INTELLIGENT DEMAND SIDE DEPLOYMENT IN RENEWABLE DISTRIBUTED GENERATION GRIDS

by

Jonathan R. Pedro

Submitted in partial fulfilment of the requirements
for the degree of Master of Applied Science

at

Dalhousie University
Halifax, Nova Scotia
July 2013

Dedication

This is dedicated to my Mother and Father whose encouragement and support allowed me to achieve my goal of earning my Masters Degree.

Table of Contents

List of tables

List of Figures

Abstract

Demand Side Management (DSM) and real-time pricing (RTP) are methods by which the consumer can participate in the electricity market and reduce electricity expenditures. By having more active consumers in the electricity market, DSM and RTP have economic advantages. By allowing users to participate in the market, a more elastic relationship between supply and demand is achieved. Furthermore, many customers are now introducing renewable sources to their homes in an attempt to reduce their current electricity bill.

The introduction of demand side renewable sources can be coupled with the existing DSM scheme by imposing new constraints to further minimize the cost to consumers and utilities (both generation and distribution). In finding the optimal load levels with information about day-ahead renewable generation capacity, a reduced consumer payout and a more desirable load profile is obtained. This allows for further studies in distributed renewable generation applications and the effects they have on the future grid.

List of Abbreviations and Symbols Used

ε	Price Elasticity of Demand
Δq	Change in Quantity
q_o	Reference Quantity
Δp	Change in Price
p_o	Reference Price
x_n	N^{th} State Variable
u_n	N^{th} Control Variable
J	Objective Function
L	Lagrange Function
λ	Lagrange Multiplier
g	Constraint Function
$q(\lambda)$	Primal Problem
$q^*(\lambda)$	Dual Problem
α	Gradient Correction Factor
$F(K, I)$	Dynamic Programming Total Cost Function
P_{cost}	Unit Operational Power Cost
S_{cost}	Unit Start-Up Cost
P_i^t	Appliance Power at Time T
P_{load}^t	Load Power at Time T
P_i^{min}	Minimum Appliance Power
P_i^{opt}	Optimal Appliance Power
P_i^{max}	Maximum Appliance Power
E_k	Total Require Appliance Power
t_s	Appliance Start Time
t_f	Appliance Finish Time
$G_k^t(p_k^t)$	Appliance Penalty Function
$C_i(P_i^t), C^t(d^t)$	Appliance Cost Function
d^t	Consumer Demand Power
R_w^t	Renewable Generation Power
p_0^t	Consumer Base Load Power
p_m^t	Consumer Must-On Appliance Power
p_k^t	Consumer Appliance Power
Obj^t	Cost Objective Value

Acknowledgements

I would first like to thank my research supervisor, Dr. Mohamed El-Hawary for his guidance, help, and support throughout the entirety of my masters program.

I would like to acknowledge Dr. William Phillips and Dr. Jason Gu for serving on my supervisory committee.

I would like to thank Shadi Shehadeh and Aaron MacNeill, PhD candidate, for listening and providing useful suggestions for my work.

I would like to thank my friends and colleagues, without them I would not have been able to complete my work.

I would finally like to thank my mother and my father whose support and helped give me the motivation needed to complete my masters requirements.

Chapter 1: Introduction

Distributed generation has become an option for residential consumers of electricity to reduce energy expenditures. As the distributed generation levels begin to increase there is a need for efficient management and scheduling of load levels. To make effective use of generation and reduce energy costs to the consumer, the concept of load management (or demand side management scheme) has been introduced. Due to the inability of many consumers to manage their loads due to time restrictions or other commitments in their day to day lives, a customer local management system is more practical and efficient. The automatic scheduling of residential loads is known as demand side management and has become an active area of study. Many researchers in the area focus upon scheduling and managing various loads such as household appliances and plug in hybrid electric vehicles. Research in demand side management has also lead to effective methods of management for loads such as the application of Lagrange Relaxation optimization. A main reason for the growing interest in demand side management is the prospects of flattening the load profile in an attempt to reduce generation and transmission costs for energy utilities. Research in the area of demand side management has shown that a flattened load profile is achievable with the methods developed in many papers [4, 5, 6].

1.1 Thesis Objective

The objective of this research is to develop a methodology that reduces consumer payout to the utility through a demand side management scheme that recognizes the availability of distributed generation. This is necessary due to the increased levels of generation present on the demand side. Without the management of the distributed generation levels, it is difficult to achieve an optimal load profile and a reduction in cost to consumers and utilities. This research will allow for further advancement in studies of the applications of distributed generation. This is done through proper management of distributed generation levels and that leads to further optimization of the electricity grid. Since many distributed generators are renewable sources, the management of such devices leads to an improvement in the development area of renewables research.

1.2 Thesis Contribution

With the introduction of demand-side management schemes there is a need to account for the generation sources accessible to the consumer. The work done in this Thesis is the integration of consumer owned generation into the optimization of residential load scheduling. To demonstrate the advantages of integrating consumer generation into the optimization problem load optimization algorithm is considered. A Matlab^{TM} program is developed to optimize the residential load with the presence of local generation to reduce energy expenditures. . The program makes use of the optimization Lagrangian Relaxation method to schedule the individual loads and produce a day ahead scheduling horizon.

1.3 Thesis Outline

Chapter 2 presents an introduction to pricing schemes and layout of the current electricity market. With an understanding of the economic effects of demand side contribution to the electricity market the importance of demand side management schemes becomes apparent. A discussion of previous work is also covered in this chapter.

Chapter 3 presents and details the optimization schemes used in the management of the residential loads. In this section the methods of dynamic programming and Lagrangian relaxation are discussed. The optimization methods outline the requirements to be met by the algorithm so that an optimal scheduling horizon is achieved.

Chapter 4 presents a review of the concept of unit commitment. Unit commitment is important in the study of demand side management problems due to the analogous characteristics of the unit commitment problem. The unit commitment methodology outlines the optimal deployment of generation units based upon the operational costs of committing a unit. The same concepts can be applied to the solution of the demand-side management problem by viewing the problem as the compliment of the unit commitment problem.

Chapter 5 presents the theory behind the new optimization algorithm and the results obtained from testing of the algorithm. The algorithm considers two separate cases where it optimizes the scheduling times for various numbers of the two classes of loads; shift-able and curtail-able loads. The sensitivity of the algorithm to parameter changes is also analysed and discussed.

Chapter 6 presents the conclusion of the research and proposes possible future advances of the concepts in this field of study.

Chapter 2: Previous Work and the Current Electricity Markets

The concept and development of demand-side management to alleviate the issues facing the current electricity market is not novel to this thesis. There is research being done in different areas of DSM to improve its performance and reliability for real systems. This section will briefly discuss other areas of research in DSM to further show the importance of the novel research developed in this thesis. To understand the need for DSM the current structure of the electricity market must also be discussed.

2.1 Current Work in Demand-Side Management

The concept of demand-side management was developed to flatten the load profile or load curve that utilities supply. From this many different papers and texts review the need for such concepts, the major reason being a reduction in transmission and generation costs by having consumer participation in the electricity market [1], [2] and [3]. The idea is that if there is more participation of consumers in the electricity market a more economical and reliable market structure is formed. With a more economical market consumers are more likely to regulate and curtail energy usage, reducing costs incurred from the utilities. More specific research relating to the implementation of DSM systems is discussed in [1], [4], [5], [6] and [12]. However, the papers of most influence on the research done by this thesis are [4], [5], [6] and [12].

One of the previous papers discusses optimization of residential appliances using a price prediction of the day-ahead prices to aid in the scheduling of each load [4]. It uses the price prediction as a control input for the scheduler during times where the information of price is not available. This is important for scheduling devices that may overlap onto another scheduling horizon. The paper also introduces a decision equation that determines the penalty cost associated with running an appliance. The equation is dependent on coefficients to determine the penalty cost for running and appliance or waiting. This is used to model the consumer's preference on the operation of a particular appliance. The authors consider only short pricing periods and state that price prediction capability is needed. However, the proposed thesis and research done shows that with a day ahead pricing schedule there will be no need for price prediction, reducing the complexity of the problem and increasing the accuracy of the results.

Present work in residential load management seeks to satisfy the objectives of reducing the load levels, also known as curtailment, or shifting the load [5]. A user dissatisfaction function is considered to model the penalty cost associated with curtailing a user load. The implementation of DSM requires information to be telecommunicated between the consumer and the utility. In communicating information, lost messages can occur which effects the reliability of the optimization. The convergence and testing of optimization with lost telecommunicated messages is shown.

Another research paper considers a method for modelling the user energy consumption using game theory [6]. The objective of [6] is to demonstrate that with communication between users on the same substation feeder and appropriate tariff structure, a game structure can be used with demand-side management to reduce to the load profile on that feeder. The authors propose that the optimal energy cost is achieved at the Nash equilibrium of the formulated energy game. The game only requires that each player submits its best load configuration in response to price. The research done in this thesis can further improve saving of each user in the scenario proposed by the paper. With local generation available to customers, the load needed to be supplied by the grid is reduced and a better load configuration can be submitted by the player in the game.

Due to the number of household appliances that consume large amounts of power, there is a need for load-shifting solution to optimally manage the loads of each appliance to reduce cost to the consumer. This is becoming more of a need due to the introduction and increasing popularity of plug-in hybrid electric vehicles (PHEVs). Many PHEVs require 0.2-0.3 KWh of charging energy for one mile of driving [12] creating a new large residential load component that cannot be curtailed. Furthermore, due to high demand during charging times of PHEVs and increasing popularity, appropriate management programs must be implemented to prevent voltage issues and power quality degradation that will stem from the increased load produced from PHEVs [12].

Research done by [5], [6] and [12] focus upon reducing energy consumption of users and thus reducing payout to the utility. However, there is a lack of focus on the integration of demand-side generation with current load optimization schemes. The results of the work done in this thesis will show that the energy levels and consumer payout can be reduced further through the implementation of distributed generation, improving the results of the previous papers.

2.2 Electricity Markets

Generating companies produce electricity and compete for bids on the competitive market. From this the electricity market is formed. The objective of competitive markets is to reduce the price paid by consumers. However, it does not behave as most other competitive commodity markets do mainly because most consumers have very little influence in the market due to a lack of expertise to contribute to the design [3]. A way to address this issue is to provide price schemes that allow consumer participation. There are many different pricing schemes in the electricity markets today. There are a variety of pricing schemes currently used in different markets: flat rate, time of use (TOU), critical peak pricing (CPP), extreme day CPP(ED-CPP), extreme day pricing (EDP) and real-time pricing (RTP) [2]. Real-time pricing will be the method that that is focused upon in this thesis and discussed in more detail further on. The importance of consumer activity in the market is to create a better balance between supply and demand, as most other commodity markets have.

From economic theory, the demand of a commodity will increase until the benefit obtained from the commodity equals the price of the commodity. An example of this would be a manufacturing process; the manufacturer will not produce a product if the price to produce the product makes the sales unprofitable. This leads to a link between the changes in price versus a change in demand. This is known as price elasticity of demand. The common equation representing this relationship is:

$$\varepsilon = \frac{\Delta q / q_o}{\Delta p / p_o} \tag{2.1}$$

where q_o and p_o are the equilibrium points for demand and price respectively. If the above equation is assumed to be normalized with respect to the equilibrium point then it becomes:

$$\varepsilon = \frac{\Delta q}{\Delta p} \tag{2.2}$$

where q and p is the demand and price associated with a commodity respectively. The above equation is normally negative because an increase of price results in a decrease in the demand. A perfectly elastic commodity has a price elasticity of demand (PED) value of negative one. However, most electricity markets have a PED value close to zero. This means that even for a large change in price there is a small change in demand. Represented graphically, common supply versus demand curve is shown in figure (2-1). However, as stated previously, current electricity markets do not behave in this manner [3, 7]. This can be easily shown in figure (2-2), where a large change in price results in small changes along the demand curve.

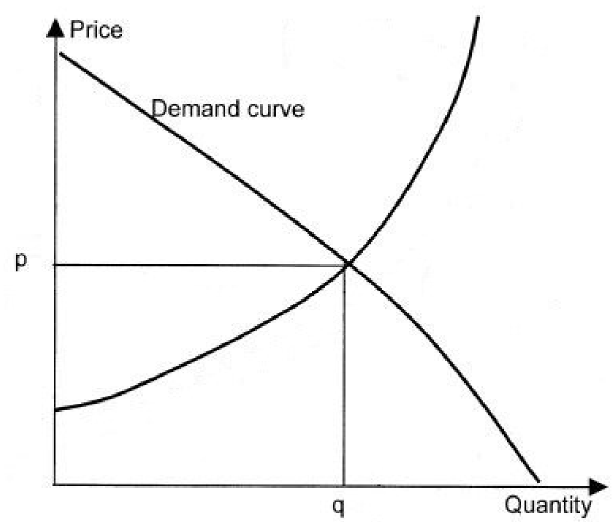

Figure 2-1. Common Supply and Demand Curve.

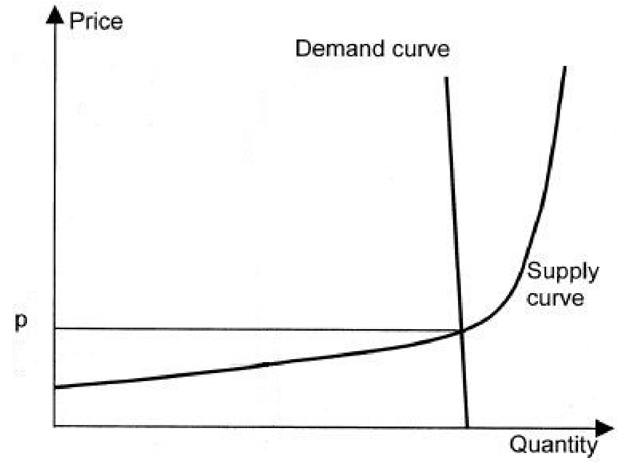

Figure 2-2. Supply and Demand Curve for Electricity Markets.

The lack of elasticity in many markets can be attributed to a variety of causes. First is that the pricing scheme used doesn't provide incentives for customers to change their demand based upon the price, this is common in flat rate markets. At the same time, incentive based programs may not provide benefits that outweigh the comfort and convenience to cut their bill by a few percent [3]. One factor is believed to be caused by the historical view of electricity usage. Since the beginning of electricity sales, it has been viewed as easy to use, always available and integral to daily life, because of this thought very few people carry out a cost/benefit analysis for their current consumption levels [3].

It is not always the state of mind of the user that causes the relationship between supply and demand to be relatively inelastic. The inelastic nature of the market also stems from which pricing schemes are used. Many types of TOU schemes such as CPP only charge a different price at times where demand is high in an attempt to cause consumers to shift loads and often the exact price is not known until the time at which the peak occurs. However, in RTP schemes, customers are charged hourly fluctuating prices that are announced on a day-ahead schedule. This allows consumers to shift loads to times where price and comfort levels can be traded off for one another. Economists believe that RTP is the most direct and efficient program suitable for competitive electricity markets [2, 7].

There are issues with many electricity market schemes currently used and not all can be corrected with simply changing the current scheme used. Even with RTP there are still problems with educating users and setting up programs between the utilities and consumers. From this demand side management (DSM) solutions have become the new focus to improve current market structures. With DSM and RTP users can actively participate in the electricity market to reduce prices and create a more elastic market.

Chapter 3: Optimization

The optimization process is a key component of the DSM problem. There are many methods of optimization, but the ones that will be focused upon are those of dynamic programming in the application of unit commitment (DP) and Lagrangian relaxation (LR). The reason for the selection of these two schemes stems from the complexity and structure of the problem. DP is effective for a wide variety of problems and reduces the problem of dimensionality, whereas LR better models the DSM problem by optimizing the price signals sent to and from the consumer in the form of the Lagrangian multiplier, **λ**. These two methods are discussed in more detail in this section.

3.1 Dynamic Programming in Unit Commitment

Dynamic programming is an optimization process present in the unit commitment problem in which a large problem is transformed into a series of smaller problems [8, 16]. This section provides an overview of dynamic programming as it is applied to the unit commitment problem; further detail is given in the following chapter. The main advantage of dynamic programming is the reduction in the dimensionality of the primal problem. This reduction is crucial for advanced problems due to the large dimensionality of problems and processes found in more complex systems. DP was developed by Richard Bellman in the 1950s and is continued to be used in many optimization schemes today [8]. This is due to the capability of DP to handle discrete and continuous problems as well as stochastic and deterministic ones. The individual problems (or sub problems) can be solved using many different optimization techniques ranging from enumeration methods to advance non-linear techniques [8, 10, 17].

Sub-optimization is a key component of DP by using Bellman's principle of optimality. Bellman stated that an optimal policy (or set of decisions) has the property that whatever the initial state and initial conditions are, the remaining decisions must constitute an optimal policy with regard to the state resulting from the first decision [8, 9, 10]. To paraphrase the previous statement, regardless of what initial conditions exist, optimizing the total system is done by obtaining the optimal set at each stage. This is demonstrated further by defining an N-step objective function as:

$$\min F = f_n(x_{n+1}, u_n) + f_{n-1}(x_n, u_{n-1}) + \cdots + f_1(x_2, u_1) \tag{3.1}$$

where x_{n+1} is the previous state or input to and u_n is the decision associated with the N^{th} stage. To illustrate this problem further figure (3-1) shows an initial value problem system as a series of stages with a decision u_i to be selected such that the corresponding objective value, x_i, is optimized.

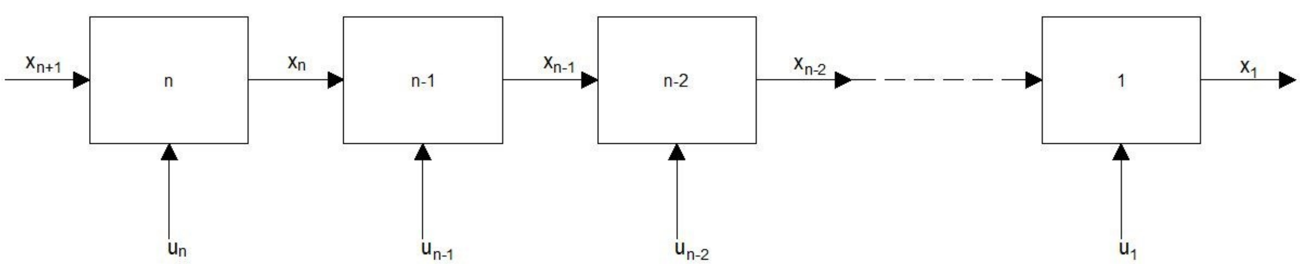

Figure 3-1. N-Stage Initial Value Problem

Considering the above figure and equation, using DP to solve this problem we start at the final stage. If the input to this stage is specified as x_2 then Bellman's principle of optimality states that u_1 must be selected such that $f_1(x_2, u_1)$ is optimized, denoted f_1^*:

$$f_1^*(x_2) = \underset{u_1}{\text{opt}}[f_1(x_2, u_1)] \tag{3.2}$$

Next, optimizing the second stage we group the last two stages together and f_2^* denote the optimal objective value for this sub problem:

$$f_2^*(x_3) = \underset{u_1 \cdot u_2}{\text{opt}}\,[f_1(x_2, u_1) + f_2(x_3, u_2)] \tag{3.3}$$

This can be further simplified by substituting $\text{opt}[f_1(x_2, u_1)]$ by $f_1^*(x_2)$ resulting in the following:

$$f_2^*(x_3) = \underset{u_2}{\text{opt}}[f_1^* + f_2(x_3, u_2)] \tag{3.4}$$

From this trend a general formula for the DP process is obtained by taking:

$$f_i^*(x_{i+1}) = \underset{u_i, u_{i-1}, \dots, u_1}{\text{opt}}\,[f_1(x_2, u_1) + \cdots + f_i(x_{i+1}, u_i)] \tag{3.5}$$

and after substitution it becomes:

$$f_i^*(x_{i+1}) = \underset{u_i}{\text{opt}}[f_{i-1}^* + \cdots + f_i(x_{i+1}, u_i)] \tag{3.6}$$

Equation (3.6) defines the general form of the DP process. As can be seen from the above equation, DP can be used to optimize any objective function. However, although DP is very useful in reducing the dimensionality of the problem, DP does not give one method by which an optimal solution may be found and various solution methods vary depending on the nature of the problem.

From this it can be seen that DP is a very powerful tool because it focuses on individual hourly optimization of loads without regard for the previous hour, greatly reducing the complexity and dimensionality of the problem. However, DP does not account for the entire optimization procedure. As was stated previously, any optimization technique can be used to obtain the set of optimal decisions for the individual stages. For this task the technique of Lagrangian relaxation is used, this if discussed in more detail in the following section.

3.2 Lagrangian Relaxation

Lagrangian relaxation has grown from a mostly theoretical concept to a useful method of optimization [8]. From this growth, more research is being conducted to expand the use of this optimization technique. It has become a popular method to solve the unit commitment problem because of its iterative technique and ability to eliminate restricting coupling constraints, which will be discussed in a later section. Due to the iterative nature of LR it is easily coupled with DP to further reduce the complexity of large scale scheduling problems.

Lagrangian relaxation is based upon the idea that complex optimization problems can be modeled as simple problems with complex constraints [8, 11]. From this, LR reduces many of the problematic constraints that are attached to the objective function in the form of a penalty term containing the level of violation of their constraints and dual value. Programming problems contain an objective function to be minimized or maximized, typical objective functions would be profit maximization or cost minimization. The objective function changes based upon a state variable which has its values bounded or constrained. As previously stated, LR relaxes these constraints to simplify the programming problem. To illustrate this concept further, consider the programming problem below:

$$\begin{cases} J = \min(\boldsymbol{bx}) \\ Subject\ to: \\ \boldsymbol{Ax} \leq \boldsymbol{c} \\ \boldsymbol{x} \geq 0 \end{cases} \tag{3.7}$$

where **x** is an $n\, x\, 1$ vector representing the state variable. This state variable has many different definitions and it depends on the nature of the problem. For example, in the context of the DSM problem the state variable are the load levels that minimize the price and in the unit commitment problem they are the generation levels that minimize the cost.

3.3 Lagrange Method and Dual Variable Problem

To understand the Lagrangian relaxation problem we need to define the concepts of Lagrange multipliers, λ, and 'dual variables'. To develop this concept easily the simple optimization problem is considered [8]:

$$\begin{cases} J(x_1, x_2) = \min(0.5x_1^2 + 0.25x_2^2) \\ Subject\ to: \\ x_1 + x_2 = 4 \end{cases} \tag{3.8}$$

The minimum value that J can assume is zero but this is a constrained problem due to the straight line constraint on x_1 and x_2. The optimum point that minimizes the objective function with respect to the constraint is the tangent to the objective function. To determine point that is tangential to both functions the gradient is introduced. If the gradient of J, denoted by ∇J, has a non-zero component along the constraint function, $g(x_1, x_2)$, then an optimal point has not been reached. A movement along the constraint function should be made until ∇J has a no components along the constraint function, this means that ∇J is 'normal', or perpendicular, to $g(x_1, x_2)$. To insure that ∇J is normal to g we require that ∇J and ∇g be linearly dependent vectors, or line up in the same direction. With this requirement we can set up the equation:

$$\nabla J + \lambda \nabla g = 0 \quad (3.9)$$

This equation creates the bases for the Lagrange equation. In essence, it states that two gradient vectors cancelling one another when one is scaled by λ, the Lagrange multiplier. The reason for the scaling is caused by one vector not being the same length as the other. Rewriting equation (3.9) without gradients we obtain:

$$L(x_1, x_2, \lambda) = J(x_1, x_2) + \lambda g(x_1, x_2), \quad (3.10)$$

which is called the Lagrange equation [11]. To solve for the values of x_1, x_2 and λ that optimize the objective function we require that the partial derivatives of $L(x_1, x_2, \lambda)$ with respect to each variable be equal to zero, which can be seen to be the same as equation (3.9). The requirements form the following set of equations:

$$\frac{\partial L}{\partial x_1} = 0 \quad (3.11)$$

$$\frac{\partial L}{\partial x_2} = 0 \quad (3.12)$$

$$\frac{\partial L}{\partial \lambda} = 0 \quad (3.13)$$

Using these equations the problem stated in equation (3.10) can be solved using the Lagrange method as follows:

$$L(x_1, x_2, \lambda) = 0.5x_1^2 + 0.25x_2^2 + \lambda(4 - x_1 - x_2)$$

$$\frac{\partial L}{\partial x_1} = x_1 - \lambda = 0$$

$$\frac{\partial L}{\partial x_2} = 0.5x_2 - \lambda = 0$$

$$\frac{\partial L}{\partial \lambda} = 4 - x_1 - x_2 = 0$$

Solving the three equations results in:

$$x_1 = 1.333$$

$$x_2 = 2.667$$

$$\lambda = 1.333$$

When more than one equality constraint is introduced, the same method can be used to solve the problem. The only change is the presence of a λ for each separate constraint.

With the concepts of Lagrange multipliers and Lagrange equations explained, the next concept to discuss is the Lagrange method using 'dual variables'. The idea is to solve for the Lagrange variables directly then solve for the problem variables using and iterative technique [11]. The equation related to the solution of the Lagrange variables is called the 'dual solution' whereas the Lagrange multiplier solution is called the 'dual problem' [11]. To demonstrate and develop the equations for the dual method, the previous example will be used where the Lagrange equation is:

$$L(x_1, x_2, \lambda) = 0.5x_1^2 + 0.25x_2^2 + \lambda(4 - x_1 - x_2)$$

Then the dual function, denoted as $q(\lambda)$, is defined as:

$$q(\lambda) = \min_{x_1, x_2} L(x_1, x_2, \lambda) \tag{3.14}$$

With the dual function defined, the dual problem, $q^*(\lambda)$, by definition is:

$$q^*(\lambda) = \max_{\lambda \geq 0} q(\lambda) \tag{3.15}$$

From the above equations, it can be seen that the dual variable method requires two separate optimization problems. The dual function states that for a value of λ we solves for the variables x_1 and x_2 that minimize the function. The dual problem then states that for the values found in the dual function, a solution to the dual problem is found by maximizing the dual function with respect to λ. This method is repeated and forms an iterative procedure for solving the optimization problem.

The Lagrange problem defined earlier by equation (3.10) is simply solved using the dual variable method and the value of the variables will always be the same as the primal problem variables. This is due to the convex nature of the objective function. In some problems, however, the objective function may be piecewise linear or other complex non-convex functions and the dual problem must be used to solve for the optimal values of the variables [11]. In some cases the function in equation (3.14) may not be described explicitly in terms of λ, therefore another method must be used to adjust lambda. Many texts, including [5, 8, 11], use the gradient search method to adjust the value of lambda with each iteration and is defined as:

$$\lambda^1 = \lambda^0 + \left[\frac{d}{\mathrm{d}\lambda} q(\lambda)\right] \alpha \tag{3.16}$$

where α is the a scaling value used to make the gradient 'behave', or converge in a reasonable amount of iterations. A simple rule for the selection of α is:

$$\alpha = 0.5 \quad \text{when} \quad \frac{d}{\mathrm{d}\lambda} q(\lambda) \text{ is positive}$$

and

$$\alpha = 0.1 \quad \text{when} \quad \frac{d}{\mathrm{d}\lambda} q(\lambda) \text{ is negative}$$

The dual variable problem assumes the variables to be a constant in each step but then adjusts the values using the gradient search method; because of this there is an error introduced between the dual problem and the and the true minimized values, referred to as the primal problem. The primal problem is:

$$J^* = \min_{x_1, x_2, \lambda} L(x_1, x_2, \lambda) \tag{3.17}$$

The error is known as the 'duality gap' and is measured as the difference between J^* and q^*. Due to the iterative nature of the dual variable problem, the duality gap can be used as a decision step to exit the iteration. However, a better measure of closeness to the optimal solution uses the duality gap and is called the 'relative duality gap', defined as:

$$\frac{J^* - q^*}{q^*} \tag{3.18}$$

If the primal problem is convex with continuous variables the relative duality gap will become zero. For many problems the cost function may be piecewise linear, in this case the dual variable method must be used to solve the optimal values of the problem [8].

With the concepts of the Lagrange method and the dual variable problem well established, the concept of Lagrangian relaxation is considered next. As was previously stated for problems with non-convex or discontinuous cost or constraint functions, the Lagrange method is unsolvable due to the non-differentiable nature of these functions. Other issues that cause the Lagrange method to fail are coupling constraints, such as those found in the unit commitment problem that will be seen later. Lagrange relaxation temporarily ignores or relaxes these constraints and uses the dual variable method to solve for the optimal values. The way in which this is done is by setting λ to a constant and adding the coupling constraints to the objective function, shown as:

$$\begin{cases} L = J(x_1, x_2) + \lambda^t g(x_1, x_2), \\ \qquad Subject\ to; \\ \qquad \boldsymbol{x} \geq 0, \end{cases} \tag{3.19}$$

Comparing equation (3.18) with equation (3.7) it can be seen that the constraint has been added to the objective function creating the dual variable problem. Setting λ to a constant value causes it to behave as a penalty factor in the objective function which can then be adjusted using the dual variable method. By utilizing the dual variable method, the optimal values for the variables can be solved for, thus defining the Lagrangian relaxation method. To define the Lagrangian relaxation method and its advantages further, the Unit Commitment problem is discussed in the following section.

Chapter 4: Unit Commitment

To show the advantages of Demand-Side Management for utilities, the Unit Commitment problem is introduced as being complementary to load de-commitment. The electric power system experiences cycles of high load periods and low load periods caused by the everyday routines of people. Loads are generally lower during the night and early morning when most people are asleep and higher during the day and early evening when businesses are operating or when following evening routines. To supply the high levels of demand, generally more expensive generation units need to be turned on. However, when loads decrease the units are turned off to reduce cost. How long do some units need to remain on to serve loads, which units should be left on, and how much does it cost to commit a unit when the load begins to increase? These questions are what form the unit commitment problem. It is the cost, and how to reduce the costs, of committing the peak time units that is the interest of Demand-Side Management. As a result the Unit Commitment needs to be discussed to understand the need of DSM.

To further the understanding of unit commitment and DSM we need to look at the behavior of the user. Suppose that the load follows a peak-valley pattern similar to that shown in figure (4-1). It follows that, to reduce costs not every generation needs to be committed to meet the demand. There could be many combinations of different units to meet the demand requirement, without regards to the cost. Other characteristics of the system demand are weather dependent and region dependent. For example, the temperature during the summer in most tropical countries can be fairly warm whereas the winters are mild. From this one expects to see higher loads in the summer than in the winter because people use climate control devices, such as air conditioners, more in summer than in winter. Because of this increased loads in summer, the number of units committed in summer is expected to be higher resulting in higher cost periods. However, meeting the demand requirement of the system is not the only constraint on the unit commitment problem.

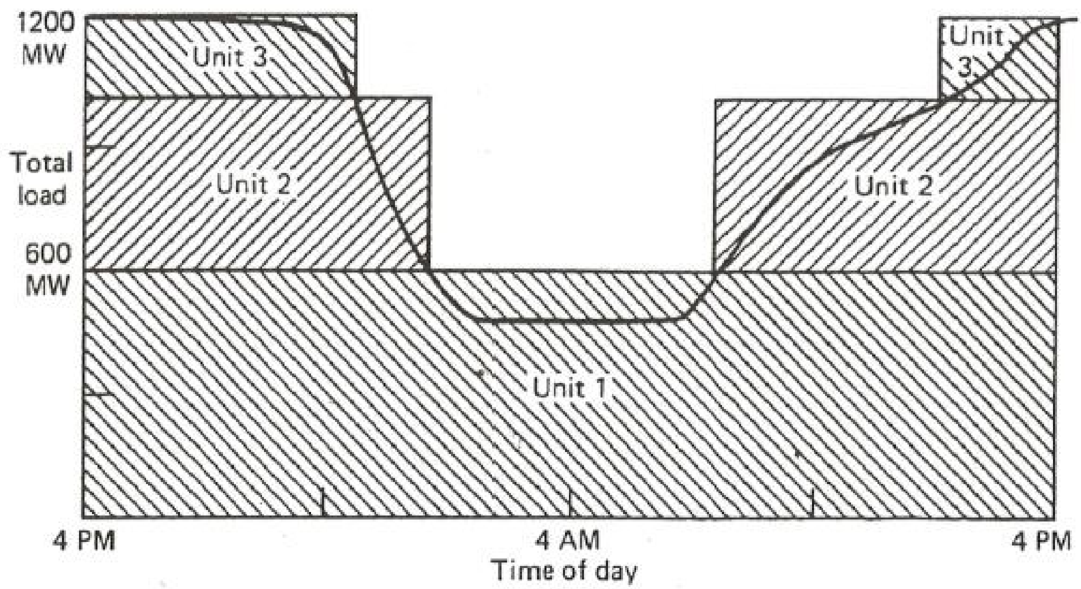

Figure 4-1. Unit Commitment with Load Profile [8]

4.1 Constraints

There are many different constraints that are placed on the unit commitment problem. Not every system will contain all of the possible constraints that can be imposed on a system. This is due to fact that not every system has the same type of generation, such as: hydro, combustion, thermal and renewables. With these different forms of generation, each has a required start-up time, a set time that they need to be run for and a required offline time to be considered. Units in the categories of hydro and combustion have a relatively short start-up time allowing them to be brought up quickly when loads begin to peak. Thermal units, on the other hand, require a longer time to come online and shut down due to the fact that the incremental temperature cannot exceed the specified value of the unit. For this reason most thermal units will form the base load, defined as the lowest load level required to be supplied that day.

Spinning reserve is another important constraint that must be present in the unit commitment problem. Spinning reserve is known as the total amount of generation present, or ‘spinning’, minus the load and losses of the system. The amount of reserve present is often calculated to be the amount needed such that the loss of one or more generation units does not cause a large drop in frequency of the system [11]. There are many different ways in which countries or companies calculate the amount of spinning reserve required. In the United States the rules that specify how much reserve is to be set to each unit are set by regional reliability councils [11]. Other rules specify that the reserve must cover a percentage of the total peak demand of the system or that the reserve must be able to cover the loss of the largest committed unit running and that the available reserve must be distributed between fast responding machines and slower response machines. With the main constraints defined the solution methods for the unit commitment problem can be developed.

4.2 Solution Methods

The major issue facing the unit commitment problem from the beginning is that of the dimensionality of the problem. Many systems have large number of units that can be committed at any given period of time. Making the following assumptions that there are N number of units that can be committed to supply the load at each M number of time periods, then it follows that the total number of combinations that need to be tried at each time period is;

$$Com(N,1) + Com(N,2) + \cdots + Com(N,N-1) + Com(N,N) = 2^N - 1$$

Where $Com(N,K)$ is the combination of N units taken K at a time and is defined as;

$$Com(N,K) = \left[\frac{N!}{(N-K)!\,K!}\right]$$

For each scheduling period there would be a $(2^N - 1)^M$ number of combinations to try to find the optimal commitment. From this is can be seen that it would not take many units for this problem to become extremely difficult to solve. This leads to the need of the alternative solution methods known as priority-list schemes, dynamic programming and Lagrangian relaxation.

4.3 Priority List Scheme

The simplest solution method would be the priority-list. As the name suggests, units are ordered by priority of lowest to highest full load average production cost. This reduces the dimensionality of the problem greatly when the selection of units must be made because the next unit that should be committed will be the cheapest to run. A simple shut-down algorithm taking into account the system constraints would be;

- As the load decreases, determine if the next unit in the priority list can be dropped such that the level of generation meets the spinning reserve and demand requirements. If the requirements are not met, keep the current commitment; if yes then drop the next unit on the list and go to the next step.

- Determine the number of H hours before the unit will need to be committed again.
- If the number of hours is less than the minimum shut-down time then keep the unit running and go to the last step; if not proceed to next step.
- Two costs need to be calculated. The first is the sum of hourly production costs for the next H hours if the unit is on. Then calculate the same cost with the unit offline and add the start-up costs. If shutting the unit down provides sufficient saving then it should be shut down otherwise keep it committed.
- Repeat this for the next unit on the list. If it is also dropped continue with the next unit.

This algorithm defines the priority-list scheme [8]. There are also other adjustments that can be made to the algorithm to suit different systems containing different types of generation. Dynamic programming also creates a similar priority list so solve the commitment problem.

4.4 Dynamic Programming Solution Method

The dynamic programming approach is similar to the priority scheme in that it too uses a list of units to solve for the optimal values for the unit commitment problem. The DP approach separates the scheduling problem into smaller optimization problems [16]. By optimizing the smaller problems, an optimal solution to the overall system can be obtained. The advantages of reducing it to smaller sub-problems are the reduction of dimensionality of the problem along with less computational power requirements because the whole system is not under consideration. The forward DP approach takes advantage of the idea of reducing the problem into sub-problems and is a successful algorithm that is used to solve the unit commitment problem.

There are two main dynamic programming algorithms that are proposed in literature, these are the forward DP approach and the backward DP approach [8, 16, 17]. The backwards DP starts at the final hour of the scheduling horizon and runs backwards to the initial time, solving for the optimal unit arrangement. Conversely, the forward DP approach begins at the initial hour and runs forward in time to the final hour. There are several advantages of forward verse backwards. The first being that if the start-up costs of the unit is a function of time that it has been offline then with forward DP you have information about how long the unit has been offline and therefore can calculate the start-up costs at each stage. The other practical advantages of using forward DP are that the initial conditions are known as well as the algorithm can run forward in time for as long as required [textbook]. The forward DP algorithm is defined in flowchart of figure 5 and the corresponding cost function that is to be optimized is;

$$F(K,I) = \min_{L}[P_{cost}(K,I) + S_{cost}(K-1,L:K,I) + F(K-1,L)] \tag{4.1}$$

where,

$$F(K,I) = least\ cost\ to\ arrive\ at\ the\ state\ (K,I)$$

$$P_{cost} = cost\ to\ produce\ power\ for\ state\ (K,I)$$

$$S_{cost}(K-1,L:K,I)$$

$$= total\ start\ of\ costs\ to\ go\ from\ state\ (K-1,L)\ to\ state\ (K,I)$$

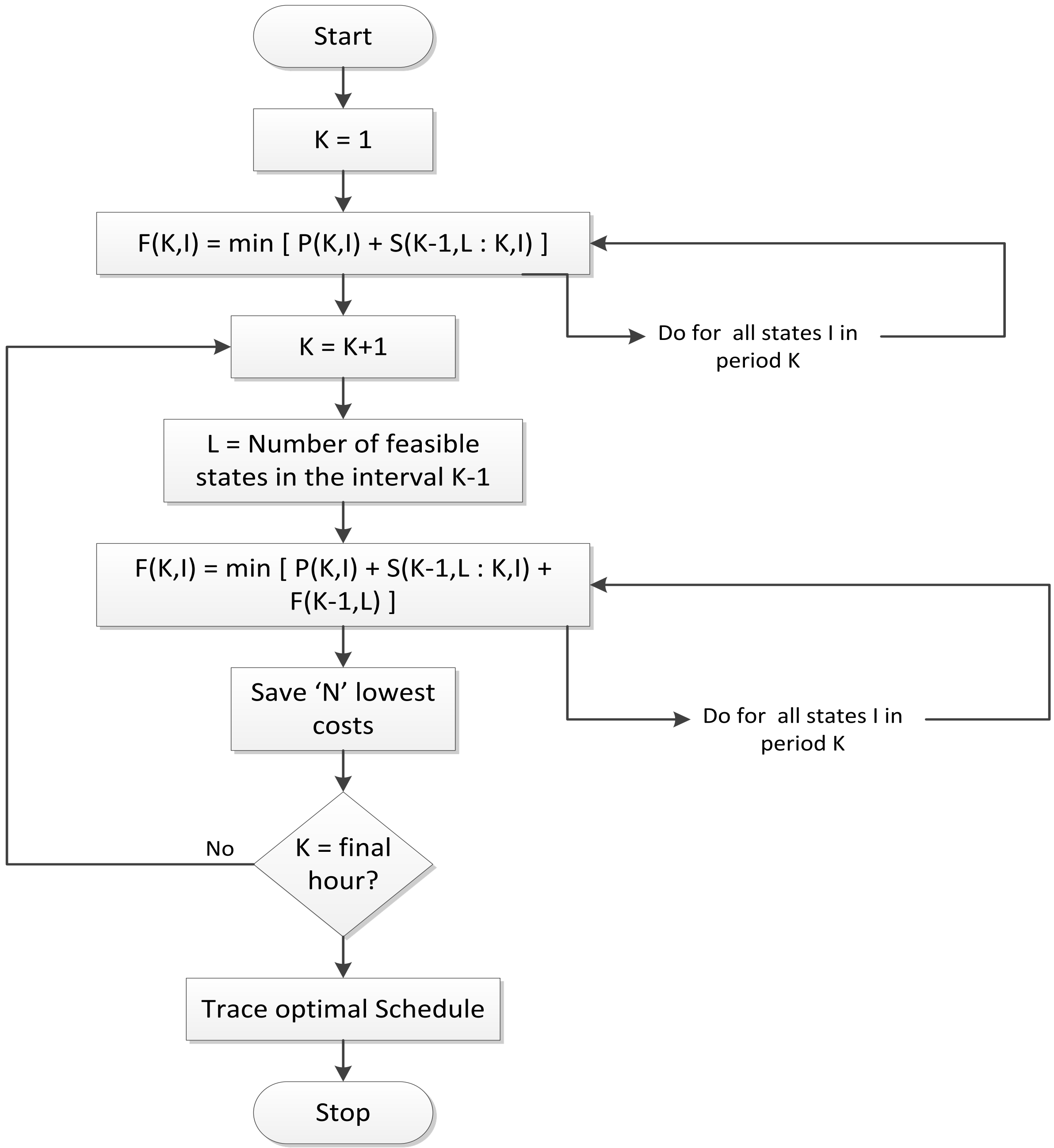

Figure 4-2. Forward DP Approach [8].

The state (K, I) represents a combination of committed units during the K^{th} hour. The variable N is introduced to keep tract of the lowest costs states. The reason for having multiple lowest cost combinations saved at each state is that the lowest cost at any given state does necessitate a following optimal state. An example of this would be if the lowest cost at state K-1 called for a unit to be shut down but at time K it required the unit to be turned on again. If the cost to start up the unit is larger than the savings acquired from turning it off than it would be been more economical to keep the unit committed during the previous time period. The main disadvantage of the forward DP approach is that as the number of units begins to increases the accuracy decreases due to the strict priority order that is imposed on the search method.

4.5 Lagrangian Relaxation Solution Method

Lagrangian relaxation has many advantages over the other solution methods of priority-list schemes and dynamic programming with strict priority-lists. The main advantage being that the Lagrangian method is not forced to search over a strict list of units to commit in a given order. Since it is not limited in the ordering of units to commit, the solution found has a more optimal configuration while still meeting the constraints placed upon the problem by the system. There are other issues that need to be addresses such as dealing with non-linearity and status variables of each unit. However, these issues can be overcome with the use of the dual variable method discussed earlier.

The first step to the development of this problem is to define the unit status variables U_i^t as;

$$U_i^t = 0 \text{ if the unit } i \text{ is off during the time period of } t$$

$$U_i^t = 1 \text{ if the unit } i \text{ is off during the time period of } t$$

The constraints and the objective function of the system must also be defined for the problem. The constraints are separated into three groups: loading constraints, unit limits and other constraints. The reason for the separation will be apparent shortly. These constraints are defined as;

$$P_{load}^{t} - \sum_{i=1}^{N} P_i^t \, U_i^t = 0 \tag{4.2}$$

$$P_i^{min} U_i^t \leq P_i^t \leq P_i^{max} U_i^t \tag{4.3}$$

where equation (4.2) is the loading constraint and equation (4.3) is the unit constraint. The other constraints that can be added to the problem are the start-up and shut-down time constraints, fuel consumption, emissions and spinning reserve limits. The objective function of the system is the cost of running each unit and is defined as;

$$\sum_{t=1}^{T} \sum_{i=1}^{N} [C_i(P_i^t) + Start\ up\ costs]\, U_i^t = C(P_i^t, U_i^t) \tag{4.4}$$

From this the Lagrange equation can be formed;

$$L(P, U, \lambda) = C(P_i^t, U_i^t) + \sum_{t=1}^{T} \lambda^t \left(P_{load}^{t} - \sum_{i=1}^{N} P_i^t \, U_i^t \right) \tag{4.5}$$

Notice that the unit constraints and the other constraints do not appear in the Lagrange equation. This is due to the fact that these constraints can be applied to each unit separately outside of the optimization function. If the values of the optimization result in the violation of one of these constraints, the value is simply set to the limit that was violated. This results in the most optimal solution that the constraints allow.

After examination of the cost function and the constraints set by the unit limits, we can see that the problem is separable over each unit. However with the introduction of the loading constraints the problem is no long separable. An adjustment of one unit results in a change in the levels of another. This poses an issue which causes the optimization of the unit commitment problem to become quite complex. The concept of Lagrangian relaxation removes this problem by relaxing or ignoring the coupling constraint. This is done through the dual variable method of maximizing the Lagrange equation with respect to the Lagrange multiplier while minimizing with respect to the other variables. The dual variable method defines this as;

$$q^*(\lambda) = \max_{\lambda} q(\lambda) \tag{4.6}$$

where,

$$q(\lambda) = \min_{P_i^t, U_i^t} L(P_i^t, U_i^t, \lambda) \tag{4.7}$$

The process solves for a value of λ that moves $q(\lambda)$ towards a larger value followed by finding the minimum of the Lagrangian by adjusting the values of P_i^t and U_i^t using the fixed value of λ previously found. To illustrate this further, setting λ to a fixed value in equation (4.5) results in the expansion;

$$L(P,U,\lambda) = C(P_i^t, U_i^t) + \sum_{t=1}^{T} \lambda^t P_{load}^t - \lambda^t \sum_{i=1}^{N} P_i^t U_i^t \tag{4.8}$$

By substituting equation (4.4) into equation (4.8), dropping the second term because it is a constant and rearranging it can be seen that the problem has been separated between the units;

$$L(P,U) = \sum_{t}^{T} \sum_{i=1}^{N} [C_i(P_i^t) + Start\ up\ costs]U_i^t - \lambda^t P_i^t U_i^t \tag{4.9}$$

With the coupling problem of the Lagrangian removed, the optimization problem becomes much simpler to solve. The unit commitment problem can be solved by optimizing each unit separately without regard for what is happening to other units. This is done by substituting equation (4.9) in equation (4.7), the minimum is found by taking the first derivative;

$$\frac{d}{dP_i^t} [C(P_i^t, U_i^t) - \lambda^t P_i^t U_i^t] = 0 \tag{4.10}$$

The values for the variable U_i^t can either be one or zero depending the on the status of the unit. When $U_i^t = 0$ the minimum is zero, where as if $U_i^t = 1$ the minimum is defined as;

$$\frac{d}{dP_i^t} C(P_i^t, U_i^t) = \lambda^t \qquad (4.11)$$

The unit constraints must also be taken into account and therefore we have three cases which the solution to the minimum problem can be found.

Case 1: If the value of $P_i^{opt} \leq P_i^{min}$ then;

$$\min[C(P_i^t, U_i^t) - \lambda^t P_i^t] \rightarrow P_i^{opt} = P_i^{min}$$

Case 2: If the value of $P_i^{min} \leq P_i^{opt} \leq P_i^{max}$ then;

$$\min[C(P_i^t, U_i^t) - \lambda^t P_i^t] \rightarrow P_i^{opt} = P_i^{opt}$$

Case 3: If the value of $P_i^{opt} \geq P_i^{max}$ then;

$$\min[C(P_i^t, U_i^t) - \lambda^t P_i^t] \rightarrow P_i^{opt} = P_i^{max}$$

Looking back at the status variables of the units, a simple method is described to identify the state of the unit. If the objective to minimize $[C(P_i^t, U_i^t) - \lambda^t P_i^t U_i^t]$ and $U_i^t = 0$ the only way to have a lower value is if;

$$[C(P_i^t) - \lambda^t P_i^t] < 0$$

Therefore once values that minimize the Lagrangian are found for a constant value of λ, the unit status variable can be determined by the above rule. The second part to the Lagrangian relaxation method is to update the value of λ .

The adjustment of λ^t is one of the most important steps in the Lagrangian relaxation method. In the application of updating λ^t, careful attention must be given to the task of updating each time period λ independently of the others before continuing on to the next iteration. Equation (4.6) states that a maximum of the Lagrangian with respect to λ must be found, however, this problem is often unbounded therefore another method must be used. Most of the literature surrounding the method of Lagrangian relaxations makes use of the gradient search and heuristic methods to obtain an accurate solution quickly. The gradient search is given as;

$$\lambda_{new}^t = \lambda_{old}^t + \left[\frac{d}{d\lambda} q(\lambda)\right] \alpha \qquad (UC.12)$$

where the selection of α is based upon heuristic methods such as past experiences using the gradient search method. Reference [11] uses the rules of;

$$\alpha = 0.01 \quad \text{when} \quad \frac{d}{d\lambda} q(\lambda) \text{ is positive}$$

and

$$\alpha = 0.002 \quad \text{when} \quad \frac{d}{d\lambda} q(\lambda) \text{ is negative}$$

Now that a strategy for the iteration scheme has been developed, a decision step to measure the closeness to the solution must be introduced. The method that is used is known the relative duality gap [8]. It represents the percentage error between the dual variable method and the optimal solution given the known status of each unit and is defined by;

$$\frac{J^* - q^*}{q^*} \tag{4.13}$$

where J^* is the optimal solution of the objective function with the status of each unit. If the status of every unit is off then the value of J^* for the given time period under consideration then J^* should be set to an arbitrarily large number. In equation (4.13) it must be noted that each term in the equation is the sum of the time incremented values. To demonstrate it further, q^* is defined as $q^* = q^1 + q^2 + \cdots + q^T$. With large systems of units the duality gap becomes quite small. The solution method is quite significant because the problem of dimensionality is removed, making it possible to analyze any system. The largest issue facing the Lagrangian relaxation method is that as the solution converges some units will begin to be switched on and off causing the solution to become unstable. With the idea of the unit commitment problem presented, the importance and solution methods of demand side management can be better understood.

Chapter 5: Distributed Generation in Demand-Side Management

5.1 Introduction

Demand-side management (DSM) is the concept of adjusting and managing the consumers load levels [5, 6]. The control of the consumer load can be done through time-varying pricing of electricity usage. From economic theory it is understood that with the time-varying prices it would be expected that the user would reduce their load levels at times of high cost and increase it again at times of lowest cost. However, this concept is not applicable to the current electricity market for various practical reasons. Some reasons include: the current market does not have time-varying prices thus it does not provide an incentive for consumers to adjust their load, consumers do not have the ability to adjust loads to times of day with low costs such as during the night when they are asleep or are not able to run a manufacturing process during times of low cost. Since it is difficult for some manufacturing processes to adjust loads at various times of the day due to time dependent production or that the cost of electricity is a small part of the costs in the manufacturing process, DSM is not an effective process to manage this area of the load.

The concept of DSM is very important for the growing grid because it makes efficient use of current energy availability without the implementation of new and expensive generation or system infrastructure [6]. In addition to the growing grid, the introduction of demand-side generation creates the need for intelligent management systems placed at the consumer level. There are many different programs that utilities implement to control the user energy consumptions, but the one focused upon is the concept of residential load management.

In this section, the concept that the consumers load can be optimally scheduled with available demand side renewable penetration is shown. The assumptions are made that each user has an intelligent metering device that allows for communication between it and the utility. The objective of this DSM approach is to optimize cost to the user by curtailing and shifting loads to times where local renewable generation is available or purchased power is at a minimum. In doing so, it will be shown that the load profile become flattened, reducing cost for utility and consumer alike. The DSM scheme is done through an automatic scheduling algorithm with user defined time constraints and utility designated real-time pricing tariff.

5.2 Real-Time Pricing

Money saving incentives is the driving force behind the effectiveness of DSM on the demand-side. Different price schemes are used by utilities to offer incentives for consumers to change their load [2]. The one focused upon here is the real-time pricing (RTP) scheme.

Real-time pricing is the most effective pricing scheme for the DSM program because of how often the price changes. RTP charges and hourly fluctuating prices which reflects the actual cost of generation [2]. Customers are notified the day ahead of the price at each hour allowing for loads to be shifted and managed accordingly. Being notified the day ahead is advantageous for the DSM process because it allows time for the management device to schedule the load according to the price. Other price schemes such as critical peak pricing and extreme day pricing do not accurately reflect the load profile of the system because the price changed for these systems only occur during contingencies or extreme loads. However, with RTP, higher prices occur at times where the load is high and lower prices occur when the load is low. The incentive needed to shift high load, occurring at high cost times, is provided through RTP thus aiding in the objective of flattening the load curve. Figure (5-1) shows how RTP is an accurate reflection of the load profile. With the knowledge of the day-ahead prices, the scheduling algorithm has enough information about the expected load profile needed to optimize the load. The information about price is sufficient for an optimal solution but user defined parameters and satisfaction need to be recognized as an important input parameter of the scheduling process.

Figure 5-1. An Example of a Real-Time Pricing Scheme

5.3 Load Scheduling Formulation

To develop the problem, consider that each residence has a meter that is capable of two-way communication with the utility and each appliance that is to be managed by the meter. It is also assumed that a day-ahead RTP scheme is provided and is separated into T time periods for the next scheduling horizon. For this application T=24, or hourly, for each scheduling horizon. Needing to be discussed is how each appliance operates within the optimization scheme, how to maximize user satisfaction and what optimization method is to be used.

5.3.1 Load Class

The residential load is comprised of four separate load types; the base load, loads that must be kept on for defined time periods, loads that are able to be shifted and loads that are adjustable or able to be curtailed. While all load classes are significant, for optimization purposes the only the latter two are of interest due to their adjustable characteristics. K_1 and K_2 represent these two classes of loads respectively. The 'must-on' load at time period t is denoted by p_m^t, where $t = 1, \ldots, T$, and be appliances such as television or computers. The base load at any time t is constant and denoted by p_0^t.

The appliances categorized as K_1 and K_2 are subsets of k and the power consumption of the k^{th} appliance for the time period t in T is denoted by p_k^t. To proceed, each class must be mathematically represented to distinguish between the one another during the optimization process [5]. This is achieved through defining each class by the defining characteristics as follows;

Class K_1 devices are defined as having a total energy requirement, E_k, that is to be met over a set amount of time slots defined by t_s (starting time) and t_f (finishing time). An example of this class of device is a dishwasher, where it has a set power consumption needed to complete the service and a set time that it requires to complete the service. Many appliances belonging to class K_1 do not complete the required service in one time period therefore the a vector of power consumption for each time period that the appliance is running and is defined as $\boldsymbol{p}_k = [p_k^1, \ldots, p_k^T]$. The mathematical expression can be given by [5]

$$P_k = \left\{ \sum_{t=t_s}^{t_f} p_k^t = E_k;\ p_k^t \epsilon \left[p_k^{min}, p_k^{max}\right];\ for\ t = t_s, \ldots, t_f;\ \ else\ \ p_k^t = 0 \right\} \quad (5.1)$$

For time periods outside of the defined time slots the power consumption is zero. The constraint $p_k^t \epsilon \left[p_k^{min}, p_k^{max}\right]$ defines the upper and lower limit of power consumption of each appliance while running.

The devices categorized as class K_2 have unspecified total energy requirement. The devices contained within this class are more challenging to determine an optimal scheduling time for due to the characteristic of having unspecified energy consumption. To overcome this issue a function that models the satisfaction of the consumer with the current energy consumption of the device. This function can be viewed as a penalty function, if the user decides to reduce consumption to cut costs; they will experience dissatisfaction in the performance of the device. An example of this kind of device would be lighting. With dimmers, the lights may be adjusted to various levels but in reducing the amount of energy consumed to save on money the light level may not be satisfactory. The function to be selected for modelling the dissatisfaction is chosen to be convex. As the consumption varies from the optimal point of satisfaction the 'cost' of comfort increases, adding to the minimization of the objective value. An example of this function can be seen in figure (5-2). Note that the user must define a time interval over which the device is to be running otherwise the function $G_k^t(p_k^t)$ will have a value of zero. To determine the values and nature of the dissatisfaction function user studies must be conducted in attempt to model each user comfort levels and the trade-off between satisfaction and cost reduction. One way in which this can be accomplished is through the system observing and logging consumption and tolerances of appliance load levels with reduction in cost to the consumer. From this the system can determine the required values needed for the dissatisfaction function. The energy consumption of class K_2 can be expressed as;

$$P_k = \{ p_k^t \epsilon [p_k^{min}, p_k^{max}]; \ for\ t = t_s, \dots, t_f, \quad else\ p_k^t = 0 \} \tag{5.2}$$

Equations (5.1) and (5.2) share many similarities but the major difference being the removal of the total energy requirement.

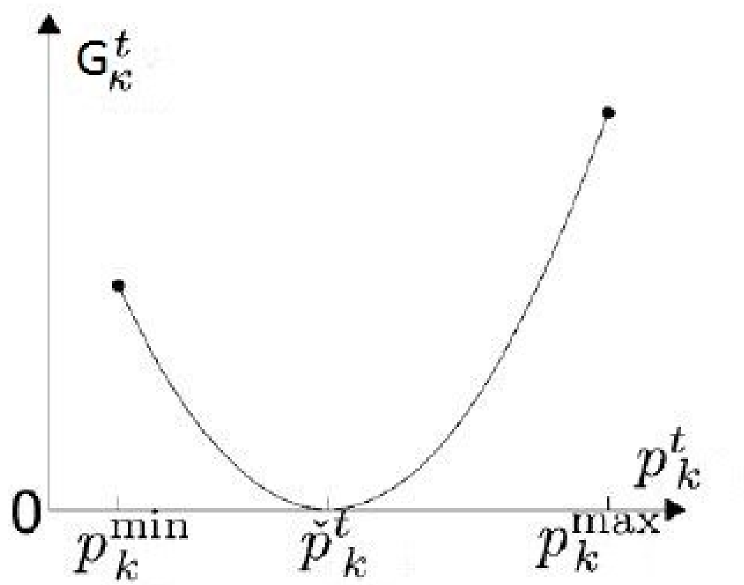

Figure 5-2. Penalty Function. [5]

5.3.2 Cost Minimization

In optimizing the consumers electricity cost payout to the supplier, an optimal load profile will be achieved [5]. To account of the change in price for various load levels, a cost function is introduced to model the costs incurred by the utility to provide electricity. The cost function must meet three requirements. These requirements are that it must be strictly increasing, it must be a convex function and it must be differentiable (or continuous) over the time slot being optimized. The third requirement is interesting in that it allows for piecewise cost functions to be used in the price scheme. From studying economic dispatch, it is understood that as the supply of a generator increases the cost to run the unit increases according to a quadratic function. This understanding leads to the first two requirements of the cost function under analysis in DSM. An example of a typical piecewise cost function can be seen in figure (5-3);

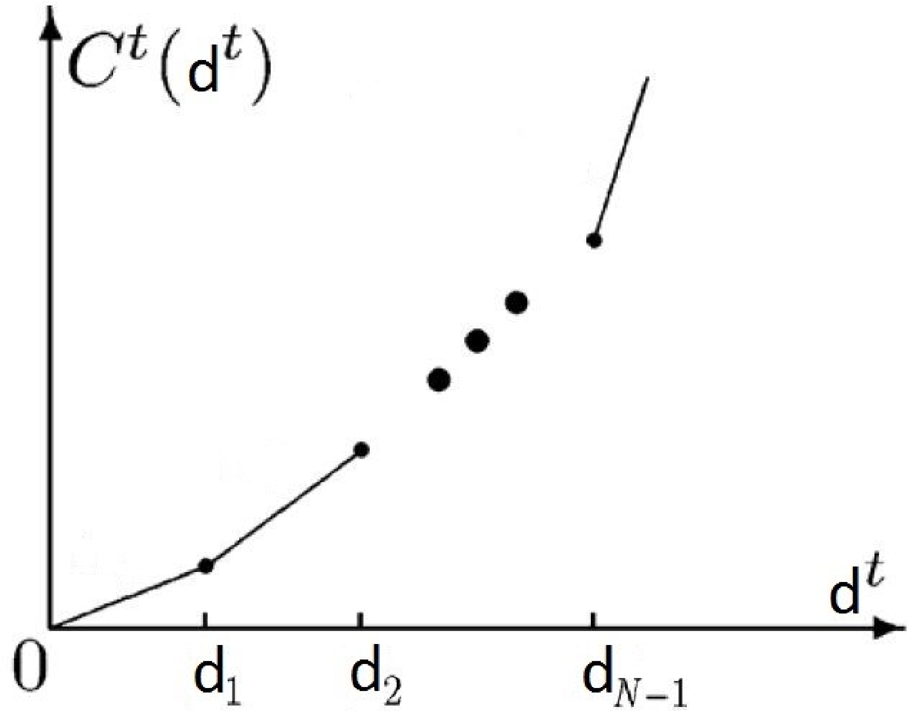

Figure 5-3. Piecewise Cost Function [5]

In the above figure $C^t(d^t)$ is the cost incurred by utility for supplying the consumers load denoted d^t. The cost function is therefore a function of the sum of energy consumption of the residence.

$$d^t = \sum_{k=1}^{N} (p_k^t) + p_0^t + p_m^t \tag{5.3}$$

The above equation is obtained from the power flow equations that the demand must equal the sum of the supply. Equation (5.3) holds for any residence containing no local generation. With the introduction of demand side units the above equation must contain the contribution supplied from local units. The modification of equation (5.3) results in;

$$d^t + \sum_{W=1}^{M} (R_w^t \, U_w^t) \geq \sum_{k=1}^{N} (p_k^t) + p_0^t + p_m^t \qquad (5.4)$$

where R_W^t is the power generated by the W[th] renewable source and U_w^t is the corresponding 'on' or 'off' status of the unit.

The residence can be viewed as an independent system with N appliances being fed by a source d^t and renewable sources R_W^t and R_S^t. Take the independent system and view it as N appliances required to satisfy the supply generated by the sources the result is analogous to that of the unit commitment problem. The results allow the cost function and constraints of the DSM problem to be set up very much like that of the unit commitment problem. The cost minimization problem can be constructed in a similar manner as that of the unit commitment problem but with the introduction of the penalty function and is defined as;

$$\min_{p,s} \sum_{t=1}^{T} \left[C^t(d^t) + \sum_{K \epsilon K_2} G_k^t(p_k^t) \right] \qquad (5.5.a)$$

$$subj.to: \quad p_0^t + p_m^t + \sum_{k=1}^{N} (p_k^t) \leq d^t + \sum_{W=1}^{M} (R_w^t \, U_w^t) \qquad (5.5.b)$$

$$\sum_{t\,=\,t_s}^{t_f} \sum_{k \in K_1} (p_k^t) = E_k; \; p_k^t \epsilon \left[p_k^{min}, p_k^{max} \right] \qquad (5.5.c)$$

$$0 \leq |d^t| \leq d_{max} \qquad (5.5.d)$$

The constraint defined in equation (5.5.d) is introduced to ensure a safety cap of power flow to account for security and reliability for the distribution network [5]. The absolute value is taken to account for times at which there is more local generation than local consumption therefore electricity can be sold back to the system. It must be noted that in cases where users could provide electricity to the grid, the grid would view the residence as a demand side generator and contracts would need to be established to account for user responsibilities of security. The objective function and constraints defined in equation (5.5) provide the required information for minimization.

5.3.3 Formulation of the Lagrangian Optimization Problem

With the function of $C^t(d^t)$ chosen to be convex, strictly increasing and differentiable an optimal point satisfying equation (5.5.b) can be obtained. Because the cost function chosen is convex there is an optimal point where (5.5.b) becomes an equality constraint, meaning that a feasible set exists. With the existence of the feasible values of p_k^t and d^t which cause (5.5.b) to hold as a strict inequality, the Slater's constraint qualification is met; resulting zero duality gap between the primal problem and the dual problem and the existence of optimal Lagrange multipliers [5, 12]. This is important to the optimization process since the dual variable problem may be used to find the optimal solution.

To develop the Lagrange equation for equation (5.5) let λ^t represent the Lagrange multipliers at each time period $t = \{1, \dots, T\}$. The Lagrange equation developed for the thesis problem is a modified form of the Lagrangian equation found in [5] and is given as;

$$L(p_k^t, d^t, \lambda^t) = \sum_{t=1}^{T}\left[C^t(d^t) + \sum_{K\epsilon K_2} G_k^t(p_k^t)\right]$$
$$+\sum_{t=1}^{T}\lambda^t\left[p_0^t + p_m^t + \sum_{k=1}^{N}(p_k^t) - d^t - \sum_{W=1}^{M}(R_w^t\, U_w^t)\right] \tag{5.6}$$

Constraints (5.5.c) and (5.5.d) are limitations on the values for the optimal solution and therefore are not present in the Lagrange equation. These values will by the optimization algorithm as will be seen in a later section. Using the dual variable problem defined in previous sections, the dual problem for this Lagrange equation is;

$$q(\lambda) = \min_{\substack{0\le|d^t|\le d_{max} \\ \sum_{t=t_s}^{t_f}\sum_{k\in K_1}(p_k^t)=E_k;\; p_k^t\epsilon[p_k^{min}, p_k^{max}]}} L(p_k^t, d^t, \lambda^t) \tag{5.7}$$

$$q^*(\lambda) = \max_{\lambda\ge 0} q(\lambda) \tag{5.8}$$

Since the problem has zero duality gap, as shown by Slater’s constraint qualification, the optimal values for the Lagrange multipliers can be obtained. Looking back to real-time pricing, if the price of electricity is optimized then so too is the load curve. The Lagrange multipliers in this problem act as the price signal between the consumer and the utility [13]. Thus, by optimizing the Lagrange multipliers we achieve the objective of reducing cost and lowering the load profile of the demand side with the presence of demand side generation.

At the optimal solutions for p_k^t and d^t obtained from solving the optimization problem in (5.5) the constraint of (5.5.b) becomes equal to zero. Looking at the dual problem of (5.7) the same optimal values for p_k^t and d^t are obtained for when λ^t is at its optimized value found from equation (5.8). This is due to the zero duality gap between the primal problem and the dual solution. The result is that with the use of the dual variable problem and Slater's conditions, the optimal values for p_k^t, d^t and λ^t are obtained. Furthermore the problem can be separated to view the individual costs incurred by the utility and consumer as shown in;

$$L = \sum_{t=1}^{T} (C^t(d^t) - \lambda^t d^t) + \sum_{t=1}^{T} \lambda^t (p_0^t + p_m^t)$$

$$+ \sum_{t=1}^{T} \left\{ \sum_{K \epsilon K_2} G_k^t(p_k^t) + \lambda^t \left[\sum_{k=1}^{K} (p_k^t) - \sum_{W=1}^{M} (R_w^t \, U_w^t) \right] \right\} \tag{5.9}$$

where the first term is the net cost incurred by the utility and the latter two are the costs incurred by the user. With the introduction of the demand-side generation the cost of the incurred by the user is further reduced. With the Lagrange problem formulated, an algorithm is used to solve this problem in the following section.

5.4 Optimization Algorithm

With the development of the cost profiles and the Lagrangian problem set, an algorithm to produce an optimized scheme is presented. The objective of the algorithm is to obtain an optimal day ahead scheduling period for each appliance participating in the demand-side management program. The minimization is based upon day-ahead hourly pricing scheme, known as real-time pricing, given to the management device located on the demand side. The algorithm achieves the objective by taking advantage of the dynamic programming methods of separating the problem into hourly sub-problems and using the Lagrangian relaxation solution technique known as the dual variable problem to solve the sub-problem independently of other time periods.

5.4.1 Optimization of the Objective Function

The criterion that the objective function must meet is that of the minimization of the cost payout to the utility from the customer with feasible level of user comfort. The feasibility of the user's comfort level is measured as a penalty factor of the cost trade-off between comfort and cost reduction, as mentioned in a previous section. The objective function, shown in equation (5.5.a), and the constraints are separable into a minimization at the utility and at the demand-side. In equation (5.9) it can be observed that the terms in the first summation are terms concerning the utility whereas the remaining terms relate to the demand-side. This allows for an optimization process to be split between the utility and the demand-side. With this view λ^t can be viewed as price signal between the utility and the demand side. The objective to minimize the payout to the utility translates to the optimization of the price signal, λ^t.

To achieve the objective of cost minimization the dual variable solution is used. Equation (5.7) states that the first step is to minimize the Lagrange equation with respect to the demand and each appliance load for a constant value of the Lagrange multiplier. From optimization theory of the Lagrange equation, it is known that to find an extremal the derivative of a convex Lagrange equation is taken with respect to the minimization variable and is equated to zero. Due to the characteristic of equation (5.9) being convex the derivatives can be taken to find the values of d^t and p_k^t that minimize the problem of (5.7) as shown by;

$$|d^t| = \min\left[\left(C^{t'}\right)^{-1} * \lambda^t, d_{max}^t\right] \tag{5.10}$$

$$p_k^t = \min_{k \in K_2}\left\{\max\left[\{G_k^{t'}(p_k^t)\}^{-1} * (-\lambda^t), p_k^{min}\right], p_k^{max}\right\} \tag{5.11}$$

where $\left(C^{t'}\right)^{-1}$ is the inverse slope of the utility incurred cost curve and $\{G_k^{t'}(p_k^t)\}^{-1}$ is the inverse slope of the satisfaction penalty cost curve. Note the (5.11) does not optimize for appliances contained in the class K_1 because there is no corresponding convex penalty cost function. Instead, a heuristic approach must be taken to optimize the scheduling time allocated for each appliance in class K_1. The approach taken to schedule shift-able loads is explained in the following subsection.

5.4.2 Heuristic Method to Solving Class K_1 Appliance Schedules

A heuristic approach must be taken for the scheduling of the appliances belonging to class K_1, or the shift-able loads [5, 6]. The major difference between the two classes is that shift-able loads have a set amount of energy consumption required to finish the service that it provides [5]. Since curtail-able loads have a cost penalty function that governs the energy level at which they operate, the appliances load levels belonging to class K_2 can be solved for using a mathematical approach explained in the previous section. For the same method used for class K_2, class K_1 load levels are undefined within the bounds of the device limitations and can have any value as shown;

$$\frac{dL}{d\,p_k^t} = \lambda^t = 0; for\ k \in K_1$$

The above equation shows that there does not exist sufficient conditions to solve for p_k^t due to the non-convex nature of the minimization problem defined by shift-able loads. However, from the scheduling time requirements defined by the user and the maximum and minimum load level requirements defined by the appliance; a scheduling method can be created.

The objective of the heuristic method is to schedule the appliance loads to times that result in the minimization of cost to the consumer. The price signals sent to the local meter contain the information required to minimize cost payout for operating the appliances. Times where demand is low, a lower price is set as an incentive for consumers to shift load levels. The method introduced takes advantage of this information and allocated loads to the time periods where the cost to run the appliance is lowest. However, the time periods in which the load is scheduled must fall within a user defined feasible time frame. The steps taken for the load shifting method is as follows;

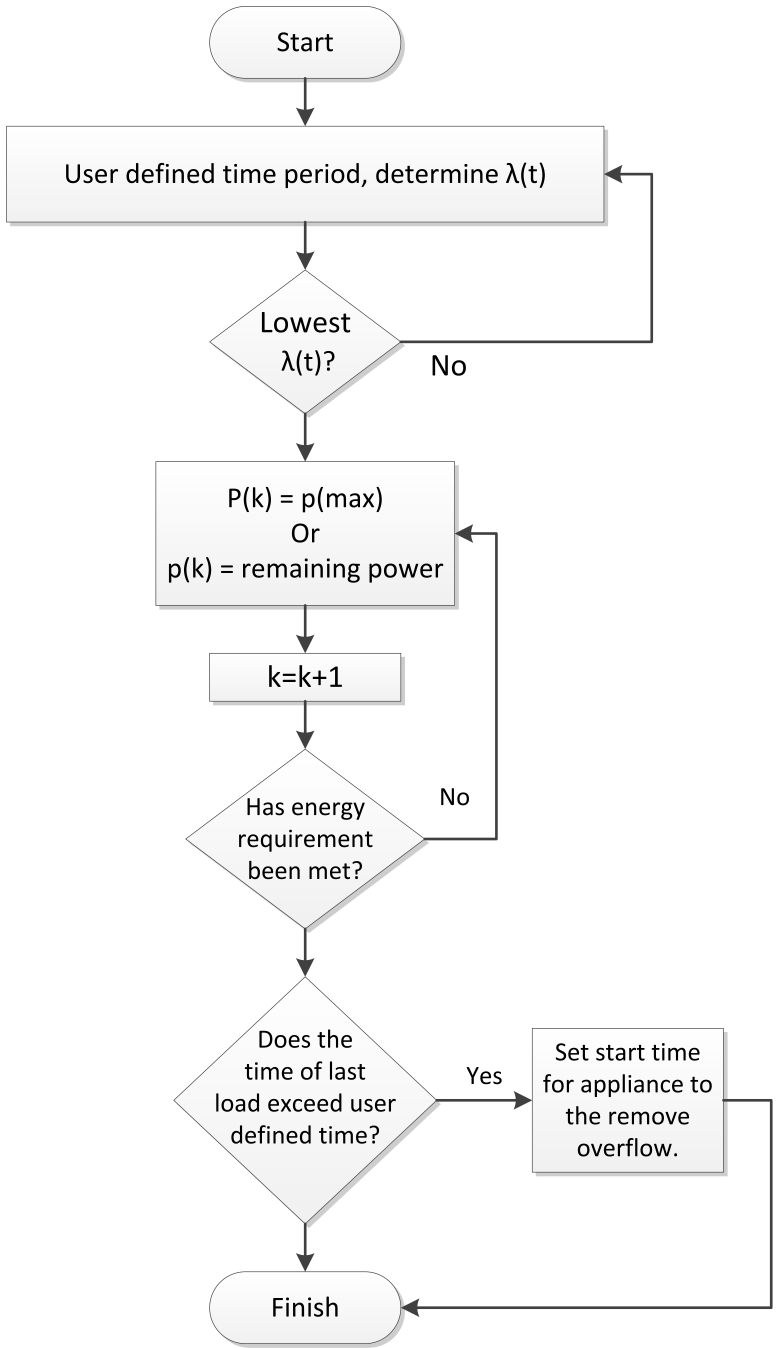

Figure 5-4. Load Shifting Method [5]

The above flowchart show demonstrated the heuristic method used for shift-able loads. If the allowable time needed for the appliance to finish its process exceeds the user defined time period, the appliance is deemed unfeasible and the user must relax the time requirements, forfeit the process or pay a higher rate to run the appliance at another time.

The method used for the scheduling of class K_1 is now defined and meets the required condition outlined in (5.7) of the optimization process. With the requirements of cost minimization of both classes of appliances and by the cost associate with supplying the demand from the utility, the next stage of the dual variable problem is the maximization of (5.7) in terms of the Lagrange multipliers for each hour, λ^t.

5.4.3 Subgradient Iteration Method

To minimize the objective function of the primal problem, the dual variable method states that the Lagrange equation must be maximized with respect to the Lagrange multiplier. This is mathematically represented by equation (5.8). Because the Lagrange multiplier does not have a specified upper bound, the subgradient method is used to solve for the optimal value of the Lagrange multipliers. The subgradient method is advantageous for the solution process of lambda because of its capability to solve convex unconstrained minimization problems effectively. It uses the gradient search method to solve for the point of steepest decent or increase in slope of the minimization function. The mathematical representation is shown as;

$$\lambda_{new}^t = \lambda_{old}^t + \alpha \left[p_0^t + p_m^t + \sum_{k=1}^{N} (p_k^t) - d^t - \sum_{W=1}^{M} (R_w^t\, U_w^t) \right] \tag{5.12}$$

In the above equation, λ_{new}^t is the new value of lambda, λ_{old}^t is the previous value of lambda and α is an adjustment value used to make the gradient search converge to a solution. The previous chapter on optimization discusses the value of α in more detail. The term in the brackets of equation (5.12) is the derivative of the Lagrange equation with respect to the Lagrange multiplier. The gradient search method is moved along the curve to find the point of greatest decrease or increase in slope, this equates to the normal of the slope have no components in the λ^t direction.

Note that from the structure of the Lagrange equation in (5.9) the process of minimization is done separately between the utility and the demand side scheduling device and the information is telecommunicated between the two. The information sent from the utility is that of the hourly day-ahead prices represented as the Lagrange multipliers. The information of price, in conjunction with available generation local to the demand side, is used by the demand side scheduling device to determine the amount of energy that will be purchased from the utility. This value is defined as;

$$d^t = p_0^t + p_m^t + \sum_{k=1}^{N} (p_k^t) - \sum_{W=1}^{M} (R_w^t\, U_w^t) \tag{5.13}$$

The information is telecommunicated to the utility which uses it to update the values for the day ahead pricing and the process repeats to balance the load profile [5]. The subgradient method explained here can be found in [5, 6, 8, 9, 11] and is explained to aid in the solution to the demand-side management scheduling.

5.5 Sensitivity

The sensitivity analysis examines the change in the objective value of equation (5.5.a) due to a change in the parameters of the cost functions. In other words, by examining the parameters of $C^t(d^t)$ or $G_k^t(p_k^t)$ a change in the objective value is evaluated. The parameters of the cost function may be the scalar value 'b' in $C^t(d^t) = a + bd^t + c[d^t]^2$.

The importance of the sensitivity lies in the ability to determine a change in the objective value for a change in a parameter. This testing is done through derivatives of the objective value with respect to the parameter that is being changed. From the derivatives, three properties of the sensitivity can be seen; the sign of the derivative indicates a decrease or increase of the objective value with respect to the parameter. Second, the more dominant parameters can be identified. Third is that the value of the derivative can be multiplied to the change in the parameter to identify the change in the objective value [5].

The assumptions made on the cost function and penalty function is that they are convex and continuous differentiable. The constraints of the objective function are also assumed to hold to the Slater constraint qualification. To develop the sensitivity equations for the penalty function and the cost function assume that there exists optimal values p_k^{t*} and d^{t*} for corresponding values of each parameter. The two functions making up the objective value are;

$$C^t(d^t) = a + bd^t + c[d^t]^2$$

$$G_k^t(p_k^t) = (e_k p_k^t - f_k)^2$$

$$Obj = \sum_{t=1}^{T} \left[C^t(d^t) + \sum_{K \epsilon K_2} G_k^t(p_k^t) \right]$$

Note that the parameter 'f' is the optimal value of the appliance load of p_k^t that result in a zero penalty cost and will be excluded because to change the value will change the whole problem. Since $C^t(d^t)$ and $G_k^t(p_k^t)$ are both continuous and differentiable in terms of p_k^{t*}, d^{t*}, 'b', 'c', 'e' and then under the regularity conditions to be explained shortly, the sensitivities at each time period are as follows;

$$\frac{\partial Obj^t}{\partial b} = \frac{\partial C^t(d^t)}{\partial b} = d^t \qquad (5.14.a)$$

$$\frac{\partial Obj^t}{\partial c} = [d^t]^2 \qquad (5.14.b)$$

$$\frac{\partial Obj^t}{\partial e_k} = 2e_k {p_k^t}^2 - 2f_k p_k^t \qquad (5.14.c)$$

For the above equations to hold, a regularity condition must hold. The regularity condition requires that the gradient vectors corresponding to the equality constraints are linearly independent [14, 15]. By examining the constraints in equation 5.5.b and 5.5.c it can be seen that the condition is met for each time period under consideration.

To determine which parameter has the largest effect on the objective values, the equations (5.14.a – 5.14.c) will be evaluated for a case of two curtail-able loads with nominal values of 12kw and 15kw respectively. The objective value under consideration is the cost payout to the consumer. Table (5-1) shows the change in the objective value for a 1%, 5% and 10% change in the parameter under sensitivity observation.

Table 5-1. Sensitivity of Objective Function

Objective Value Parameter	Δ = 0.01	Δ = 0.05	Δ = 0.1
b	23.533	117.66	235.33
c	104.86	524.29	1048.6
e_1	-1.89	-9.49	-18.99
e_2	-2.01	-10.05	-20.09

From observing the results of Table (5-1) it can be easily seen that the objective function is most sensitive to changes in the 'c' parameter of the cost function. Also, for changes in the parameter of the penalty function there are small changes in the cost savings. This is expected because only one appliance's effect on the overall cost is being analyzed whereas the cost function of demand includes all devices and loads. Upon further observation in the next section it will be shown that the savings will come from a reduction in energy purchased from the utility in conjunction with the availability of local generation. It must be noted that a negative Δ will result in a reduction in the objective value by the same value shown in Table (5-1).

5.6 Analytical Results

The results presented here compare the differences of the demand-side management solution with and without generation local to the demand side. Separate cases will also include various numbers of shift-able and curtail-able loads in the model. The time horizon for the pricing scheme is day ahead with time periods one hour in length resulting in 24 periods for the scheduling horizon. The scheduling time begins at 1a.m. and continues through until 12a.m. of the next day. The base load is taken to be constant throughout the day and the appliance process labeled 'must on' are added to the base load levels. Figure (5-5) shows the curve of the base load with the addition of the 'must on' load for case 1. The various configurations for the controllable loads are giving in the following cases.

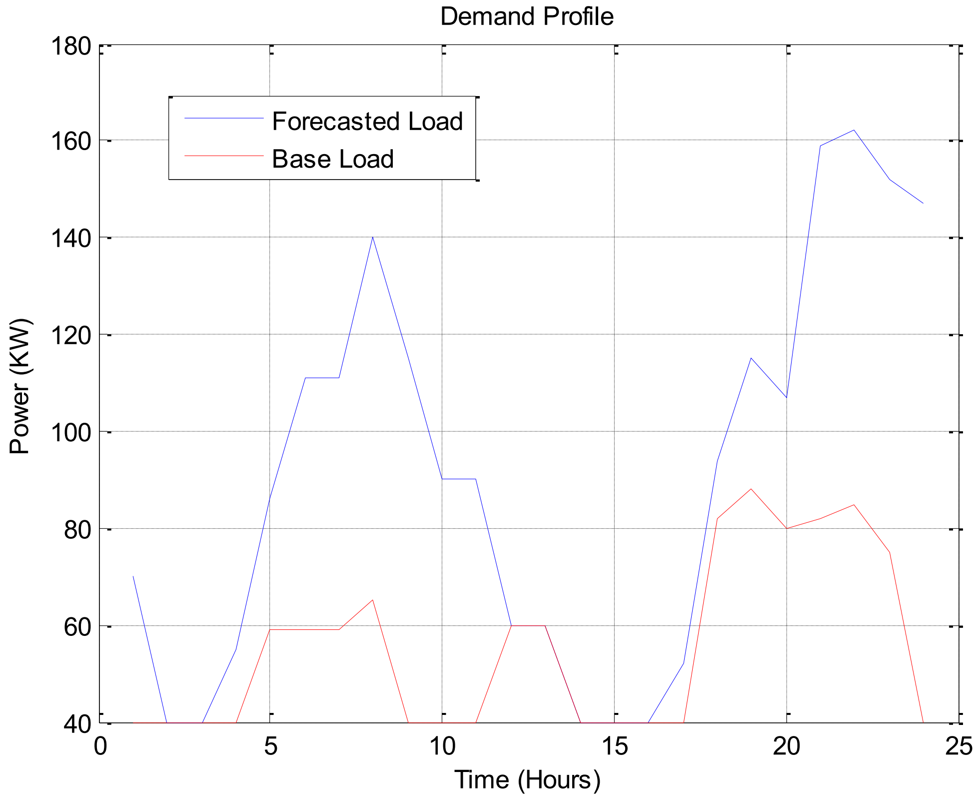

Figure 5-5. Demand Profile Vs. Base Load for Case 1.

5.6.1 Case 1: Three Shift-able Loads and Two Curtail-able Loads

The case under study in this section has the configuration of three shift-able loads and two curtail-able loads. The amount of generation available to the user are two 15 KW machines, the forecasted generation for the next scheduling period is shown in figure (5-6). The scheduling optimization runs until the term multiplied by the Lagrange equation in equation (5.6) is equivalent to zero or the error is sufficiently small.

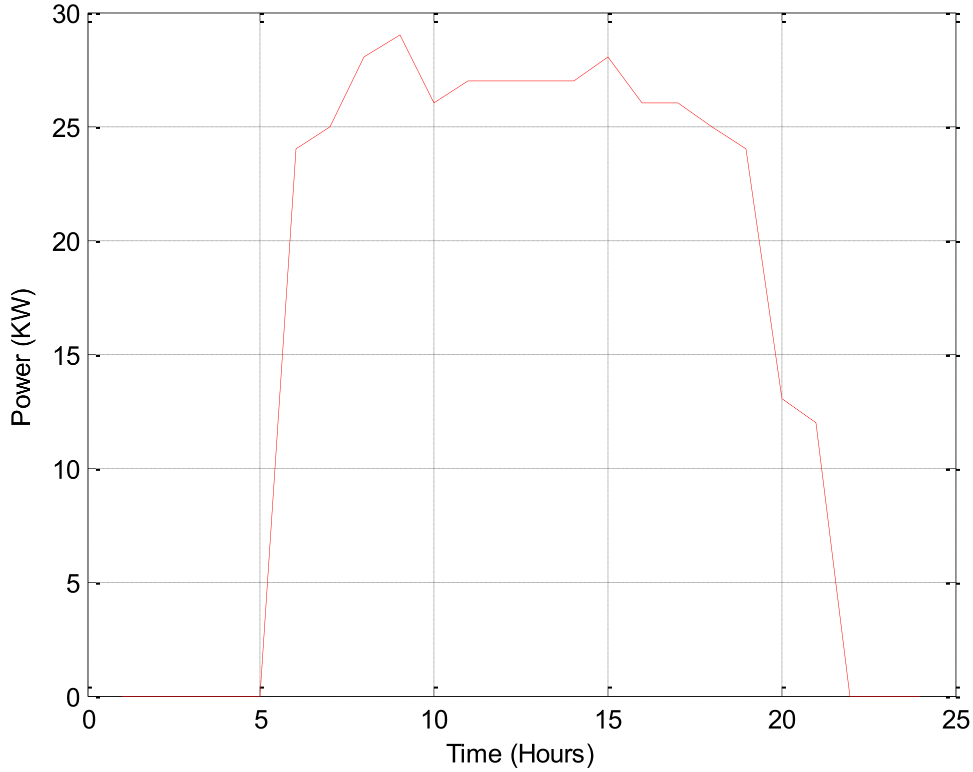

Figure 5-6. Case 1 Forecasted Local Generation

The parameters for each individual shift-able load including the user define run times and the total required loads are;

Table 5-2. Case 1 Shift-able Load Properties.

Shift-able Load	Start Time (Hour)	End Time (Hour)	Total Power (KWh)	Max Energy per Hour (KW)
1	8a.m.	3p.m.	200	50
2	9p.m.	4a.m.	200	50
3	6a.m.	6p.m.	100	25

For loads that are to be curtailed the user selected parameters for each load is defined by the following table;

Table 5-3. Case 1 Curtail-able Load Properties

Curtail-able Load	Run Time (Hour)	Optimal Energy (KWh)	Minimum Curtailment Energy (KWh)
1	5a.m. – 7a.m. 5p.m. – 12a.m.	12	8
2	4a.m. – 6a.m. 7p.m. – 12a.m.	15	10

The objective of the optimization scheme is to optimize consumer payout to the utility when local generation is available. The way in which the cost is minimized is though the management and scheduling of the consumer's loads. With the defined load parameters above and the generation forecast, in figure (5-6), the optimized day ahead load schedule generated by the algorithm is;

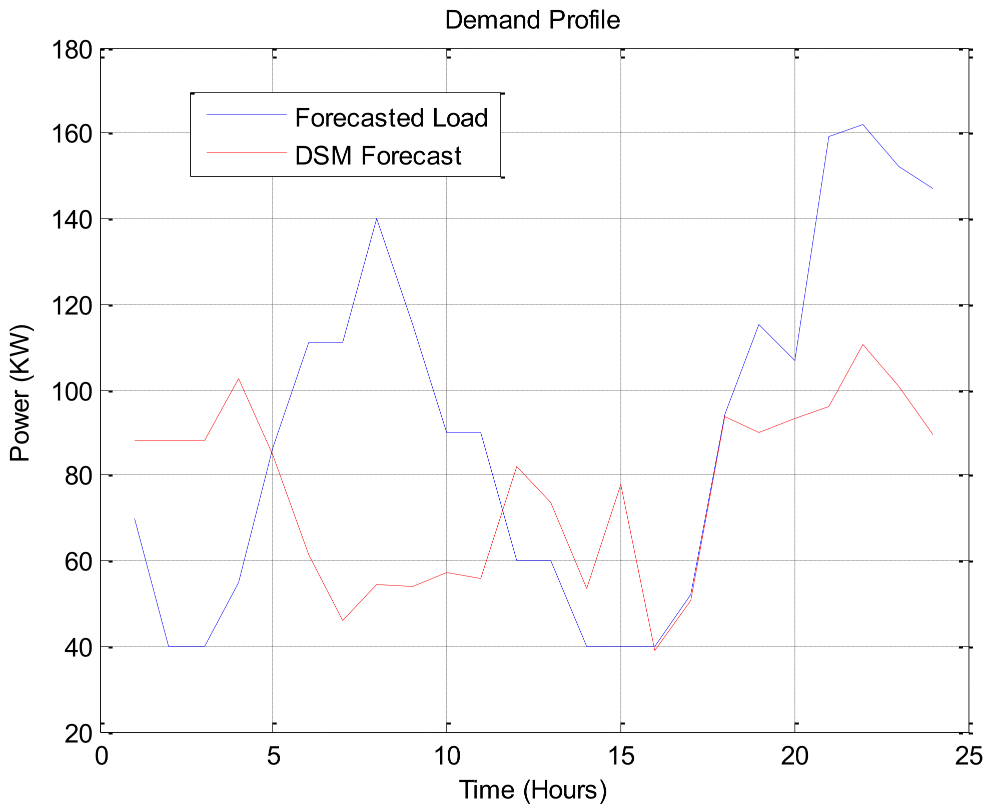

Figure 5-7. Case 1 DSM Profile with Generation

The above figure can be compared to that of the DSM profile without available generation, which is shown in figure (5-8) below.

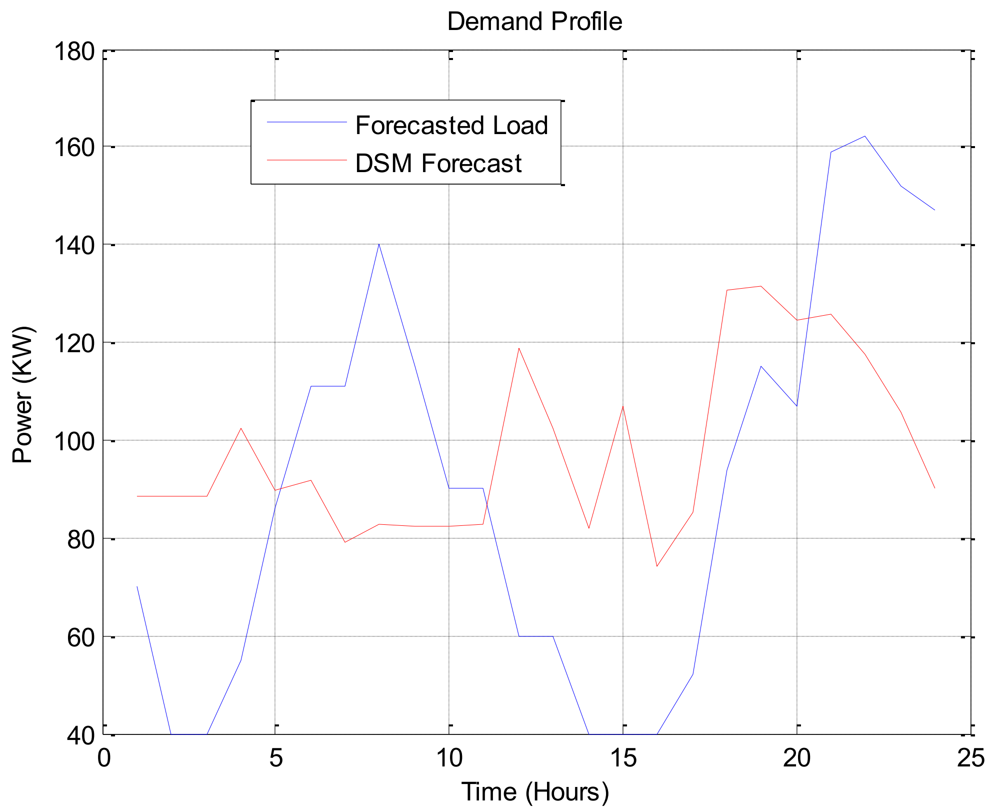

Figure 5-8. Case 1 DSM Profile without Generation

From observation of the separate graphs and from a utility perspective a more satisfactory load profile is formed from the scheduling algorithm. This is due to the reduction in the magnitude of the peak load times and the low load levels have been elevated. For utilities, this creates a more feasible usage of assets due to the reduction in cost incurred as the result from a flattened load profile.

At the demand side, a change in price highly depends upon the original pricing and original load of the consumer. Therefore in order to compare results between the DSM schedule with and without the availability of generation a comparison between figure (5-9) and figure (5-10) is made. Figure (5-8) shows that for a DSM schedule without generation the average consumer payout is larger than that of the average payout for a residence with available generation during the scheduling horizon, shown in figure (5-10). Table (5-4) compares the objective values with and without generation. The difference between the two is attributed to the presence of generation. The presence of generation gives way to the added benefit for curtail-able loads to operate closer to optimal levels while maintain lower payout as can be seen in the lower penalty cost of Table (5-4). The analysis done can be applied to a larger case with a larger number of schedulable loads as will be shown in the following section.

Table 5-4. Case 1 Objective Values of DSM

	Objective Value	Penalty Cost	Demand Cost
With Generation	1418.0	4.84	1413.16
Without Generation	1910.3	5.57	1904.73

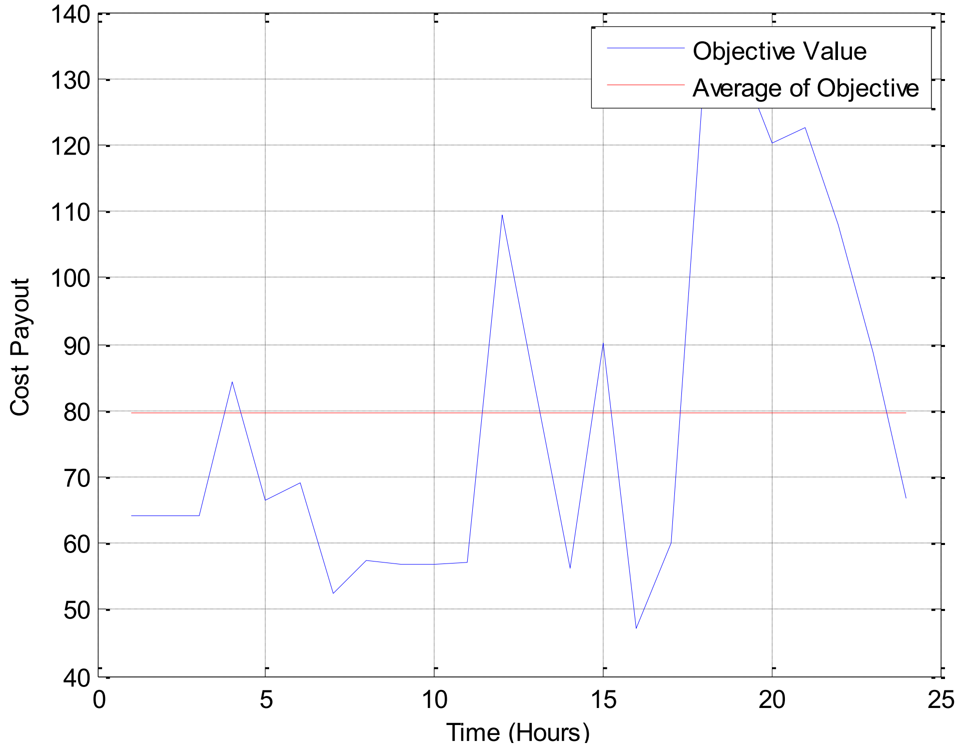

Figure 5-9. Case 1 Objective Value vs. Average without Generation

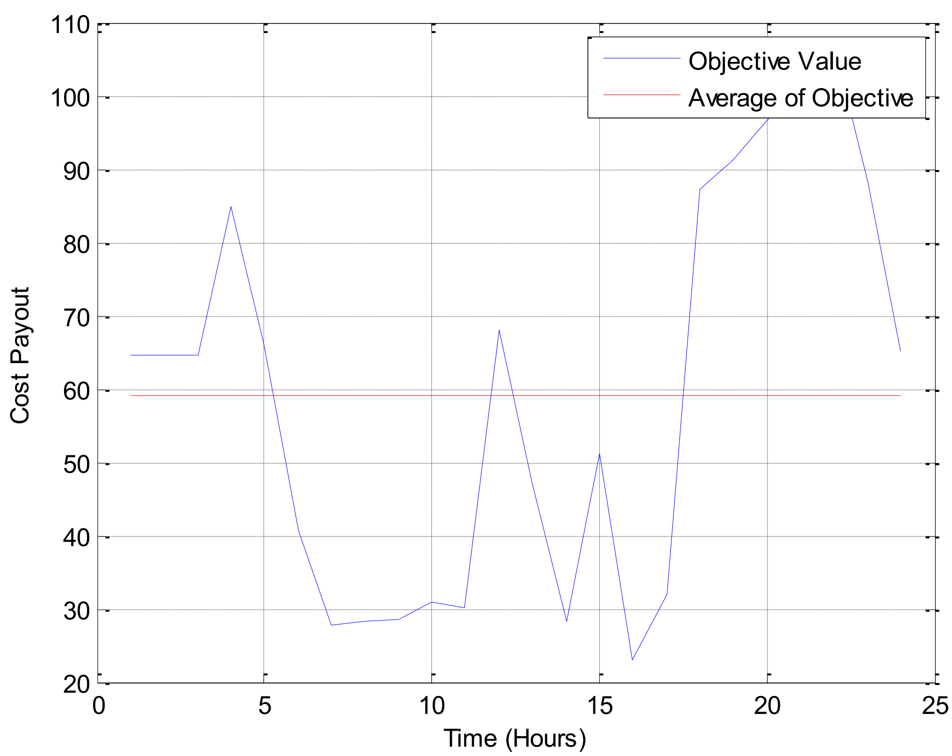

Figure 5-10. Case 1 Objective Value vs. Average with Generation

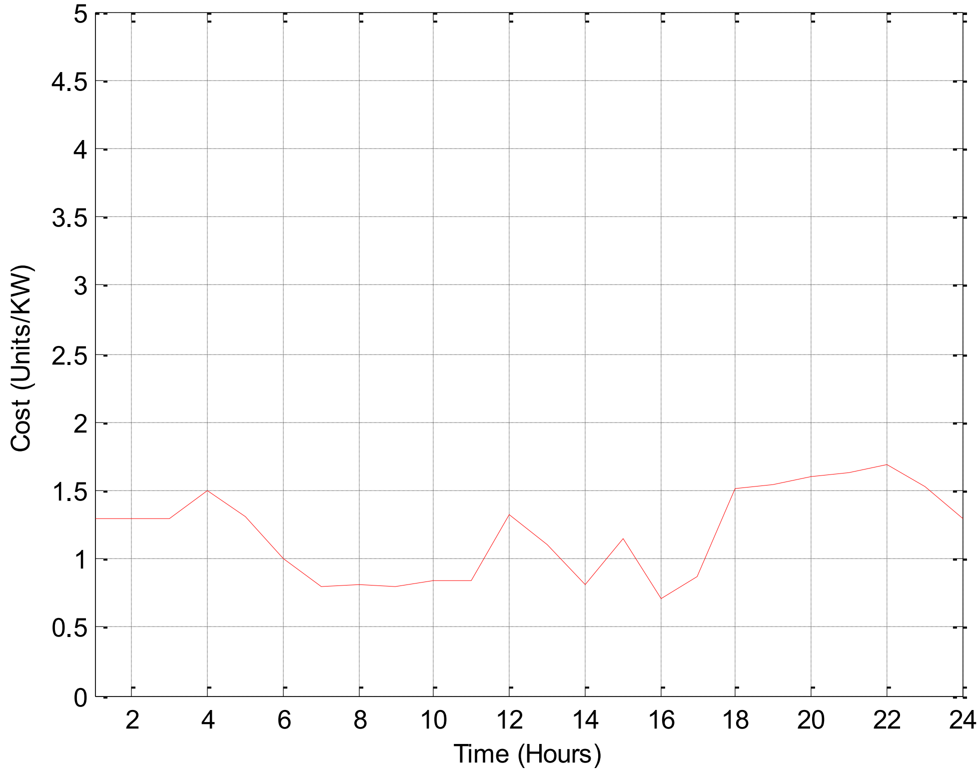

Figure 5-11. Case 1 Optimal Lambda with Generation

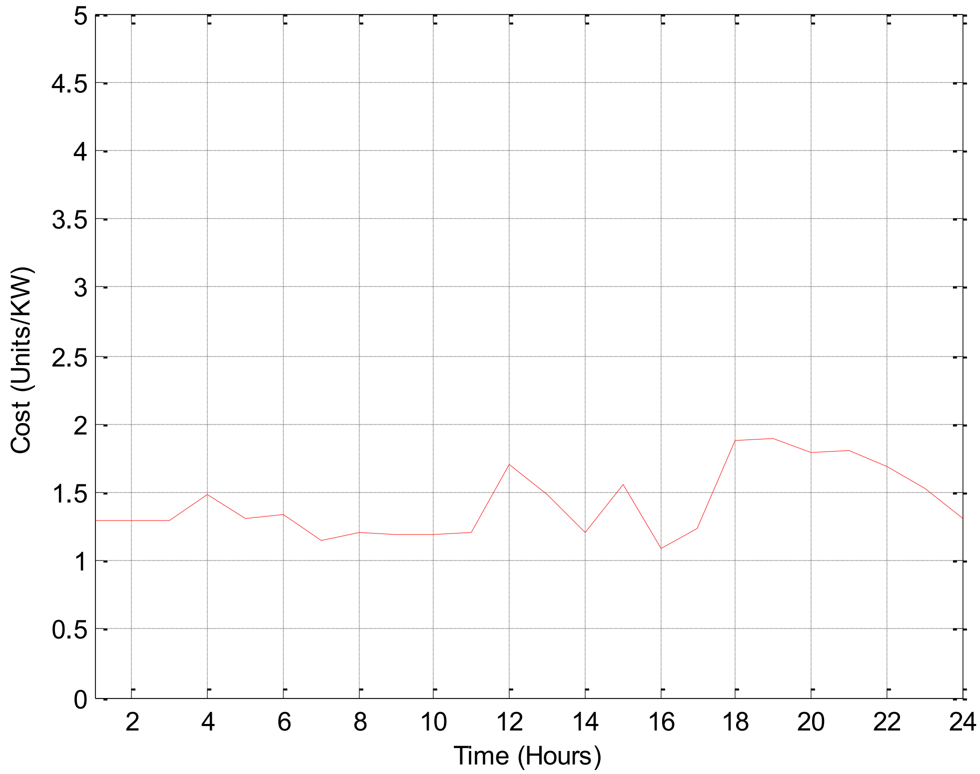

Figure 5-12. Case 1 Optimal Lambda without Generation

The figures (5-11) and (5-12) show the optimal Lagrange multipliers. The presence of generation results in lower multipliers as expected because they are the price signals sent from the utility to the residential unit. Referring back to an optimal economical market as demand decreases price should also decrease to create and incentive to buy more of a commodity. The involvement of the demand side is shown to have created a more economical electricity markets as was expected.

5.6.2 Case 2: Five Shift-able Loads and Six Curtail-able Loads

To further the results obtained in case 1, a larger number of scheduled devices are observed. The case under study in this section has the configuration of five shift-able loads and six curtail-able loads. Like the previous analysis, the amount of generation available to the user is a set of 15 KW machines; the forecasted generation for the next scheduling period is shown in figure (5-13). The scheduling optimization runs until the term multiplied by the Lagrange equation in equation (5.6) is equivalent to zero or the error is sufficiently small.

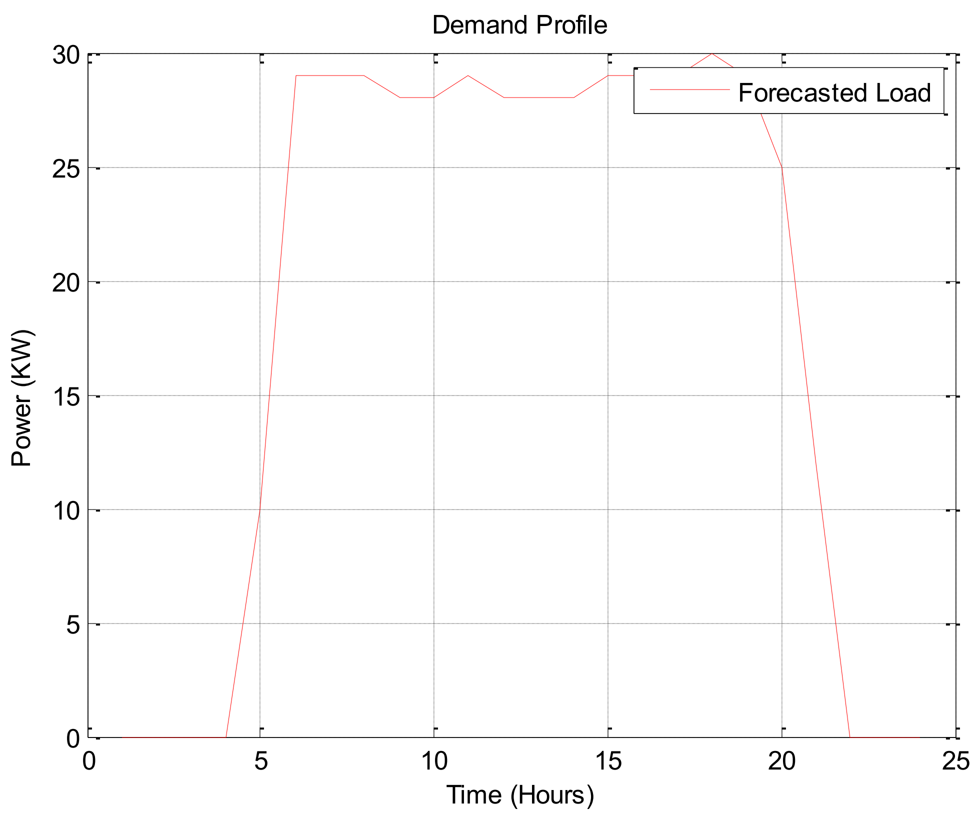

Figure 5-13. Case 2 Forecasted Local Generation

The parameters for each individual shift-able load including the user define run times and the total required loads are;

Table 5-5. Case 2 Shift-able Load Properties.

Shift-able Load	Start Time (Hour)	End Time (Hour)	Total Power (KWh)	Max Energy per Hour (KW)
1	8a.m.	3p.m.	200	50
2	9p.m.	4a.m.	200	50
3	6a.m.	6p.m.	100	25
4	7p.m.	6a.m.	100	30
5	6a.m.	5p.m.	210	30

For loads that are to be curtailed the user selected parameters for each load is defined by the following table;

Table 5-6. Case 2 Curtail-able Load Properties

Curtail-able Load	Run Time (Hour)	Optimal Energy (KWh)	Minimum Curtailment Energy (KWh)
1	5a.m. – 7a.m. 5p.m. – 12a.m.	12	8
2	4a.m. – 6a.m. 7p.m. – 12a.m.	15	10
3	1p.m. – 4p.m. 11p.m. – 5a.m.	18	11
4	5a.m. – 7a.m. 1p.m. – 8p.m.	15	10
5	2a.m. – 10a.m.	16	12
6	1a.m. – 12a.m.	15	12

The objective of the optimization scheme is to optimize consumer payout to the utility when local generation is available. The way in which the cost is minimized is though the management and scheduling of the consumer's loads. With the defined load parameters above and the generation forecast, in figure (5-13), the optimized day ahead load schedule generated by the algorithm is;

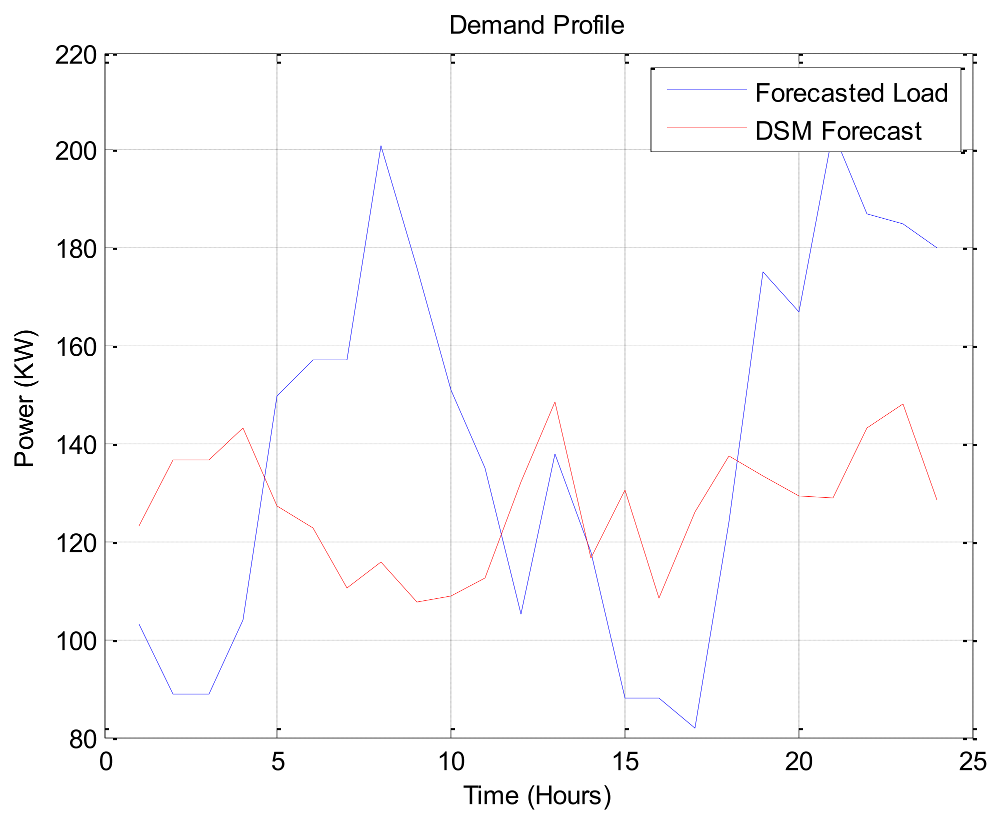

Figure 5-14. Case 2 DSM Profile With Generation

The above figure can be compared to that of the DSM profile without available generation, which is shown in figure (5-15) below.

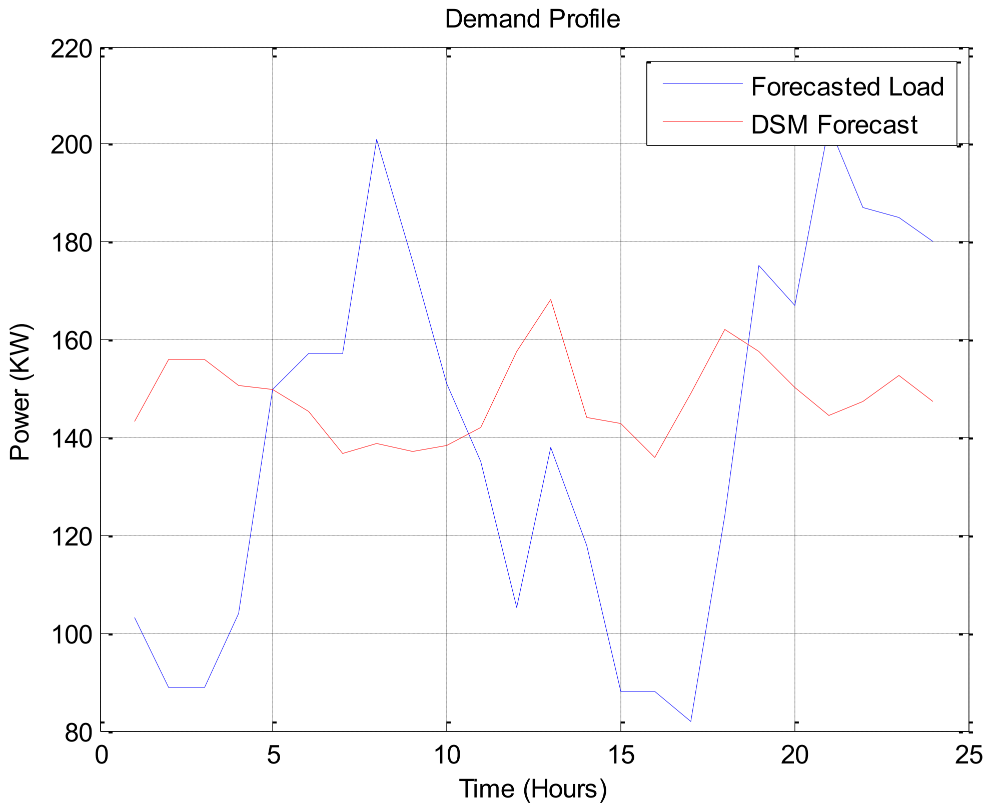

Figure 5-15. Case 2 DSM Profile without Generation

From observation of the separate graphs and from a utility perspective a more satisfactory load profile is formed from the scheduling algorithm. This is due to the large reduction in the magnitude of the peak load times and the low load levels have been elevated. For utilities, this creates a more feasible usage of assets due to the reduction in cost incurred as the result from a flattened load profile.

At the demand side, a change in price highly depends upon the original pricing and original load of the consumer. Therefore in order to compare results between the DSM schedule with and without the availability of generation a comparison between figure (5-16) and figure (5-17) is made. Figure (5-15) shows that for a DSM schedule without generation the average consumer payout is larger than that of the average payout for a residence with available generation during the scheduling horizon, shown in figure (5-16). Table (5-7) compares the objective values with and without generation. The difference between the two is attributed to the presence of generation. The presence of generation gives way to the added benefit for curtail-able loads to operate closer to optimal levels while maintain lower payout as can be seen in the lower penalty cost of Table (5-7). The analysis done can be applied to a larger case with a larger number of schedulable loads as will be shown in the following section.

Table 5-7. Case 2 Objective Values of DSM

	Objective Value	Penalty Cost	Demand Cost
With Generation	6907.5	45.76	6953.26
Without Generation	9187.8	56.72	9244.52

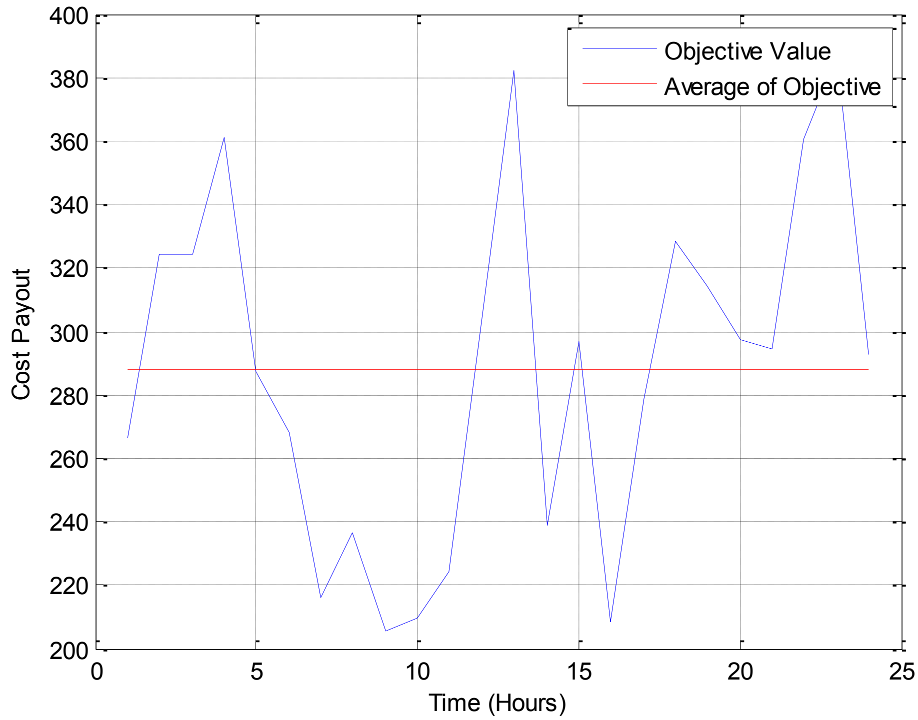

Figure 5-16. Case 2 Objective Value vs. Average without Generation

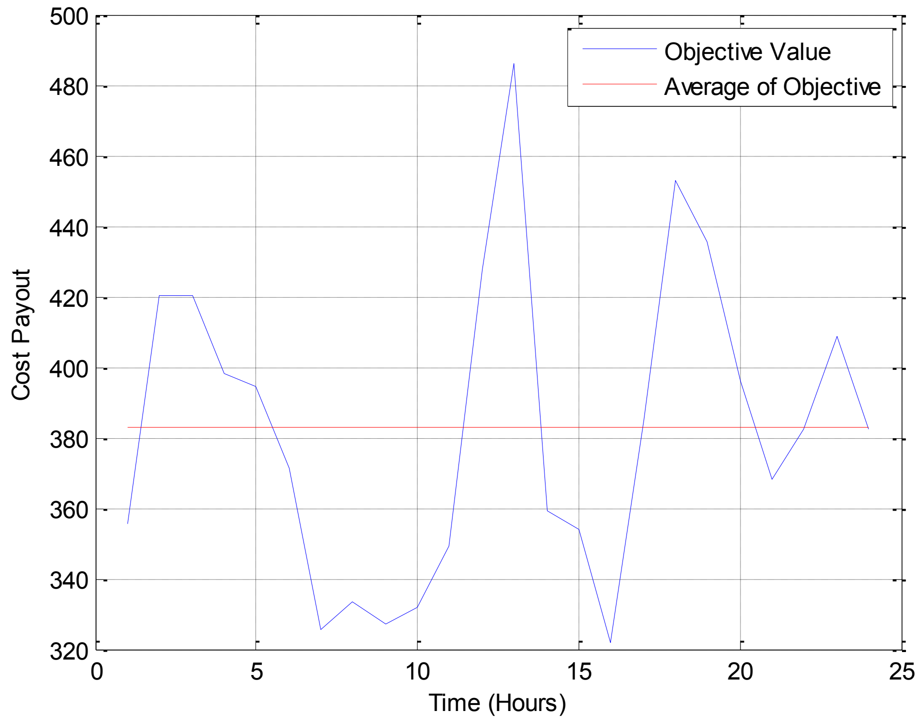

Figure 5-17. Case 2 Objective Value vs. Average with Generation

The same comparison from Case 1 about the optimal lambda values with and without generation can be made. The figures (5-18) and (5-19) show the optimal values of lambda obtained for Case 2.

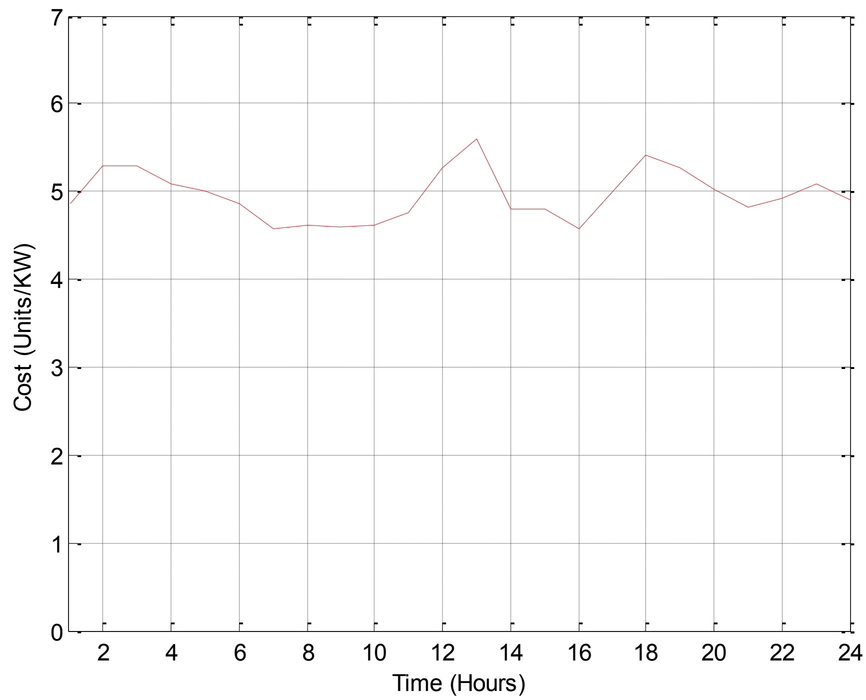

Figure 5-18. Case 2 Lambda without Generation

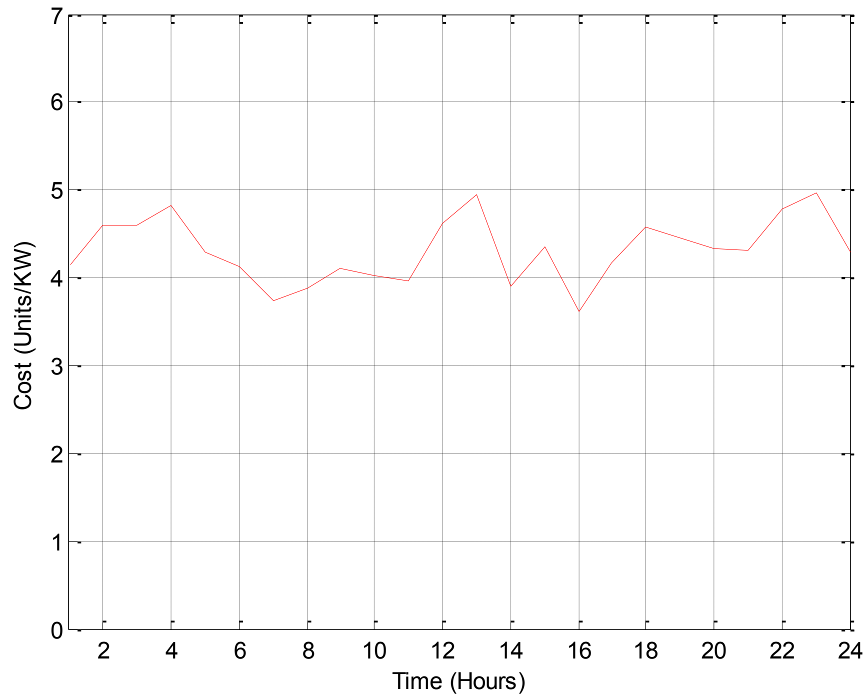

Figure 5-19. Case 2 Lambda with Generation

From the above results, it is shown that with the incorporation of distributed generation the payout and pricing levels, seen by lambda, are reduced further than those of DSM systems without available generation. The concept of incorporating renewable distributed generation into the DSM optimization is novel to the research in this thesis. The results obtained pertain to a single residential unit.

Chapter 6: Conclusions and Future Work

The following chapter summarizes the results obtained and the contributions. The future work is also explained.

6.1 Conclusions

In the thesis the requirements and analysis of the demand-side management scheme with distributed generation local to the consumer were discussed. Chapter 2 reviews issues faced by the current electricity market and alternative price schemes. Previous work in the field of demand-side management is also discussed. Chapter 3 discusses optimization techniques used by other researches to solve the demand-side management problem. It details the techniques used by the thesis to obtain and optimized scheduling horizon. Chapter 4 outlines the unit commitment problem to optimally schedule generation units to a forecasted load demand. In Chapter 5 two separate cases of device scheduling was analyzed with and without consumer local generation. The incorporation of renewable distributed generation results in lower demand levels and price paid for power by the consumer. The novel idea of optimizing appliance run times with the availability of distributed renewable generation improves the results obtained when studying demand side management optimization case studies.

These results follow economic theory in that as the demand for a commodity is reduced, the price will decrease to create and incentive to purchase the commodity until and equilibrium point is reached. The importance of this work is two-fold. First, a management scheme is needed in response to the increased interest of local generation caused by consumer's attempts to reduce electricity expenditures. Second, the cost reduction seen by the utilities and electricity distribution companies from having an optimized load profile is more beneficial than current market schemes. The results shown accomplish both objectives of reducing cost to the consumer and creating a more desirable load profile for utilities.

6.2 Future Work

The findings of this thesis show that more work can be done to integrate renewables and consumer generation with the current electricity grid. Future work in this area can be a study to see how the reliability of the forecasted consumer generation affects the optimized values for the electricity price. A weighting value could be assigned to each generation unit to adjust for the reliability and the effect it has on the objective value. This research could be expanded to explore the reduction of emission levels from the optimization of the load profile using demand-side management. The work done can be expanded to incorporate multiple residences and aim to optimize all loads on a substation feeder.

References

[1] Althaher, S. Z., Mutale, J., "Management and Control of Residential Energy through Implementation of Real Time Pricing and Demand Response", University of Manchester, IEEE, 2012

[2] Albadi, M. H., El-Saadany, E. F., "Demand Response in Electricity Markets: An Overview", University of Waterloo, IEEE, 2007

[3] Kirschen, Daniel S., "Demand-Side View of Electricity Markets", IEEE Transactions on Power Systems, vol. 18, no. 2, May 2003

[4] Mohsenian-Rad, A. H., Leon-Garcia, A., "Optimal Residential Load Control with Price Prediction in Real-Time Electricity Pricing Environments", IEEE Transactions on Smart Grid, vol. 1, no. 2, Spetember 2010

[5] Gatsis, N., Giannakis, G. B., "Residential Load Control: Distributed Scheduling and Convergence with Lost AMI Messages", IEEE Transactions on Smart Grid, vol. 3, no. 2, June 2012

[6] Mohsenian-Rad, A. H., et. Al., "Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid", IEEE Transactions on Smart Grid, vol. 1, no. 3, December 2010

[7] Roop, J. M., et. Al., "Price Response can Make the Grid Robust: An Agent-Based Discussion", Pacific Northwest Nation Laboratory, Richland, WA, 2005

[8] Momoh, J. A., "Electric Power System Applications of Optimization," 2nd Edition", CRC Press, Boca Raton, FL, 2009

[9] "Application of Optimization Methods in Power System Engineering", IEEE Tutorial Course Text 76CH1107-2-PWR, IEEE, New York, 1976

[10] Wilde, P. J., Beightler, C.S., "Foundations of Organization", Prentice-Hall, Englewood Cliffs, NJ, 1967

[11] Wood, A. J., Wollenberg, B. F., "Power Generation, Operation and Control," 2nd Edition", John Wiley & Sons Inc., Somerset, NJ, 1996

[12] Ipakchi, A., Albuyeh, F., "Grid of the Future", IEEE Power Energy Mag., vol. 7, no. 2, pp. 52-62, Mar.-Apr. 2009

[13] Bertsekas, D. P., "Nonlinear Programming", Belmont, MA, Athena Scientific, 1999

[14] Fiacco, A. V., "Introduction to Sensitivity and Stability Analysis in Nonlinear Programming", New York, Academic, 1983

[15] Castillo, E., et. Al., “A Closed Formula for Local Sensitivity Analysis in Mathematical Programming”, Eng. Optim., vol. 38, no. 1, pp. 93-112, January 2006

[16] Park, Joon-Hyung, et. Al., “Modified Programming Based Unit Commitment Technique”, Power and Energy Society General Meeting, pages 1-7, 2010

[17] Singhal, P. K., Sharma, R. N., “Dynamic Programming Approach for Large Scale Unit Commitment Problem”, International Conference on Communication Systems and Network Techniques, pp. 714-717, 2011