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Hierarchical and Distributed Architecture for Large-Scale Residential Demand Response Management

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Hierarchical and Distributed Architecture for Large-Scale Residential Demand Response Management

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Abstract

The implementation of smart grid brings several challenges to the power system. The 'prosumer' concept, proposed by the smart grid, allows small-scale 'nano-grids' to buy or sell electric power at their own discretion. One major problem in integrating prosumers is that they tend to follow the same pattern of generation and consumption, which is un-optimal for grid operations. One tool to optimize grid operations is demand response (DR). DR attempts to optimize by altering the power consumption patterns. DR is an integrated tool of the smart grid. FERC Order No. 2222 caters for distributed energy resources, including demand response resources, in participating in energy markets. However, DR contribution of an average residential energy consumer is insignificant. Most residential energy consumers pay a flat price for their energy usage and the established market for residential DR is quite small.

In this dissertation, a survey is carried out on the current state-of-the-art in DR research and generalizations of the mathematical models are made. Additionally, a service provider model is developed along with an incentive program and user interfaces (UI). These UIs and incentive program are designed to be attractive and easily comprehended by a large customer base. Furthermore, customer behavior models are developed that characterize the potential customer base, allowing a demand response aggregator to understand and quantify the quality of the customer. Optimization methods for DR management with various characteristics are also explored in this dissertation. Moreover, A scalable demand response management framework that can incorporate millions of participants in the program is introduced. The framework is based on a hierarchical architecture. To improve DR management, hierarchical load forecasting method is studied. Specifically, optimal combination method for hierarchical forecast reconciliation is applied to the DR program. It is shown that the optimal combination for reconciliation of hierarchical predictions could reduce the stress levels of the consumer close to the ideal values for all scenarios.

Dedication

This dissertation is dedicated to my mother, father, sister, brother and everybody that supported me throughout my PhD.

Acknowledgments

I would like to express my sincere gratitude to my advisor Dr. Ganesh Kumar Venayagamoorthy for the continuous support of my PhD research, for his patience, motivation, and immense knowledge. His guidance helped me in all the time of research and writing of this dissertation.

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Chapter 1

Introduction

1.1 Background

The never-ending quest for the most efficient and reliable power grid has led to the invention of ingenious technologies of power generation and delivery. The consumption side, on the other hand, was dictated by the consumer and was treated as a given. It took an energy crisis to bring the 'efficient consumption' into spot light [55]. Efficient consumption of energy in this sense means consuming electrical energy in such a way that the electric energy generation is efficient. Since electricity has to be generated as it is being consumed, electricity generation efficiency depends on the consumption patterns. Efficient consumption of energy creates numerous benefits for the power system as well as for the environment. It allows for efficient generation of power, longevity of power system equipment as well as high penetration of renewable energy [16]. The concept behind demand response (DR) is exactly that: improving energy efficiency by altering the electricity consumption patterns [54].

Electric energy is different from other commodities in that, electricity is difficult to be efficiently stored. Battery technologies available to-date are not cost effective enough for the average household deployment. Therefore, electricity must be generated at the moment a consumer demands it and the generation has to vary with the highs and lows of demand. Since common day-to-day schedules of electricity consumers causes a very high energy demand at a limited time interval and very low demand at all other times, the power generation is forced to follow the same pattern. The power demand for one day of the New York Independent System Operator is shown in Fig. 1.1.

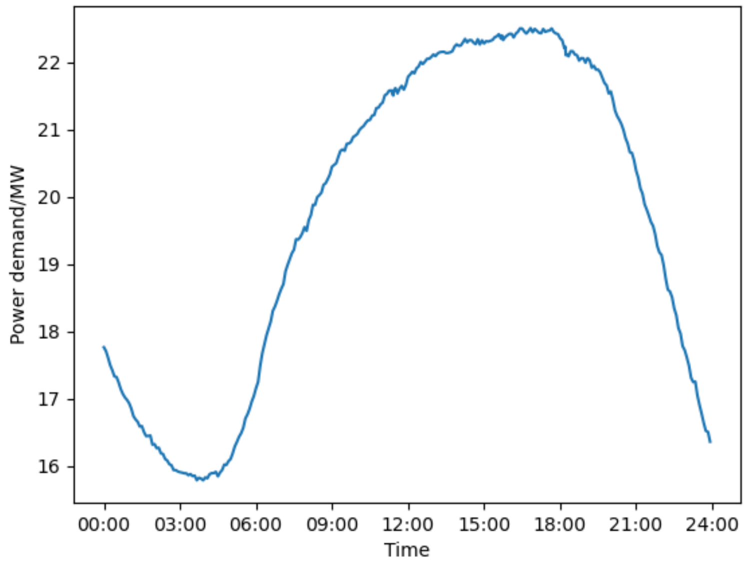


Figure 1.1: Power demand of NYISO for September 23, 2021

Thus, the electric grid is constructed to support power flows much higher than it would need in the average case. Additional power generation plants have to be maintained just to support the peak and the grid equipment have to bear much higher power flows than the average case. All of this just to maintain the reliability just for a few peak hours of the day. The straightforward way to make the power grid more efficient is to alter the consumption to allow a flat flow all day long utilizing DR.

Traditionally, DR is proposed to maintain the stability of the grid or to avoid higher market prices at peak times. In fact, Federal Energy Regulatory Commission (FERC) of USA defines DR as "changes in electric usage by demand-side resources from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" [15]. But DR offers much more benefits. DR could aid in incorporating more renewable resources, for instance [84]. Unlike other energy sources, renewable energy sources tend to vary in availability throughout the day. The variation of renewable generation usually is at odds with the variation of the power demand. DR could move some of the power demand to follow the renewable generation patterns, allowing better penetration of green energy. DR is particularly important in microgrids. These small-scale grids try to maintain their own generation and attempt at being independent of the larger main-stream power grid. DR aids in avoiding time intervals of higher market prices and incorporating maximum local generation in a microgrid. Microgrids improve the resiliency of the power grid [24].

But even after the benefits of efficient consumption has been amply made clear, DR takes a back seat in the modern power system operations. The major reason is that it traditionally calls for a change in social behavior. But today, with the wide-spread enthusiasm of 'smart devices', there is hope to convert the call for a behavior change to a chore taken care of by the technology. Smart IoT (internet of things) technologies are now affordable and widely available [7]. These technologies are converting homes to 'smart homes'. Smart homes can control the efficiency of household appliances. Together with these smart devices, smart homes could cooperate (or even compete) with each other to make the power flow more grid friendly.

Furthermore, recognizing the plentiful benefits of DR, it has been given a prominent place in smart grid. The smart grid is promised to break down the generation, transmission, distribution and consumption one-way power flow paradigm. Instead, a consumer is expected to be a 'prosumer' that buys from as well as sells to the power grid. To enable this interaction the 'energy bit' concept has been proposed. In this paradigm, the information and power flow happen in parallel, working hand-in-hand. Information manages, protects, routes and enables purchasing energy while energy enables creating and processing information. These future advancements create the ideal background for enabling DR information flow. Smart grid conceptual model introduced by the National Institute of Standards and Technology (NIST) [25] is shown in Fig. 1.2.

It is clear that the necessary infrastructure for DR has been developed or being developed rapidly. The next necessary steps are to develop DR specific algorithms and models that fit the real-world practical application of DR. The current research rarely addresses practical issues of DR. The practical issues involve the grid limitations, privacy issues and attracting the interest of the customer to the DR program. These problems become even worse when it comes to the residential sector of energy customers. In addition to the above list of issues, the residential sector has the problem of the consumer illiteracy on DR. Yet almost a 40% of energy consumption in USA is in residential sector [1]. A breakdown of electrical energy usage by sector is shown in Fig. 1.3.

Solving practical issues and developing practically viable DR service provider models enable DR being deployed in large scale and turn profits. Such technology would allow new businesses

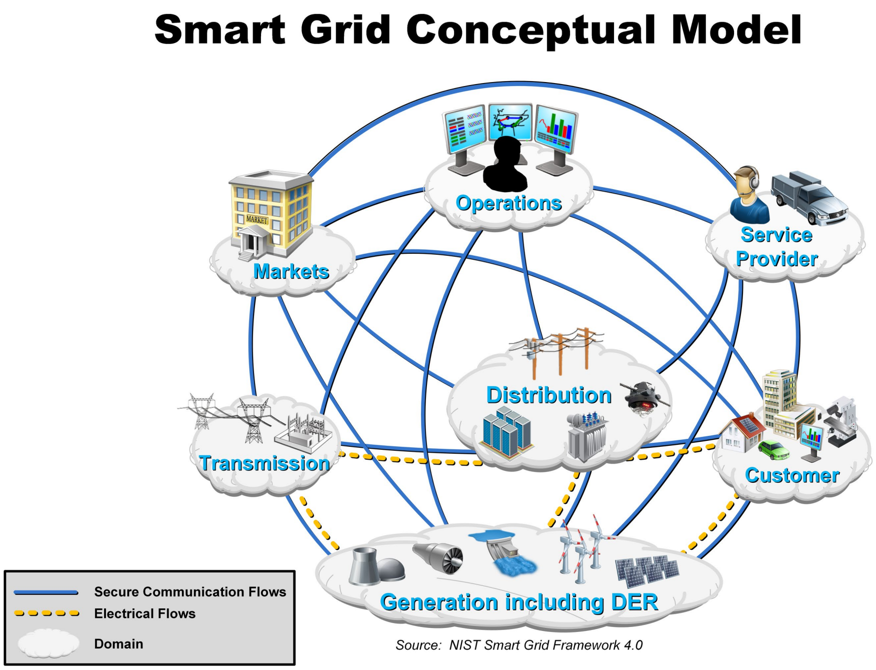


Figure 1.2: NIST smart grid conceptual model

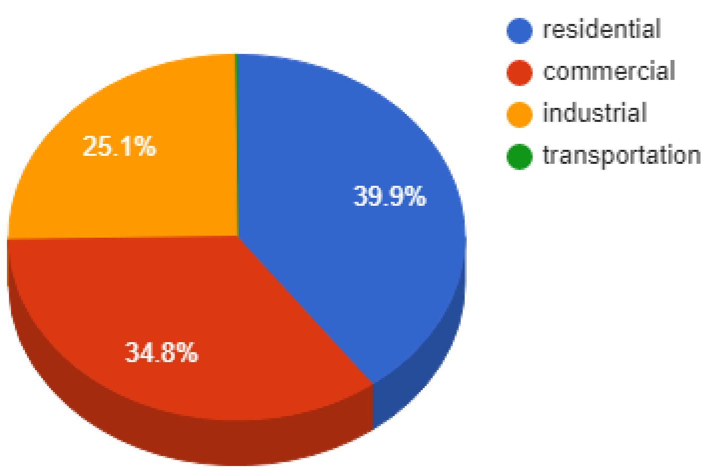


Figure 1.3: Power usage breakdown by sector [1]

to pop-up and a more developed competitive marketplace to be created for DR. This would take the burden of DR off the consumers, allow them to generate a profit, create opportunities for entrepreneurs, optimize the power system operations and make the power grid more environmentally friendly. The target of this dissertation is to introduce technologies that could incorporate a very large number of residential DR customers in a DR program (large enough to turn a profit as an independent DR business).

1.2 Research Objectives

The primary focus of this dissertation is to make practical application of DR more scalable. The following are the specific objectives achieved in this dissertation.

1.2.1 Carry out a Survey and Generalizations of Current State-of-Art in Demand Response Management

DR has been an active research field for several decades. A substantial amount of research has been produced over time. Summarizing and generalizing this body of research is extremely important to recognize the gaps in research and to understand the direction the research is headed.

1.2.2 Develop Service Provider and Customer Behavior Models for Large-Scale Demand Response

The developed service provider models have to be neutral towards the consumer and the electric utility while being attractive to more customers. Additionally, the customer models have to represent the changing behavior of the customer over time.

1.2.3 Explore Optimization Algorithms for Large-Scale Demand Response

It is necessary to choose the ideal optimization algorithm to optimize the DR model. Various algorithms offer different features such as parallelizability, scalability and ability to handle multiple objectives. These methods must be explored to decide on the best method for DR optimization.

1.2.4 Develop a Scalable Residential Demand Response Management Architecture

Residential loads are highly distributed and are connected to the grid at various points. Develop an architecture to aggregate a large number of participants, an algorithm that could consider the limitations of the grid at these points has to be developed. To allow quick and efficient operation, the algorithm has to be highly parallelizable. Such an algorithm must have a very limited change in computation time when new participants are added to the DR program.

1.2.5 Exploring the effects of the Accuracy of Load Forecast and Reconciled Forecasts on DR

Day ahead DR requires the prior knowledge of loads on the day of DR execution. Inaccurate load predictions could lead to less satisfactory results. These inaccuracy effects on the hierarchical optimization have to be explored and quantified. Furthermore, the hierarchical nature of the power system has to be utilized to reconcile available forecasts and improve on them.

1.3 Contributions

The newly available computing power and 'smart devices' could convert a home to a valuable DR resource. By employing crafty algorithms and business models with a detailed understanding on the customer, this resource can be tapped, and a high resilience and stability of the power system can be achieved while saving money for the consumer as well as the electric utility. With the following contributions, this dissertation has made this target more viable.

1.3.1 Survey and Generalizations of Current State-of-the-Art in Demand Response Management

An extensive survey on the available DR research has been carried out, which generalizes the available mathematical formulations for consumers, loads and electric utilities [29]. Additionally, enabling technologies such as internet-of-things technologies have been discussed.

1.3.2 Service Provider and Customer Behavior Models for Large-Scale Demand Response

The 'service provider' [36] model has been introduced that acts neutral towards consumer and electric utility. In addition, a rewards program and membership program has been introduced that could attract more customers [4]. Furthermore, customer analysis has been carried out to assist the service provider in targeting the most suitable customer base [32].

1.3.3 Optimization Algorithms for Demand Response

Several optimization algorithms have been implemented and tested on DR programs. These algorithms include large-scale optimization algorithms (Cooperative Particle Swarm Optimization and Success-History based Parameter Adaptation for Differential Evolution algorithms) [32, 34] and multi-objective optimization methods (MOPSO) [31].

1.3.4 Scalable Demand Response Framework

A scalable DR framework has been introduced that does not increase the computational time when new participants are added. The framework could handle more than a million participants. The framework also allows handling the limitations in different nodes in the power system [28].

1.3.5 Load Predictions for Demand Response Management

The effects of under forecasting and over forecasting on a hierarchical DR program is explored. The observations are measured through participation index, effectiveness index and stress matrices. Additionally, hierarchical forecasting is applied to the hierarchical DR architecture and the resulting DR response is evaluated through the same set of success measurements mentioned above. [30].

1.4 Dissertation Outline

This dissertation is organized as follows:

Chapter 2 in this dissertation explores the state-of-art in DR, exploring the generalized models, algorithms, business models, pilot programs and other supporting technologies. The generalizations pave way to better models and shines a light on the gaps in research.

Chapter 3 discusses DR service provider models as well as customer behavior models and analyses the load behavior. It proposes business a better service provider model that could attract a diverse set of customers for DR. The service provider model includes user interfaces and points and membership methods that can retain the current customer and attract new customers.

Chapter 4 explores optimization algorithms employed to carry out DR optimization. The chapter explores various algorithms with various features such as large-scale optimization ability, parallelization ability and ability handle multi-objective problems.

Chapter 5 discusses a scalable DR framework in detail. The handling of the power system limitations and various levels of participation is also discussed. Additionally, measurements are proposed that could measure the success of a DR program.

Chapter 6 discusses the effects of accuracy of the forecasts on a scalable hierarchical DR program. The effects are measured through the metrics introduced in the previous chapter. In addition, hierarchical reconciliation of the forecasts is also carried out and the resulting forecast is applied to the program and the results are compared against the original forecasts.

Chapter 8 summarizes all chapters and concludes.

1.5 Summary

DR is a key component of smart grid that could be effectively utilized to maintain the stability of the power system. It enables integration of renewable energy, extends the life span of the equipment of the power grid and allows the full and efficient utilization of the available power grid. However, despite the value of DR, only a fraction of the available DR resources is utilized. No large-scale business for DR exists today. This dissertation introduces algorithms and business models to make DR practically viable. In addition, customer analysis methods are also introduced which could be employed to take important business decisions for a successful DR program.

Chapter 2

Survey and Generalization of Current State-of-Art in Demand Response Management

2.1 Introduction

DR research has been an active research field for several decades. A significant body of research has been added to the wealth of knowledge in this time period. The research focus has been turned to various aspects of the field. These aspects include theoretical and practical considerations of deploying DR programs. With the development of accompanying technologies, DR research has grown to incorporate the new technologies.

At the very start of electrification, the pricing was set only considering the total energy consumed. For instance, Brighton Electric Light Co. charged 1s per KWh consumed if more than 10 kWh were consumed per lamp or 1s 4d if less than 10 kWh were consumed [13]. It was soon realized that the power flow is more critical designing and maintaining the power system than the total energy consumed. With this understanding, DR concept was created. However, at the beginning of home electrification, DR was not a part of the contract between the consumer and the electric utility.

Several advancements have been made in DR research so far. The earliest methods for DR were direct load control (DLC) methods via separate circuits for energy hungry appliances. These lines had power only at designated times of the day (when the rest of the grid was at off-peak), and the two lines had two separate meters which were billed at separate rates. Although ripple control methods were suggested and were used to control demand side management in World War II era, it was not much used for home energy management later in more prosperous days [63].

More serious and wide-spread DR research began with the energy crisis of 1970s. Various methods of DR were implemented in the late 70s and early 80s. Many pricing methods were introduced in these decades. Since then, the attention has been turned to solution algorithms as well as hardware implementations [27]. Recently, application of AI technologies has been considered for DR management [77].

As an attempt at bringing these technologies into practical life, pilot programs have been implemented in various countries [18]. Despite many available pilot programs, most available DR methods are no more than simple pricing methods. Such pricing methods have been available in many countries. Currently, several DR programs are in operation USA. A tree diagram showing the major topics in DR research is shown in Fig. 2.1.

All these advancements have been compiled in several DR overview and review studies [37, 57]. However, these reviews do not attempt at finding the common characteristics and generalizing the approaches. Such generalizations open new pathways to further research by bringing the gaps in research into spotlight. In this chapter, some of these general formulations as well as the incorporating technologies are discussed.

2.2 Load Modeling

To quantify the comfort of using an electrical appliance as well as to quantify its effect on the electric power grid, the loads have to be mathematically modeled. In this section generalizations of these models are discussed.

2.2.1 Uncontrollable Appliances

The energy usage of these appliances depends only on the time. That is, no DR control input would change the power usage of these appliances. In other words, these appliances are out of the control of DR. However, the energy usage of these appliances must be considered for the scheduling

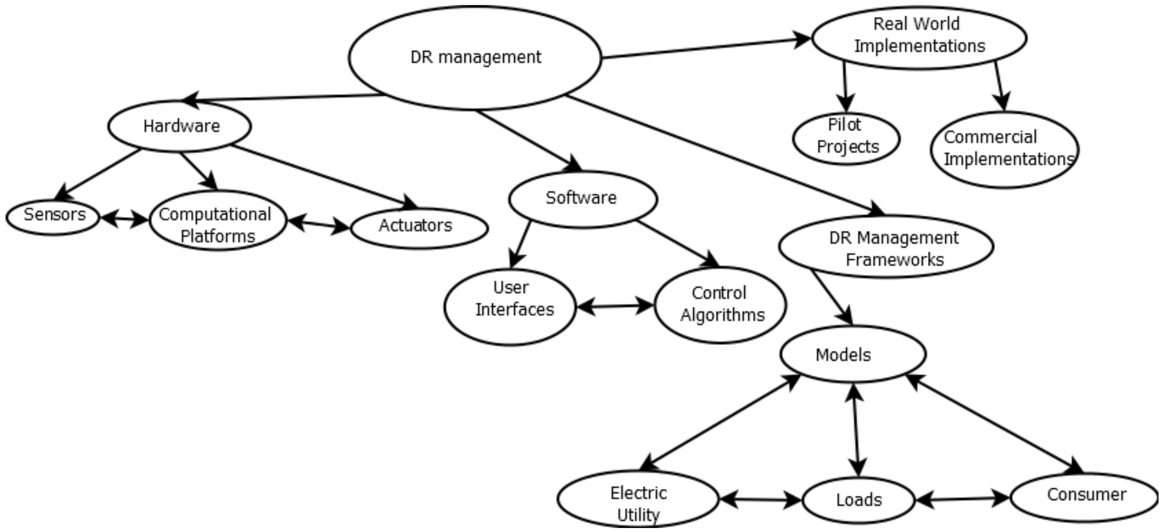


Figure 2.1: Major research topics in demand response

of other appliances. That is, other appliances have to be scheduled around these appliances. The uncontrollable appliances can be represented by the following equation:

$$E(t) = f(t) \tag{2.1}$$

where $E(t)$ is the energy at time t and $f(t)$ is some function that depends on uncontrollable behavior of appliances and consumers. For DR purposes, the energy usage is only dependent on the time.

2.2.2 Shiftable Appliances

Shiftable appliances are one type of appliances that are under DR control. The decision whether these appliances can be turned on or not can be taken as a part of the DR control process. However, once turned on, the energy consumption of these appliances is difficult to control. Such attempt at controlling the energy consumption or interrupting the device cycle could result in unsatisfactory outcome or even device damage. The washing machine and clothes dryer are examples of such appliances. These appliances are modeled in studies such as [12]. The energy usage of these appliances can be shown as:

$$sgn(x) = \begin{cases} 0, & t < t_a^s \\ f(t - t_a^s), & t_a^s \geq t \geq t_a^s + n_a \\ 0, & t > t_a^s + n_a \end{cases} \tag{2.2}$$

Here, t_a^s is the starting time of the appliance, n_a is the running time of the appliance, $f(.)$ is the function returning the energy usage depending on the running time. The comfort of these devices depends on the turn-on time of the device. For instance, it would be comfortable to turn the washing machine on in the afternoon when the consumer is free, but it would be quite uncomfortable to turn it on at 2 in the morning. This can be modeled by a value given by the consumer for each time interval modeling the comfort of the consumer at that time period.

$$c_a = f(t_a) \tag{2.3}$$

2.2.3 Interruptible Appliances and Controllable Appliances

These appliances can be either turned off in the middle of operation without damage or the input energy could be controlled without damage depending on the design of the device. Appliances that could be interrupted (i.e., turned off) in the middle of the operation are 'interruptible' appliances. By repeatedly turning these devices on and off, a target energy amount could be consumed with these appliances during a given period of time. For instance, HAVAC appliances and EV chargers can be turned on and off. On the other hand, controllable appliances can be run with lower power input than the rated values. For instance, the power input to electric lighting can be changed. Instances of this kind of appliance modeling can be found in studies such as [42, 82, 5].

However, changing the electric energy input to these appliances have consequences towards the user comfort in various ways. The current comfort of some devices depends on not only the current energy consumption but also the whole history of energy consumption starting from the initial time. For instance, in HAVAC and water heaters, the current temperature depends on initial condition as well as the temperatures that have been maintained throughout the whole time period. There is a non-linear relationship between the input power and the change of comfort (comfort measurement is the temperature in the case of HVAC). The following formula could model these devices:

$$c(t) = c(t-1) + f(w_t) - l(c(t-1)) \tag{2.4}$$

where $c(t)$ is the comfort of the device at the current time interval w_t is the power input to the device at the current time interval, $f(.)$ is the relationship between the power input and the change in comfort and $l(c(t-1))$ is the leakage of comfort happened in the last time period. Since the constraints of these appliances are bound with the comfort factor instead of the energy input, these appliances are called 'comfort constrained' appliances in this research.

For other appliances like lighting the current comfort only depends on current energy input. The comfort of these devices can be depicted as:

$$c(t) = f(w_t) \tag{2.5}$$

For some devices such as the EV charger, there is no comfort requirement for each time period. Instead, there is a deadline to meet. For instance, the charger might need to finish charging by the time the consumer needs to use the vehicle.

$$\sum_t W_t \geq W_r \tag{2.6}$$

where W_t is the power input at time t and W_r is the required energy level. Since the comfort of these devices have a direct relationship with the energy input, the constraints associated with these devices can be defined with the energy input. Therefore, these appliances are called 'energy constrained' appliances in this research. For all these devices discussed above, there are minimum and maximum energy input limits.

$$W_l \geq W(t) \geq W_m \tag{2.7}$$

where W_l is the minimum power input and W_m is the maximum power input. Block diagrams of these appliances are shown in Fig. 2.2.

2.2.4 Positive and negative loads

EV and battery can work either as a positive or negative load. That is, they are positive loads when they charge and negative loads when discharging. Many studies consider EV as a positive

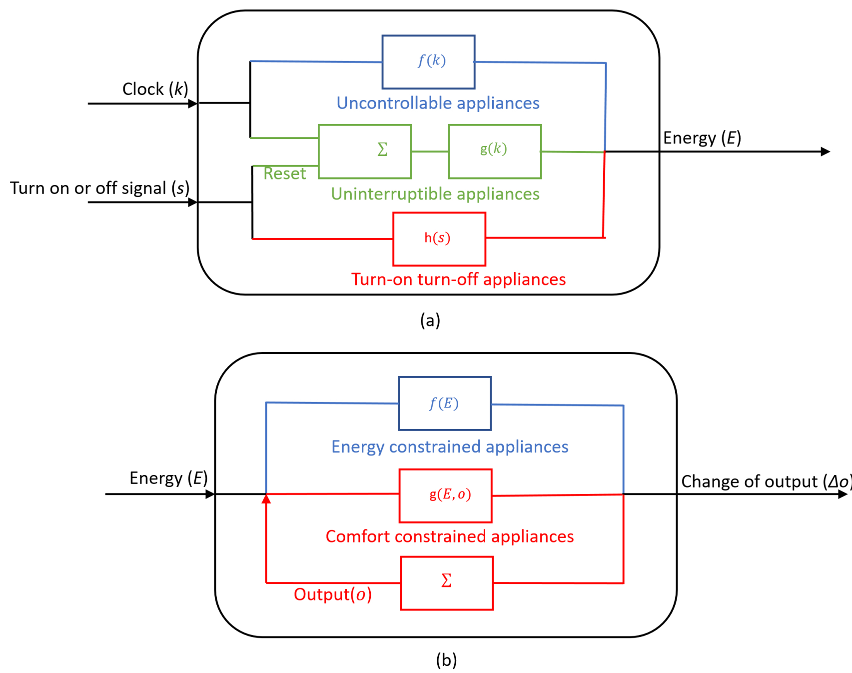


Figure 2.2: (a) Block diagram for uncontrollable, uninterruptible and turn-on-or-off devices, (b) Block diagram for energy constrained and comfort constrained devices

load only ([68, 69, 23]). An appliance that can be either positive or negative load can be modeled as follows:

$$E(t+1) = E(t) + \gamma_1 i(t) - \gamma_2 o(t) - \gamma_3 E(t)^{\gamma_4} d(t) \tag{2.8}$$

where $E(t)$ is the energy stored in the negative load at time t, γ_1 is the efficiency term associated with the energy storage operation, $i(t)$ is the energy input to the load, γ_2 is the efficiency term associated with the energy discharge operation and $\gamma_3 E(t)^{\gamma_4} d(t)$ is the term associated with self-discharging of the battery. Some research work that model the batteries are [12, 3, 68, 58] [67]–[69].

2.2.5 Aggregated load modeling

Another way to model the DR loads is to consider the 'elasticity' of the aggregated load rather than the considering individual loads. Reference [40] and [36] makes use of this modeling method. Elasticity of the energy demand is defined as the amount of change of energy usage the user is willing to make when the price is change in a unit. This modeling is mostly used in electricity pricing methods. [43] makes a similar assumption.

2.3 Participant Objective Modeling

The participants in a DR program includes the electric utility, the customer and possibly the aggregator of DR. In this section the modeling methods for these entities are discussed.

2.3.1 Electric Utility Objective Modeling

The electric utility modeling in this context depends on the motivation of the electric utility for initiating a DR program. There could be several objectives. If the utility contributes to an electricity market, then buying price minimization could be a target. Minimize,

$$c = \sum_{t} f(w, t) \tag{2.9}$$

where w is the total energy demand of the consumers and $f(w, t)$ is the time dependent price of electric energy in the market. Another target for the electric utility could be the minimize the peaks and valleys of energy demand in the system. In this case, the objective could be minimizing the peak to average ratio (PAR) of the energy demand. That is, minimize,

$$c = \frac{\max(w(t))}{\sum_t w(t)} \tag{2.10}$$

where $w(t)$ is the energy demand at time interval t. Another possibility is that the electric utility is looking to maximize the utilization of renewable energy. Unlike other energy sources, renewable energy sources tend not to be available in certain time periods of the day. Most of the time, conventional energy generation methods like coal power generation have to be used to generate enough power to satisfy the demand at other times. DR could be used to incentivize the consumer to shift most of the energy usage to high renewable energy generation time of the day. In this case, the utility might attempt to minimize the difference between the energy demand and the renewable energy generation. That is, minimize,

$$c = \sum_{t} |w(t) - g(t)| \tag{2.11}$$

where $w(t)$ is the power demand at time t and $g(t)$ is the renewable power generation at time t. Other objectives of the utility would be shaving the peak demand to stop the demand from exceeding the capacity (to prevent brownouts and blackouts) and to extend the lifetime of electric grid equipment.

2.3.2 Consumer Objective Modeling

The consumer usually has two objectives: minimize cost and minimize discomfort. The comfort of the appliances is discussed in the earlier section. However, in some research work, the consumer has been modeled as a much simpler model using a utility function. It is assumed that the utility of the consumer has a quadratic relationship with the energy consumption.

$$U(t) = a[w(t)]^2 + bw(t) + c \tag{2.12}$$

2.4 Problem Formulation Methods

Given the complexity of the appliance modeling, the DR problem can be seen as a mixed-integer non-linear problem which is very difficult to solve. However, different formulations and applications of decomposition methods could reduce the problem into an easier form to solve, usually as iterative methods. For instance, generalized Benders Decomposition is applied in [52]. Other formulations include mixed integer linear programming (MILP), convex programming and integer programming.

A popular method to form the problem is as a game theory problem. This allows iterative solution of the problem while preserving the privacy of the consumers. That is, direct information on the home energy consumption does not have to be given out to anybody to carry out the optimization [51].

2.5 Control Methodologies

In this section, methods used to actually carry out the calculated DR targets is discussed. There are basically two methods of carrying out DR: direct load control (DLC) method and pricing methods.

2.5.1 Direct Load Control Method

In DLC method, the aggregator would take the control of the appliance over. In its early days, some houses used to have separate circuits for certain equipment like boilers which only delivered power at a certain time of the day. (For instance, Economy 7 program in UK). Currently, many DR programs involve remote control of smart thermostats.

But more and more studies concentrate on using Home Energy Management Systems (HEMS) to control the energy consumption instead of the aggregator remotely controlling the appliances. The aggregator would merely provide an energy target to meet, and HEMS would take this input and optimize the appliances to meet it.

2.5.2 Pricing Methods

In this method, a pricing signal is communicated to the consumer expecting the consumer to adjust their power demand accordingly. There are several possible pricing mechanisms available. Examples using these pricing programs are studies such as [79]. Reference [76] uses automatic meter reading techniques to come up with a real-time pricing based on the power demand. Reference [83] introduces "coupon-incentive" based pricing scheme which operates near real-time for volunteers while still offering a flat rate for others. Reference [53] presents a methodology that involves scheduling of the appliances as well as a pricing scheme. Reference [38] presents a framework that uses several pricing methods with multiple pricing rates.

2.5.2.1 Real-Time Pricing

In this pricing method the consumer is completely exposed to the real-time pricing of the real-time market. The prices are rather unpredictable and depend on the current state of the market and power grid.

2.5.2.2 Day-Ahead Pricing

In this method the prices are communicated a day before. Usually, these prices are set hourly. However, real-time whole-sale prices might vary in the market. The electric utility might have to bear the risk of unexpected high prices.

2.5.2.3 Peak Time Pricing

The utility would set up a higher price for the time period that is conceived as high demand times. This allows a lower price for the lower demand times.

2.5.2.4 Time-of-Use Pricing

Although the pricing changes throughout the day, this pricing scheme is more permanent than the real-time pricing. The prices at the less critical times are kept low and at the more critical times are set at a higher rate. This kind of pricing schemes are susceptible for 'rebound peaks'. That is, a new peak could appear at otherwise lower demand time.

Currently in research, the pricing schemes are provided intended at HEMS. HEMS could take a pricing scheme instead of a target energy and optimize home energy.

2.6 Internet of Things and Home Energy Management Systems

A home energy management system (HEMS) is an intelligent system that manages the energy of the house. The basic use of a HEMS is to optimize the power usage such that the energy usage is minimized. However, by providing a target energy or a pricing signal HEMS could be used to cooperate for a DR program. HEMS is enabled by the smart internet-of-things (IoT) devices. IoT includes the smart sensors, smart actuators and the intelligent control system that takes decisions. DR enabled IoT devices in modern homes is shown in Fig. 2.3.

2.6.1 Sensors

Sensors provide the information an optimization algorithm needs to take a decision on the next control step. Several smart sensors are available in the market at the moment such as light sensors and power monitors. Below is a discussion on some of the sensors that are useful for DR purposes.

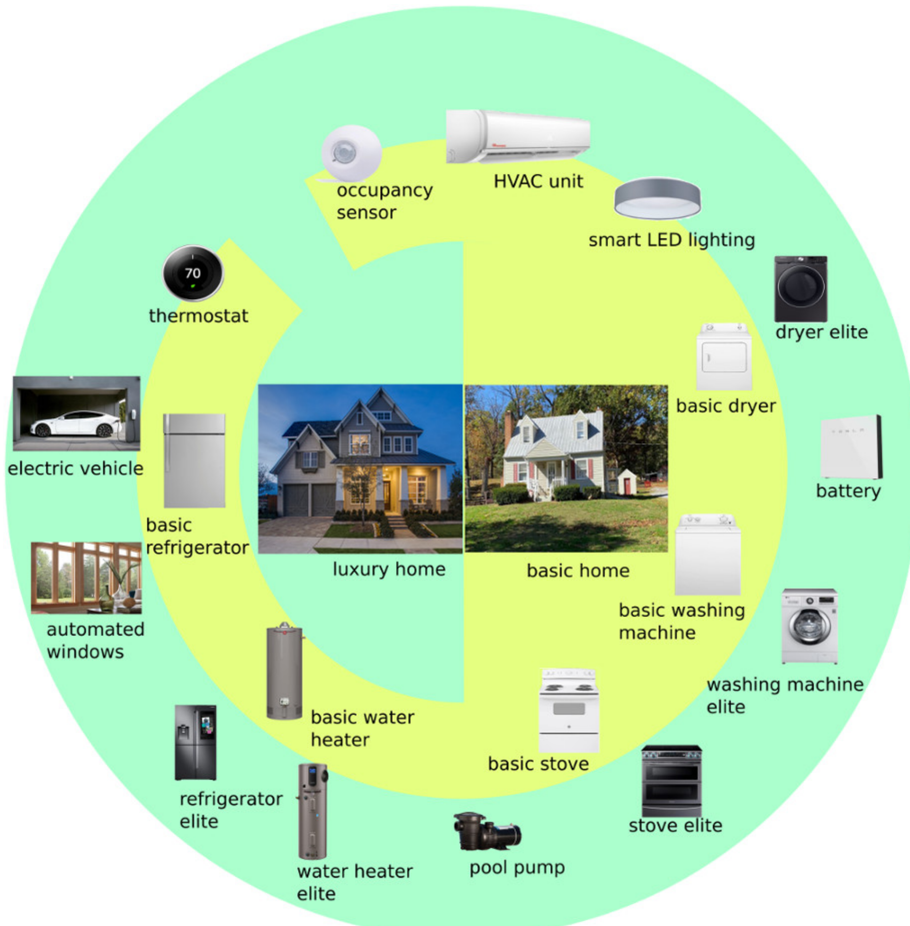


Figure 2.3: IoT Devices Available for Demand Response

2.6.1.1 Motion Sensors

The energy consumption of a home can be changed according to the fact that the residents are at home or not. For instance, the temperature could be set to a lesser comfortable temperature and the lighting could be dimmed or turned off. Motion sensors can detect whether the residents are occupying the home or not allowing the DR algorithm to carry out such optimization tasks.

2.6.1.2 Open/Close Sensors

Open doors affect the energy consumption of the HVAC to maintain temperature. The state of the doors can help the algorithm to predict the energy needed for the HVAC to maintain the temperature inside the house. The data collected from these sensors coupled with other measurements such as occupancy and outside temperature could help a learning algorithm to build a data driven model for the thermal characteristics of a house which is useful in predicting future energy usages.

2.6.1.3 Temperature and Humidity Sensors

These sensors allow efficient DR with the HVAC unit. By controlling the temperature at the optimal levels instructed by the DR algorithm these sensors make sure the residents' comfort is not compromised.

2.6.1.4 Light sensors

Few years ago, lighting was considered a 'critical load'. That is, a load that does not contribute to DR. However, with state-of-the-art light sensing technologies, a modern home is able to contribute to DR using lighting load. Accounting for natural lighting from outside, these sensors contribute to maintaining lighting at the optimal level without the wastage of electricity.

2.6.1.5 Power Monitors

Power monitors allow the efficient employment of real time prices in a DR environment. They also allow the consumer to be aware of the DR situation in the residence.

2.6.2 Actuators

Actuators carry out the decisions made by the DR algorithm which is fed with information using the sensors. Light monitor, temperature monitor and power monitors have actuators which will efficiently reduce or increase the power usage of the corresponding device, striking a fine balance between user comfort and energy saving. Smart appliances such as smart refrigerators, smart TV and smart washing machines are popular devices that enables the IoT technologies. Smart plugs on the other hand, allows the non-smart devices to act as smart devices under the guidance of a controlling algorithm. For a complete review of IoT, the interested reader is referred to [7]. A complete description of an IoT based building energy prediction system can be found in [6].

2.7 Other Technologies

2.7.1 Advanced Metering Infrastructure (AMI)

Although automatic reading was first developed a long ago back in 1972 [56], the commercial popularity is more recent. The large-scale availability of AMI technologies have enabled demand based pricing capabilities and responding to real-time prices [81], [76].

2.7.2 Communication Networks

The wide-spread communication networks have contributed much to residential DR problem. Specially in home energy management problems LAN plays a major role. Other technologies such as ZigBee has also been utilized in developing DR solutions.

2.7.3 PV and Battery

The availability of cheap PV systems is rapidly increasing in the current era. Additionally, the advancements of battery technology have enabled the efficient use of the PV power. Few studies have taken the availability of PV and battery in their DR optimization.

2.8 Implementations and Pilot Projects

2.8.1 Implementations

DR implementations have been deployed throughout the history as described in the introduction. Economy 7 plans, for instance, have been active since 1970s [20]. US Energy Information Administration states that the total peak demand savings from DR programs in US is around 12,000 MW [21]. There are several DR programs currently active in US. The most popular DR programs available for the residential sector is the TOU pricing schemes. Examples of such pricing schemes are Pacific Gas and Electric Company TOU scheme [59], Southern California TOU plan [66] and Sempra Energy TOU plan [67]. These companies also offer critical peak pricing (CPP) and other pricing plans too. Florida Power and Lighting (FPL) company offers few DLC programs. For instance, the "On Call" program offers credit on monthly bills to let the utility to switch off pool pumps water heaters and HVAC systems when the need arises. Using this method, FPL attempts to control the high energy demand in Florida summer times. Xcel Energy also offers few DR programs for their customers. Curtailment programs, critical peak pricing programs, as well as EV critical peak pricing programs which are specifically designed for electric vehicles are among them.

2.8.2 Pilot Programs

Few pilot programs have been carried out on DR and few publications can be found in the literature that discusses the experiences of DR pilot programs. Reference [75] discusses a DR pilot project that employs specific appliances that would automatically respond to pricing schemes. The authors test several types of commercially available devices and come to conclusions as to which appliances perform better in a real-life scenario. Reference [45] discusses DR implementation in China. The authors discuss the pilot programs carried out in cities such as Shanghai, Foshan, Beijing, Suzhou and Tangshan and report savings. Reference [19] discusses pilot program in Belgium which included shiftable appliances, hot water buffers and electric vehicles. In this case, the authors also discuss the practical issues associated with DR such as users not being able to configure the smart appliances properly and failed logging of the data due to communication failures. The study also measures the fatigue of the customers for the program. That is, the customer losing interest in the program over time. The study quantifies the fatigue response of the customer. A pilot program in United Kingdom is described by [10]. This program was designed around the concept of "fear of losing motivates more than the prospect of gaining". The authors note that, although 125 invitations have been sent out to the residents on a flat, only 10 of them have agreed to participate on the trial program. Authors also go on to analyze the demographic of the participants and their responses to the trial. A pilot program in Norway is described by [64]. A simulation study in Cairo, Egypt is presented in [9]. The authors have collected real data from Cairo and have carried out a simulation on the set of real data. A microgrid based ancillary service demand response framework is introduced by [8]. The authors take four microgrids from rural communities and interlink them to provide the ancillary services in Nigeria using this framework. The current state of Portugal energy grid is discussed in [2]. The authors analyze three scenarios: a business-as-usual scenario, a carbon-free system scenario in 2050, and a scenario without heavy carbon emission restrictions. The long-term effects of DR on the Portuguese power system are discussed in this paper.

2.9 Cyber Security and Privacy

As the theory and applications advance, DR operations now increasingly depend on communications as well as electronics, opening up opportunities for cyber attacks. Therefore, DR systems must be secured to ensure privacy and security of the parties as well as the equipment involved in DR activities. There are three classic objectives of a security system: confidentiality, integrity, and availability. Confidentiality refers to the privacy of the data and operations whereas integrity refers to making sure that only the authorized personnel gain access to the data and operations. Availability refers to the fact that the system has to be able to be accessed whenever the authorized personnel want to access them. The security of the DR program can be assessed along these lines. Several attacks are possible in a smart residential DR environment. These attacks could be motivated by several targets such as personal gain, jeopardizing the grid stability and even personal vendettas to attack and damage personal properties.

One of the main attacking points could be the smart meter. The smart meter is enabled with 'net metering' technology that receives a price signal which guides the smart scheduling of the appliances. If an attacker is able to broadcast fake pricing signals breaching the integrity objective of the security system, they could manipulate the EMS to reduce their own bill or to destabilize the grid by increasing the peak of the system. These attacks could be mitigated by building statistical models to detect unnatural changes in pricing signals [47], [46]. Additionally, the attacker could carry out the attack at the DR resource aggregator level by manipulating the load signals received by the DR load aggregators. This kind of attacks are called ”direct load control altering” attacks. Creating frequent fake changes in the loads could lead to a jeopardized system. A similar learning system or a private key encryption mechanism can help mitigate this problem. This attack is discussed in [50].

2.10 Summary

In this chapter an overview of the currently available DR technologies is presented. The chapter generalizes the available models in the literature. There are several categorizations of the appliances available in the literature for the purpose of DR optimization. The generally considered appliances are uncontrollable appliances, shiftable appliances, interruptible appliances and controllable appliances. The consumer objectives include minimizing cost and maximizing comfort. The objectives of the utility include minimizing cost, reducing peaks and incorporating renewable energy. The DR problem can be formulated as a MILP problem. To carry out DR, HEMS and IoT devices are commonly deployed. These IoT devices include sensors and actuators. An accompanying need would be privacy and security for the network and the devices. Currently, there are several DR programs that have been deployed commercially. In addition, there have been several successful pilot projects around the world that have implemented DR programs and have reported their results.

Chapter 3

Service Provider and Customer Behavior Models for Large-Scale Demand Response

3.1 Introduction

The traditional task of a DR aggregator (or a service provider) is to gather DR resources from the consumer on behalf of an electricity utility. That is, the aggregator is providing the service to a utility for a price. Although DR aggregation has been an active business venture for a while, large-scale DR aggregation has not been very successful yet. Especially, most of DR resources from the residential size is being underutilized. Many of the residents still pay a flat rate for the energy they use all year through. Not only the electric utilities miss out on resources that could stabilize their power grid, but also the consumer misses out on a huge opportunity of saving money. To tap into this resource, novel business models are needed that are more customer friendly and more neutral towards both consumer and utility than an aggregator that would profit solely through the electric utility.

A successful business should carry out proper market research to understand the customer base. The entrepreneur has to target the most potential customer base. The difficulty involving DR is that it depends on human behavior changes. Human behavior changes time to time and therefore, the ability for the consumer to contribute to DR also changes from time to time. The ability of the consumer to contribute to DR changes over the day. Therefore, it has to be analysed as a function of time.

Additionally, the objectives of the consumer are numerous. A diverse customer base is important for a DR program. To attract these consumers with the different targets, the incentives offered have to be diversified too. Furthermore, effective communication of the information regarding DR has to be implemented. Accomplishing this requires implementing of online user interfaces. This allows effective control of DR such as easy method of opting-out of DR.

This chapter discusses business models and customers. It introduces methods to characterize customers and introduces interfaces to improve customer participation.

3.2 Service Provider Model

The 'Service Provider' is essentially a DR aggregator that works independently from the consumer and the utility. Generally, the utility themselves offer the DR program and the associated benefits. In this case, the DR program is tailored to be more inline with the interests of the electric utility than the consumer. The Service Provider, on the other hand, is a third party, which benefits from both the electric utility and the consumer. For their own benefit, the service provider tends to strike the best balance between the utility and the consumer leading to a 'win-win-win' situation for consumer, electric utility and the Service Provider (as opposed to a traditional win-win situation). A graphical representation of the service provider model is shown in Fig. 3.1.

3.2.1 Customer Attraction and Involvement Methods

The casual consumer might not understand the implications of DR or may lack the time to participate in these schemes. Many consumers are also unaware of the price changes and therefore will not make changes to their behavior. To mitigate this problem some utilities send text messages to customers informing them of price changes. However, the customer must still make an intelligent decision concerning the efficient control of their appliances. An attractive and easily understood interface is needed to convey the information needed in a simple manner. Furthermore, the customer has to be incentivized by easy to understand and attractive incentives to attract them to the DR program. There are few graphical interfaces that have been designed to achieve similar goals in

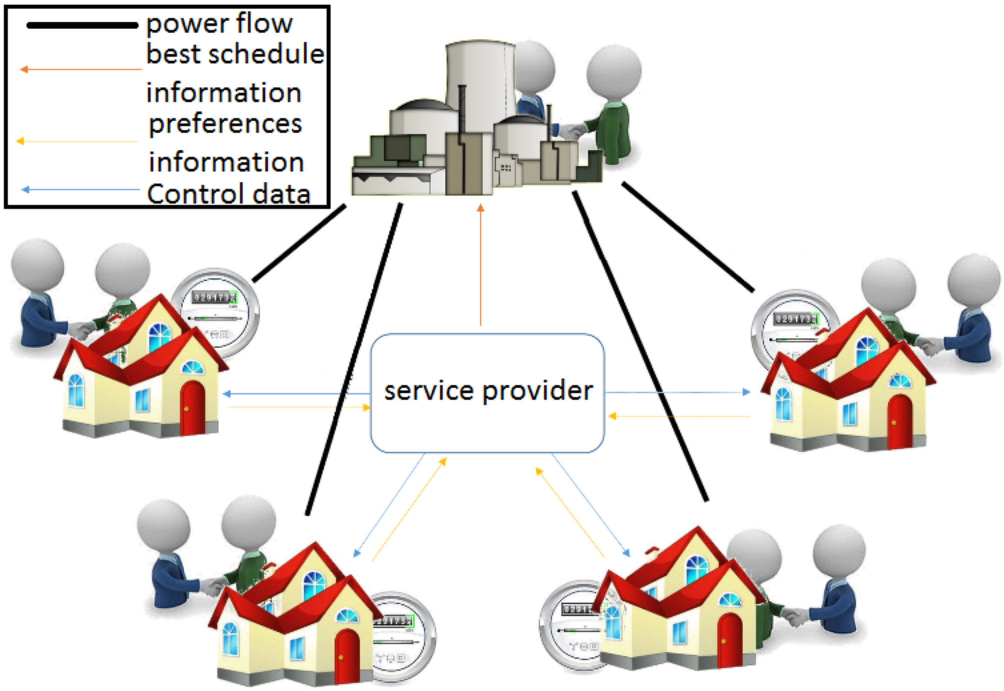


Figure 3.1: Service Provider Model for Demand Response

literature. For example, an interactive dashboard has been proposed for demand response with multiple facilities oriented to the electrical companies [48]. An interface that the customers can use to change their load priority and preference settings has been developed in [60], while [22] describes an interface that permits to participate in demand response events in a smart home. All these proposals assume the customers are fully aware of the unique demand response model that is proposed. However, this is not the case for most consumers. The following study aims at overcoming these problems and increasing the general public participation of DR.

3.2.2 Shift MyPower Program

Shift MyPower is a DR program that is designed to attract the customer to participate in the DR program. It implements the aforementioned Service Provider model and, based on it, implements the business model. The business model aims to diversify the consumer base and effectively communicate the DR information to the consumer.

3.2.2.1 Customer Diversity

Most of the 300 million citizens, representing a diverse and large customer database in the United States, have access to electricity. As the goal of this study is to encourage that customer base to use this demand response system, the customers are categorized into three groups. The first group consists of those who are environmentally conscious; the second group consists of those more concerned about the financial gain of demand programs; and the third group consisting of those unwilling to participate in such a program due to the perceived complexity and time required for participation. These groups were chosen based upon the perpetual motivations of saving money and the societal trend of environmental sustainability. The decision to use such criteria to create these large groups will ensure that the program satisfies a majority of the population.

3.2.2.2 Communication

Effective demand response programs require that customers receive information that they can quickly comprehend. Currently, this lack of communication is characterized by a lack of understanding among most consumers regarding how their individual power usage affects the grid and the subsequent difficulties to the utility. Shift MyPower ensures clear lines of communication in an easy and relatable format based upon the Service Provider model to connect all the main roles and provide communication solutions. Therefore, the focus of this study is one of adapting the system to user preferences while encouraging greater user involvement in the demand response

3.2.2.3 Interface

The interface is shown in fig. 3.2. Instead of just showing the number values, this dashboard is designed to show values that are easier to understand. For instance, the dashboard shows your 'place' in DR in comparison to your neighborhood. That is, it shows how well you are doing in comparison to others. To preserve privacy, this dashboard would only give out a number, a 'place' rather than showing information about others. In addition, the dashboard provides a switch to opt-out of the DR program quickly and easily.

Figure 3.2: Shift MyPower Dashboard Interface

3.2.2.4 Rewards Program

One method of increasing user interest from a commercial perspective is through concrete rewards. For example, users completing satisfaction surveys have a probability to win items for simply completing survey. Other schemes involve discounting items it two are purchased together or through the use of a premium account as offered by Amazon, eBay and Walmart to increase customer purchases [70]. The rewards program in Shift MyPower which was created to entice the customers to participate here was based upon these earlier innovative concepts. Customers, including those of a power utility are drawn into certain behaviors when the reward is inherently associates with their preferences. Therefore, a user interested in electronics may be offered discounts to purchase a smart TV, a mobile phone or a laptop. In this specific case, such users are classified in different groups with the items associated according to individual preference. Likewise, to be offered a specific item, the user needs to fulfill certain requirements such as completing a product registration (perhaps online), or purchasing an additional product or following specific instructions. The schedule is adapted to the user preferences and experience. Hence a novice user with little experience in the system requires a simpler schedule than that of veteran user. Similarly, users following very strict schedules due to experience and interest should be rewarded with different items than users following a more variable schedule. Membership levels are introduced to adapt the system to the above-mentioned diversity.

3.2.2.5 Membership Level and Points System

There are four levels of membership. Basic membership is the lowest level in which merely enrolling means the customer will begin earning rewards. The membership levels continue as listed from lowest to highest (i.e., silver, gold, and platinum). The service provider will offer a customized schedule for each customer devised for their specific needs through which will yield the most rewards (provided the customer adheres to this schedule). The schedule is broken down into 48 segments with a projected value of usage for each customer for each segment. These segments are used to distribute points to the customers, and the points are awarded and redeemable under a variety of conditions (see subsection for the specific information on redemption). The membership level and points are directly connected with each customer having a customer factor number, δ, that considers all customer factors including their present membership level. The higher the membership, the more that is included into their customer factor, which opens the possibility of accruing more points. Following the schedule means that customer usage must be within five percent of the projected usage on the schedule developed by the service provider. Through this system, the customers receive more points if they follow the schedule. More customers following the schedule in turn helps the utility develop a clearer plan to decrease their peak load.

3.2.2.6 Rewards Program Type

Multiple methods of appealing to a diverse customer base are necessary to ensure support. Although every customer will receive points there are three methods for redeeming these points. Again, the three-tiered customer criterion is used: i) those who are environmentally conscious ii) those who are motivated by money, and iii) those uninterested in demand response programs believing them to be complex and time consuming. For example, environmentally conscious customers may use the points to donate to a local environmental organization. They will not see a significant decrease in their bill but will have nonetheless contributed to a greener environment. For group two, they may redeem the points as dollar amounts off of the next bill. These customers then relate these points into something that they understand and of tangible benefit to them. Finally, to accommodate the desires of group three with no specific motivation for participation, they have the option of redeeming for a variety of items (e.g., electronics, or gift cards to the store of choice). The myriad of possibilities combined with an easy-to-use system increases the interest of this last group of customers to participate via points to buy items not otherwise available.

3.2.2.7 Implementation

The service provider divides the day into time intervals with the load scheduled into each interval. The projected usage for each customer for each section is represented as in Watts, and the actual usage for each customer is represented by in Watts. This equation will produce a coefficient, X, which is then multiplied by δ. This factor is a 'customer factor' that the service provider has assigned the customer after completing the initial contract. It also ensures that those customers who are more flexible will have the opportunity to receive the most points. The customer factor also reflects the customers past behavior, particularly if the customer typically follows their schedule to ensure a higher factor. This factor can represent many aspects of the customers that affect their usage. The result of equation four yields the total number of points the customer has received for that day. The membership upgrading is conducted when the number of total points exceeds a certain threshold, which is chosen by the service provider. The service provider may also adjust this threshold as needed to meet the different needs of the different regions. The customer will simply redeem a set number of points and will be awarded the new membership level for the next year of service or until the membership is upgraded to a higher level. These points are a very important aspect of the rewards program that is used to upgrade the membership levels and improve customer benefits. Each time the customer follows one action they will obtain some points, the number of which depend on the complexity of the actions they must follow, and the membership level. The different number of points that are possible to amass are represented in the following equations:

$$X = \frac{U_{projected}}{|U_{projected} - U_{actual} + 1|} \tag{3.1}$$

$$p_j = \begin{cases} \frac{x_j \delta_j}{\sum_i x_i \delta_i} & \text{if } X_j \geq k \\ 0 & \text{otherwise} \end{cases} \tag{3.2}$$

where $U_{project}$ and U_{actual} are power usages at each interval as explained above. Next, the coefficient is calculated for each customer using and the number of customer is calculated using making points for the use of the coefficient calculated for all customers previously. The constant in is a threshold excluding those customers who rarely adhere to the schedule from earning points.

3.3 Case Studies

Three different samples were prepared to provide to the user a thorough description of the utility rewards program. The first example is targeted to those users whose primary interest is economic, the second to those whose primary interest is environmental, and the third to those who have little interest in participating. Regardless of type, all users must be registered in the system and prompted for personal data, preferences and appliances they wish to control. Once they provide such information, they are given access, via log in to the main interface with the sections explained above. The usage data is on the left and the on the right are the rewards and demand response items. Users are then presented the points program, the total they have amassed, the current benefits associated with those points and actions that may take to improve their status. These features depend on the kind of costumer registered, according to the three categories described above.

3.3.1 First Case Study: How to Save Money

As the average monthly electric bill is approximately $100 many end-users are looking for ways to cut costs. For this group the rate ρ is used to convert points to US currency, the result of which is a point conversion that is deducted from one monthly bill.

3.3.2 Second Case Study: Taking Care of the Environment

The increased environmental consciousness of the utility customer means that they now wish to do their part to contribute to the environmental conservation and to mitigate climate change. With this in mind the Shift MyPower software offers a program for the eco-friendly customer through which they may contribute to local environmental clubs or organizations. A rate, ρ , is also available here to represent that contribution. Again, it is used to convert customer points to US dollars. The service provider then contributes that amount awarded to the customer to their favorite environmental cause. The end-user is then notified of the contribution (e.g., a message stating their contribution of planting five trees).

3.3.3 Third Case Study: Involving Skeptic Users

Here, the goal is to encourage greater user involvement in the demand response. Given the nebulous motivation for these customers, unlike the other case studies, a variety of items have been provided to persuade them to participate. No conversion mechanism from points to dollars are needed here as the reward items that the customers wish to purchase have point values. Essentially these customers may receive free gifts (e.g., headphones, gift cards, clothing) merely for participating in the program.

The data sets established the authors preliminary studies were used to test the suggested points system [33]. This data set contains electric load schedules of electricity customers (collected through a small-scale survey). Using these schedules, another series of schedules were created with a small deviation from the original data set to represent the actual power usage. The customers were then separated into different membership levels arbitrarily and the points for each customer were calculated. The projected points for customers in silver, gold and platinum tiers for a particular schedule are shown in Fig. 3.3.

3.4 Customer Behavior

3.4.1 Customer Potential

The behavior of the customer is highly dependent on the economic and other demographics. The 'potential' of the customer is the amount of energy available to be moved at a given point of time. This depends on the appliance size as well as the flexibility of the consumer. One possible definition would be:

$$\text{potential} = \sum_j f_j \text{wattage}_j \tag{3.3}$$

where $wattage_j$ is the wattage of the appliance and f_j is the binary variable deciding whether the appliance is allowed to reschedule at this time or not.

3.4.2 Customer Potential based on Demographic

A study was conducted to understand the potential of customer DR potential with the demographic. The following is a detailed description of the study. A data set was collected using census

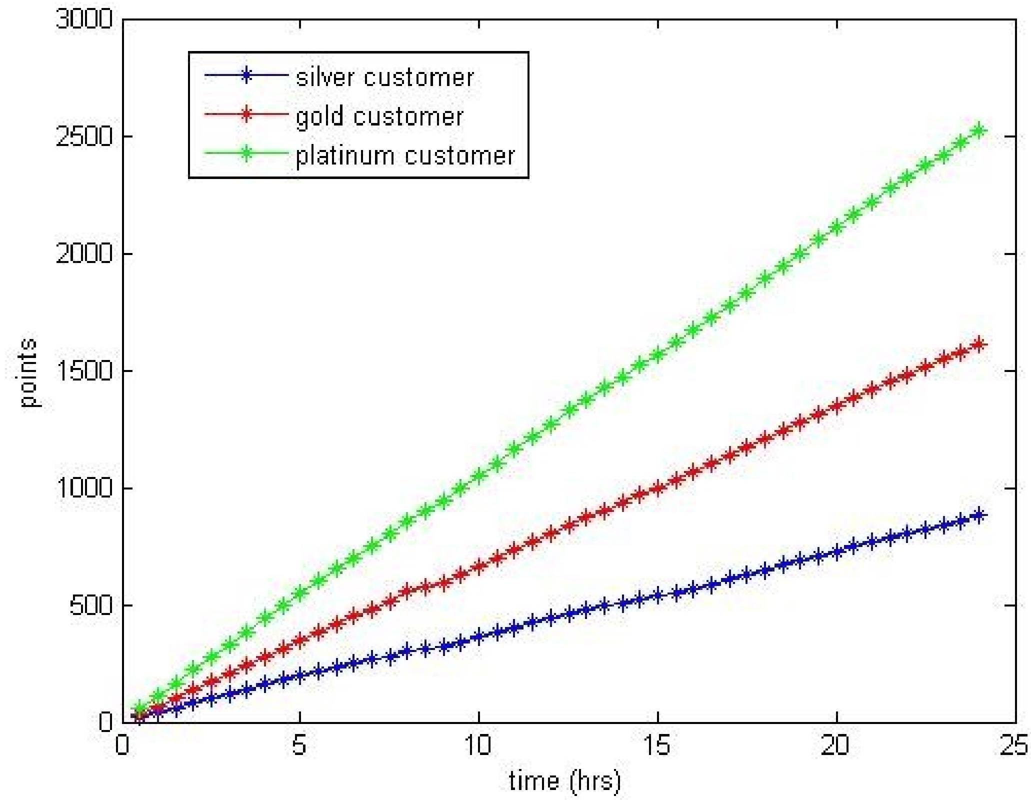


Figure 3.3: Points accumulation for customers

data as well as interviews with Clemson University students. In this data set, several demographics were identified to be considered for DR potential. The categories and their distribution are shown in Fig. 3.4. Each demographic is given a 'type'. The type labelling is shown in Table 3.1. A DR model was deployed, and the contribution of each category was quantified. The result without and with DR for each category is shown in 3.5 and 3.6. A participation measurement was introduced to quantify the contribution from each category. The participation measurement is defined as:

$$\text{participation}_{cat} = \sum_{n=1}^{l} \sum_{a=1}^{m} |{}_n i^a_{des} -_n i^a_{sch}| \times w_a \tag{3.4}$$

here participation$_{cat}$ is the participation measurement of the household category cat, ${}_n i^a_{des}$ is the time interval the ath appliance of the nth house is desired to be used, ${}_n i^a_{sch}$ is the time interval the ath appliance of the nth house is actually turned on and w_a is the wattage of the appliance.

Table 3.1: Household model and the labeled type

Household Model	type
Lower class single person	type1
Middle class single person	type2
Upper class single person	type3
Lower class couple with no children	type4
Middle class couple with no children	type5
Upper class couple with no children	type6
Lower class one child two parent family	type7
Middle class one child two parent family	type8
Upper class one child two parent family	type9
Lower class two children two parent family	type10
Middle class two children two parent family	type11
Upper class two children two parent family	type12

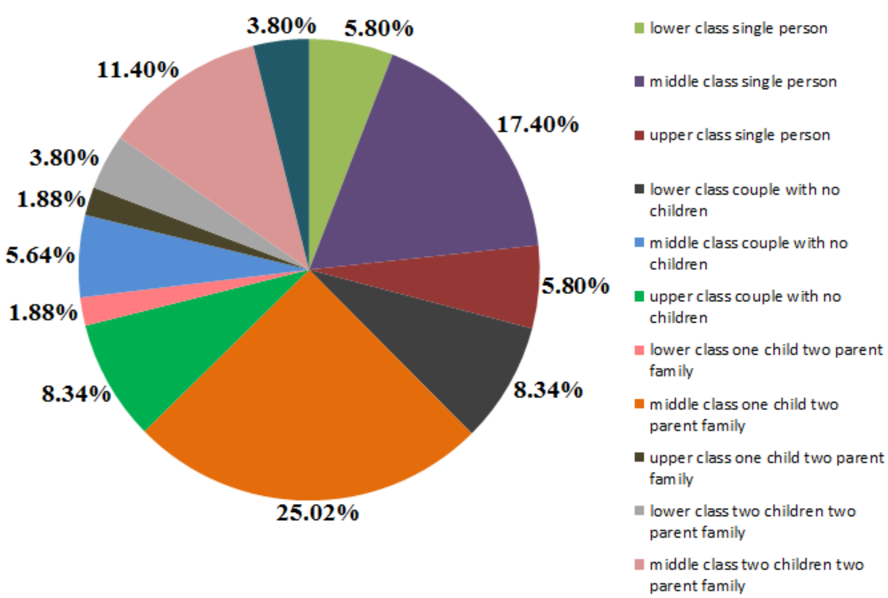


Figure 3.4: The demographics of the survey and corresponding percentages

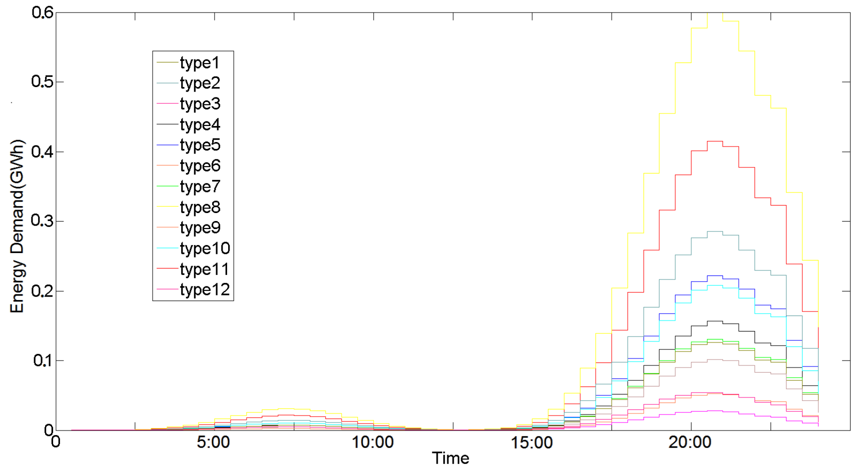


Figure 3.5: The power demand for each demographic without demand response

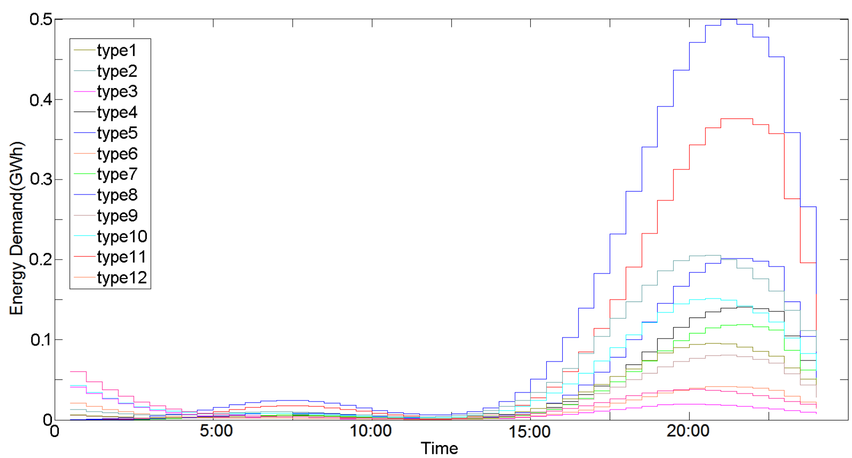


Figure 3.6: The power demand for each demographic with demand response

Table 3.2: Energy Moved and Participation Measurement for each Household Model

Household Model	Energy Moved	Participation Measurement
middle class one child two parent family	494.234	0.500
middle class two children two parent family	463.721	0.487
middle class single person	386.93	0.3832
middle class couple with no children	291.84	0.3825
lower class two children two parent family	215.15	0.1598
lower class couple with no children	175.83	0.1592
lower class one child two parent family	148.28	0.1281
lower class single person	129.79	0.1274
upper class one child two parent family	1313.79	0.1234
upper class two children two parent family	118.50	0.1229
upper class couple with no children	95.35	0.0904
upper class single person	93.70	0.0891

3.4.2.1 Results

The normalized participation metric result is given in Table 3.2. The results show that the middle class households have the maximum ability to participate in demand response. This is expected since the middle class consists of the larger part of the society. The upper class participation could be lower due to few reasons. One reason would be that the appliances used by the upper class is less power hungry due to their quality and since they are willing to pay more for a much comfortable life, they might participate less in the demand response schemes. A more energy-oriented measurement of demand response is shown in the same table. This measurement measures the amount of energy moved from each time interval. Additionally, the potential over time for each category was measured. The results are shown in Fig.3.7. The results show that the most DR potential is in the afternoon and some potential in the morning.

3.5 Summary

In this chapter the business models, customer involvement and customer behavior were explored. A service provider model was introduced that creates a 'win-win-win' situation for all parties: customer, electric utility and the service provider. The Shift MyPower program with the attractive and easy-to-understand features was introduced. This program incorporates methods to increase customer diversity and attraction with its rewards program. Several case studies are presented that tests the program. Additionally, the DR potential and of customers of different demographics along with most effective time periods of the day for these demographics were explored.

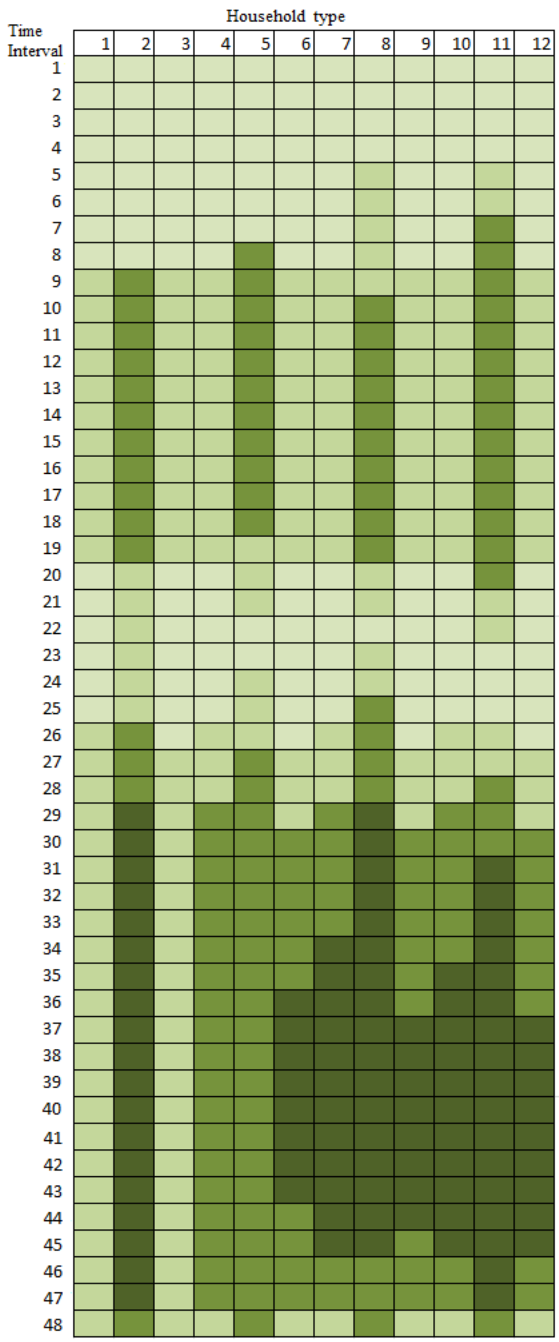


Figure 3.7: The potential of each category over time

Chapter 4

Optimization Methods for Scalable Demand Response Management

4.1 Introduction

Optimization methods are at the heart of a DR management program. The optimization algorithm depends on the mathematical models used in optimization. Optimization algorithms used for DR are divided in to two categories in this dissertation: computational intelligence based meta-heuristic methods and mathematical optimization methods. Computational intelligence methods include population-based algorithms that could optimize very complex non-linear non-convex functions taking them as black box problems. Since these are population-based, they are easily adopted to parallel and distributed computing models.

Mathematical methods on the other hand, sometimes are restricted to specific groups of problems. For instance, linear or convex problems. However, these restricted optimization methods could guarantee an optimal solution. Therefore, in some cases, modifying or relaxing the problem such that they fall into one of the groups could generate a much better result than employing a meta-heuristic optimization algorithm to the exact problem. These methods are usually better at handling constraints than meta-heuristic optimization methods.

Both mathematical and meta-heuristic methods have their pros and cons. Much thought and research should be put into the choice of algorithm to solve the optimization problem at hand effectively. In this chapter, the benefits of some of the optimization algorithms are discussed with their results.

4.2 Conventional Mathematical Optimization Methods

4.2.1 Interior Points Method

This is a class of algorithms that could solve convex programming problems. By including a 'barrier' these methods can successfully handle constraints. The method is based on 'cutting through' the feasible region iteratively to get to the solution.

4.2.2 Branch and Bound Method

This framework repeatedly divides the problem into sections and attempts to reduce the solution space to find the best solution. Branch and bound mechanism has to be coupled with another (approximate) solution method to find a better solution.

4.2.3 Gurobi Optimization Software

Gurobi solver [26] is a commercially available software that could solve many types of optimization problems. Gurobi can solve linear programming, quadratic programming, mixed integer linear programming, mixed integer quadratic programming, and mixed integer programs with quadratic terms in the constraints. Gurobi can interface with a several programming languages such as Python and Matlab and could solve the optimization problems quickly and efficiently.

4.3 Computational Intelligence Based Methods

Computational intelligence (CI) could be generally defined as the ability of a computer to learn from given data and learn a task. A more smart-grid-oriented definition would be the capability of a computer to take in numerical sensory data and process them to generate reliable responses with fault tolerance. Computational intelligence methods include swarm intelligence, artificial neural networks, fuzzy systems and other CI paradigms. A diagram showing CI concepts are shown in Fig. 4.1.

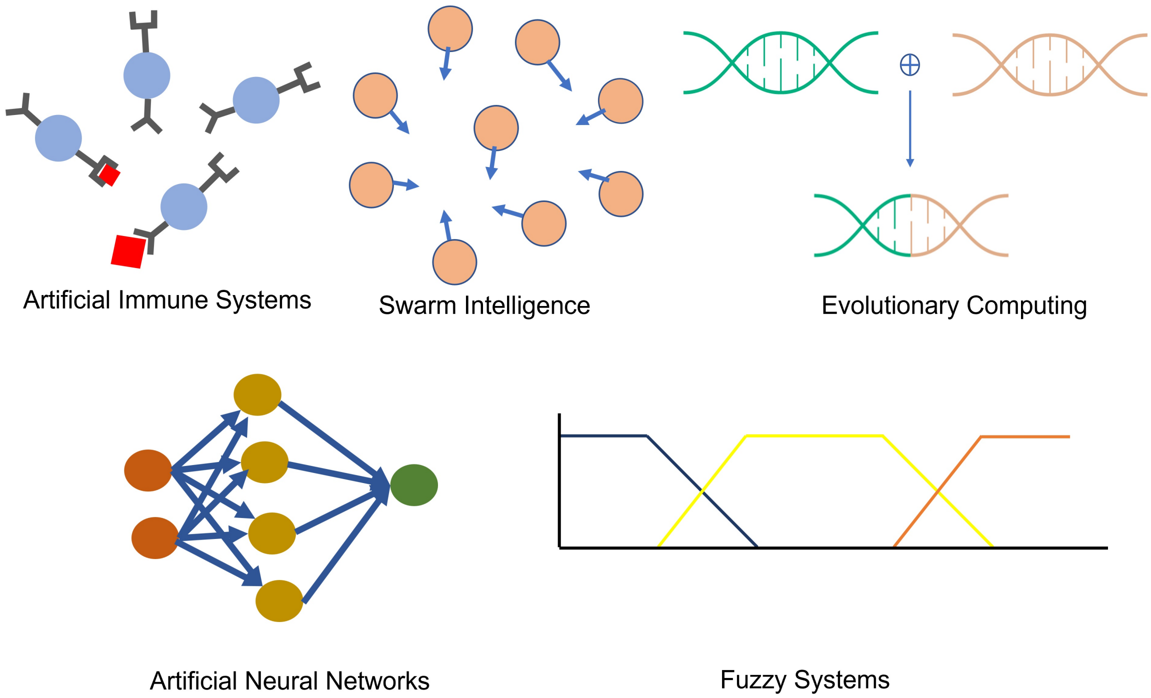


Figure 4.1: Computational Intelligence Concepts

4.3.1 Cooperative Particle Swarm Optimization

Cooperative Particle Swarm Optimization (CPSO) is the application of cooperative co-evaluation framework for the basic Particle Swarm Optimization (PSO) method. The two basic concepts are discussed in next sub-subsections.

4.3.1.1 Particle Swarm Optimization

Kennedy and Eberhart [44] first proposed Particle Swarm Optimization as a heuristic optimization method inspired by nature. Here, a number of 'particles' that fly through a solution space are used. These particles are actually agents that calculate the value for the objective function at the current location of the solution space. A particle has a certain 'velocity' with which it flies. The particle calculates the value of the objective function at the current point at every iteration. A global best for all the particles and a personal best for each of the particle is then calculated. The velocity of each particle for $k + 1$st iteration is calculated according to the equation:

$$V_{id,k+1} = wV_{id,k} + c_1 rand_1(X_{pbestid,k} - X_{id,k}) + c_2 rand_2(X_{gbestd,k} - X_{id,k}) \tag{4.1}$$

where, w is the inertia weight, $V_{id,k}$ is the velocity in the dth dimension of ith particle at iteration k, c_1 and c_2 are cognitive and social acceleration constants, respectively, $rand_1$ and $rand_2$ are random numbers between 0 and 1, $X_{pbestid,k}$ is the personal best in dth dimension of ith particle at iteration k. $X_{id,k}$ is the current position of the ith particle in the dth dimension and $X_{gbestd,k}$ is the global best position so far found by the system in the dth dimension at iteration k. Once the velocity is calculated, the next position the particle would move to, can be calculated with the following equation:

$$X_{id,k+1} = X_{id,k} + V_{id,k} \tag{4.2}$$

Algorithm1 shows the basic PSO algorithm using the above two equations.

4.3.1.2 Cooperative Particle Swarm Optimization

The concept of cooperative co-evolution is to subdivide the problem into multiple divisions and let subswarms to handle each of these divisions. The objective value is calculated using the current gbest by the particle replacing the relevant variables with its own subset of variables and then calculating the objective value. each subswarm will take turns calculating the next step while all other subswarms are frozen. The initial gbest would be built by selecting one particle randomly from each swarm putting together their variable values. The CPSO algorithm is shown in algorithm 1. The interested reader could refer to [74] for more in-depth explanation. Algorithm 2 shows the pseudo code for the CPSO algorithm.

4.3.2 Success-History Based Parameter Adaptation for Differential Evolution

In this subsection, Differential Evolution and Success-History Based Parameter Adaptation for Differential Evolution is introduced.

4.3.2.1 Differential Evolution

Differential Evolution (DE), introduced by Storn and Price [71] has been one of the most successful heuristic search algorithms devised. This algorithm is based on a population of vectors where each one of them is potentially the best solution. A new trial vector is created by carrying out a mutation operation and a cross-over operation. This trial vector is compared against the original

Algorithm 1: Basic Particle Swarm Optimization Algorithm

```
Input: objective function, lower boundaries b_l, upper boundaries b_u
Output: solution gbest with minimal value found
particles ← U(b_l, b_u) /*initialize particles with uniform random values*/
velocities ← U(b_l, b_u) /*initialize velocities with uniform random values*/
gbest ← none
gbest_val ← ∞
/*initialize gbest and pbest values */
for each particle number p do
    result ← objective_function(particle[p])
    pbest[p] ← particles[i]
    pbest_values[p] ← result
    if result < gbest_val then
        gbest_val ← result
        gbest ← particle[p]
/* iterations*/
while termination criterion not met do
    for each particle number p do
        velocities[p] ← value computed by 4.1
        particles[p] ← value computed by 4.2
        result ← objective_function(particle[p])
        pbest[particles[p]] ← particles[i]
        pbest_values[p] ← result
        /*update pbest*/
        if result < pbest_values[p] then
            pbest_values[p] ← result
            pbest[p] ← particle[p]
    /*update gbest*/
    for each particle number p do
        if pbest_values[p] < gbest_value then
            gbest_value ← pbest_values[p]
            gbest ← pbest[p]
return gbest
```

Algorithm 2: Cooperative Particle Swarm Optimization Algorithm

Input: objective function, lower boundaries b_l, upper boundaries b_u
Output: solution gbest with minimal value found
dimension ← 0
for ***each*** *sub-swarm* ***in*** *the set of sub-swarms* **do**
    initialize sub-swarm with random values of the current dimension
    initialize velocity of all particles to zero
    dimension ← dimension + 1
sub-swarm ← 0
for ***each*** *dimension* ***in*** *the problem* **do**
    gbest[dimension] ← random particle value in the current sub-swarm
    sub-swarm ← sub-swarm + 1
for ***each*** *sub-swarm* ***in*** *the set of sub-swarms* **do**
    for ***each*** *particle* ***in*** *the sub-swarm* **do**
        solution ←
          gbest solution but current dimension value replaced by the current particle
        result ← objective_function(solution)
        pbest of the particle ← result
return *gbest*

'target vector' in a trial where the winner is allowed in the population and the loser is evicted. This procedure is carried out over several generations (iterations), successively improving the population over time until a termination criterion is met.

4.3.2.2 Success-History Based Differential Evolution

In the modified version Success-History based Differential Evolution (SHADE) [72], the mutation operation is as follows:

$$v_{i,g} = x_{i,g} + F \times (x_{best,g} - x_{i,g}) + F \times (x_{r1,g} - x_{r2,g})$$

Here $v_{i,g}$ is the ith trial vector of the gth generation, $x_{i,g}$ is the target vector with which the trial vector is compared against, F is a scaling factor, $x_{best,g}$ is a random vector chosen from the top p percent of the best vectors in the population, $x_{r1,g}$ is the randomly chosen vector from the population and $x_{r2,g}$ is a randomly chosen vector from a pool of vectors that include the current population as well as an external archive of previously successful vectors. The percentage p decides the balance between exploration and exploitation. A larger percentage opens the opportunity for the combination with a vector with a vast range in fitness value allowing more exploration while a lower p closes the selection window, gravitating all solutions towards the already found best results. The created vector is then crossed over with $x_{i,g}$ according to the following equation:

$$u_{i,g}^{i} = \begin{cases} v_{i,g}, & \text{rand} \leq CR \text{ or } j = j_{rand} \\ x_{i,g}, & \text{otherwise} \end{cases}$$

to create the new trial vector $u_{i,g}$. This trial vector is then compared with the target vector to decide which vector to be kept. The final solution highly depends on the variables CR and F. In the basic DE algorithm these variables are set manually. In the SHADE algorithm, these values are set by a collection of historical values. The selection of CR and F vales are carried out as follows. Archives M_{CR} and M_F of mean values for CR and F are initialized at 0.5, initially. The size of these archives, H, is set manually. At each generation, CR and F variables are chosen as a random variable value with one of these historical values as the mean for each target vector.

$$CR_g = randn_g(M_{CR,ri}, 0.1)$$

$$F_g = randc_g(M_{F,ri}, 0.1)$$

where randn and randc are normal and Cauchy distributions. Each successful set of CR, F parameters (i.e., parameters that were able to generate an offspring that is better than the parents) are recorded in temporary archives S_{CR} and S_F. At the end of evaluation of that generation, new values for the kth slot of archives M_{CR} and M_F are calculated as follows:

$$M_{CR,k,g+1} = \begin{cases} mean_{WA}(S_{CR}), & S_{CR} \neq \emptyset \\ M_{CR,k,g}, & \text{otherwise} \end{cases}$$

$$M_{F,k,g+1} = \begin{cases} mean_{WL}(S_F), & S_F \neq \emptyset \\ M_{F,k,g}, & \text{otherwise} \end{cases}$$

where

$$\text{mean}_{WA}(S_{CR}) = \sum_{k=1}^{|S_{CR}|} w_k . S_{CR,k}$$

$$\text{mean}_{WL}(S_F) = \frac{\sum_{k=1}^{|S_f|} w_k.S_{F,k}^2}{\sum_{k=1}^{|S_F|} w_k.S_{F,k}}$$

$$w_k = \frac{\Delta f_k}{\sum_{k=1}^{|S_{CR}|} \Delta f_k}$$

4.3.3 Multi-Objective Optimization

DR optimization involves several parties. Mainly, the utility and the consumer. In previous cases the objectives of these parties are condensed into one objective by considering a weighted sum of all objective values. Another possibility is considering the DR problem as a multi-objective problem. In this case, a list of possible solutions is generated. Each individual party involved in the program has their own objective and these objectives might conflict. That is, improving one could worsen the other. For instance, the best strategy for a home to reduce the energy bill is to use all the appliances at a time with low energy cost. However, this affects negatively to the demand flatness objective. Therefore, the best a muti-objective optimization algorithm could do is to present a set of solutions with varying degrees of values, ranging from good to bad, to each of the objective. The parties in the program could then choose a solution among those by agreement. However, what the algorithm must not do is to produce results that could be further improved. For instance, if the bill of a home could be further reduced without affecting the flatness of the load, then that solution is not an acceptable solution. Instead, the algorithm should produce a solution where the costs cannot be further minimized without jeopardizing the demand flatness objective. This idea is captured by the 'domination' concept. When comparing solution A and B, if B is better than A, that is, B could be obtained by improving the objectives of A without reducing any of the objective values, then A is considered to be dominated by B. The set of solutions that are not dominated by any of other solutions is called the 'pareto front' of the problem. A pareto front example is shown in fig. 2.

However, there could be millions of solutions which qualify to be in pareto front. At one point the algorithm has to reject some of the solutions even if they're perfectly acceptable solutions in the interest of limiting the number of solutions. Having too many solutions is not preferred, not only because the computer running the algorithm would find it difficult to handle, but also because the users could be overwhelmed by the number of solutions presented. Therefore, a more diverse solution is preferred instead of too many solutions.

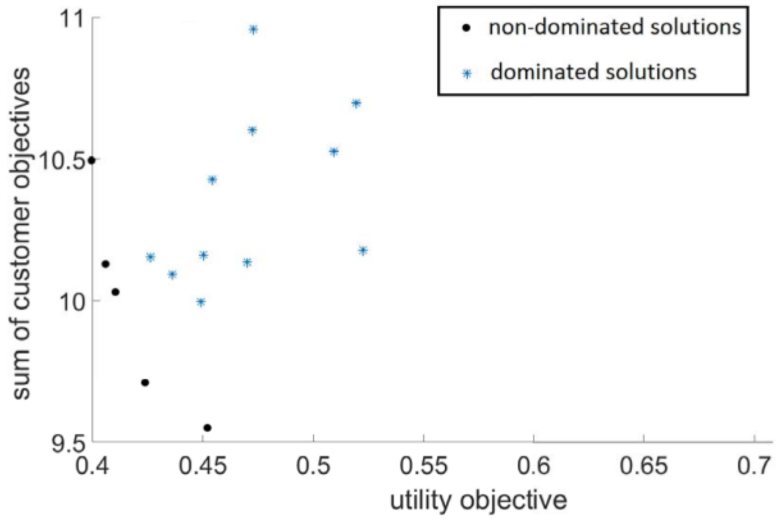


Figure 4.2: Dominated and Non-dominated Solutions Illustrated for a Bi-Objective Problem

4.3.3.1 Multi-Objective Particle Swarm Optimization

As discussed earlier, the aim of a multi-objective optimization is to find the pareto optimal set with the most diverse set of solutions. Unlike the single objective case which returns one global minimum, an array of results which are in the pareto set should be returned by the multi-objective optimization algorithm. MOPSO implemented in this study achieves this task using an external 'solution archive'. Each of these solutions is associated with a vector of objective values. In this case, a solution contains twenty-one objectives in total. Twenty for the twenty homes considered and one utility objective for demand flatness.

In MOPSO, instead of the normal velocity formula of the PSO, the following formula is used:

$$V_{id,k} = wV_{id,k} + c_1\text{rand}_1(X_{pbestid,k} - X_{id,k}) + c_2\text{rand}_2(X[h] - x_{id,k}) \tag{4.3}$$

here, w is an inertia (constant) value between 0 and 1. $V_{id,k}$ is the velocity of the dth dimension of the ith particle at the kth iteration (initially zero), c_1 and c_2 are cognitive and social acceleration constants, rand_1 and rand_2 are random values, $X_{id,k}$ is the current position of the particle in the search space, $X_{pbestid,k}$ is the personal best of the particle and $X[h]$ is a selected particle from the external archive. The position update of the particles is as:

$$X_{id,k+1} = X_{id,k} + V_{id,k+1} \tag{4.4}$$

For 4.3, a particle value from the repository is needed to be selected as $X[h]$. This selection is made a chance to enforce the diversity requirement of the solution. For this $X[h]$ is selected to be a most different solution from the rest of the solutions in the repository. To measure the difference between the solutions in the archive an approximate clustering method is utilized. The explored search space is divided into 'hyper-cubes' by dividing each dimension into a selected number of equal parts. The solutions in the archive are placed inside these hyper-cubes. Less the number of solutions in the same hyper-cube, the more 'different' the solutions in that hyper-cube is considered to be. An $X[h]$ is then selected randomly with more probability towards more diverse (different) solutions to be selected as the $X[h]$. An example of a solution space with two dimensions and two objective functions where the solutions are located inside a hyper-cube is shown in Fig. 4.3. The number of non-dominated solutions placed inside the archive is limited. To limit the number, some of the solutions have to be removed from the archive at some point. For this, random solutions are evicted from the more 'crowded' hyper-cubes. This MOPSO version is adapted from [14].

4.4 Case Studies

4.4.1 Case Studies with Cooperative Particle Swarm Optimization

The CPSO algorithm is applied to a problem of 2000 resident optimization problem. The objective functions are as follows. The objectives of the consumer were twofold: cost minimization and comfort maximization. The cost minimization objective is formed as:

$$cost_n = \frac{1}{2} \sum_{t=0}^{t=48} \sum_{a}^{a=k} {}_n d_t^a \times w_h^a \times p_t$$

where $cost_n$ is the total cost of energy of the customer n, ${}_n d_t^a$ is the decision variable that decides whether appliance a of the house n is turned on in the time interval t, w_h^a is the wattage of the ath appliance of the nth house and p_t is the price offered at time t.

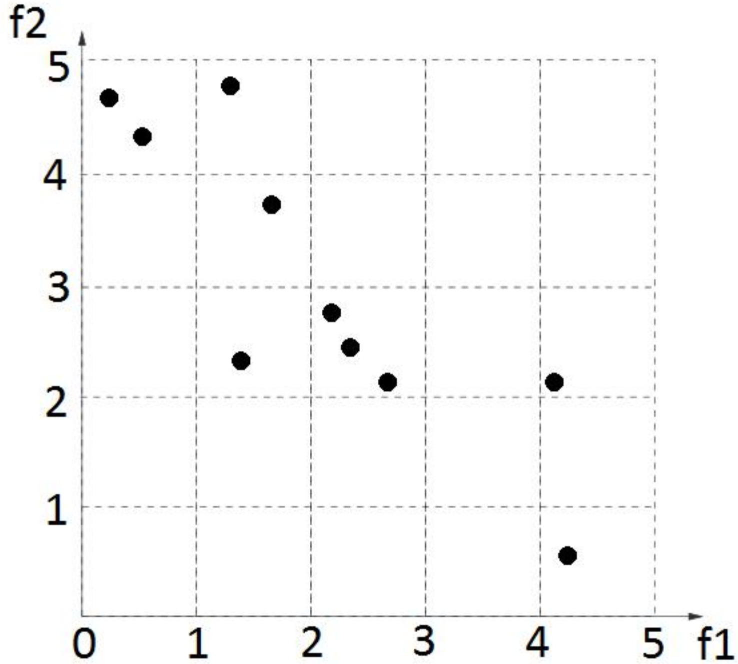


Figure 4.3: Solutions located in a hyper-cube

The customer comfort is measured by the time difference from the original time.

$$comfort_n = \sum_{a=0}^{a=k} |_n i^a_{des} -_n i^a_{sch}|$$

where $comfort_n$ is the comfort factor of house n, $_n i^a_{des}$ is the time interval the ath appliance of the nth house is desired to be used and $_n i^a_{sch}$ is the time interval the ath appliance of the nth house is actually turned on. To set the balance between these two objectives, both objectives are be normalized between 0 and 1 and a new variable, λ_n can be used. The complete objective for customers would be:

$$O_{cu} = \sum_{n=1}^{n=p} (\lambda_n \times \lambda_1 \times cost_n + (1 - \lambda_n) \times \times \lambda_2 \times comfort_n)$$

where p is the size of the population. here n represents the nth customer. The first part of the two added terms represents the comfort factor for the customer and the second part represents the total cost of energy for the customer under the day ahead pricing scheme. The tuning variable λ_n sets the balance between the comfort of the user and the cost while λ_1 and λ_2 are normalizing factors. By setting λ_n value could set the characteristics for the user. The community welfare objective on the other hand is keeping the electric power demand flat all day long.

$$O_{co} = \sum |1 - \frac{d_i}{a_i}|$$

here a_i is the average power consumption of the whole neighborhood and d_i is the actual power consumption on the ith time interval. The total objective function can be then declared as:

$$O = k_1 \times O_{cu} + k_2 \times O_{co}$$

where k_1 and k_2 are normalization factors for the two sub-objectives.

4.4.1.1 Results

The results of the above optimization shows that, given the constraints of the homes, the algorithm manages to optimize the power requirements.

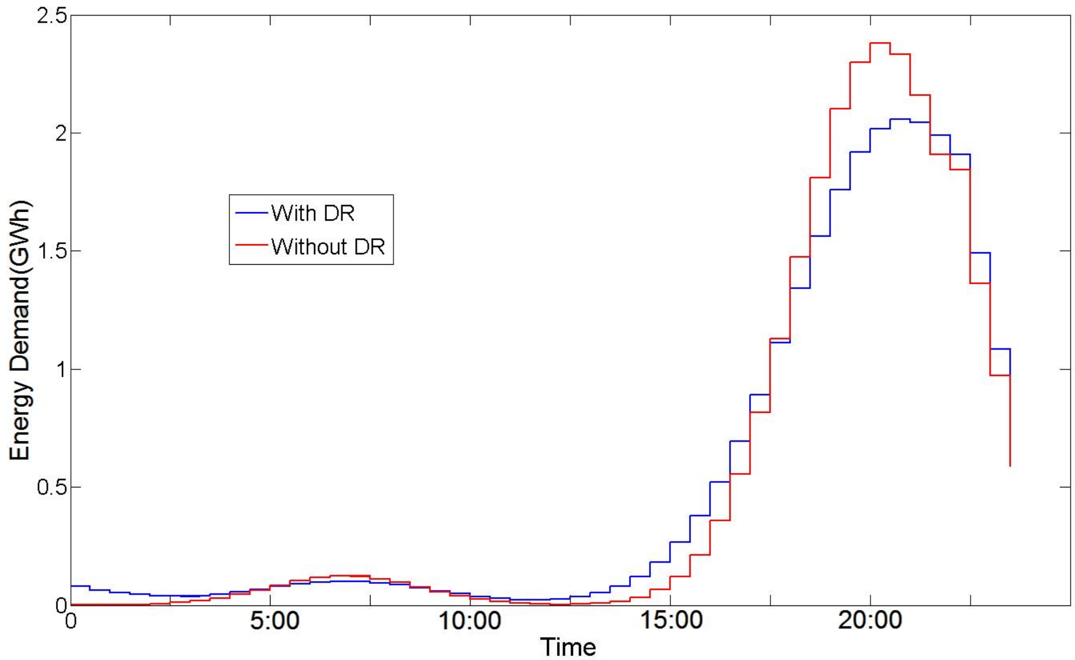


Figure 4.4: Result of Optimization with CPSO

4.4.2 Case Studies with Success-History Based Parameter Adaptation for Differential Evolution

A similar implementation as the previous implementation was tested with SHADE algorithm. The optimization was carried out on a neighborhood of 1280 customers was tested. The net effect on the grid by the optimization is shown in Fig. 4.5.

4.4.2.1 Objective Functions

The Objective functions had one objective per customer and one objective for the utility. Each customer has two objectives: comfort objective and the cost objective. The two of them are combined with a weighting factor λ depending on whether they are more interested in cost savings or comfort. The objective of the utility was demand.

4.4.3 Case Studies with Multi-Objective Particle Swarm Optimization

MOPSO algorithm was applied to a DR problem and the results were observed. Data from a survey carried out at Real-time Power and Intelligent Systems Laboratory at Clemson University

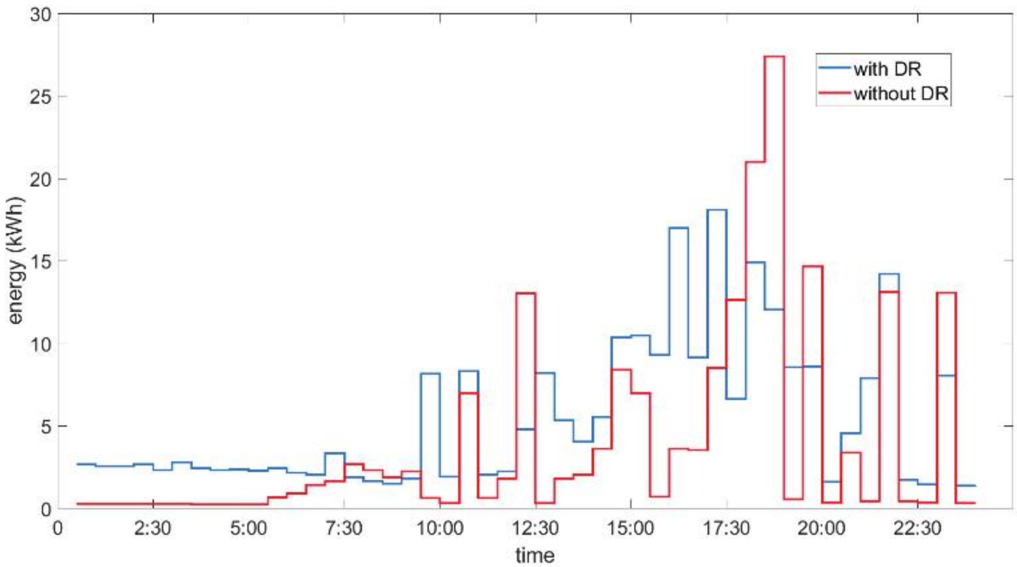


Figure 4.5: Result of Optimization with SHADE

was utilized to generate electric appliance usage and flexibility information for some twenty homes. As expected, a set of results were generated by MOPSO algorithm. The set of results include best case to worst case for each of the objective.

Few of the results obtained are described in the following passages.

4.4.3.1 Diversity of the Solutions

The resulting solution set is quite diverse. The customers could get different levels of costs each offering a varying degree of comfort. The cost for one selected customer across the set of generated solutions is shown in Fig. 5. The comfort of each of the customer is shown in 6. Although the minimization function attempts to find the least costly and most comfortable solution for the customers, this is affected by the neighborhood objective of demand flatness. Therefore, even if there is a general trend of reduced cost reducing the comfort, this is not clearly seen in the result.

4.4.3.2 Demand Flatness

Although the demand flatness is one of the objectives, it is hard limited by the flexibility of the appliances. Therefore, a perfect flatness cannot be achieved. Instead, a lowered peak with power usage spread around the flexible area could be obtained. On the other hand, the worst-case for the demand flatness is also interesting. Between the best case and the worst case scenarios, the effect

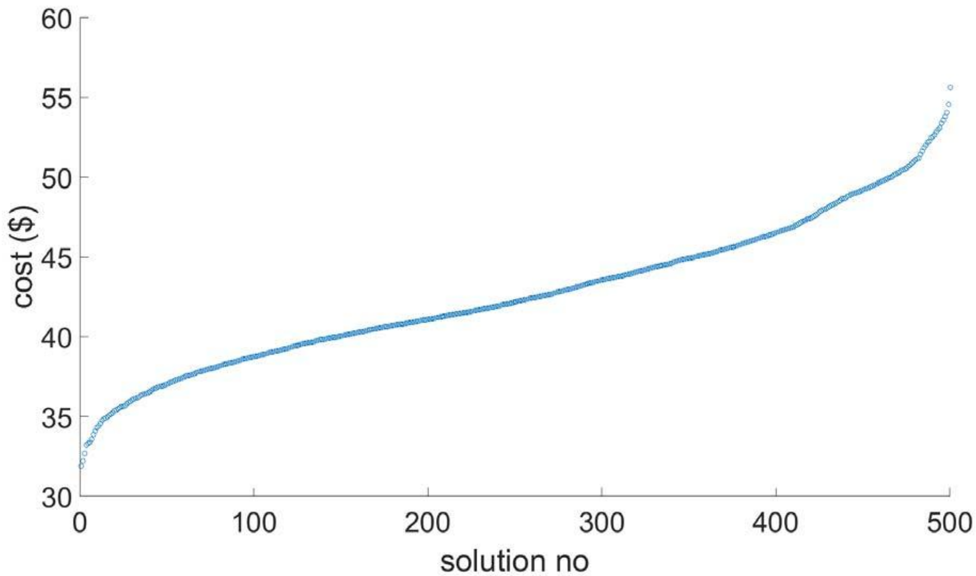


Figure 4.6: Costs for one customer across all solutions

of the objective of monetary savings could be observed. That is, demand flatness and the monetary savings are correlated. Since high prices in the time-of-use pricing usually coincide with peak hours, money saving generally means more demand flatness. Therefore, even at the worst case, there still is some divergence from the original demand. The power demand in best, worst, and no demand response cases are shown in Fig. 7.

4.4.3.3 Customer Comfort and Savings

On the other hand, on the side of the customers, depending on the weighting value which sets the objective of the customer, different costs savings have been achieved. The savings of have been tabulated in Table I. Although some of the customers have more weighting values set to save money, the flexibility of the customer also has an effect on the final solution. The flexibility is the range of time slots that the customer limits the turning on of the appliance. The service provider is not allowed to operate the appliance outside this range. However, a better weighting value generally tends to generate better monetary savings.

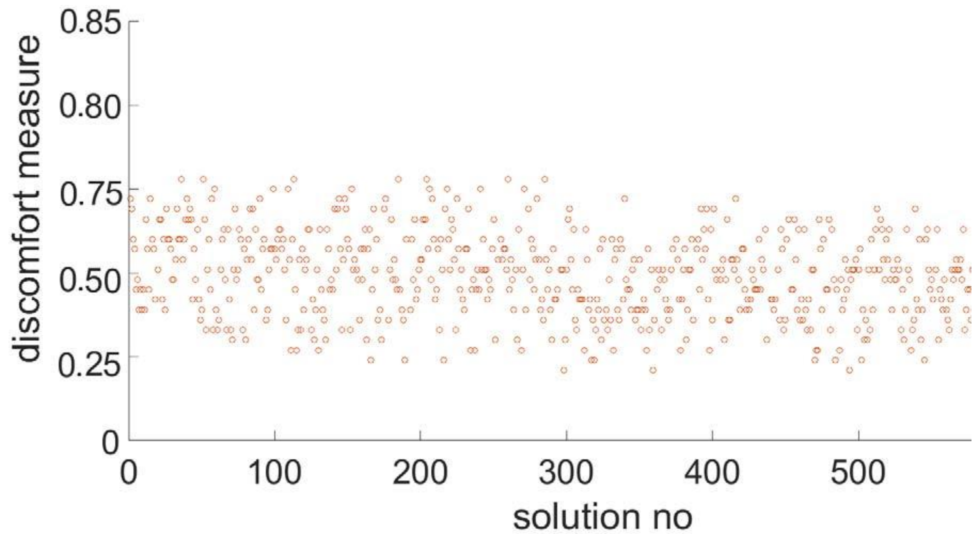


Figure 4.7: Solutions located in a hyper-cube

4.5 Summary

In this chapter, the solution methods for DR optimization methods are explored. The optimization methods were divided into conventional mathematical optimization methods and computational intelligence methods. While the mathematical methods could provide good solutions for the restricted group of problems they can provide the answer with. On the other hand, population-based computational intelligence methods could applied to any problem and it is easy to apply parallel and distributed computing paradigms. However, there is no guarantee of reaching the optimal solution and it is difficult to apply constraints. This chapter presents results on CPSO, SHADE and MOPSO DR optimization algorithms.

Chapter 5

Scalable Residential Demand Response Management

5.1 Introduction

Although DR has been a practiced for a long time, the participation of residential customers has been somewhat low in the practical world. The reasons behind this situation include the difficulty in control of such spread-out amount of loads controlled separately by many individuals with different needs and behaviors. Many consumers would be reluctant to be dedicated enough to carry out DR. However, the new IoT and smart home technologies have made it easier to contribute for DR. Other concerns would be the privacy issue. But several research work has been carried out that would preserve the privacy of the consumer at the optimization [51]. The aforementioned distributed load handling problem, however, is yet to be addressed. Although many research work has been published that would break the problem down into pieces ([49] and [17]) , none of them have considered scaling them up into millions of users. In this chapter, a scalable DR framework is introduced that could be optimize millions of users while incorporating the power flow constraints of the power system.

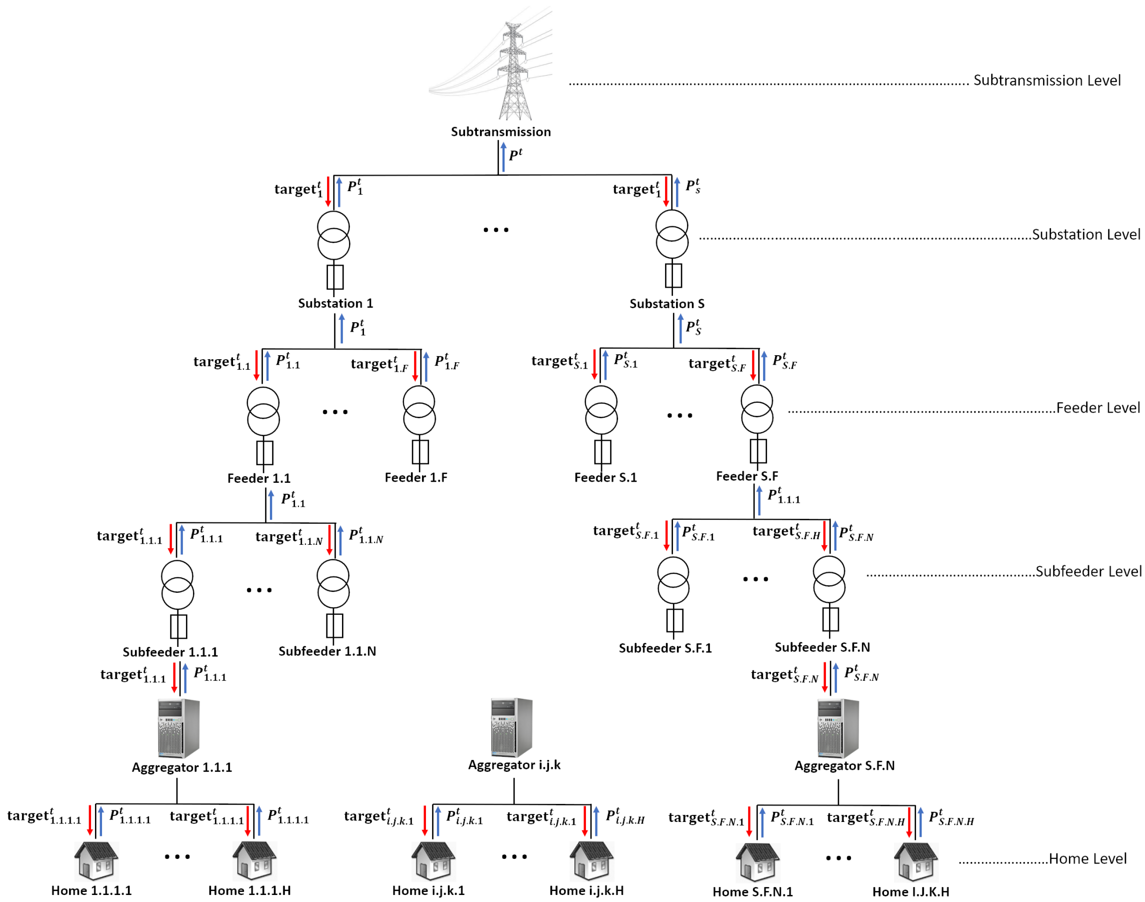


Figure 5.1: The hierarchical architecture of power delivery from subtransmission to home. The arrows show the information flow directions. The power demand flows upwards and the targets flow downwards. Each level computes independently in parallel and the other levels would wait for the lower (or the upper) level to finish

5.2 Hierarchical Architecture

In order to carry out this optimization, a hierarchical structure that lies along side the power system is introduced. This allows the handling of power flow limitations in the grid. The hierarchical structure is as follows. A subtransmission supplies power for several substations. One substation supplies power to several feeders. One feeder delivers power to several subfeeders. One subfeeder powers several homes. The group of homes on the same subfeeder is referred to as a 'Smart Neighborhood' in this study. A Smart Neighborhood is a collection of homes in close proximity with appropriate contracts in place with the DR aggregator [33].

5.3 Demand Response Optimization

The optimization is executed at the neighborhood level and is a day-ahead optimization. To enable this, either the aggregator can carry out a direct load control over the appliances in homes (as permitted by the contracts), or home energy management systems can carry out their own optimizations coordinated by the aggregator. The aggregator will impose penalties as agreed in the contracts for not following the agreed power schedule. For the optimization, both the DR target and the comfort of the consumer are considered. The optimization is carried out throughout the hierarchical architecture as follows. First, to establish a baseline, each home in the system optimizes only for its own comfort. The optimization is a day ahead optimization planning for the next day. The tentative power schedule will then be communicated to the subtransmission level through the hierarchy. As discussed earlier, the subtransmission controls a number of substations. At this point, the subtransmission would observe the aggregated power requirements for the next day at each substation. The subtransmission will then dispatch a target power usage for each substation considering the amount of power requested by each substation and considering physical power flow limitations of the substation. To set the target, the objective of the subtransmission has to be considered. In most cases, the objective of a DR program is to minimize the disparity between the peak and the average power demand. In this case, the average power demand would be a candidate target. However, other objectives could also considered, such as the effective incorporation of renewable energy generation. In that case, the target could follow the energy generation forecast of the renewable power plants.

Upon receiving the dispatched target from the subtransmission, each of the substations will dispatch a target (calculated by a similar logic as the subtransmission) to each feeder controlled under them. By recursively repeating the above process, a target dispatch would flow down to each home, using which, each individual home would optimize their own power usage. This optimization is further discussed in the next section.

As mentioned earlier, at each entity, possible power flow *capacity* limits have to be applied. The *capacity* of an entity at a certain level is the sum of *capacity* values of the levels under that entity. That is,

$$capacity = \sum_{s=1}^{SS} capacity_s \tag{5.1}$$

$$capacity_s = \sum_{f=1}^{F} capacity_{s.f} \tag{5.2}$$

$$capacity_{s.f} = \sum_{n=1}^{SF} capacity_{s.f.n} \tag{5.3}$$

Analyzing the hierarchy presented in Fig. 5.1, it can be seen that if the optimization is carried out in a fully distributed manner, that is, if every home carries out its own optimization in parallel to all other homes, then the optimization time will depend on the number of levels in the system. That is, the optimization time would be in order of $O(n)$, where n is the number of levels. The reason for this is that all the homes carry out their optimization in parallel. This fact implies that adding more homes to the system does not change the optimization time largely proving the system to be scalable.

5.4 Demand Response Optimization

The DR optimization is a day-ahead optimization. The day is divided into several time intervals, and for each time interval, an amount of power is dedicated by the optimization. The DR aggregator initially has to come to an agreement and sign a contract with the participants to regulate the power usage. In addition, the participant agrees to a certain 'flexibility' offered for the purpose of DR. The agreed upon flexibility is denoted by $\epsilon_{init,s.f.n.h}$ in this study. More details on this flexibility parameter are discussed in the next subsections. The remainder of the Section describes each optimization step in detail.

5.4.1 Baseline Calculation

The homes that contribute to optimization are assumed to be 'smart homes'. That is, each home is equipped with smart devices that could execute optimization algorithms and control home appliances. Given the growth of electronic devices in the market, this is not an unrealistic assumption. The smart device can optimize power usage in one of two modes: with DR signal or without DR signal. The first step is to optimize without the DR signal. This optimization is carried out to establish the baseline power usage. For this optimization, the home electric appliances are categorized into the four categories of uncontrollable appliances, shiftable appliances, interruptible appliances and controllable appliances. A discussion on these appliances was carried out in previous sections.

The power usage profile of a shiftable appliance can be represented with a vector with symbols, $\{{}^1_he_i, {}^2_he_i, ..., {}^{{}_hn_i}_{h}e_i\}$. Each element of this vector represents the power demand of the appliance at each time interval. For the ease of modeling, each of these elements in the profile will be treated as a separate appliance but with the restriction that if the first one is turned on at one time interval, the second one must be turned on in the next time interval and so on and so forth. Since these appliances are just turn-on or turn-off, the decision variable would be a binary vector with the size of number of intervals in the day. For a shiftable appliance that runs ${}_hn_i$ number of time intervals when turned-on, ${}_hn_i$ such size T vectors will represent the decision on that appliance. To make sure each part of the power usage profile follows the previous part, the necessary constraint is,

$$ {}^k_hb^t_i = {}^{k-1}_{h}b^{t-1}_i \qquad \forall h \in 1, .., H, \forall k \in 2, .., {}_hn_i, \forall i \in 1, .., {}_ha_s, \forall t \in 2, .., T \tag{5.4} $$

To make sure that one appliance turns-on only one time during the day the following constraint should be held:

$$ \sum_{t=1}^{T-{}_hn_i} {}^k_hb^t_i = 1 \qquad \forall h \in 1, .., H, \forall k \in 2, .., {}_hn_i, \forall i \in 1, .., {}_ha_s \tag{5.5} $$

This makes sure that the appliance turns-on with sufficient time for the completion of the cycle and it turns-on only once in the day. The comfort of using these appliances depends on the time of the day that it is turned-on on. For instance, it could be rather uncomfortable if the washing machine is turned on at 2 a.m. in the morning. To capture this, a 'discomfort' value is defined for each time interval the appliance is turned-on. This discomfort value has to be defined by the consumer and should be based on their experiences and daily schedule. The total discomfort value for a given schedule for all shiftable appliances of a given home would be:

$$ C^{sh}_h = \sum_{i=1}^{{}_ha_s} \sum_{t=1}^{T} \left({}^1_hb^t_i \times {}_hc^t_i \right) \tag{5.6} $$

Notice that only ${}^1_h b^t_i$ is considered here since the discomfort is defined for turn-on time intervals.

The interruptible appliances on the other hand, include appliances that can have variable power supply but a deadline to meet. For instance, the electric vehicle battery can be charged at a variable power input rate per time interval by repeatedly turning on and off but has the need to finish charging by a specific time period. For instance, the charging might need to be completed by 8 O'clock in the morning when the consumer needs to go out to work. For each interruptible appliance, a vector of size T is used to represent it in the optimization. Each element of this vector $[{}_hu^1_i, {}_hu^2_i, {}_hu^3_i, ..., {}_hu^T_i]$ represents the power supplied at each of the time interval to the appliance. As mentioned earlier the main constraint for these appliances is the amount of power scheduled before a given interval.

$$\sum_{t={}_hs_i}^{{}_hf_i} {}_hu^t_i \geq {}_hL_i \forall h \in 1,..,H, \forall i \in 1,..,{}_ha_i \tag{5.7}$$

In addition, these appliances have a minimum power supply limit, maximum power supply limit as well as a capacity limit.

$${}_hu^t_i \geq {}_hl_i, \forall h \in 1,...,H, \forall i \in 1,...,_h a_i, \forall t \in 1,...,T \tag{5.8}$$

$${}_hu^t_i \leq {}_hv_i, \forall h \in 1,...,H, \forall i \in 1,...,_h a_i, \forall t \in 1,...,T \tag{5.9}$$

$$\sum_{i=0}^{T} {}_hu^t_i \leq {}_hY_i \forall i \in {}_ha_i, \forall h \in 1,...,H \tag{5.10}$$

The final type of appliance considered is the controllable appliances. The controllable appliances can have a variable power supply but have to meet a certain comfort criterion which has a non-linear relationship with the history of power consumption. Examples for these appliances would be the HVAC unit and water heaters. The current temperature in both of these cases depend on the power supplied throughout the day. And the comfort target is to maintain the current temperature of water/air between the right values. For this research, HVAC is chosen to be modeled. The general model used for the HVAC system is:

$${}_htemp^t = {}_h\alpha \times {}_htemp^{t-1} + (1 - {}_h\alpha) \times ({}_otemp^t + {}_h\beta \times {}_hw^t) \tag{5.11}$$

The discomfort of the HVAC is measured by the deviation of inside temperature from a given comfortable temperature set by the consumer.

$$C_h^{co} = \sum_{t=1}^{T} ({}_h temp^t - T_h)^2 \tag{5.12}$$

Using the above discomfort measurements, the following objective to be minimized can be established. Minimize,

$$C_h^{init} = C_h^{sh} + C_h^{co} \tag{5.13}$$

With this scheduling the total power usage for a given time interval t for one home can be calculated as follows:

$$p_{s.f.n.h}^t = {}_hB^t + \sum_{i=1}^{{}_ha_s} \sum_{k=1}^{{}_hn_i} {}_h^k e_i \cdot {}_h^k b_i^t + \sum_{i=1}^{{}_ha_i} {}_hu_i^t + {}_hw^t$$

$$\forall t \in 1, ..., T, \forall h \in 1, ..., H \tag{5.14}$$

5.4.2 Demand Response Optimization

Once the baseline is established, DR process could be started. The DR process includes the upward flow of information on the baseline power usage, downward flow of the targets calculated considering the baseline, and the optimization considering the target set for each home. Each of these steps are explained in detail below.

5.4.2.1 Upward Flow of Information

By considering the results of the basic optimization, at the subfeeder, these values will be summed together to get the total power usage.

$$p_{s.f.n}^t = \sum_{h=1}^{H} p_{s.f.n.h}^t \forall t \in 1, .., T \tag{5.15}$$

The feeder, substation as well as the subtransmission use a similar equation to calculate their total power demand levels.

$$p_{s.f}^t = \sum_{n=1}^{SF} p_{s.f.n}^t \forall t \in 1, .., T \tag{5.16}$$

$$p_s^t = \sum_{f=1}^{F} p_{s.f}^t \forall t \in 1, .., T \tag{5.17}$$

$$p^t = \sum_{s=1}^{SS} p_s^t \forall t \in 1, .., T \tag{5.18}$$

5.4.2.2 Downward Flow of the Target

The subtransmission will have a target to accomplish. This target could either depend on the total energy usage of the system or it can be independent of it. For example, the target at the subtransmission can be to set to the average power consumption at subtransmission.

$$target^t = \frac{\sum_{s=1}^{SS} \sum_{t=1}^{T} p_s^t}{T} \tag{5.19}$$

Or if there's a specific solar PV profile to be followed, a different target value can be calculated. The subtransmission level then spreads out the target among the lower substations with consideration to their 'DR potential'. The DR potential is the ability to meet DR targets. DR potential can be defined in several ways. One such analysis has been carried out in [32].

When distributing the targets among the substations, the following points should be taken into consideration. The target should be set in proportion to the potential of each substation. If the target exceeds the power limit of the substation, the target for that specific substation has to be capped at that limit. The excess power after capping has to be distributed among the rest of the substations, again in proportion to their potential. Once the target for a substation is set, the substation, in-turn, distributes the target among the feeders under its control using a similar logic. A similar logic is also carried out by the subfeeder to assign targets to homes, except that the power demand of the opting out homes has to be deducted from the target and then the target has to be assigned to the homes that contribute to DR. A common algorithm for all entities (subtransmission, substation, feeder and subfeeder) to calculate the target is given in Algorithm 3.

5.4.2.3 Final Optimization

The DR optimization is a multi-objective problem that aims to strike a balance between accomplishing the power consumption target and maintaining the comfort of the consumer. This balance is set by the constant $\epsilon_{s.f.n.h}$ defined for each home separately. This constant (unique to

Algorithm 3: Target setting algorithm

```
Result: list of subtargets
current_target = target - inflexible_load;
list_of_potentials = list of potentials of each contributing entity;
sum of potentials = sum(list of potentials);
list of limits = list of limits for each contributing entity;
list of subtargets = list of zeros representing each contributing entity;
while current_target ¿ 0 do
    reduced_target = 0;
    reduced_potential = 0;
    for i th entity in list of entities do
        if list_of_subtargets[i] == limit_of_potentials[i] then
            continue;
        end
        t = current_target*list_of_potentials[i];
        added_target = t/sum_of_potentials;
        if added_target ¿ list_of_limits[i] then
            added_target = list_of_limits[i];
            reduced_potential = reduced_potential + list_of_potentials[i];
            reduced_target = reduced_target + added_target;
        end
    end
    current_target = current_target - reduced_target;
    sum_of_potentials = sum_of_potentials - reduced_potential;
    if sum_of_potentials == 0 and current_target ¿ 0 then
        return infeasible;
    end
end
return list_of_subtargets;
```

each home) defines a constraint which a consumer should obey in power usage. This new constraint is:

$$(p^t_{s.f.n.h} - target^t_{s.f.n.h})^2 \leq (\epsilon_{s.f.n.h} \times target^t_{s.f.n.h})^2 \tag{5.20}$$

That is, the power usage of the home at a time interval cannot deviate more than a $\epsilon_{s.f.n.h}$ fraction from the given target. (How this $\epsilon_{s.f.n.h}$ fraction is set will be explained in the following paragraphs). While maintaining this constraint, the consumer is allowed to optimize the power usage for the maximum comfort. That is, the optimization in (5.13) will be carried out again but with the constraint given by (5.20) as the final optimization step.

The constant $\epsilon_{s.f.n.h}$ can be interpreted as the constant deciding the point in the pareto front of the multi-objective optimization at which the optimization balances at. This method (called ϵ optimization method) was first proposed by Haimes et. al. in 1971 [80]. In this case, deviation from the target at each time interval for each home is considered a separate objective and is converted into a constraint. Instead of generating a separate value for each of these objectives, a single $\epsilon_{s.f.n.h}$ value is employed to limit all of them. This framework has the advantage of having a strong mathematical base while having an easy-to-understand physical interpretation.

The value for $\epsilon_{s.f.n.h}$ is decided in the following manner. First, minimum possible $\epsilon_{calc,s.f.n.h}$ value for the home is calculated using the following minimization:

$$\epsilon_{calc,s.f.n.h} = \min \max_t \frac{(p^t_{s.f.n.h} - target^t_{s.f.n.h})^2}{(target^t_{s.f.n.h})^2} \tag{5.21}$$

Then the initially agreed upon $\epsilon_{init,s.f.n.h}$ value is compared with the $\epsilon_{calc,s.f.n.h}$ value and the smaller value is chosen to be $\epsilon_{s.f.n.h}$ for the optimization. The reasoning behind this choice is that, although the consumer initially agrees to an $\epsilon_{s.f.n.h}$ value, given the target, it might not be feasible. In this case, smallest possible ϵ (calculated by (5.21)) is used for the optimization.

$$\epsilon_{s.f.n.h} = \min(\epsilon_{calc,s.f.n.h}, \epsilon_{init,s.f.n.h}) \tag{5.22}$$

5.5 Demand Response Metrics

In this Section, analysis methods for DR effectiveness are presented. In this study, three indices are introduced to measure the various aspects of DR program. These are explained in the following subsections.

5.5.1 Performance Indicator

The success of the DR method can be measured as the adherence to the target at each time interval. More specifically, the new optimized values can be compared with the baseline case values for a better measurement of the success of DR. To quantify the success of DR, the current adherence to the target is taken as a fraction of the adherence to the target by the baseline case. The averaged sum of all these values is considered as a performance indicator (PI). That is,

$$PI = \frac{1}{T} \sum_{t=0}^{T} \frac{|target^t - p^t| - |target^t - p^t_{new}|}{|target^t - p^t|} \tag{5.23}$$

where p^t_{new} is the optimized power usage at time interval t. Similar PI values imply similar DR effectiveness.

5.5.2 Effectiveness Indicator

Although higher PI values mean better DR, a better DR generally requires a larger participation of consumers. However, as discussed before, if a certain consumer does not participate in DR, the remaining consumers attempt to balance out the impact by changing their own power consumption within their limits. In some cases, the DR participants are able to remove the impact of the non-participants completely. In this scenario the contribution from the non-participating consumer is unnecessary in the first place. In these scenarios, similar PI values occur. Since convincing consumers to participate in DR programs is difficult, utilities may find it more useful to get the maximum out of less number of participants. To measure this an 'effectiveness indicator' (EI) is introduced. To emphasize on the necessity of DR performance, PI is squared in this measurement, and to encourage the less participation, it is divided by the participation percentage. EI is thus defined as:

$$EI = \frac{sgn(PI) \times PI^2}{participation\%} \tag{5.24}$$

where $sgn(.)$ function represents the sign function which is defined as:

$$sgn(x) = \begin{cases} -1, & \text{x} < 0 \\ 1, & \text{otherwise} \end{cases}$$

5.5.3 Stress Factor of Demand Response Participant

Even if less number of consumers can fulfill the requirements of the utility, the '*stress*' of the consumer increases as more deviation of power usage is demanded by the DR program. That is, when lesser number of members participate, the available members have to shift the power that those who do not shift. To measure this additional 'burden' on the participating consumers a new *stress* measurement is introduced. This measurement is defined by the difference between the power shift of the consumers when they shift power for the whole community and the power shift of the same consumers if only that population existed in the DR community. To mathematically represent this, first, initial and final power of the system is defined as follows:

$$_{initial}E^t_{100} = \sum_{s=1}^{SS}\sum_{f=1}^{F}\sum_{n=1}^{SF}\sum_{h=1}^{H} p^t_{s.f.n.h} \tag{5.25}$$

$$^k_{final}E^t_{100} = \sum_{s=1}^{SS}\sum_{f=1}^{F}\sum_{n=1}^{SF}\sum_{h=1}^{H} {}_{new}p^t_{s.f.n.h} \tag{5.26}$$

$$^k_{initial}E^t_{k} = \sum_{s=1}^{SS}\sum_{f=1}^{F}\sum_{n=1}^{SF}\sum_{h=1}^{H} p^t_{s.f.n.h}.d_{s.f.n.h} \tag{5.27}$$

$$^k_{final}E^t_{k} = \sum_{s=1}^{SS}\sum_{f=1}^{F}\sum_{n=1}^{SF}\sum_{h=1}^{H} {}^k_{new}p^t_{s.f.n.h}.d_{s.f.n.h} \tag{5.28}$$

Here $_{initial}E^t_{100}$ denotes the total power of all 100% of the consumers at time interval t before optimization and $^k_{final}E^t_{100}$ represents the total power after k% of the consumers have optimized the system at time t. The variable $^k_{initial}E^t_{k}$ represents the initial demand of only the k% of the consumers that participate in the DR program. Notice that, each term of power is multiplied by $d_{s.f.n.h}$ which is a binary decision variable denoting whether the consumer contributes to DR or not. When the consumer contributes to DR, this variable gets the value of 1 and it gets a 0 otherwise.

Variable ${}^{k}_{final}E^{t}_{k}$ is the same calculation after optimization. Notice that ${}^{k}_{new}p^{t}_{s.f.n.h}$ is different from ${}_{new}p^{t}_{s.f.n.h}$. This is because the optimal demand when 100% of the load is considered is different from the optimal demand when only k% of the demand is considered. The deviation from the target could be then defined as:

$$\Delta^k E_{100} = \sum_{t=0}^{T} \left| \frac{\sum_{t=0}^{T} {}^{k}_{initial}E^{t}_{100}}{T} - {}^{k}_{final}\, E^{t}_{100} \right| \tag{5.29}$$

The deviation from the average when k% of the consumers would participate in the optimization can be calculated as:

$$\Delta^k E_{k} = \sum_{t=0}^{T} \left| \frac{\sum_{t=0}^{T} {}^{k}_{initial}E^{t}_{k}}{T} - {}^{k}_{final}\, E^{t}_{k} \right| \tag{5.30}$$

Finally, the *stress* experienced by k% consumer participation by the participating consumers can be calculated as a percentage of the ratio between $\Delta^k E_{100}$ and $\Delta^k E_k$

$$stress_k = \frac{\Delta^k E_{100}}{\Delta^k E_k}\% \tag{5.31}$$

5.6 Results, Analysis and Discussion

The simulation studies were carried out for a million homes with the following structure. Fifty substations for the subtransmission. Twenty feeders per substation. Fifty subfeeders per feeder. Twenty homes per subfeeder. Simulation studies were carried out to explore the effects of optimization on individual homes and the power system. Specifically, the case studies were designed to observe the effects of ϵ and the percentage of participation on the system. These case studies were implemented on RTPIS Lab high performance computing cluster of Clemson University [61].

5.6.1 Data set

The data set is mostly based on Pecan Street Inc. Dataport data. However, the HVAC data was generated with a selected outside temperature using the HVAC model in use. Since the data set is far small for a one million user base, a random normal noise was added to the initial data template to get the one million home power demand. The HVAC model requires the thermal characteristic parameters to be set. These were set by adding a normal random value to common parameters of a home. The power demand for HVAC was generated for particularly cold day in the winter causing the power demand for the early morning and later afternoon to shoot up. The mid-day power demand is quite low since the most appliances are turned off in the mid-day. The huge disparity between the mid-day and the rest of the day is caused by the lack of industrial and commercial power demands.

5.6.2 Demand Response Potential Quantification

As described in Section 5.4, a DR potential quantification is needed to run Algorithm 3. In this study DR potential is assumed to be proportional to the total power usage. Since the target is calculated in proportion to the potential, the DR potential could just be assumed as the total power usage. Therefore:

$$U_s^t = p_s^t \tag{5.32}$$

$$U_{s.f}^t = p_{s.f}^t \tag{5.33}$$

$$U_{s.f.n}^t = p_{s.f.n}^t \tag{5.34}$$

$$U_{s.f.n.h}^t = p_{s.f.n.h}^t \tag{5.35}$$

5.6.3 Experiments

The optimization framework was simulated with several different ϵ values and participation percentages. ϵ values were generated in a normal distribution with a specific mean value. Several such mean ϵ values were tested with several different participation percentages. The effect of each ϵ value and participation percentage is shown in Figs. 5.2 - 5.6. Furthermore, the community might not be as easy to characterize with a mean ϵ value as a Gaussian distribution. The electricity consumers are usually categorized in categories which have similar behaviors. Therefore, another possible model would be a mixture model which is a combination of multiple Gaussian distributions with different ϵ values. Mixture models are used extensively in data-driven technologies [78]. Fig. 5.7 shows the result of the optimization of a population where 50% of the population contributes to with a mean ϵ value of 0.1 and 25% of the population contributes with 0.2 mean ϵ value.

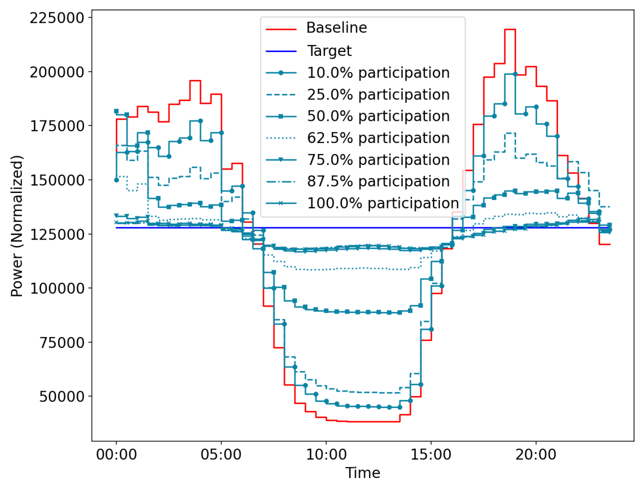


Figure 5.2: Different total power demands for different participation percentages at $\epsilon = 0.1$

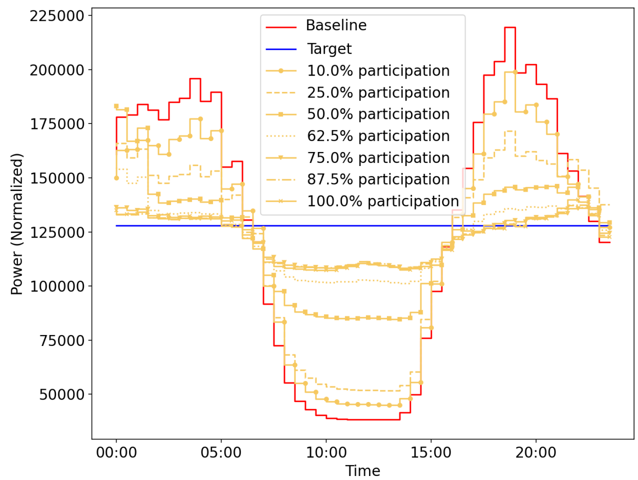


Figure 5.3: Different total power demands for different participation percentages at $\epsilon = 0.2$

5.6.4 Effects at different levels of the hierarchical architecture

The optimization is carried out from bottom up, starting at homes. At various levels of the hierarchical architecture, the changes in power usage add up and the effects of DR start to appear more and more as the levels go up. In Figs. 5.8-5.11 this fact is demonstrated. These figures illustrate effects of DR carried out with 0.1 ϵ and 75% participation at selected entities of the hierarchy and at each figure, it is easily noticed that the valleys are being filled and peaks are being shaved more and more, which is the target of the DR program.

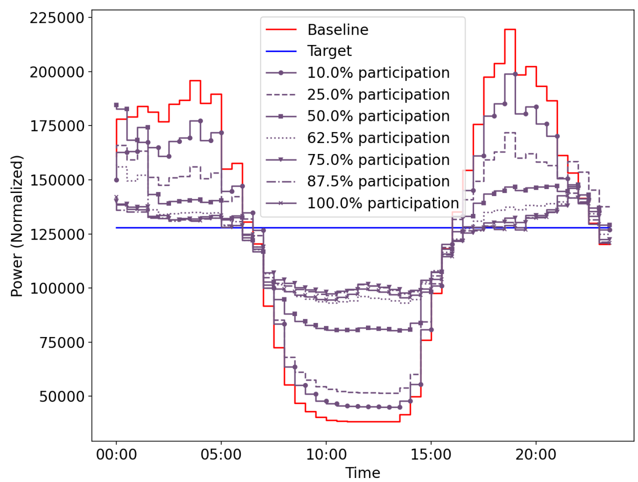


Figure 5.4: Different total power demands for different participation percentages at $\epsilon = 0.3$

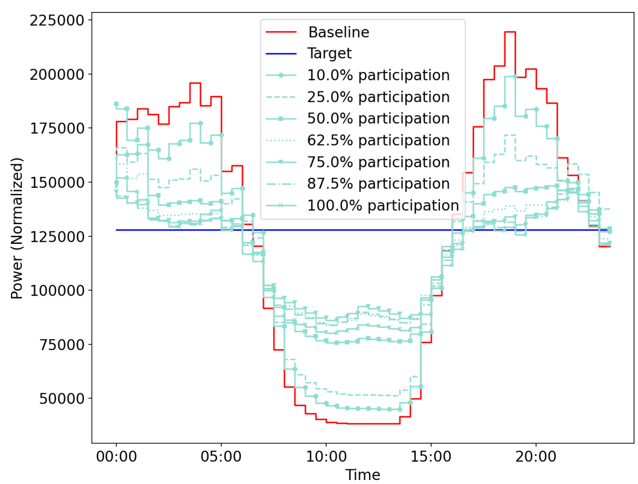


Figure 5.5: Different total power demands for different participation percentages at $\epsilon = 0.4$

5.6.5 Effects on an Individual Home

The effects of the optimization on individual home were explored by changing the ϵ value over a range of values and measuring the discomfort values. For the shiftable devices, the average deviation of the appliance from the most comfortable scheduling time was measured. As seen in Fig. 5.12, the results show that the shiftable appliances remain mostly at the desired scheduling intervals. This is because DR on HVAC unit and interruptible appliances dominates over shiftable appliances. The thermal discomfort was measured by the average deviation of temperature from the desired temperature. Fig. 5.12 also shows the thermal comfort changes as the ϵ increases.

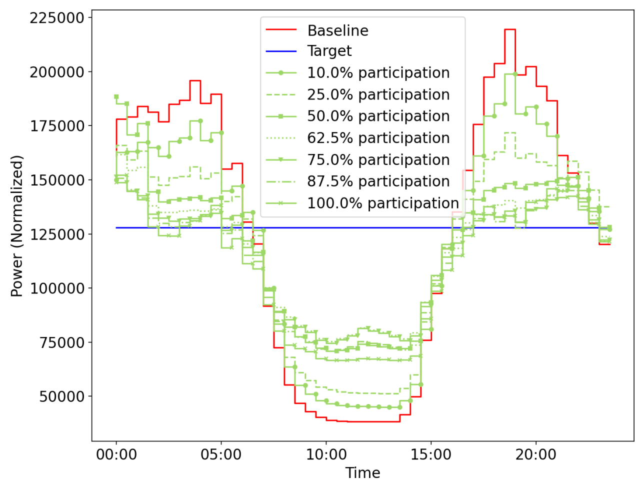


Figure 5.6: Different total power demands for different participation percentages at $\epsilon = 0.5$

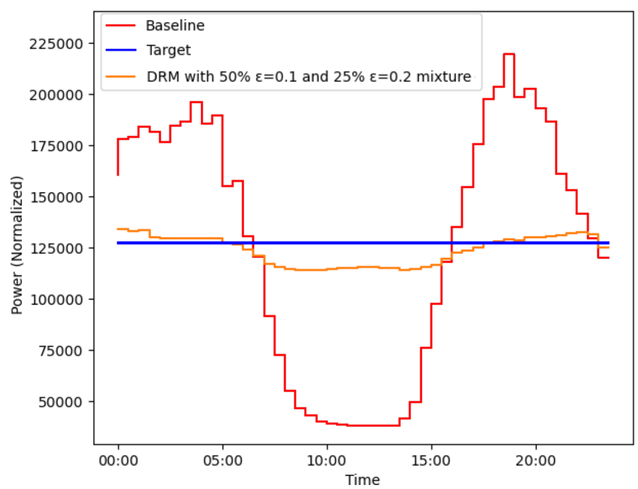


Figure 5.7: Total power demand for a population of 50% of $\epsilon = 0.1$ and 25% of $\epsilon = 0.2$ and rest non-contributing.

5.6.6 Performance and Effectiveness Indicators

The performance indicator calculated for the current data set is shown in Fig. 5.13 and it reveals several facts about the optimization. At high contribution percentages and low ϵ values, more contribution increases PI as generally expected. However, it can also be noticed that for large mean ϵ values, the optimization could get worse as participation increases. This is because as the participation increases, less flexible contributions increase in the DR program.

The EI graph is shown in Fig. 5.14. Notice that in $\epsilon = 0.1$ graph 75% participation has a better EI value than 100% participation. Since 75% can achieve the same effect as 100%

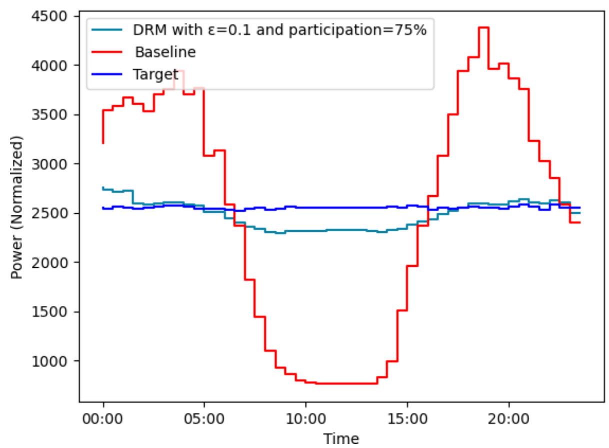


Figure 5.8: Results for the substation 34 for $\epsilon = 0.1$ and 75% participation. This specific substation had 70.52% participation

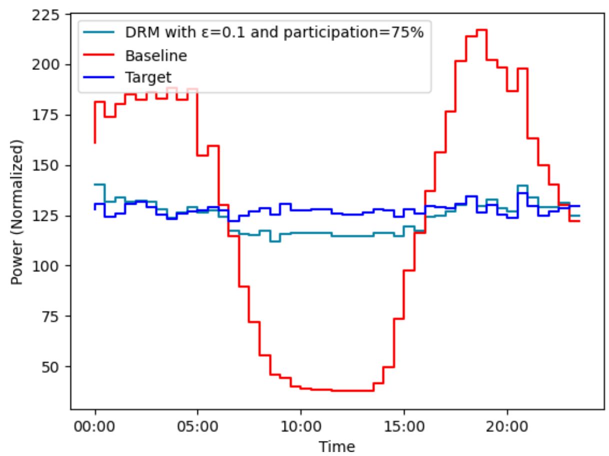


Figure 5.9: Results for 3rd feeder of the 29th substation for $\epsilon = 0.1$ and 75% participation. This specific feeder had 72.0% participation

participation, this indicator shows a better value for 75% case than 100% case. The effectiveness of DR at the 75% case over other cases can be seen in the overall power usage graph (See Fig. 5.2). In this graph the 75% and 100% graphs look quite similar and yield the same amount of DR while the rest progressively worsen as the participation percentage goes down. The *stress* calculation is shown in Fig. 5.15. The graph shows that the *stress* for programs with very low participation is very high, but as participation grows, the *stress* on the consumer goes down. It can be noted that at 75% participation, the *stress* values almost converge and at 87%, they converge entirely. And the performance indicator graph (Fig. 5.13) shows that the performance indicator (i.e., the contribution towards DR) is similar in 75% and 87.5% cases. (For further comparison, The total demand for the

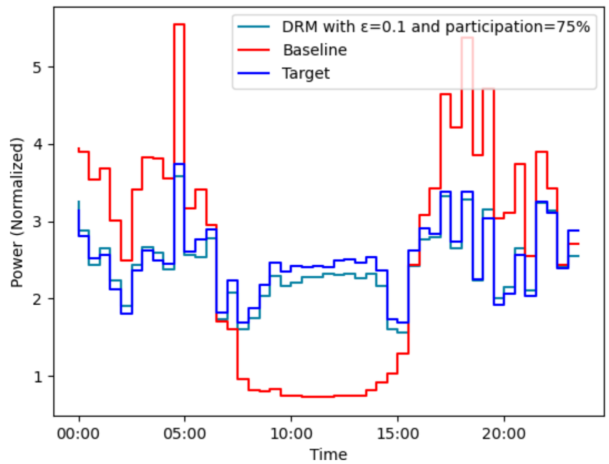


Figure 5.10: Results for subfeeder 1 of the 9th feeder of the 20th substation for $\epsilon = 0.1$ and 75% participation. This specific subfeeder has 85% participation

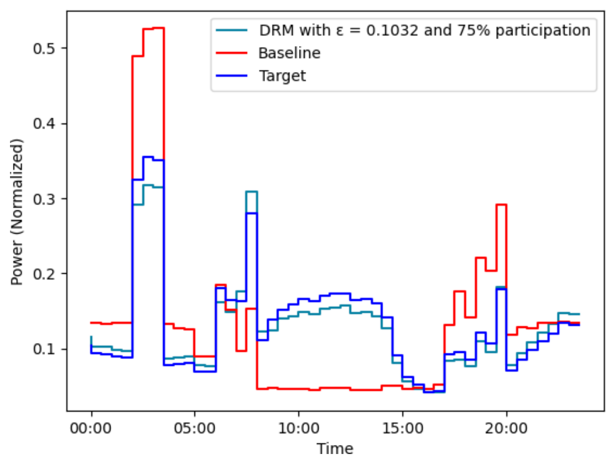


Figure 5.11: Results for home no 1 of the 29th subfeeder of the 41st feeder of the 15th substation for $\epsilon = 0.1$ and 75% participation. 17 out of 20 homes in the specific subfeeder where this home is located contributed towards DR. (85%)

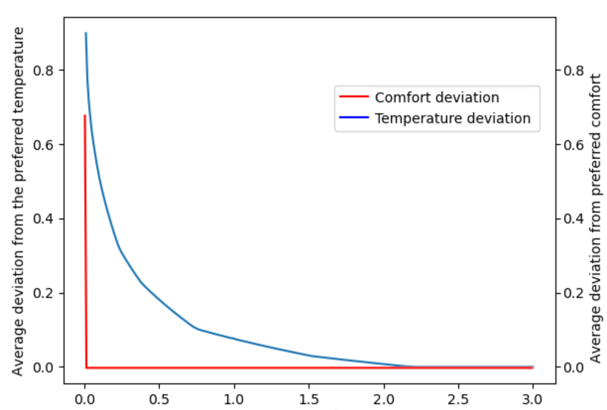


Figure 5.12: Average deviation of temperature and comfort from the preferred values of a home.

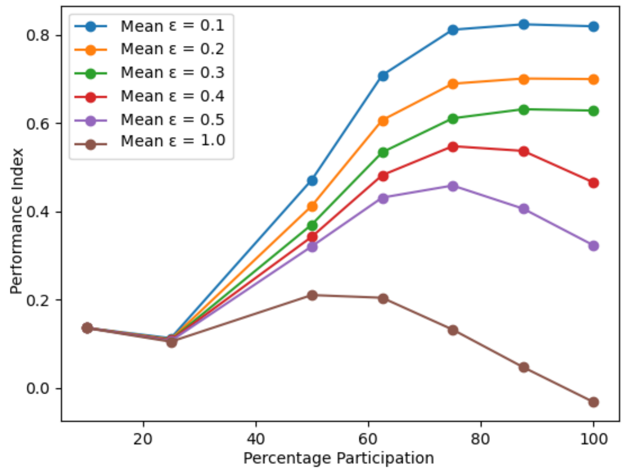


Figure 5.13: Performance indicator values for different ϵ values and participation values

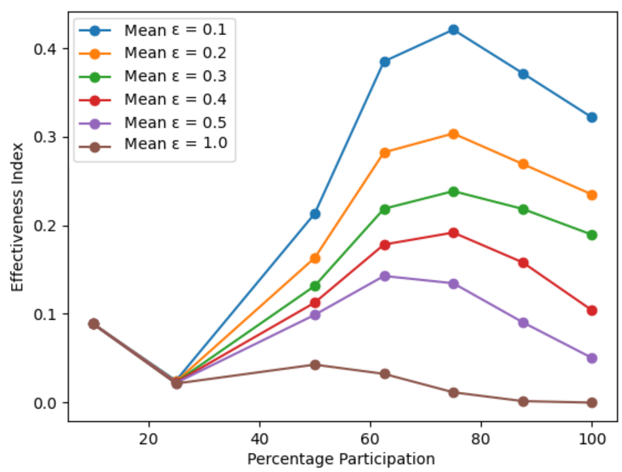


Figure 5.14: Effectiveness indicators for different ϵ and participation percentage values

75% and 87.5% case is shown in Fig. 5.16) That is, in both cases, both the utility target of flattening the demand and the consumer target of maintaining more comfort (less stress) are achieved at 75% of participation of the community. The remaining 12.5% participants do not add much to the optimization. This is because the target is divided to the consumers, and the consumers carry out their own optimizations without knowing the amount of optimization the others are carrying out. This analysis reveals that, careful analysis on the participant has to be carried out in order to not to let the DR program performance degrade. The utility has to carry out the effectiveness calculation and the *stress* calculation on the population before deciding on the number of participants for the optimization.

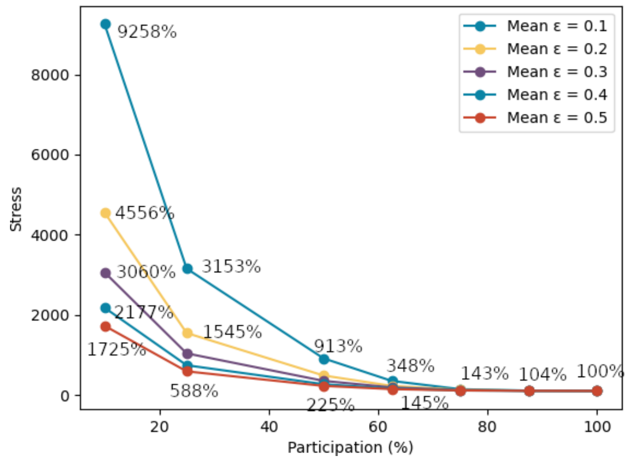


Figure 5.15: *Stress* calculation for the different mean ϵ values and participation percentages. The results show that as the participation increases, the *stress* decreases.

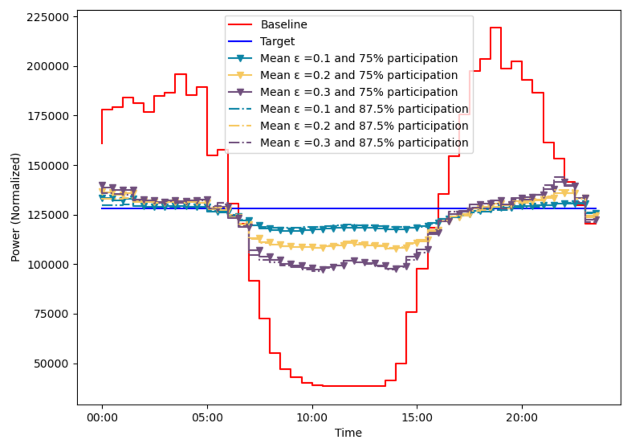


Figure 5.16: Different total power demands for differentϵ values for participation percentages 75% and 87.5%

5.7 Summary

A scalable framework for demand response optimization is introduced in this paper. The hierarchical architecture is centric to this framework and allows the addition of participants to the DR program without slowing down the optimization. Furthermore, it allows the optimization to take power flow limits in the power system to consideration, which is necessary for the practical implementation of a large-scale DR program. The presented case study and results obtained illustrate the success of the framework. The proposed framework has been successfully illustrated in a one million home case study. This framework could be applied to other power systems with different numbers of homes, subfeeders, feeders and substations.

Additionally, new metrics to measure the success of the demand response program as well as the stress of the demand response participant have been presented. These measurements not only allow the utility to decide on the number of participants to incorporate in the DR program but also allows the participants to judge the stress they undergo in participating in DR. The application of these metrics in the explored case study shows that incorporating all possible participants might not be the best case for the utility. This result illustrates the fact that the DR aggregator needs to know the behavior of the electricity consumers in the population before involving the consumers in the DR program.

The proposed scalable DR framework can be expanded by the inclusion of distributed energy resources including generation and storage. The quality of DR program depends on the accuracy of the base load prediction. To have a maximum leverage of the demand response capability, the time between the demand response scheduling and execution needs to be reduced. To achieve this, a near real-time scheduling can be implemented such as an hour-ahead or even a smaller time-horizon.

Chapter 6

Hierarchical Load Forecasting Reconciliation for Scalable Residential Demand Response Management

6.1 Introduction

This chapter concentrates on improving and application of forecasts for a hierarchical DR program. Hierarchical DR architecture was introduced in [35] as a solution to the scalability problem of DR and is discussed in the previous chapter. Although several solutions have been proposed as fast and distributed DR solutions [49, 73, 11], the hierarchical architecture has been presented as scalable for millions of consumers. The hierarchical DR structure relies on an accurate forecast for the next day's load. Since the consumption targets are distributed throughout the hierarchy, the forecasting used at each level and each node should agree with each other.

However, in reality, this is not the case. For instance, consider several homes supplied by one Level 4 node. Each home would generate a forecast for tomorrow's load profile using some internal model. This could include human behavior models, Markov Chain models, time series models, etc.

The Level 4 node would generate a forecast for tomorrow's load too, using the historical data it has at its disposal. However, the Level 4 node would not have the luxury of human behavior modeling. It would have to depend on some other techniques. As a result, the sum of the forecasted load of each home does sum up to the value forecasted by the Level 4 node. Therefore, several predictions for the total energy demand can be made each having a different accuracy. That is, the sum of forecasts of all nodes at each level results in a foreast for the total energy demand. In this chapter, the effects of forecasting accuracy on the DR program is explored. Additionally, reconciliation of these available forecasts to generate a combined forecast and the effects of this new forecast is compared against the other forecasts.

6.2 Forecasting Accuracy Effects

The target set for the consumer to meet directly depends on the demand forecast by the DR 'service provider'. The overall target for the Level is usually set by the following equation:

$$target^t = \frac{\sum_{s=1}^{SS} \sum_{t=1}^{T} p_s^t}{T} \tag{6.1}$$

where, $target^t$ is the Level 5 target at time t, SS is the number of nodes at Level 4, T is the total number of time intervals of the day and p_s^t is the unoptimized load demand of Level 4 node s at time t. That is, the target is the average of total energy demand forecast over the period of the day. Therefore, targets set for the homes directly depend on the forecasts used. In this section, the effects of different targets on homes and the effects of forecast accuracy on the population is explored through simulations.

6.2.1 Data set

For the simulation, 1500 homes were simulated. The hierarchy is set up as follows. Five Level 4 nodes under the Level 5 node, five nodes in Level 3 under each Level 4 node (total of $4\times5 = 20$ Level 3 nodes), five nodes in Level 2 under each Level 3 node ($4\times5\times5 = 100$ Level 3 nodes), and fifteen homes under each Level 2 node ($4\times5\times5\times15 = 1500$ homes). The data set was downloaded from Irish Social Science Data Archive Smart Metering Project Electricity Customer Behavior Trial [41].

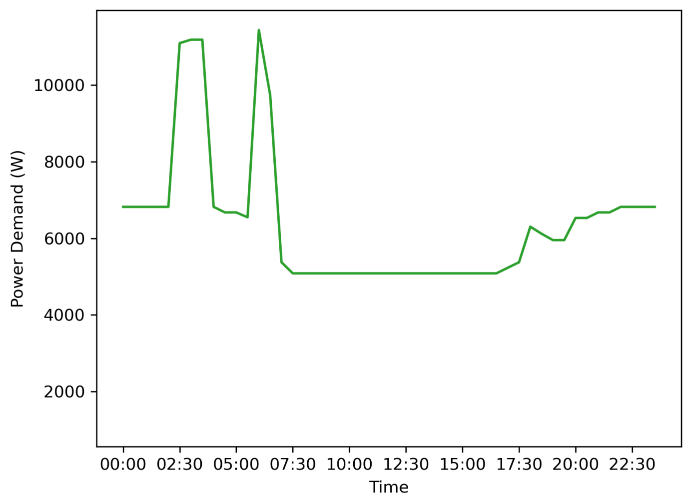


Figure 6.1: The unoptimized load of the simulated home. Initial spikes are due to the electric car charging, and the latter increase of demand is due to the consumers running home equipment.

6.2.2 Variation of Demand Response Target

Ideally, each home should receive a target equal to their potential of demand response. That is, the home should be able to meet the target without compromising the comfort of the consumer. However, due to forecasting errors this might not be the case. The target set for the consumer could be over or under the comfortable range of targets the consumer can handle. In case the consumer is given a target that cannot be met, the consumer would simply fall back to the closest target they could handle. To illustrate this fact, a single home is simulated, and the target is varied, ranging from too small to be met through easily met, to too high to be met. A very small target cannot be met by a consumer due to the existence of an inflexible load and a very large target cannot be met due to the flexible appliances reaching their energy consumption limits. Fig. 6.1 shows the total load of the simulated home without optimization. The home initially has a spike in the demand due to the electric car being charged in the early morning and the residents getting ready for work. In the night, when the residents arrive, some interruptible and shiftable loads run as a result of residents carrying out various tasks about the home. The adherence to the given target can be measured as the absolute difference between the target and the actual demand. Fig. 6.2 shows this difference for all 48 hour time slots for the home. Sum of all these differences of all time slots can be considered as a metric to measure the adherence to the target by the home.

$$M_h = \sum_{t=0}^{T} |{}_h target_t - p_h^t| \tag{6.2}$$

where, ${}_h target_t$ is the target for home h at time t and p_h^t is the actual demand by the home h at time t. Additionally, in this DR architecture, a home has some 'leeway' defined by the constant ϵ, which is the fraction of the target the home is allowed to deviate from the given target. That is, the requirement of the home is to maintain the following inequality:

$$(p_h^t -_h target_t)^2 \leq (\epsilon_h \times_h target_t)^2 \tag{6.3}$$

This allows a band of freedom around the target for the home. This characteristic is not considered in the previous metric. To include this characteristic in the metric, the difference between the target and the actual demand is considered zero if the difference falls in the range defined by ϵ_h of the home. The metric is now modified as:

$$M_h = |{}_h target_t - p_h^t| \times (H(p_h^t - U_h^t) - H(p_h^t - L_h^t) + 1) \tag{6.4a}$$

$$U_h^t =_h target_t \times (1 + \epsilon_h) \tag{6.4b}$$

$$L_h^t =_h target_t \times (1 - \epsilon_h) \tag{6.4c}$$

where $H(x)$ is the standard Heaviside step function defined as:

$$H(x) = \begin{cases} 0 & x \leq 0 \\ 1 & x > 0 \end{cases} \tag{6.5}$$

The response of a home for several ϵ values are shown in Fig. 6.3 A home might find it difficult to meet the given load for several reasons. First, there are several constraints in each home to meet. These constraints include capacity constraints, minimum energy consumption constraints and time constraints. For instance, air conditioners have a maximum energy consumption limit and a minimum energy consumption limit without turning it off. Additionally, an electric car charger could

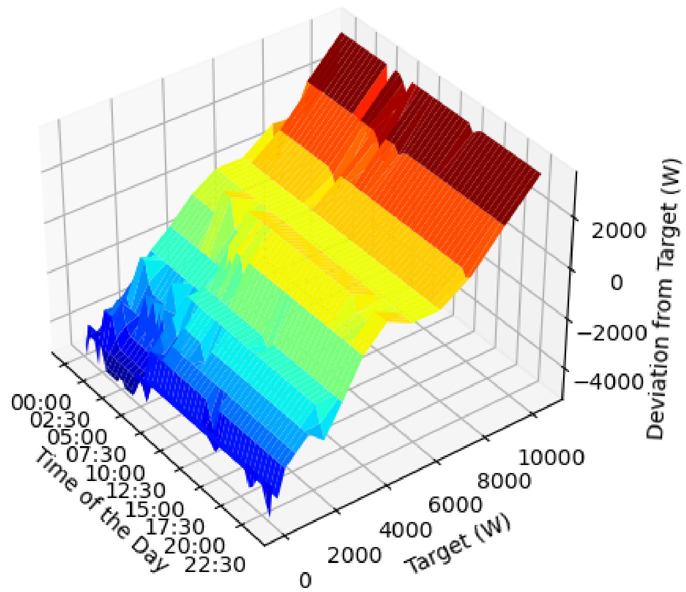


Figure 6.2: The adherence to the target of a home, measured by the absolute difference between the load and the target at each time interval. The target is kept a constant for the whole 48 time intervals of the day.

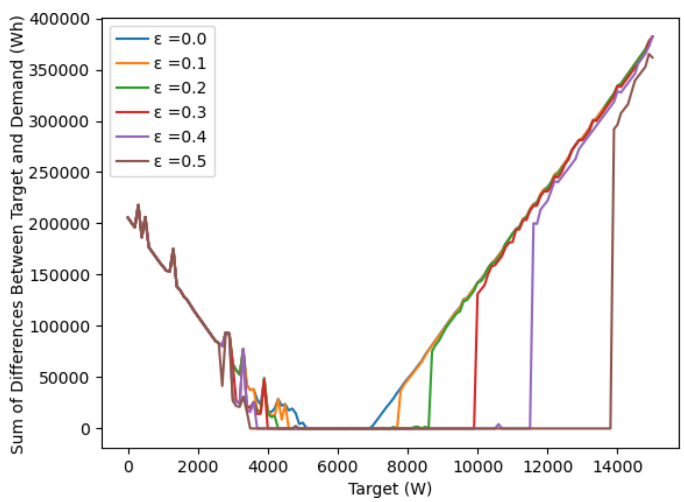


Figure 6.3: The adherence to the target of a home, measured by the area between the target and the load of the home except in the allowed band by ϵ. The target is kept a constant for the whole 48 time intervals of the day.

have a time limit before which it has to gain a certain charge so the consumer could leave for the job without delay. Second, the shiftable appliances have an energy consumption profile which cannot be changed. The energy consumption rate of a washing machine cannot be changed, for instance. A home could exactly match the given target only if these conditions can be met. That is, the target

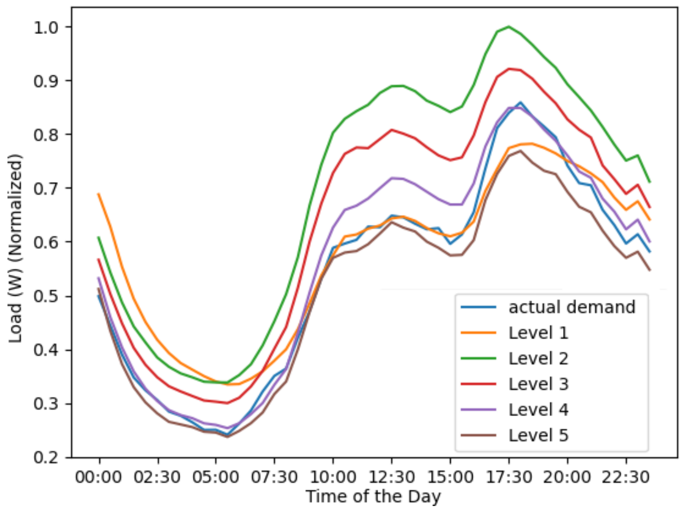


Figure 6.4: Aggregated load forecast at each level. These forecasts are generated by feeding DeepAR algorithm with 3 months of load profiles for 1500 homes.

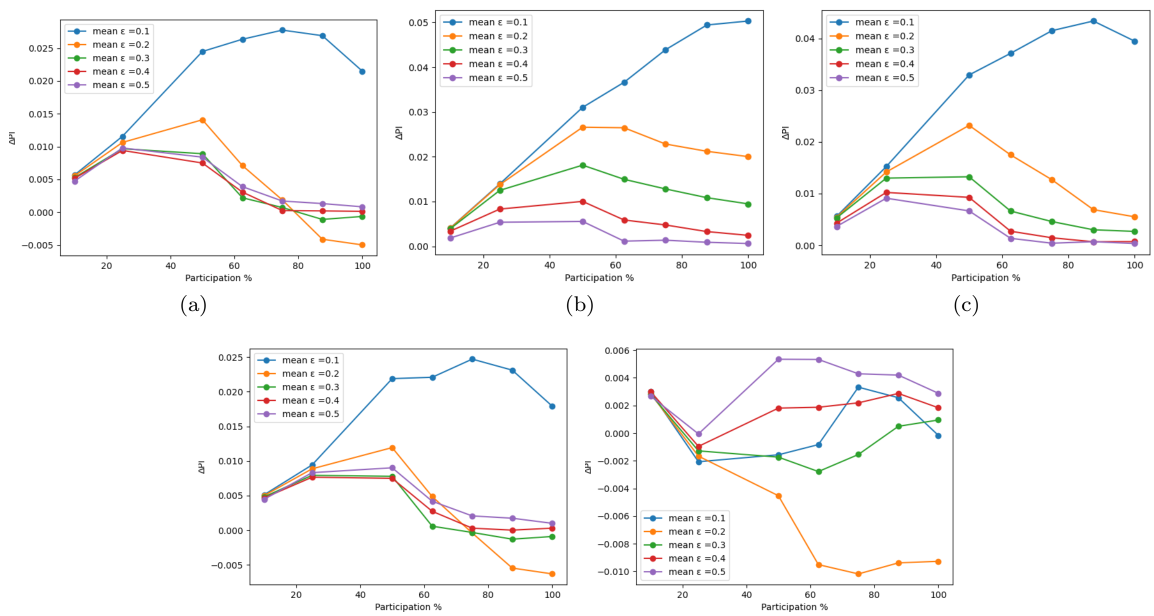
should be higher than the inflexible load and the shiftable load profile. Any remaining dissimilarities should be able to be filled with interruptible load without violating the given constraints. These conditions are met on a narrow band of targets.

6.2.3 Forecasts and Simulation of the Population

To explore the effects of forecasting accuracy, a series of predictions are utilized to generate different targets and optimize accordingly. The forecasts are applied at the Level 5 to calculate targets for lower levels. The Level 5 requires an estimate of the overall demand of the whole system in order to set the target. This overall energy demand can be calculated in several ways: by summing up all forecasts of contributing homes, by summing up all forecasts of Level 2, by summing up all forecasts of Level 3, by summing up all forecasts at Level 4, or by using Level 5 forecasts. These forecasts were generated by employing DeepAR [65] algorithm at each level. The aggregated results of these forecasts are shown in Fig. 6.4. The following can be observed with the forecasts. Level 5, Level 4, and Level 1 forecasts are the most accurate forecasts. Naturally, upper levels of the power system are able to predict the net demand more accurately than the lower levels. However, at the home level, DeepAR has more similar energy curves to train on. Therefore, the home level generated a good forecast. The Levels 2 and 3 have over-estimated the energy demand while Level 5 has mostly underestimated the energy demand.

6.2.3.1 Results

To measure the impact on the optimization by the forecast, the difference between the PI values of the optimization with the forecast and PI values of the ideal forecast are used. That is, ΔPI is calculated by subtracting the ideal PI value from the predictions PI value. The result is shown in Figs. 6.5a to 6.5e. The EI values can be seen in Figs. 6.6a to 6.6e. And the stress values can be seen in Figs. 6.7a to 6.7e. The effectiveness indices (EI) for all the methods tested are shown



(a) (b) (c)

(d) (e)

Figure 6.5: PI value differences between optimization run with different levels of forecasts and ideal optimization. These are calculated by subtracting the ideal PI value from the PI values resulted by the DR program employing the forecast. (6.5a) PI for DR with Level 1 forecast, (6.5b) PI for DR with Level 2 forecast, (6.5c) PI for DR with Level 3 forecast, (6.5d) PI for DR with Level 4 forecast, (6.5e) PI for DR with Level 5 forecast

in Fig. 6.6.

6.3 Forecast Reconciliation

Several methods are available for the reconciliation of such forecasts in a hierarchical setting [62]. The available linear methods for reconciliation are bottom-up, top-down, and middle-out methods. The bottom-up method ignores the forecasts from all other levels and assumes the sum of the bottom-level forecasts is the most accurate forecast. The top-down method assumes the

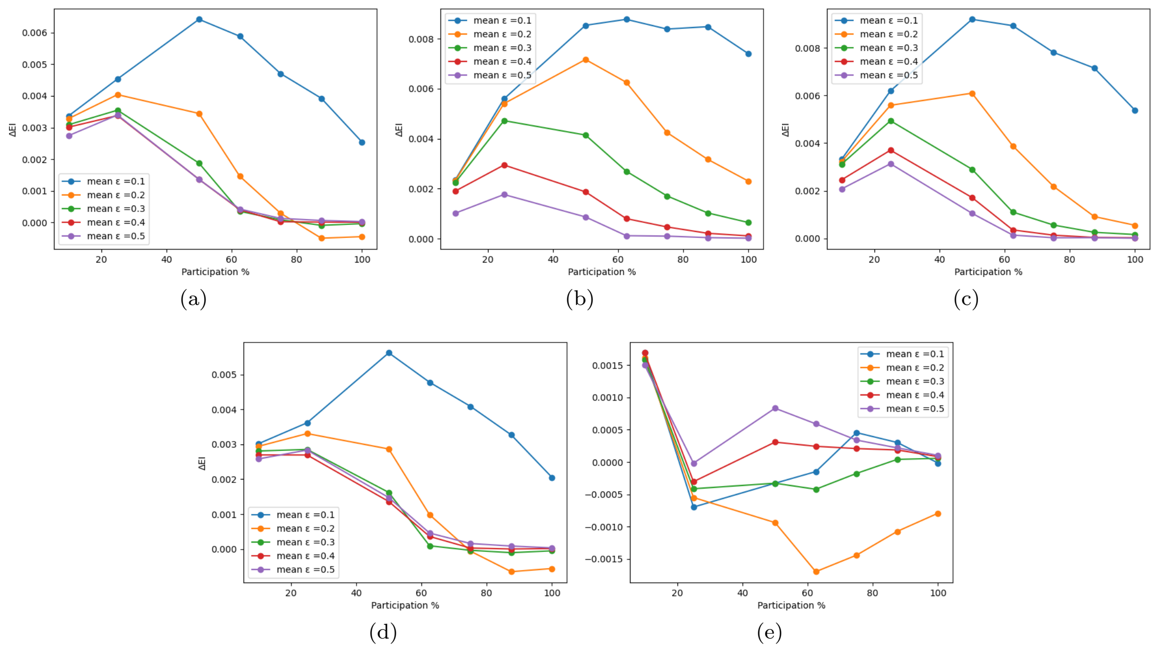


Figure 6.6: EI value differences between optimization run with different levels of forecasts and ideal optimization. These are calculated by subtracting the ideal EI value from the EI values resulted by the DR program employing the forecast. (6.6a) EI for DR with Level 1 forecast, (6.6b) EI for DR with Level 2 forecast, (6.6c) EI for DR with Level 3 forecast, (6.6d) EI for DR with Level 4 forecast, (6.6e) EI for DR with Level 5 forecast

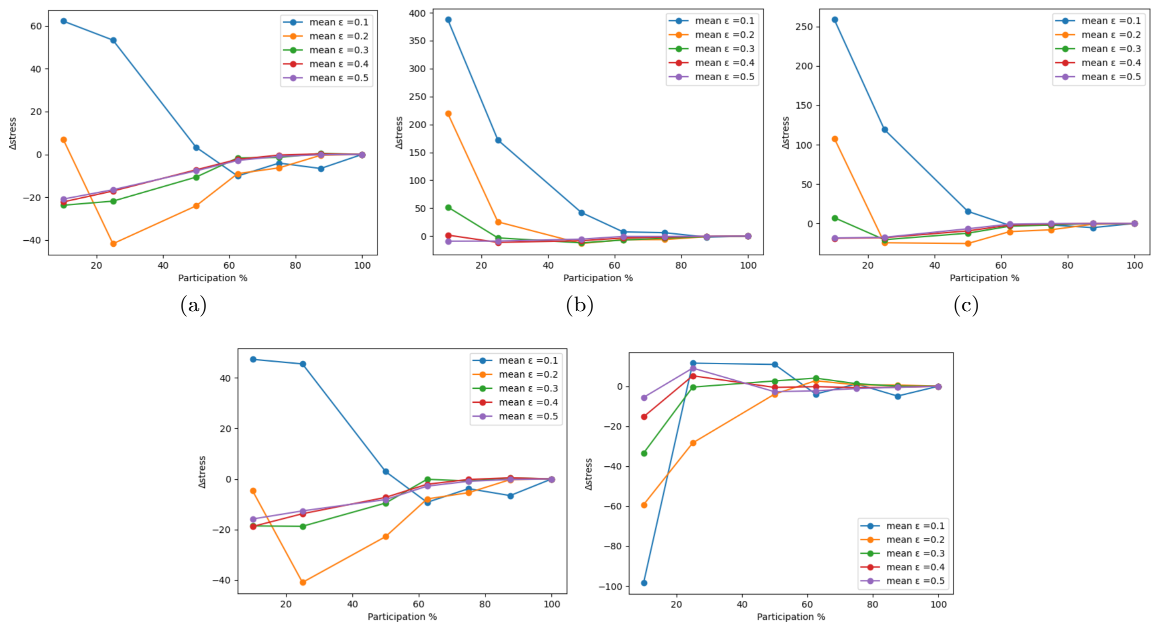
top forecast is the most accurate one and to generate the lower-level forecasts, divides the summed forecast into some ratios. The middle-out method does some combination of the earlier two methods. Hyndman et. al. [39] formulated the linear forecast combination method as a regression problem and showed that solving this system could lead to optimal forecast combination. In this section the optimal combination forecasting method is discussed as applied to the hierarchical DR structure.

All power demands across the hierarchy can be represented by the following vector:

$$\mathbf{Y}^t = [p^t, p^t_1, ..., p^t_B, p^t_{1.1}, ..., p^t B.F, p^t_{1.1.1}, ..., p^t_{B.F.N},, ..., p^t_{1.1.1.1}, ..., p^t_{B.F.N.H}]' \tag{6.6}$$

where B is the total number of homes in the architecture. But, given the above hierarchy, the following equalities hold.

$$p^t_{b.f.n} = \sum_{h=1}^{H} p^t_{b.f.n.h} \tag{6.7}$$



(a) (b) (c) (d) (e)

Figure 6.7: Stress value differences between optimization run with different levels of forecasts and ideal optimization. These are calculated by subtracting the ideal stress value from the stress values resulted by the DR program employing the forecast. (6.7a) stress for DR with Level 1 forecast, (6.7b) stress for DR with Level 2 forecast, (6.7c) stress for DR with Level 3 forecast, (6.7d) stress for DR with Level 4 forecast, (6.7e) stress for DR with Level 5 forecast

$$\begin{aligned} p^t_{b.f} &= \sum_{n=1}^{N} p^t_{b.f.n} \\ &= \sum_{n=1}^{N} \sum_{h=1}^{H} p^t_{s.f.n.h} \end{aligned} \tag{6.8}$$

$$\begin{aligned} p^t_{b} &= \sum_{f=1}^{F} p^t_{b.f} \\ &= \sum_{f=1}^{F} \sum_{n=1}^{N} \sum_{h=1}^{H} p^t_{s.f.n.h} \end{aligned} \tag{6.9}$$

$$
\begin{aligned}
p^t &= \sum_{b=1}^{B} p_b^t \\
&= \sum_{b=1}^{B} \sum_{f=1}^{F} \sum_{n=1}^{N} \sum_{h=1}^{H} p_{s.f.n.h}^t
\end{aligned} \tag{6.10}
$$

That is, all power demands at all nodes can be represented by the home level power demands. Therefore, the vector in (6.6) can be expanded as follows:

$$
\begin{aligned}
\mathbf{Y}^t = [p_{1.1.1.1}^t + ... + p_{S.F.N.H}^t, p_{1.1.1.1}^t + ... + p_{1.F.N.H}^t, ..., p_{S.1.1.1}^t + ... + p_{S.F.N.H}^t, p_{1.1.1.1}^t + ... \\
+ p_{1.1.N.H}^t, ..., p_{S.F.1.1}^t + ... + p_{S.F.N.H}^t, p_{1.1.1.1}^t + ... + p_{1.1.1.H}^t, ..., p_{S.F.N.1}^t + ... \\
+ p_{S.F.N.H}^t, p_{1.1.1.1}^t, ..., p_{S.F.N.H}^t]'
\end{aligned} \tag{6.11}
$$

Therefore, $\mathbf{Y}^t$ vector can be built by pre-multiplying the home level energy usage vector $\mathbf{Y}_h^t$ by a "summing matrix" $\mathbf{S}$.

$$
\mathbf{Y}^t = \mathbf{S}.\mathbf{Y}_h^t \tag{6.12}
$$

where,

$$
\mathbf{Y}_h^t = [p_{1.1.1.1}^t, ..., p_{S.F.N.H}^t]' \tag{6.13}
$$

The summing matrix $\mathbf{S}$ depends on the structure of the hierarchy. If an ordered architecture with every Level 4 node having exactly H homes, every Level 3 node having exactly N Level 4 nodes, every Level 4 node having exactly F Level 3 nodes and a total of S Level 4 nodes, then the summing matrix would look like in 6.18. The dimensions of this matrix are $(1 + S + SF + SFN + SFNH) \times SFNH$.With this definition, a general linear combination hierarchical forecasting reconciliation (HFR) can be shown to be an additional pre-multiplication of a $\mathbf{p}$ matrix.

$$
\tilde{\mathbf{Y}}^t = \mathbf{S}.\mathbf{P}.\hat{\mathbf{Y}}_h^t \tag{6.14}
$$

For instance, you can come up with the bottom-up method by setting $\mathbf{P}$ to be a zero matrix combined with an identity matrix.

6.3.1 Hierarchical Combination Forecasting as Regression

As shown in ref. [39], the forecasting problem can be formulated as follows:

$$\hat{\mathbf{Y}}^t = \mathbf{S}\beta + \epsilon \tag{6.15}$$

β_h is an unknown. By assuming $\epsilon \approx \mathbf{S}\epsilon_h$, [39] approximates:

$$\hat{\beta} = (\mathbf{S}'\mathbf{S})^{-1}\mathbf{S}'\mathbf{Y} \tag{6.16}$$

Once β value is approximated, the reconciled forecasts can then be written as:

$$\tilde{\mathbf{Y}}^t = \mathbf{S}(\mathbf{S}'\mathbf{S})^{-1}\mathbf{S}'\hat{\mathbf{Y}}^t \tag{6.17}$$

$$
\mathbf{S} = \begin{bmatrix}
1,1,1,...(S \times F \times N \times H) \text{ times} \\
1,1,1,...,(F \times N \times H) \text{ times}, 0,0,0,((S-1) \times F \times N \times H) \text{ times} \\
0,0,0,...,(F \times N \times H) \text{ times}, 1,1,1,...,((F \times N \times H) \text{ times}, 0,0,0,...,((S-2) \times F \times N \times H) \text{ times} \\
. \\
0,0,0,...,((S-1) \times F \times N \times H) \text{ times}, 1,1,1,...,(F \times N \times H) \text{ times} \\
1,1,1,...(N \times H) \text{ times}, 0,0,0,...((S \times F - 1) \times N \times H) \text{ times} \\
0,0,0,...(N \times H) \text{ times}, 1,1,1,...(N \times H) \text{ times}, 0,0,0,...,((S \times F - 2) \times N \times H) \text{ times} \\
. \\
0,0,0,...((S \times F - 1) \times N \times H) \text{ times}, 1,1,1,...(N \times H) \text{ times} \\
1,1,1,...H \text{ times}, 0,0,0,...(S \times F \times N \times (H-1)) \text{ times} \\
0,0,0,...H \text{ times}, 1,1,1,...H \text{ times}, 0,0,0,...(S \times F \times N \times (H-2)) \text{ times} \\
. \\
0,0,0,...(S \times F \times N \times (H-1)), 1,1,1,...H \text{ times} \\
1,0,0,0,...(S \times F \times N \times H - 1) \text{ times} \\
0,1,0,0,0,...(S \times F \times N \times H - 2) \text{ times} \\
. \\
. \\
0,0,0,...(S \times F \times N \times H - 1) \text{ times}, 1
\end{bmatrix} \tag{6.18}
$$

6.3.2 Iterative Reconciliation

There have been several approximations to solve this system including Hyndman's approximation itself. However, when computing forecasts for hierarchies with a very large number of entities, further simplifications might be necessary. Since different nodes could be under different controlling entities, not all information might be available at every level and every node of the hierarchy. Therefore, an iterative reconciliation method is employed in this study. That is, reconciliation is carried out for each of the two levels. For instance, Fig. 6.8 shows the Levels 5 and 4 to which the reconciliation algorithm could be applied. Since Levels 4 and 3 have the same architecture, the same algorithm could be applied again until convergence. The calculation of these reconciliation values

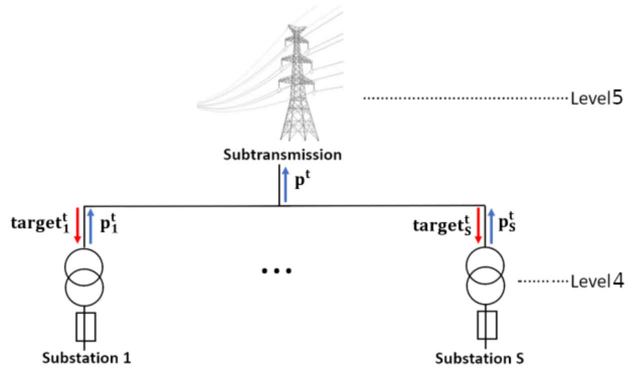


Figure 6.8: Sub-Hierarchy for Level 5. The hierarchy is built with similar recursive structures. This characteristic can be applied throughout the tree structure, allowing hierarchical reconciliation.

Table 6.1: Sizes of S matrices involved in iterative reconciliation.

Levels Reconciled	S matrix size
Level 5 and Level 4	(1+No of Level 4 Nodes) x No of Level 4 Nodes
Level 4 and Level 3	(No of Level 4 Nodes + No of Level 3 Nodes) x No of Level 3 nodes
Level 3 and Level 2	(No of Level 3 Nodes + No of Level 2 Nodes) x No of Level 2 nodes
Level 2 and Level 1	(No of Level 2 Nodes + No of Level 1 Nodes) x No of Level 1 nodes

is computationally intensive and information on every node might not be available at all the time. Therefore, instead of calculating the reconciliation for the whole hierarchy for the at the same time, sub-reconciliation is calculated at each node. For instance, at the sub-transmission, the hierarchy would reflect Fig. 6.8. The summing matrix for this hierarchy would be:

$$\begin{bmatrix} 1...S \text{ times} \\ 1,0,0,...,0,(S-1) \text{ times} \\ 0,1,0,0,0...,0(S-2) \text{ times} \\ : \\ 0,0,0,...0(S-1) \text{ times}, 1 \end{bmatrix} \tag{6.19}$$

From the top of the hierarchy, each level is reconciled with the level below down to the leaf level. Then, starting from the leaf level, a new reconciliation is calculated from bottom to top. Several such iterations are carried out from top to bottom and bottom to top until convergence is reached. The flowchart showing the iterative reconciliation is shown in Fig. 6.9. This greatly reduces the size of a matrix that has to be inverted at a time. The size of matrices involved in this algorithm is shown in Table. 6.1. The forecasting error comparison of all methods of forecasting and the

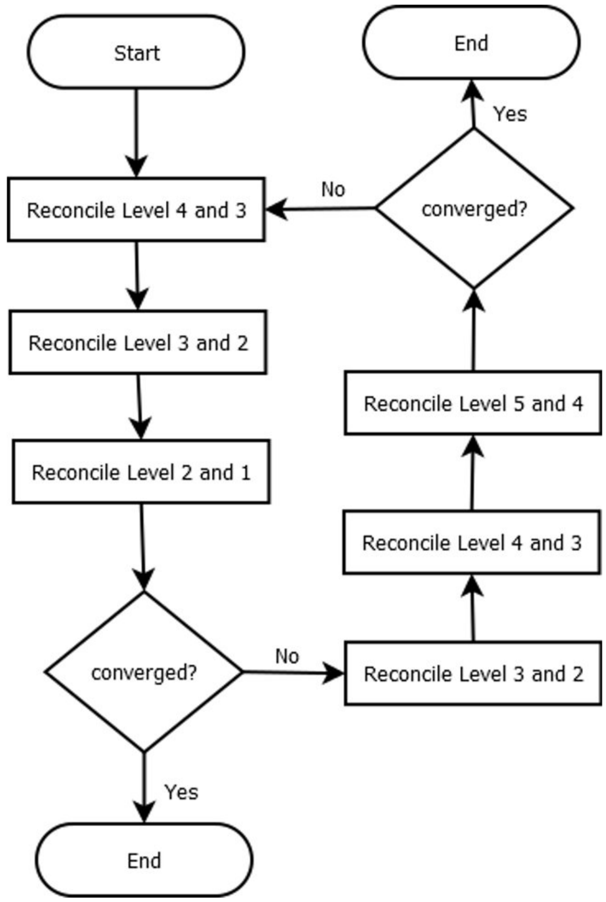


Figure 6.9: The flowchart showing the execution of the iterative algorithm.

reconciled forecasting is shown in Fig. 6.10. The results of DR optimization with the reconciled results can be seen in Figs. 6.11, 6.12 and 6.13. These figures show the deviation from the ideal values of PI, EI and stress from the ideal values when the reconciled forecast is employed instead of using the ideal values.

6.3.3 Comparison against Other Methods

The summary of the results found can be seen on Table 6.2. These results are generated by labelling the results using the ranges depicted in Table 6.3. When there are conflicts between two data points, the average of the two are taken. The following can be observed by the results. Reconciled forecast results in a DR program with the minimum deviation of EI and PI values from the ideal DR program for all scenarios, which neither over forecasting nor under forecasting

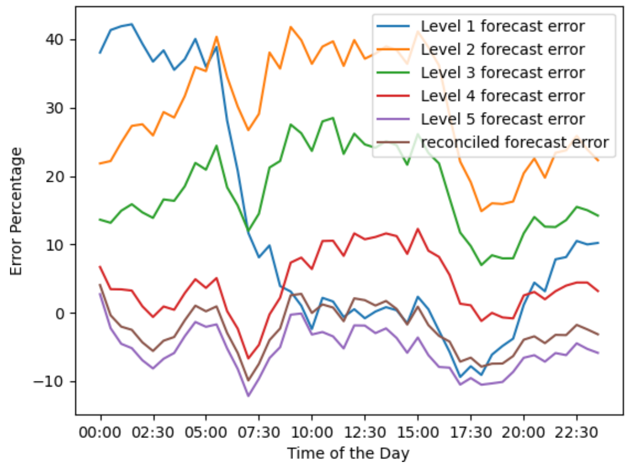


Figure 6.10: Forecasting error comparison for all forecasting methods tested in the study.

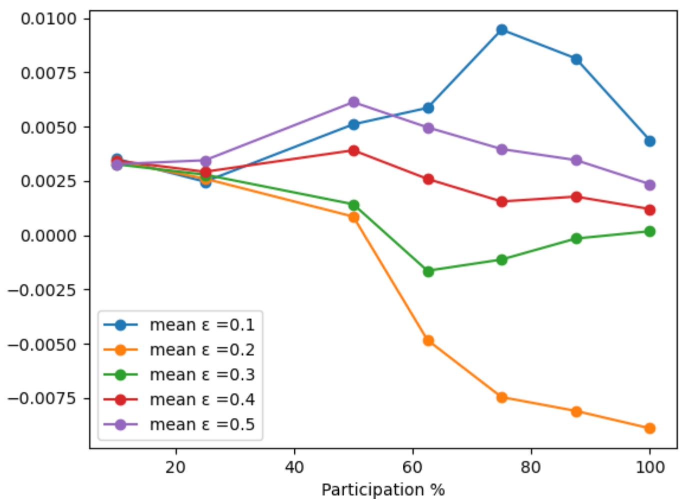


Figure 6.11: PI deviation from the ideal values when reconciled forecast are used as the prediction.

could achieve. This research could be further expanded by including local generation and battery availability of the consumers.

Table 6.2: comparison of under, over and reconciled forecasting using the metrics PI, EI, and stress published in [35]

	Participation	ϵ	PI	EI	Stress
Under Forecasting (Figs. 6.5e, 6.6e,6.7e)	Low (33%)	Low (0.1, 0.2)	+ **(VL)**	+ **(VL)**	- (L)
		High (0.4, 0.5)	- (VL)	+ **(VL)**	**- (VL)**
	Medium (33%,66%)	Low (0.1, 0.2)	- (VL)	- (VL)	**- (VL)**
		High (0.4, 0.5)	+ **(VL)**	+ **(VL)**	**- (VL)**
	High (66%)	**Low (0.1, 0.2)**	- (VL)	- (VL)	**- (VL)**
		High (0.4, 0.5)	+ **(VL)**	- (VL)	**- (VL)**
Over Forecasting (Figs. 6.5b, 6.6b,6.7b)	Low (33%)	Low (0.1, 0.2)	+ (L)	+ (L)	+ (VH)
		High (0.4, 0.5)	+ **(VL)**	+ (L)	+ (VL)
	Medium (33%, 66%)	Low (0.1, 0.2)	+ (H)	+ (VH)	**- (VL)**
		High (0.4, 0.5)	+ **(VL)**	+ (L)	**- (VL)**
	High (66%)	Low (0.1, 0.2)	+ (VH)	+ (VH)	**- (VL)**
		High (0.4, 0.5)	+ **(VL)**	+ **(VL)**	**- (VL)**
reconciled Forecasting (Figs. 6.11, 6.12, 6.13)	Low (33%)	Low (0.1, 0.2)	+ **(VL)**	+ **(VL)**	**- (VL)**
		High (0.4, 0.5)	+ **(VL)**	+ **(VL)**	**- (VL)**
	Medium (33%,66%)	Low (0.1, 0.2)	+ **(VL)**	+ **(VL)**	**- (VL)**
		High (0.4, 0.5)	+ **(VL)**	+ **(VL)**	**- (VL)**
	High (66%)	Low (0.1, 0.2)	+ **(VL)**	+ **(VL)**	**- (VL)**
		High (0.4, 0.5)	+ **(VL)**	+ **(VL)**	**- (VL)**

+ indicates an increase and - indicates a decrease.
VL - Very Low, L - Low, M - Medium, H - High, VH - Very High

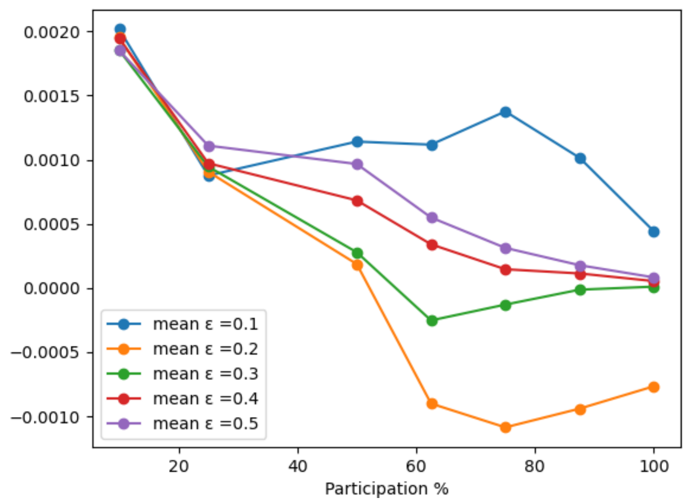


Figure 6.12: EI deviation from the ideal values when reconciled forecast are used as the prediction.

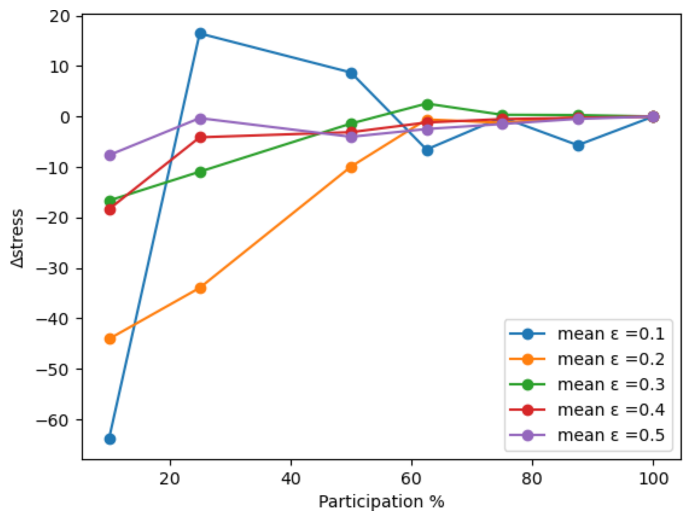


Figure 6.13: Stress deviation from the ideal values when reconciled forecast are used as the prediction.

Table 6.3: Ranges of the Labelling Used in Table 6.2

	Very Low (VL)	Low (L)	Medium (M)	High (H)	Very High (VH)
PI range (Fig. 6.5)	0 - 0.01	0.01 - 0.02	0.02 - 0.03	0.03 - 0.04	0.04 - 0.05
EI range (Fig. 6.6)	0 - 0.0016	0.0016 - 0.0032	0.0032 - 0.0048	0.0048 - 0.0064	0.0064 - 0.008
Stress range (Fig. 6.7)	0 - 80	80 - 160	160 - 240	240 - 320	320 - 400

6.4 Summary

In this chapter, the effects of the accuracy of predictions on a scalable hierarchical DR optimization program are explored. To explore these effects, a hierarchical DR architecture of 1500 homes is simulated, and various forecasting methods are applied and the effects of the errors for many scenarios are measured against the ideal case where there is no forecasting error. It is shown that higher forecasts than the ideal could create higher performance and higher stress for the consumer. Furthermore, hierarchical reconciliation of the said forecasts is carried out and the resulting forecast is employed on the DR program and the results are compared against the DR effects of the original forecasts. It is shown that the reconciliation could produce a close to ideal result in any scenario of the system. Reconciliation results in a reduced stress in all scenarios.

Chapter 7

Conclusion

7.1 Introduction

DR is a key component of smart grid that could be effectively utilized to maintain the stability of the power system. It enables integration of renewable energy, extends the life span of the equipment of the power grid and allows the full and efficient utilization of the available power grid. However, despite the value of DR, only a fraction of the available DR resources is utilized. No large-scale business for DR exists today. This dissertation introduces algorithms and business models to make DR practically viable. In addition, customer analysis methods are also introduced which could be employed to take important business decisions for a successful DR program.

7.2 Summaries of Dissertation Chapters

7.2.1 Survey and Generalization of Current State-of-Art in Demand Response Management

In this chapter an overview of the currently available DR technologies is presented. The chapter generalizes the available models in the literature. There are several categorizations of the appliances available in the literature for the purpose of DR optimization. The generally considered appliances are uncontrollable appliances, shiftable appliances, interruptible appliances and controllable appliances. The consumer objectives include minimizing cost and maximizing comfort. The objectives of the utility include minimizing cost, reducing peaks and incorporating renewable energy. The DR problem can be formulated as a MILP problem. To carry out DR, HEMS and IoT devices are commonly deployed. These IoT devices include sensors and actuators. An accompanying need would be privacy and security for the network and the devices. Currently, there are several DR programs that have been deployed commercially. In addition, there have been several successful pilot projects around the world that have implemented DR programs and have reported their results.

7.2.2 Service Provider and Customer Behavior Models for Large-Scale Demand Response

In this chapter the business models, customer involvement and customer behavior are explored. A service provider model was introduced that creates a 'win-win-win' situation for all parties: customer, electric utility and the service provider. The Shift MyPower program with the attractive and easy-to-understand features was introduced. This program incorporates methods to increase customer diversity and attraction with its rewards program. Several case studies are presented that tests the program. Additionally, the DR potential and of customers of different demographics along with most effective time periods of the day for these demographics were explored.

7.2.3 Optimization Methods for Scalable Demand Response Management

In this chapter, the solution methods for DR optimization methods are explored. The optimization methods were divided into conventional mathematical optimization methods and computational intelligence methods. While the mathematical methods could provide good solutions for the restricted group of problems they can provide the answer with. On the other hand, population based computational intelligence methods could applied to any problem and it is easy to apply parallel and distributed computing paradigms. However, there is no guarantee of reaching the optimal solution and it is difficult to apply constraints. This chapter presents results on CPSO, SHADE and MOPSO DR optimization algorithms.

7.2.4 Scalable Residential Demand Response Management

A scalable framework for demand response optimization is introduced in this paper. The hierarchical architecture is centric to this framework and allows the addition of participants to the DR program without slowing down the optimization. Furthermore, it allows the optimization to take power flow limits in the power system to consideration, which is necessary for the practical implementation of a large-scale DR program. The presented case study and results obtained illustrate the success of the framework. The proposed framework has been successfully illustrated in a one million home case study. This framework could be applied to other power systems with different numbers of homes, subfeeders, feeders and substations.

Additionally, new metrics to measure the success of the demand response program as well as the stress of the demand response participant have been presented. These measurements not only allow the utility to decide on the number of participants to incorporate in the DR program but also allows the participants to judge the stress they undergo in participating in DR. The application of these metrics in the explored case study shows that incorporating all possible participants might not be the best case for the utility. This result illustrates the fact that the DR aggregator needs to know the behavior of the electricity consumers in the population before involving the consumers in the DR program.

The proposed scalable DR framework can be expanded by the inclusion of distributed energy resources including generation and storage. The quality of DR program depends on the accuracy of the base load prediction. To have a maximum leverage of the demand response capability, the time between the demand response scheduling and execution needs to be reduced. To achieve this, a near real-time scheduling can be implemented such as an hour-ahead or even a smaller time-horizon.

7.2.5 Hierarchical Load Forecasting Reconciliation for Scalable Residential Demand Response Management

In this chapter, the effects of the accuracy of predictions on a scalable hierarchical DR optimization program are explored. To explore these effects, a hierarchical DR architecture of 1500 homes is simulated, and various forecasting methods are applied and the effects of the errors for many scenarios are measured against the ideal case where there is no forecasting error. It is shown that higher forecasts than the ideal could create higher performance and higher stress for the consumer. Furthermore, hierarchical reconciliation of the said forecasts is carried out and the resulting forecast is employed on the DR program and the results are compared against the DR effects of the original forecasts. It is shown that the reconciliation could produce a close to ideal result in any scenario of the system.

7.3 Future Work

The research work in this dissertation can be extended as follows:

- Finer, more granular models for the appliances can be introduced for the DR optimization problem. The models used at the moment are convex approximations for appliances. However, the appliances do not behave this way. More complicated appliance models will require to more complicated algorithms to solve the optimization problem. These algorithms, while providing a more accurate result, would require more computing power and better distributed algorithms.
- More interactive, competitive and co-operative service provider models and consumer models could be introduced. The current homes work by themselves to achieve the given goal. However, introducing competitions and cooperativeness could improve the DR response greatly.
- The concept of potential can be further expanded by including the combination of factors such as behavior patterns of the consumer. The potential is a measurement of how well the home could respond to a DR signal. This might depend on myriads of complicated factors.
- The consumer can be modeled better by modeling the consumer behavior in a more detailed manner. Human behavior is difficult to model, specially when it depends on the behavior of other humans. This has to be more carefully modeled for an accurate market scenario.
- PV and storage devices could be included in the optimization. This allows sharing storage and generated local power working as a nano/microgrid, greatly improving the response to DR signals.

7.4 Summary

In this chapter, the research work in this dissertation has been summarized. This dissertation introduces methods to convert demand response to a practically viable, large-scale venture that benefits all contributors as well as the environment. This chapter also suggests future directions that this research could be expanded to.

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