OPTIMIZING LOAD CONTROL FOR A RESIDENTIAL MICROGRID
IN A COLLABORATIVE ENVIRONMENT

by

MAJID AHMADI

Presented to the Faculty of the Graduate School of
The University of Texas at Arlington in Partial Fulfillment
of the Requirements
for the Degree of

MASTER OF SCIENCE

THE UNIVERSITY OF TEXAS AT ARLINGTON
MAY 2013

Copyright © by Majid Ahmadi 2013

All Rights Reserved

Acknowledgements

I would like to thank Dr. Jay Rosenberger for all his support and guidance throughout my graduate studies. I would like to thank my committee members Dr. Victoria Chen and Dr. Jamie Rogers for their invaluable insights. Finally, I would also like to thank my parents which without their help and support I could not have accomplished what I have.

April 18, 2013

Abstract

OPTIMIZING LOAD CONTROL FOR A RESIDENTIAL MICROGRID

IN A COLLABORATIVE ENVIRONMENT

MAJID AHMADI, M.S.

The University of Texas at Arlington, 2013

Supervising Professor: Dr. Jay Rosenberger

This research is aimed to develop an analytical model for a Residential Microgrid under a collaborative environment. In order to maximize profit, Collaborative Consumption (C.C) as a community-based social agreement has been developed in a model to capture consumer behavior, and modeling Residential Microgrids in such environment has been investigated in this research for the first time. This study will introduce a framework for Residential Microgrids using a unique method of demand response based on the particular characteristics of residential loads. Moreover, such a framework enables consumers to participate actively in the supply side of the electricity market. Indeed, consumers assign priority to their appliances based on the necessity of their services. Then the Microgrid informs consumers about their real time consumption and economic benefits associated with their participation in collaborative consumption. Accordingly consumers can evaluate their options and make better decisions. Based on acquired results, the study will show that the proposed model has successfully achieved desired objectives.

Table of Contents

List of Illustrations

Chapter 1

Introduction

1.1 Background

Electricity grids consist of different sections, such as generation, transmission, and distribution. Each section has its own characteristics. During previous decades, researchers have conducted many studies to analyze and improve the performance of power systems. Among the various types of electricity grids, this paper will study a particular type of future electricity grids called a Microgrid. There are some similarities and differences between existing electricity grids and the next generation of these grids, which are Smartgrids and Microgrids. In this chapter, we briefly address some of the commonalities, differences, and improvements of future grids compared with the existing ones and then shall explain some of the challenges that arise from incorporating the new grids into existing infrastructures. Furthermore, such challenges and problems shall be addressed and we will attempt to solve them through our model.

Among a range of improvements that we expect to see in the next generation of power systems, I would like to describe those that are related to our research.

First of all, future grids will use new communication technologies such as online metering. Even as of today utilities are trying to put more information in the hands of consumers and allow them to see their current consumptions, and thus more online information would be an essential part of future grids. Smart metering will provide more information for both consumers and suppliers.

Another distinction between the existing and upcoming grids is the extensive integration of renewable resources with fuel generators. Although using new modes of electricity generation, such as renewable resources, could significantly drop electricity prices by about two thirds of existing prices, stabilizing supply in the electricity market is still an issue. Another distinction between new types of grids and older ones is the existence of new electricity loads such as controllable loads and electric vehicles (PHEVs) in future power grids. This is while such loads and PHEV’s do not entirely exist in ordinary power systems.

Finding a protocol for selling electricity or buying it from adjacent Microgrids or main grids is still one of the unsolved issues. This is not an issue in regard with the current or older grids. The ability to borrow energy from other grids instead of main grids can decrease the electricity cost by alleviating congestion and other inefficiencies.

Moreover, there are some other issues that could be considered for building a Microgrid in practicality. As in other networks, a Microgrid has a maximum and minimum capacity of load. Finding appropriate values for those upper and lower bounds is greatly dependant on the reliability and also the purpose of the network. For example, a Microgrid that has been established in a residential area has a different reliability level in comparison with one that has been established in a commercial area. In addition, since storage systems are very expensive, careful planning of resources might decrease the grid dependency to large scale batteries. Designers should find the most reliable resources for the Microgrid regarding the type of consumers and other constraints. For instance, large scale wind turbines are not suitable for using in residential areas.

Furthermore, the idea of dynamic pricing has been used in some of the communication systems, and it is also applicable in power grids. In all of the proposed methods, the stability of prices and loads is very important. The success of dynamic pricing depends on the implementation details, contract type, and most importantly, the mathematical relationships between the cost functions of producers and the value functions of customers [3]. If a consumer becomes aware of historical and upcoming prices, he would be able to adjust his usage.

Generally, there are a couple of technical constraints in any small scale grid such as power flow constraints (KVL, KCL laws), generation capacity constraints, and local reserve capacity requirements that should be considered. For real time analyses, we could make these constraints near a steady state point and then solve a linear optimization as a dispatch problem. Additionally, we could solve the problem from the supply side. For example, if we solve the problem from the suppliers perspective, we would schedule the controllable loads. On the contrary, we could define the problem as a resource scheduling problem and consider economic conditions. In that case, the scheduler needs a precise forecasting tool and flexible resources in order to keep balance between demand and supply. Thus, the objective of optimization should be defined clearly and then the decision parameters and variables would be determined based on the existing constraints.

From the demand side, reviewing demand profiles reveals consumption patterns. Firstly, different seasons have different effects on consumption patterns, so we would have different amount of forecasted loads in various seasons. Thus, to forecast the consumption of residential consumers, the input data include weather conditions and historical consumption. Secondly, reliability affects the energy price. For instance, having a reliable source of energy is more important for critical loads such as hospitals versus non critical loads. After that, there are some techniques that help designers to improve the efficiency of networks. As we know combining the heat and power consumption together could improve the efficiency of provided services. Using CHP (Combined Heat and Power) is one of the applicable examples of this. Specially, in some seasons it can really decrease the cost of energy consumption, and it would be useful to use CHP. Moreover, collaboration of adjacent power grids could alter the demand profile and as mentioned earlier. One Microgrid could borrow energy from a neighboring grid. This would provide some economical and environmental advantages for both MicroGrid and main grid. Finally, some researchers addressed maintenance and other possible costs of a real MicroGrid. Therefore, for achieving complete economical analysis of a real MicroGrid, we should even calculate those costs for finding the total price of energy.

Overall, we need to clearly define characters and conditions of our problem. After that, if needed, we could propose an algorithm for computing dynamic energy prices associated with a residential Microgrid and then schedule resources or even controllable loads. Accordingly, we should define the objective problem and its constraints very precisely. For instance, if we want to use a storage system in the supply side in order to store excess generation, we have to consider the efficiency of that system. A problem solver aims to propose a framework that encourages consumers for changing their consumption patterns that might decrease the dependency of network storage systems. Furthermore, controllable loads are important since they enable a scheduler to shape demand in order to achieve an ideal consumption. As we know, we expect to have fluctuations in the supply side, since weather dependent resources such as wind turbines and solar panels were used largely in the grid. Consequently, we should consider these variations precisely in our mode.

Like any other service system, determining relevant prices and doing analysis related to those prices are a critical part of electricity grids. In order to set fair prices while both suppliers and consumers are satisfied, we need to understand the characteristics of electricity grids by doing economical analysis. First of all, there are several methods for computing electricity prices. Each method has its own parameters and generally the electricity prices change by altering the load level. One of the existing methods of computing electricity price is Locational Marginal Pricing (LMP). LMP is a method for estimating the price of electricity according to characteristics of generators and consumers like forecasted load and capacity of generators. LMP has three components: congestion price, energy price, and loss price.

On the other hand, Continuous Locational Marginal Price (CLMP) is an adaptable method for estimating the price and results in a relatively smooth price curve in comparison with LMP. It presents future limit risk (FLR) as the forth component of LMP. Another method is Probabilistic LMP forecasting, considering load uncertainty, which is a novel technique for projecting the electricity price [1]. This approach considers normally distributed random variables for actual loads at different hourly times. Thus, computing a probability mass function of probabilistic LMP at various hours is the next step of this technique. Considering a confidence level for an LMP forecast based on tolerance percentage (α) is the next step. Excepted value of the probabilistic LMP is the last step of this method, so these amounts can be calculated based on the standard deviation (σ) and appropriate formulas.

Given the different methods of price calculation in electricity grids, the next step is to consider the extent of our electricity grid. The larger grid needs more computations, so the range of grid should be determined before solving the problem. Moreover, finding different consumption patterns based on the customer behavior, consumption time, and levels of energy usage is very important for economic analyses of a Microgrid. Therefore, we need to gather various types of data to cover different aspects of the problem. For instance, in order to have an accurate price forecast we need to have historical consumption data and weather conditions.

What is more, there are some important assumptions for solving a Microgrid problem. As mentioned previously, one of them is determining the extent of the grid. The impact of a user’s consumption on price will change based on the extent of the grid and type of consumers. Moreover, we should find a model for considering the impact of effective factors since there are different types of generators in a Microgrid, and each one has its own characteristics like price offering, generating capacity, and technical constraints. These assumptions could include an internal policy for setting electricity price. As an example, based on the location of a supplier, we can establish the cost of using his own resources is less than the cost of buying electricity from a neighboring Microgrid and a main grid. The cost of buying energy from the main grid could be higher than others as it includes transmission service charges and congestion constraints. However, some research shows that the time and direction of trade could cause some changes in the cost of trading power [3]. Further, based on the extent of the grid and the amount of demand, we may have transmission constraints in our grid. Finally, determining the maximum and minimum capacity of generating electricity and relative costs is another step for computing price of electricity.

1.2 Introducing a Real Case Microgrid

The Consortium for Electric Reliability Technology Solutions (CERTS) has established a Microgrid for doing tests and research. CERTS researchers have addressed some economic aspects of future grids in their Microgrid. There are three types of economic aspects that CERTS Microgrids address. One of them is considering the cost of maintenance plus the cost of storage systems that may influence the economic advantage of a Microgrid over a large scale grid. The popular methods of economic engineering can determine which types of technologies apply in a Microgrid. They believe that because of the similarities between a large scale grid and a Microgrid, the lowest possible cost combination of resources must be found at all times [4].

Furthermore, high-capital and low-variable cost technologies are suitable for base demand, and generators with opposite qualities are better for peak demand. But, the combined optimization of heat and power supply besides loads and supply in Microgrid require more investment. Since a Microgrid is going to move power generation toward using waste heat, CHP would be an integral part of Microgrid economics. Thus, using CHP in the following applications has economic advantages for consumers: space heating, industrial processes, and space cooling through use of absorption chilling. In addition, a Microgrid should determine the cost of electricity based on these three parameters: marginal cost of providing power at any point in time, equivalent costs of investments in energy efficiency, and cost of curtailment [4].

Chapter 2

Literature Review

2.1 Residential Load Types

There are many studies on residential energy monitoring. Some researchers have studied different types of users and classified them based on their consumption level into groups such as high user, medium user, and low user [32]. Others have investigated the characteristics of residential load patterns at an aggregate level from the view point of supplier. In 2008, Carpaneto and Chicco conducted a study on probabilistic characterization of residential loads and tested various probability distributions to find the best fit for aggregated load pattern during the day [33]. Although these models could be helpful for distribution engineers to improve the accuracy of the estimation of the system's efficiency, they are not useful for the purpose of our study since they are time invariant models.

Another approach to residential energy monitoring is analyzing the daily consumption of main appliances separately and finding their distribution patterns. Based on this approach, the main residential loads are AC, Domestic Water Heating (DWH), heating, dryers, pools, ranges, dish washers, refrigerators, TVs, lights, and miscellaneous. According to research that was conducted by PATH (Partnership for Advancing Technology in Housing), 60% of total energy usage relates to space conditioning and water heating in each home [17].

Therefore residential loads can be classified into main groups. Although the contribution of each group might change from region to region, these groups cover almost the entire consumption of each home. But the critical point is finding a relationship between these groups and their controllability. Indeed, we need to classify residential loads into main groups in which appliances have similar controllability. For example, we could not put a refrigerator and a cloth washer into one group since a controller has no control over refrigerator unlike cloth washer.

According to Moholkar, home appliances can be categorized into three main groups based on their ability to be schedule [16]:

- Non-reschedulable usage and service loads: There are some appliances like lights, a refrigerator, and a TV which are not able to be deferred to later periods since they provide necessary services for users.
- Re-schedulable usage loads: This type of load includes home appliances that use thermal storage such as a water heater, a space heater, and an air conditioner.
- Re-schedulable usage and service loads: This group of load corresponds to appliances that provide deferrable services for residents such as a dishwasher, a range, and a cloth dryer.

We will use these groups as the basic types of residential loads and assign priorities to each group. As mentioned earlier, the advantage of the above categories is grouping loads regarding their ability to be scheduled rather than their consumption patterns or model. Our method will be explained in the next chapter, and we will describe how we have used those load categories.

2.2 Forecasting

This section starts with a brief summary about existing issues and then continues with our approach to handle one of these issues. As described above, the accuracy of forecasted prices is suntil an issue in our upcoming grids. Since a Microgrid deals with end users and individual consumers, it requires using more precise forecasting methods. In 2006, Funabashi et al. proposed a method to forecast short term loads in a Microgrid by using neural networks and fuzzy systems [5]. They also reviewed forecasting short term production of wind turbines and solar cells based on weather forecast and generation data. In their approach, the neural network had been trained using historical demand and then comparing historical temperature plus the average daily consumption and the real time data. Then, by computing a correction factor based on a used data set, primary future demand was computed. Indeed, a correction factor was added to the past day's average demand. Finally, for special days, like holidays or sudden climate change, fuzzy systems was used for finding another correction factor. Moreover, in case of insufficient reserved power, they used a modification of the operation plan for short time cycles from 15mins to 3hrs. Essentially, future demand was calculated based on the current demand profile and then correction factors were applied for special cases.

In 2007, researchers at Galvin electricity initiative published their research about forecasting loads in a Microgrid [6]. Their research mentioned that there are many inputs to a demand forecasting algorithm such as historical profile data for different load elements, historical weather data like temperature and humidity in order to correlate heating and cooling with weather conditions, and actual load information from the load controllers. Moreover, considering different periods such as on-peak consumption and off-peak consumption could also be an effective input to the algorithm. Also a forecaster could assume that some of the variable costs, such as fuel cost, etc. are fixed during the forecasting horizon. Furthermore, forecasting is an integral part of energy dispatch for a couple of reasons, including meeting peak demand, achieving more isolation from the main grid, developing a daily plan to charge and discharge storage systems, and maximizing profit as a result of selling electricity to a main grid. Thus, a controller should use accurate future prices and update those forecasted values.

On the other hand, as mentioned in the Galvin report, there are some uncertainties associated with renewable resource energy generation. Therefore forecasting renewable generation could be the next issue of the forecasting process. In 2010, Amjady and his colleagues asserted that load forecasting for a Microgrid is a complex process because of the nonlinear behavior of the load time series, but generally load forecasting could be divided into two parts: short-term (less than 24hrs) and long-term [7]. Therefore they used neural network as the lower level of forecaster, and then applied evolutionary algorithm to optimize the performance of the forecaster for long-term as they called it a bilevel prediction strategy.

They emphasized that there are many differences between large power system loads and Microgrid loads, such as more volatility in both time domain and frequency domain, and demand fluctuation or sharp behavior. Thus, they preferred to use neural networks because of their flexibility and easy implementation. As they mentioned, a combination of these methods enables them to avoid getting trapped in a local minimum or suffering from over fitting. A combination of neural networks and evolutionary algorithms proposed as a hybrid forecast engine after applying a redundancy filter for removing irrelevant inputs. After that, they applied differential evolutionary algorithms since they could use the distance and the direction information from the current population to guide the search process. In order to evaluate accuracy of their forecasts "Weekly Mean Error" has been used in their research. Also variance of the prediction error has used for comparing stability of various forecasting method.

Moreover, there are some basic assumptions that a forecaster should consider for specific characteristics of a demand profile. First of all, in our short term forecasting method, the forecasting block could be divided into two parts: time variant and time invariant. For example, seasonal, weakly, and holiday effects are among time invariant inputs for short time forecasting, since these inputs do not change during a short-term forecasting horizon. As a result, we could partition the input into the two mentioned groups, then solve them separately, and combine the results in order to find a final forecasted demand. Indeed in this approach the forecasting block is historical, seasonal, and other similar data, and then the output would be a relative forecasted demand regarding to these time invariant data. This part of the problem could be modeled based on differential equations, and so the output is like $D_n = f(D_{n-1}, D_{n-2}, \ldots)$ in which n-1 and n-2 are similar past situation periods that are related to invariant data such as seasonal effects.

The challenging part of the aforementioned approach is figuring out the relationship between different inputs and their suitable coefficients. The equation might be nonlinear with variable or constant coefficients or even linear with variable or constant coefficients. On the other hand, we should find the related forecasting data to time variant input such as weather factors and random disturbance. Therefore, the output of these two separate blocks should be part of the final forecasting values [12].

In another scenario, we could diminish the duration time of forecasting fairly and then consider all of the inputs as time invariant. Then, we could find the total formulation of the problem and determine the best way to solve it by applying state space methods. However, most of the time, the answer is not sufficient because of the volatile nature of electricity prices, unless we consider a very close forecasting interval.

In addition, the derivation of a demand profile might be a good indicator of upcoming demand. For instance having historical demand and its derivatives and then finding the correlation between those numbers might be useful for that purpose. As mentioned earlier, there might be some probabilistic components in a suitable model in order to capture the unusual behaviors of consumers or even unusual surrounding conditions such as weather conditions that cause price spikes.

So far we have revealed the importance of finding an accurate price forecasting method. It is worth restating that the importance of accurate price forecasting method increases since a Microgrid deals with a smaller size of users and controls their consumption. As it was mentioned before, there are many different types of price forecasting methods, such as time series, auto regressive integrated moving average (ARIMA), and so on. For example by applying basic time series techniques with using the Matlab toolbox for an hourly consumption data of the Ontario city, the below shape has been generated [14]. The accuracy of prices could be evaluated by using methods such as Mean Square Error (MSE) and Absolute Percentage Error (APE). The figure shows the fitted line vs. the original data.

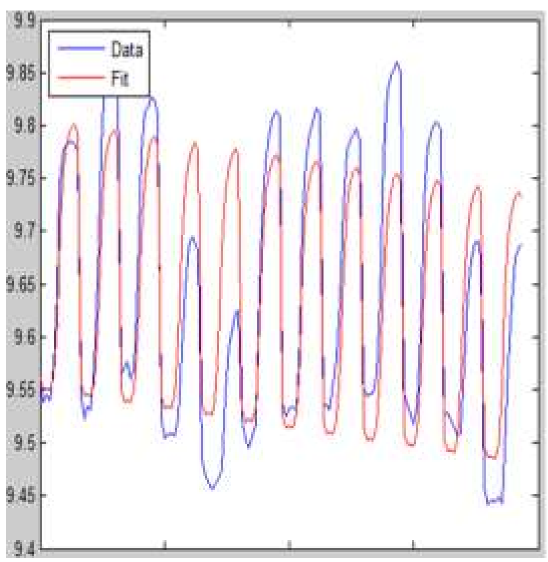

Figure 0-1 Price forecasting by using time series techniques for Ontario City (Residuals are almost less than 5 %)

2.3 Scheduling

Another unsolved challenge of implementing Microgrids is the problem of optimal load control and resource scheduling. In 2009, Logenthiran and Srinivasan asserted that scheduling is a non-linear mixed integer optimization problem [8]. Resource scheduling could be divided into two main parts: unit commitment, and economic dispatch. As they mentioned, unit commitment could have integer variables while economic dispatch could have continuous variables. Therefore the problem consists two parts: integer and continuous variable optimization. Unit commitment has the responsibility for scheduling of power production during daily operation based on a generator and system constraints. Thus, an objective function could include costs associated with energy generation in order to maximize possible economic profits. Accordingly, there might not be an exact and unique solution or technique for a large scale optimization problem. The unit commitment problem grows exponentially in with the number of units in a Microgrid.

Some techniques like lagrangian relaxation, genetic algorithms, and combinations of them plus applying dynamic programming could be used to solve integer and non-linear optimization with continuous variables. As Logenthiran and Srinivasan applied those techniques in their research appropriately, they decomposed the problem into three steps while using lagrangian relaxation and dynamic programming [8]. First of all, initial conditions for thermal unit commitment was set up, and then a scheduler solved the problem by optimizing the renewable thermal dispatch based on the thermal unit commitment. The preliminary feasible solution was initiated by minimizing the total necessary amount of thermal energy for the first step. Then the next step is minimizing total production costs, which is equal to summation of fuel cost and start-up costs over the scheduling horizon. Finally, optimization of renewable-thermal dispatch based on unit commitment results was done.

Moreover, Ahn and Moon explained various issues regarding economic scheduling of a Microgrid in the same year. They formulated different constraints related to operation of a Microgrid by using some constraints that a direct search method is applied to solve the economic dispatch problem [9]. Thus, a Microgrid's central controller (MGCC) is responsible for load & heat forecasting and economic dispatch. During the peak demand in a main grid, a Microgrid should try to participate in an electricity market by energy generation to decrease the price of energy. They asserted that the goal of economic dispatch is minimizing total generation cost while power balance and limited generation units are considered. In their method, three different types of constraints and flow limits were considered to solve the problem. Also a Direct Search Method (DSM) was applied in their approach in order to have the ability to handle different cost functions. Finally, in 2010, Logenthiran and his colleagues resolved the above problem with an artificial intelligent algorithm [10].

2.4 Pricing

Currently, utilities use different methods for setting electricity prices based on some factors, such as the time of consumption. Some of these methods do not require any communication with the main grid, and they are called time-of-use or TOU. On the other hand, there are some other ways of setting prices by using time varying rates that are called dynamic pricing [11]. Although utilities might be able to control some loads of their customers, they prefer to apprise consumers about existing and upcoming prices and their possible alternatives. Indeed, that improves satisfaction level of consumers besides demand reduction especially during peak times, which yields a decrease in the volume of computations.

While the importance of dynamic pricing and its effects on demand response is clear, there are some disadvantages for establishing dynamic pricing. Smart meters facilitate data acquisition in electricity grids besides providing two way communications between utility and users, which help dynamic pricing. However, there are unsolved technical and legal issues related to these meters [29]. For example, the cost of smart meters and AMI (advanced metering infrastructure) is high, and it costs billions of dollars for large utilities to pay. Moreover, it is a complex and volatile way of computing energy prices and may confuse some consumers, so it is more applicable for nonresidential users. Although setting dynamic prices instead of flat rates provides consumers with economic benefits, passing wholesale market locational prices on end users may undermine stability of system [30]. That enables utilities to calculate their revenue precisely rather than profits and losses. But, if utilities could overcome these difficulties, both consumers and utilities acquire economic advantages accordingly. Besides, dynamic pricing alone could not decrease the gas emissions by that much since the amount of consumption does not change. Thus, for the sake of environmental improvements, utilities should be encouraged to establish more renewable resources.

Given the above concerns, there are some other aspects of pricing that must be considered in a pricing algorithm to achieve a comprehensive program. Generally speaking, there are some other sources that could affect the final prices while the Microgrid is operated in a grid connected mode. This means that in order to find a dynamic solution for price calculation, forecasting the demand of neighbor grids could be part of the problem. After that, dealing with the process of bidding as a result of short forecasting and real time pricing could also be another useful topic while we want to set prices [31]. Even if consumers are able to forecast their consumption by their own, it decreases the complexity of forecasting, which results in improving accuracy of the overall process.

As mentioned above, demand side bidding could be useful in a Microgrid in which each consumer indicates the priority of his usage into high or low. Low priority loads can be supplied on cheap prices. In our research we assumed that the price of grid energy and Microgrid energy is the same. But, in some cases setting selling energy prices to the main grid more than buying from the grid especially in peak times may result in encouraging end users to supply some portion of demand and reduce the price spikes.

At the end, there are some periods that buying energy from the main grid might be cheaper than generating it. However, this completely depends upon the consumption level and other conditions. Thus, this might be part of a scheduling problem. As a result, an actual scheduling program should determine the suitable reaction of a Microgrid in any load consumption whether just using energy, or buying from the main grid, or even selling electricity to the grid. Then evaluating the stability of a Microgrid by creating a formula to measure and test it might be another open topic for further research.

2.5 Modeling

So far we have introduced important parameters that must be factored in an inclusive scheduling model. Now we are going to select those parameters and variables that have the most significant effect on the output. As we mentioned earlier, a consumer's behavior can be modeled by using some data, such as a historical demand profile. It also might be a simple method of modeling the consumer's behavior if we consider a constant amount of usage for all consumers and then apply an adaptive pricing method based on the projected future consumption. As part of this approach, the model should clearly distinguish between production costs of various resources.

In addition, Mohsenian-Rad and his colleagues modeled the optimal load control problem with using price prediction for upcoming electricity grids [28]. But they solved a general problem, and they did not consider specific characters of Microgrid and its load types. Moreover, they did not propose a convenient method for load rescheduling since users have to determine their acceptable rescheduling time horizon for each appliance. Their method has these components:

- Weighted average price predictor filter with daily coefficients to forecast short term prices.
- Waiting Cost function in order to model costs associated with rescheduling.

Additionally, utilities might be interested in giving incentives to consumers to shape their usage. As an example, they could offer lower energy prices for off-peak periods in order to increase the number of consumers who are interested in shifting their loads to later hours. These incentives would be useful while they can reshape the demand profile into a smoother curve especially during peaks. However, because of the characteristics of a Microgrid, such as using renewable resources, these incentives might not be applicable in such a grid. Therefore, the combination of micro turbines and other generators with renewable resources enables the grid to overcome this issue.

After doing all the above, one of the questions that might be brought up is: how we can evaluate the accuracy of a proposed model and compare it to other ones. There are some defined measurements that help us to answer the question. One of these metrics is using mean absolute percentage error (MAPE) particularly during peak loads. As we know, price spikes occur when the load level reaches its generating capacity limit. Moreover, price volatility in a restructured power market is much higher than load volatility. According to Shahidehpour and his coworkers, it is useful to compute the probability of price spikes under different load levels and also the probability distribution of prices under different loads level. They asserted that “The load curve is relatively homogeneous and its variations are cyclic, but the price curve is non-homogeneous and its variations show a little cyclic property” [12]. Interestingly, the accuracy of price forecasting is near 10%, but the accuracy of load forecasting is near 3%. Consequently, we should determine that either we want to focus and analyze the behavior of users or we want to deal with shaping their consumption automatically.

Going back to the incentive based algorithm, the model can be defined clearly by finding an appropriate cost function. According to Caron and Kesidis, a cost function for an incentive algorithm of a smart grid could be considered as "$C_L(\lambda(t)) = C_0 + C^{'} (\lambda(t) - L)^+$ where C_0 reflects the base cost and the overage rate $C^{'}$ is a positive constants (x^+ denotes max(0, x))" [13]. L represents the corresponding threshold to load before reaching upper generation limits, and therefore it raises the electricity cost in order to dissuade customers from scheduling their loads. For instance, the second term in the above equation represents the marginal costs of producing electricity by going over determined generation capacity. The plant's nominal operation occurs once $\lambda < L$. They asserted that "Utilities may charge customer i with an amount bi proportional to both the energy he consumed and the global cost, e.g., $b_i = C_0 d_i \tau_i \times GC_{ramp} / GC_0$". Their study concentrated on finding an optimal schedule of consumption of every consumer based on the probability of other users' consumptions during the next interval. As they mentioned, the minimum costs occur at maximum information by using different strategies based on the degree of network sharing information. For example, one of the studied cases was that informing consumers about their real time demand at an aggregate level. Based on their results, we can conclude that their approach might be applicable in similar research. Generally, they assumed two different cases as residential and heterogeneous consumers.

According to Roozbehani and his colleagues, "In particular, it appears that real-time pricing as defined above, in the absence of well-designed financial instruments for hedging, could potentially aggravate price volatility in wholesale markets. Whether real-time pricing will mitigate, or aggravate wholesale price volatility depends on many factors including implementation details, contract types, and most importantly, the mathematical relations between the cost functions of the producers and the value functions of consumers" [2]. Thus, the success of a real-time pricing method most importantly depends on cost functions of producers and the value functions of consumers.

Further, each model typically has some nodes and lines plus several generators in order to capture the characteristics of real grid accurately. After that, by using relevant constraints such as current of transmission lines and so on the scheduler attempts to minimize the difference between total cost of producers and total value of consumers as the social welfare function. In some models, consumers have the ability to adjust their usage as they see real time and upcoming prices. Models that deal with dynamic prices could assume that the retail pricing entity do not know the utility function of users, which means they are not aware of consumer responses to price signals. Thus, one important question is: how could we estimate the behavior of consumers in an adaptive network?

To summarize this section, the following sentences give us a comprehensive overview about the problem. "In particular, operation of the real-time balancing markets involves solving a constrained optimization problem with the objective of maximizing the aggregate benefits of the consumers and producers. The constraints include power flow constraints (Kirchhoff's current and voltage laws (KCL and KVL)), transmission line constraints, generation capacity constraints, and local and system-wide reserve capacity requirements, and possibly a few other ISO-specific constraints" [2].

2.6 Collaborative Consumption

Collaborative Consumption is a network driven technology in which one or more actors integrate their resources in collaboration with others to co-create value and contribute to meaningful service for the benefit of themselves or others [20]. In order to achieve mentioned objectives we have to use developed infrastructure, which includes communication and network technology. This infrastructure provides new services to consumers as well as using an advanced approach to demand response. Hence we propose our new approach to demand control according to network technology and economic systems. There are two essential characteristics of this approach which differentiate it from existing methods. The first consists in the use of collaborative consumption to build community and reduce cost. The next is priority based scheduling in the integrated environment that will be discussed in the next chapter.

End users are interested to change their role as the just-consumer into being more active participants in the market. Existing technology provides the platform that enables each user to be involved in the market both as the consumer and supplier. It facilitates communication and interaction between users such as customer-customer and customer-supplier relationships instead of one-sided relationship between consumers and utilities. Furthermore, it provides information on current usage, real-time, and future prices.

In addition, the next concern of consumers regarding new electricity grids is the ability to share resources. They desire to benefit from the economic advantages of collective consumption. Once again, technology makes it possible to use small size resources such as renewables and micro turbines while everyone has access to them. It requires a community of residents as local collaboration to supply their required amount of energy in a sustainable and economic way. Consequently sharing and collaboration are happening in ways and at a scale never before possible and creating their own economy and culture [19]. The above would be achieved by applying “Collaborative Consumption” to electricity grids.

Recent studies have mentioned that Smart grid and real-time technologies are removing outdated modes of hyper-consumption and create innovative systems based on shared usage that bring environmental benefits by increasing efficiency, reducing waste, and eliminating over-production and over–consumption [19]. Accordingly, we are going to discuss the basic principles of collaborative consumption besides their applications in a residential Microgrid and problem formulation. Collaborative consumption uses the following principles: belief in the commons, critical mass, trust between strangers, and idling capacity [19].

Principal I- Belief in the commons: The basic component of collaborative consumption is consumer responsibility about shared resources. In such an environment, a consumer's behavior reflects not only such individual expressions but also the efforts by people to engage in joint activities with others [21]. Residents would get various advantages of cooperation that improve their belief in local community. The more consumers who participate in the collaboration, the more role they can play in the market. For instance, consumers could install more solar cells on their roofs to generate more electricity or even could postpone their consumption to store more energy in storage systems and also benefit from lower prices.

Principal II- Critical mass: This principle implies that the grid has to contain an adequate number of consumers and suppliers. Actually, this basis changes the current monopolistic market for the consumers into the competitive one in which users will have more choices than ever before. Indeed, there already are a huge number of electricity consumers on the demand side and the existing technology would enable them to participate in the network as the suppliers as well. The establishment of Smart grids and Microgrids would pave the way for changing a consumer's role into suppliers and then they would sell electricity to each other in addition to supply their own usage. For instance, consumers could store electricity at off-peak periods and derive a benefit from negative prices and then sell it back to the network later.

Principal III- Trust between strangers: In a residential Microgrid, users mostly are neighbors, which is a major shift from “traditional” trust between supplier and consumers. In every collaboration system, participants get benefit based on their collaboration level that is closely tied into their trust level. The proposed approach incentivizes consumers to take part in a collaboration by calculating a consumer’s profit based on its contribution. In addition, it secures a consumer’s highly prioritized privacy and data protection against misuse. Equivalently, the Microgrid central controller will be in charge of grid-wide data acquisition and processing, where each individual user access is limited to its own consumption and public data. This access includes a consumer’s current and overall consumption, real-time and future prices, and a consumer’s gain from participating in collaboration. Therefore, a central controller is responsible for calculating all required information and functions as the actor between supplier and user.

Principal IV- Idling capacity: As in other networks, electricity grids have some periods in which the generation is over the demand, and there is unused generation capacity, referred to as idling capacity. Utilization of idling capacity has been employed both in small size applications for some industries by using captive power plans [22]. We are going to evolve a new method of utilization of unused capacity for grid size applications. Therefore, we want to store capacity at off-peak hours in order to redistribute it for supplying the internal and external demands. The collected electricity from all resources stores in the central battery storage system, and it forms the inventory of Microgrid. This inventory plays a critical role in demand satisfaction, and its economic advantages will be discussed in the following sections.

After explaining collaborative consumption, in the next chapter, we will proceed to the next pillar of demand control, which is priority based scheduling in a collaborative environment. In such an environment, consumers have accepted that they are playing in an integrated grid in which they benefit together.

Chapter 3

Problem Definition

3.1 Contribution

A. Kulvantichaiyanunt, et al. [27] developed a model for controlling PHEV charging stations. The research described here is an extension on their model for scheduling loads for a residential Microgrid. The major contribution of this work is thus modeling different types of flexibility of consumer demand and incorporating a waiting cost function to penalize distribution delays. In addition, we show computational experiments demonstrating how various parameters affect profit. In particular, we demonstrate that of these parameters consumer flexibility provides the greatest profit benefit a Microgrid.

3.2 Microgrid

Based on the definition, a Microgrid is a set of local generators and consumers that can act as a grid-connected or isolated mode. Typically, it has a mixture of renewable resources and micro turbines. A Microgrid has some advantages such as helping the main grid in supplying demand, especially during peak loads, which will yield a more flat rate of supply. As mentioned, this type of grid consists of supply and demand. On the demand side, we could support new types of loads like PHEVs and controllable loads. On the supply side, we might use CHP that can cause efficiency improvement.

3.2.1 Grid Characteristics

Besides using new methods for solving the problem (like reshaping the demand profile by giving incentives), using CHP could help us improve energy efficiency. CHP also has some environmental advantages, since it decreases emissions of gases like NOx and SO2. On the other hand, if we use CHP in resource section, we should consider both heat and electricity consumption. That means we need to consider both cost of consuming heat and generating electricity. CHP operation modes are based on the consumer heat demand which yield to variable outputs. Thus, after selecting an appropriate CHP based on the grid's size, an additional boiler is used for the sake of reliability. Thermal-storage tank improves the CHP operations and also voltage regulation of the grid. This additional boiler (when needed) and thermal-storage tank deliver heat to the consumers. As a result, CHP always supplies base heat demand of a grid rather than peak demand, and the additional boiler covers the extra needed heat.

But, there are some limitations on using CHP. First of all, CHP has its maximum efficiency when it acts in a heat-driven mode. So it forces each consumer to have a small CHP unit because of different heat consumption patterns of consumers. Moreover, the efficiency of CHP drops during transient time once we move from heat-driven mode into load-following mode. Therefore, we do not use CHP as a part of our supply side.

3.2.2 Supply Side (Generation)

As mentioned earlier, there is two different types of generators in Microgrid: renewable resources and micro turbines. These two kinds of generators have different characteristics, such as power fluctuations and production cost. In general, resource allocation in a Microgrid uses stable resources, such as micro turbines and fuel cells, for supplying the base load and uses high variable resources, like renewables, for demand spikes. The maximum generation capacity of the grid has been determined, so the excess demand should be supplied from main grid.

Different grids have various combinations of generators, but mostly they have wind and solar cells. There are two different ways of using wind power. Firstly, consumers could establish various types of wind turbines based on their potentials. For example, home owners can install small size turbines that produce less than 5 KWh.

Using mid-sized turbines is not applicable for those consumers. Another way is signing a contract with offshore wind farms and buying some percentage of their generation. In that case, grid needs enough storage systems to use that energy effectively.

3.2.3 Appliances

Appliances are an integral part of a residential Microgrid. There are new types of loads that would expect to be part of upcoming electricity grids. The major characteristics of those loads are their ability to communicate to others, and they are also controllable. Actually, the idea of controlling appliances in an electricity grid is going to be more applicable after establishing these types of loads and grids. These infrastructures would provide multiple communications between suppliers and consumers. These grids enable central controllers to schedule and control the various appliances of a customer such as a dish washer, an air conditioner, and so on, which will be discussed later.

Before discussing various demand profiles in a residential Microgrid, we need to address some technical challenges of load control policy. First of all, the waiting cost function that plays an important role in a control process should be defined properly. For example, electricity cost (consumers' bill) and reliability of service such as waiting time could be possible causes of such a function. Second, scheduling could be done by considering different objective functions in different chains such as a Microgrid, a smart grid, and a main grid. Then considering environmental and economic costs of electricity generation according to available resources is another issue.

Finally, we should consider the controllability of loads, which reflects the control level of a Microgrid over the consumers. For example, if each consumer has some resources that could supply enough energy in some periods, then the inventory level of batteries can be controlled by either a user or central controller. As a result, each customer (node) could be either a supplier or consumer. Accordingly, the Microgrid should have a hierarchy control over resources that avoids interference between resources. On the other hand, finding the optimal capacity or even the number of resources could be useful for studying various cases.

3.3 Defining Objective Function

Controlling electricity load is a controversial topic. Some researchers believe we could not control a consumer’s load effectively. On the other hand, some academics believe that controlling a consumer’s load increases the efficiency of the electricity grid, and we need to schedule a consumer’s usage in this regard. We are going to develop an analytical model for the problem of optimal load control and show how it could improve network efficiency. Based on the following categories of residential loads, a Microgrid could exert control on some of those re-schedulable loads. Therefore, consumers assign priorities to their loads, and then a controller determines the optimal load schedule in each period. In other words, a controller asks users to identify their flexible loads with their priorities (related to their controllability degree). Then a controller schedules consumption of each appliance after receiving a consumer’s demand signal. The main goal of this research is finding the optimal schedule of electricity consumption for each user, which has many applications under a collaborative consumption environment.

3.3.1 Priority Based Scheduling

In general, the mentioned methods of load management techniques in electricity market could be categorized into two types. The first ones deal with supply side management. Storing electricity during off peak periods by using a battery in our proposed Microgrid relates to supply side techniques. The storage system gives the opportunity to sell electricity to the main grid during price spikes, which gives consumers economic benefit. Indeed, it mainly enables a Microgrid to participate in the supply side of the market and facilitates congestion relief during peak load periods. The next type of load management takes action on the demand side management in order to alleviate price spikes. We will explain it later how prioritizing demand helps a Microgrid to manage its demand side.

Demand side management techniques have been developed to reshape the load curve and also reduce peak demand. They include a variety of technical and behavioral solutions in order to modify electricity demand and then improve the reliability of power grids. An effective solution could both reduce energy consumption and provide economic benefits for consumers. Although our approach does not guarantee consumption reduction, it provides nearly a flat rate of consumption by shifting unnecessary loads. It also attains economic benefit by selling electricity to the market at higher prices.

As stated above, demand side management includes behavioral techniques, which are designed to adapt residential consumption in a convenient way. Therefore, we have to analyze the residential load characteristics from a consumer’s view to propose an efficient solution while applying collaborative consumption as the universal agreement among consumers. Based on aforementioned characters of collaborative consumption, all consumers have access to shared resources, and they will gain more benefit by increasing their collaboration level. This collaboration frequently happens with prioritizing demand and rescheduling less priority demand to later periods. Actually consumers assign priority to their loads base on demand necessity. They could also evaluate economic benefits associated with their decision by comparing current prices with future ones. Consequently, the load priority and price forecasting are a basis of the demand shifting process.

3.4 Residential Load Types

Because of the dynamics of electricity grids, such as demand fluctuation, transmission/distribution congestion, and time variant resources, electricity prices vary in different periods. During on-peak periods even small percentages of increase or decrease in electricity usage could considerably change electricity prices. However, demand reduction should not hurt a consumer's satisfaction. Maybe the best price scenario occurs once there is a nearly flat rate of consumption every time since it needs a constant rate of production? Studying the residential consumption patterns reveals that there are some schedulable loads. We would like to restate from the last chapter that home appliances could be categorized into three main groups based on their ability to reschedule [16]:

- Non-reschedulable usage and service loads
- Re-schedulable usage loads
- Re-schedulable usage and service loads

Non-reschedulable usage and service: Nearly 38% of each electricity bill belongs to these loads [17]. Since their deferment may cause reduction in their quality, they are not reschedulable into later periods. Thus we consider them as the "first priority loads" which means they have to satisfy once requested.

Re-schedulable usage: Because of using thermal inertia, these loads could be postponed to the upcoming periods. They approximately consume 60% of home electricity [17]. Consequently, we consider them as the "second priority loads" since their consumption could be delayed for a few periods.

Re-schedulable usage and service: This 12% of electricity consumption can be used at longer period of times. Hence we name them as the "third priority loads."

The above priorities are considered as the basis of residential load priorities, and we will formulate the platform based upon them. However, consumers could modify these priorities according to their own preferences. Since participants get benefit based on their collaboration level, the larger portion of second and third priority loads increases a Micrigrid's ability to be a stronger market player. Moreover, every priority has its own maximum interval of supply based on the load characteristics and consumer agreement. In a collaborative environment, these intervals should be determined according to the consumer agreement before running the problem. A typical example for these intervals could be zero (immediately) for the first priority loads, four hours for the second priority loads, and twelve hours for the last priority loads. While these maximum satisfaction times have been set up, consumers can put every appliance into one of these groups (manual mode) or use the basic predetermined priorities (automatic mode). Since a good price predictor provides accurate information for both consumers and Microgrid controller, consumers may make decisions while they can compare prices and see the possible financial incentives.

3.5 Problem Statement

After running the problem, an expected output is the consumption vector of each consumer at each period classified separately for 2nd and 3nd priority loads. Indeed, if consumers have set their entire demand as first priority loads then there is no need to do scheduling. In that case the consumption vector would be the same before and after running the model. There are some assumptions for defining the objective function of the load scheduling problem.

First of all, in Microgrid we need high accuracy both in forecasting and scheduling, since we deal with a small number of end users, such as homes and business units, unlike large electricity grids. Moreover, since the price forecasting process generates results prior to load scheduling, therefore the scheduling process is largely influenced by those forecasting amounts. For example, once the controller is informed about the future prices, then its decision will be made about supplying each appliance or postponing its satisfaction based on the price rates. Generally, if the price is increasing in the short term, appliances are supplied immediately; otherwise their consumption would be delayed until reaching the cheapest price in the scheduling horizon.

3.5.1 Scheduling Intervals

Now the question is: how can the scheduling intervals be defined and determined correctly? One of the basic answers to the question is introducing scheduling horizons by using price patterns. The dispatch unit should support all loads before the next time, which has the same price as current period (i.e., there is no cumulative loads from prior schedules). Since the total time horizon is 24 hours and the program runs quarterly, the maximum number of scheduling periods is 96 (=24×4). On the other hand, consumers allocate their demand into one of the available categories regarding to their priorities such as 1st priority, 2nd priority, and 3nd priority.

Below figure shows the standard hourly profile (price pattern) for typical residents [18].

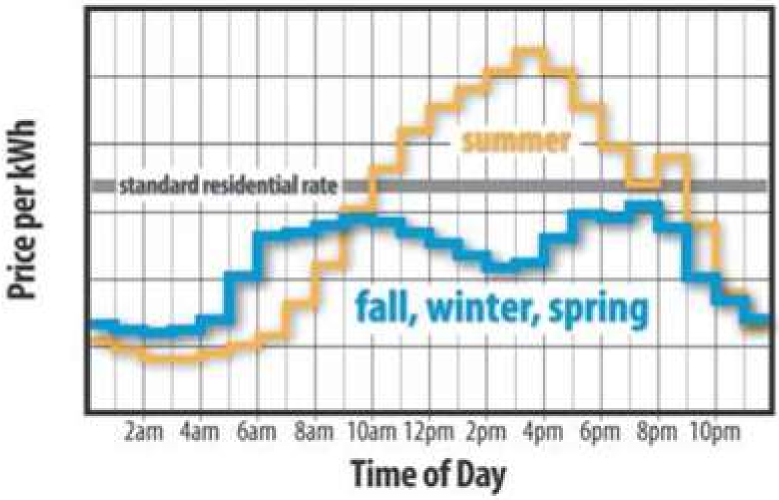

Figure 3-1 Standard residential profile

There are two types of periods, short term and long term. As we see in the picture, in short term the price might drop after waiting a few hours. For example, that case can be observed in the picture around 1 PM, and the price hits the same level after 4 hours. Another drop happens after waiting a larger period of time as it is visible in the picture around 9 AM and price goes back to the same level in about 12 hours. So one possible scenario for second and third priority demand could be equal to T_2=4 and T_3=12. However, users can determine those values based on their preferences.

Then we need to define a metric for evaluating the controllability of grid. We assign Θ_1, Θ_2, and Θ_3 to the total amount of first, second, and third priority demand in KW respectively. If consumers allocate the first priority to most of their appliances, they miss the advantage of load scheduling. It means they are not interested in using electricity at lower costs, and they just care about their comfort. Accordingly, we define the “control level” φ, which is equal to the total consumption of controllable loads (2nd and 3nd priorities) divided by the total consumption. So

$$\varphi = \frac{\theta_2 + \theta_3}{\theta_1 + \theta_2 + \theta_3}$$

The "control level" alters between zero (No control) and one (Absolute control) which is the base case for the controller. One of the advantages of "control level" is that it enables us to schedule resources more efficiently. If we have a "control level" that is close to 1, we are able to sell more electricity to the main grid. The Φ values that are close to zero indicate that we should use most of the resources for the internal consumption of the Microgrid.

Moreover, we assume that all the loads are interruptible. Although it is an acceptable assumption because of the characteristics of loads and electricity price, the model could be modified by putting a minimum for demand satisfaction at each period in case of uninterruptible loads.

Afterwards, the Microgrid typically has the minimum and maximum amount of battery capacity. Each appliance also has the minimum and maximum amount of capacity and period of consumption. These are fixed amounts which form the technical issues of the grid. Therefore, a comprehensive model should include these two basic conditions as constraints of the objective function.

The explained grid is planned to supply the base demand by its own resources and supply the extra internal or external consumption by batteries. So the best scenario happens when the controller is able to sell energy as much as possible during peak load periods.

It is worth mentioning that since we assume that the Microgrid is grid connected, there is no voltage and frequency challenge. Furthermore, the Microgrid could always buy and sell electricity, but it might not be effective at some periods. Another condition, which begets the next constraint is the charging and discharging rates of batteries and finding their appropriate capacities. We should define some related values according to selected batteries.

3.5.2 Problem Formulation

In order to develop the model we start defining an objective function. A. Kulvantichaiyanunt, et al. have been working on the problem of controllability of PHEV charging stations. In their approach the supply side was divided into two separate parts: inventory and direct charge [27]. Although we are going to use some components of their model such as battery constraints, and splitting the supply side into inventory and direct charge, we need to expand their model in order to capture characteristics of a Microgrid by adding new components such as

- Different demand types
- A waiting cost function
- Different generations such as micro turbines, fuel cells and so on
- Different battery efficiencies

Our objective function consists of buying and selling energy at each period and a waiting cost function for rescheduled loads. It also should cover those parameters, variables, and functions for future periods. After a concise study on the problem the objective function has defined as below:

$$\sum_{\kappa=\tau}^{\tau+H} C_\kappa (x_\kappa + R_\kappa) - B_\kappa y_\kappa + \sum_{\kappa=\tau+H+1}^{\tau+T} \left[\hat{C}_\kappa (x_\kappa + R_\kappa) - \hat{B}_\kappa y_\kappa \right] - \sum_{\kappa=\tau}^{\tau+T} \sum_{\gamma=\kappa}^{\kappa+T_2} \hat{Z}_{\kappa\gamma}^2 (DD_{\kappa\gamma}^2 + DI_{\kappa\gamma}^2) - \sum_{\kappa=\tau}^{\tau+T} \sum_{\gamma=\kappa}^{\kappa+T_3} \hat{Z}_{\kappa\gamma}^3 (DD_{\kappa\gamma}^3 + DI_{\kappa\gamma}^3)$$

In the above formula, C_K and B_K representing the selling price to the grid and buying price from the grid respectively. In our study, we assume that these prices are always the same. x_κ used for capturing the amount of electricity that the Microgrid sells to the main grid by pulling out of its direct charge (including all generators such as renewable and others). In addition, R_K symbolizes the amount of energy that the Microgrid sells to the main grid from its inventory (including storage systems). After that, the y_κ models the amount of electricity that Microgrid buys from the main grid either for supplying current demand or storing in batteries.

Then the next term represents the same variables for the future periods. Since those variables are forecasted values, we used ^ for distinguishing them from real-time variables. Here *H* is equal to the number of periods in which the Microgrid receives determined and fixed prices from the main grid.

After that, Z_2 and Z_3 have been used for waiting cost values related to second and third priority loads. Obviously those costs increase, so waiting cost is an increasing function. Here the first subscript (κ) is used for capturing the incurred period and the second subscript (γ) is used for showing the supply period. Finally, DD_2 and DI_2 symbolize the amount of second priority demand that would be supplied from direct charge and inventory respectively. Also DD_3 and DI_3 symbolize the amount of third priority demand that would be supplied from direct charge and inventory respectively.

After defining the objective function, we need to figure out the related constraints. We want to start from the inventory transition and it is equal to:

$$I_\kappa = I_{\kappa-1} + BC_\kappa - \frac{R_\kappa + DI_\kappa}{e_d}$$

In the above equation, the current inventory is equal to the last period inventory plus the battery charge during current period subtracted by the energy that we pull out from our inventory in order to supply demand and sell to the main grid. As we see in the formula, there is an efficiency coefficient related to discharging the battery that captured in the formula by e_d. Typically, this parameter is greater that the charging rate, which will be discussed later. The next equation describes the battery charge which used in the above formula.

$$\frac{BC_{\kappa}}{e_c} = W_{\kappa} + S_{\kappa} + G_{\kappa} + y_{\kappa} - x_{\kappa} - DD_{\kappa}$$

The charging efficiency is symbolized by the e_c. On the right side of the equation, *W* represents total wind generation in current period. After that, *S* represents the total amount of solar generation. Then *G* is equal to the total amount of generation from other resources such as fuel cells and micro turbines. As we know the controller might decide to buy energy from the main grid that comes to the battery. Finally there are some amounts of energy that we sell to the grid and also supply some part of demand from the battery that should be subtracted from our battery charge. The above equation could be restated for the future periods as below:

$$\frac{BC_{\kappa}}{e_c} = \hat{W}_{\kappa} + \hat{S}_{\kappa} + \hat{G}_{\kappa} + y_{\kappa} - x_{\kappa} - DD_{\kappa}$$

This equation replicates the first battery charge equation for the future periods. There is also a technical limit for all type of batteries related to the charging rate of the battery. As we know there are some limitations on charging rate of batteries depending on the battery type. Generally this constraint can be described as:

$$BC_{\kappa} \leq \mathrm{e}_c * \text{charging rate}$$

That tells about the maximum amount of electricity that we practically can store in the battery in each period. There is some upper and lower limit for our inventory.

$$I_{\min} \quad \leq \quad \mathrm{I}_{\kappa} \quad \leq \quad I_{\max}$$

Usually the reliability and quality of service could change the above limits. Obviously the better service requires larger amount of $I_{\min}$ in order to diminish the risk of energy shortage. There are some technical constraints that determine the total capacity of our inventory.

The next important constraint deals with the demand. First of all, there is limit on the amount of demand that we supply from our inventory. The equation below models this type of constraint:

$$R_{\kappa} + DI_{\kappa} \leq e_d * \text{charging rate}$$

According to this equation, the amount of energy that we pull from our inventory in order to supply demand (*DI*) and also sell to the grid (*R*) should be equal or less than the charging rate of the battery multiplied by the discharging efficiency. Moreover, there are some balances regarding different types of demand such as first priority demand and so on. As we know, our demand could be supplied from inventory or direct charge. Therefore:

$$DI_{\tau}^{1} + DD_{\tau}^{1} = D_{\tau}^{1}$$

This formula shows the relationship between different parts of demand. As we said earlier, the amount of first priority demand at each period is equal to the portion of first priority demand that we supply from the inventory plus the amount of first priority demand that we supply from direct charge. There is the same equation for the future periods:

$$D\hat{I}_{\kappa}^{1} + D\hat{D}_{\kappa}^{1} = \hat{D}_{\kappa}^{1}$$

There are projected values for the both sides of the equation. After that, the next part is finding the same type of equation for the lower priority demands. It is obvious that those equations would be more complex since the controller might reschedule some portion of the incurred second priority demand into future periods. Accordingly we have:

$$\sum_{\gamma=\tau}^{\kappa+T_2} (DI_{\tau\gamma}^2 + DD_{\tau\gamma}^2) = D_\tau^2$$

In which there is summation operator in order to add all of the rescheduled demand from now until the maximum acceptable scheduling horizon for second priority loads. Therefore, the incurred second priority demand (D^2) at current period is equal to the summation of the portion of second priority load that incurred at the beginning of current period and would be supplied from inventory in later periods until T_2, plus the portion of second priority load that incurred at the beginning of current period and would be supplied from direct charge until the end of the scheduling horizon for second priority loads (T_2). The same equation exists for the future periods:

$$\sum_{\gamma=\kappa}^{\kappa+T_2} (DI_{\kappa\gamma}^2 + DD_{\kappa\gamma}^2) = \hat{D}_\kappa^2$$

Moreover, there should be similar formula for the third priority load with minor changes. The third priority demand constraint is equal to:

$$\sum_{\gamma=\tau}^{\kappa+T_3} (DI_{\tau\gamma}^3 + DD_{\tau\gamma}^3) = D_\tau^3$$

T_3 is equal to the end of the scheduling horizon for third priority loads. Therefore, the incurred third priority demand (D^3) at current period is equal to the summation of the portion of third priority load that incurred at the beginning of current period and would be supplied from inventory in later periods until T_3, plus the portion of third priority load that incurred at the beginning of the current period and would be supplied from direct charge until the maximum scheduling horizon of third priority loads (T_3). Like other prioritized loads for the future periods we have:

$$\sum_{\gamma=\kappa}^{\kappa+T_3} (DI_{\kappa\gamma}^3 + DD_{\kappa\gamma}^3) = \hat{D}_\kappa^3$$

On the other hand, at each period there are some loads that incurred in the past periods and rescheduled for current period. So we need to formulate total amount of energy that we pull from inventory and direct charge. Therefore, the total demand that we pull out of inventory is equal to:

$$DI_{\kappa}^{1} + \sum_{\gamma=\kappa-T_2}^{\kappa} DI_{\gamma\kappa}^{2} + \sum_{\gamma=\kappa-T_3}^{\tau} DI_{\gamma\kappa}^{3} = DI_{\kappa}$$

DI is equal to the first priority demand that we pull out of inventory plus the summation of second priority demand that has incurred in the last T_2 periods until now and rescheduled to supply from inventory at current period plus summation of third priority demand that has incurred so far from the last T_3 periods and rescheduled to supply from the inventory at current time.

A similar formula could be used for modeling the total demand that we pull out of direct charge. Accordingly:

$$DD_{\kappa}^{1} + \sum_{\gamma=\kappa-T_2}^{\kappa} DD_{\gamma\kappa}^{2} + \sum_{\gamma=\kappa-T_3}^{\tau} DD_{\gamma\kappa}^{3} = DD_{\kappa}$$

In the above formula, the right side (*DD*) is equal to the first priority demand that we pull out of direct charge plus summation of second priority demand that has incurred in the last T_2 periods until now and rescheduled to supply from direct charge at current period plus summation of third priority demand that has incurred so far from the last T_3 periods and rescheduled to supply from the direct charge at the current time.

Finally the last constraint explains the termination condition. We only apply this constraint for the inventory level. Although there might be some other conditions that require termination such as the demand side, we do not use those constraints since they are not practical and also they restrict the solution. Therefore for the inventory constraint we have:

$$I_\kappa = I_{\kappa-T}$$

After 96 (=T) periods, the inventory level goes back to its original level. So if we start from midnight, the inventory goes back to the same level after 24 hours.

Finally, many of our variables are defined as nonnegative variables. As a result we have:

$$I_\kappa, BC_\kappa, R_\kappa, x_\kappa, y_\kappa, D_{\tau\kappa}^P, DD_{\tau\kappa}^P, DI_{\tau\kappa}^P \quad \geq \quad 0 \qquad\qquad P = 2,3$$

The inventory level is a nonnegative value since it is defined as the available energy in all of the storage systems. In addition, we already restricted the lower limit of inventory by I_{min}; which is greater than or equal to zero. The battery charge (*BC*) is defined as a nonnegative variable. All of the demand variables and selling and buying amounts of energy are defined as nonnegative values.

Chapter 4

Results

4.1 Case Study

The basic outline of the Microgrid model was discussed in the last chapters. In this chapter we are going to solve the linear programming problem for our case study. We are going to see the results of the case study and analyze them. The examined case in this study has the following characteristics and conditions:

First of all, in our case study the maximum scheduling horizon for second priority loads is assumed equal to 4 hours because of the load characteristics as discussed earlier. Since we assumed that demand happens at the beginning of each period, and each period is equal to 15 minutes, we have to satisfy the second priority demand that happens at the beginning of the current period by the next 15 periods after the current time. Therefore, the T_2 is considered equal to 15 in our case.

The maximum scheduling horizon for third priority loads is assumed equal to 12 hours as mentioned previously. Since the demand happens at the beginning of each period, we have to satisfy the third priority demand that happens at the beginning of the current period by the next 47 periods after the current time. T_3 is considered equal to 47 in this study. Moreover, we will run the program for the next 24 hours including the current period, which means T is equal to 95.

There are efficiency related issues regarding charging and discharging batteries depending on the battery type. We are going to use the Lead-Acid battery, assuming e_d= 0.85 and e_c=0.789. There are many studies related to the conditions and characteristics of this type of battery [23].

Based on the selected battery type, we assumed the I_{min} is equal to 3.6 MW and also the initial condition I_0 is equal to that value. The I_{max} is considered to be equal to 18

MW. On the other hand, the charging rate is considered to be equal to 10. After that, we need to determine the waiting cost functions related to second and third priority demand. As we know the waiting cost function should be an increasing function by its nature. We are going to use a primary function and we will study the effects of using different functions later on. So that basic function is $Z_{t2,t1} = t_2 - t_1$. So $Z_2 = \{0,1,2,\dots,14,15\}$ and $Z_3 = \{0,1,2,\dots, 46,47\}$.

4.1.1 Demand Profile

The studied Microgrid consists of 1000 houses, and we used the gathered data at the aggregate level for the area that was studied [24]. Since we needed to have the demand profile for every 15 minutes and the source data was an hourly consumption, we divided the hourly consumption by 4. In our demand profile, the maximum total requested quarterly demand is about 2.6 MW, and the minimum is about 1.2 MW (base demand). Figure 4.1 provides more details about different loads by their type [24].

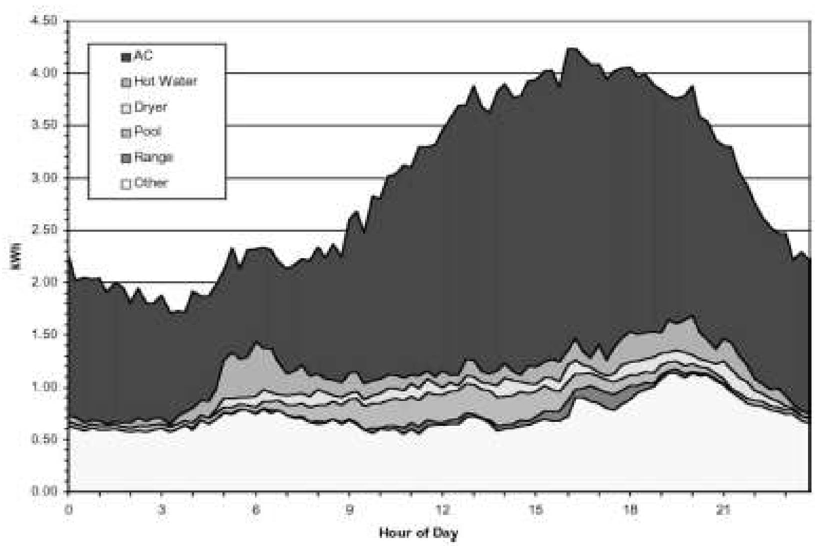

Figure 4-1 Hourly consumption by load type

4.1.2 Generation Profile

After explaining the load profile as the demand side of our problem, we also have to explain the supply side. First we start with solar generation. We assume that each building has a solar hydrogen energy system (SHES) which requires about $47m^2$ of space [25]. We assume that the output of our solar panels (E(PV-OUT)) directly come to our battery or go to the network (including the Microgrid and the main grid) without any loss or inefficiencies.

In addition, parts of our direct charge comes from wind turbines. Again we assume that each user has small wind turbines and figure 4.3 shows total wind generation at an aggregate level [26].

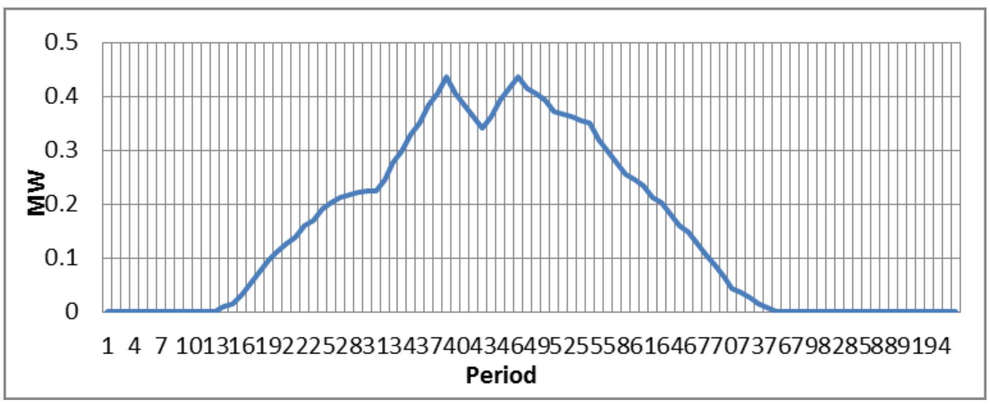

Figure 4-2 Solar generation at aggregate level

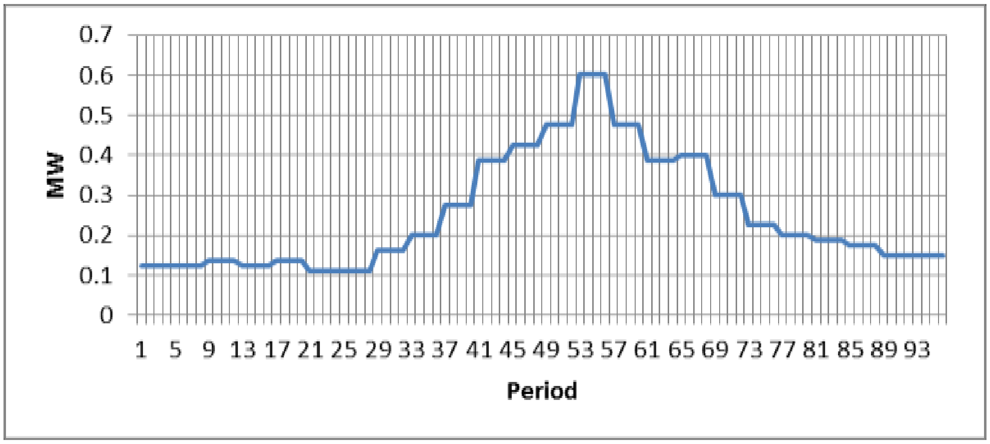

Figure 4-3 Wind generation at aggregate level

The last part of the supply side is the generation of electricity from all other resources excluding wind and solar. Since in this stage generation changes very quickly and depends on different factors such as the load profile, we used a random generation function in order to capture the basic generation profile. Obviously this profile could be updated after preliminary runs. Figure 4.4 shows the aggregate generation profile.

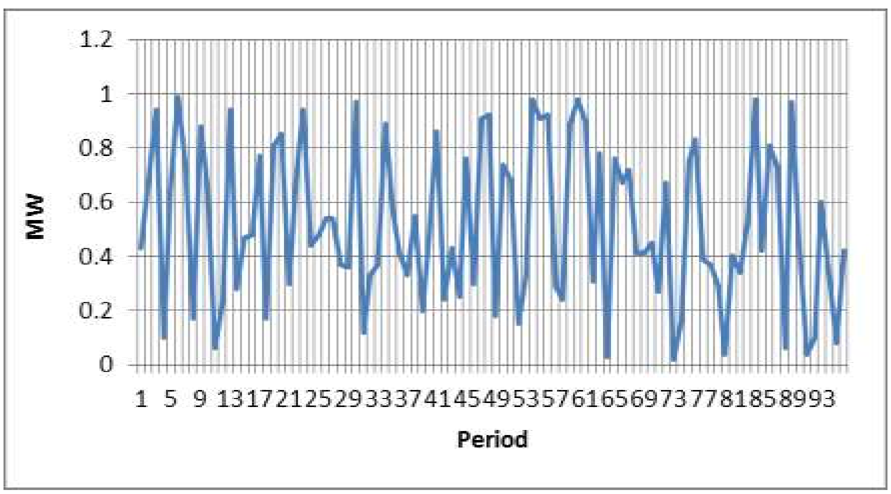

Figure 4-4 Total generation out of other resources such as micro turbines and fuel cells

4.1.3 Market Price

In our case study, market price would be the same for both buying and selling electricity. Those numbers have been provided by ERCOT for the first day of March 2011 as below:

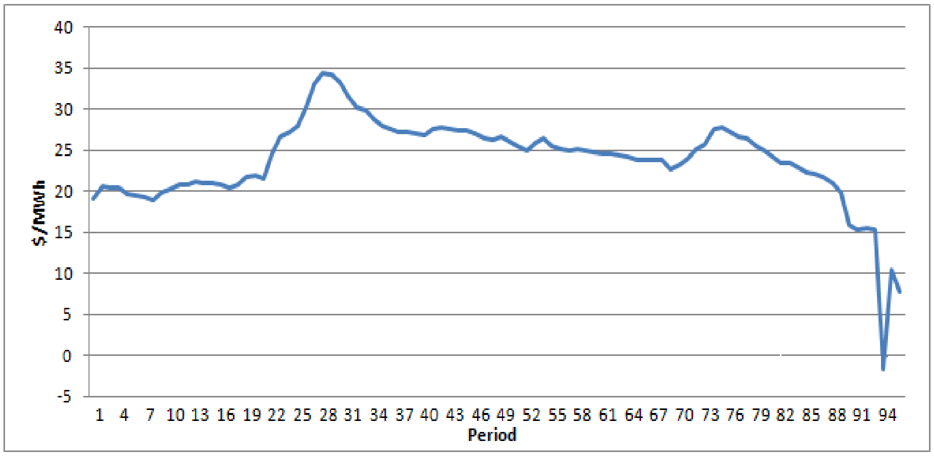

Figure 4-5 Market price

It is worth mentioning that the problem has about 12,864 variables and we used the Matlab software and the "Linprog" function in order to run the program.

In each period of time (15 minutes), the first, second, and third priority demands come into the Microgrid controller and thus demand will be satisfied in order to maximize profit. As we mentioned before, the first priority demand is satisfied immediately, and the second demand will be addressed up until the next four hours.

4.2 Demand Response

After solving the optimization problem with Matlab, the basic results are as indicated in the below figures. Figure 4.6 shows the satisfaction of first priority demand from inventory and direct charge. As we can see in the figure, most first priority demand is supported from direct charge, because there is no energy loss through direct charge (no battery inefficiency). However, supplying first priority demand through direct charge may not always be applicable and is dependent upon the generation mixture.

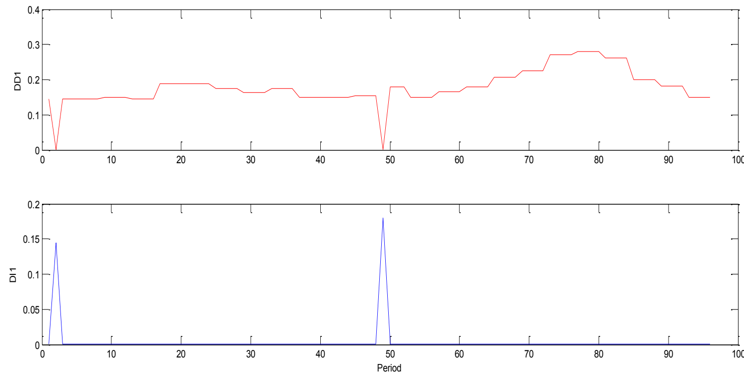

Figure 4-6 First priority demand satisfaction (DD, DI) for the studied case

Now we will show the second priority demand profile and the satisfaction of demand in the next four hours (including current time). The red line shows the cumulative demand profile, and the blue line indicates the cumulative supplied 2nd priority demand. The gap between those two curves reflects the waiting cost function effect.

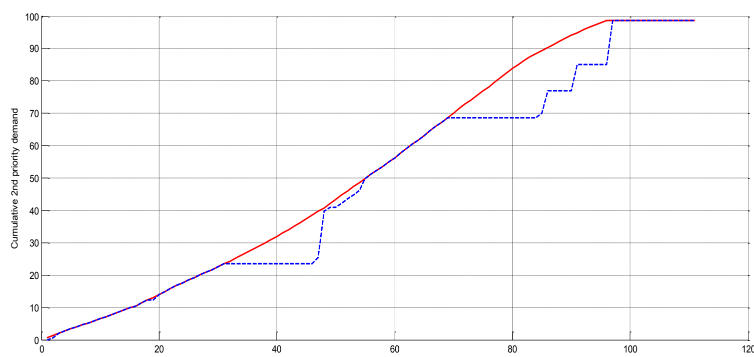

Figure 4-7 Second priority demand satisfaction

The next plot would be the satisfaction of the third priority demand at the next twelve hours. The rescheduled amounts would act as the first priority demand of the rescheduled time periods. As we can see, the third priority demand would be delayed to later periods, mostly when we have high energy prices. Similar as before, the red line shows the original demand profile, and the blue line shows the rescheduled demand.

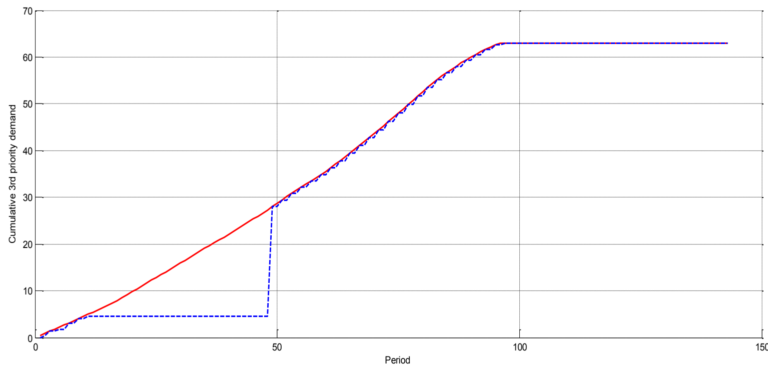

Figure 4-8 Third priority demand satisfaction

In the following figures, we have provided information about the total amounts of energy that the Microgrid would sell to or buy from the main grid.

Figure 4-9 indicates that the Microgrid has sold some portions of its generation to the main grid:

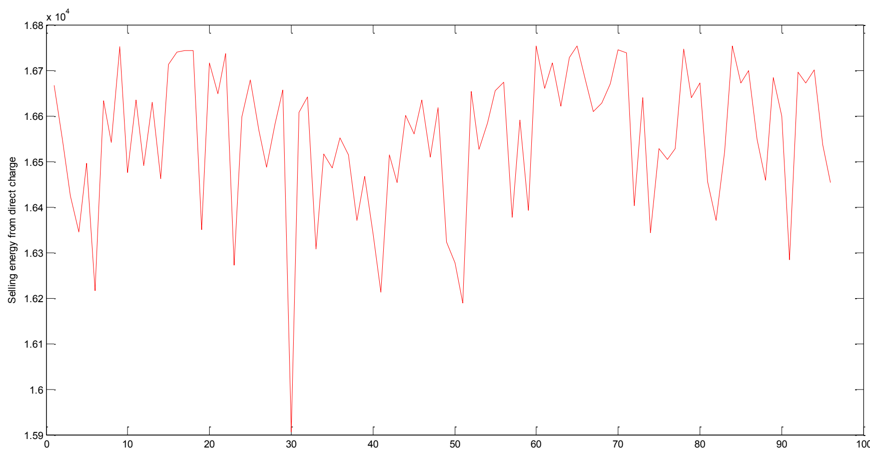

Figure 4-9 Selling energy from direct charge

4.3 Waiting Cost Function Analysis

The red line indicates the total amount of electricity that is sold to the main grid from the direct charge of each period. Obviously different values of the waiting costs (frustration costs) could change these figures.

Accordingly, the influence of five different waiting cost functions has been studied. The first scenario is using the maximum waiting cost function. For each period we have the same waiting cost function equal to *M*. After some calculations we came up with *M* = 59.0201. The second scenario used a logarithmic function equal to $\ln\left(\frac{t_2 - t_1}{47} e^{M} + 1 - \frac{t_2 - t_1}{47}\right)$. Then an exponential function as $e^{\frac{t_2 - t_1}{47}\ln(M)}$ that increases for each period was used in the third scenario. The fourth scenario consisted of a linear function in which the waiting cost was equal to $\frac{M}{48}(t_2 - t_1)$. Finally, the last scenario put waiting costs as zero which means there is no cost associated with delaying demand satisfaction.

The figure below provides us with a comparison between cumulative second type demand satisfaction for different scenarios:

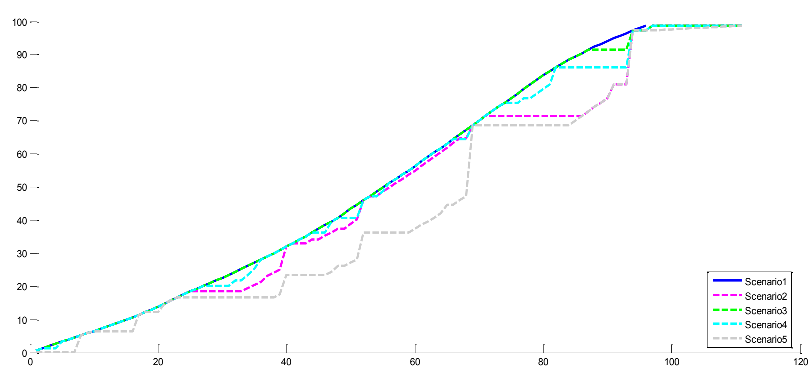

Figure 4-10 Waiting cost analysis related to 2nd priority loads

According to the above figure, the gap between incurred demand curve and rescheduled demand curve increases for smaller waiting cost functions. Then the same scenarios have been applied for third priority demand. The results can be seen in figure 4-11:

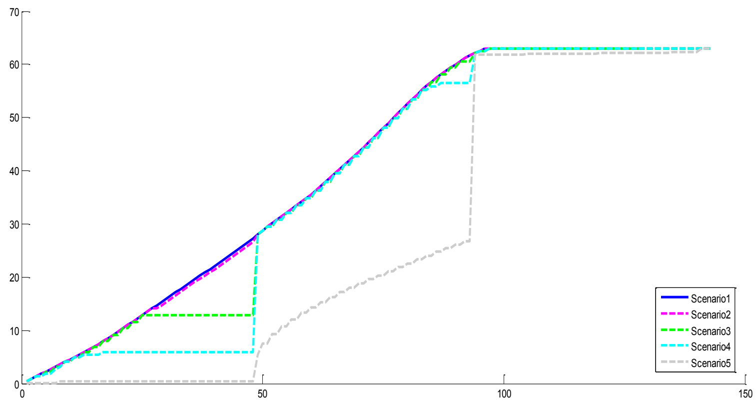

Figure 4-11 Waiting cost analysis related to 3rd priority loads

4.4 Final Analysis

Also, the impact of charging rates and discharging rates has been studied. As we expected, the objective function value increases by increasing (improving) battery efficiency.

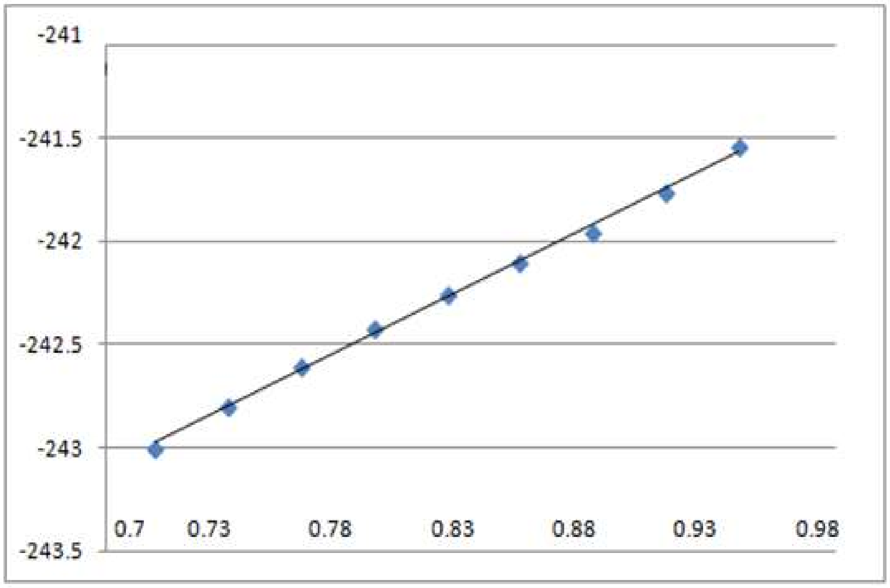

Figure 4-12 Impact of efficiencies on the on the objective value

Now the next analysis is related to impact of demand mixture on the objective function value. As mentioned earlier, control ability reflects the flexibility of incurred demand. After running ten different demand profiles, results have been shown in the following figure. It is worth mentioning that demand mixture also changes the result. For example by fixing control ability at 70% could include various ratios of second priority demand to third priority demand such as 30% 2^{nd} and 40% 3^{rd}, 35% 2^{nd} and 35% 3^{rd}, and so on. In each controllability level, there are various scenarios for various possible demand mixtures. Although demand mixture can alter the objective function value, we do not investigate on its impacts in this step. As expected control ability has positive impact on the objective function value:

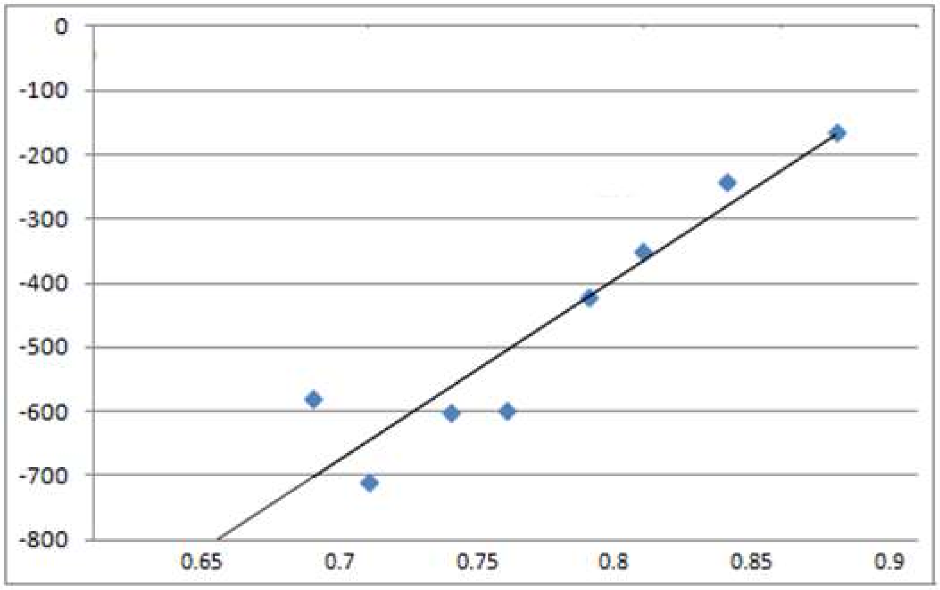

Figure 4-13 Impact of different demand profile on the objective function value

Another factor that might have impact on the optimal solution is electricity price. Different price profiles have been run and their objective values could be seen in the next figure. Mainly there have been two categories of prices: real prices and manipulated price. Manipulated prices have been studied to capture some possible cases that electricity prices jump into unusual prices like having a very cold winter or so on. Since those prices are somehow having similar trends of normal electricity prices, we multiplied or tripled real prices. Therefore there are two types of price profiles as we can see in the last figure. Obviously those price spikes have bigger impact on the optimal solution as below:

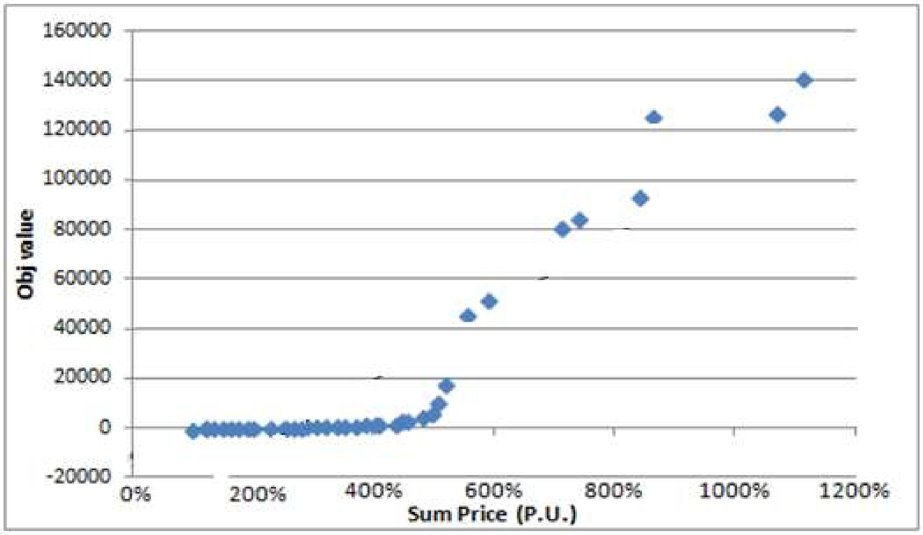

Figure 4-14 Impact of different demand profile on the objective function value

As we expected, the summation of price does not have significant impact on the objective function value unless we are in such a price spike case. However, price variation might have bigger impact on profit rather than price summation.

Chapter 5

Conclusion

To summarize, based on the results we can conclude that the model has successfully achieved the optimal load strategy for a residential Microgrid. The proposed model could be run for every period (15 minutes) with updated values. Moreover, the accuracy of our model depends on the accuracy of its inputs -- demand and price forecasts. Since in the upcoming future grids, the main grid would provide consumers with precise short-term price forecasts and real time prices, our model grid could be deemed reliable.

Furthermore, the observed results show that the model has successfully taken advantage of cheaper prices of electricity. This means residents would benefit from participating in sharing activities based on their collaboration level. Therefore, the proposed grid has various advantages for both suppliers and also end users. Suppliers would prefer to have more flat rates of generation without any jumps and spikes. On the other side consumers like to participate in the electricity market and acquire benefit from their energy saving and collaboration.

References

1) R. Bo, and F. Li, “Probabilistic LMP Forecasting Considering Load Uncertainty,” *IEEE Trans. Power Syst.*, vol. 24, no. 3, pp. 1279-1289, Aug. 2009
2) M. Roozbehani, M. Dahleh, and S. Mitter, “Dynamic Pricing and Stabilization of Supply and Demand in Modern Electric Power Grids,” *1st IEEE International Conference on Smart Grid Communications (SmartGridComm),* pp. 543-548, 2010
3) A. N. Kleit, and J. D. Reitzes, “Geographic Integration, Transmission Constraints, and Electricity Restructuring,” Nov. 2004
4) R. Lasseter, and et al. “Integration of Distributed Energy Resources The CERTS MicroGrid Concept”, California Energy Commission, Consultant Report, Oct. 2003
5) T. Funabashi, G. Fujita, K. Koyanagi, and R. Yokoyama, “ Field Tests of a Microgrid Control System” Proceedings of the 41st International Universities Power Engineering Conference, *UPEC '06*, pp. 232-236, Sep 2006
6) “Master Controller Requirements Specification for Perfect Power Systems,” Galvin Electricity Initiative, Feb. 2007
7) N. Amjady, F. Keynia, and H. Zareipour, “ Short-Term Load Forecast of Microgrids by a New Bilevel Prediction Strategy” *IEEE Trans. Smart Grid*, vol. 1, no. 3, pp. 286-294, Dec. 2010
8) D. Srinivasan, and T. Logenthiran, “Short Term Generation Scheduling of a Microgrid,” *IEEE 2009, TENCON*, pp. 1-6
9) S.J. Ahn, and S. Moon,” Economic Scheduling of Distributed Generators in a Microgrid Considering Various Constraints,” *IEEE 2009*, pp. 1-6
10) T. Logenthiran, D. Srinivasan, A. M. Khambadkone, and H. N. Aung, “ Multi-Agent System (MAS) for Short-Term Generation Scheduling of a Microgrid” *IEEE ICSET 2010*, Dec. 2010
11) S. Hatami, and m. Pedram, “ Minimizing the Electricity Bill of Cooperative Users under a Quasi-Dynamic Pricing Model,” *IEEE 2010*, pp. 421-426
12) M. Shahidehpour, H. Yamin, and Z. Y. Li, “Market Operations in Electric Power Systems”. New York: Wiley, 2002
13) S. Caron, and G. Kesidis, “Incentive-based Energy Consumption Scheduling Algorithms for the Smart Grid,” IEEE 2010, pp. 391-396
14) http://www.ieso.ca/imoweb/ marketdata/marketData.asp
15) A. Conejo, M. A. Plazas, R. Espinola, and A. Molina, “Day-Ahead Electricity Price forecasting using the Wavelet transform and ARIMA models,” IEEE trans. Power Syst., vol. 20, no. 2, pp. 1035-1042, May. 2005
16) A. A. Moholkar, “Computer Aided Home Energy Management System,” M.Sc. dissertation, Dept. Electrical Eng., Univ. West Virginia University, 2005.

17) J. Wiehagen and D. Harrell. (2001, July), "Review of residential electrical energy use data," NAHB Research Center, Inc., Upper Marlboro, MD. [Online]. Available: http://www.toolbase.org/PDF/CaseStudies/ResElectricalEnergyUseData.pdf
18) http://www.powersmartpricing.org/media/PSP-Average-Price-Pattern.jpg
19) R. Botsman and R. Rogers, *What's Mine Is Yours*. 1 ed. New York: HarperCollins Publishers, 2010, p. xv.
20) R. Belk, "Sharing," Journal of Consumer Research, vol. 36, No. 5, pp. 715-734, Feb. 2010.
21) M. Felson and J. L. Spaeth, "Community structure and collaborative consumption: a routine activity approach," American Behavioral Scientist, vol. 21, pp.614-624, Mar. 1978.
22) B. Bhushan and S. K. Soonee. (2012, Jan.). Utilization of idling capacity of captive power plants – A viable alternative. Power System Operation Corporation Limited. [online]. Available: http://www.nldc.in/docs/CEOPapers/Utilization%20of%20Idling%20Capacity%20of%20Captive%20Power%20Plants%20-%20A%20Viable%20Alternative.pdf
23) IEEE Recommended practice for Sizing Lead-Acid batteries for Stationary Applications, IEEE Standard Association, Sponsored by the stationary Batteries Committee, Apr. 15th, 2011.
24) D. S. Parker, "Research highlights from a large scale residential monitoring study in a hot climate," *Energy and Building*, Vol. 35, pp. 863-876, 2003.
25) M. Santarelli, and S. Macagno, "Hydrogen as an energy carrier in stand-alone applications based on PV and PV-micro-hydro systems," *Energy*, Vol. 29, pp.1159-1182, 2004.
26) Z. W. Geem, "Size optimization for a hybrid photovoltaic-wind energy system," *Electrical Power and Energy Systems*, Vol. 42, pp.448-451, 2012.
27) A. Kulvanitchaiyanunt, P. Sarikprueck, V. Chen, J. M. Rosenberger, W. J. Lee, et al., "Adaptive Design for Controllability of Charging Stations for Plug-in Hybrid Electric Vehicles," *INFORMS Annual Meeting*, Oct. 2012.
28) A.H. Mohsenian-Rad, A.Leon-Garcia, "Optimal Residential Load Control With Price Prediction in Real-Time Electricity Pricing Environments," *IEEE Transon Smart Grid*, V.1, No.2, pp. 120-133, Sep. 2010.
29) R. H. L. Rodriguez, R. H. G. Cespedes, "Challenges of Advanced Metering Infrastructure Implementation in Colombia," *IEEE PES Conference on Innovative Smart Grid Technologies (ISGT Latin America)*, 2011.
30) M. Roozbehani, M. Dahleh, and S. Mitter, "On the Stability of Wholesale Electricity Markets under real-Time Pricing," *49th IEEE Conference on Decision and Control*, Dec. 2010.

31) A. K. Basu, et al., "Key Energy Management Issues of Setting Market Clearing Price (MCP) in Micro-Grid Scenario," 42nd International Universities Power Engineering Conference, UPEC 2007, pp. 854-860
32) M. A. Alahmad, P. G. Wheeler, A. Schwer, J. Eiden, and A. Brumbaugh, "A Comparative Study of Three Feedback Devices for Residential Real-Time Energy Monitoring," *IEEE Trans. on Industrial Electronics*, vol.59, no. 4, pp. 2002-2013, Apr. 2012
33) E. Carpaneto, G. Chicco, "Probabilistic Characterisation of the Aggregated Residential Load Patterns," IET Gener. Transm.Distrib., vol. 2, no. 3, pp. 373-382, 2008
34) C. S. Chen, T. H. Wu, C. C. Lee, Y. M. Tzeng, "The Application of Load Models of Electric Appliances to Distribution System Analysis," IEEE Trans. Power Syst., vol. 10, no. 3, pp. 1376-1382, Aug. 1995

Biographical Information

Majid Ahmadi has earned his bachelor degree in Electrical Engineering at Tehran Polytechnic. He began studying Industrial Engineering in 2011. After finishing his first semester at UTA, he became involved with research related to optimization of energy grids at COSMOS lab. He has received academic award from Alpha Pi Mu (Industrial Engineering honor society) and also earned his Six Sigma Green Belt and Supply Chain Risk Management certifications.