AN APPROACH FOR DEMAND RESPONSE AT RESIDENTIAL LEVEL USING INTEGRATED DYNAMIC CONSUMER END ELASTICITY MODEL

by

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A thesis submitted to the faculty of
The University of North Carolina at Charlotte
in partial fulfillment of the requirements
for the degree of Master of Science in
Electrical Engineering

Charlotte

2016

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ABSTRACT

SHYAMAL PATEL. An approach for demand response at residential level using integrated dynamic consumer end elasticity model. (Under the direction of DR SUKUMAR KAMALASADAN)

Reducing the difference between on peak and off peak demand has long been recognized by utilities as an effective way of cutting the cost of producing electricity. Moreover, having prior knowledge about dynamic electricity rates gives the consumer an opportunity to optimize the consumption. Hence, an efficient demand response program promises the advantage on both sides. Owing to high flexibility, real-time pricing based demand response are considered to possess the highest potential among all the other programs. But, the current practice of same suffers from a lack of consumer level behavioral understanding and hence, making it difficult to predict and map the response. As a result, demand response programs are inducing the uncertainty in terms of real time demand. This uncertainty poses difficulty for power generation entities as well as load serving entities in predicting the consumer’s behavior in response to advance price signals. Current research focuses on the development of consumer psychology model for predicting and imitating the consumer’s response scenario to advance price signals and mapping the same in the form of elasticity matrix. Elasticity matrix is further integrated in the model to modify the price signals. These modified price signals based on elasticity matrix reduces the uncertainty in the system.

DEDICATION

Dedicated to my parents Dr. Hareshkumar Patel and Daksha Patel. Without whom none of my success would have been possible.

ACKNOWLEDGMENTS

Foremost, I would like to express my sincere gratitude to my advisor Dr Sukumar Kamalasadan for his patience, motivation, enthusiasm, and immense knowledge. His guidance helped me in all the time of research and writing of this thesis. I could not have imagined having a better advisor and mentor for my MS study. Besides my advisor, I would like to thank the rest of my thesis committee: Dr Badrul Chowdhury and Dr Valentina Cecchi for all the knowledge I gained related to my thesis during their coursework. My sincere thanks to the university for providing me with 24 x 7 access to the lab facilities throughout my research tenure. I, also thank my fellow labmates and all my friends for morally supporting and cheering up for me throughout my research. Last but not the least, I would like to thank my family: my parents Dr Hareshkumar Patel and Daksha Patel for providing me with an opportunity to study in US..

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CHAPTER 1: INTRODUCTION

Constant effort is being made to reduce the imbalance between the growing demand and limited generation. To overcome these issues, demand side participation features such as distributed generation, distributed energy storage, and demand response program were introduced. [1] [2] [3] These features, along with increasing flexibility of the system, also increases the complexity and uncertainties in the grid. For example, if advance price signals are made available to the consumers, they may respond by either shifting the load to lower price period, curtailing the load during peak price period or using the stored the distributed generation and storage during same. This response action may temporarily relieve spikes during peak load in the load profile. However, it would also introduce the high deviation of resultant load profile from forecasted load profile. Also, in a situation where all consumers shift their load from peak load period to the same off-peak period, it may result in a spike during the off-peak period. [4] Thus, in short-term power system operation like day ahead market, it may increase the complexity for the system operator to predict the demand and plan the generation dispatch. Moreover, it may also affect the long term planning of generation and transmission capacities.

Electricity market deregulation has been suggested as an effective measure for better utilizing generation and transmission resources as well as reducing electricity cost on both supply and demand sides by introducing competition among generating entities. In many deregulated electricity markets, bid-based auctions determine the electricity rate and generation schedules by solving optimization problems. This process makes the resultant electricity rate and generation schedules dependent variables on the forecasted demand. Because of unexpected changes that bidders may face between the forecasted and spot scenario in the restructured electricity market, the design and implementation of demand side participation feature such as demand response programs, under the deregulated market context, is a significant challenge [5].

To mitigate the above issue, this thesis presents a new demand response approach by providing the consumers with advance price signals, considering the residential consumer's consumption sensitivity on price. Elasticity matrix is used to represent the demand sensitivity with respect to price. The model classifies the overall consumption of consumer into constant, shiftable and curtailable components for better response prediction. Elasticity matrix maps consumer's response/price sensitivity between different time-period and helps in modifying the price signals to mitigate the chances of demand surges. Previous studies on sensitivity studies considering elasticities were based on assumptions [6][7][36][37]. Whereas, in the current study, consumer psychology model was prepared to simulate the curtailment and shifting type responses of the consumer based on advance price signals. Elasticity matrix obtained in this case is based on the solid ground of consumer behavior and their reaction to advance price signals. Considering the elasticity matrix, the bidding and hence the price signals are modified to achieve higher demand response efficiency.

Section 1.1 Introduces the US energy market and briefly explains its evolution and restructuring. Section 1.2 describes the electricity pricing mechanism. Section 1.3 introduces the Demand response programs.

1.1 ELECTRICITY MARKETS

An electricity market is a system for selling and purchasing electricity, using supply and demand bids to set the prices and schedules under given physical constraints. The design of an electricity market defines the physical dispatching procedure in the short term, and thus affects the power system's planning decision in the long term. A basic understanding of electricity market is essential for us to study the pricing mechanisms and the demand side participation activities in the environment. This section introduces the modern electricity market structure and mechanism governing the electricity prices.

1.1.1 RESTRUCTURING OF US ELECTRICITY MARKETS

Throughout most of its history, the U.S. electricity market has been dominated by large, vertically integrated, and heavily regulated utilities. Beginning in 1978, reforms began to transform this traditional "monopolized" structure of the industry. By the late 1990s, a transformed industry had started to take shape, characterized by substantial de-integration, significantly looser regulation, and more market-oriented operation. [8] Restructuring of electricity market promised competition which in turn would result in cost-efficient production and lower price to retail consumers. Over the past few years, a number of studies have been conducted evaluating the benefits of the restricted market. Electricity reforms have involved several different policy initiatives adopted at different times, at various government levels, and often phased in over a long period. The first restructuring initiative dates back to the Public Utility Regulatory Policies Act (PURPA) of 1978. It sought to promote energy conservation by requiring traditional utilities to purchase cogenerated power. PURPA also promoted wholesale power transactions between utilities. While PURPA demonstrated the feasibility of a broader market for wholesale power, it also highlighted the difficulties of ensuring access by buyers and sellers to the transmission grid required to transact power over longer distances.

The limitations on access to the transmission grid were one motivation for the passage of the Energy Policy Act of 1992 and the orders issued by the Federal Energy Regulatory Commission (FERC) in 1996 under the 1992 Act. FERC Orders 888 and 889 required utilities to file non-discriminatory “open access” tariffs for their transmission services and eliminated the sequential marking up of transmission charges that hindered long distance transactions. While these policies had some effect in prying open access in some regions, continued ownership and operating control of the transmission grid by the integrated utilities thwarted realization of full access to the transmission system. As a result, four years later, FERC Order 2000 sought to wrest operating control of the transmission grid from the traditional utilities by promoting regional transmission organizations (RTOs). Shortly thereafter FERC proposed a Standard Market Design that sought not only to improve transmission access, but also to encourage regional energy markets. In principle, FERC intended that all utilities in a region would turn over control (but not ownership) of their transmission infrastructure to an RTO.

Many states have required or promoted divestiture of generation assets from transmission and distribution by the traditionally integrated utilities. The purpose of such separation was to eliminate any competitive advantage for the incumbent owner of distribution and transmission, thereby at least theoretically opening up the market to multiple independent generation suppliers.

Also, some states, beginning in 1996 with the high electricity cost areas of New England and California, have allowed entry by competitive or alternative electricity providers. These competitive providers are essentially marketers of power that is generated by others and ultimately distributed to final consumers on lines that continue to be owned and operated by the local distribution utility. Finally, at the retail level, restructuring has been accompanied by rate freezes or other agreements designed to ensure benefits to consumers during the initial few years of the program. In short, all of these changes were intended to create alternative sources of power for wholesale and retail consumers. The plan was to foster competition among independent generators by creating a level playing field for wholesale power transactions that permitted retail consumers and local distribution utilities to shop for power supply. All this was expected to lower wholesale costs and retail prices.

By the year 2000, about half the states either had restructured their electricity sectors or were planning to do so. The transmission grid was increasingly operated by RTOs and in some places relatively free of artificial constraints. While the problems in California and elsewhere brought further restructuring to a halt, many states were irreversibly committed to deregulation and, in any event, reforms at the federal level continued. The result is that electricity restructuring is substantially complete in some regions of the country but has scarcely affected other regions.

1.2 ELECTRICITY PRICING

Electricity is essentially non-storable, which implies that it must be generated at the instant that it is demanded, thus requiring a constant balancing of supply and demand by a system operator. Furthermore, consumers' demand for electricity varies considerably over time, on an hourly, daily, and seasonal basis. As a result of these two factors, power systems tend to be characterized by a range of generation technologies that differ regarding their capital and operating costs. These range from highly capital-intensive base load plants designed to run continuously at low operating costs, to peaking plants that are relatively inexpensive to install, and can start quickly to meet changing demand, but have high operating costs during the relatively few hours of the year that they are designed to run. Furthermore, to ensure that capacity is available to meet demand during conditions of extreme load conditions or unexpected generator outages, a certain amount of reserve capacity is typically maintained. These factors imply that the hourly marginal cost of electric energy, which reflects largely the operating cost of the highest cost generator that is dispatched to run, varies considerably across hours, days, and seasons. This variability of electricity costs has been well understood by utility planning and operations staff. However, before the deregulation of wholesale power markets, these costs were largely internal to individual utilities and not visible in public markets. As wholesale power market was opened up, generators offered blocks of power for various time periods at prices that reflected their operating costs. System operators matched supply to expected hourly loads, thus determining which generators to dispatch, and setting hourly market prices as the highest bids accepted. As a result, time-varying power generation costs became reflected in wholesale energy prices.

Traditional utility rate design focused largely on the recovery of allowed costs and on methods for allocating those costs fairly across various consumer types. The economic efficiency of the resulting price structures, in the sense of establishing prices that reflect utilities' time-varying marginal costs, has typically been given a low priority. As a result, while wholesale costs vary hourly, retail prices for most consumers differ seasonally at most (e.g., higher prices during the summer months than in non-summer months, due to higher costs are driven largely by air conditioning loads). Only for large consumers do prices typically differ by time period during the day, in the form of time-of-use demand and/or energy charges. Moreover, only for relatively few consumers on real-time pricing (RTP) programs do prices vary hourly to match hourly wholesale costs.

Under the regulation, utilities are allowed to set retail rates to cover their expected energy costs, sometimes including fuel-adjustment factors that adjust rates periodically to reflect changing fuel prices. In an environment characterized by competitive wholesale and retail electricity markets, however, energy providers' perspective on cost recovery changes dramatically. Looking to the future, an energy supplier in a competitive market faces considerable risk due to uncertainty about future wholesale power costs. At the same time, most consumers are likely to prefer the certainty of fixed or guaranteed prices (e.g., a fixed price per kWh) for some time into the future. Load serving entities (LSEs) will contract with those consumers to provide power at a certain retail price, and then arrange to buy energy and ancillary services on the wholesale market to fulfill those contracts. LSEs face one dominant theme in deciding how to price their products to various consumer types—how to manage the financial risk associated with uncertainty about future consumer loads and wholesale power prices. That is, looking at a future period, LSEs do not know exactly how much electricity each of their consumers will consume, nor what the wholesale prices for that power will be at the time they will have to supply it. LSEs face three sources of risk from offering guaranteed prices—wholesale price variability, load variability, and the correlation between wholesale prices and consumer loads. First, they do not know what wholesale prices will be in the future when they have to purchase the power needed to meet their consumers' demands. Second, they do not know how much their consumers will consume in any given period in the future. Therefore, for example, they cannot enter forward contracts to meet all of their consumers' demands; they will always have to purchase or sell back some power in spot markets. Finally, many consumer's loads tend to be correlated with wholesale power prices. For example, residential and commercial consumer usage tends to rise on hot summer days, which are the same time periods in which wholesale power prices tend to increase due to higher overall system loads. Thus, in the very hours in which wholesale prices are unusually high, many consumers' loads will be unusually high as well. Price-load correlation of this type makes the cost of serving certain consumer types both higher and more uncertain than it is for others. The above three components of financial risk imply the need for LSEs to incorporate a risk premium into any guaranteed price offering. Demand response programs, on the other hand lowers the financial risk and aims at increasing the global welfare and thereby, the market efficiency.

1.3 DEMAND RESPONSE

Reducing the difference between on peak and off peak demand has long been recognized by utilities as an effective way of cutting the cost of producing electricity. To achieve the same, consumers are encouraged to modify their consumption and thereby the overall load pattern in a beneficial way. Special tariff schemes are designed with intent to achieve the same. While these special tariffs are mutually beneficial, it is yet ambiguous if quantification of benefits gained by companies are proportional to what consumers may receive.

The liberalization of the electricity markets has led in many parts of the world to the replacement of tariffs by hourly or half-hourly prices. In an economist's perspective, these prices are a powerful way to encourage consumers to behave in an economically optimal way. One must make a distinction between the long and short-term effects of such prices. In the long term, the average price will affect the overall level of consumption. Wide differences in prices between day and night or between weekends and weekdays may also encourage consumers to install thermal or material storage that will help them avoid consuming electricity during the hours of peak prices. [9] [10] [11] [12]

In the short term, some consumers have the ability to reduce or reschedule their demand in response to the electricity prices. [13] [14] [15] For example, if prices are high, some industrial consumers may forego production if it is not profitable at that price level. Consumers who have the ability to store energy or some intermediate product may reorganize their production. Considering the above possibilities at the short term, the concept of spot pricing was developed. A system can be envisaged, where consumers would adjust their demand up or down depending on the spot price. The spot prices would be updated in real time to take into account these load adjustments. As a result, both load reduction during peak time can be achieved, and high dips during off-peak period can be achieved. In such situation consumers can be benefitted by saving at peak periods and generating companies can be benefitted by avoiding operations of peaking units and market participation at spot rates. Thereby, the approach can maximize the global welfare.

1.3.1 CLASSIFICATION OF DEMAND RESPONSE PROGRAMS

As shown in Figure 1.1, demand response programs can be primarily classified into two broad categories [16]:

1. Incentive-Based Programs(IBP)

IBP programs are further classified into:

i. Classical Incentive Programs

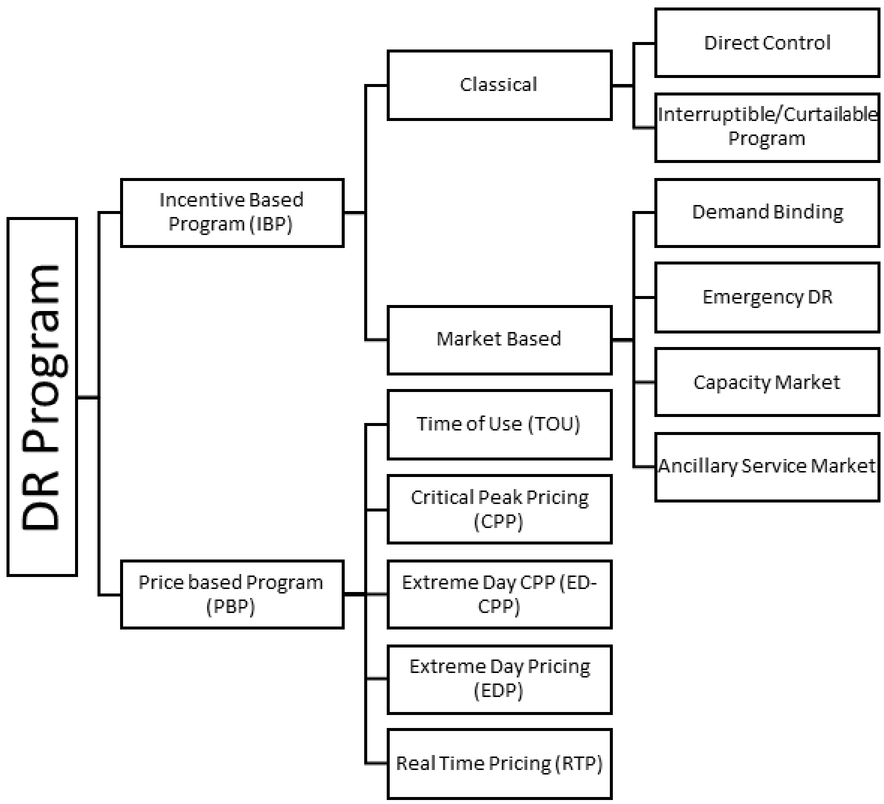


Figure 1.1: Classification of demand response program

Participants of classical incentive-based programs receive participation payment either in the form of bill credit or discounts for their response during peak load situation. Classical programs are further classified as:

a. Direct Control

Under this program, the utility installs smart regulator over the major load consuming devices like air conditioners and refrigerators. The regulators can be remotely controlled by the utility and during peak load, the regulators are used to operate the loads at optimum levels. Under critical situation loads like air conditioners can also be switched off.

b. Interruptible or curtailable programs.

Under curtailable programs, participants are asked to constrain their consumption within the certain limit or predefined values. Depending on terms and condition, against the discomfort faced by the consumer, they are awarded the incentives, and if not able to meet the constraint, they may also be charged with a penalty.

ii. Market-Based Programs

Participants of market-based programs are rewarded with money depending on their response during peak load period. Market-based are further classified into:

a. Demand Bidding: Participating consumer's bids for the curtailment of the load at the retail level. A bid lower than market price is accepted. If a consumer consumes more than the bided price, he my either face the high price or face penalty.

b. Emergency DR: During exigency period, utility curtails the consumption by shedding up the loads of participating consumer.

c. Capacity Markets: Participants are provided a prior notice for load curtailment during forecasted contingent periods. Failing to do so, they have to face the penalty.

d. Ancillary Service Market: Customers are allowed to bid on load curtailment in the spot market as operating reserve. When bids are accepted, participants are paid the spot market price for committing to be on standby and are paid spot market energy price if load curtailment is required

e. Price-Based Programs: Under price based program, consumers are subjected to varying rates of electricity. Based on high rates during peak period or low rates during of peak period, consumers may curtail the load or shift the consumption to the of peak period.

Price based program's tariff are further classified into:

i. Time of Use (TOU): Consumers are charged with average market price during on and off peak period.

ii. Critical Peak Pricing: It includes pre-specified higher rates on TOU or normal/base rates. They are used during a contingency or high market prices for a limited number of days.

iii. Extreme Day Pricing (EDP): For days, with high average consumption, high rates are imposed for the whole day with prior notice of change given to the consumer. It is analogous to CPP but for the whole day rather than small duration.

iv. Extreme Day CPP(ED-CPP): Extreme day rates are further subjected to rate variation for on and off peak periods.

v. Real Time Pricing: Under RTP programs, consumers are charged at hourly fluctuating spot/real time prices of the wholesale market.

1.3.2 DEMAND RESPONSE PROGRAM BENEFITS AND COSTS

Benefits of DR programs can be broadly be classified at 4 different levels [17]:

a. Participant: Participating consumers are either receiving the incentives for participation regarding credits, discounts, and cash rewards or under different pricing scheme, by optimizing the usage, they are saving over the electricity bill.

b. Market-Wide: Overall, by curtailment of the load during peak time, market rates during peak time will decrease eventually saving for entities dealing at spot price. Also, eventually DR effects can be considered by forecasting algorithms and hence considering the curtailment during load, generating and load serving entities can save during the bids. Also, it opens up the scope for differing the investment on infrastructure serving only during the peak period. Also, if peak time load are efficiently shifted to off-peak periods, it leads to efficient use of existing infrastructure.

c. Reliability: Reliability benefits can be considered as one of the market-wide benefits because they affect all market participants (Generating entities, load serving entities as well as consumer). By having a well-designed DR program, participants have the opportunity to help in reducing the risk of outages. Simultaneously and as a consequence, participants are reducing their own risk of being exposed to forced outages and electricity interruption. On the other hand, the operator will have more options and resources to maintain system reliability, thus reducing forced outages and their consequences.

d. Market Performance: DR program participants can bid for more optimum rates considering the effect of DR program, and thereby reducing the market power. Moreover, consumer especially participants of real-time pricing programs and the bid based program has the power to interact directly with the market leading to lower peak rates. Another important market improvement is the reduction of price volatility in the spot market. Demand responsiveness reduces the ability of main market players to exercise power in the market. It has been reported that a small reduction of demand (5%) could have resulted in a 50% price reduction during the California electricity crisis in 2000–2001.

1.4 MOTIVATION AND SCOPE OF RESEARCH

With increasing penetration of smart meters at residential level, provides flexibility in implementing the demand response programs. On the other hand, smartphone applications has aided in increasing the connectivity among the consumers by offering them with the updates regarding the rate structure. Spot pricing programs are the one which may require real-time as well as the forecasted declaration of price trend among consumers. Also, smart thermostats and concept of “smart homes” focuses in optimizing the energy consumption during peak price periods. Modernization and ease in outreach as well as smart-home automation helps consumers in optimizing their consumption in response to advance electricity rates. Moreover, the consumers are paying the exact amount based on amount and time of their consumption. Owing to high flexibility and less market surplus, the real-time based demand response programs offers the highest market efficiency.

Inducting the demand response program at residential level may on one hand increase the flexibility and options at both supply and demand end, it may also introduce the complication in the operation of the system. In the absence of demand to market communication, ISO may face difficulty in understanding the rate of response and accurately the forecast the demand, thus complicating the demand and supply balance in real time. Under higher scheduled generation, the additional cost may be imposed upon the market. Also, under opposite situation, real-time rate will highly deviate from the forecasted, leading to lower consumer end participation benefits and hence proving the inefficiency of the DR program. [18] [19] Moreover, in long term planning, planners may face difficulties in estimating the generation and transmission capacity. [20] [21]

In order for demand response programs to result in increased market efficiency, and not simply create additional uncertainty, it is critical that information regarding load behavior is provided to the market administrator and incorporated into the appropriate market price. [22]. For this reason, prior knowledge of consumer’s behavior and sensitivity to prices may aid power generating entities to bid at optimum values and load serving entities to optimize the market participation.

Research work presented in current thesis aims at mapping the consumer's behavior to advance price signals in terms of load shift and load curtailment in form of elasticity matrix for mitigating the unrequired deviation. Chapter 2 discusses on the development of wholesale market framework. Chapter 3 integrates the wholesale market framework to the real-time based demand response program. Chapter 4 explains the development of consumer psychology model for modelling the consumer's reaction in real-time based demand response programs. Chapter 5 discusses on the extracting the elasticity matrix from the demand response model and using the same to revising the advance price signals for sensitivity based demand response. After chapter 2, apart from theoretical description of the relevant terms, all the contributions is original.

CHAPTER 2: DC OPTIMAL POWER FLOW AND LOCATIONAL MARGINAL PRICING

Concept of demand response in wholesale power market was discussed in chapter 1. In order to study consumer's reaction to advance price signals, a framework is required to simulate the wholesale market scenario. The forecasted rates which consumer may receive would be based on based on bids settled based on forecasted load. Real time rates, reflects the deviation of demand from the forecast getting settled in real-time market. Based on the forecasted demand, as well as real time demand, nodal rates or market clearing rates are determined using optimal power flow considering the system constrains along with generation and demand balance. Hence, the nodal locational marginal pricing would reflect the cost of highest clearing bid along with the congestion charges. Section 2.1 introduces the concept of locational marginal price. Current chapter focuses on the development of above mentioned wholesale power market framework. Section 2.2 and 2.3 discusses the wholesale market framework. DC Optimal power flow problem is formulated in section 2.4. The model is implemented on IEEE 6 bus system in section 2.5. Section 2.6 discusses the results and concludes the chapter.

2.1 INTRODUCTION

The concept of an LMP (also called a spot price or a nodal price) was first developed by Schweppe et al. [23]. LMPs can be derived using either an AC OPF model or a DC OPF model. The AC OPF model is more accurate than the DC OPF model, but it is prone to divergence. Also, the AC OPF model can be up to 60 times slower than the DC

OPF model. The DC OPF model (or the linearized AC OPF model) has been used for LMP calculation for power market operation. Several commercial software tools for power market simulation such as Ventyx Promod IV®, ABB GridViewTM, Energy Exemplar PLEXOS® and PowerWorld use the DC OPF model for power system planning and LMP forecasting [24].

There are two forms of DC OPF models, “full structured” and “reduced form.” The full-structured DC OPF model has a real power balance equation for each bus. This is equivalent to imposing a real power balance equation for all but a “reference” bus, together with a “system” real power balance equation consisting of the sum of the real power balance conditions across all buses. The reduced-form DC OPF model solves out for voltage angles using the real power balance equations at all but the reference bus, leaving the system real power balance equation. The market simulation model developed in present research uses “reduced form” of DCOPF for LMP calculation.

2.2 OVERVIEW OF THE FRAMEWORK

In April 2003 the U.S. Federal Energy Regulatory Commission proposed a Wholesale Power Market Platform (WPMP) [25] for common adoption by all U.S. wholesale power markets (FERC,2003). Agent-based modeling of electric system (AMES) developed by Junjie Sun and Leigh Tesfatsion was adopted to simulate WPMP. AMES framework consists of an Independent System Operators (ISO) and a collection of bulk energy traders further consisting of Load-Serving Entities (LSEs) and Generators distributed across the nodes of the transmission grid. DC OPF formulation for wholesale power market requires detailed information about the transmission grid, supply and demand bids, transmission line parameters thermal constraints and computation of losses.

the model of power market structure is divided into three parts: Generators, Transmission Lines and Load Serving Entities (LSE).

2.3 STRUCTURE OF TRANSMISSION GRID

Transmission Grid consists of three phase balanced AC network with $N \geq 1$ branches and $K \geq 2$ nodes. The reactance of the branches is total reactance. All transformers are assumed to have zero phase angle shifts and 1 tap ratio. All line-charge capacitances are assumed to be 0 and temperature is assumed to be constant. No isolation of nodes exists in the system. The indirect connection between two nodes may be through more than 2 branches, but direct connection assumes to be via a single branch. In wholesale power markets restructured by FERC's proposed market design [25], the transmission grid is overlaid with a commercial network consisting of "pricing locations" for the purchase and sale of electric power. A pricing location is a location at which market transactions are settled using publicly available LMPs. It is assumed that the set of market pricing location coincides with the set of transmission grid nodes.

2.3.1 STRUCTURE OF LOAD SERVING ENTITY

Load serving entities (LSEs) purchases bulk power in the wholesale power market to service consumer demand (load) in a downstream retail market. LSEs do not engage in production or sale activities in the wholesale power market. Hence, LSEs purchase power only from Generators, not from each other. At the beginning of each operating day D, each LSE submits a daily load profile into the day-ahead market for day D + 1. This daily load profile indicates the real power demand $p_{Lj}(h)$ that must be serviced by LSE (denoted by j) in its downstream retail market for each of 24 successive hours h

2.3.2 STRUCTURE OF POWER GENERATING ENTITY

Power generating entities are basically electric generating stations. Generators perform energy transactions with load serving entities. Each generator is supposed to have variable and fixed cost of production. Fixed cost is also termed as quasi-fixed costs, as it may also involve the no-load costs as well as ramp-up/down costs. For the following simulation model, we are ignoring the ramping and no load costs as well as ramp-up/down time. Generators in the simulation are supposed to have maximum and minimum generation limits for per hour generation denoted by equation 2-1

$$p_{gi}^{L} \leq p_{gi} \leq p_{gi}^{U} \qquad 2\text{-}1$$

Where,

p_{gi} is power generated by the ith generator

p_{gi}^{L} is minimum generation limit of ith generator

p_{gi}^{U} is maximum generation limit of ith generator

Total cost function for generator is given by,

$$tc_i = vc_i + fc_i \qquad 2\text{-}2$$

Where,

fc_i or $tc_0$is the fixed cost of generator.

vc_i is the variable costs and is further denoted by second order quadratic equation.

$$vc_i = a_i p_{gi} + b_i p_{gi}^2 \qquad 2\text{-}3$$

Marginal cost of production is defined as cost of generating additional 1 megawatt of power. Equation 2-4 represents the marginal cost function of the generator i.

$$mc_i = \frac{dtc_i}{dp_{gi}} = a_i + 2b_i p_{gi} \qquad 2\text{-}4$$

Power generating entities performs the LMP calculation as well as load forecasting for the upcoming day. Based on the forecasted LMPs, and linearizing the generating cost of power, bids are placed for a specific quantity of energy in the wholesale market. Based on supply bids and generation bids, the ISO lands up to equilibrium market point and LMP for a specific time is fixed. Generation cost offer tends to be more strategic as rather than following the marginal cost of generation; it may also tend to maximize the profit as well as optimize the chances of getting over-ruled. For ease of simulation, it has been assumed that power generating entities report their true marginal costs instead of optimized bids considering profit margin at its true feasible production interval.

2.4 DCOPF FORMULATION

ACOPF is more accurate compared to DCOPF problem, but computation time required for a complex system is quite large. Also, with an increase in complexity of the network, chances of divergence of optimization algorithm increases. DCOPF problem is an approximation of an ACOPF problem considering few assumptions and simplification of restrictions regarding voltage magnitudes, admittances, reactive power and voltage angles. The variables in the algorithm are normalized in “per unit” form.

2.4.1 CONVERSION OF ACOPF TO DCOPF

An optimization problem for ACOPF as well as DCOPF consists of minimizing an objective function subjected to constraints. The key component of ACOPF to DCOPF conversion is the representation of real and reactive power flows in a line.

Let,

P_{ij} denote real power (MW) flow from i to j in a network.

Q_{ij} denote real power (MVAR) flow from i to j in a network.

V_i and V_j denote voltage magnitudes at nodes i and j.

δ_i and δ_j denote the voltage angles at nodes i and j.

g_{ij} and b_{ij} denote the conductance and susceptance for branch ij.

$$P_{ij} = V_i^2 * g_{ij} - V_i * V_j * \left[g_{ij} * \cos\left(\delta_i - \delta_j\right) + b_{ij} * \sin(\delta_i - \delta j)\right] \quad 2\text{-}5$$

$$Q_{ij} = -V_i^2 * b_{ij} - V_i * V_j * \left[g_{ij} * \cos\left(\delta_i - \delta_j\right) - b_{ij} * \sin\left(\delta_i - \delta_j\right)\right] \quad 2\text{-}6$$

Following assumptions are considered for converting ACOPF formulation to DCOPF:

A1. The resistance of each branch is negligible compared to the reactance of the branch.

$$\text{Ie. } x_{ij} \gg r_{ij} \;\; => \;\; r_{ij} \approx 0 \quad 2\text{-}7$$

$$\text{Hence, } \; g_{ij} = 0 \;\&\; b_{ij} = [-\frac{1}{x_{ij}}] \quad 2\text{-}8$$

A2. Voltage magnitude at each node is equal to base voltage.

$$\text{Hence, } V_i = V_j = V_0 \quad 2\text{-}9$$

A3. The difference between voltage angle across each line is negligible.

$$\text{So, } \cos\left(\delta_i - \delta_j\right) \approx \cos(0) = 1 \quad 2\text{-}10$$

$$\& \sin(\delta_i - \delta j) \approx (\delta_i - \delta j) \quad 2\text{-}11$$

$$\text{Hence, } P_{ij} = V_0^2 * \left(\frac{1}{x_{ij}}\right) * (\delta_i - \delta j) \quad 2\text{-}12$$

$$Q_{ij} = V_0^2 * \left(\frac{1}{x_{km}}\right) - V_0^2 * (1/x_{ij}) = 0 \quad 2\text{-}13$$

Per unitization of the system requires basic assumptions of base values of two parameters: Apparent Power (Base MVA) and Voltage. All other base parameters of the system can be derived using the base MVA and voltage. Assuming a three phase balanced network with base MVA S_0 and base line to line voltage V_0, base impedance can be represented by

$$z_O = V^2/s_0 \quad 2\text{-}14$$

Per unit reactance x_{ij} can be represented as

$$x_{ij}(pu) = \frac{x_{ij}}{Z_0} \quad 2\text{-}15$$

Per unit suscepetance b_{ij} can be represented as

$$b_{ij}(pu) = -\frac{1}{x_{ij}(pu)} \quad 2\text{-}16$$

Per unit real power flow for branch ij is represented as

$$F_{ij} = \frac{P_{ij}}{S_0} \quad 2\text{-}17$$

If the generator is connected at node i. Then real power injected into the system via node i regarding PU is represented by

$$P_{Gi} = \frac{p_{Gi}}{S_0} \quad 2\text{-}18$$

where, p_{Gi} is real power generation by the generator G_i.

If load is connected at node i. Then real power withdrawn from the system from node i in terms of PU is represented by

$$P_{Li} = \frac{p_{Li}}{S_0} \quad 2\text{-}19$$

where, p_{Li} is real power consumed by load L_i.

Thus the generator cost function can also be per unitized as

$$TC_i = VC_i + FC_i \quad 2\text{-}20$$

$$VC_i = A_i P_{gi} + B_i P_{gi}^2 \quad 2\text{-}21$$

Where, A_i and B_i are pre-adjusted cost functions such that,

$$A_i = a_i * S_0 \quad 2\text{-}22$$

$$B_i = b_i * S_0 \quad 2\text{-}23$$

2.4.2 DCOPF STRUCTURE

This section represents the DCOPF problem in PU form along with objective function and constraints.

DCOPF problem:

Minimize:

$$\sum_{i=1}^{i=n} \mathrm{A_i} * \mathrm{P_{Gi}} + \mathrm{B_i} * \mathrm{P_{Gi}^2} \qquad 2\text{-}24$$

With respect to:

$\mathrm{P_{Gi}}$ for i=1, 2, 3…n

δ_i for i=1, 2, 3…n

Subject to:

I. Real/active power balance constraint for all nodes (i):

$$P_{Li} - P_{Gi} + P_{INi} = 0 \qquad 2\text{-}25$$

Where $\mathrm{P_{INi}}$ is the net power flowing from the all the nodes j connected to node i

$$\mathrm{P_{INi}} = \sum_{j=1}^{N,j\neq i} \mathrm{Fji} = \sum_{j=1}^{n,j\neq i} \mathrm{B_{ij}} * (\delta_j - \delta_i) \qquad 2\text{-}26$$

II. Transmission line thermal constraint:

$$|\mathrm{F_{ij}}| \leq \mathrm{F_{ij}^U} \qquad 2\text{-}27$$

Where, $\mathrm{F_{ij}^U}$ is the upper limit/thermal limit of transmission line connecting ith and jth node.

III. Generation constraint:

$$\mathrm{P_{Gi}^L} \leq \mathrm{P_{Gi}} \leq \mathrm{P_{Gi}^U} \qquad 2\text{-}28$$

Here, $\mathrm{P_{Gi}^L}$ and $\mathrm{P_{Gi}^U}$ is the upper and lower generation limit of generator connected to node i.

IV. Voltage angle at node 1:

$$\delta_1 = 0 \qquad 2\text{-}29$$

2.4.3 AUGMENTATION OF STANDARD DCOPF FORM

The objective equation of DCOPF problem can further be augmented with a penalty function on the sum of squared voltage angle differences for all the nodes j connected to node i.

Augmented form of DCOPF problem can be represented as,

$$\sum_{i=1}^{n} (A_i * P_{Gi} + B_i * P_{Gi}^2) + \pi \sum_{i,j \in BR} (\delta_i - \delta_j)^2 \qquad 2\text{-}30$$

Here, π is the penalty factor.

This augmented form transforms DCOPF problem into SCQP (strictly convex quadrating programming) form which can be solved to generate solutions for the optimum generation, LMP, voltage angles, real power injections and branch flows. Augmentation also has additional potential benefits based on physical and mathematical considerations. [26]

a) Physical considerations:

DCOPF problem relies on assumptions A1-A3. According to assumption A3, the accuracy of the problem relies on the actual difference between the voltage angles of two nodes connecting the branches. In fact, small voltage angle difference is the major assumption based on which ACOPF is approximated to DCOPF. Standard DCOPF problem does not take voltage angle difference into consideration. So, in case the difference is beyond the approximation consideration, it may induce high error/difference in the output when compared to ACOPF. Also, it will introduce large errors in the LMP values. According to an analysis conducted by Overbye et al.,2004, by taking both quantity and price solution into account on two case study were optimistic regarding quantity but negative impact on LMP results. For example, in the authors' second case study, the DC approximation missed almost 50% of the binding constraints for the AC problem. Although many of these were "near misses," the effects of these near-misses on the LMP approximations were in some cases significant.

Augmenting the objective problem by introducing the penalty function on voltage angle difference permits the sensitivity checks on DCOPF solutions imposed to a precondition for AC-DC approximation. Ideally, small values of penalty function would reproduce almost the same result obtained without imposing penalty function.

b) Mathematical Considerations:

A suitable augmentation to objective function (over here DCOPF problem) helps in improving the convexity/concavity of maximization/ minimization problem as well as increase the stability and thereby increase the convergence to the optimum solution [27]. DCOPF problem can be represented under augmented version as follows:

a) Objective function

Branch Connection matrix:

$$B = \begin{bmatrix} 0 & \mathrm{I}(1 \leftrightarrow 2) & \mathrm{I}(1 \leftrightarrow 3) & \cdots & \mathrm{I}(1 \leftrightarrow n) \\ \mathrm{I}(2 \leftrightarrow 1) & 0 & \mathrm{I}(2 \leftrightarrow 3) & \ldots & \mathrm{I}(2 \leftrightarrow n) \\ \mathrm{I}(3 \leftrightarrow 1) & \mathrm{I}(3 \leftrightarrow 2) & 0 & \ldots & \mathrm{I}(3 \leftrightarrow n) \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \mathrm{I}(n \leftrightarrow 1) & \mathrm{I}(n \leftrightarrow 2) & \mathrm{I}(n \leftrightarrow 3) & \cdots & 0 \end{bmatrix} \qquad \text{2-31}$$

Where $\mathrm{I}(i \leftrightarrow j) = 1$, if nodes i and j are interconnected

$= 0$, if nodes i and j are not interconnected

Weight matrix denoting (voltage angle difference) weight matrix:

$$W = 2 * \pi * \begin{bmatrix} \sum_{n \neq 1} E_{n1} & -E_{12} & -E_{13} & \cdots & -E_{1n} \\ -E_{21} & \sum_{n \neq 2} E_{n2} & -E_{23} & \dots & -E_{2n} \\ -E_{31} & -E_{32} & \sum_{n \neq 3} E_{n3} & \dots & -E_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -E_{n1} & -E_{n2} & -E_{n3} & \cdots & \sum_{n \neq n} E_{nn} \end{bmatrix} \tag{2-32}$$

For $\delta(n)^T = [\delta_1, \delta_2, \dots . \delta_n]$

As per the previous assumption, $\delta_1 \equiv 0$, Thus Weight matrix can be reduced to

$$W_{rr} = 2 * \pi * \begin{bmatrix} \sum_{n \neq 2} E_{n2} & -E_{23} & -E_{24} & \cdots & -E_{2n} \\ -E_{32} & \sum_{n \neq 3} E_{n3} & -E_{34} & \dots & -E_{3n} \\ -E_{42} & -E_{43} & \sum_{n \neq 4} E_{n4} & \dots & -E_{4n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -E_{n2} & -E_{n3} & -E_{n3} & \cdots & \sum_{n \neq n} E_{nn} \end{bmatrix} \tag{2-33}$$

W_{rr} is an (n-1) x (n-1) matrix for $\delta(n)_{rr}{}^T = [\delta_2, \delta_3, \dots . \delta_n]$

Hence, $\frac{1}{2} * \delta(n)^T * W(n) * \delta(n) = \frac{1}{2} * \delta(n)_{rr}{}^T * W_{rr}(n) * \delta(n)_{rr}$

$$= \pi \left[\sum_{1i \in BR} \delta_i^2 + \sum_{ij \in BR} \left(\delta_i - \delta_j\right)^2 \right] > 0 \tag{2-34}$$

Generator cost attribute matrix U can be represented as,

$$U = diag[2B_1, 2B_2 \dots 2B_i] \tag{2-35}$$

Here, U is an (i x i) semi definite positive matrix.

Generation matrix (G) is defined by:

$$G = blockdiag[U \; W_{rr}] = \begin{bmatrix} U & 0 \\ 0 & W_{rr} \end{bmatrix} \tag{2-36}$$

G is a positive definite matrix associated with vector x^T

Thus the quadratic component of the cost function can be represented as,

$$\frac{1}{2} * x^T G x = \sum_{i=1}^{n} [B_i * P_{Gi}^2] + \pi \left[\sum\nolimits_{1i \in BR} \delta_i^2 + \sum\nolimits_{ij \in BR} \left(\delta_i - \delta_j\right)^2 \right] > 0 \qquad 2\text{-}37$$

b) Constraint Formulation

Bus admittance matrix can be represented as,

$$B' = \begin{bmatrix} \sum_{n \neq 1} B_{n1} & -B_{12} & -B_{13} & \cdots & -B_{1n} \\ -B_{21} & \sum_{n \neq 2} B_{n2} & -B_{23} & \ldots & -B_{2n} \\ -B_{31} & -B_{32} & \sum_{n \neq 3} B_{n3} & \ldots & -B_{3n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -B_{n1} & -B_{n2} & -B_{n3} & \cdots & \sum_{n \neq n} B_{nn} \end{bmatrix} \qquad 2\text{-}38$$

Where,

$B_{ab} = \frac{1}{x_{ab}(pu)}$, if $ab \in BR$

$= 0$, otherwise

Reduced bus admittance matrix by omitting first row and column can be represented as,

$$B'_{rr} = \begin{bmatrix} \sum_{n \neq 2} B_{n2} & -B_{23} & -B_{24} & \cdots & -B_{2n} \\ -B_{32} & \sum_{n \neq 3} B_{n3} & -B_{34} & \ldots & -B_{3n} \\ -B_{42} & -B_{43} & \sum_{n \neq 4} B_{n4} & \ldots & -B_{4n} \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ -B_{n2} & -B_{n3} & -B_{n3} & \cdots & \sum_{n \neq n} B, k_{nn} \end{bmatrix} \qquad 2\text{-}39$$

Let BR be branch index list, consisting all the interconnections listed in increasing order or indices. Branch incidence matrix for a network with i nodes and n branches can be represented as:

$$A = \begin{bmatrix} \psi(1, BR_1) & \psi(2, BR_1) & \cdots & \psi(i, BR_1) \\ \psi(1, BR_2) & \psi(2, BR_2) & \cdots & \psi(i, BR_2) \\ \vdots & \vdots & \ddots & \vdots \\ \psi(1, BR_n) & \psi(2, BR_n) & \cdots & \psi(i, BR_n) \end{bmatrix} \qquad 2\text{-}40$$

Where $\psi(i, BR_n)$ is the indicator function such that,

$\psi(i, BR_n)$ = +1, if for BR_n, starting node indices is less than the incident node indices

= -1, if for BR_n, starting node indices is greater than the incident node indices.

= 0, otherwise.

Reduced incidence matrix can be represented as

$$A_{rr} = \begin{bmatrix} \psi(2, BR_1) & \psi(3, BR_1) & \cdots & \psi(i, BR_1) \\ \psi(2, BR_2) & \psi(3, BR_2) & \cdots & \psi(i, BR_2) \\ \vdots & \vdots & \ddots & \vdots \\ \psi(2, BR_n) & \psi(3, BR_n) & \cdots & \psi(i, BR_n) \end{bmatrix} \qquad 2\text{-}41$$

For generator $G = [g_1, g_2 \dots g_l]$, connected to nodes of the system, generator connection matrix is represented as,

$$G_c = \begin{bmatrix} \chi(1,1) & \chi(2,1) & \cdots & \chi(l, 1) \\ \chi(1,2) & \chi(2,2) & \cdots & \chi(l, 2) \\ \vdots & \vdots & \ddots & \vdots \\ \chi(1,3) & \chi(2,3) & \cdots & \chi(l, i) \end{bmatrix} \qquad 2\text{-}42$$

Where $\chi(l, i)$ is the indicator function such that,

$\psi(l, i)$ = +1, if generator l is connected to node i

= 0, if generator l is not connected to node i

Let D be the diagonal matrix representing distinct branch connection I the network according to branch indices.

$$D = diag[D_1, D_2, \dots D_n] \qquad 2\text{-}43$$

Where, $D_n = B_{ij}$

c) SCQP Form

Based on the matrices defined from 2-31 - 2-43, the SCQP based DCOPF problem can be formulated as:

Minimize: $f(x) = \frac{1}{2}x^{T}Gx + a^{T}x$ 2-44

With respect to

$$x = [P_{G1}\ P_{G2} \ldots P_{GI}\ \delta_2\ \delta_3 \ldots \delta_i]^{T}$$ 2-45

Subject to

$$C_{eq}^{T}x = b_{eq}$$ 2-46

$$C_{iq}^{T}x \geq b_{iq}$$ 2-47

In the above formulation,

G is the generation matrix as represented in equation 2-36

$a^{T} = [A_1\ A_2 \ldots A_I\ 0 \ldots 0]$, 2-48

where A_i is the generator cost coefficient

Equality constraint:

$$C_{eq}^{T} = [II - B_{rr}^{\prime T}]$$ 2-49

$$b_{eq} = [P_{L1}\ P_{L2}\ P_{L3} \ldots P_{Li}]^{T}$$ 2-50

Inequality Constraint:

$$C_{iq}^{T} = \left[C_{t}^{T} - C_{t}^{T}\ C_{p}^{T} - C_{p}^{T}\right]^{T}$$ 2-51

Where $C_{t}^{T} = [O_{t} - DA_{rr}]$ 2-52

Here, O_t is NxI zero matrix

Also, C_t and $-C_t$ denote the thermal constraint coefficient for flow in both direction.

$$C_{p}^{T} = \left[I_{p}\ O_{p}\right]$$ 2-53

Here, Ip is IxI identity matrix and O_p is Ix(K-1) zero matrix.

$$b_{iq} = \left[b_t\ b_t\ b_{pL}\ b_{pU}\right]^T \tag{2-54}$$

Where,

$$b_t = \left[-F^U_{BI_1} - F^U_{BI_2} \dots . -F^U_{BI_i}\right]^T \tag{2-55}$$

$$b_{pL} = [P^L_{G1}\ P^L_{G2} \dots . . P^L_{Gi}] \tag{2-56}$$

$$b_{pU} = \left[-P^U_{G1}, -P^U_{G2} \dots . -P^U_{Gi}\right]^T \tag{2-57}$$

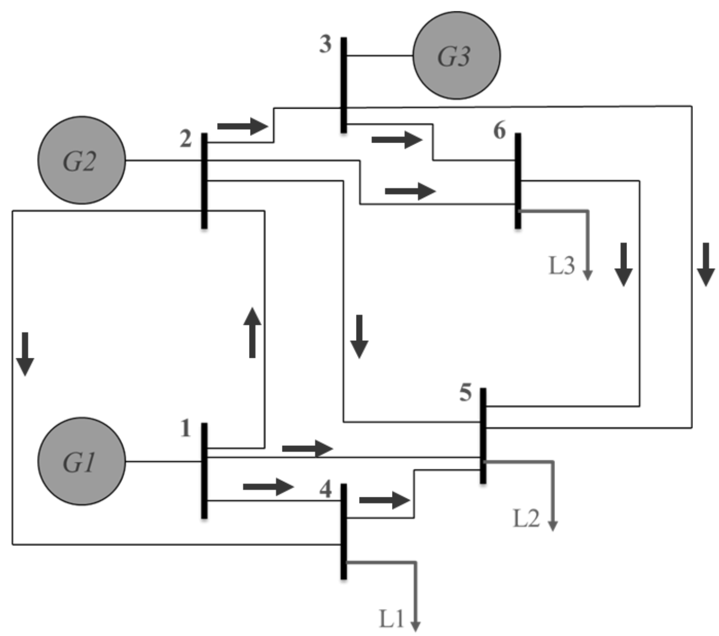


Figure 2.1: Test System: 6 Bus

2.5 IMPLEMENTATION OF DCOPF ON IEEE 6 BUS SYSTEM

As shown in Figure 2.1, six bus system consists of 3 generators and 3 loads. The generator and load connected loads are distinct in the system. 6 nodes are interconnected by 11 branches.

Number of Nodes: K=6

No of Generators: I=3

No of loads: J=3

Number of Branches: N=11;

Equation 2-58 to 2-67 represents the system into matrix form for the DCOPF formulation.

Based on the system data, branch connection matrix for the system can be represented as

$$E = \begin{bmatrix} 0 & 1 & 0 & 1 & 1 & 0 \\ 1 & 0 & 1 & 1 & 1 & 1 \\ 0 & 1 & 0 & 0 & 1 & 1 \\ 1 & 1 & 0 & 0 & 1 & 0 \\ 1 & 1 & 1 & 1 & 0 & 1 \\ 0 & 1 & 1 & 0 & 1 & 0 \end{bmatrix} \quad \text{2-58}$$

The weight matrix represented the augmentation by subjecting the penalty factor to voltage angles, is represented as

$$W = 2 * \pi * \begin{bmatrix} 3 & (-1) & 0 & (-1) & (-1) & 0 \\ -1 & 0 & -1 & -1 & -1 & -1 \\ 0 & -1 & 0 & 0 & -1 & -1 \\ -1 & -1 & 0 & 0 & -1 & 0 \\ -1 & -1 & -1 & -1 & 0 & -1 \\ 0 & -1 & -1 & 0 & -1 & 0 \end{bmatrix} \quad \text{2-59}$$

Considering the voltage angle of slack bus as 1, the reduced form of weight matrix can be written as

$$W_{rr} = 2 * \pi * \begin{bmatrix} 0 & -1 & -1 & -1 & -1 \\ -1 & 0 & 0 & -1 & -1 \\ -1 & 0 & 0 & -1 & 0 \\ -1 & -1 & -1 & 0 & -1 \\ -1 & -1 & 0 & -1 & 0 \end{bmatrix} \quad \text{2-60}$$

Here, penalty factor: $\pi= 0.01$.

Matrix representing the generator cost function can be written as

$$U = \begin{bmatrix} 0.0107 & 0 & 0 \\ 0 & 0.0178 & 0 \\ 0 & 0 & 0.0148 \end{bmatrix} \quad \text{2-61}$$

Branch admittance matrix B and its reduced form B_{rr} for the system can be represented as:

$$\text{B}= 1000 * \begin{bmatrix} -1.33 & 0.5 & 0 & 0.5 & 0.33 & 0 \\ 0.5 & -2.73 & 0.4 & 1 & 0.33 & 0.5 \\ 0 & 0.4 & -1.78 & 0 & 0.3846 & 1 \\ 0.5 & 1 & 0 & -1.75 & 0.25 & 0 \\ 0.33 & 0.33 & 0.3846 & 0.25 & -1.6346 & 0.33 \\ 0 & 0.5 & 1 & 0 & 0.33 & -1.83 \end{bmatrix} \qquad \text{2-62}$$

$$\text{B}_{\text{rr}} = 1000 * \begin{bmatrix} -2.73 & 0.4 & 1 & 0.33 & 0.5 \\ 0.4 & -1.78 & 0 & 0.3846 & 1 \\ 1 & 0 & -1.75 & 0.25 & 0 \\ 0.33 & 0.3846 & 0.25 & -1.6346 & 0.33 \\ 0.5 & 1 & 0 & 0.33 & -1.83 \end{bmatrix} \qquad \text{2-63}$$

The adjacency matrix A and its reduced version A_r with entries of 1 for the “from” node and -1 for the “to” node can be expressed as

$$\text{A} = \begin{bmatrix} 1 & -1 & 0 & 0 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & 0 & -1 & 0 \\ 0 & 1 & -1 & 0 & 0 & 0 \\ 0 & 1 & 0 & -1 & 0 & 0 \\ 0 & 1 & 0 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & 0 & -1 \\ 0 & 0 & 1 & 0 & -1 & 0 \\ 0 & 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & 0 & -1 & -1 & 0 \\ 0 & 0 & 0 & 1 & 1 & -1 \end{bmatrix} \qquad \text{2-64}$$

$$\text{A}_\text{r} = \begin{bmatrix} -1 & 0 & 0 & 0 & 0 \\ 0 & 0 & -1 & 0 & 0 \\ 0 & 0 & 0 & -1 & 0 \\ 1 & -1 & 0 & 0 & 0 \\ 1 & 0 & -1 & 0 & 0 \\ 1 & 0 & 0 & -1 & 0 \\ 1 & 0 & 0 & 0 & -1 \\ 0 & 1 & 0 & -1 & 0 \\ 0 & 1 & 0 & 0 & -1 \\ 0 & 0 & -1 & -1 & 0 \\ 0 & 0 & 1 & 1 & -1 \end{bmatrix} \qquad \text{2-65}$$

Also, matrix II and D can be written as

$$\mathrm{II} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \qquad 2\text{-}66$$

$$\mathrm{D} = \mathrm{diag}[\mathrm{B}_{12}\ \mathrm{B}_{14}\ \mathrm{B}_{15}\ \mathrm{B}_{23}\mathrm{B}_{24}\ \mathrm{B}_{25}\ \mathrm{B}_{26}\ \mathrm{B}_{35}\ \mathrm{B}_{36}\ \mathrm{B}_{45}\ \mathrm{B}_{56}] \qquad 2\text{-}67$$

Based on the equations, the DCOPF problem for the 6 bus system can be formulated as:

$$\text{Minimize: } f(x) = \frac{1}{2}(x^{T}Gx) + a^{T}x \qquad 2\text{-}68$$

With respect to

$$x = [P_{G1}\ P_{G2}\ P_{G3}\ \delta_2\ \delta_3\ \delta_4\ \delta_5\ \delta_6] \qquad 2\text{-}69$$

Subject to following constraints:

$$C_{eq}^{T}x = b_{eq} \qquad 2\text{-}70$$

$$C_{iq}^{T}x \geq b_{iq} \qquad 2\text{-}71$$

Based on matrices representing the system, input parameters for the optimization, $G, a^{T}, C_{eq}^{T}, b_{eq}^{T}, C_{eq}^{T}$ and b_{iq} in the problem can be represented as:

$$G = \mathrm{blockdiagonal}[U\ W_{rr}] \qquad 2\text{-}72$$

$$a^{T} = [11.669\ 10.333\ 10.833\ 0\ 0\ 0\ 0\ 0] \qquad 2\text{-}73$$

Equality constraint can be written as:

$$C_{eq}^{T} = [\mathrm{II} - B_{r}^{\prime T}] \qquad 2\text{-}74$$

Where, II and $B_{r}^{\prime T}$ are defined in equation 2-66 and 2-63 respectively.

Inequality constraint can be written as,

$$b_{eq} = [0\ 0\ 0\ 100\ 100\ 100]^{T} \qquad 2\text{-}75$$

$$C_{iq}^{T} = \left[C_{t}^{T} - C_{t}^{T}\ C_{p}^{T} - C_{p}^{T}\right]^{T} \qquad 2\text{-}76$$

Where,

$$C_t^T = [O_t - DA_r] \qquad 2\text{-}77$$

$$O_t = \text{zeros}[11 \times 3] \qquad 2\text{-}78$$

$$C_p^T = [I_p \; O_p] \qquad 2\text{-}79$$

$$I_p = \text{Identity}[3 \times 3] \qquad 2\text{-}80$$

$$O_p = \text{zeros}[5 \times 4] \qquad 2\text{-}81$$

$$b_{iq} = [b_t \; b_t \; b_{pL} \; b_{pU}]^T \qquad 2\text{-}82$$

Where,

$$bt = [-100 - 100 - 100 - 60 - 60 - 60 - 60 - 60 - 60 - 60 - 60]^T \qquad 2\text{-}83$$

$$b_{pL} = [50 \; 37 \; 45] \qquad 2\text{-}84$$

$$b_{pU} = [200 \; 150 \; 180] \qquad 2\text{-}85$$

The results of the 6 bus system are discussed in section 2.6. The results are also verified for the consistency with the same from example 8C; Wood and Wollenberg (1996, Chpt. 8, [28]).

2.6 RESULTS AND DISCUSSION

Table 2.1 6 Bus System: DCOPF Generation Output

Bus	Voltage Angles	Generation		LMP	
	DCOPF O/P	Ref. O/P	DCOPF O/P	Ref. O/P	DCOPF O/P
Bus1	0	102.34	102.3398	12.760	12.7599
Bus2	-0.0328	122.18	122.1818	12.505	12.5054
Bus3	-0.0551	75.48	75.4784	11.952	11.9516
Bus4	-0.0928			13.089	13.0894
Bus5	-0.1185			12.648	12.6476
Bus6	-0.1151			13.149	13.1494

Table 2.2 6 Bus System DCOPF Output

Flow in transmission line		
From Bus (k)	To Bus (m)	Power Flow (MW) (F_{km})
1	2	16.41829
1	4	46.41829
1	5	39.50325
2	3	8.907705
2	4	60
2	5	28.55772
2	6	41.13463
3	5	24.38611
3	6	60
4	5	6.41829
5	6	-1.13463

The 6 bus test system represented in Appendix A is solved using the method described in 2.4. Inbuilt Matlab© algorithm of interior point convex method has been used for solving the quadratic programming problem. The 'interior-point-convex' algorithm attempts to follow a path that is strictly inside the constraints. It uses a presolve module to remove redundancies and to simplify the problem by solving for components that are straightforward [29]. The optimization algorithm took 7 iterations to converge down to the optimum results.

Power generation and nodal LMP results are presented in Table 2.1.

Table 2.2 represents the power flow among the branches of the test system. Branches connecting nodes 2 with 4 and 3 with 6 can be seen reaching up to the thermal limits. As a result, the effect of the congestion is reflected in higher LMP values for branch 4 and 6.

Moreover, the generation and output results are verified with the results of example 8C; Wood and Wollenberg (1996, Chpt. 8, [28]). The results of developed algorithm can be seen matching with the book results up to 4 decimal places hence, assuring the accuracy of the code.

The standard IEEE 118 bus test system is described in Appendix B. The optimization algorithm took 10 iterations to converge down to the optimum results.

The output of SCQP DCOPF for 118 bus system is compared with MatPower output for consistency. Generation and LMP output follow the MatPower output with almost 100% accuracy. But, an average error of 8% exists between the outputs for power flowing through the system. Augmentation and difference in the optimization solving algorithm could be the reason for this deviation. Line flow constraint has been removed in the above 118 bus illustration. As a result, LMP values is same at all the nodes reflecting the marginal cost of the generator, and no congestion cost is reflected in LMP values.

2.7 SUMMARY

A wholesale market framework using DCOPF was presented in this chapter. Considering the high accuracy in solving the optimal power-flow problem and nodal locational marginal pricing, this framework is further used for simulating both day-ahead as well as real-time market.

CHAPTER 3: ARCHITECTURE FOR REAL TIME PRICING BASED DEMAND RESPONSE

The concept of demand response and types of DR programs was discussed in 1.3. Also, wholesale power market platform was developed in chapter 2. The current chapter discusses the real-time based demand response architecture using wholesale power market platform.

Consumers would be planning the consumption pattern based on day ahead market clearing price and would be charged at real time market LMPs. Real time LMP varies from the forecasted rates in accordance with the change in consumption. Hence, the response action can be represented in the form of a feedback loop. This chapter focuses on the development of a feedback loop architecture for scenario simulation of generalized real-time price based demand response programs. Topic 3.1 discusses closed loop DR architecture in detail. An implementation of the approach is discussed in 3.1.1 followed by discussion and conclusion in 3.2.

3.1 CLOSED LOOP DEMAND RESPONSE ARCHITECTURE

As represented in Figure 3.1 based on the load forecast, each load serving entities present their load requirement in the day ahead market. Here, $\mathrm{Q_{forecast}}$ represents the 24 hours forecasted load. Based on the generator bids, the day ahead prices are fixed. As explained in 2.3.2, generators are assumed to bid at the marginal cost of generation. Hence, the bids are reflecting the cost function of the generators. So, the DCOPF results provide the LMP value representing the day ahead market clearing prices. Any change or deviation

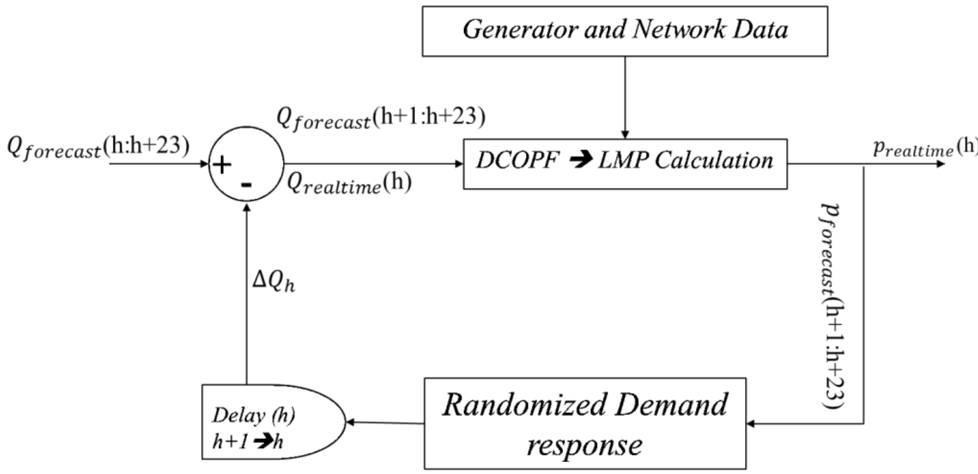


Figure 3.1: Closed loop demand response architecture

in the real time load from the forecasted load is settled in the real-time market at the real-time price. Hence, in the above figure, $\mathrm{P_{forecast}}$ represents the day ahead market clearing price based on the forecasted load. To study the effect of demand response program, it is assumed that the load forecast process does not take consumer's reaction into consideration. It seems to be a fair assumption based on the fact that the consumers sensitivity and behavior to advance price is not easy to predict in the absence of any firm references.

Based on these advance price signals, consumer reacts by both curtailing and shifting their loads. Because of consumer's response to the price, the real-time consumption deviates from the forecasted consumption. The resulting load change $\Delta \mathrm{Q_h}$ for each hour h is received as the feedback, giving up the real time consumption along with the response action. The resultant change in consumption is settled real-time market. Here $\mathrm{Q_{realtime}}(\mathrm{h})$ represents the real-time consumption and $\mathrm{p_{realtime}}(\mathrm{h})$ represents corresponding the real-time price.

Under the ideal situation where the forecasted load has 100% match with the real-time load, the real-time price and forecasted price are same. However, in response to advance price signals, if consumers change their consumption, the real-time rates and forecasted rates deviate accordingly. Also, the consumers are charged at real-time rates. Moreover, it can be assumed that consumer would respond by increasing the consumption during lower price period and decreasing the same during the on-peak period, provided the benefits of response or the incentives are attractive enough. To simulate the response action, controlled randomization is performed for the load change during on peak and off peak price periods.

3.1.1 RANDOMIZED RESPONSE

Randomized response to the forecasted price signal is generated using the Gaussian distribution curve. According to this model, the response of consumers to advance price signal is mapped via normal distribution of the forecasted LMP signals. Higher is the deviation of any price signal from the daily mean; higher would be the magnitude of response. Considerable work has been done in interpreting and analyzing the probabilistic demand response models [30, 31]. The model used in the present chapter aims at illustrating the response action via calculating the load change based on Gaussian's Normal distribution model. Change in load is represented by equation 3-1

$$\Delta Q^{lse}(h) = k_p * \mathrm{rand}(1, x) * \left(Q^{lse}(h) - Q^{lse}_{avg}\right) \quad 3\text{-}1$$

Where, x>1

$$\alpha = \frac{\left|Q^{lse}(h) - Q_{avg}\right|}{\mathrm{Max}\left(Q^{lse}\right) - \mathrm{Min}\left(Q^{lse}\right)} \quad 3\text{-}2$$

In above equation

k_p is percentage increase or decrease α percent deviation of load point from average with respect to the total deviation of the load curve

$\mathrm{rand}(1, \mathrm{x})$ is a degree of randomness between 1 and x.

$\mathrm{Q}^{\mathrm{lse}}(\mathrm{h})$ forecasted load at hour h

$\mathrm{Q}^{\mathrm{lse}}_{\mathrm{avg}}$ average forecasted load.

$$\text{Hence, } Q^{lse}_{realtime} = Q^{lse}_{forecast} - \Delta Q^{lse} \qquad 3\text{-}3$$

$\mathrm{k_p}$ values are user defined in this case, and it represents the percentage change in the load observed or expected for particular time period. They could be modified to be a function of the variance of the forecasted load. Here the values are assumed to be 0.3, representing around 30% of load change during the extreme on peak and 0.6 during extreme off peak morning durations. The values of $\mathrm{k_p}$ from different zones on Gaussian distribution, is represented in Table 3.1. Additionally, the period amid 1 am to 7 am is considered as non-responsive period, where inclination for any sort of reaction is less when compared to responsive periods. Real time load consumption after the consumer's response to price according to probabilistic model is represented by equation 3-3. α accounts for the ratio of deviation of forecasted load from average to the total deviation between two extreme points observed by the load profile. Also, if rand(1,x) represents the randomness degree that can be expected from the consumer behavioral simulation. Then, rand(1,x) x α represents the proportional randomness. Which means, the randomness is scaled based on the value of α.

3.2 RESULTS AND DISCUSSION

Result representing a response to advance price signals leading to change in consumption and LMP are shown for all 3 load serving entities are shown in Figure 3.2. It

Table 3.1 Model Parameters

Range	k_p
$p_f^{lse}(h) > \mu^{lse} + 2\sigma^{lse}$	0.3
$\mu^{lse} + 2\sigma^{lse} > p_f^{lse}(h) > \mu^{lse} + \sigma^{lse}$	0.2
$\mu^{lse} + \sigma^{lse} > p_f^{lse}(h) > \mu^{lse} + 0.5\sigma^{lse}$	0.15
$\mu^{lse} + 0.5\sigma^{lse} > p_f^{lse}(h) > \mu^{lse} + 0.1\sigma^{lse}$	0.1
$\mu^{lse} + 0.1\sigma^{lse} > p_f^{lse}(h) > \mu^{lse}$	0.05
$\mu^{lse} > p_f^{lse}(h) > \mu^{lse} - 0.1\sigma^{lse}$	0.05
$\mu^{lse} - 0.1\sigma^{lse} > p_f^{lse}(h) > \mu^{lse} - 0.5\sigma^{lse}$	0.6
$\mu^{lse} - 0.5\sigma^{lse} > p_f^{lse}(h) > \mu^{lse} - \sigma^{lse}$	0.6
$\mu^{lse} - \sigma^{lse} > p_f^{lse}(h) > \mu^{lse} - 2\sigma^{lse}$	0.6
$\mu^{lse} - 2\sigma^{lse} > p_f^{lse}(h)$	0.6
$\mathrm{randomization{:}\ rand}(1,2)$	
Inactive Period: 1 am to 7 am.	

can be observed that in all three areas, the consumers are responding to higher price period by load curtailment or shifting load to lower price periods. Although, model lacks representing the type of response. Also, the parameters like economic class, demographics, the size of the residential buildings, etc. aren't considered by the model. Hence, the model is only good for benefit study analysis on the grid. But, the approach fails to give a clear understanding of the consumers regarding sensitivity to prices, nature of response and level

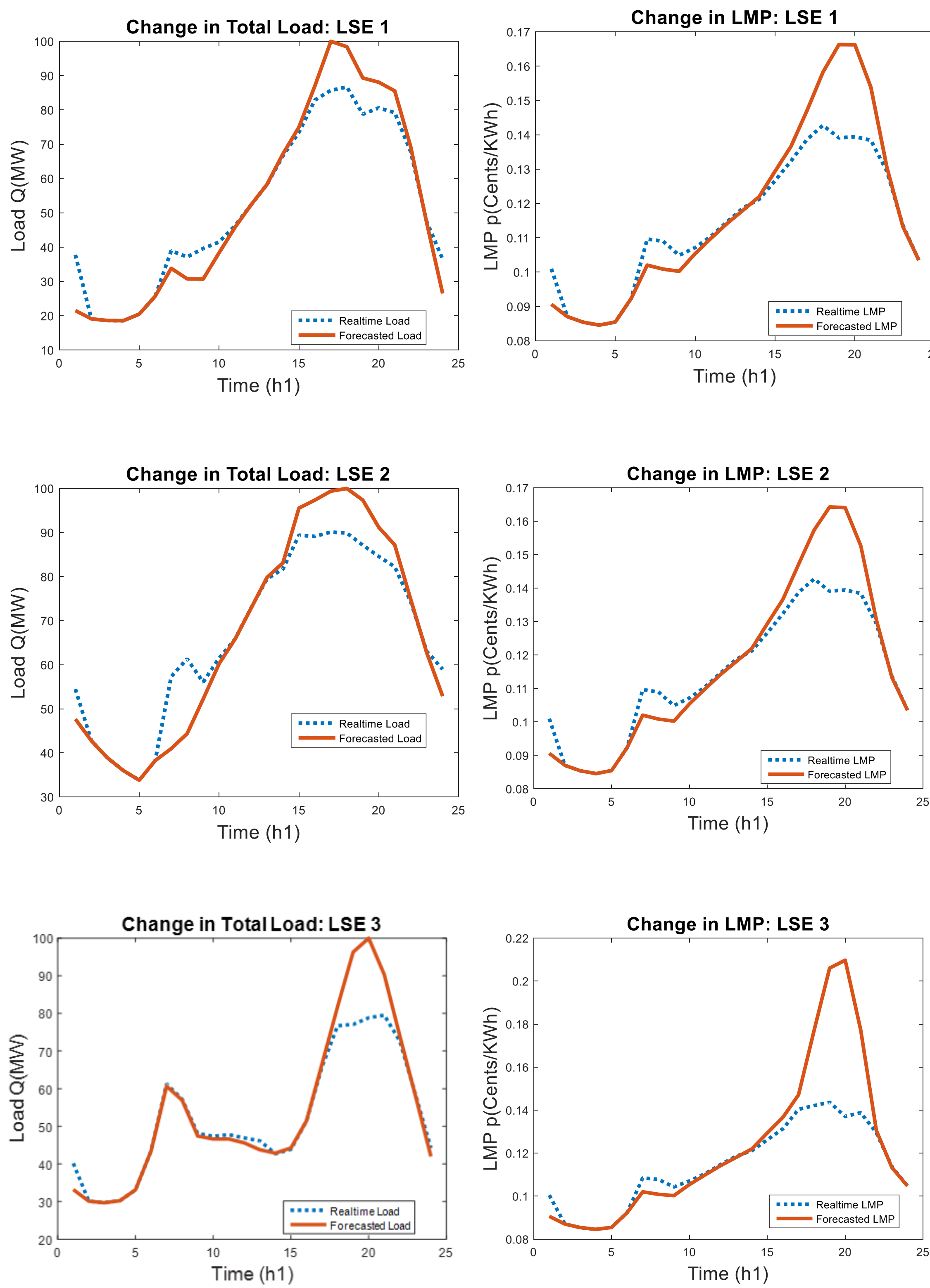


Figure 3.2: Load change and corresponding LMP change for 3 LSEs based on probabilistic demand response model

of load shift. As a result, the probabilistic or statistical model's capability in predicting the consumer's behavior is limited. Also, it fails to provide information about the magnitude of load shift, intertemporal information regarding the load shift and magnitude of curtailment. In market operator's perspective, the model may help in predicting the approximated change due to advance price signals under normal condition. However, uncertainties in demand variation because of advance rates cannot be predicted. Hence, the issue of complexity in demand prediction under demand response program remains unsolved. Hence, the model reflecting the consumer's psychology to advance price signals and type of the response action needs to be developed.

3.3 SUMMARY

Closed loop architecture of real-time based demand response program was discussed in this chapter. As statistical model lacks in providing the clear understanding of consumer behavior, a model reflecting the detailed consumption and response characteristics is required. Hence, the development of consumer psychology model is discussed in next chapter.

CHAPTER 4: CONSUMER PSYCHOLOGY MODEL AND DEMAND RESPONSE

A closed loop representation of demand response scenario in electricity market was discussed in Chapter 3. The simple regression of consumer's response action is not reliable because the change in over-all consumption depends on type and magnitude of the response action. It also depends on non-quantifiable characteristics- social, economic and demographic. Hence a detailed information of end use level demand modification in response to advance price signals is required to understand the response action of the consumer. This chapter aims at modeling the consumer psychology towards the demands response programs. Section 4.2 discusses the requirement of consumer psychology based demand response model. Classification of total load profile using the artificial neural network is explained in Section 4.3. Section 4.4 introduces the consumer psychology model and explains the load change under same. Section 4.5 explains the integration of consumer psychology model is integrated into demand response loop. The concept of consumer psychology model based demand response is implemented on 6 bus system in section 4.6.

4.1 INTRODUCTION

Modeling the consumer's responses to advance price signals plays a vital part in understanding the effectiveness of demand response model. The change in the consumer's consumption as a response to the advance pricing depends on various factors like consumer demographics, location, weather situation, type and size of residential loads, etc. Almost all of existing approaches on pricing decision rely on modeling approaches, which can be classified into three categories: consumer psychology based modeling approach, the price-elasticity matrix of demand, and the statistics based model. The so-called consumer psychology based modeling is a kind of black-box model that only cares about the relationship between input and output data, and it could be used in a situation unrelated with psychology. [32] Although psychological parameters could play a major role in modifying the black box model to suit the required simulation environment. Previously, the psychology model was developed to study TOU demand response programs with three price levels: Peak price period, flat price period and valley price period [32]. The concept is modified to simulate the dynamic pricing based demand response scenario.

4.2 REQUIREMENT OF CONSUMER PSYCHOLOGY MODEL

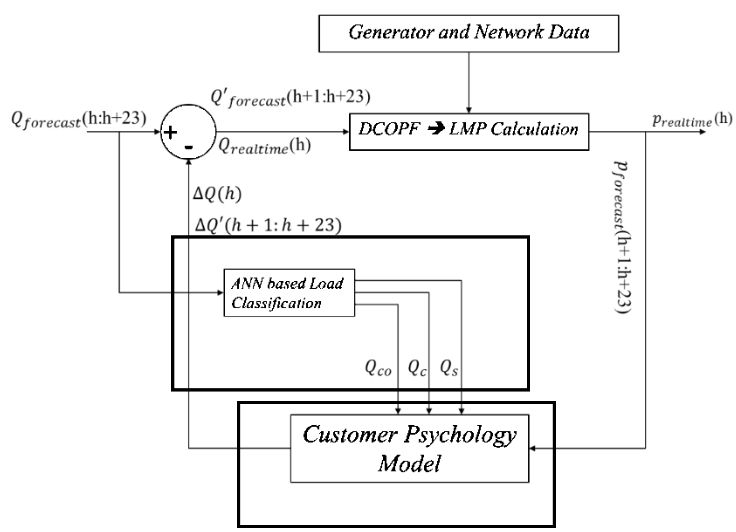


Figure 4.1: Consumer psychology model based demand response

The price difference or incentive of participation in DR program serves as the prime motivation behind modification of consumption. Considering these factors, a model has been developed which can simulate the consumer's behavior to advance price signals.

Previous work in the area of consumer psychology model based demand response study for TOU pricing, merely simulated the load shift in response to price differences. It did not take into consideration, the components of the loads in the total load profile

The psychology model based demand response, as shown in Figure 4.1, comprises of two participating blocks.

a. Load Classification: This block, based, uses the survey and end-use data to classify the type of loads. The data also reflects the consumer's geographical and demographical aspects. It also takes into account the information regarding the appliances and type of residential construction. Section 4.3 describes the process of load classification in detail.
b. Consumer behavioral simulation: Based on the classified load, the shiftable and curtailable type of response is simulated. It reflects consumer's interest in DR participation as well as economic condition. Section 4.4 describes the Consumer's behavioral simulation via consumer psychology model in detail.

4.3 ANN BASED LOAD CLASSIFICATION

Consumer's overall load profile constitutes of three major components:

i. Shiftable Loads: Certain loads holds the flexibility of shifting the consumption from peak price periods to lower price periods. This type loads are classified as shiftable loads. Examples of major residential loads holding this flexibility are washer drier, dish washer, electric stove, microwave and oven.

ii. Curtailable Loads: The load, whose consumption can be varied by relaxing up the operating set-points and compromising partly on its output is termed as curtailment. Curtailable loads primarily comprise of HVAC loads i.e.,. Air Conditioner, Space Heating, water heater and fans. During peak periods, relaxing the operating point of these loads may contribute highly in savings.

iii. Constant Loads: The loads, considering their absence/curtailment may lead to high level of inconvenience and discomfort, are classified under constant loads. Lighting loads are categorized under constant loads.

If the total load profile can be bifurcated into the three components, the better estimation can be gained in forecasting the consumer's behavior and sensitivity to prices. It can be achieved by doing the survey of end use consumption [33].

A similar approach was used in this research for identifying the consumer's consumption pattern. Detailed residential consumption data was obtained from openEI. OpenEI portal hosts, simulated residential consumption load profile as per NREL and DOE's "Building America House Simulation Protocols" for all TMY3 locations and weather conditions. The simulation also takes U.S. Energy Information and Administration's Residential Energy Consumption Survey (RECS) information to include the demographics, end-use fuels and appliances and structural as well as geographical characteristics. Consumption of HVAC load and the constant load is highly dependent on weather conditions and irradiation respectively. Meteorological data utilized in the residential load data simulation was obtained from NREL's data repository for three different locations: Phoenix (Arizona), San Diego (California) and Rochester (New York) was used to train the neural network. A neural network can learn and therefore be trained to find solutions, recognize patterns, classify data, and forecast future events. [34] [35]. The behavior of a neural network is defined by the way its individual computing elements are connected and by the strengths of those connections, or weights. The weights are automatically adjusted by training the network according to a specified learning rule until it performs the desired task correctly. The human behavioral pattern cannot be directly correlated using any equations. Hence neural network emerges as the best option for prediction and classification of the same. HVAC consumption depends on temperature whereas, consumption by constant load depends on irradiance. Hence, as depicted in Figure 4.2 for classification the input parameters used are Total Load, temperature, Irradiance and Month and Time. One year of the complete data set was used for training and neural network with ten neurons. 70 percent of data was allotted for training, 15 % of data was allotted for validation and remaining 15% for testing. Figure 4.4 represents the performance plot of ANN. The optimum mean square error of 0.07% approaches 105 iterations. Figure 4.3 represents set of individual regression plot for a training class, testing class, validation class and the fourth one considering all three classes. The slope of the regression line is near to the ideal fitness of 1. Figure 4.5 represents an error histogram with mean lying at 0.1%. Data being used is an output of a residential scenario. Hence, high accuracy is being observed. In a practical scenario, the accuracy of this level is not expected.

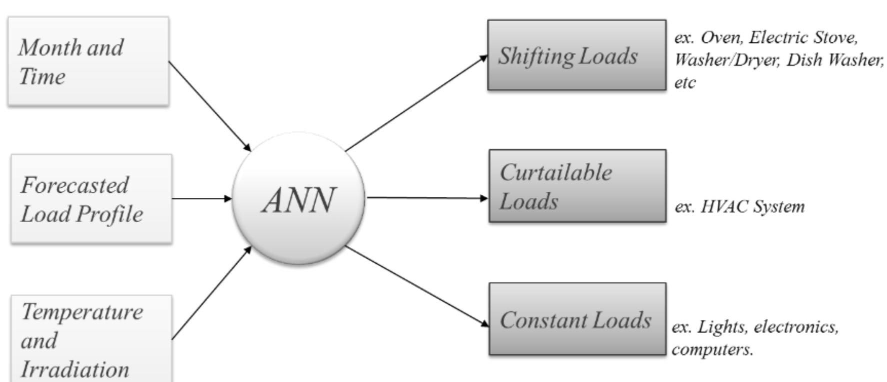


Figure 4.2: Input and output parameters of an Artificial Neural Network for load classification

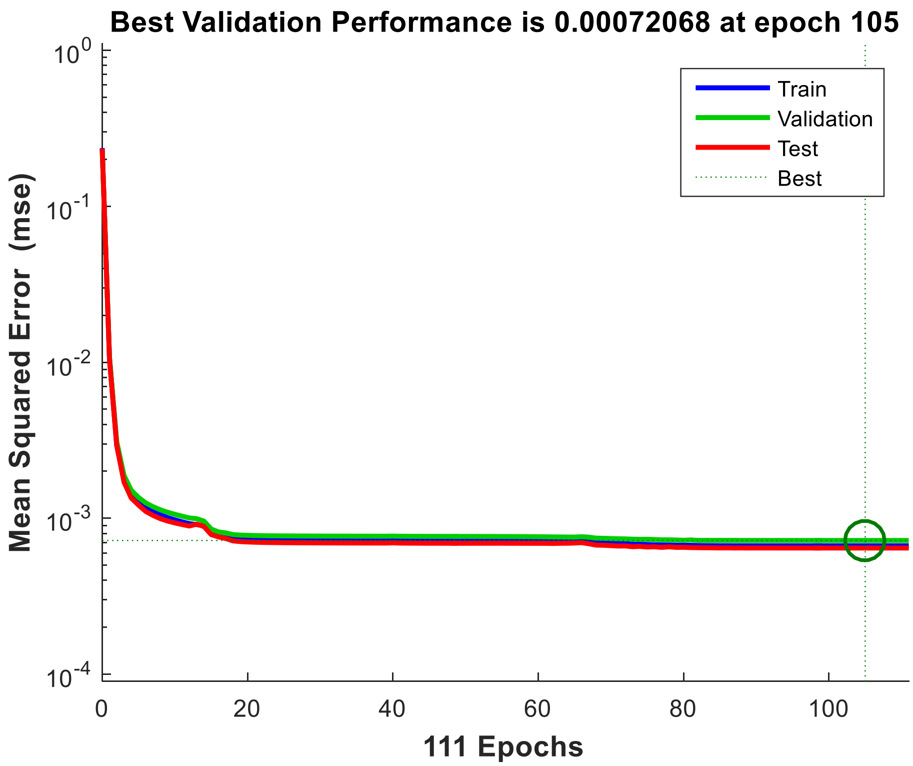


Figure 4.4: Performance plot indicating mean square error during traing validation and testing phase

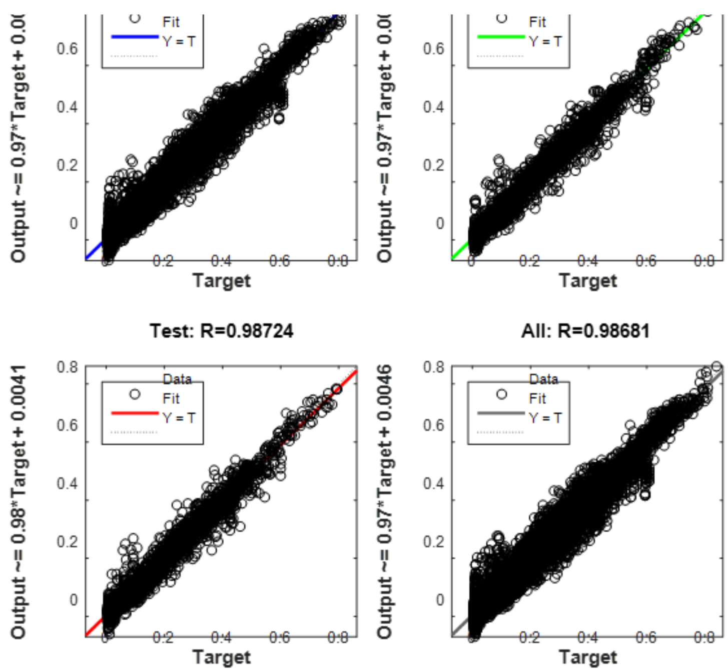


Figure 4.3: Regression plot for training, testing and validation

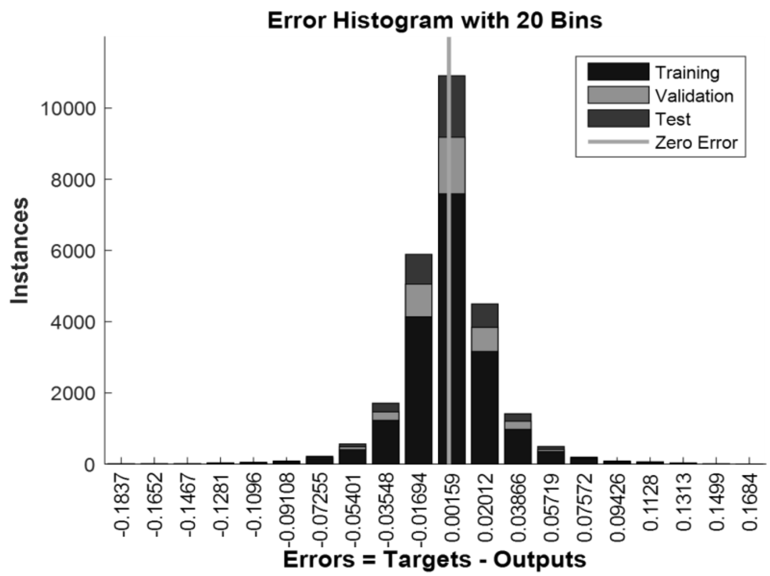


Figure 4.5: Error histogram

The approach serves the purpose of classifying the overall load profile and providing with consumption for different types of load. Trained artificial neural network was used for classification of load patterns from three different zones. The actual load pattern was scaled at the system level by per unitizing and multiplying with base values accepted by the system's range of operation. This helped in preserving the load pattern and making it compatible within the system limits. Figure 4.6 represents the load classification for zone 1 corresponding to consumption data of San Diego, California. Total Load consists of 36.2% of curtailable Loads, 53.9% of shiftable loads and 10.67% of constant loads. Hence this zone holds the scope for both load shift as well as load curtailment type responses. Figure 4.7 represents the load classification for zone 2 corresponding to consumption data of Phoenix, Arizona. Total load of this zone constitutes 79.6 percent of curtailable loads, 16.1% of shiftable loads and 4.25% of constant loads. Hence, it can be inferred that zone 2 holds high potential for load curtailment and very low potential for shifting. Load classification for zone 3 corresponding to Rochester, New York is represented in Figure 4.8. Total load constitutes of 16.73% of curtailable loads, 54.97% of shifting loads and 28.31% of constant loads. Based on the proportion of load, zone holds higher potential for shifting type responses compared to curtailment type.

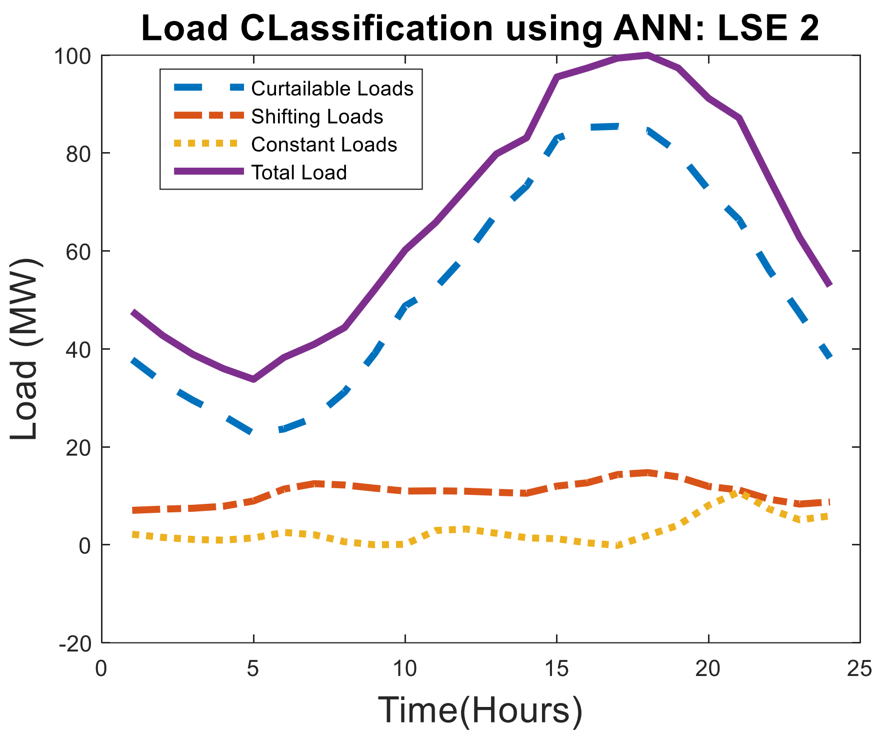


Figure 4.6: ANN based load classification: LSE 1

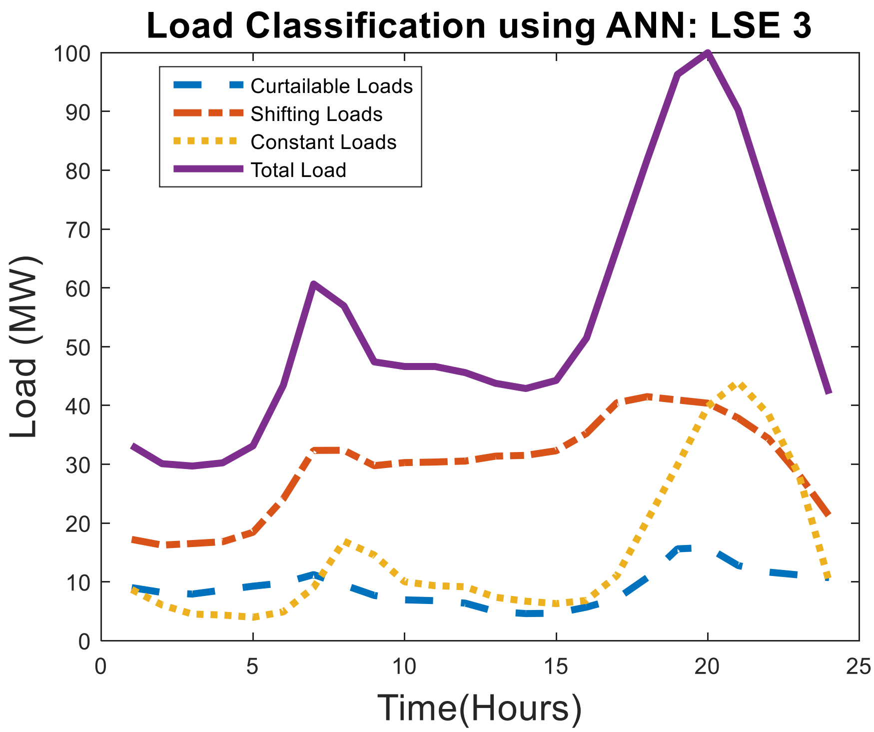


Figure 4.7: ANN based load classification: LSE 2

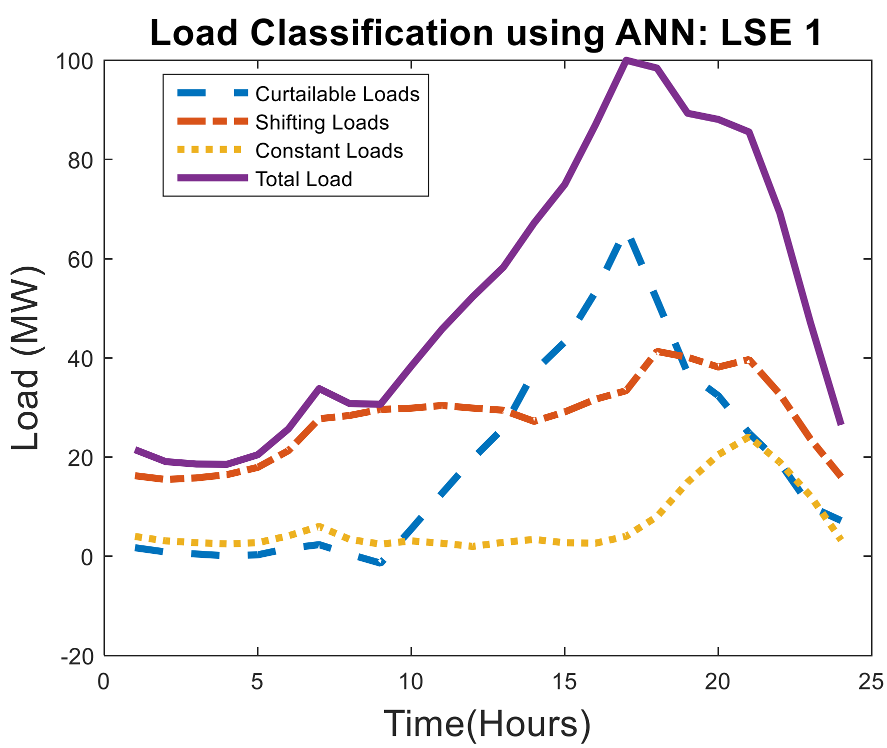


Figure 4.8: ANN based load classification: LSE 3

4.4 CONSUMER PSYCHOLOGY MODEL BASED RESPONSE

Consumer psychology was used by Shen Zhao [36] in modeling the TOU based demand response scheme. The concept of psychology model on 3 level price structured demand response program was modified in the present research for real-time pricing. The principle of consumer psychology model is discussed in section 4.4.1. Section 4.4.2 and 4.4.3 articulates the principle to real time pricing for modelling the load curtailment and load shift respectively.

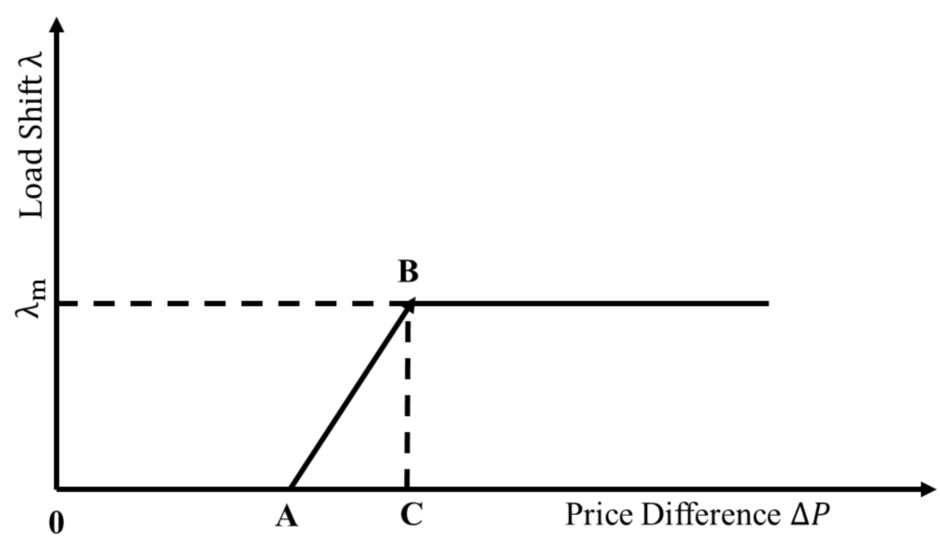


Figure 4.9: Consumer Psychology Model: Principle

4.4.1 CONSUMER PSYCHOLOGY MODEL(CPM): PRINCIPLE

According to consumer psychology, there is a noticeable difference when consumers are stimulated. The response of consumers is negligible within difference threshold usually called insensitive zone (or dead zone), whereas the response is obvious outside the dead zone. We can call this range normal response zone (or linear zone) and the response is connected with the degree of the benefit. When exceeding the saturation value, the benefit will not cause a further response of consumers, and we call this zone as response limit zone (or saturation zone). It can be implied that the benefit foreseen for any response action to advance price signals is the driving factor in the psychology model. Slope (k)of the psychology model gives the rate of response to the change in price. Figure 4.9 represents the principle of psychology model. The dead zone is represented by price difference OA. AC is the linear zone reflecting the load change as the response. Beyond C, the load change is zero, thereby representing the saturation zone. No response action to change in price can be expected in beyond the price benefit OC.

The model can also be represented in the form of Equation 4-1.

$$\lambda = \begin{cases} 0, & (0 \leq \Delta P \leq a) \\ k(\Delta P - a), & (a \leq \Delta P \leq c) \\ \lambda_m, & (\Delta P \geq c) \end{cases} \qquad \text{4-1}$$

Articulating the concept of modeling the psychology for demand curtailment and shifting is represented in section 4.4.2 and section 4.4.3 respectively.

4.4.2 LOAD CURTAILMENT

Load curtailment can be human controlled or autonomous in nature considering the recent developments in the smart thermostats. Average of forecasted LMP is considered as the reference LMP. Load curtailment is assumed to take place when LMP of that particular period is higher than average reference LMP.

Load curtailment behavior can be articulated to the concept of consumer psychology model. ΔP in case of curtailment has been considered as difference between the forecastd LMP during h^{th} hour and the average of 24 hours forecasted LMP. Depending on the economic class of the consumer, the threshold can be varied. For areas with economically weaker sections, ΔP_{OA} would be low, whereas for the economically stronger section, ΔP_{OA} would be high. The slope of the line AB under the response zone represents the degree of flexibility for load curtailment. A Higher value of slope represents higher curtailment response to the price. In the curtailment, model k is represented by k_c (curtailment coefficient).

Value of curtailment coefficient k_c is derived as represented by Equation 4-2, 4-3, and 4-4

$$k_c^{lse}(h) = k_{cc}^{lse} * k_{cp}^{lse}(h) * k_{cr}^{lse}(h) \quad 4\text{-}2$$

$$\text{Where } k_{cc}^{lse} = \frac{\sum_{h=1}^{24} Q^{lse}(h)}{\sum_{h=1}^{24} lmp_L^{lse}(h)} \quad 4\text{-}3$$

$k_{cp}^{lse}(h)$ is curtailment percentage

$$k_{cr}^{lse}(h) = \frac{Q_{lc}^{lse}(h)}{Q_l^{lse}(h)} \quad 4\text{-}4$$

$$\text{Also, } \Delta p(h) = p^{lse}(h) - p_{avg}^{lse} \quad 4\text{-}5$$

Components of curtailment coefficient k_c are represented by equations 4-3 and 4-4. k_{cc}^{lse} in Equation 4-3 is the ratio of average load to average LMP for the load-serving entity under consideration. It serves the purpose of mapping the variables of LMP to the load. k_{cp} represents the curtailment percentage for h_{th} hour. Its value can be the user defined based on the observations or simulation requirement. k_{cr} represents the ratio of curtailable load entity to the total load for h^{th}hour.

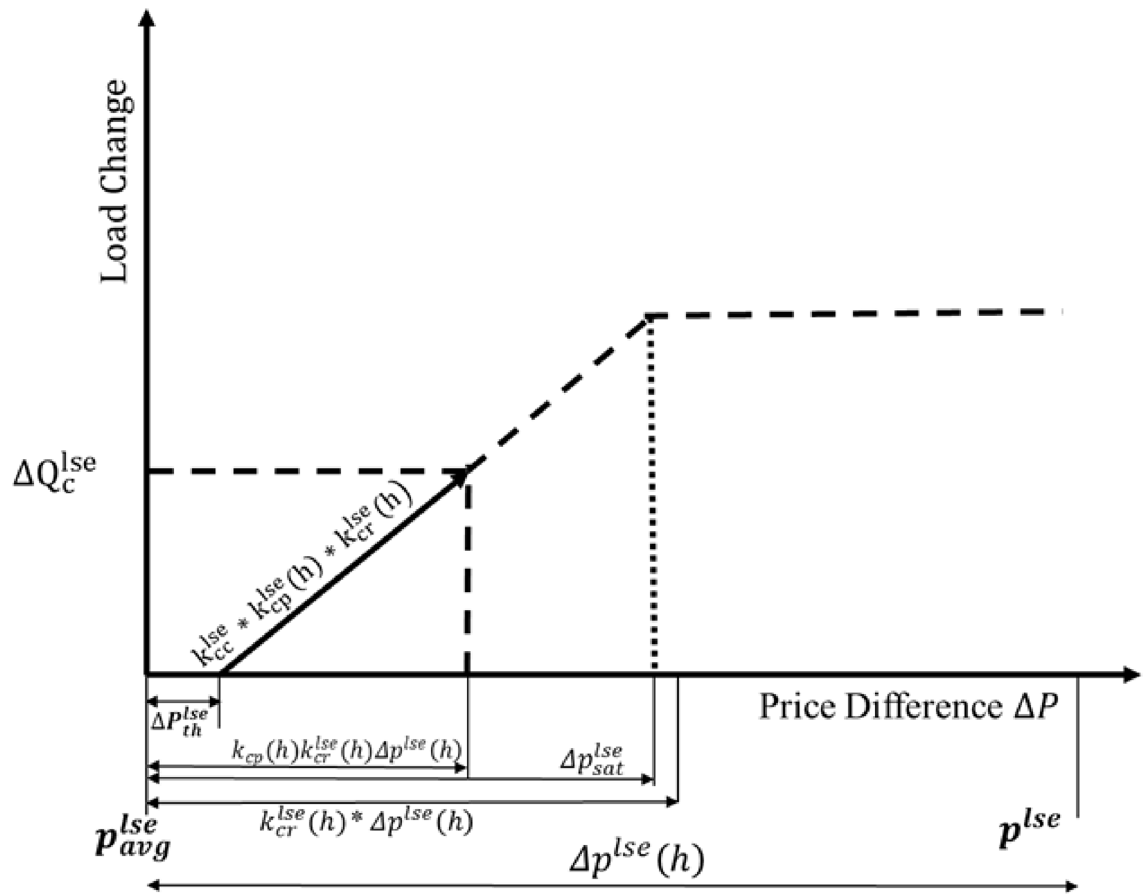


Figure 4.10: Consumer Psychology Model for load curtailment

As shown in Figure 4.10, if Equation represents the variation of LMP from the average LMP(reference value), then $k_{cr}^{lse}(h) * \Delta p^{lse}(h)$ represents the curtailable component within the price difference. $k_{cp}(h) * k_{cr}^{lse}(h) * \Delta p^{lse}(h)$ will represent the percentage curtailment action in terms or price. $k_{cc}^{lse} * k_{cp}^{lse}(h) * k_{cr}^{lse}(h) * \Delta p^{lse}(h)$ will map the percentage curtailment from dollar value to MWs.

Hence, curtailed load can be represented by

$$Q_{crtld.}^{lse}(h) = Q_{c}^{lse}(h) - \Delta Q_{c}^{lse}(h) \qquad 4\text{-}6$$

$$\text{Where, } \Delta Q_{c}^{lse}(h) = 0 \qquad \text{if } \Delta p_{th}^{lse}(h) > \Delta p^{lse}(h) \qquad 4\text{-}7$$

$$Q_{c}^{lse}(h) = k_{c}^{lse}(h) * \Delta p^{lse}(h) \quad \text{if } \Delta p_{th}^{lse}(h) < \Delta p^{lse}(h) < \Delta p_{sat}^{lse}(h)$$

$$\Delta Q_{c}^{lse}(h) = \Delta Q_{cmax}^{lse}(h) \qquad \text{if } \Delta p^{lse}(h) > \Delta p_{sat}^{lse}(h)$$

Here, $Q_{crtld.}^{lse}$ is curtailed load after curtailment type consumer response.

Q_{c}^{lse} is curtailable load before consumer response

ΔQ_{c}^{lse} represents change in curtailable load

Δp_{th}^{lse} represents the threshold point rate difference

Δp_{sat}^{lse} represents the saturation point rate difference

ΔQ_{cmax}^{lse} represents maximum limit curtailable load change.

Equation 4-6 represents the relation for obtaining the curtailed load after the response action. Equation 4-7 completely models the curtailment type response under consumer psychology model

4.4.3 LOAD SHIFTING

Load shifting is a completely human-controlled response to advance price signals. Response under this category indicates the flexibility to shift the loads from peak price period to lower price periods. The difference in the peak and off-peak period’s forecasted rates serves as the major motivation factor behind shifting of the flexible loads. Hence to simulate the load shift, the intertemporal price difference needs to be identified as it reflects the benefit of the response to the consumer. If this intertemporal difference of forecasted rates between two periods is more than the threshold, the periods may contribute to the load shift from higher price period to lower price period.

Load shifting behavior can be articulated to the concept of consumer psychology model. ΔP in the case of the shift has been considered as the intertemporal price difference between the hours of forecasted LMP. Depending on the economic class of the consumer, the threshold can be varied. For areas with economically weaker sections, ΔP_{OA} would be low, whereas for the economically stronger section, ΔP_{OA} would be high. The slope of the line AB under the response zone represents the degree of flexibility for load shift. A Higher value of slope represents a higher shift-type response to the price. In the load-shift model, k is represented by k_s (shifting coefficient).

Value of shifting coefficient $k_s^{lse}(h_1, h_2)$ representing load shifting rate from hour h_2 to hour h_1 for load serving entity under consideration is given by Equation 4-8.

Components of shifting coefficient k_s are represented by equations 4-8, 4-9, 4-10 and 4-11. k_{sc}^{lse} in Equation 4-9 is the ratio of average load to average LMP for the load-serving entity under consideration. It serves the purpose of mapping the variables of LMP to the load. k_{sp} represents the average percentage of load shift taking place in the DR environment for the load-serving entity under consideration. The value can be the user defined based on the observations or based on observation or simulation requirement. k_{sr} represents the ratio of average shiftable load present in the total load. The denominator represents the active hours participating in the load shift. Midnight is considered as an inactive duration where load shifting potential is negligible. As, each intertemporal price difference is considered individually for load shift, dividing the load shifting rates by active hours, avoids the overshoot errors by scaling down the individual shift over the active hour duration.

$$k_s^{lse}(h_1, h_2) = \frac{k_{se}^{lse}(h_1) * k_{sp}^{lse}(h1, h2) * k_{sc}^{lse} * k_{sr}(h)}{\text{number of active hours}} \quad \text{4-8}$$

Where $k_{sc}^{lse} = \frac{\sum_{h=1}^{24} Q^{lse}(h)}{\sum_{h=1}^{24} lmp_L^{lse}(h)}$ 4-9

$$k_{sp}(h) = \text{shift percentage} \quad \text{4-10}$$

$$k_{sr} = \frac{Q_{lc}^{lse}(avg)}{Q_l^{lse}(avg)} \quad \text{4-11}$$

$k_{se}^{lse}(h_1)$ is the sensitivity of h_1 towards load shift

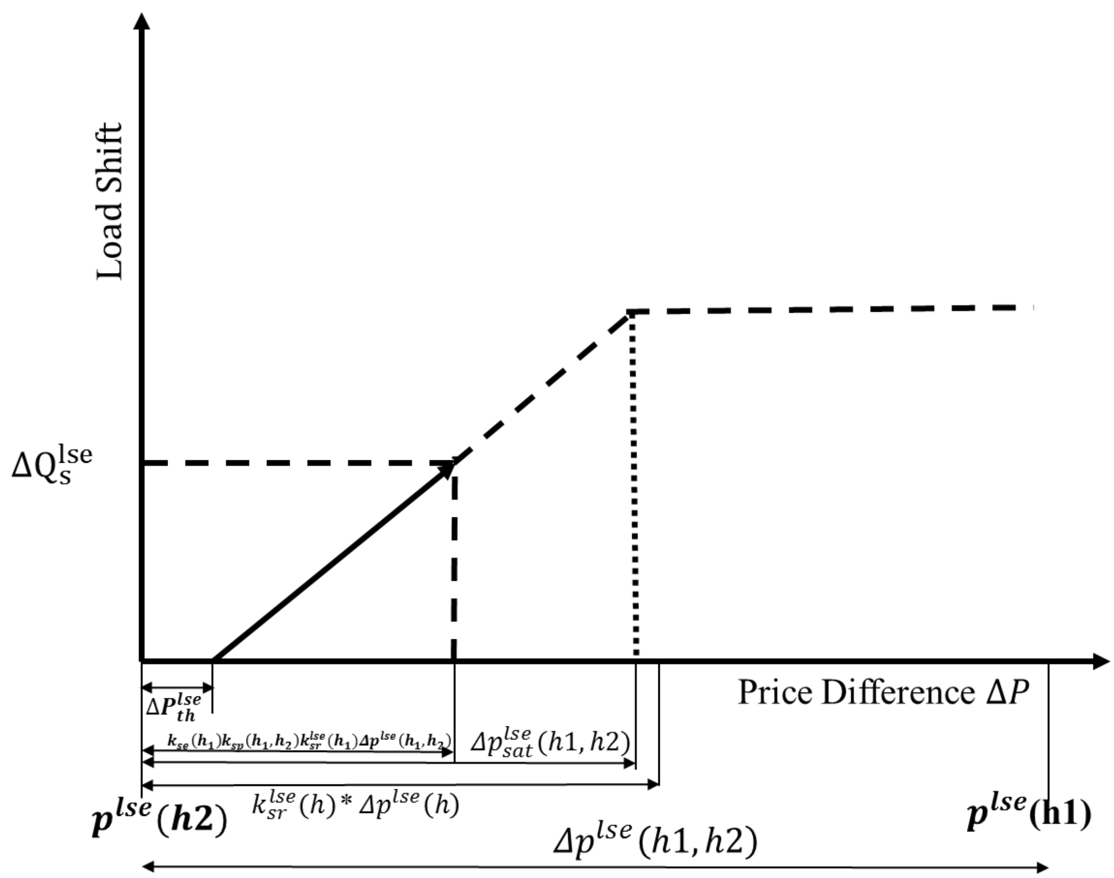


Figure 4.11: Consumer Psychology Model for load shift

Depending on the convenience, consumer may be prone to shift most of the shiftable loads to a particular period $k_{se}^{lse}(h_1)$ with lower price and high convenience. Hence, this parameter reflects the sensitivity towards the period h_1.

$$\text{Hence, } \quad \Delta p^{lse}(h_1, h_2) = p^{lse}(h_2) - p^{lse}(h_1) \qquad \text{4-12}$$

Hence, shifted load can be represented by

$$Q_{shftd.}^{lse}(h_2) = Q_s^{lse}(h_2) + \sum_{h1=1}^{24} \Delta Q_s^{lse}(h_1, h_2) \qquad \text{4-13}$$

$$\text{Where, } \Delta Q_s^{lse}(h_1, h_2) = 0 \quad \text{if } \Delta p_{th}^{lse}(h_1, h_2) > \Delta p^{lse}(h_1, h_2) \qquad \text{4-14}$$

$$\Delta Q_s^{lse}(h_1, h_2) = k_s^{lse}(h_1, h_2) * \Delta p^{lse}(h_1, h_2)$$

$$\text{if } \Delta p_{th}^{lse}(h_1, h_2) < \Delta p^{lse}(h_1, h_2) < \Delta p_{sat}^{lse}(h_1, h_2)$$

$$\Delta Q_c^{lse}(h_1, h_2) = \Delta Q_{cmax}^{lse}(h_1, h_2)$$

$$\text{If } \Delta p^{lse}(h_1, h_2) > \Delta p_{sat}^{lse}(h_1, h_2)$$

Here, $Q_{shftd.}^{lse}$ is shifted load after shifting type consumer response.

Q_s^{lse} is shiftable load prior to consumer response

ΔQ_s^{lse} represents change in shiftable load

$\Delta p_{th}^{lse}(h_1, h_2)$ represents the threshold point rate difference

$\Delta p_{sat}^{lse}(h_1, h_2)$ represents the saturation point rate difference

$\Delta Q_{cmax}^{lse}(h_1, h_2)$ represents maximum limit curtailable load change.

As shown in Figure 4.11, Equation 4-13 represents the relation for obtaining the curtailed load after the response action. Equation 4-14 completely models the curtailment type response under consumer psychology model.

4.5 DEMAND RESPONSE USING CONSUMER PSYCHOLOGY MODEL

If the components of load are known, it becomes easy to analyze the consumer's behavioral pattern and response to the price signals. 4.3 illustrates the use of artificial neural network data for load classification. The data used to train ANN network has already taken into consideration the social, geographic and demographic characteristics of

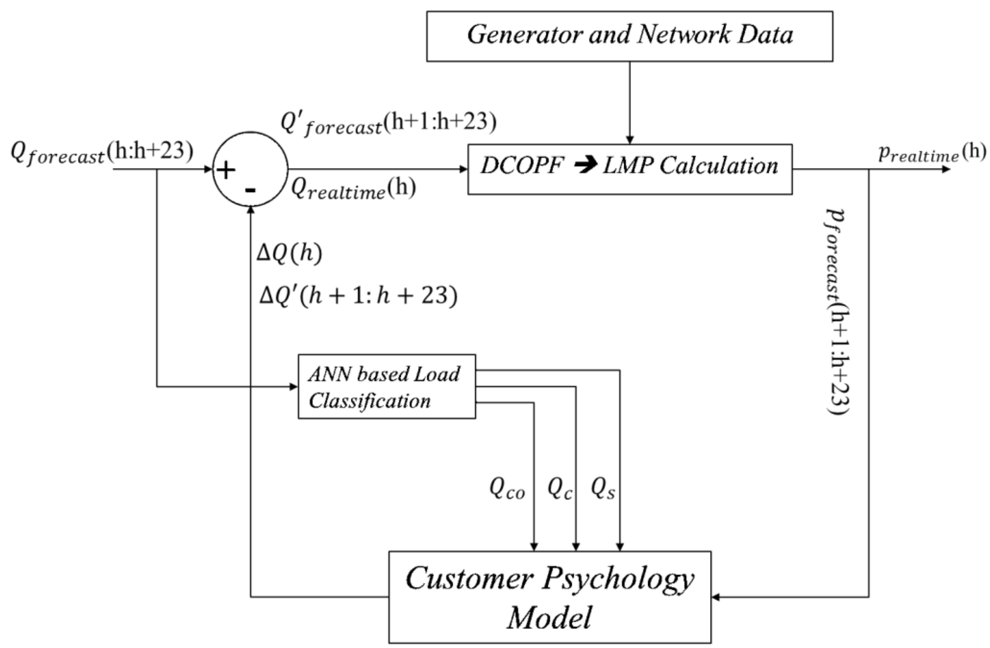


Figure 4.12: Demand response using Consumer Psychology Model

consumers from each residential zones. Hence, as explained in 4.4, the consumer behavior can be effectively modeled. Demand response using consumer psychology model is represented in Figure 4.12. Initially, based on the forecasted load $Q_{forecasted}$ for all the load serving entities in the system, the LMP is calculated via DCOPF. This forecasted rate signal $p_{forecasted}$ is made available to consumers 24 hours in advance. Based on the curtailment and shifting characteristics, the consumers may modify their consumption. The rates are re-calculated in the real-time market based on the modified demand for h_{th} hour and consumers are billed at this rate for their consumption. Because of load shift for $\mathrm{h_{th}}$ an hour from the past and future period, the values of forecasted $\mathrm{Q'_{forecasted}}$. loads also change, but the changes are not made available to the consumers. This load change may be estimated by the operators to optimize the scheduling of generators.

4.6 RESULTS AND DISCUSSION

Figure 4.13 represents the forecasted load profile assuming no demand response behavior. Based on this forecast, the LMP for the load-serving entities is calculated using DCOPF. The LMP's represent the forecasted price signals which consumer receives before 24 hours. Figure 4.14 represents the forecasted price signal, the consumer receives. Bifurcation of the load profile for the curtailable and shiftable component is shown in Figure 4.6, Figure 4.7 and Figure 4.8. These profiles along with the forecasted rates are taken as input by the consumer psychology model to simulate the load curtailment and load shift. Model parameters guiding the load curtailment and load shift and curtailment for a normal and a surge scenario are defined in Table 4.1 and

Table 4.2 respectively. Figure 4.15 represents the motivation factor for load curtailment and corresponding load change. Figure 4.16 represents the benefit factor behind load shift (intertemporal price difference) and corresponding load shift. Figure 4.17 represents the overall change in consumption pattern from the forecasted rates and load because of advance price signals. Figure 4.18 represents the overall change in the load and LMP due to consumer participation on real-time demand response program. The scenario of DR described in this illustration is considered as an idea because sensitivity to load shift among the periods is same. Practically, the consumers may be prone to shift the load to the off-peak period with higher convenience. The scenario under this situation is illustrated in

Figure 4.19 Figure 4.20 and Figure 4.21. Iterations of consumer psychology model run in real-time and can be used to map the precise scenarios to the real-world demand response environment. Unlike other models, it considers both social as well as psychological aspects of simulation the DR scenario. Work still needs to be done in relating the model parameters to the actual scenario via machine learning algorithm. Also, the model provides with the load change values which can be further used in calculating the elasticity matrix. Elasticity matrix would also represent the shift sensitive time periods as illustrated in scenario 2. Moreover, it can be used to improve the architecture further by providing the consumers with optimum forecasted price signals which can suppress the spikes or overshoot due to load shift.

Table 4.1: Model Parameters: Scenario 1

k_{sp} (shift percentage)	0.4
k_{se} (shift sensitivity)	1
k_{cp} (curtailment percentage)	0.4
Active Hours	7:00 to 24:00

Table 4.2: Model Parameters: Scenario 2

k_{sp} (shift percentage)	0.4
k_{se} (shift sensitivity) $k_{se}(8)$, (shift sensitivity at h=8:00)	1 25
k_{cp} (curtailment percentage)	0.4
Active Hours	7:00 to 24:00

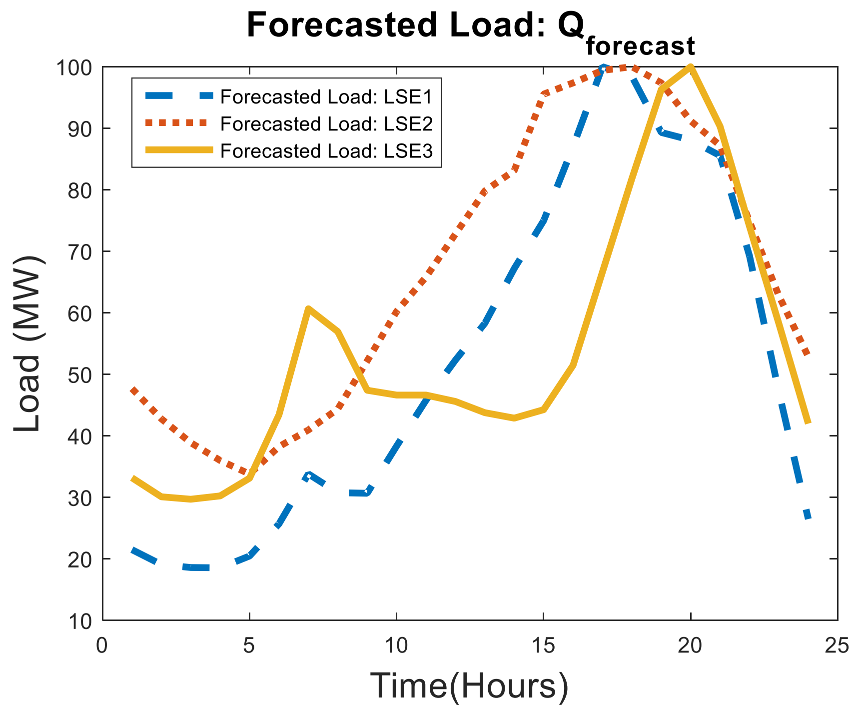


Figure 4.13: Forecasted load

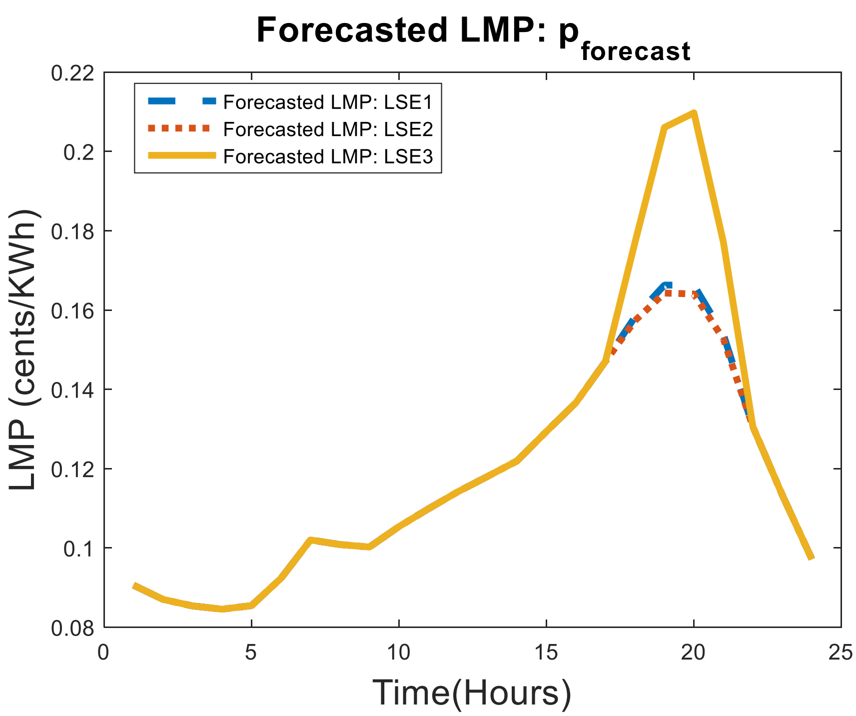


Figure 4.14: Forecasted LMP

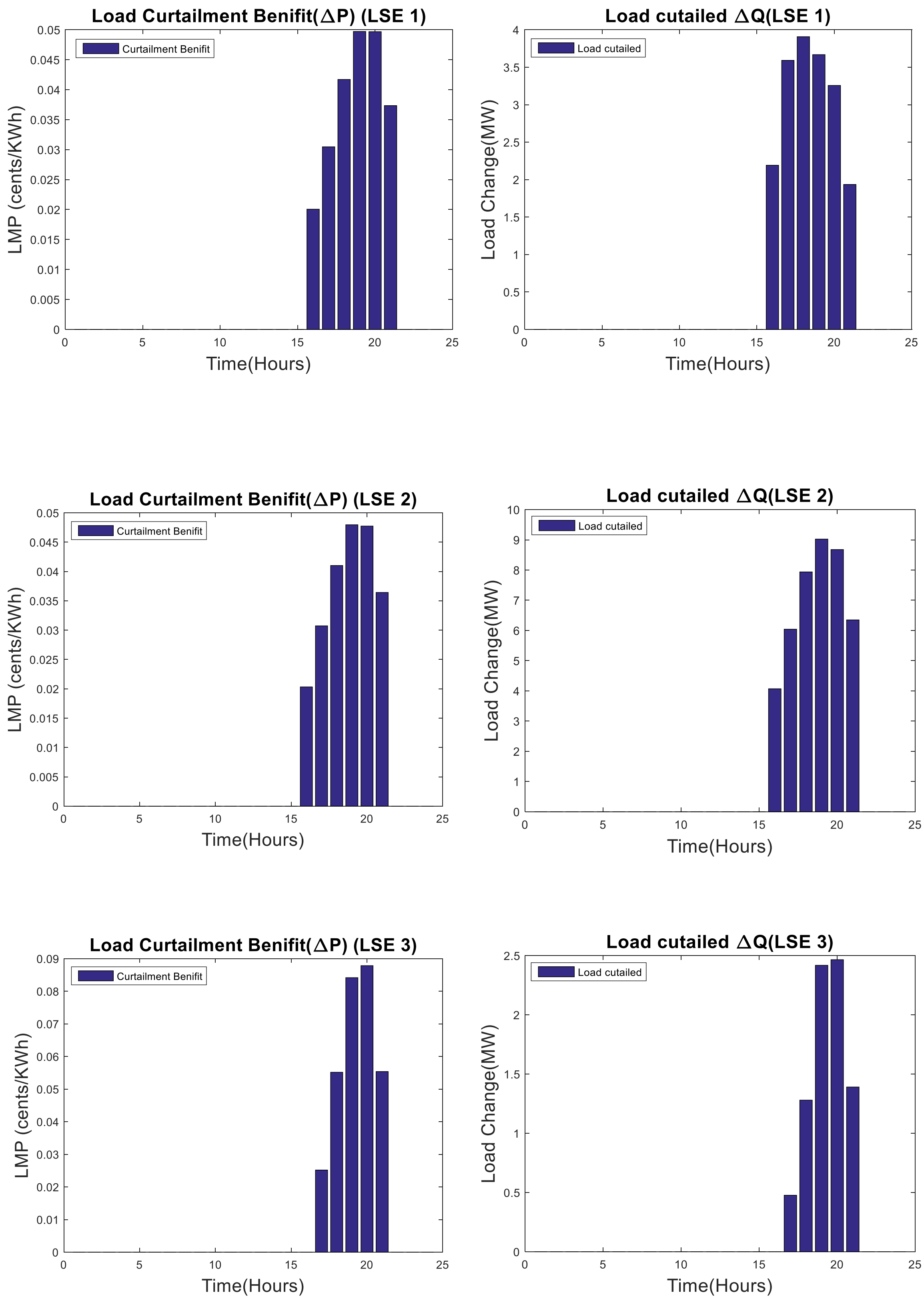


Figure 4.15: Benefit factor and corresponding load curtailment

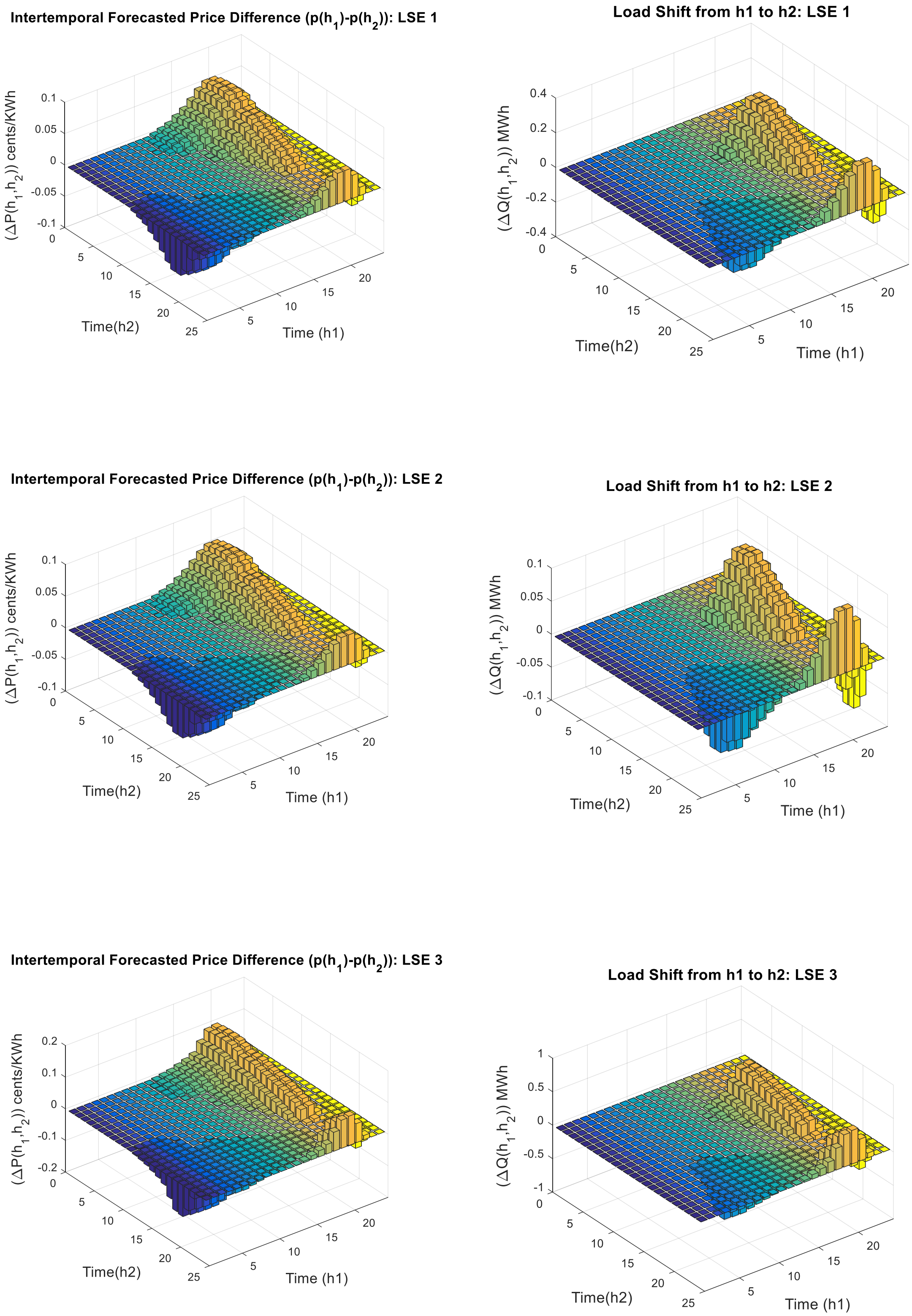


Figure 4.16: Benefit factor and corresponding load shift (Scenario 1)

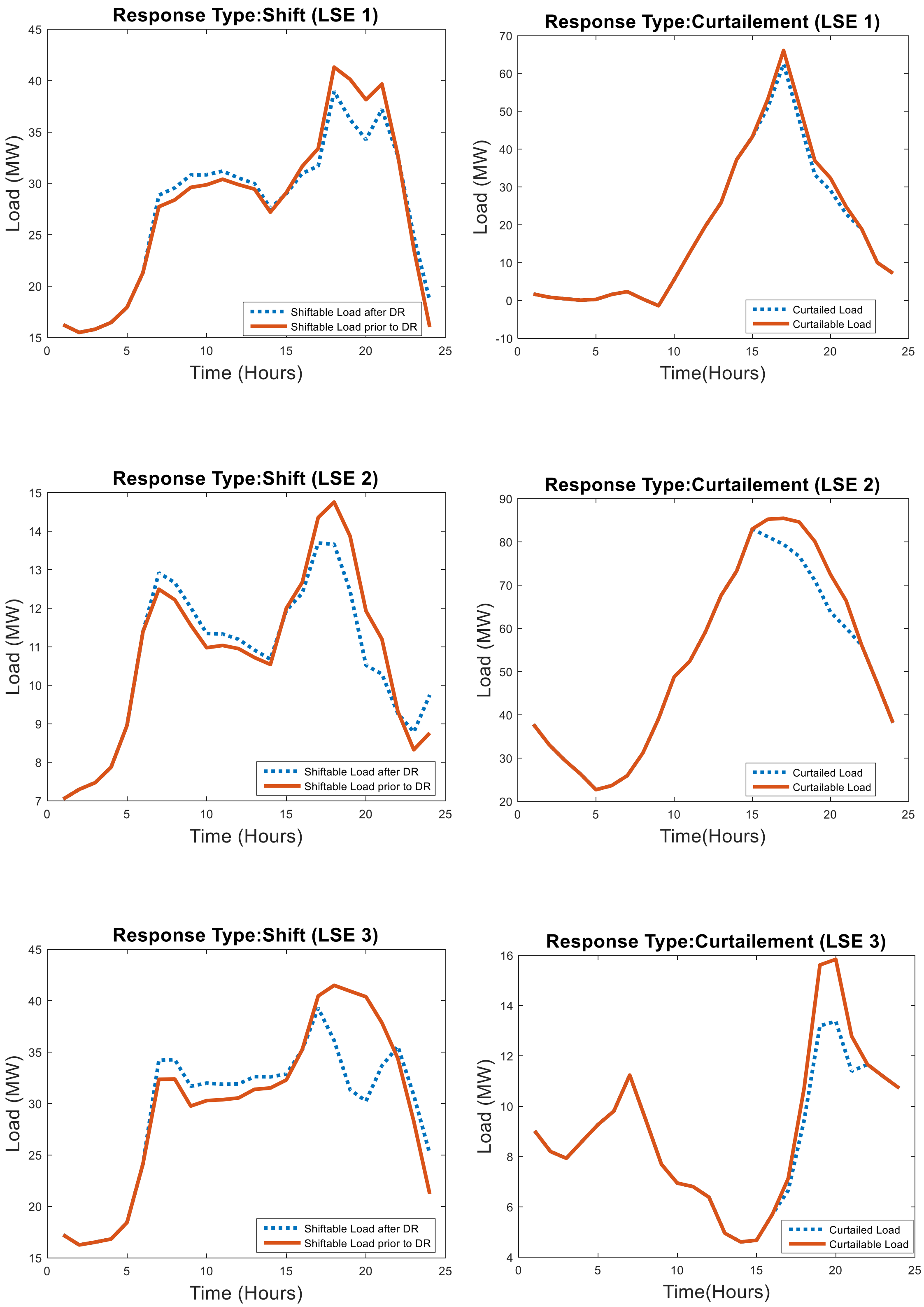


Figure 4.17: Curtailment and shift type reponse based on Consumer Psychology Model (Scenario 1)

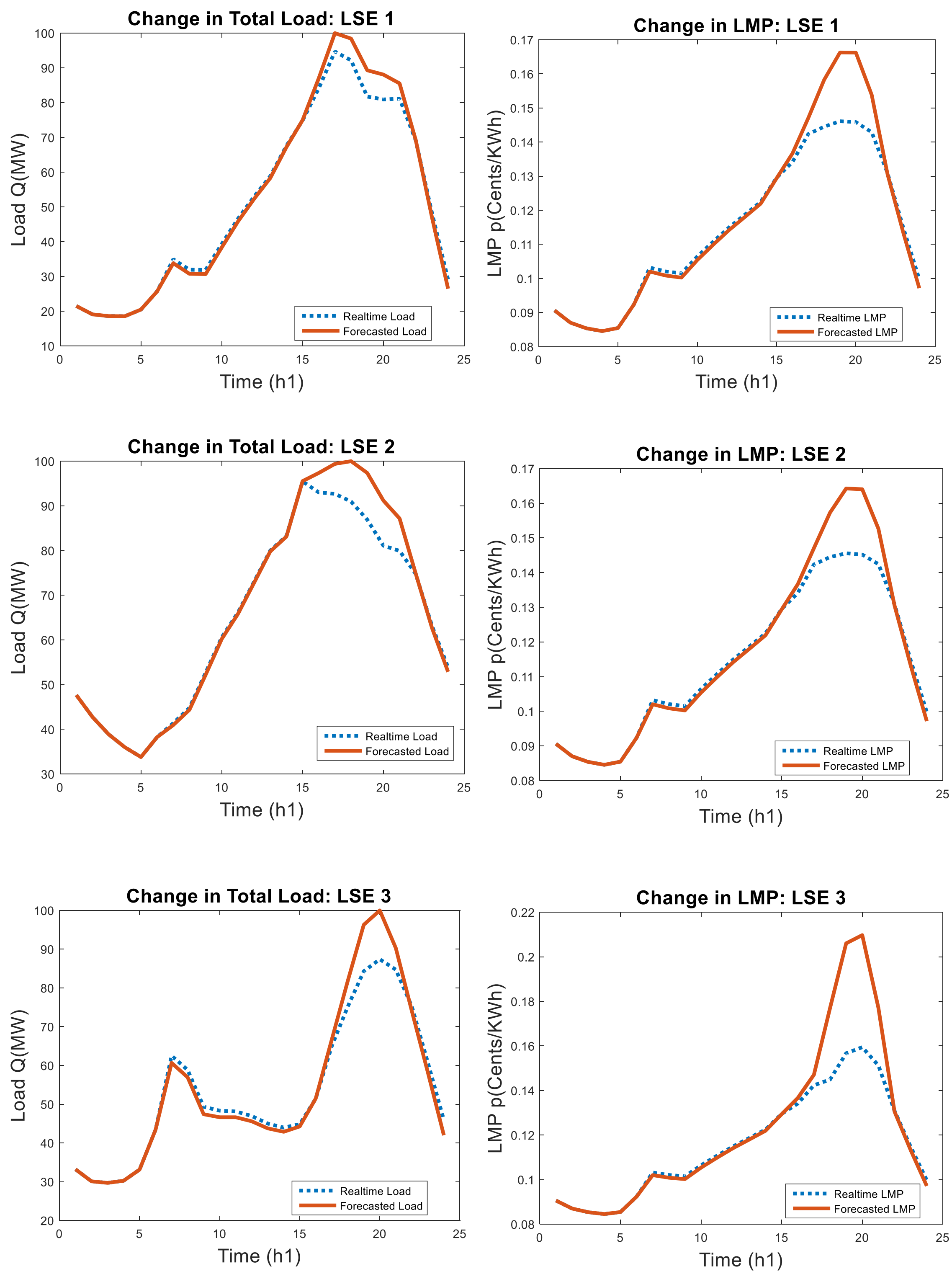


Figure 4.18: Consumer Psychology Model based demand response (Scenario 1)

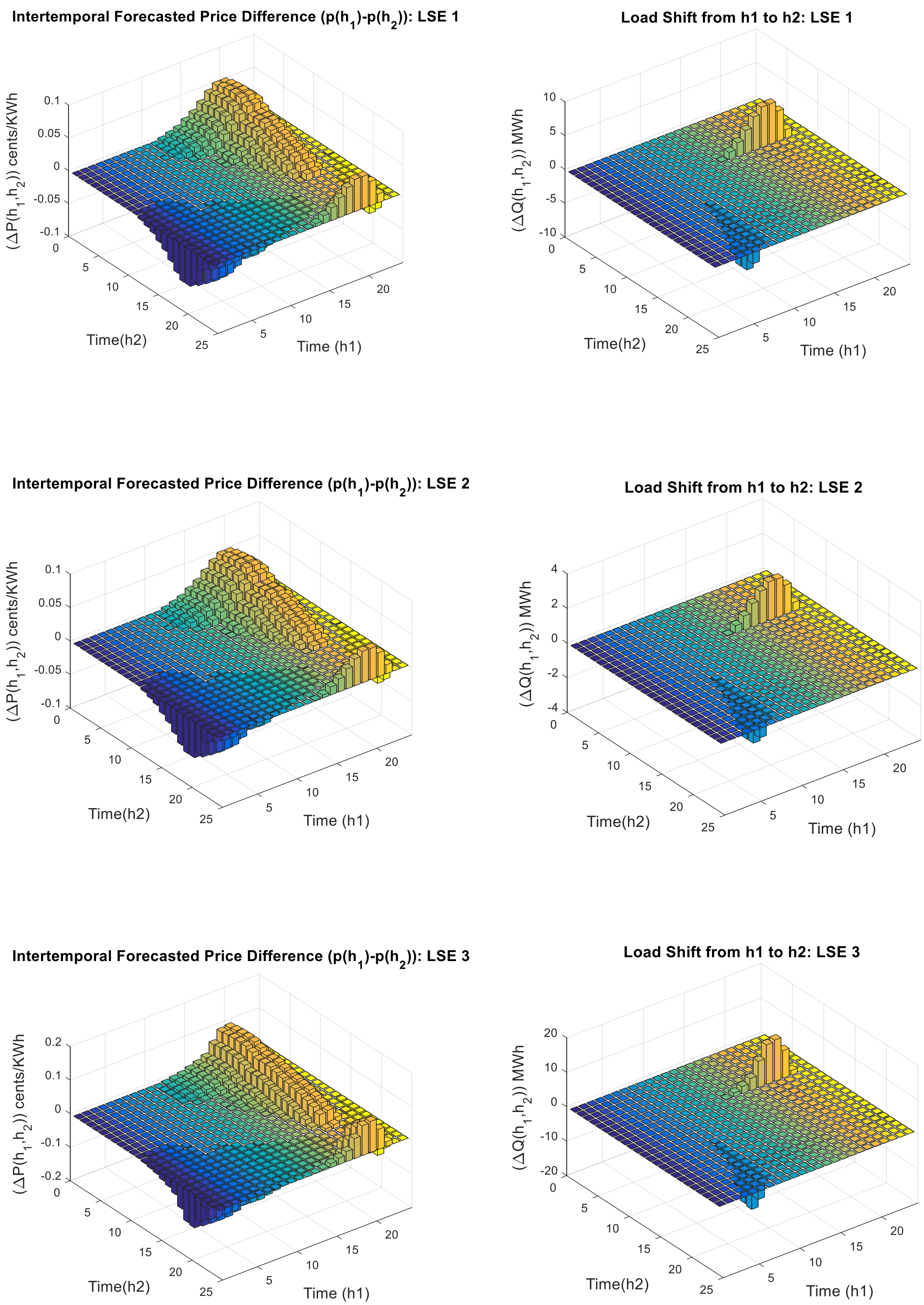


Figure 4.19: Benefit factor and corresponding load shift (Scenario 2)

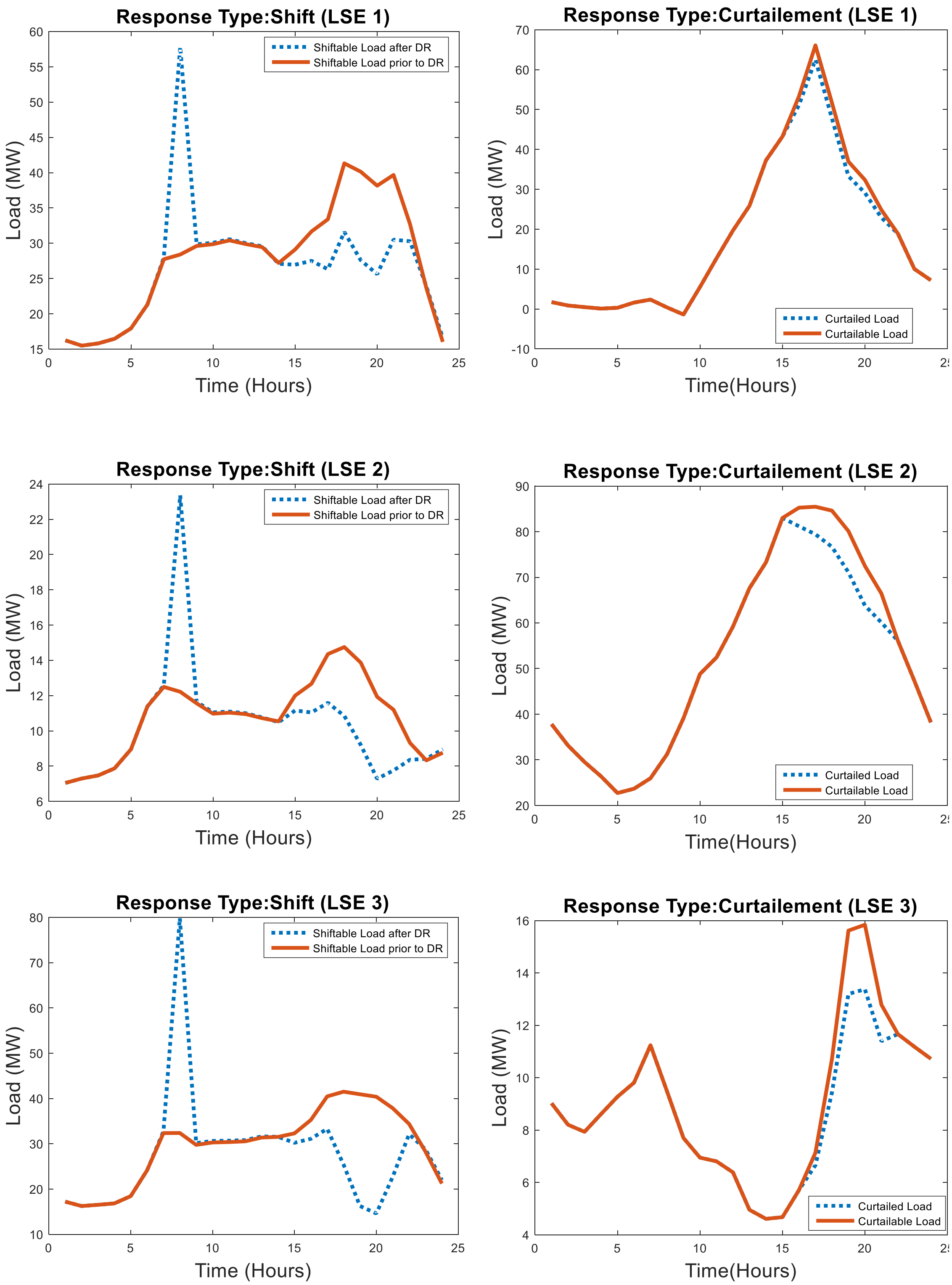


Figure 4.20: Curtailment and shift type reponse based on Consumer Psychology Model (Scenario 2)

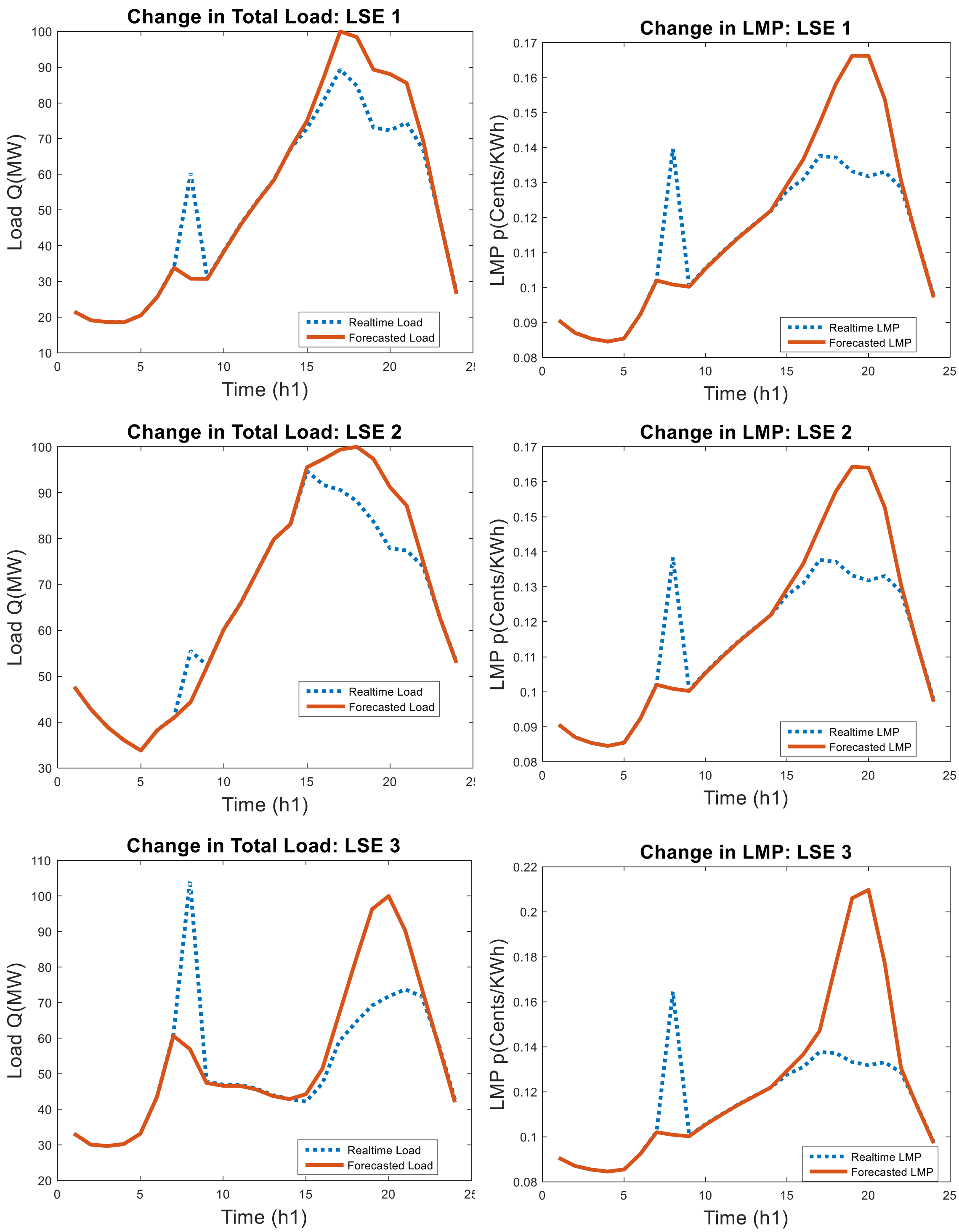


Figure 4.21: Consumer Psychology Model based demand response (Scenario 2)

4.7 SUMMARY

Consumer psychology model gives a detailed understanding of consumer’s behavior. A measure is required to indicate the sensitivity of the consumer, which can be used to decrease the uncertainty of the system and increase the demand response program efficiency. Hence, the concept of elasticity is introduced in chapter 5.

CHAPTER 5: ELASTICITY AND DEMAND RESPONSE

Consumer psychology model based demand response gives the characteristics of the consumer load pattern and corresponding consumption. However, it does not provide with the information regarding of sensitivity. Hence, elasticity matrix, which represents consumer's sensitivity is developed in this chapter and is used further to improve demand response program efficiency. Section 5.2 introduces the concept of elasticity. Architecture for estimating the elasticities is explained in section 5.3. Section 5.4 discusses the application of elasticities in mitigating the abnormal demand surges. Section 5.5 presents the result and discussion.

5.1 INTRODUCTION

Elasticity is a measure of a variable's sensitivity to a change in another variable. In economics, elasticity (supply/demand) refers the degree to which (consumers/producers) change their demand/supply in response to price or income changes.

Increasing the price of a commodity even by a small amount will or may decrease the demand. If there is a precipitous change in the demand based on the changes on the cost, the commodity or market is said to be elastic. If the changes in demand is negligible compared to changes in the price, the demand is considered as inelastic.

Mathematically elasticity can be represented as:

$$E = \frac{\%\Delta Q}{\%\Delta P} \tag{5-1}$$

Where,

$\%\Delta Q$ is change in quantity

$\%\Delta P$ is change in product

The elasticity of any commodity also depends on rates and demand of its substitutes. Consider product B to be a substitute of product A. Cross elasticity is said to exist when rates of product B decreases leading to shifting of consumers from product A to product B, and thereby affecting the demand of product A.

$$E_{AB} = \left(\frac{\%\Delta Q_A}{\%\Delta P_B}\right) \tag{5-2}$$

Where, ΔQ_A is the change in demand with change in rates of commodity B.

$\Delta P_B$is the change in the rates of commodity B.

5.2 ELASTICITY IN ELECTRICITY MARKET

The method proposed during the research focuses on the reaction of consumers depending on short-term forecasted rates. Here, short-term forecasted rates can be defined as a day ahead forecasted rates.

Market equilibrium point in the energy market is assumed to be the forecasted electrical demand without any interference by DR programs. Rates corresponding to the demand are considered to be the equilibrium rates. This equilibrium point or equilibrium rates are time dependent and specific for that particular hour. Based on the day and location, each hour is considered to have different equilibrium values of load and price. As per many researches and pilot-projects, electricity being one of the primary needs of humans, the

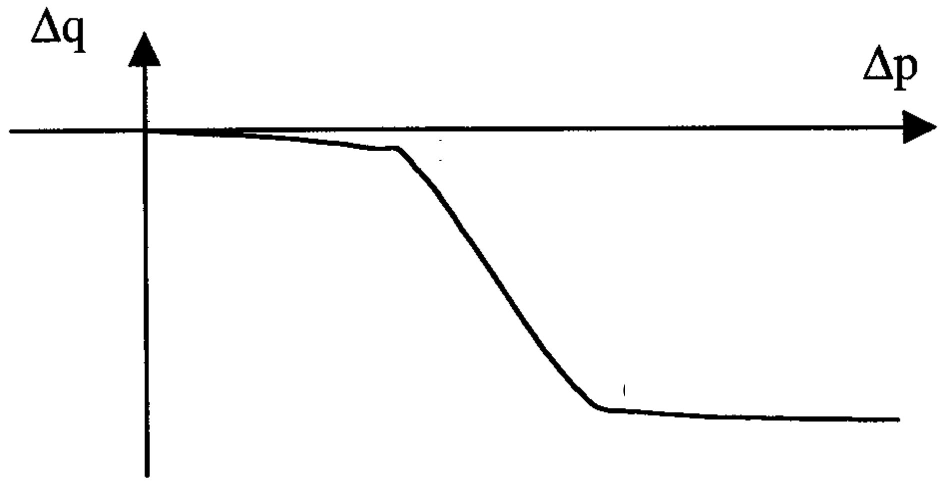


Figure 5.1: Market elasticity function [18]

electricity market is considered to be inelastic. Electricity market elasticity function can be represented as shown in Figure 5.1.

The elasticity curve can be classified in three phase. Phase AB is quite inelastic depicting a situation where consumers are not ready to compromise their comfort for a minor increase in price up to point B. Phase BC represents threshold situation, where consumer's sacrifices unnecessary consumption to save on the rates. Point C is akin to the threshold of curtailment. Beyond that consumers cannot curtail the load as it may be near to basic required level consumption of the consumer. Moreover, it would also be a misuse of market power to increase the rates beyond the saturation limit capacity to gain the curtailment.

An elasticity matrix, if available for any load serving entity, represents the characteristic of load belonging to respective LSE. It holds the information such as the proportion of curtailable and shiftable load and type of consumer's response to advance price signals. Diagonals of the matrix represents the self-elasticity, and remaining elements will represent cross elasticity due to change in price of i^{th} hour on consumption of j^{th} hour (here, i is row entity, and j is column entity).

$$\Delta Q_m = \begin{bmatrix} E_{11} & \cdots & E_{1n} \\ \vdots & \ddots & \vdots \\ E_{m1} & \cdots & E_{mn} \end{bmatrix} * \Delta P_n \;, \quad \text{Here m=n=24.} \qquad 5\text{-}3$$

Based on elasticity matrix consumers can be classified into five types.

a) Anticipating consumer: Consumer in this category tend to complete the tasks requiring higher consumption of electricity before the peak price period.

b) Postponing consumer: Consumer in this category tend to finish the task after the peak price period.

c) Flexible Consumer: Consumer can either prepone or postpone the load schedules.

d) Inflexible consumer: Consumer are unable to curtail the load and shift to other time periods.

e) Optimizing consumer. The consumer shifts the consumption to off peak period.

5.3 ESTIMATION OF PRICE ELASTICITY MATRIX (PEM)

In a wholesale power market, the information contained by price elasticity matrix can be useful in submitting the bids. Hence, it is the retailer’s responsibility to estimate the elasticity matrix for the optimum bidding considering the consumer’s response. Values of PEM can be estimated with multiple methods. The most common method is end user survey. Another method is to regress demand curve with past data, and derive the PEM from the obtained demand curve by doing partial differentiation. The advantage of this method is that it is faster and getting more accurate with more data accumulated in the regression. Learning effect can be applied to the regression if other exogenous disturbances, such as weather, exist. The disadvantages of this method are the complexity to regress a multi-dimensional function (not to mention in the DA markets the dimension can be 12 or 24), and it will be difficult to do the regression at the beginning with few data available. However, the regression can be simplified, and better accuracy can be achieved if the end use survey is merged with the same. Psychology models help in achieving that objective. The ANN module is already trained to classify the loads based on meteorological data. Also, the history of data used in training the ANN module considers social, economic,

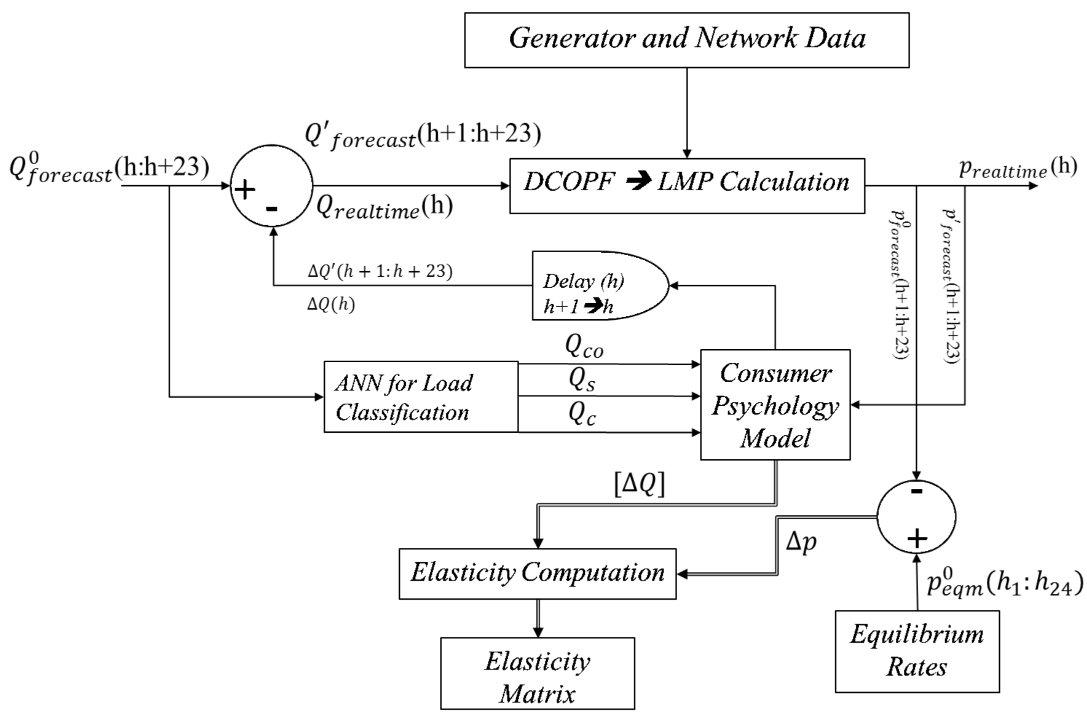


Figure 5.2: Architecture for estimating elasticity

geographic and demographic survey data for the classification. Hence, by regressing the sensitivity parameters, ANN model can be used in estimating the price response and hence the load change. Because of lack of location-specific demand response data, the simulated load change data from consumer psychology model was directly considered for the price elasticity matrix computation.

Elasticity, as represented in 5-2 is the ratio of percentage change in load to the percentage change in price. Information regarding the change in load is obtained from CPM. Taking the ratio of change in load to the difference between maximum and minimum load values of forecasted load profile gives the percentage change on load variation.

$$\text{Hence, } \%\Delta Q^{lse}_{h_1 h_2} = \left(\frac{\Delta Q^{lse}(h1,h2)}{Q^{lse}_{Max} - Q^{lse}_{Min}}\right) \qquad 5\text{-}4$$

However, for calculation of $\%\Delta P_h$, the reference price is required to calculate the change. Hence the concept of equilibrium price is used in reference to the context.

5.3.1 EQUILIBRIUM PRICE

Equilibrium price concept has been derived from the concept of equilibrium point in a Demand Response Curve. The equilibrium point is the intersection of demand curve with the supply curve. When supply and demand are equal (i.e. when the supply function and demand function intersect), the economy is said to be at equilibrium. At this point, the allocation of goods is at its most efficient because the amount of goods being supplied is the same as the amount of goods being demanded. At the given price, suppliers are selling all the goods that they have produced and consumers are getting all the goods that they are demanding. However, in the perspective of energy consumption, under the absence of advance price signals, consumer’s energy consumption is in a un-optimized manner. It can be implied that, with the knowledge of advance price signals, the consumer may optimize the consumption and demand curve may shift from the original, leading to a new equilibrium point.

Hence, it can be hypothesized that every time instant has an individual equilibrium point determining the level of requirement of electricity consumption. As shown in Figure 5.1, if demand curve in the absence of advance price signal is represented by D, the in case of off peak hours, it may shift to D^L owing to lower price and during peak periods, it may shift to D^U representing the consumption optimization during the peak period. Similarly, all the time periods would be having an individual demand curve gradually shifting upwards from peak price periods to off peak periods. The intersection of these demand curves with supply curve represents the market equilibrium. Price corresponding to market equilibrium (p_{eqm}) can be used as a reference for the calculation of elasticity.

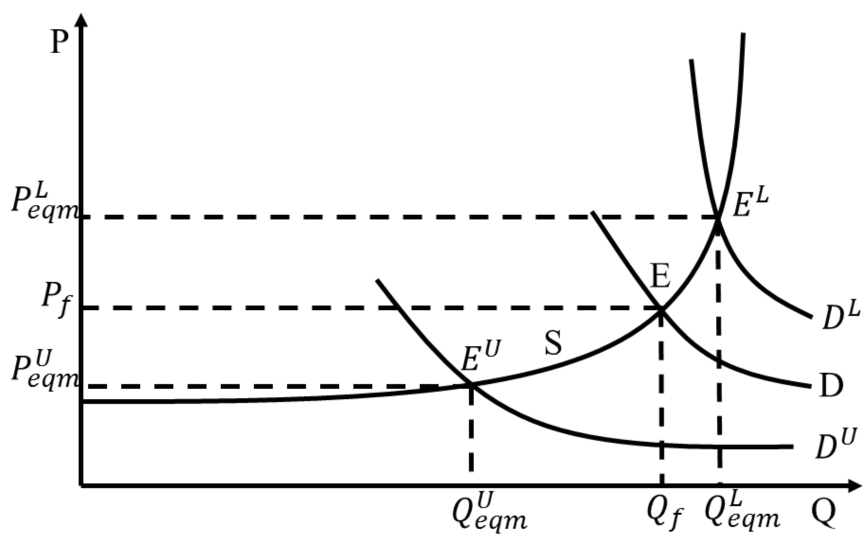


Figure 5.3: Equilibrium price concept

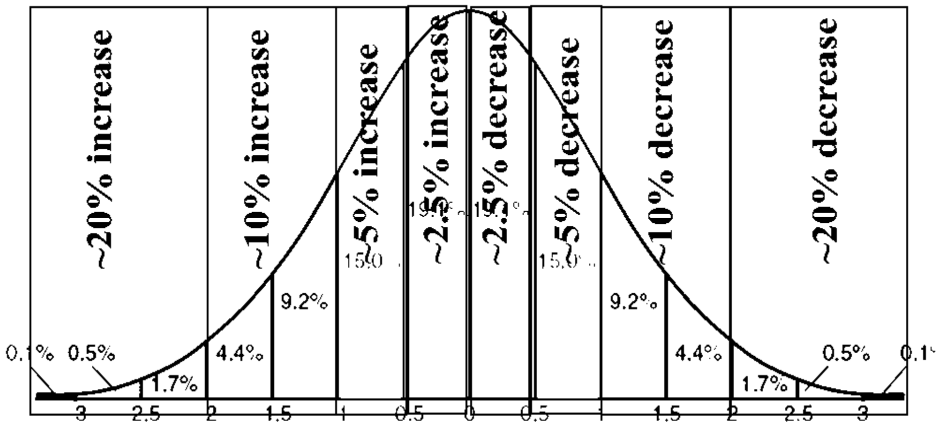


Figure 5.4: Generating equilibruim price

Based on surveys and DR program reports [37], it was observed, that upto a maximum of 20 percent load shedding was observed during on peak periods. Same, observation was taken into consideration in determining the equilibrium price points.

Average and standard deviation of load data is calculated. Extreme data, i.e., lying beyond variance are supposed to be extreme on peak or off peak loads. Maximum response (20% change) is assigned to points lying in this category. Another class is assigned to points lying between 1st and 2nd variance range. 10% change is assigned to this set of points. Class of load points lying between 1st and 0.5th variance is assigned with 5%change. Moreover, for points lying near the mean point, i.e., optimum price level, only 2.5% variation is considered.

Based on above distribution, the equilibrium price points are assumed. This price points acts as reference points for the calculation of Δp.

$$\text{Hence,} \qquad \%\Delta P_{h1} = \left(\frac{p_{forecast}^{lse}(h1) - p_{eqm}^{lse}(h1)}{P_{forecast}^{Max} - p_{forecast}^{Min}} \right) \qquad 5\text{-}5$$

Based on equation 5-4 and 5-5, elasticity can be calculated for each load serving entity.

As shown in Figure 5.5, Figure 5.6 and Figure 5.7, equilibrium price provides a fair approximation for the elasticity calculation. Few researches take the mean value as the reference value for LMP calculation. However, the mean value does not reflect the concept of market equilibrium which keeps on changing depending on the level of requirement. Moreover, electricity being the basic need, the market equilibrium is expected to be dynamic for all the time periods.

Table 5.1 Average end-use load type (Based on ANN output)

Zone	Curtailable Load	Shiftable Load	Constant Load
Zone 1	36.2%	53.9%	10.67
Zone 2	79.6%	16.1%	4.25%
Zone 3	16.73%	54.97%	28.31%

Figure 5.5, Figure 5.6 and Figure 5.7 represents the elasticity matrix for the areas served by all three load serving entity. It can be observed that, self-elasticity values lying on the diagonal of the matrix as negative. It represents the load curtailment. Negative values suggest that, with an increase in the price, the consumption decrease. Whereas, cross elasticity values are positive. Positive values indicate that with an increase in the peak period rates, the load on the off peak period increases and thereby representing the shift of load from peak period to off peak period.

The magnitude of the bars in the elasticity matrix also represents the proportion of the type of load component. It can be observed that the lower percentage of shiftable load and a higher proportion of the curtailable load is reflected in the values for elasticity matrix for LSE 2 in Figure 5.6. The majority of the load in zone 3 is shiftable in nature. Hence, the self-elasticity values are lower in the case of zone 3 (Figure 5.7).

Moreover, information regarding the different type of consumer behaviors as discussed in 5.2 is also reflected by the elasticity matrix. By varying the sensitivity, various behavioral scenarios(explained in 5.1) were simulated. Results of same are summarized in Table 5.2. Hence, with the availability of big data for demand response, any sensitivity factor in psychology model can be regressed to study and obtain the elasticity matrix for any region.

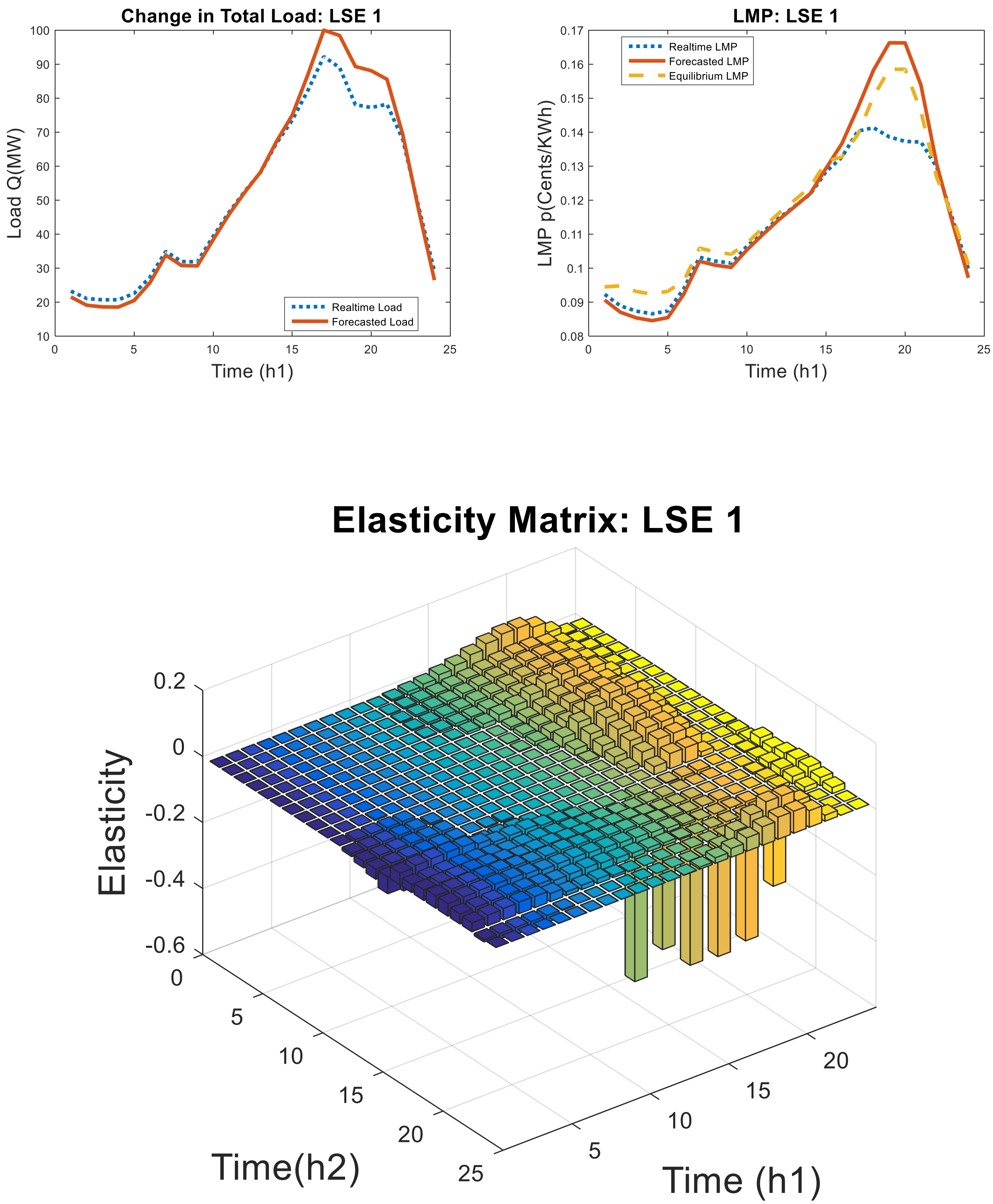
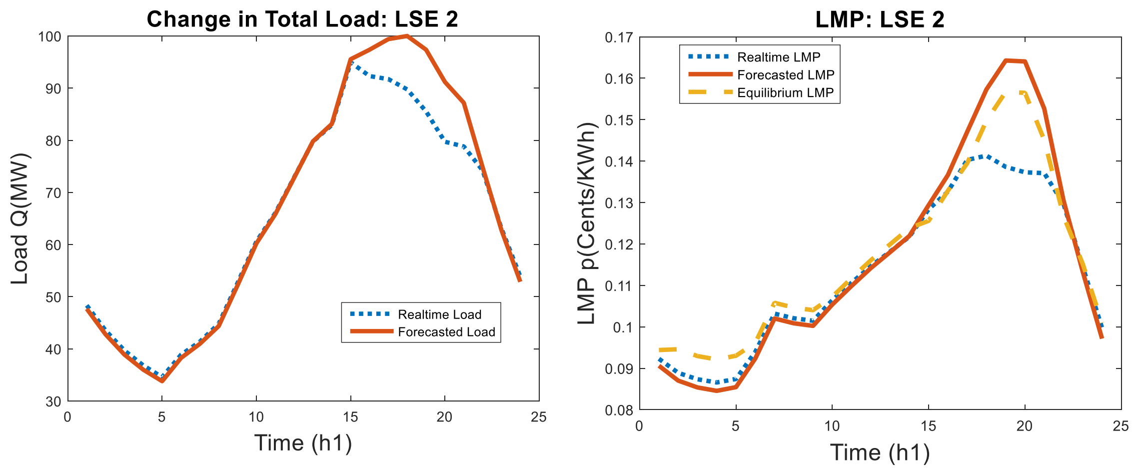


Figure 5.5: Elasticity matrix: LSE 1



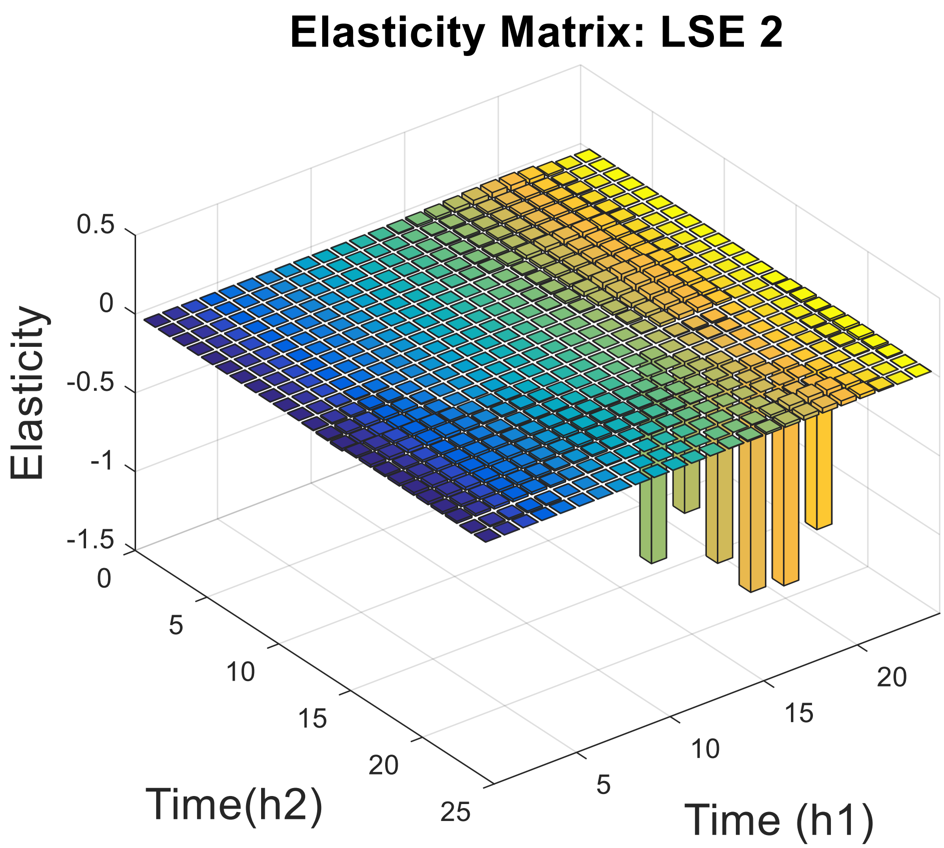


Figure 5.6: Elasticity matrix: LSE 2

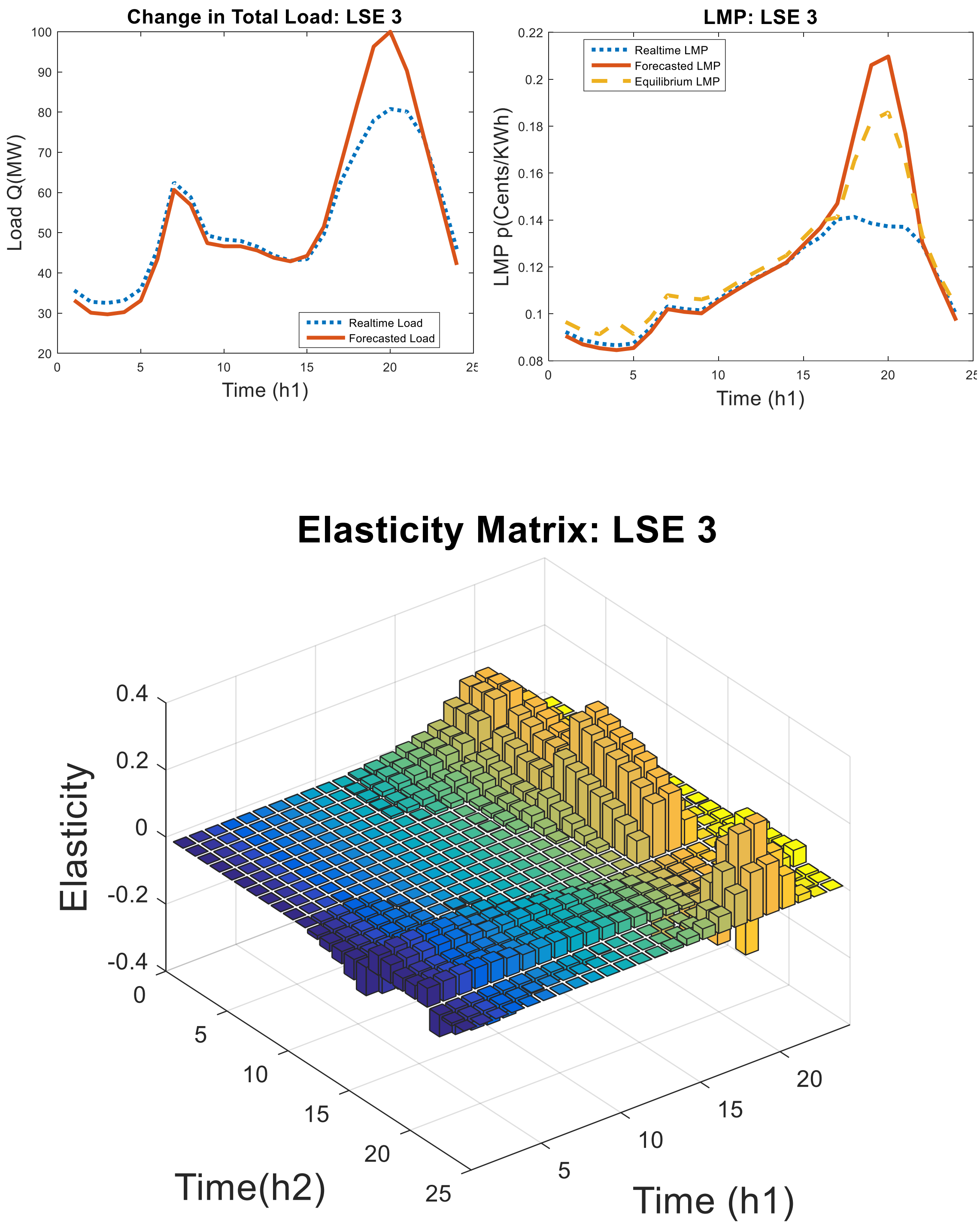


Figure 5.7: Elasticity matrix: LSE 3

Table 5.2 Consumer behavioral representation using elasticity matrix

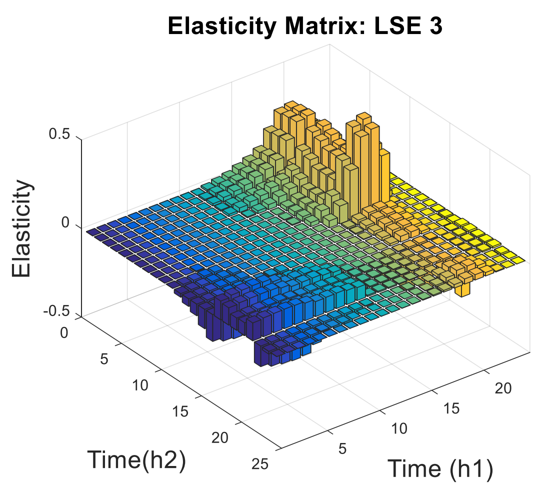
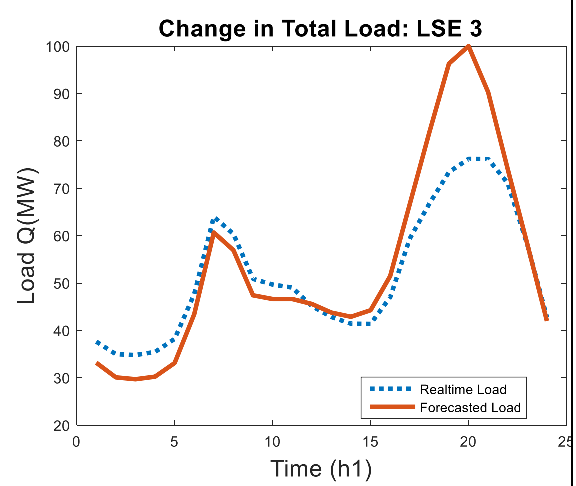
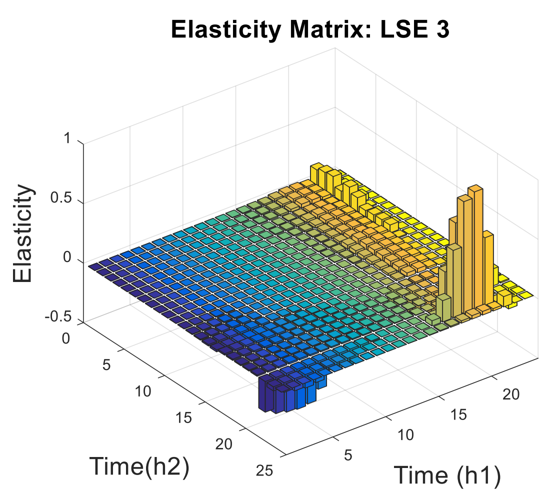
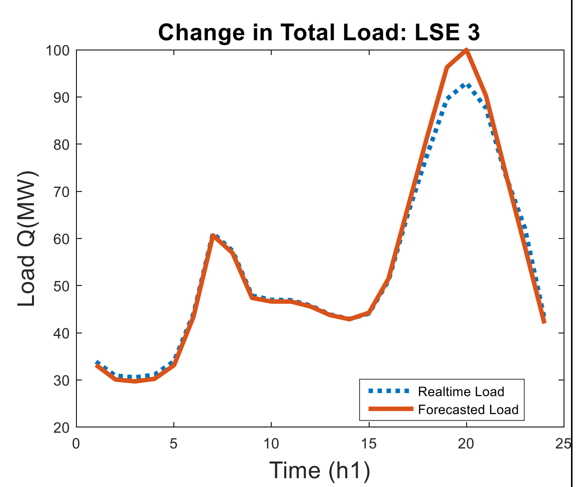
<table>
<tr><td>Elasticity Matrix</td><td>Load Change</td></tr>
<tr><td colspan="2">Customer Type: Anticipating
k_{se} =1.8 for $(0 < h < 12)$ and k_{se} $= 0.2$ for $(12 \leq h)$</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Customer Type: Postponing
k_{se} =4 for $(21 < h < 24)$ and k_{se} $= 0.2$ for $(h \leq 21)$</td></tr>
<tr><td>
</td><td>
</td></tr>
</table>

Table 5.2 (Continued)

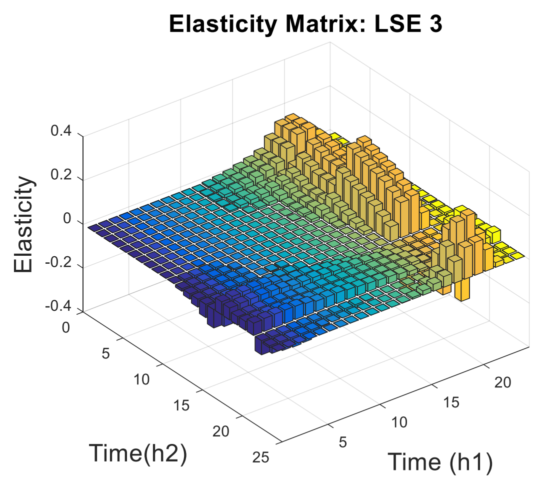
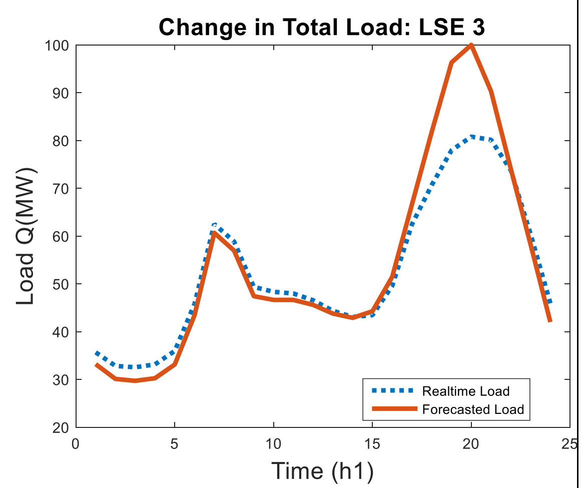
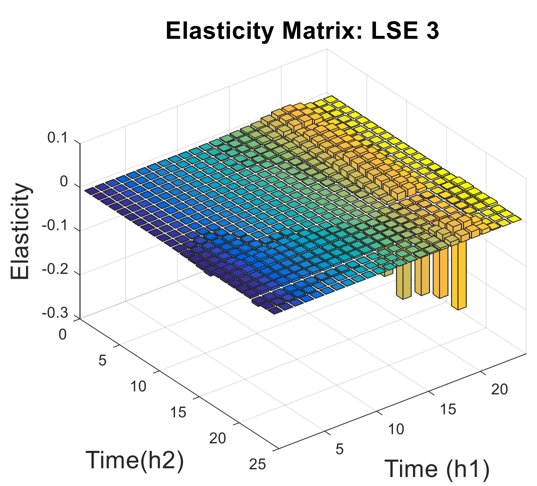
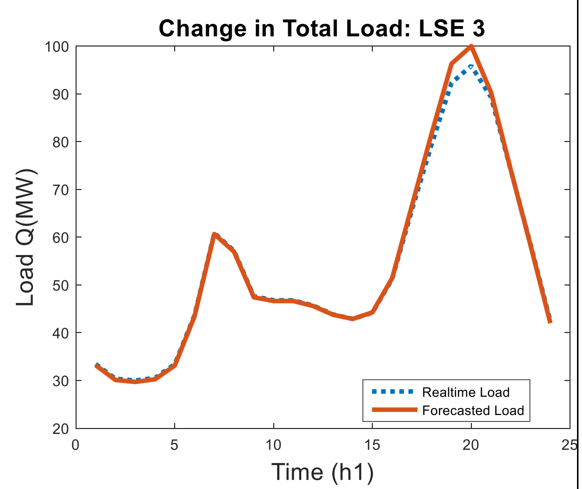
<table>
<tr><th>Elasticity Matrix</th><th>Load Change</th></tr>
<tr><td colspan="2">Customer Type: Flexible
$k_{se} = 1$ for $\forall h$</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Customer Type: Inflexible
k_{se} =0.1 for $\forall h$</td></tr>
<tr><td>
</td><td>
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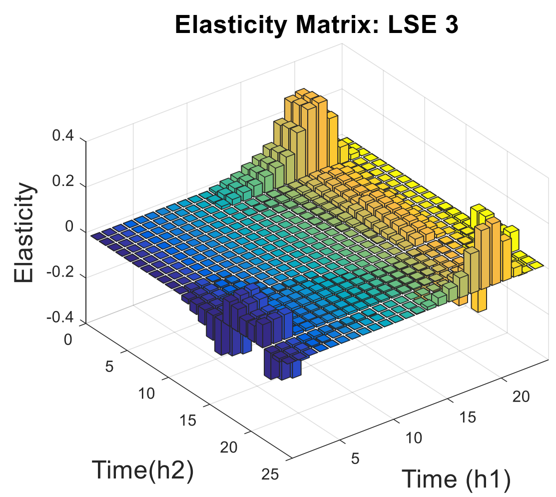
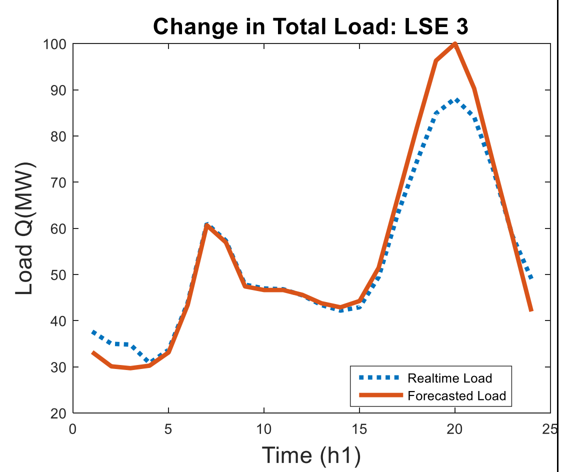
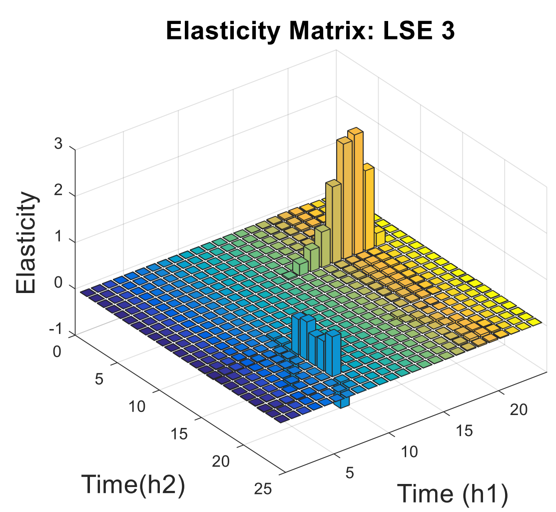
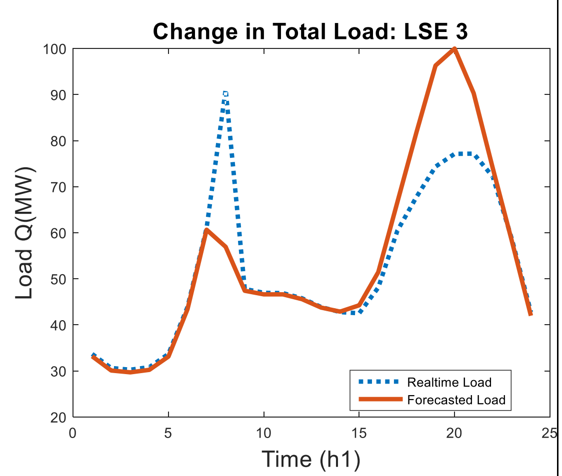
Table 5.2 (Continued)

<table>
<tr><th>Elasticity Matrix</th><th>Load Change</th></tr>
<tr><td colspan="2">Customer Type: Optimizing
k_{se} =1.8 for $23 < h \leq 24$ and $0 \leq h \leq 4$</td></tr>
<tr><td>
</td><td>
</td></tr>
<tr><td colspan="2">Customer Type: Mutual Convenience (Surge Scenario)
$k_{se} = 18$ for $(h = 8;)$ and $k_{se} = 0.2$ for $(h \neq 8)$</td></tr>
<tr><td>
</td><td>
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</table>

5.4 SURGE MITIGATION USING ELASTICITY MATRIX

The efficiency of demand response program depends on the fact of how effectively can the advance rates modify the consumption and decrease the load variation. Any sudden spikes or surges may reduce the efficiency of same. Unexpected demand surges have been one of the major issue faced by the existing real time based demand response programs like ComEd. Figure 5.9, Figure 5.10 and Figure 5.11 represents one such scenario where consumers are sensitive to shift the consumption more toward 8:00 compared to other off peak time period. As a result of same, spike in the real time demand as well as LMP can be seen which reduces the participation benefit of demand response program. If elasticity matrix representing the sensitivity to price is used to modify the available price signals, the demand surges can be mitigated. Figure 5.8 represents the architecture which can be integrated with demand response programs for modifying the advance price signals based on the sensitivity. Elasticity matrix represents the consumer’s behavior characteristics as shown in Figure 5.9, Figure 5.10 and Figure 5.11. It is a normal behavioral tendency of the consumer to shift the load to the most convenient off-peak period. This may result in an unexpected surge in the real time demand and hence the LMP. If this information is known in prior via elasticity matrix, it could be taken into consideration during the day ahead bidding. Figure 5.8 represents the architecture of revising the forecasted LMP or the day ahead price signals which customer may receive to control the demand and avoid any unexpected demand surges. As per the approach presented in 5.3, the elasticity matrix of consumers can be obtained using consumer psychology model. This elasticity represents the characteristics of the consumers in terms of price sensitivity as well as load shift. Hence, the forecasted rates provided to the consumers can be fed-in along with the reference equilibrium rates to forecast the real-time consumption $Q'_{forecast}$ or the demand response to advance price signals. If any anomalies exist in the same, the consumption is re-evaluated by taking a weighted average of forecasted load $Q_{forecsat}$ and the elasticity matrix based forecasted load $Q^0_{forecast}$. By taking the weighted average of both the rates, through an appropriate weighting factor, the revised forecasted load $Q^1_{updatedforecast}$ can be obtained. By using this forecasted load to clear up the market price, an optimum elasticity based forecasted rates or day ahead rates $P^1_{forecast}$ can be generated. This rates would be made available to consumers. Based on this rates, consumer will be optimizing the consumption and plan their consumption. Moreover, spike in the real time would be mitigated, thereby reducing the uncertainty induced by demand response programs. A scenario with elasticity based demand response is implanted on 6 bus system in section5.5 with consumers sensitive to load shift at 8:00.

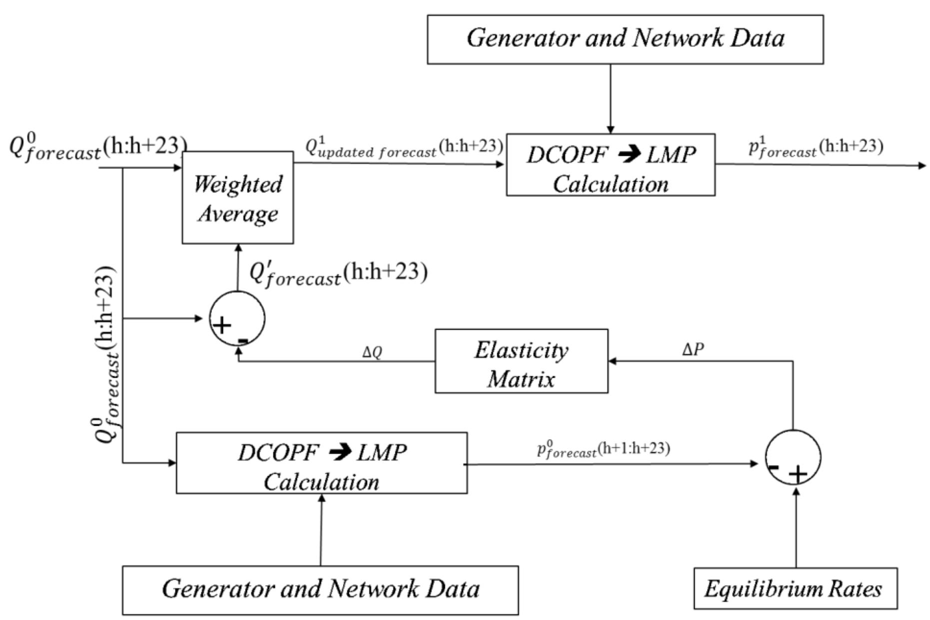


Figure 5.8: Surge mitigation using elasticity based DR

5.5 RESULTS AND DISCUSSION

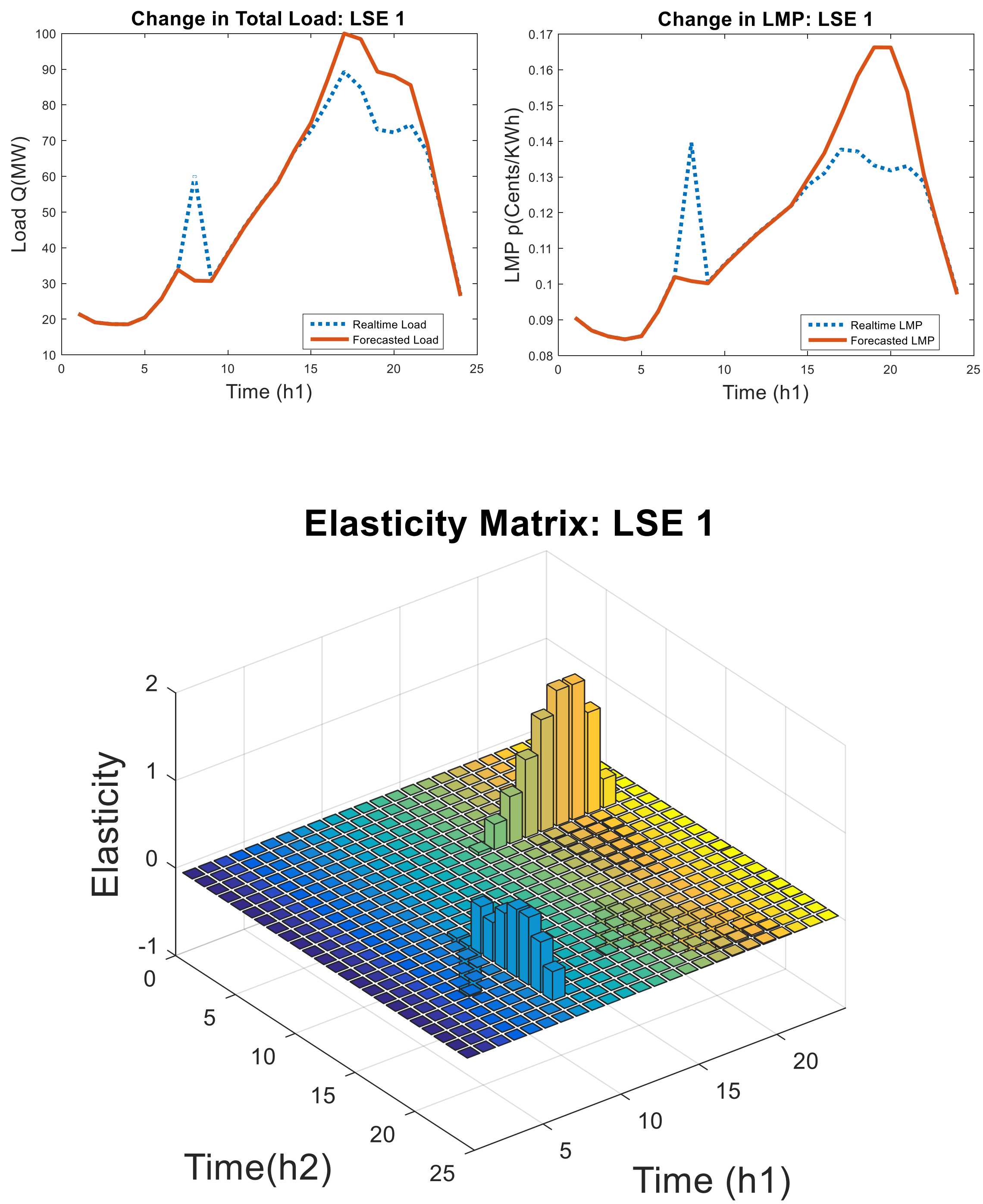


Figure 5.9: Surge situation under normal demand response program (LSE 1)

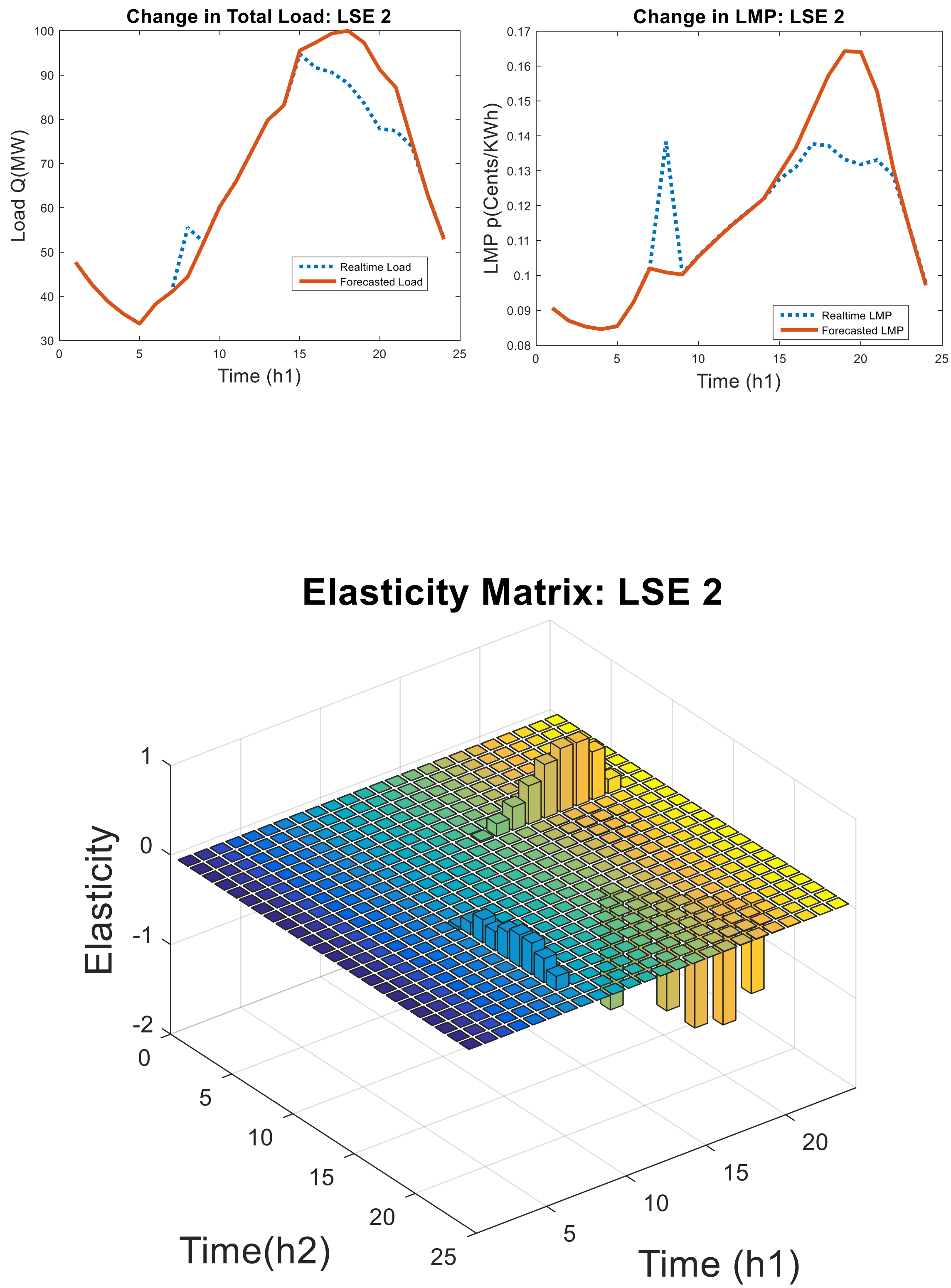


Figure 5.10: Surge situation under normal demand response program (LSE 2)

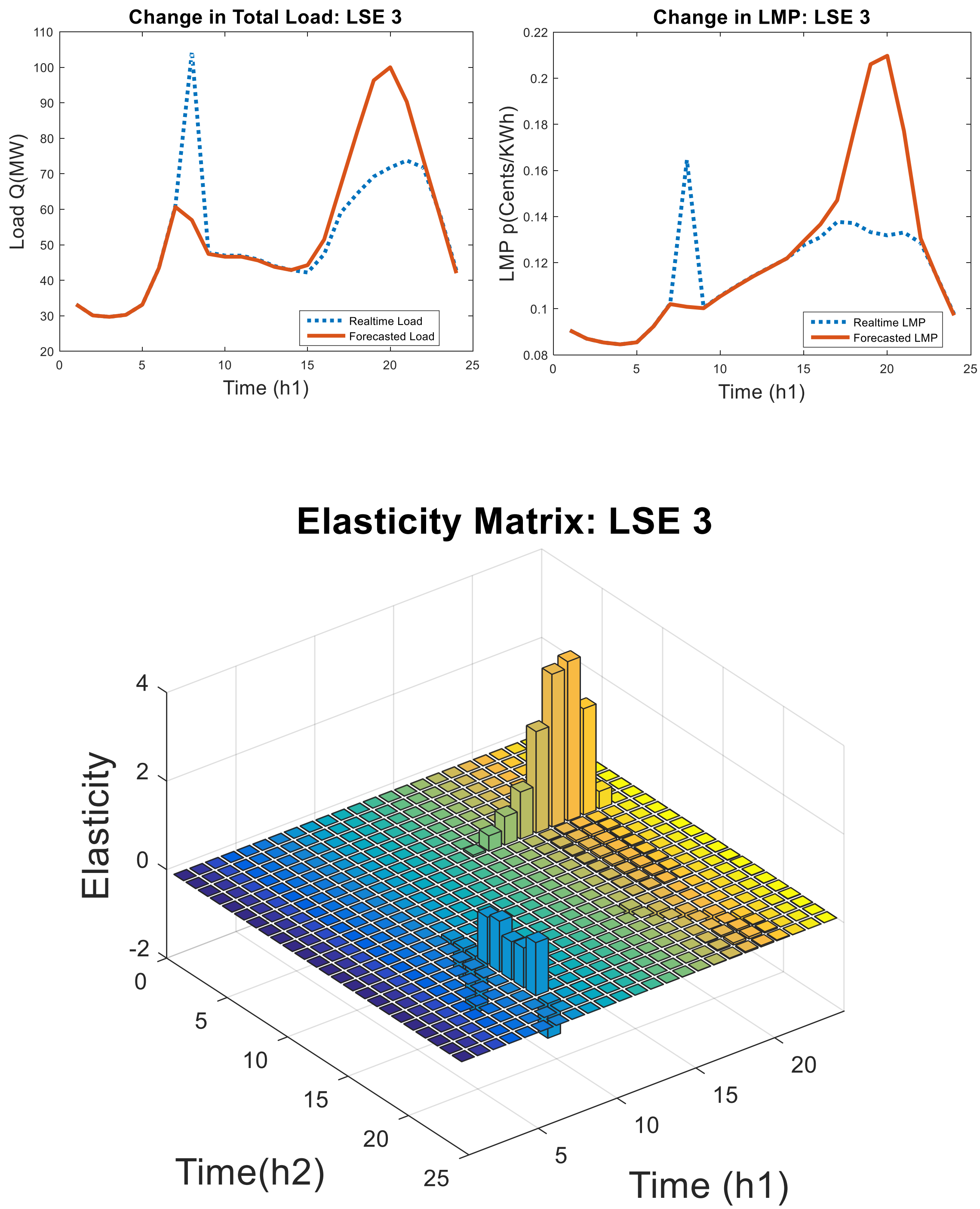
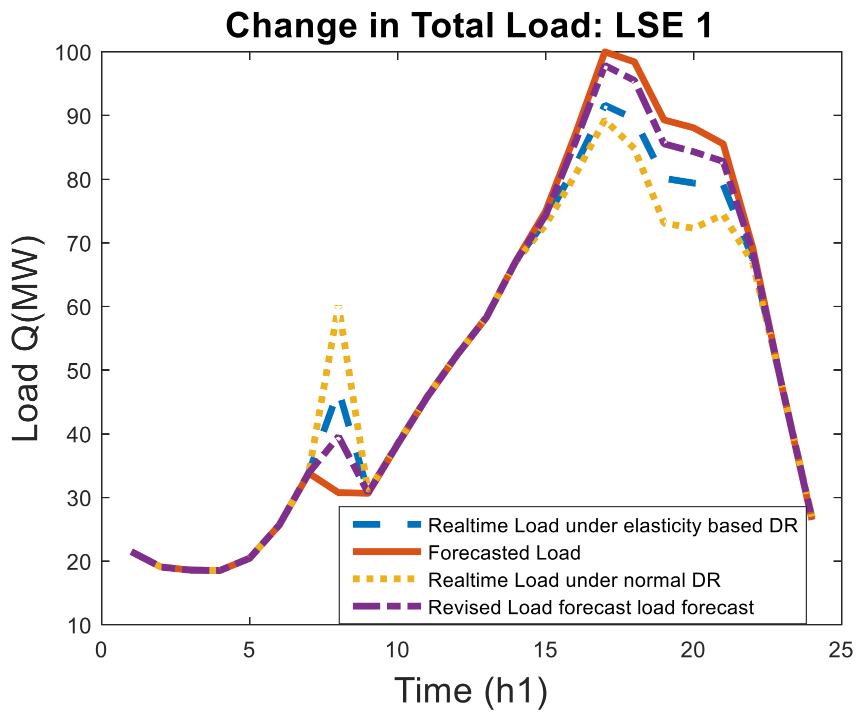


Figure 5.11: Surge situation under normal demand response program (LSE 3)



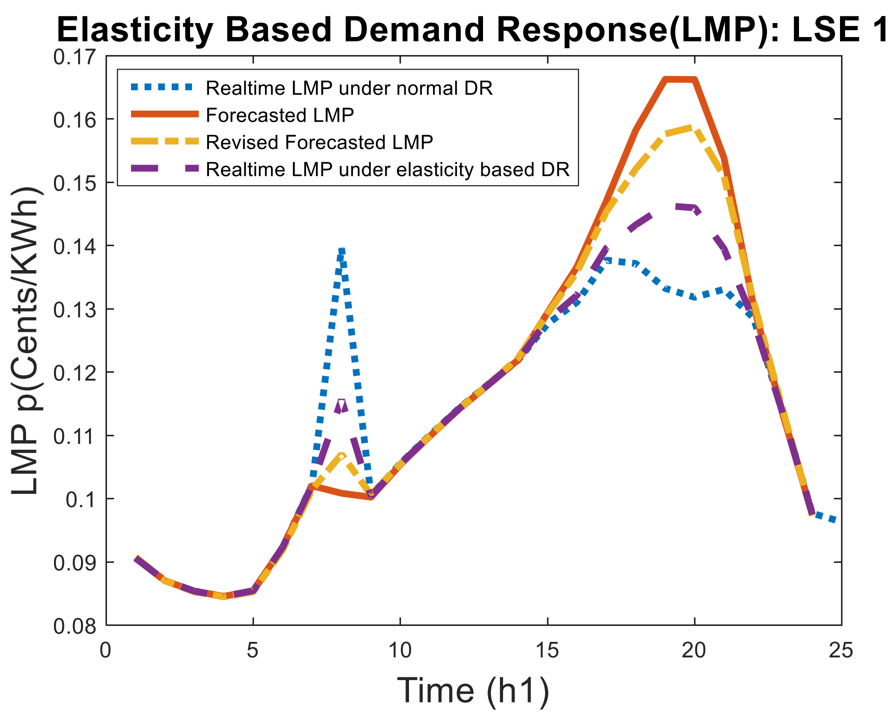
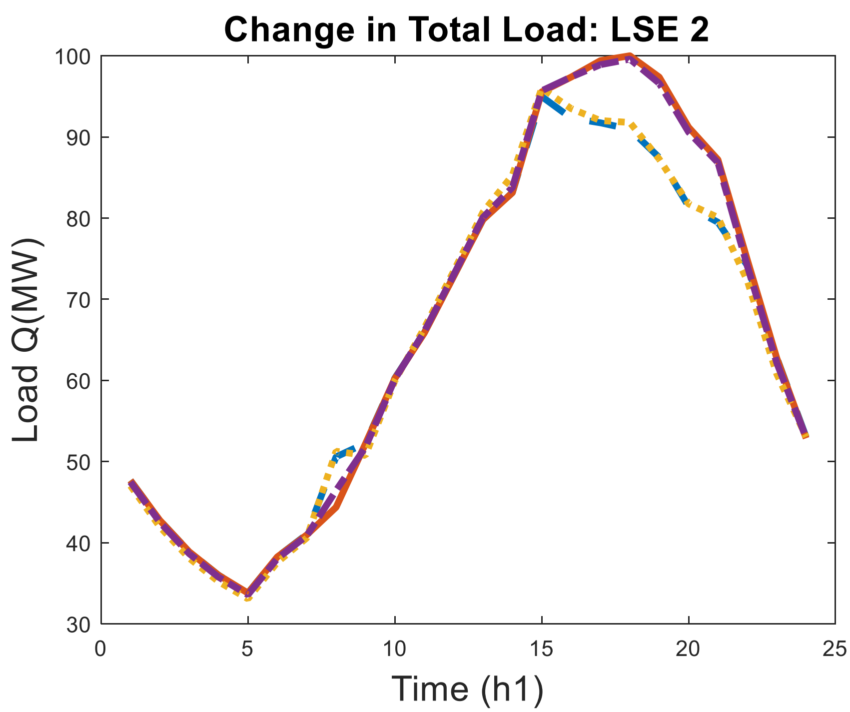


Figure 5.12: Surge mitigation (Load and LMP) under elasticity based forecasted rates (LSE 1)



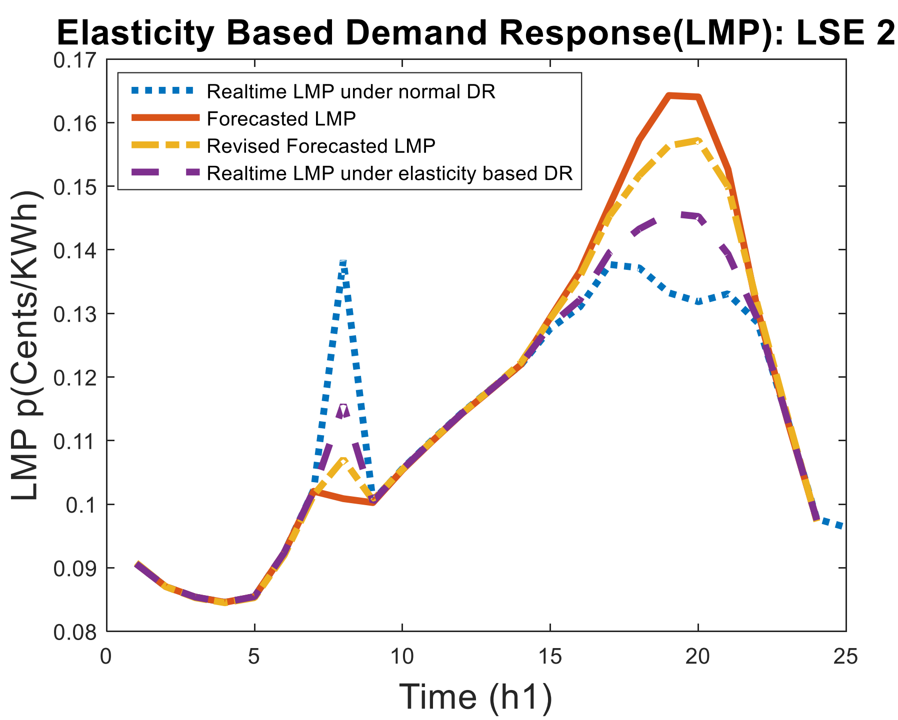


Figure 5.13: Surge mitigation (Load and LMP) under elasticity based forecasted rates (LSE 2)

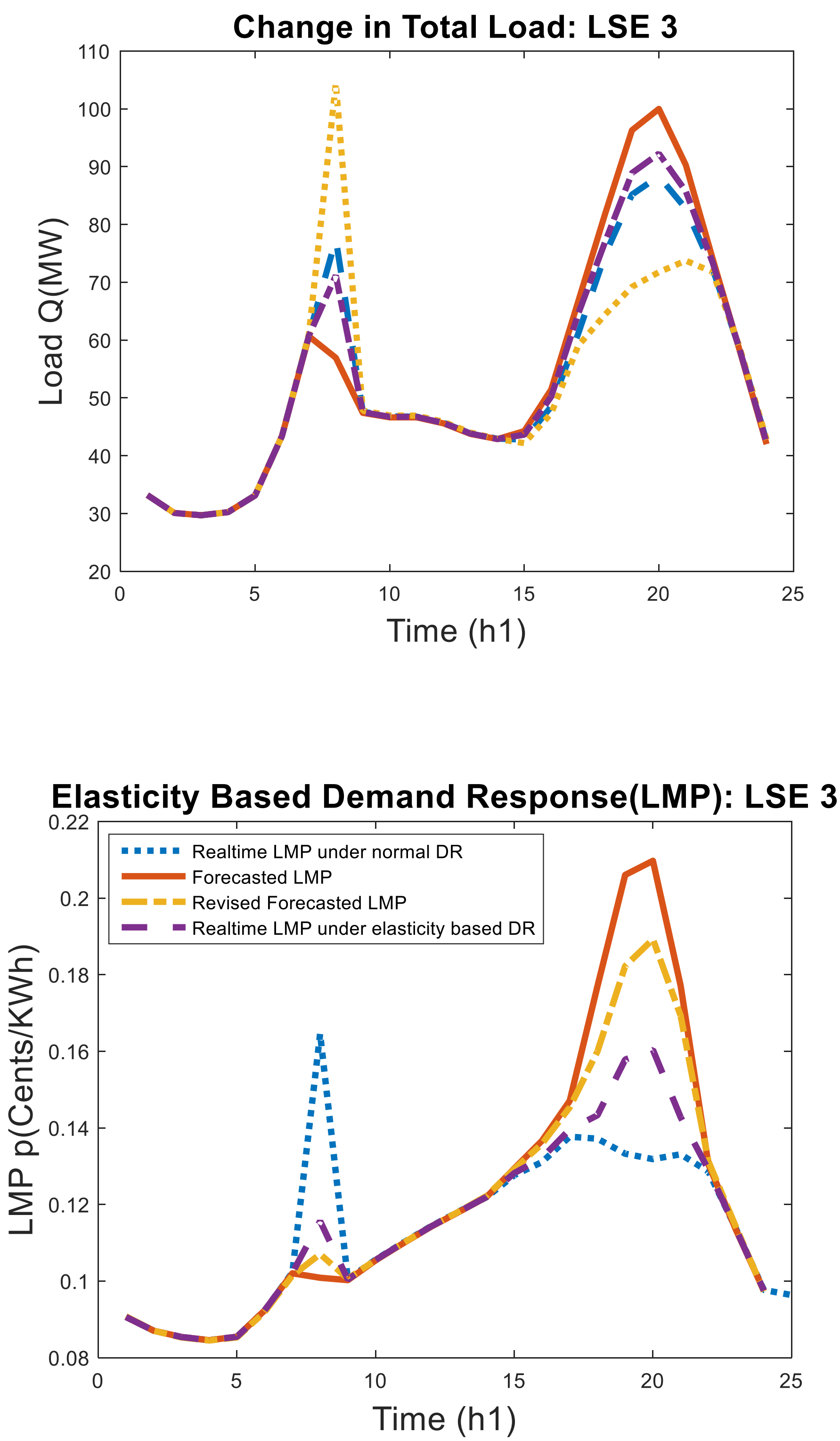


Figure 5.14: Surge mitigation (Load and LMP) under elasticity based forecasted rates (LSE 3)

Figure 5.9, Figure 5.10 and Figure 5.11 represents typical DR scenario illustrating the accumulated shifting of load to 8th hour. As a result, spikes in both LMP and load can be observed. Also, the load serving entities with a higher ratio of the shiftable load may see the higher magnitude of spikes. For example, it can be seen in Figure 5.11, LSE 3 has a large proportion of shiftable load. Hence, the demand shoots up at 8:00 am. Moreover, the system being interconnected, the spike in rates is observed by LSE with a lower proportion of shiftable load (Figure 5.10). Figure 5.12, Figure 5.13 and Figure 5.14 represents the forecasted rates before and after considering the elasticity matrix along with DR scenario under revised forecasted rates. It can be observed that by increasing the rates by 20% during the peak time period the spike gets mitigated by 50%.

5.6 SUMMARY

Architecture for calculation of elasticity matrices was discussed in the present chapter. Moreover, the information of elasticity metrics was further used to reduce the uncertainty of in the system, which may arise because of demand response program.

CHAPTER 6: CONCLUSION AND FUTURE WORK

One of the biggest challenges that the existing demand response programs have been facing is forecasting the uncertainties. A new approach of predicting the uncertainties via estimated elasticity matrix for consumers at residential level was presented in the current research

Initially, a consumer psychology model was developed. Based on the detailed end-use data, the artificial neural network was used to classify the total consumption into shiftable, curtailable and constant loads. Consumer psychology model considered the detailed response to advance price signals in terms of shifting and curtailable type. Also, it consisted of control parameters which holistically reflected the tendency as well as the limit of participation.

Consumer psychology model gave the change in the consumption pattern as an output. A new concept of equilibrium reference rates was introduced in work to reflect 2-way participation based market equilibrium. These market equilibrium rates were used as a reference for estimating the elasticity matrix.

Elasticity matrix holds the valuable information consisting the consumption pattern, types of load and sensitivity of consumption to the prices. Information in the elasticity matrix was further used to study different kinds of consumer behavior. An architecture to forecast the uncertainties, using the information from the elasticity matrix was proposed in the research.

Elasticity matrix based demand response program promises benefit on all fronts. On generation end, it helps the power generating entities to plan the generation schedules accordingly. Also, it helps them to optimize the operation of peaking generators. Moreover, by using the consumer sensitivity information during generation bidding, it can assist them in optimizing the bid values with better profit margin during the day ahead bidding. Elasticity matrix contributes by improving the forecast during demand response programs at load serving entity level. With better forecast, the load serving entities can also optimize the profit during the demand bids. Hence elasticity based demand response in real time market promises higher market efficiency along with lesser uncertainties.

6.1 FUTURE WORK

Current research has not considered the penetration of renewable and distributed generation in the energy markets. Demand response programs can be made more efficient with the integration of distribution end renewable generation and energy storage. Energy storage can be simulated as shiftable load whereas renewable can be simulated as a curtailable load. Moreover, in future, it can also enable consumers to participate in energy arbitrage activities.

Also, works need to be done in tuning the consumer psychology model presented in the current research with the residential areas participating in real-time demand response program. Big data of an ongoing real-time based demand response program is required to tune the consumer psychology model via machine learning algorithms like an artificial neural network which would help in generating the precise elasticity matrix. This elasticity matrix would represent the consumer behavioral characteristics towards demand response program.

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APPENDIX A: IEEE 6 BUS SYSTEM

Table A-1 Load Data

Load Entity	Bus	P_{load} (MW)
L1	4	100
L2	5	100
L3	6	100

Table A-2 Generator Data

Gen.	Bus	Cost Function ($Cx^2 + Bx + A$)			Generator Constraint	
		C	B	A	Min	Max
G1	1	0.00533	11.669	213.1	50	200
G2	2	0.00889	10.333	200	37.5	150
G3	3	0.00741	10.833	240	45	180

Table A.1 Branch Data

Bus		Line Resistance (r)	Line Reactance(x)	Flow Limit (F_{km})
From (k)	To (m)	pu	Pu	MW
1	2	0.1	0.2	100
1	4	0.05	0.2	100
1	5	0.08	0.3	100
2	3	0.05	0.25	60
2	4	0.05	0.1	60
2	5	0.1	0.3	60
2	6	0.07	0.2	60
3	5	0.12	0.26	60
3	6	0.02	0.1	60
4	5	0.2	0.4	60
5	6	0.1	0.3	60

APPENDIX B: IEEE 118 BUS SYSTEM

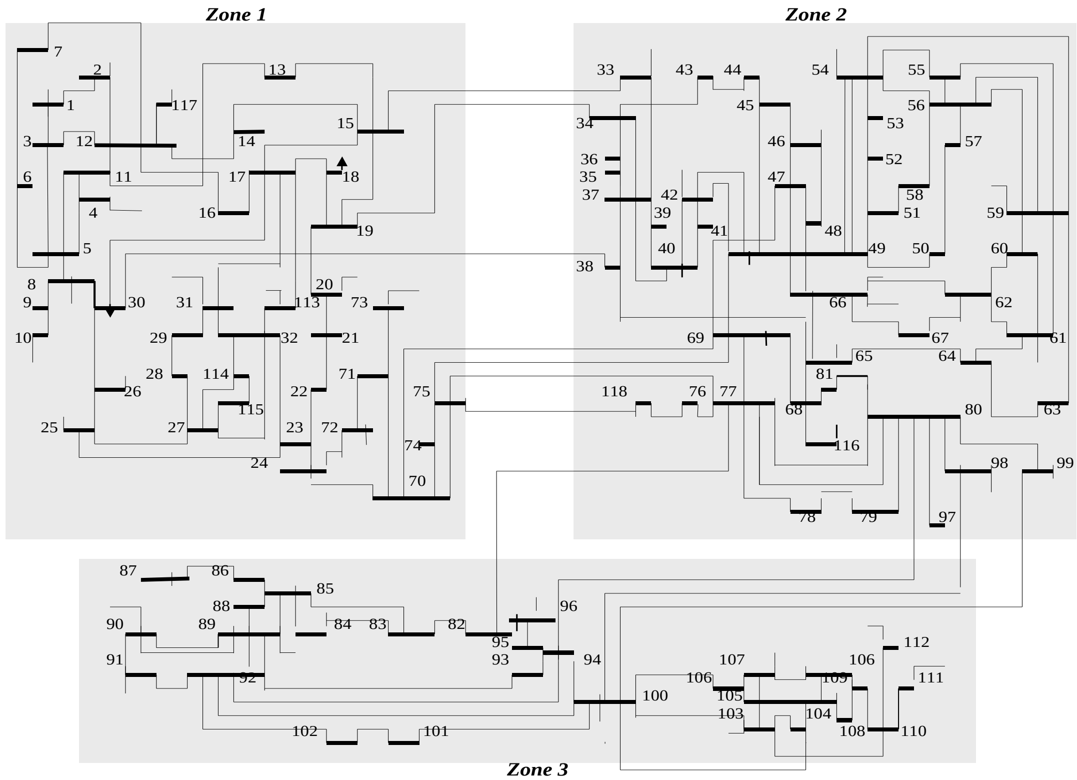

Table B.1: Generator Data

U	Bus No.	Unit Cost Coefficients			Pmax (MW)	Pmin (MW)
		a	b	c		
1	4	31.67	40	0.01	100	0
2	6	31.67	40	0.01	100	0
3	8	31.67	40	0.01	100	0
4	10	6.78	40	0.01	100	0
5	12	6.78	20	0.022222	550	0
6	15	31.67	20	0.117647	185	0
7	18	10.15	40	0.01	100	0

8	19	31.67	40	0.01	100	0
9	24	31.67	40	0.01	100	0
10	25	6.78	40	0.01	100	0
11	26	32.96	20	0.045455	320	0
12	27	31.67	20	0.031847	414	0
13	31	31.67	40	0.01	100	0
14	32	10.15	20	1.428571	107	0
15	34	31.67	40	0.01	100	0
16	36	10.15	40	0.01	100	0
17	40	31.67	40	0.01	100	0
18	42	31.67	40	0.01	100	0
19	46	10.15	40	0.01	100	0
20	49	28	20	0.526316	119	0
21	54	28	20	0.04902	304	0
22	55	10.15	20	0.208333	148	0
23	56	10.15	40	0.01	100	0
24	59	39	40	0.01	100	0
25	61	39	20	0.064516	255	0
26	62	10.15	20	0.0625	260	0
27	65	64.16	40	0.01	100	0
28	66	64.16	20	0.025575	491	0
29	69	6.78	20	0.02551	492	0
30	70	74.33	20	0.019365	805.2	0
31	72	31.67	40	0.01	100	0

32	73	31.67	40	0.01	100	0
33	74	17.95	40	0.01	100	0
34	76	10.15	40	0.01	100	0
35	77	10.15	40	0.01	100	0
36	80	6.78	40	0.01	100	0
37	82	10.15	20	0.020964	577	0
38	85	31.67	40	0.01	100	0
39	87	32.96	20	2.5	104	0
40	89	6.78	20	0.016474	707	0
41	90	17.95	40	0.01	100	0
42	91	58.81	40	0.01	100	0
43	92	6.78	40	0.01	100	0
44	99	6.78	40	0.01	100	0
45	100	6.78	20	0.039683	352	0
46	103	17.95	20	0.25	140	0
47	104	10.15	40	0.01	100	0
48	105	10.15	40	0.01	100	0
49	107	17.95	40	0.01	100	0
50	110	58.81	40	0.01	100	0
51	111	10.15	20	0.277778	136	0
52	112	10.15	40	0.01	100	0
53	113	10.15	40	0.01	100	0
54	116	58.81	40	0.01	100	0

Table B.2 118 Bus: Line data

Line No.	From Bus	To Bus	R (pu)	X (pu)	Flow Limit (MW)
1	1	2	0.0303	0.0999	100000
2	1	3	0.0129	0.0424	100000
3	4	5	0.00176	0.00798	100000
4	3	5	0.0241	0.108	100000
5	5	6	0.0119	0.054	100000
6	6	7	0.00459	0.0208	100000
7	8	9	0.00244	0.0305	100000
8	8	5	0	0.0267	100000
9	9	10	0.00258	0.0322	100000
10	4	11	0.0209	0.0688	100000
11	5	11	0.0203	0.0682	100000
12	11	12	0.00595	0.0196	100000
13	2	12	0.0187	0.0616	100000
14	3	12	0.0484	0.16	100000
15	7	12	0.00862	0.034	100000
16	11	13	0.02225	0.0731	100000
17	12	14	0.0215	0.0707	100000
18	13	15	0.0744	0.2444	100000
19	14	15	0.0595	0.195	100000
20	12	16	0.0212	0.0834	100000
21	15	17	0.0132	0.0437	100000
22	16	17	0.0454	0.1801	100000

23	17	18	0.0123	0.0505	100000
24	18	19	0.01119	0.0493	100000
25	19	20	0.0252	0.117	100000
26	15	19	0.012	0.0394	100000
27	20	21	0.0183	0.0849	100000
28	21	22	0.0209	0.097	100000
29	22	23	0.0342	0.159	100000
30	23	24	0.0135	0.0492	100000
31	23	25	0.0156	0.08	100000
32	26	25	0	0.0382	100000
33	25	27	0.0318	0.163	100000
34	27	28	0.01913	0.0855	100000
35	28	29	0.0237	0.0943	100000
36	30	17	0	0.0388	100000
37	8	30	0.00431	0.0504	100000
38	26	30	0.00799	0.086	100000
39	17	31	0.0474	0.1563	100000
40	29	31	0.0108	0.0331	100000
41	23	32	0.0317	0.1153	100000
42	31	32	0.0298	0.0985	100000
43	27	32	0.0229	0.0755	100000
44	15	33	0.038	0.1244	100000
45	19	34	0.0752	0.247	100000
46	35	36	0.00224	0.0102	100000

47	35	37	0.011	0.0497	100000
48	33	37	0.0415	0.142	100000
49	34	36	0.00871	0.0268	100000
50	34	37	0.00256	0.0094	100000
51	38	37	0	0.0375	100000
52	37	39	0.0321	0.106	100000
53	37	40	0.0593	0.168	100000
54	30	38	0.00464	0.054	100000
55	39	40	0.0184	0.0605	100000
56	40	41	0.0145	0.0487	100000
57	40	42	0.0555	0.183	100000
58	41	42	0.041	0.135	100000
59	43	44	0.0608	0.2454	100000
60	34	43	0.0413	0.1681	100000
61	44	45	0.0224	0.0901	100000
62	45	46	0.04	0.1356	100000
63	46	47	0.038	0.127	100000
64	46	48	0.0601	0.189	100000
65	47	49	0.0191	0.0625	100000
66	42	49	0.0715	0.323	100000
67	42	49	0.0715	0.323	100000
68	45	49	0.0684	0.186	100000
69	48	49	0.0179	0.0505	100000
70	49	50	0.0267	0.0752	100000

71	49	51	0.0486	0.137	100000
72	51	52	0.0203	0.0588	100000
73	52	53	0.0405	0.1635	100000
74	53	54	0.0263	0.122	100000
75	49	54	0.073	0.289	100000
76	49	54	0.0869	0.291	100000
77	54	55	0.0169	0.0707	100000
78	54	56	0.00275	0.00955	100000
79	55	56	0.00488	0.0151	100000
80	56	57	0.0343	0.0966	100000
81	50	57	0.0474	0.134	100000
82	56	58	0.0343	0.0966	100000
83	51	58	0.0255	0.0719	100000
84	54	59	0.0503	0.2293	100000
85	56	59	0.0825	0.251	100000
86	56	59	0.0803	0.239	100000
87	55	59	0.04739	0.2158	100000
88	59	60	0.0317	0.145	100000
89	59	61	0.0328	0.15	100000
90	60	61	0.00264	0.0135	100000
91	60	62	0.0123	0.0561	100000
92	61	62	0.00824	0.0376	100000
93	63	59	0	0.0386	100000
94	63	64	0.00172	0.02	100000

95	64	61	0	0.0268	100000
96	38	65	0.00901	0.0986	100000
97	64	65	0.00269	0.0302	100000
98	49	66	0.018	0.0919	100000
99	49	66	0.018	0.0919	100000
100	62	66	0.0482	0.218	100000
101	62	67	0.0258	0.117	100000
102	65	66	0	0.037	100000
103	66	67	0.0224	0.1015	100000
104	65	68	0.00138	0.016	100000
105	47	69	0.0844	0.2778	100000
106	49	69	0.0985	0.324	100000
107	68	69	0	0.037	100000
108	69	70	0.03	0.127	100000
109	24	70	0.00221	0.4115	100000
110	70	71	0.00882	0.0355	100000
111	24	72	0.0488	0.196	100000
112	71	72	0.0446	0.18	100000
113	71	73	0.00866	0.0454	100000
114	70	74	0.0401	0.1323	100000
115	70	75	0.0428	0.141	100000
116	69	75	0.0405	0.122	100000
117	74	75	0.0123	0.0406	100000
118	76	77	0.0444	0.148	100000

119	69	77	0.0309	0.101	100000
120	75	77	0.0601	0.1999	100000
121	77	78	0.00376	0.0124	100000
122	78	79	0.00546	0.0244	100000
123	77	80	0.017	0.0485	100000
124	77	80	0.0294	0.105	100000
125	79	80	0.0156	0.0704	100000
126	68	81	0.00175	0.0202	100000
127	81	80	0	0.037	100000
128	77	82	0.0298	0.0853	100000
129	82	83	0.0112	0.03665	100000
130	83	84	0.0625	0.132	100000
131	83	85	0.043	0.148	100000
132	84	85	0.0302	0.0641	100000
133	85	86	0.035	0.123	100000
134	86	87	0.02828	0.2074	100000
135	85	88	0.02	0.102	100000
136	85	89	0.0239	0.173	100000
137	88	89	0.0139	0.0712	100000
138	89	90	0.0518	0.188	100000
139	89	90	0.0238	0.0997	100000
140	90	91	0.0254	0.0836	100000
141	89	92	0.0099	0.0505	100000
142	89	92	0.0393	0.1581	100000

143	91	92	0.0387	0.1272	100000
144	92	93	0.0258	0.0848	100000
145	92	94	0.0481	0.158	100000
146	93	94	0.0223	0.0732	100000
147	94	95	0.0132	0.0434	100000
148	80	96	0.0356	0.182	100000
149	82	96	0.0162	0.053	100000
150	94	96	0.0269	0.0869	100000
151	80	97	0.0183	0.0934	100000
152	80	98	0.0238	0.108	100000
153	80	99	0.0454	0.206	100000
154	92	100	0.0648	0.295	100000
155	94	100	0.0178	0.058	100000
156	95	96	0.0171	0.0547	100000
157	96	97	0.0173	0.0885	100000
158	98	100	0.0397	0.179	100000
159	99	100	0.018	0.0813	100000
160	100	101	0.0277	0.1262	100000
161	92	102	0.0123	0.0559	100000
162	101	102	0.0246	0.112	100000
163	100	103	0.016	0.0525	100000
164	100	104	0.0451	0.204	100000
165	103	104	0.0466	0.1584	100000
166	103	105	0.0535	0.1625	100000

167	100	106	0.0605	0.229	100000
168	104	105	0.00994	0.0378	100000
169	105	106	0.014	0.0547	100000
170	105	107	0.053	0.183	100000
171	105	108	0.0261	0.0703	100000
172	106	107	0.053	0.183	100000
173	108	109	0.0105	0.0288	100000
174	103	110	0.03906	0.1813	100000
175	109	110	0.0278	0.0762	100000
176	110	111	0.022	0.0755	100000
177	110	112	0.0247	0.064	100000
178	17	113	0.00913	0.0301	100000
179	32	113	0.0615	0.203	100000
180	32	114	0.0135	0.0612	100000
181	27	115	0.0164	0.0741	100000
182	114	115	0.0023	0.0104	100000
183	68	116	0.00034	0.00405	100000
184	12	117	0.0329	0.14	100000
185	75	118	0.0145	0.0481	100000
186	76	118	0.0164	0.0544	100000

Table B.3: 118 Bus Load data

Bus No	Load (MW)
1	51
2	20
3	39
4	39
6	52
7	19
11	28
12	70
13	47
14	34
15	14
16	90
17	25
18	11
19	60
20	45
21	18
22	14
23	10
27	7
28	13
29	71

31	17
32	24
33	43
34	59
35	23
36	59
39	33
40	31
41	27
42	66
43	37
44	96
45	18
46	16
47	53
48	28
49	34
50	20
51	87
52	17
53	17
54	18
55	23
56	113

57	63
58	84
59	12
60	12
62	277
66	78
67	77
70	39
74	28
75	66
76	12
77	6
78	68
79	47
80	68
82	61
83	71
84	39
85	130
86	54
88	20
90	11
92	24
93	21

94	48
95	163
96	10
97	65
98	12
100	30
101	42
102	38
103	15
104	34
105	42
106	37
107	22
108	5
109	23
110	38
112	31
114	43
115	50
117	2
118	8

Table B.4: DCOPF Result: 118 Bus Generation

Bus	Generation	Generation
	P (MW)	P (MW)
	SCQP DCOPF	MatPower
1	0	0
4	0	0
6	0	0
8	0	0
10	436.080833	436.08
12	82.370837	82.37
15	0	0
18	0	0
19	0	0
24	0	0
25	213.195052	213.2
26	304.287484	304.29
27	0	0
31	6.78348098	6.78
32	0	0
34	0	0
36	0	0
40	0	0
42	0	0
46	18.4123034	18.41

49	197.689978	197.69
54	46.5152954	46.52
55	0	0
56	0	0
59	150.20562	150.21
61	155.050953	155.05
62	0	0
65	378.905747	378.91
66	379.87482	379.87
69	500.426875	500.43
70	0	0
72	0	0
73	0	0
74	0	0
76	0	0
77	0	0
80	462.245608	462.25
85	0	0
87	3.87627338	3.88
89	588.224396	588.22
90	0	0
91	0	0
92	0	0
99	0	0

100	244.205234	244.21
103	38.762738	38.76
104	0	0
105	0	0
107	0	0
110	0	0
111	34.8864699	34.89
112	0	0
113	0	0
116	0	0

Table B.5: DCOPF Result: 118 Bus Nodal LMP

Bus	Lambda	Lambda
	SCQP DCOPF	MatPower
1	39.38137	39.381
2	39.38137	39.381
3	39.38137	39.381
4	39.38137	39.381
5	39.38137	39.381
6	39.38137	39.381
7	39.38137	39.381
8	39.38137	39.381
9	39.38137	39.381

10	39.38137	39.381
11	39.38137	39.381
12	39.38137	39.381
13	39.38137	39.381
14	39.38137	39.381
15	39.38137	39.381
16	39.38137	39.381
17	39.38137	39.381
18	39.38137	39.381
19	39.38137	39.381
20	39.38137	39.381
21	39.38137	39.381
22	39.38137	39.381
23	39.38137	39.381
24	39.38137	39.381
25	39.38137	39.381
26	39.38137	39.381
27	39.38137	39.381
28	39.38137	39.381
29	39.38137	39.381
30	39.38137	39.381
31	39.38137	39.381
32	39.38137	39.381
33	39.38137	39.381

34	39.38137	39.381
35	39.38137	39.381
36	39.38137	39.381
37	39.38137	39.381
38	39.38137	39.381
39	39.38138	39.381
40	39.38138	39.381
41	39.38138	39.381
42	39.38138	39.381
43	39.38137	39.381
44	39.38137	39.381
45	39.38137	39.381
46	39.38137	39.381
47	39.38137	39.381
48	39.38137	39.381
49	39.38137	39.381
50	39.38137	39.381
51	39.38137	39.381
52	39.38137	39.381
53	39.38137	39.381
54	39.38137	39.381
55	39.38137	39.381
56	39.38137	39.381
57	39.38137	39.381

58	39.38137	39.381
59	39.38137	39.381
60	39.38137	39.381
61	39.38137	39.381
62	39.38137	39.381
63	39.38137	39.381
64	39.38137	39.381
65	39.38137	39.381
66	39.38137	39.381
67	39.38137	39.381
68	39.38137	39.381
69	39.38137	39.381
70	39.38137	39.381
71	39.38137	39.381
72	39.38137	39.381
73	39.38137	39.381
74	39.38137	39.381
75	39.38137	39.381
76	39.38137	39.381
77	39.38137	39.381
78	39.38137	39.381
79	39.38137	39.381
80	39.38137	39.381
81	39.38137	39.381

82	39.38137	39.381
83	39.38137	39.381
84	39.38137	39.381
85	39.38137	39.381
86	39.38137	39.381
87	39.38137	39.381
88	39.38137	39.381
89	39.38136	39.381
90	39.38137	39.381
91	39.38137	39.381
92	39.38136	39.381
93	39.38137	39.381
94	39.38137	39.381
95	39.38137	39.381
96	39.38137	39.381
97	39.38137	39.381
98	39.38137	39.381
99	39.38137	39.381
100	39.38137	39.381
101	39.38137	39.381
102	39.38137	39.381
103	39.38137	39.381
104	39.38137	39.381
105	39.38137	39.381

106	39.38137	39.381
107	39.38137	39.381
108	39.38137	39.381
109	39.38137	39.381
110	39.38137	39.381
111	39.38137	39.381
112	39.38137	39.381
113	39.38137	39.381
114	39.38137	39.381
115	39.38137	39.381
116	39.38137	39.381
117	39.38137	39.381
118	39.38137	39.381

Table B.6: DCOPF Result: 118 Bus Power Flow

Branch	From	To	From Bus	From Bus
	Bus	Bus	P (MW)	P (MW)
			SCQP DCOPF	MatPower
1	1	2	-11.8569596	-11.92
2	1	3	-39.1430404	-39.08
3	4	5	-103.226621	-102.95
4	3	5	-68.8478275	-68.71
5	5	6	86.8008392	86.56

6	6	7	34.8008392	34.56
7	8	9	-436.080833	-436.08
8	8	5	335.745375	334.79
9	9	10	-436.080833	-436.08
10	4	11	64.2266208	63.95
11	5	11	76.8700872	76.56
12	11	12	36.0097631	35.73
13	2	12	-31.8569596	-31.92
14	3	12	-9.2952129	-9.37
15	7	12	15.8008392	15.56
16	11	13	35.0869449	34.79
17	12	14	18.27141	17.94
18	13	15	1.08694485	0.79
19	14	15	4.27140998	3.94
20	12	16	7.75785682	7.43
21	15	17	-104.874562	-104.79
22	16	17	-17.2421432	-17.57
23	17	18	80.0500146	79.96
24	18	19	20.0500146	19.96
25	19	20	-11.6379979	-11.34
26	15	19	11.3698755	11.22
27	20	21	-29.6379979	-29.34
28	21	22	-43.6379979	-43.34
29	22	23	-53.6379979	-53.34

30	23	24	8.04383432	8.65
31	23	25	-160.399108	-160.28
32	26	25	84.8411284	84.42
33	25	27	137.637073	137.33
34	27	28	32.9183098	32.77
35	28	29	15.9183098	15.77
36	30	17	227.028891	227.9
37	8	30	72.3354588	73.29
38	26	30	219.446355	219.87
39	17	31	13.069575	13.44
40	29	31	-8.08169023	-8.23
41	23	32	91.7172756	91.3
42	31	32	-31.2286343	-31
43	27	32	12.8753334	12.77
44	15	33	8.86304142	8.3
45	19	34	-1.94211202	-2.49
46	35	36	0.73653044	0.83
47	35	37	-33.7365304	-33.83
48	33	37	-14.1369586	-14.7
49	34	36	30.2634695	30.17
50	34	37	-92.8890627	-93.8
51	38	37	239.738551	242.13
52	37	39	54.593327	55.01
53	37	40	44.3826723	44.79

54	30	38	64.7529238	65.26
55	39	40	27.593327	28.01
56	40	41	16.6037848	17.01
57	40	42	-10.6277854	-10.22
58	41	42	-20.3962152	-19.99
59	43	44	-16.3165188	-15.86
60	34	43	1.6834812	2.14
61	44	45	-32.3165188	-31.86
62	45	46	-35.6211951	-35.37
63	46	47	-30.9997219	-30.76
64	46	48	-14.2091698	-14.19
65	47	49	-7.61810365	-8.04
66	42	49	-127.024001	-63.1
67	42	49	-127.024001	-63.1
68	45	49	-49.6953237	-49.49
69	48	49	-34.2091698	-34.19
70	49	50	51.643934	51.51
71	49	51	63.8505519	63.68
72	51	52	28.3046207	28.25
73	52	53	10.3046207	10.25
74	53	54	-12.6953793	-12.75
75	49	54	72.7443583	36.36
76	49	54	72.7443583	36.11
77	54	55	6.88709773	6.84

78	54	56	17.3307329	17.19
79	55	56	-21.2853848	-21.18
80	56	57	-22.643934	-22.51
81	50	57	34.643934	34.51
82	56	58	-6.54593122	-6.43
83	51	58	18.5459312	18.43
84	54	59	-30.6535563	-30.81
85	56	59	-58.7647867	-28.8
86	56	59	-58.7647867	-30.25
87	55	59	-34.8275174	-34.98
88	59	60	-44.4840918	-43.9
89	59	61	-53.1773221	-52.57
90	60	61	-113.067037	-112.59
91	60	62	-9.41705437	-9.31
92	61	62	26.5454323	26.54
93	63	59	153.378826	155.16
94	63	64	-153.378826	-155.16
95	64	61	37.7388391	36.65
96	38	65	-174.985627	-176.87
97	64	65	-191.117665	-191.81
98	49	66	-248.365581	-123.91
99	49	66	-248.365581	-123.91
100	62	66	-36.4809838	-36.43
101	62	67	-23.3906383	-23.34

102	65	66	-4.63761699	-5.3
103	66	67	51.3906383	51.34
104	65	68	17.4400716	15.52
105	47	69	-57.3816183	-56.72
106	49	69	-47.729883	-47.08
107	68	69	-121.695043	-124.23
108	69	70	103.603143	103.19
109	24	70	-5.87905488	-5.58
110	70	71	17.0771107	16.78
111	24	72	0.92288922	1.22
112	71	72	11.0771108	10.78
113	71	73	5.99999998	6
114	70	74	15.3743989	15.46
115	70	75	-0.7274215	-0.62
116	69	75	107.008465	106.7
117	74	75	-52.6256011	-52.54
118	76	77	-60.8720627	-60.92
119	69	77	63.0087229	62.51
120	75	77	-33.4724948	-33.54
121	77	78	47.0985464	46.97
122	78	79	-23.9014536	-24.03
123	77	80	-133.453392	-91.57
124	77	80	-133.453392	-42.3
125	79	80	-62.9014536	-63.03

126	68	81	-44.864885	-44.25
127	81	80	-44.864885	-44.25
128	77	82	-5.98098907	-6.05
129	82	83	-49.5006381	-49.51
130	83	84	-27.843634	-27.85
131	83	85	-41.6570042	-41.66
132	84	85	-38.843634	-38.85
133	85	86	17.1237266	17.12
134	86	87	-3.87627338	-3.88
135	85	88	-50.9053007	-50.91
136	85	89	-70.719064	-70.73
137	88	89	-98.9053007	-98.91
138	89	90	164.386053	56.97
139	89	90	164.386053	107.42
140	90	91	1.38605291	1.38
141	89	92	254.213978	192.66
142	89	92	254.213978	61.54
143	91	92	-8.61394708	-8.62
144	92	93	57.3705811	57.37
145	92	94	51.8110874	51.81
146	93	94	45.3705811	45.37
147	94	95	41.1796412	41.18
148	80	96	18.4714223	18.5
149	82	96	-10.4803509	-10.54

150	94	96	20.0497445	20.05
151	80	97	25.7795429	25.8
152	80	98	28.051249	28.06
153	80	99	18.7236633	18.73
154	92	100	28.9199465	28.92
155	94	100	5.95228284	5.94
156	95	96	-0.82035882	-0.82
157	96	97	-10.7795429	-10.8
158	98	100	-5.948751	-5.94
159	99	100	-23.2763367	-23.27
160	100	101	-15.4984163	-15.49
161	92	102	42.4984163	42.49
162	101	102	-37.4984163	-37.49
163	100	103	115.520079	115.52
164	100	104	54.4118569	54.41
165	103	104	31.7879714	31.79
166	103	105	42.197958	42.2
167	100	106	58.4188565	58.42
168	104	105	48.1998283	48.2
169	105	106	8.33538988	8.34
170	105	107	26.2457536	26.25
171	105	108	24.8166428	24.82
172	106	107	23.7542464	23.75
173	108	109	22.8166428	22.82

174	103	110	57.2968873	57.3
175	109	110	14.8166428	14.82
176	110	111	-34.8864699	-34.89
177	110	112	68	68
178	17	113	0.79259581	1.14
179	32	113	5.20740417	4.86
180	32	114	9.15657055	9.21
181	27	115	20.8434295	20.79
182	114	115	1.15657055	1.21
183	68	116	184	184
184	12	117	20	20
185	75	118	40.1279372	40.08
186	76	118	-7.12793724	-7.08