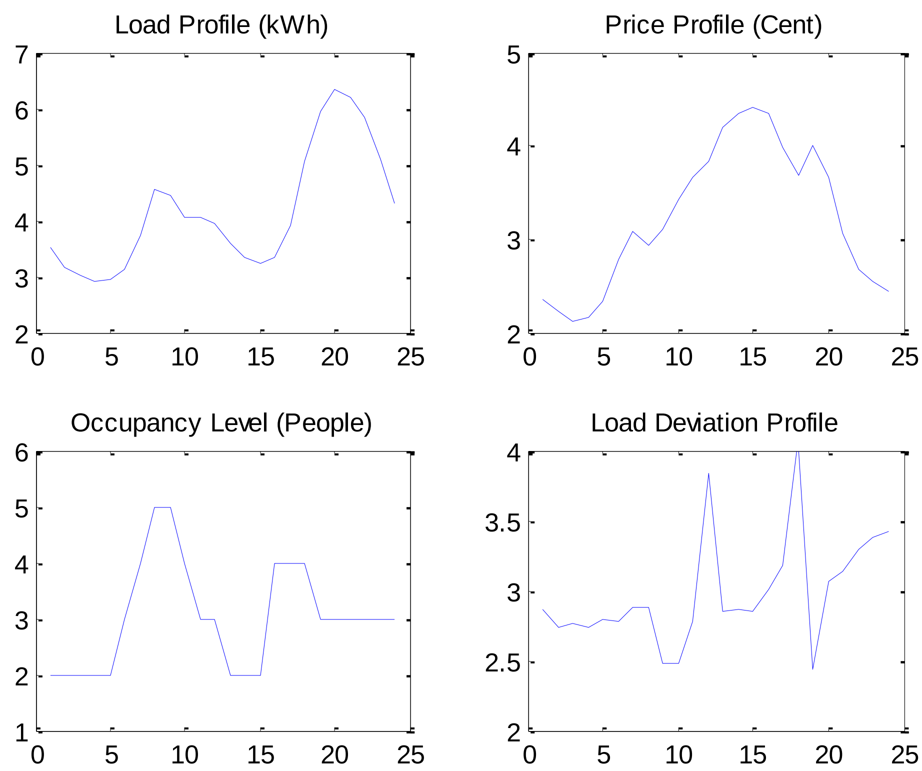

Figure 8.1: Principal Input Variables for Load Scheduling

This section provides the outcome of an attack event specifically on the pricing profile on the central controller within the smart HEMS. In all cases, it is assumed that no other external factor is capable of prevented the HEMS from running the algorithms as expected. In order words, the algorithm which is under attack is still expected to process all data available unless the attack is able to interrupt or terminate the normal operation of the system. Hence, any possible interruptions or other disruptive events are being investigated and results obtained are presented here. At the end of the day, the essence of incorporating a robust response to such attacks at the original design for secure HEMS would have been appreciated. Understanding and managing possible scenarios is therefore expected to assist the system so that it will be capable of managing such attacks even without the knowledge of the users. The next section is an analysis of such attacks with respect to DoS attacks.

8.2.1 Impact of DoS Attack on Pricing Data

The results obtainable due to an exemption of the pricing-data component of Equation 25, from participating in load scheduling optimisation due to a DOS attack is presented. It is observable that if there is a DoS attack on the HEMS thereby creating a delayed or non-availability of a specific variable within the fitness function, there will be consequences. In this case, pricing data is the victim and the resultant optimized load profile is observed to re-trace the original forecast load profile as shown in Figure 8.2. This is expected because pricing information is not available to the scheduler due to a DoS attack on pricing data stream and this therefore, causes the optimized load profile to retain approximately same profile as the original forecast load profile. In other words, such an attack will render the scheduling operation temporarily dormant and non-functional without any new results.

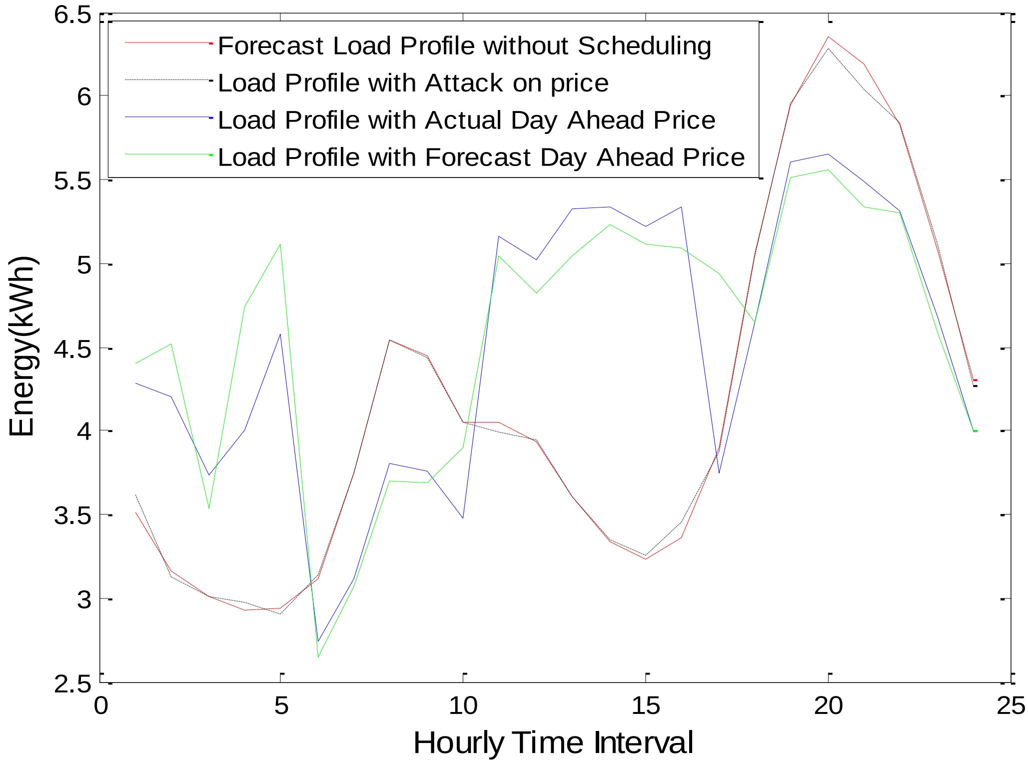

Figure 8.2: DoS Impact on Load Profile and Possible Correction

<u>Attack detection and recovery</u>:

There are two major ways to detecting this attack and they are:

1. The scheduler should be designed such that at the beginning of each scheduling day, all input data are reset to zero before data updates for computation are loaded. This is to enable any null or zero-valued input data cell to be detected and instantly declared a victim of a DoS attack.

2. The chances of generating a scheduled load profile which is exactly same as the forecast load profile is practically zero under normal circumstance. Only a zero-valued pricing data can generate such data as an optimized load profile hence, such an outcome is possibly as a result of a DoS attack.

A reliable way to recovering from this attack is by locally generating a forecasted load profile using acknowledged forecasting techniques as discussed in section 4.2.4, with the aid of stored historical price profiles accessible within the HEMS. Following this action, it is also very important to inform the user so that any further protective action might be taken which may include change of passwords, software update and antivirus clean-up.

Figure 8.2 also shows an optimized Load Profile which is the corrected outcome whereby the forecast price profile was generated locally within the HEMS. It also shows the optimized load profile obtained using the actual day-ahead price as provided by the energy suppliers. It is impressive to observe how much of a good job the pricing data forecasted locally within the HEMS did, in providing a price profile that can be used as an approximate data to substitute a DoS attack on a pricing data

8.2.2 Impact of Constant-Pricing Attack

A constant-pricing attack can be modelled using Equation 26 by replacing the dynamic pricing with a fixed pricing system for different fixed pricing levels.

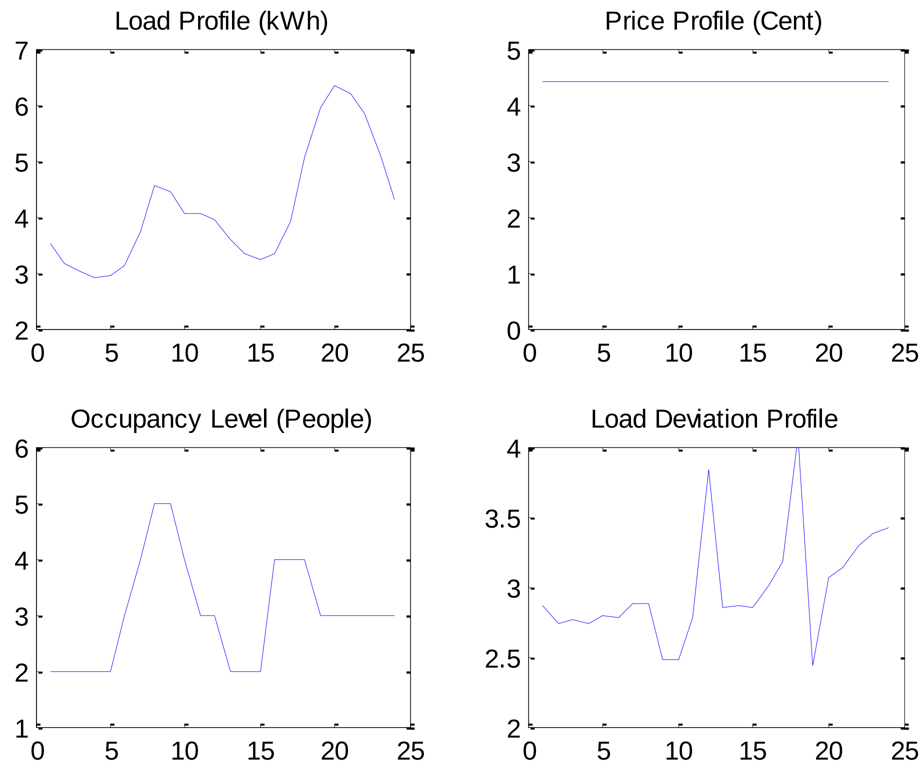

Figure 8.3: Principal Input Variables for a high-valued Constant Price attack

Figure 8.3 shows a modified version of Figure 8.1 but with a constant price of 4.4Cent/kWh in the form of a constant-pricing attack. This value represents the peak pricing of a dynamic price for the day considered, while Figure 8.4 shows the result obtainable. The key observable feature of Figure 8.4 is the fact that the optimized load profile tends to exist mainly as a mean energy value with two downward projections occasioned as a result of the high occupancy levels at about 8:00 hours as well as at about 17:00 hours. But the key deciding factor which produced the optimised load profile of Figure 8.4 was due to a constant-pricing attack which is relatively very high and further experiments involves lowering this value gradually until a significantly different result is obtained.

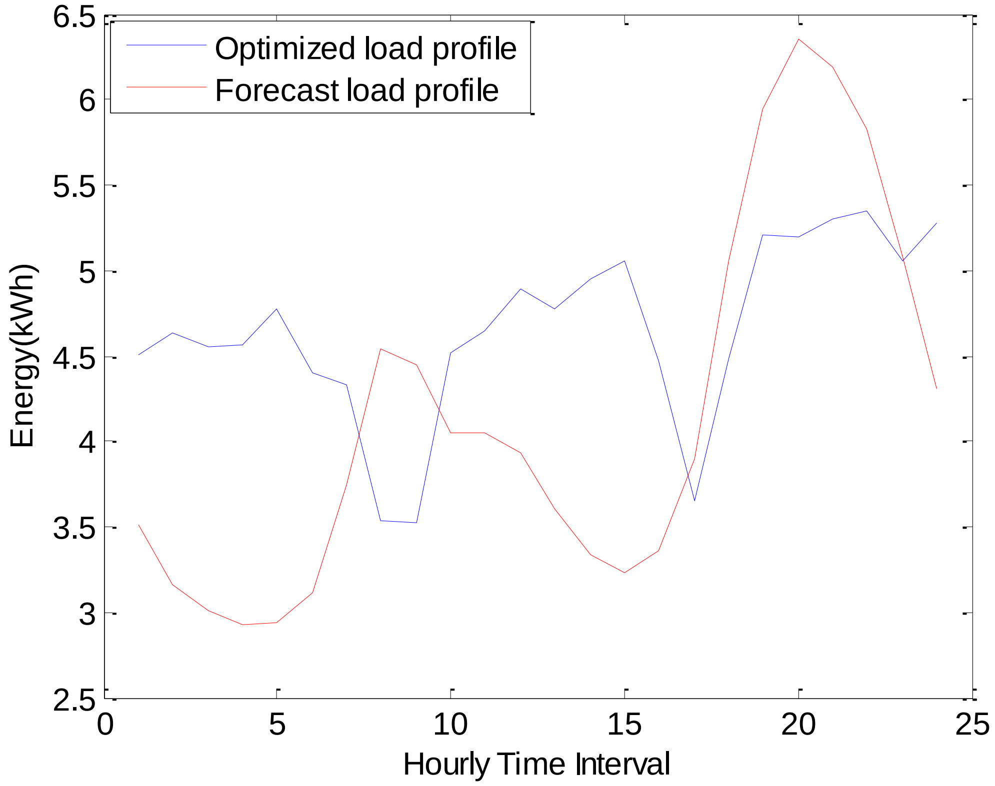

Figure 8.4: Scheduled Load Profile for a high-valued Constant Price attack

Figure 8.5 shows the input variables used when the constant price attack was lowered to a value of 3.1Cent/kWh. It can be observed from Figure 8.6 that the optimised load profile is very similar to the one obtained in Figure 8.4 except that the downward projections are more pronounced. This shows that the optimised load starts off mainly as an average energy value with some deviations which remains observable as the magnitude of the fixed pricing value drops. But this deviations does not continue all through because as soon as the price profile drops below 2Cent/kWh as shown in Figure 8.7, the resulting optimised load profile shown in Figure 8.8 transforms instantaneously thereby becoming almost indistinguishable from the original forecast load profile.

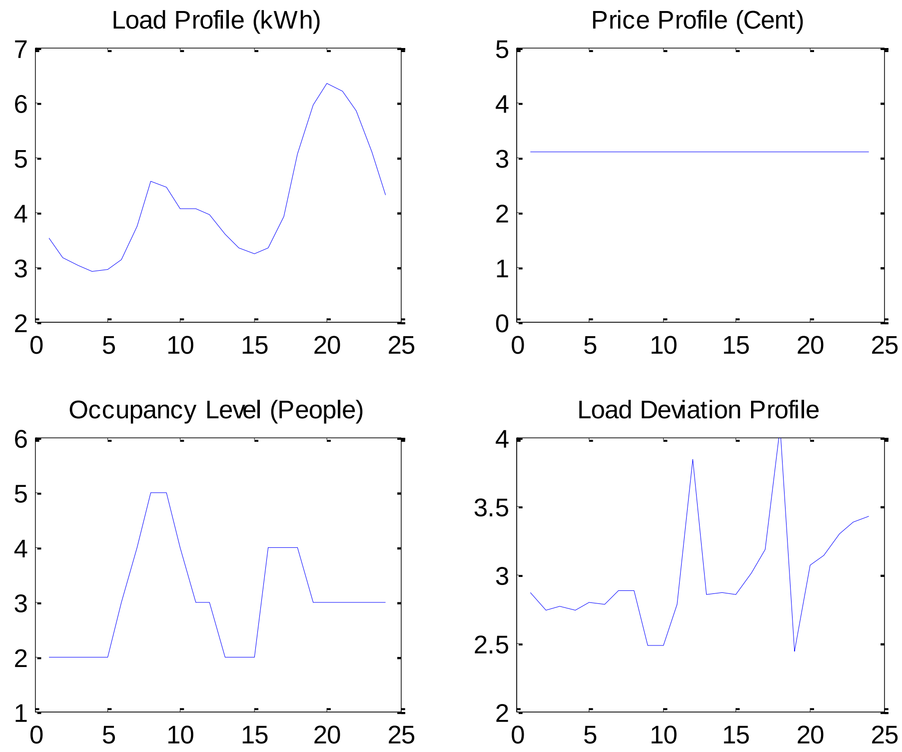

Figure 8.5: Principal Input Variables for a mid-valued Constant Price attack

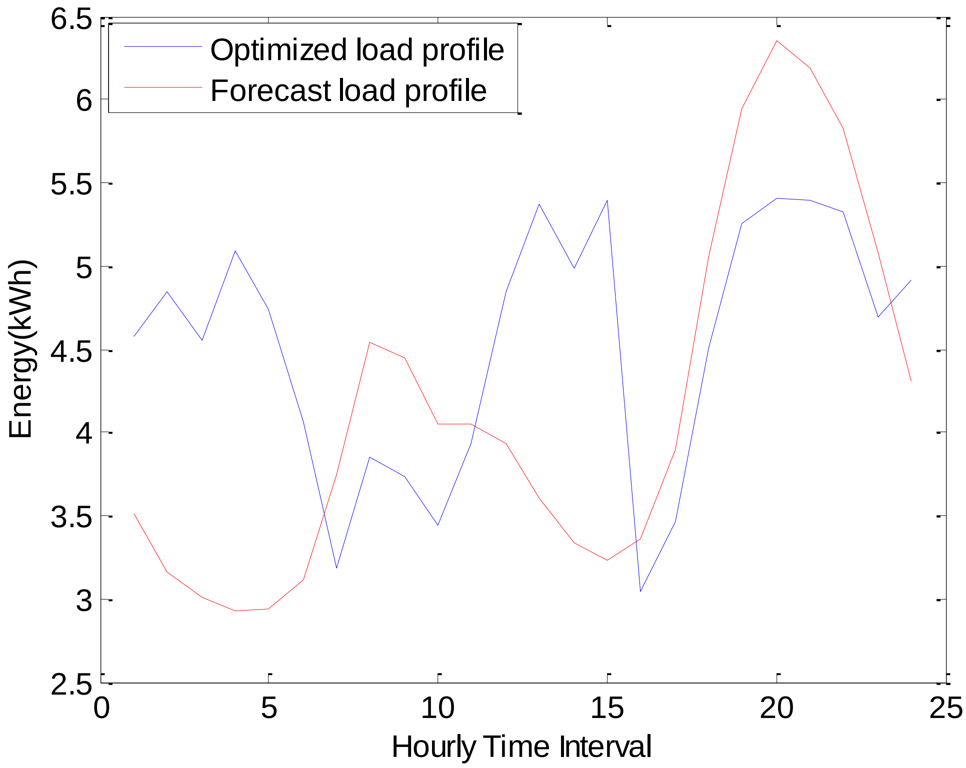

Figure 8.6: Scheduled Load Profile for Medium Constant Price

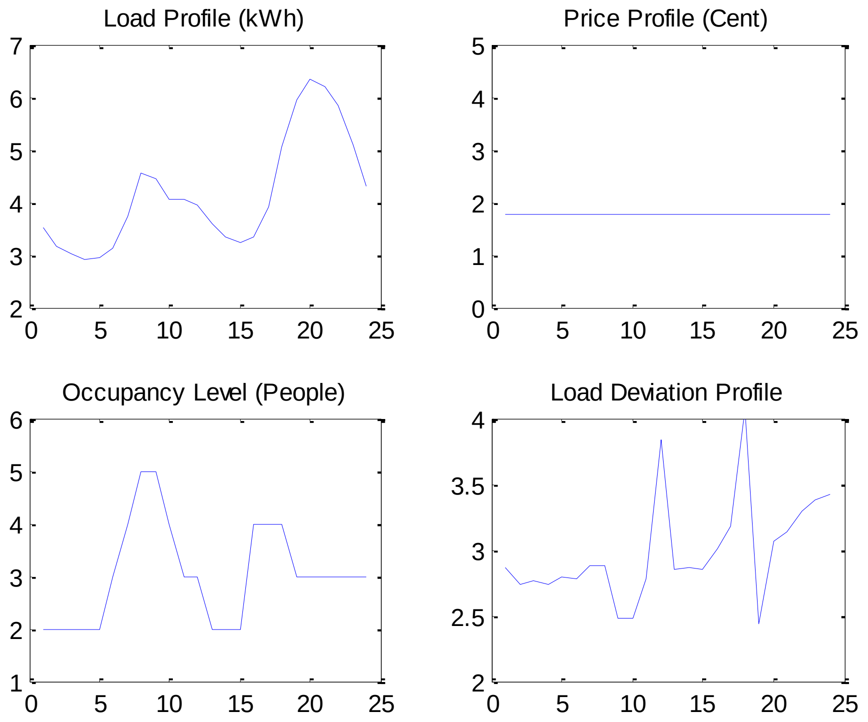

Figure 8.7: Principal Input Variables for a low-valued Constant Price attack

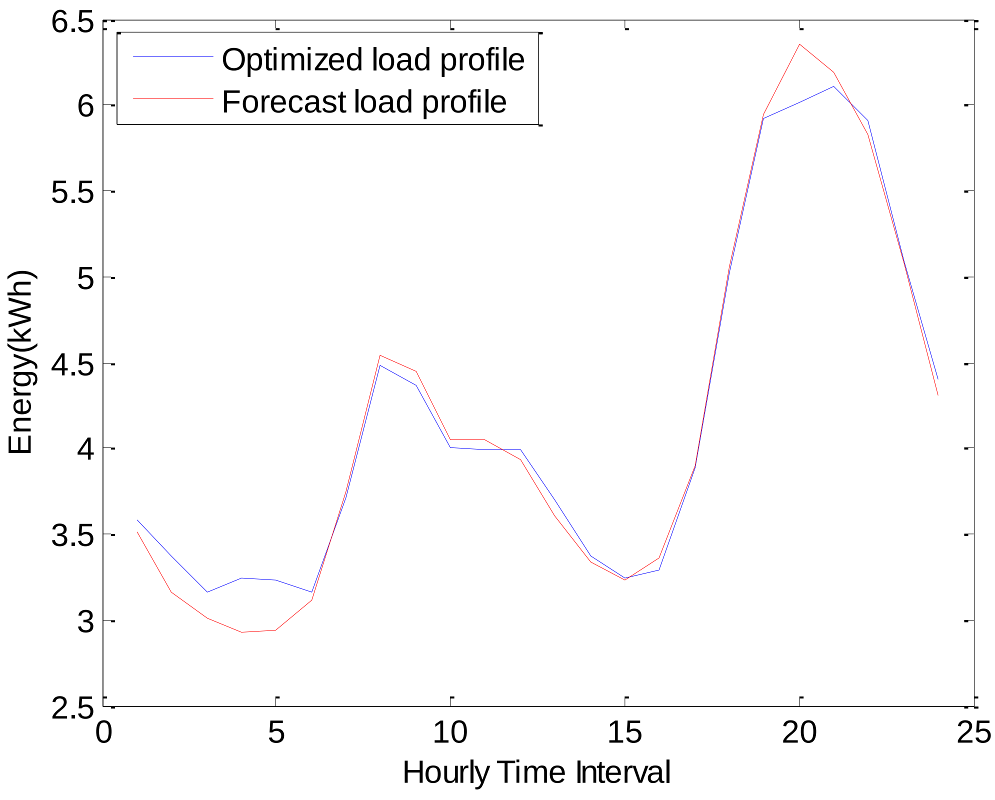

Figure 8.8: Scheduled Load Profile for low Constant Price

Finally, a summation of the changes in energy which are also deviations of the optimised load from the forecast load, were obtained for constant pricing values between 0.5$/kWh and 4.5$/kWh. This is presented on the left hand side of Figure 8.9 whereby it is observable that at low constant-pricing threshold, the deviations of the optimised load profile from the forecast load profile is almost equal to zero, which means that the optimised load profile almost equals the forecast load profile. This shows that the pricing value gives an outcome that is comparable to the pricing value for a DoS attack as discussed in section 8.2.1. However, a sharp increment is observed when the constant-pricing threshold approaches 2$/kWh and the deviations continues to increase at varying rates so long as the constant-pricing threshold is increasing.

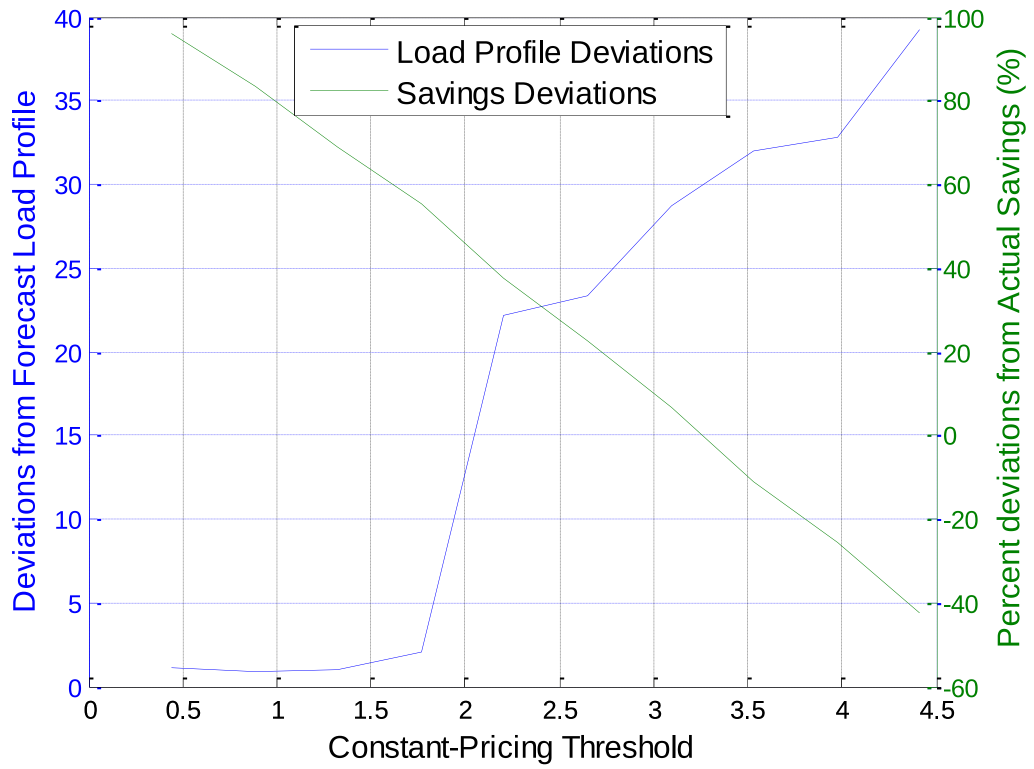

Figure 8.9: Deviations of Optimized Load profile with Increasing Threshold

The right-hand axis of Figure 8.9 shows how much of a false projection of profit obtainable when the HEMS was attacked due to a constant-pricing attack. The percent derivations were obtained using Equation 38 as given

$$\alpha = \theta - \vartheta \qquad 38$$

Where:

α = Deviations from Actual savings

θ = Actual percent profit without attack

ϑ = False Profit with constant-pricing attack

In this experiment, the actual percent profit without attack was found to be 10.4% using Equation 17. This means that from Equation 38, positive-valued deviations indicates that ϑ is less than 10.4% while negative-valued deviations shows that ϑ is greater than 10.4% as shown in Figure 8.9. Hence, all percent profit which may have been provided by a system under a constant-price attack is false except at the corresponding threshold iteration of 3.25 which produces a zero deviation when the actual percent profit without attack is equivalent to the false profit as projected by the constant-pricing attack.

Attack detection and recovery:

Fortunately, this type of attack is considered relatively easy to detect especially because constant-valued pricing data is an anomaly in a dynamic pricing system hence, the HEMS can easily detect and flag such as an error. This therefore makes it possible for the HEMS to be able to nullify its impact either by requesting for a second update on the pricing information or by relying on a localized forecasting mechanism as discussed in section 8.2.1.

8.2.3 Impact of Data Manipulation Attack

This attack as modelled in Equation 30 shows different samples of manipulated models of the price profile as described in Figure 7.3 and Figure 7.4. Table 8.1 shows the savings obtainable due to optimisation application from the four samples of price profiles generated for this experiment. It also shows the proportion of the possible losses for each sample, on the consumer.

Table 8.1: Savings obtainable due to optimisation application

Pricing Attack Model Profile	Savings Available (%)	Attacker's Impact off the Savings (%)	Consumer's Loss from Savings (%)
Original	9.90	0	0
Flipped	9.02	0.88	8.89
Inverted	5.26	4.64	46.87
Flipped and Inverted	6.51	3.39	34.24

Using the day-ahead price profile as the original price reference, the actual savings obtainable as a result of the optimisation generated a savings of 9.9% for the consumer. So depending on the price model adopted by the attackers, various amounts of losses are possible. The Inverted Price Profile sample produces the highest financial loss which is equivalent to 46.87% when compared to the actual original price profile. This attack could be reduced using antivirus software as well as educating the users about how to avoid patronizing untrusted sources.

8.2.4 Impact of False Data Injection Attack

This attack is modelled in Equation 29 using the inputs as given in Figure 8.1. Here, the impact on the optimized load profile is examined such that if an attacker infiltrates the pricing data with some randomly generated false data and then made available to the load scheduler, various responses are obtainable. Here, the false data is gradually introduced to the pricing data variable and the scheduled load is observed to respond in different ways. In order to verify the overall impact of false data injection on the pricing data, the false data is gradually introduced in a stepwise incremental fashion whose magnitude begins from amplitude of 1% of the pricing data up till 20% as the assumed allowable false data level. Figures 8.10–15 shows only three levels of false data introduction with significant variations in the results obtained whereby Figure 8.10 is used as a control, and has no false data content. However, Figure 8.12 contains 10% of false data while Figure 8.14 has 20% of same.

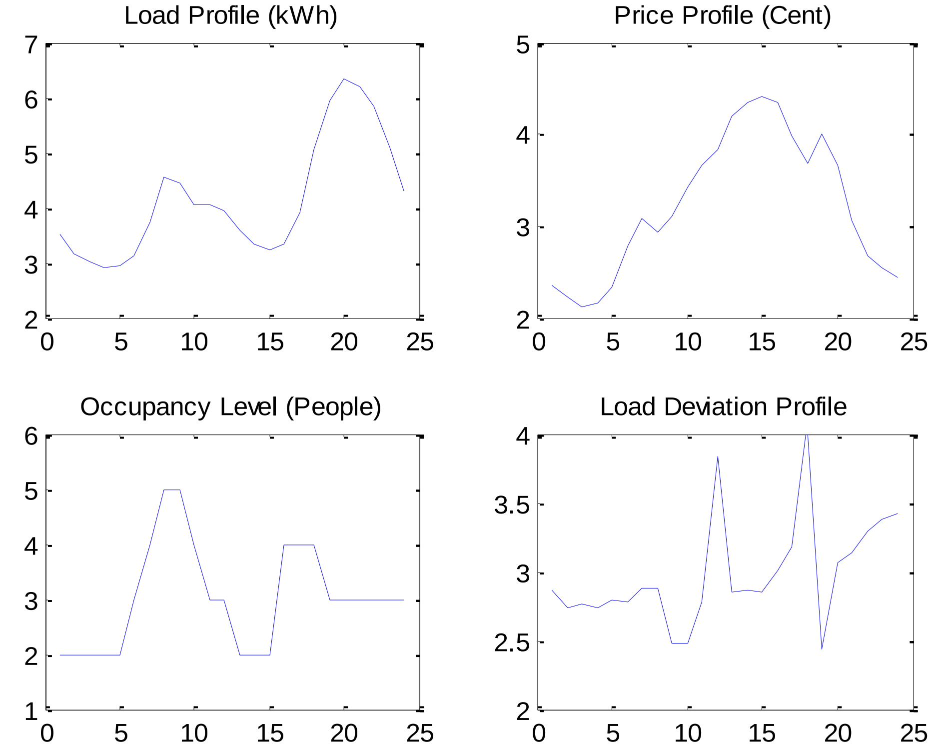

Figure 8.10: Principal Input Variables for 0 % False Data content

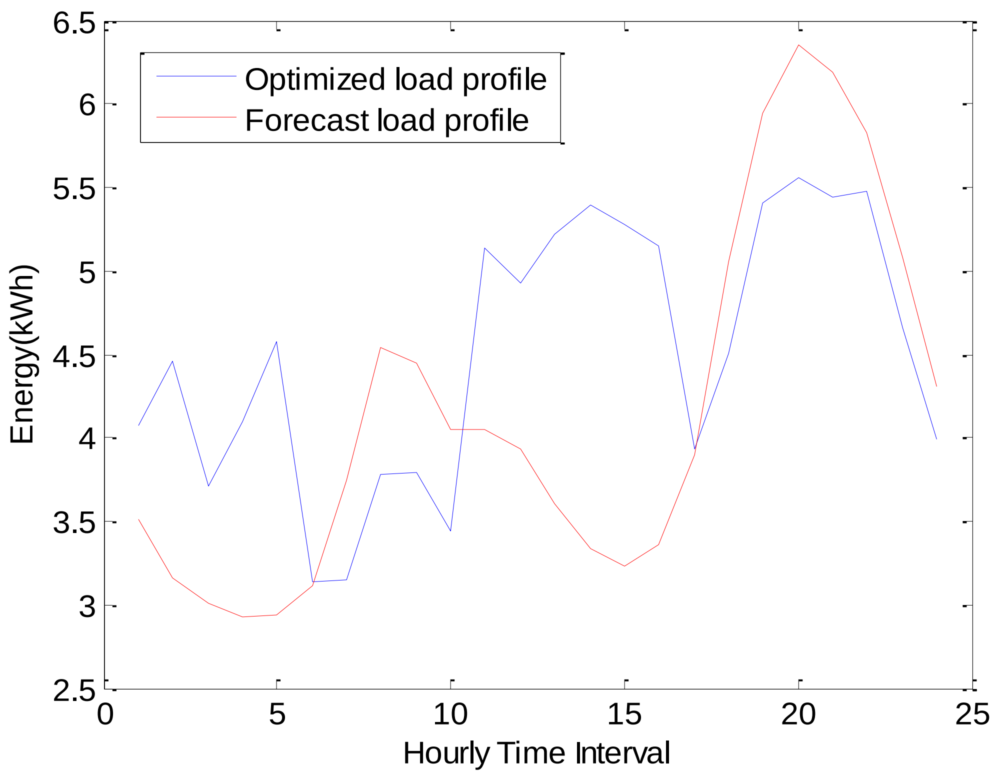

Figure 8.11: Load Schedule for 0 % False Data content

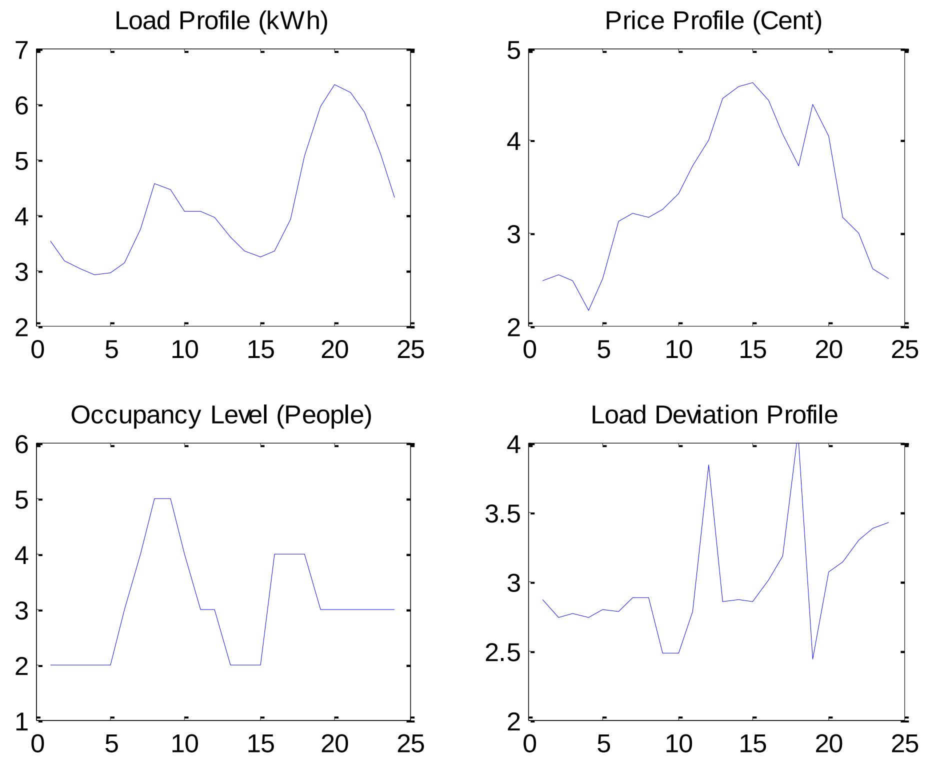

Figure 8.12: Principal Input Variables for 10 % False Data content

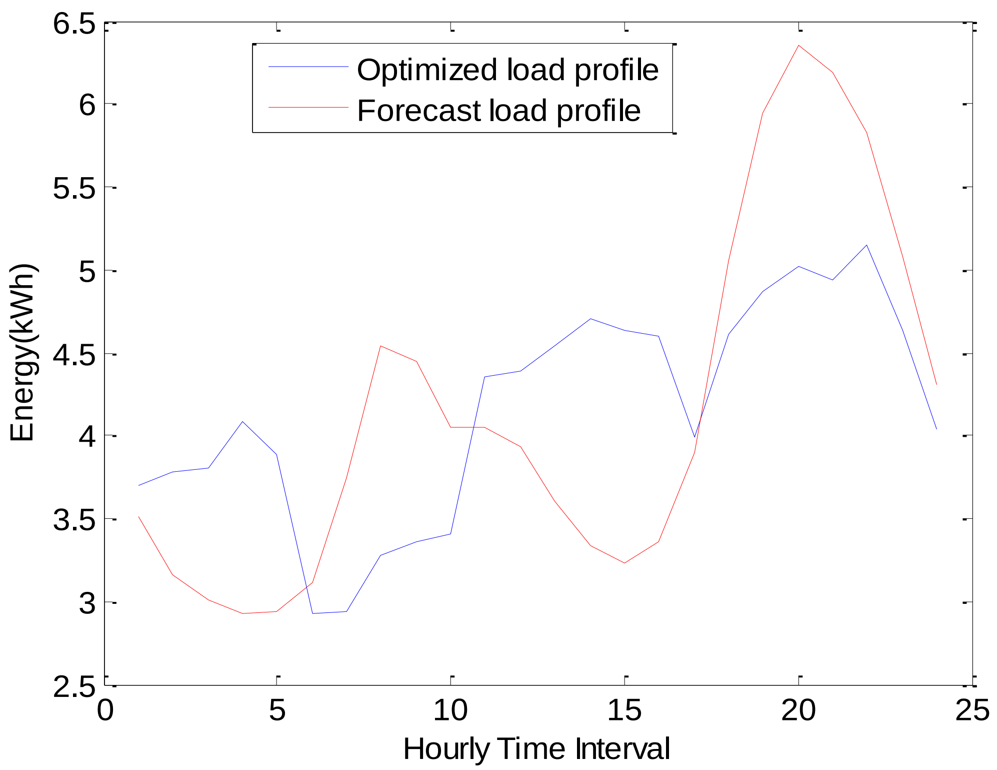

Figure 8.13: Load Schedule for 10 % False Data content

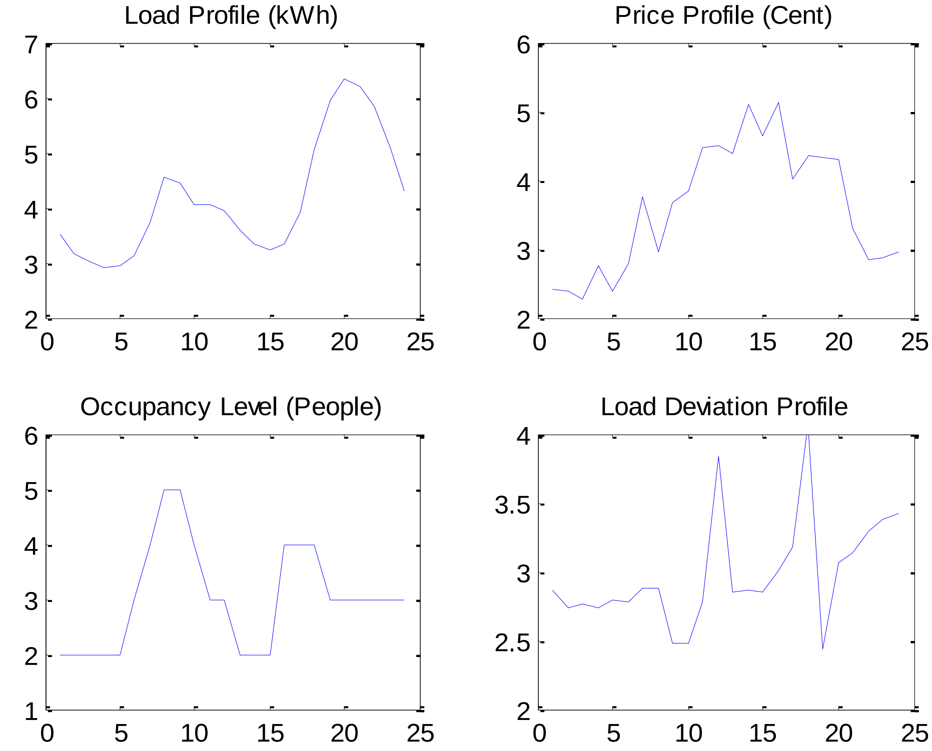

Figure 8.14: Principal Input Variables for 20 % False Data content

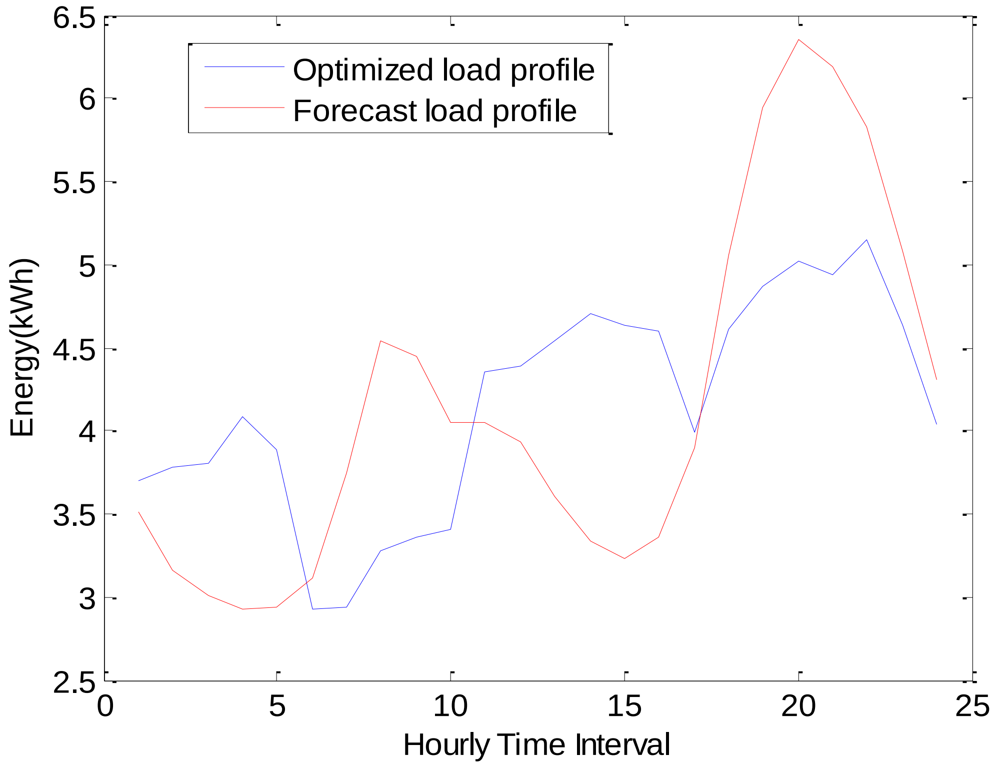

Figure 8.15: Load Schedule for 20 % False Data content

The corresponding results show that Figure 8.13 and Figure 8.15 which basically looked identical to each other, deviates significantly from Figure 8.11. This means that introducing false data can quickly degenerate the output almost instantaneously, but thereafter maintains very similar shape even with further increase in false data content on the load profile. This is the scenario as shown in Figure 8.16 whereby this instantaneous degeneration terminates at about 5% of false data injection, while the scheduled load profile deviations remains constant.

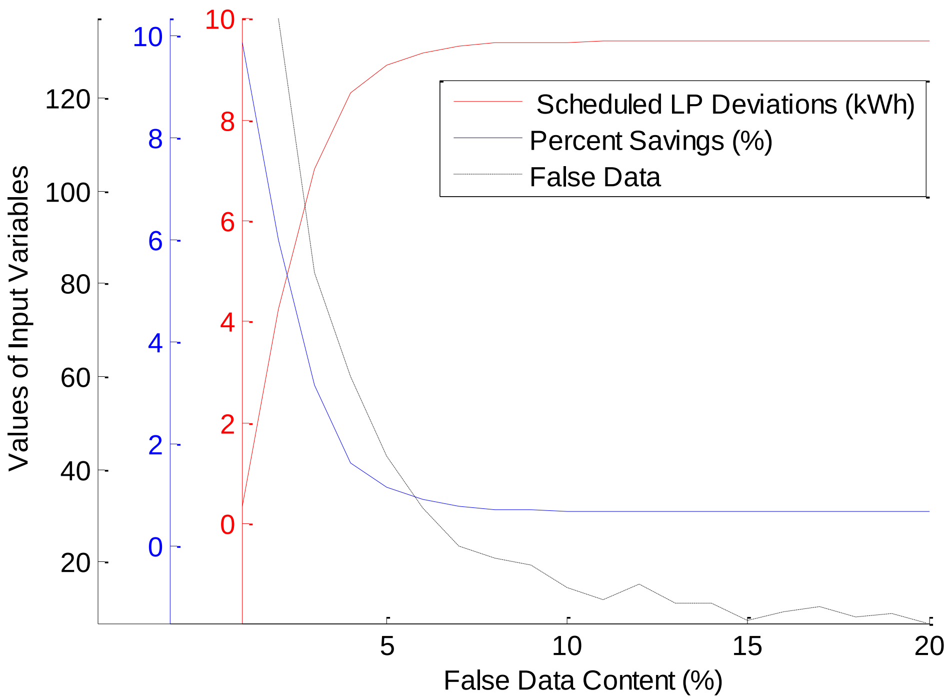

Figure 8.16: Price and Energy Changes as False Data Increases

Figure 8.16 also shows that false data introduction reduces financial savings obtainable when users participate in DR programs whereby, savings available diminish as false data content increases. The change in energy **($\Delta\mathcal{E}$)** as discussed in 4.3.3, is also observed to increase rapidly as a result of false data introduction and this impact is expected to increase discomfort.

Finally, it is observable that a very little false data injection for as little as a 5% injection at the input can quickly degenerate the results obtained and can cause huge impact on the final result generated. Unfortunately, a customer who would have made more than 10% savings while applying DR programs will end up with only about 1% savings if their pricing data is attacked in this way.

Attack detection and recovery

Nevertheless, it is remarkable to observe that there is always positive savings obtainable for any given level of false data injection on the price. This is due to the optimisation program that tends to follow the cheapest possible load profile for any given input variable. Although this attack might be difficult for the optimizer to detect depending on the magnitude of false data content and can go on for a while, following the routines as discussed in section 8.2.1 will be helpful. This is required because if no steps are taken to mitigate these types of attack, the users could become frustrated and may eventually withdraw from DR participation believing that there are no significant benefits, without acknowledging that their house has come under cyber-attack. The next section is a presentation of the results of the optimised load profile assuming the forecast load profile data is attacked by the means of false data attack injection.

8.3 Cyber Security Strategies: Attack on Load Profile

The results discussed in previous section showed the impacts of various cyber-attack on the load profile depending on the type of attack investigated. This section is a further investigation of false data injection attack on the HEMS whereby the target on this occasion is the forecast load profile, while Input data of Figure 8.1 are also used. Figures 8.17 to 8.20 show various results that are generated when various false data levels are injected based on the use of Equation 33 as the objective function. Here, the Original Load Profile is subject to attack and the result obtained produces the Optimized Load Profile (With Attack) as shown in Figure 8.17.

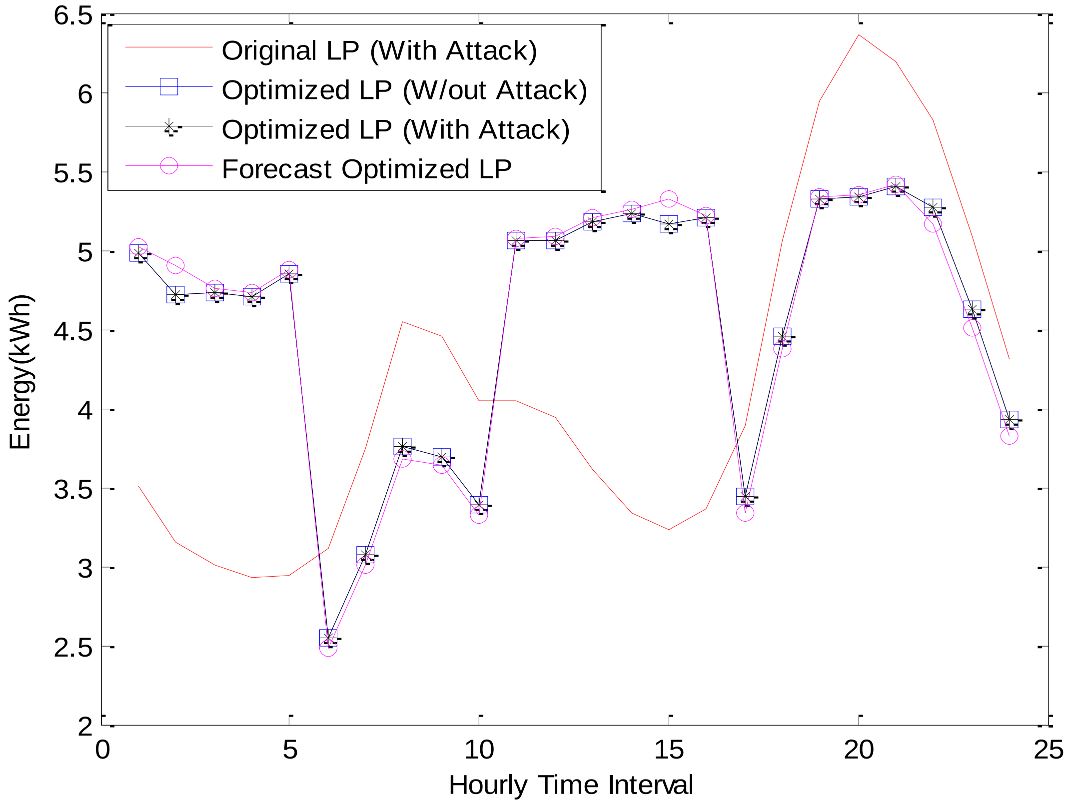

Figure 8.17**:** Load Schedule with 0 % False Data Content

The Optimized Load Profile (W/out Attack) is used as a control and is generated using the Original (Forecast) Load Profile without the introduction of any false data injection. It therefore indicates the response assuming there was no attack and hence, acts as the baseline result.

On the other hand, Forecast Optimized Load Profile is generated from Forecast Load Profile (which acts as the back-up against attack) and is generated locally from historical data of the previous 4 days of the same day of the week, as recorded within the HEMS. In this illustration, the retailer supplies the required Original Load Profile data, while the back-up Load Profile data was generated locally, although the sources of these data can be interchanged if desired. Since the false data content is zero, Figure 8.17 therefore shows that no attack is involved on the forecast load profile which thereafter generates the optimized load profile with all results approximately same for all outcomes as expected.

The second scenario as shown in Figure 8.18 shows a false data injection of 20%. Here, the Optimized Load Profile (with Attack) begins to pull away from the optimized load profile (without Attack) and this continues consistently even at 50% as shown in Figure 8.19.

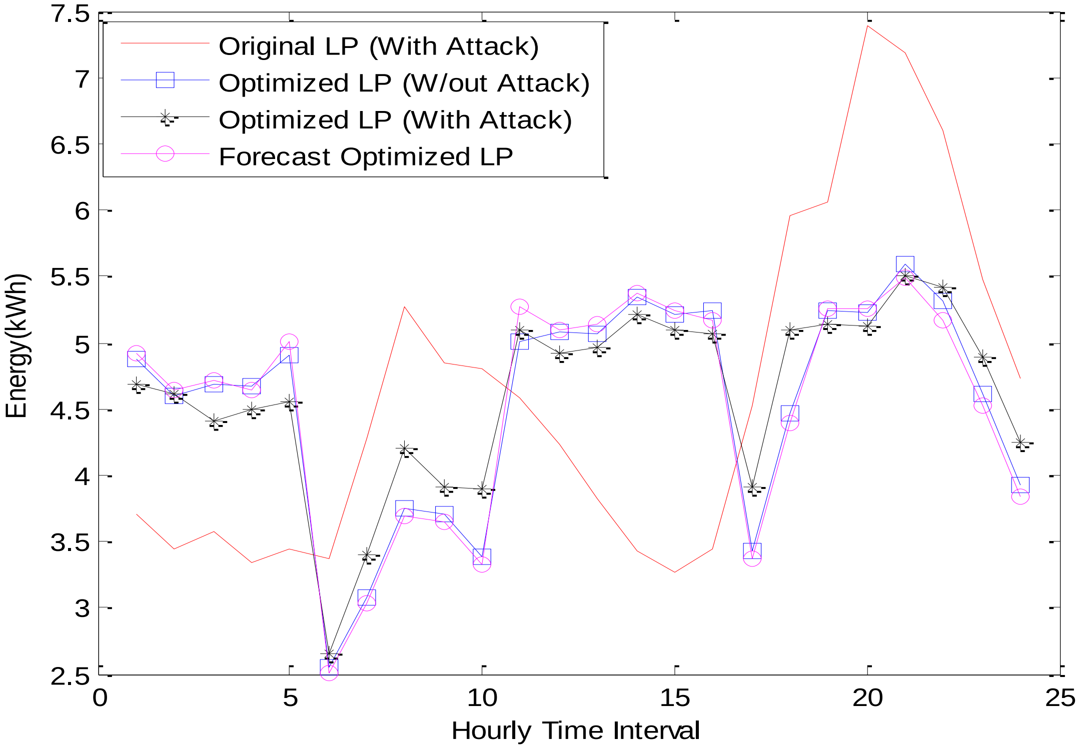

Figure 8.18: Load Schedule with 20 % False Data Content

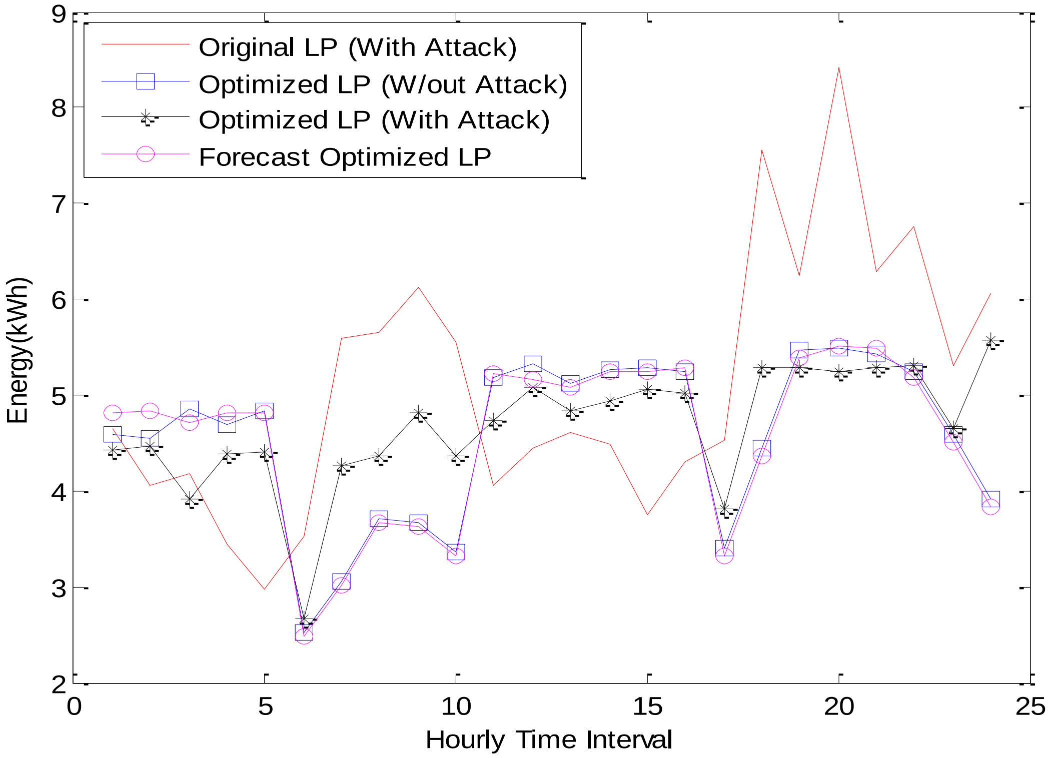

Figure 8.19: Load Schedule with 50 % False Data Content

In Figure 8.20 and at 80% of false data injection as shown, it can be observed that the Optimized Load Profile (with Attack), is nearly flattened out except for the spike at 6:00 hours. This is a very key result as it clearly shows the effect of introducing false random data to the original load profile. On the other hand, the Forecast optimized load profile shows that it is a reasonably good back-up to rely upon in case the HEMS detects irregular random or unexpected data within Load Profile data. It is also appropriate to mention that the Optimized Load profile (without Attack) which is the baseline result remained the same with minimum and maximum values of about 2.5 kWh and 5.5 kWh respectively.

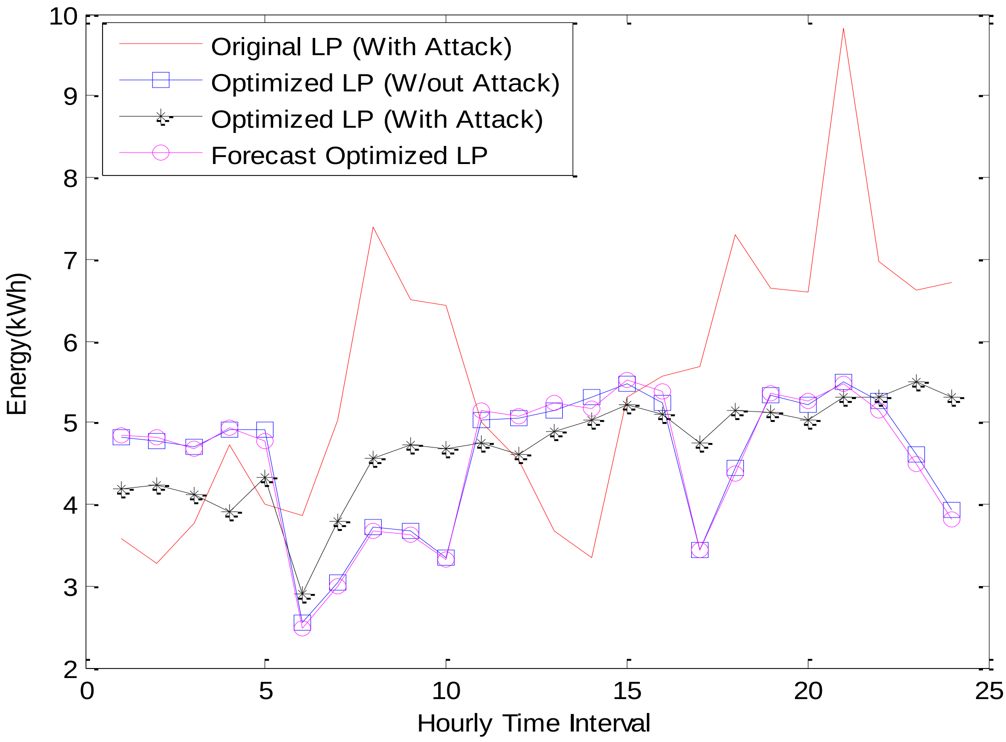

Figure 8.20**:** Load Schedule with 80 % False Data Content

Two key observations are derivable from these results and they include:

1. It is observable that as false data levels increases, the optimized load profile shrinks towards a straight line which represents the average value of the original load profile. This is an interesting result because we could see the effect of false data in diminishing the efficiency of the load scheduling process.
2. The implications as deducible from the graphs is that such shrinking is capable of effecting significant load shifting whereby several loads could be turned ON when they are expected to be OFF and vice versa.

Therefore, this can be a worrisome scenario for consumers who participate in DR programs and may not realize that their load profile has come under attack. They may conclude that participating in DR programs is highly discomforting or that perhaps, their HEMS system is dysfunctional. Therefore preventing this attack is important and a means of doing so is same as already discussed in section 8.2.

Figure 8.21 shows the changes in the deviations of the load profile with attack and the changes when the corrected mechanism is introduced. It is observable that the deviations of the load profile with attack increases significantly as the injected false data increases, while the deviations of load profile with backup remains fairly stable. In this way, it can be shown that backups can be used as a key means of preventing and diminishing the potency of such attacks.

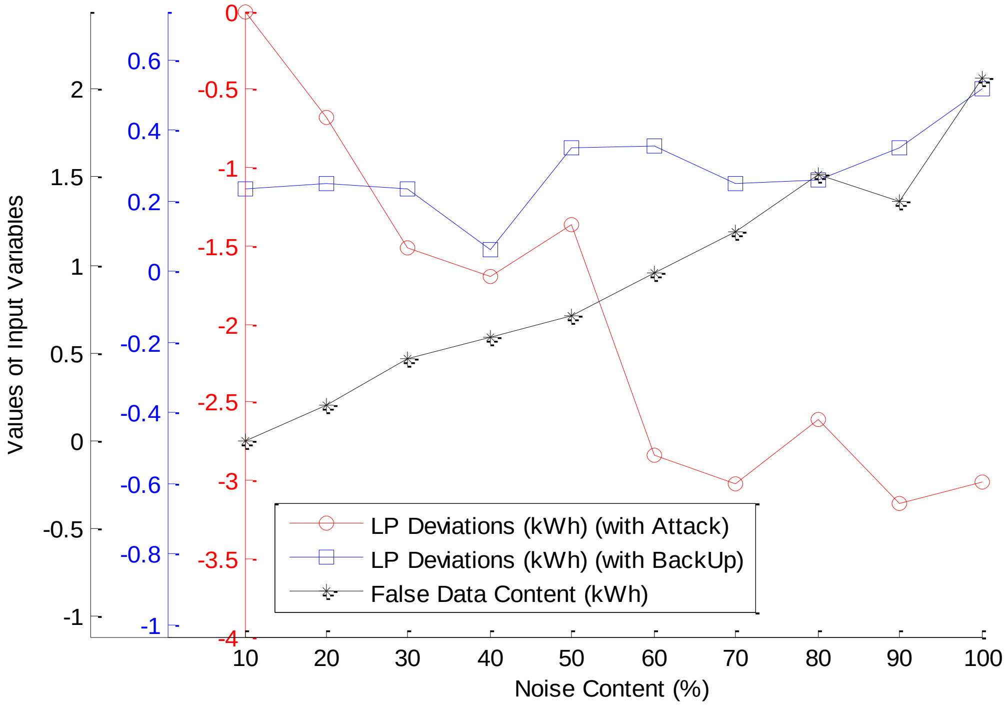

Figure 8.21: Load Profile Changes as False Data Content Increases

8.4 Chapter Summary

In this chapter, various possible types of cyber-attacks on the HEMS have been simulated with various impacts on the scheduled load profile assessed. The solutions suggested are designed to enhance a more robust system design. Virtually any device with internet connection can be susceptible to attack and this therefore places the HEMS within the reach of the attackers since all IOT devices within the smart home have a connection with the HEMS according to Figure 5.1.

The two critical input data simulated for attack included the dynamic pricing data and forecast load profile data. Results show that for every attack, the system is degraded in one way or the other especially the forecast load profile which changes from optimal to less optimal load profile. This impact is capable of leading to a failure to meeting the grid's objectives in price setting as well as energy savings. It has also been demonstrated that using techniques such as applying localized forecasting to help as an alternative remedy is effective in deflating these impacts such that a near optimum schedule can be achieved even while under attack, while a more permanent solution is processed. Access authentication is naturally a key part of any proposed solutions and a provision for this security measures should be included in design frameworks of automated HEMS. It is important to ensure consumer confidence else, the dream of having a robust and efficient smart home could become elusive. The next chapter is an overall discussion and relevance of all results obtained, evaluated in context of behavioural response to DR programs.

Chapter 9: Discussions

9.1 Evaluation of Load Scheduler Performance

With the completion of all designs and experiments for a proposed future smart home, this chapter critically evaluates the results and the inferences deducible from previous four chapters, while comparing them with the literature review. This chapter therefore assesses of all these results and events within the context of the smart home as well as on the grid, while keeping in perspective; a comparison with the state-of-the-art research as outlined in chapters 1 and 2, towards a sustainable grid operation which serves not only the consumers but the retailers as well.

9.1.1 Evaluating the Accuracy of Algorithm Developed

With respect to Figure 5.14 and based on Equation 4, it is observable that the result obtained recognised a user-specific application of load schedules which caters for the behaviour of the user in a personalised way based on their individual characteristics. Apart from the price profile data which is universal for all the customers as supplied by a specific retailer, the uniqueness of the schedule generated is based on the characteristics of the users as a result of their occupancy as well as the standard deviation of the load profile. Figure 5.14 showed that the profile obtained allocated appropriate appliance use depending on the input data supplied. A scheduling objective of cost minimisation for instance, is achieved such that more load allocation is assigned during lower energy prices while lesser load allocation is obtained during higher energy prices. In this way, it can acknowledged that the load scheduler is performing its tasks effectively as required.

Accuracies of results based on costs evaluation is found to be true as shown also in Figures 5.4, 5.5, 5.7 and 5.9 whereby both maximised and minimised cost evaluations are observed to respond accurately. The other variables which include the occupancy as well as the standard deviation of the load profiles as given in the basic input variables of Figure 5.1 are also found to affect the resultant optimised load profile accordingly, depending on their respective values. This therefore proves that the fitness function generated as well as the methodology applied in either minimising or maximising any variable as defined, is efficient, accurate and also implementable so that realistic outcomes can be achieved. Although analysis of the occupancy as well as the standard deviation of the load profile was not conducted in so much details just as it was done for the cost variable, the obtained results are enough to show that the methodology and accuracy of the algorithm developed is reliable.

9.1.2 Evaluating the Relevance of Discomfort Application

Discomfort considerations and minimisation during load scheduling applications is found to be an important factor which encourages improved and sustained user participation in DR programs. With respect to Figures 6.5, 6.6 and 6.7, it is observable that the load profile generated continuously stabilises and tends to follow directly the limitations imposed by the user. This is an amazing result to observe because the user is firmly kept in control of the final schedules obtained which practically eliminates any complains about incessant undesired load schedules imposed by a localised scheduler or the utility. Although it is acknowledged that only the load profiles are scheduled, the experiments could have been more completed if the actual loads that exists at the specified times on the load profiles are scheduled. This is also another interesting aspect of this research but it is reserved as a future work.

Another incomplete aspect of this work is based on actually testing the results obtained in the field. For instance, the discomfort obtained can be tested in a real home whereby the user will implement the schedule without discomfort limitations in one application, and then apply the discomfort considerations and then a comparison about the user experiences can be made. This is therefore an evaluation of actual discomfort obtainable based on the experiences the user reports. Other actual data obtainable such as actual cost and the application of the actual load schedules for evaluation in the next day according the description of Figure 3.5, are also other aspects whereby this research can be further enhanced. This will ensure that more complete deductions can be made although despite these limitations cited, the methodology applied is the key outcome and any further improvement can be built on the work already done. The next section discusses the basis for optimisation and is argued using the five W's and one H formula for obtaining a complete research analysis which include: When, Where, Why, Who What and How.

9.1.3 Justification of Load Scheduling for Smart Homes

Why schedule loads? In most cases where load scheduling is applied for optimum energy distribution and consumption, the major reason for optimisation is usually to reduce peak demand. However in this work the application is not necessarily to reduce the peak demand of the individual's load profile, but to use the various factors that affect user behaviour in order to affect specific load scheduling provided the new load profile generated remains within the forecast load profile. The estimation is that the overall effect on the grid where there is an impressive participation will ensure reduced peak demand, since energy prices are usually high during peak demand thereby causing a more diffused load profile away from the peak demand. This aim is clearly achieved in all scheduling results obtained thereby sustaining the need for load scheduling application. The key advantage of this activity is to reduce carbon foot print on the environment as well as avoiding the need to build additional power plants which only serves to supply marginal demand of energy, which typically occurs only during peak demand in a day. Figure 5.15 shows the result of a simulated optimized load profile in comparison with a non-optimized load profile whereby it is observable that there is a significant shift of the TOU for various appliances which results to financial savings shown in Figure 5.16. This therefore confirms that the optimisation process is valid

Another reason to schedule loads is the need to achieve energy or financial savings which therefore, naturally becomes an incentive and a motivation for the consumers to become interested to participate in DR programs. This is because energy costs of optimized load with minimized costs are usually lower when compared with non-optimized energy costs provided dynamic pricing is available in the energy market. This is therefore applicable for every dynamic pricing scheme including day ahead dynamic pricing which is observed in this work, and also according to authors in [45], savings of about 13%-15% on energy bill are possible depending on the user.

How is load scheduling done? This involves an automated moving loads from critical times characterised by high energy cost and demand, to non-critical times, achieved by the use of appropriate load management algorithm which considers various user preferences while making a decision towards redesigning a new load profile that suit their preferences. It is an interactive design whereby the user has the capability to key in their preferred input variables such as price thresholds and discomfort limits, while also being able to see a suggested load profile for use the next day. The discomfort threshold applied in Figure 6.8 shows that the user has override capabilities to use any specific load as desired, assuming they do not want to follow the prescribed load profile. The issue of occupancy is also accounted for in the algorithm and the results show that user comfort changes depending on how the fitness function is formulated based on whether the aim was to minimize or to maximize variables of interest. The weightings on the fitness function also affects the output whereby higher weightings propagates the impact of certain variables more than others. This algorithm was also evaluated for different household types and similar results were obtained.

When to schedule? Scheduling opportunities are identified depending on the user's preferences and lifestyle whereby the right combination of energy prices and standard deviation of the user's load profile plays key role is ascertaining this, as discussed in section 4.5.1 whereby high energy prices and low high standard deviation was found to be best conditions for identifying load scheduling opportunities. Identifying these specific times is vital because it recognises and considers the behaviour as well as the impact on the user before attempting to apply scheduling. This is a novel approach whereby discomfort associated with load scheduling is minimized.

Who can schedule? There are principally three types of energy consumers which include: Domestic, Industrial and Commercial users. The experiments presented here are based on domestic users only, although same methodology is applicable for a wider range of consumers so long as considerations are made towards acknowledging the importance of user behaviour which is critical in making decisions to schedule loads, accompanied with cost considerations. It is expected that industrial and commercial users may not be as flexible as domestic users due to consistent use of most of their load during working hours, and may therefore not necessarily be able to participate effectively in DR programs as presented in this work. It is also expected that the standard deviation of their historical load profiles will remain very low for most parts of the day, although investigating exactly how these will be affected will be an interesting work for the future.

Where to schedule? The forecast load profile is an expected load profile that the user will follow assuming that load scheduling was not applied, while optimized load profile shows the newly suggested load profile for use. The difference between these load profiles clearly shows where to reduce energy consumption as well as where to add the changes to. Therefore, the TOU for all appliance schedules is available on the optimized load profile. This aspect of the project was not implemented here and it is a good subject matter required for a future work.

What gets scheduled? The realisation that specific loads can become schedulable at one instant and then non-schedulable at other times even on the same day is an interesting aspect of this work. Therefore, if one develops the habit of using a particular appliance at a particular time on a daily basis, that appliance instantly becomes a non-schedulable load only at those times. This means that it is unwise to expose such an appliance to scheduling because it will most likely upset the user more significantly. It therefore shows that schedulable loads can be identified in a dynamic fashion whereby the strength of this technique is based on using standard deviation of load profiles in understanding a user's behavioural pattern in order to optimize load scheduling.

After identifying load scheduling opportunities as well as the specific schedulable and non-schedulable appliances as discussed in section 4.5.1 and 4.5.2, the expected TOU for all schedulable loads are identified and the user can be assisted in deciding what time they get used whereby it is expected to fit within the newly proposed load profile. Furthermore, the threshold chosen is observed to play a very key role in making decisions on the status of each appliance at any given time. Choosing an optimal threshold depending on the user's preferences could be a future area to research because it was observed that the choice of the threshold value is critical in determining how actively a user can be able to participate in load scheduling. We acknowledge that this technique can be used not only in markets with dynamic pricing, but in power industry in general because a knowledge about the base loads is key to understanding how to sustain critical loads especially in developing countries where energy supply may not be sufficient for the entire community.

9.2 Justification of Feedback in Energy Management Systems

Feedbacks are known to be stabilising factor in any system design because of the need to always compare the output with the input which in this case involves, comparing the results obtainable with the user's historical behavioural characteristics. This is expected to bring stability as well as long term user participation and engagement with a third party energy provider by ensuring that lumped scheduling either from the utility or by users themselves, who rush towards low energy prices at one time thereby causing potential new peaks, are prevented. It also prevents the automated scheduler from inadvertently forcing undesirable schedules on users. For instance with reference to table 6.1, the major reason why the status profile of appliances D, E, G and H showed ZERO output throughout was because they possessed zero standard deviation at all times, thereby constantly making them non-schedulable (base) loads. This means that such loads are exempted from scheduling, a decision derived from the usefulness of feedback, hence user discomfort can be reduced.

Another aspect of the importance of feedback as presented in this work has to do with the results that describes effective means of limiting discomfort as desired by the user. Section 6.5 showed results of effective discomfort management in DR program participation and the outcomes are based on effective communication between the user and the display of the HEMS which presents the discomfort available. In this way the user can effectively manage how load scheduling within their homes can be applied. Feedback can therefore be described as an inseparable aspect of DR application.

9.3 User Participation Evaluation in Energy Management

In energy market, several factors could prompt utility providers to seek information about the possibilities of encouraging users within a community to participate more actively in DR programs. In developing countries where energy supply is usually inadequate, active participation will help in improving the quality of energy supply. The load profiles of households analysed represents a model of what could be expected in a community where DR programs are applied. A critical analysis of the results obtained in this aspect of the work is discussed whereby the numerical evaluation of user participation is key in determining the participation levels of various users available.

An observation from Figure 6.14 shows that the three indicators of the various HPI provided limited information about the overall user's actual engagement in DR programs unlike UPI values in Figure 6.10 that provides numeric values for the same evaluation. It can be said that Fuzzy logic methodology has an advantage in this regard over Boolean logic technique since actual and specific participation levels can be evaluated. Conversely, Boolean logic technique has the capability to provide information about what happens amongst users on hourly basis which is important information that Fuzzy logic method did not provide. This can be applied in a useful way for instance, assuming an energy provider is keen on having an instant and specific response to DR program say, between 4:00 and 7:00 hours on the day as shown in Figure 6.14. Results from Boolean logic methods can therefore indicate whom amongst the households that are more probable to accept DR engagements more than others. Although it can be seen on the overall evaluation that occupants in Household-2 are better participants in DR programs than occupants in Household-1, but given the specified times of DR requests, the latter becomes better participants to respond more actively to such requests than the former. This means that Boolean technique permits hourly appreciation of the user engagement unlike the Fuzzy logic method that gives only the overall daily performance, although their respective strengths complement each other.

Another observation made is that the UPI is significantly affected by the standard deviation of load profile. This is because householders with rigid energy consumption pattern such as in Household 3 are poor DR participants but they can be encouraged to improve their participation if possible. From the results obtained, it is possible for energy providers to use a simply fuzzy application or Boolean logic technique to understand the activities of users in their network. A key advantage is the fact that the computations are done locally within the household by an intelligent HEMS, hence the problems associated with privacy breach are avoided. This is because only the final results obtained are sent to the utility so the actual load profile details of the users are not made available to a third party.

The ability of being able to see what happens on the user side at regular time intervals will enable any desired improvements on the user behaviour to become achievable more easily. This means that community load scheduling can easily be implemented where users with higher chances of active participation can be targeted in order to reduce their load during intervals of peak demands. Finally, another important advantage of applying the techniques presented herein in analysing user participation capabilities is the absence of the need to calculate the probabilities of appliance use which therefore reduces the computational time in sourcing for the extra information

9.4 Sustaining a Secure Future Smart Home

The key to an efficient and active DR participation is on provision of a secured network with the correct and up-to-date levels of authentication and malware security applied, in order to prevent intrusion. In a case where an attack on the HEMS is successfully achieved, the response by any installed security mechanisms becomes critical. In all the experiments carried out, it can be observed that there is no disruption of the optimisation process due to the attack which means that neither the HEMS nor the users will be able to detect any anomalies by themselves since there will always be optimized load as results. It is therefore obligatory for the designers of load optimisation algorithms to include means of flagging any unexpected results and as well, include means of deriving instant solutions. Fortunately, the optimisation constraints played key roles in ensuring that the optimized load profile stayed within certain boundaries of the original (forecasted) load profile irrespective of the type of attack on the scheduler. This offers a great relief in appreciating that the impact of such attacks on the grid can be localized and the possibility of the attackers causing all the appliances in a household to turn ON at the same time can be suppressed.

The metering system can be a reliable source to detecting anomalies within the HEMS which is in view of the availability of the historical load consumption stored in the HEMS. So if an unexpected scheduling pattern which has no resemblance and differs remarkably with the historical load profile is generated, the system could call for a reassessment and vetting of all the input data. For instance in this case as presented in Figure 8.2, having an untrusted result can require the HEMS to generate forecast load data locally, or use the last accurate load data and apply it with the current price and occupancy data, assuming they too are not affected by the attack. This is a good step towards effective error detection which will in turn create the avenue to seek the best solution depending on the type of attack involved.

Result from the billing system is also another means of effective error detection. Although it is recognized that consumers' attitude or conditions may change instantaneously thereby creating a remarkable change in energy consumption costs, such a change can be a trigger for the HEMS to call for an error check. The retailers can also assist by publishing forecasted cost estimate of which remarkable deviation from the localized schedule could trigger a call for error check. This therefore provides an increased means towards error detection.

Finally, every attack investigated is observed to produce results which lead to a reduction in savings obtainable as well as reduction in customer satisfaction. This therefore creates the potential to discourage consumers from active engagement in DR programs which may end up defeating the aim for its design. But with improved security, there will be a long term benefit and advancement of the grid.

9.5 Chapter Summary

In insight into the usefulness and relevance of the experimental results obtained was discussed in this chapter whereby the important aspects of the discussion were based on the impact of automated DR participation which specifically caters for user behaviour. The utility providers have important roles to play which apart from ensuring the application of dynamic pricing strategy, there should also be a constant evaluation of user participation capabilities which assesses user engagement levels in DR programs. The use of GA provides a comprehensive optimisation methodology which allows the input variables to be added to the fitness function while also using evolutionary technique to converge the output variables. The application and evaluation of user behaviour based on assessment of historical load data is important in almost all the results obtained which included the discomfort measurements and this factor can be effectively managed during the optimisation process depending on user preferences.

An evaluation of results obtained justified the methodology applied whereby these results were able to establish a direct relationship with the objectives of the research, given the specified input variables. This enabled interesting aspects of the output such as the need to minimize discomfort, identification of schedulable and non-schedulable loads, as well as evaluation of user Participation capabilities within a community, to be fully analyzed in order to maximize efficient resource allocation for energy providers, thereby estimating various activity participation levels. Finally the issue of security and data protection is inevitable and results obtained showed that specific security measures need to be in place and should be a part of any original HEMS design in order to be more proactive in protecting the home from unsolicited intruders. At the end of the day, a robust and reliable system design which the home owners will be proud of can be obtained which serves not only the users but the grid as well.

Chapter 10: Conclusions and Future Work

10.1 Prologue

In this research it has been demonstrated that allowing all the key players involved in DR programs to participate effectively in such programs, is a means of ensuring a successful implementation of the virtues of DR program. This work places the consumer at the centre of this implementation whereby specific users are permitted to participate according to their behavioural attributes and lifestyles thereby preventing sudden withdrawal from such programs. This is effectively captured as an aim of the research whereby the impact of DR programs on users have been evaluated and the impact on such users minimised, thereby increasing the chances of improved user participation. Further evaluations of the research are appreciated based on the content of the chapters presented which took care of the objectives of the research and are summarised further.

Analysis of the Chapters

Chapter 3 focused on the design architecture of a smart home upon which the testbed for the experiment was developed. Chapters 4 and 5 analysed the methodology applied towards achieving the stated aims and objectives while chapters 6, 7 and 8 showed all the results obtained. Here, the aspect of human behaviour during load scheduling was made very important for effective management of the impact of DR programs on consumers as well as the security mechanisms required to ensure continued user participation. Together, all these chapters converges to form a single story which is based on ensuring that the user was given adequate care and consideration as a key player in the management of the grid for effective energy consumption. The rest of this section analyses the achievement of the objectives of this research as enumerated in section 1.2.

10.2 Achieving the Proposed Objectives of Research

Statistical approach to managing load scheduling for domestic applications is paramount in this work whereby the novelties lie in ascertaining the state and behaviour of each consumer household with respect to their appliance use before implementation. This helps in optimizing the best times of engagement which is peculiar to the individual households, thereby managing the discomfort associated with load scheduling to a considerable and predictive levels. Application of historical considerations for user behaviour accounts for the elimination of undesired choices in load management thereby making it an important aspect of this work. Automation of the scheduling process is also a requirement since it is difficult for users to manually track changes in prices as they occur daily. The four objectives of this research were successfully met and are further discussed.

Effective Identification of Schedulable and non-Schedulable Loads

The first objective met was a demonstration that appliance status is only relative when determining and differentiating between schedulable and non-schedulable loads for smart homes. This is important because it has been shown that the status of an appliance depends on the consistency of appliance use in the day based on the customer's historical load profile. The methodology applied was aimed at preventing loads which show little or no deviation at specific times in a day from being scheduled even when all other factors such as lower price, etc. suggests otherwise. The opportunity to schedule loads are identified only when they are suitable to the user and the major benefit is to encourage users to participate more actively in DR programs. Although many optimisation schemes are published, in this contribution, integrating the behaviour of consumers in identifying opportunities to schedule so that the user experiences low discomfort has been highlighted as critical to design of HEMs.

Effective Management of Discomfort Associated with DR Programs

The second objective met was a measure discomfort function as used in the fitness fiction which helps to monitor and automate scheduling mechanisms thereby accounting for the actual user behaviour. The issue of occupancy was also accounted for in the algorithm and results show that the costs as well as user comfort can be effectively managed based on user preferences, depending on whether the aim was to minimize or to maximize those variables of interest. A discomfort factor was proposed to demonstrate the role of the discomfort function which is capable of improving the quality and essence of load scheduling. The introduction of discomfort clipping which can be set by the user helps in stabilizing the optimisation process. This can be viewed as a feedback system which is also a major contribution to the field of DR management and can be implemented in order to encourage more user participation in DR programs as well as improving their confidence to engage more actively.

<u>Effective Evaluation of User Participation Capabilities in DR Programs</u>

The third objective met involves the use of statistical analysis of historical load profile data, combined with other data that constantly changes in magnitude such as dynamic price, to determine user participation levels. Based on the results obtained, a self-evaluation can be made in accessing a user's participation level. The results can also be of benefit to a third party energy provider who can be precisely informed on the best decisions to make which may include having to encourage the less active users to improve their engagements. Another key advantage of this process is the provision of confidentiality of user's data since all analysis are made locally within the smart home EMS and only the final crisp value of the household's performance is made available to the third party. Utility providers can understand their consumer behaviours more effectively using Fuzzy and Boolean-based evaluations of UPI and HPI which can enable them to set their priorities as appropriately as desired. In this work, a method of evaluating consumer energy consumption behaviours has been presented whereby the results obtained can be useful in designing grid network with improved active user participation in DR programs. The essence is to understand the consumer behaviours and then enhance the design and planning of a robust and effective micro grid network.

Effective Recovery Mechanism from Cyber-attacks in DR Programs

Finally, the fourth objective met has also shown that Cyber-attacks on HEMS are a real possibility and care should be taken towards ensuring the protection of the infrastructure that constitutes the network, whereby a provision for this security measures should be included in the original design frameworks of automated HEMS. The vulnerable links within the HEMS were identified and the critical one was determined to be the link between the HEMS and the retailer. Security of the HEMS from cyber-attacks is important and several types of attacks were described, their impacts assessed as well as suggested solutions provided and analysed. One of such assessment is the simulation of cyber-attack on the HEMS, modelled as false data injection onto the load profile data. Results obtained showed that such an attack diminishes the optimisation mechanism as well as the system performance by forcing the load profile to flatten out. Having such a flattened load demand throughout the day may seem to be the most optimal energy supply for a community from the grid perspective in terms of ensuring a supply of constant energy capabilities thereby eliminating peak load demand but in practice, a flattened load profile is neither realistic nor comfortable for the users. Using previously known accurate data was adjudged as a possible solution which can help minimize the impact of such attacks. This means that the HEMS should keep a record of recent data and also perform some forecasting mechanisms on all data available to support the contingency response. Nevertheless, preventing unauthorized access remains the best possible solution and access authentication should naturally be a key part of any proposed solution as this is important so that consumer confidence can be guaranteed.

10.3 Future work

Practically every research conducted usually leaves room for improvement. These constitutes the limitations which can be extended as a future work in an attempt to minimise or eliminate these limitations. There are aspects of this research that can be further improved and they are discussed in this section.

<u>Hardware Implementation</u>

The most important aspect for consideration in the future is the implementation of an actual hardware application of the design whereby the HEMS application as described in this work can be tested in a real home. This will entail having volunteering households within a community as well as the availability of an energy market that operates on day-ahead dynamic pricing as already obtainable in US markets. The major aim for this application is to observe the key aspects of this research such as:

- Discomfort measure and the practical effect of minimising or not minimising it.
- Evaluation of participation levels in DR programs for users within a community.
- Identification of schedulable and non-schedulable loads using statistical analysis of the historical load profiles.
- Application of the actual load scheduling form original forecast position to the new optimised location.

Primary Data Harvesting

Sourcing for data is usually not a very easy task to accomplish due to a variety of reasons which includes privacy concerns. Although the data used are obtained online based on the published data for various customers in the US, it would have been preferred if these data were obtaining directly from consumer homes so that a more realistic outlook to the results can be justified. Although the approach presented here can serve as a template, a more reliable result can be attained when smart plugs are physically mounted so that the appliances of interest can be monitored more effectively. This means that a pilot field trial to collect data can be carried out.

Testing the various pricing models

This is another aspect of the design that requires further research. The issue of different dynamic pricing models were analysed and simulated but in the real presentation, it is required for these models to be tested so that their relative effects can be evaluated. In order words, a specific set of households used for a test analysis should be supplied with various realistically and applicable dynamic pricing strategies so that the various effects can be evaluated. This therefore requires the support of not only the home owners who will have to volunteer for this exercise, but also the support of energy suppliers in order to ensure a successful and a more complete outcomes.

Evaluating the Actual Impacts on Individual Homes

This is another aspect of the research that can be further investigated. Although factors like discomfort and user participation evaluations were modelled and mathematically calculated, in the real sense comfort is an abstract noun or an imaginary feeling which is quite debatable to be measurable. Therefore unless the actual application is implemented and then the users are able to give a feedback on their satisfaction levels maybe through questionnaires, the discomfort measure cannot be considered an absolutely accurate outcome. Although theoretically the mathematical derivations makes a lot of sense, it still requires to be confirmed with practical and on-the-field results.

Further Development of the Algorithm

The algorithm proposed can be further developed in order to be able to play more dynamic roles other than those discussed in this work. These improvements includes but may not be limited to:

- More investigation into the effect of weightings which will improve certain specific outcomes by the user can be carried out.
- Improving the speed of convergence of the algorithm with the aim for adaptation in real-time implementation for online applications.
- Provision and the use of actual discomfort can be investigated to see how it can be used to determine the discomfort threshold. This may

involve the use of more complex computational capabilities and some sort of artificial intelligence.

- Evaluation of this algorithm for different household types in order to improve the version created can be investigated.
- Investigation of load profiles commercial and industrial consumers in order to find out their DR capabilities.
- An automated mechanism for choosing an optimal and preferred thresholds for the user can be investigated, which can be applied based on the user's tendency towards choosing certain thresholds.

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Appendix: List of Equations

Equation 1	$\mathcal{E}_{H_0}, \mathcal{E}_{H_{-1}}, \mathcal{E}_{H_{-2}}, \ldots, \mathcal{E}_{H_{-(n-1)}}$
Equation 2	$\mathcal{E}_H = \frac{\mathcal{E}_{H_0} + \mathcal{E}_{H_{-1}} + \mathcal{E}_{H_{-2}} + \cdots + \mathcal{E}_{H_{-(n-1)}}}{n} \Rightarrow \frac{1}{n}\sum_{i=0}^{n-1} \mathcal{E}_{H_{-i}}$
Equation 3	$\mathcal{E}_H = \frac{1}{n}\sum_{i=0}^{n-1} \mathcal{E}_{H_{-i}} + \frac{\mathcal{E}_{H_0} - \mathcal{E}_{H_{-n}}}{n}$
Equation 4	$F_i = (w_a * \sum A_i + w_b * \sum B_i) - (w_c * \sum C_i + w_d * \sum D_i)$
Equation 5a	$e_{min} \leq x \leq e_{max}$
Equation 5b	$\sum_{j=1}^{24} e_j = \sum_{j=1}^{24} x_j$
Equation 6	$\Delta\mathcal{E}$ = Abs (Forecast Load – Optimized Load) per iteration.
Equation 7	$\Delta\mathcal{E} = \mid \mathcal{E}_{f_{t,n}} - \mathcal{E}_{P_{t,n}} \mid$
Equation 8	$\Delta\mathcal{E} = \mid \mathcal{E}_{f_{t,n}} - \mathcal{E}_{R_{t,n}} \mid$
Equation 9	$A = H_c \cdot (\mid \sum_{t=1}^{T} \mathcal{E}_{f_{t,n}} - \sum_{n=1}^{N}\sum_{t=1}^{T} \mathcal{E}_{R_{t,n}} \mid)$
Equation 10	$B_t = \mathcal{E}_{P_{t,n}} . \mathrm{D}_{P_{t,1}}$
Equation 11	$B_t = \sum_{n=1}^{N}\sum_{t=1}^{T} \mathcal{E}_{P_{t,n}} . \sum_{t=1}^{T} \mathrm{D}_{P_{t,1}}$
Equation 12	$C = \Delta\mathcal{E}/\sigma$
Equation 13	$C = (\sum_{t=1}^{T} \mathcal{E}_{f_{t,n}} - \sum_{n=1}^{N}\sum_{t=1}^{T} \mathcal{E}_{R_{t,n}})/\sum_{t=1}^{T} \mathrm{D}_{P_{t,1}}$

Equation 14	$D = \sum_{n=1}^{N}\sum_{t=1}^{T} \mathcal{E}_{P_{t,n}} / \sum_{t=1}^{T} \mathcal{E}_{f_{t,n}}$
Equation 15	$\mathcal{E}_{f_{t,n}} > \mathcal{E}_{P_{t,n}}$
Equation 16	$\mathcal{E}_{P_{t,1}} = \mathcal{E}_{P_{t,2}} = \mathcal{E}_{P_{t,3}} = \cdots = \mathcal{E}_{P_{t,n}}$
Equation 17	$\mathrm{SP} = \frac{\mathrm{Cns} - \mathrm{Cs}}{\mathrm{Cns}}$
Equation 18	$\mathrm{F}_{j,i} = \mathrm{w}_a * \sum \mathrm{A}_{j,i} + \mathrm{w}_b * \sum \mathrm{B}_{j,i} + \mathrm{w}_c * \sum \mathrm{C}_{j,i} - \mathrm{w}_d * \sum \mathrm{D}_{j,i}$
Equation 19	$f(D_t) = \begin{cases} D_{th}, & D_t > D_{th} \\ D_t, & D_t < D_{th} \end{cases}$
Equation 20	$P = \frac{1}{\sigma\sqrt{2\pi}} e^{-\frac{(x-\mu)^2}{2\sigma}}$
Equation 21	$f(\sigma_t) = \begin{cases} 1, & \sigma > SD_{th} \\ 0, & \sigma < SD_{th} \end{cases}$
Equation 22	$f(C_t) = \begin{cases} 1, & C > C_{th} \\ 0, & C < C_{th} \end{cases}$
Equation 23	$f(P_i)_t = \begin{cases} 0, & P_i > P_{th} \\ 1, & P_i < P_{th} \end{cases}$
Equation 24	$f(L_i)_t = \begin{cases} 0, & L_i = Non - schedulable\ load \\ 1, & L_i = Schedulable\ Load \end{cases}$
Equation 25	$B = \mathrm{D}_{P_{t,1}} * \sum \mathcal{E}_{P_{t,n}}$
Equation 26	$F_{j,i} = w_a * \sum A_{j,i} + 0 - w_c * \sum C_{j,i} - w_d * \sum D_{j,i}$
Equation 27	$F_{j,i} = w_a * \sum A_{j,i} + w_b * {}'\Upsilon_t * \sum \mathcal{E}_{P_{t,n}} - w_c * \sum C_{j,i} - w_d * \sum D_{j,i}$
Equation 28	$\mathrm{R_t} = \mathrm{D}_{P_{t,1}} + \eta_t$

Equation 29	$\mathrm{D}_{P_{t,1}\,\min} \leq \mathrm{R_t} \leq 1.2\mathrm{D}_{P_{t,1}\,\max}$
Equation 30	$F_{j,i}$=$w_a * \sum A_{j,i} + w_b * R_t * \sum \varepsilon_{P_{t,n}} - w_c * \sum C_{j,i} - w_d * \sum D_{j,i}$
Equation 31	$F_{j,i}$=$w_a * \sum A_{j,i} + w_b * \beta_t * \sum \varepsilon_{P_{t,n}} - w_c * \sum C_{j,i} - w_d * \sum D_{j,i}$
Equation 32	$q_t = \varepsilon_{f_{t,n}} + \eta_t$
Equation 33	$\varepsilon_{f_{t,n}\,\min} \leq q_t \leq 2\varepsilon_{f_{t,n}\,\max}$
Equation 34	$F_{t,i} = w_a * \sum A_{new_{t,i}} + w_b * \sum B_{t,i}$- $w_c * \sum C_{new_{t,i}}$- $w_d *$ $\sum D_{new_{t,i}}$
Equation 35	$A_{new_{t,i}} = (q_t - x) * H_c$
Equation 36	$C_{new_{t,i}} = (q_t - x)$ /σ
Equation 37	$D_{new_{t,i}} = x/q_t$
Equation 38	$\alpha = \theta - \vartheta$

Publications

Published Conference Papers:

1. Anuebunwa Ugonna, Rajamani Haile-Selassie, Raed Abd-Alhameed and Pillai Prashant, “Investigating the Impacts of Cyber-Attacks on Pricing Data of Home Energy Management Systems in Demand Response Programs” for IEEE PES General Meeting, Portland, Oregon, US. 2018.

2. Anuebunwa Ugonna, Rajamani Haile-Selassie, Pillai Prashant and Okpako Oghenovo, "Evaluation of user participation capabilities in Demand Response programs for smart home applications," Presented at IEEE PES Power Africa Conference, 2017.

3. Anuebunwa Ugonna, Rajamani Haile-Selassie, Pillai Prashant and Okpako Oghenovo, “Investigating the Impact of Cyber-Attack on Load Profile of Home Energy Management System.” Presented at 9th EAI International Conference on Wireless and Satellite Systems, Oxford, UK. 2017

4. Okpako Oghenovo, Rajamani Haile-Selassie, Pillai Prashant, Anuebunwa Ugonna and K. Shanti Swarup, “A new performance index for evaluating community virtual power plant with domestic storage”. Presented at IEEE Power and Energy Society General Meeting, Chicago, US. 2017.

5. Okpako Oghenovo, Rajamani Haile-Selassie, Pillai Prashant and Anuebunwa Ugonna, “A Comparative Assessment of Embedded Energy Storage and Electric Vehicle Integration in a Community Virtual Power Plant” Presented at 9th EAI International Conference on Wireless and Satellite Systems, Oxford, UK. 2017.

6. Anuebunwa Ugonna, Rajamani Haile-Selassie and Pillai Prashant, "Identification of Realistic Scheduling Opportunities and Base Loads in Smart Homes using Dynamic Pricing and Standard Deviation of Load Profiles," Presented at IEEE Conference on Power Systems Technology (IEEE APPECC 2016), 2016.

7. Anuebunwa Ugonna, Rajamani Haile-Selassie, Pillai Prashant and Okpako Oghenovo, "Investigating the Impact of Discomfort in Load Scheduling Using Genetic Algorithm," Presented at IEEE Conference on Power Systems Technology (IEEE POWERCON2016), 2016.

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9. Okpako Oghenovo, Rajamani Haile-Selassie, Pillai Prashant and Anuebunwa Ugonna, “Evaluation of Community Virtual Power Plant Under Various Pricing Schemes” Presented at IEEE Conference on Smart Energy Grid Engineering (SEGE). Ontario, Canada. 2016

10. Okpako Oghenovo, Rajamani Haile-Selassie, Pillai Prashant, Anuebunwa Ugonna and K. Shanti Swarup, “Investigation of an optimized energy resource allocation algorithm for a community based virtual power plant”, Presented at IEEE Power Africa Conference, Livingstone, Zambia. 2016

Submitted Journal Papers:

1. Anuebunwa Ugonna and Rajamani Haile-Selassie “Community Based Evaluation and Hourly Assessment of User Participation Levels in Demand Response Programs”. Submitted at IEEE Transaction on Industrial Electronics.

2. Anuebunwa Ugonna, Rajamani Haile-Selassie, Raed Abd-Alhameed and Pillai Prashant “A Study of the Impact of Cyber-Attacks on Load Scheduling Applications in Demand Response Programs” Submitted at IEEE Transaction on smart grid.