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Electricity Market Designs for Demand Response from Residential Customers

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I am submitting herewith a dissertation written by Ailin Asadinejad entitled "Electricity Market Designs for Demand Response from Residential Customers." I have examined the final electronic copy of this dissertation for form and content and recommend that it be accepted in partial fulfillment of the requirements for the degree of Doctor of Philosophy, with a major in Electrical Engineering.

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Electricity Market Designs for Demand Response from Residential Customers

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Abstract

The main purpose of this dissertation is to design an appropriate tariff program for residential customers that encourages customers to participate in the system while satisfying market operators and utilities goals. This research investigates three aspects critical for successful programs: tariff designs for DR, impact of renewable on such tariffs, and load elasticity estimates. First, both categories of DR are modeled based on the demand-price elasticity concept and used to design an optimum scheme for achieving the maximum benefit of DR. The objective is to not only reduce costs and improve reliability but also to increase customer acceptance of a DR program by limiting price volatility. A time of use (TOU) program is considered for a PB scheme designed using a monthly peak and off peak tariff. For the IBDR, a novel optimization is proposed that in addition to calculation of an adequate and a reasonable amount of load change for the incentive also finds the best times to request DR.

Second, the effect of both DR programs under a high penetration of renewable resources is investigated. LMP variation after renewable expansion is more highly correlated with renewable's intermittent output than the load profile. As a result, a TOU program is difficult to successfully implement; however, analysis shows IBDR can diminish most of the volatile price changes in WECC. To model risk associated with renewable uncertainty, a robust optimization is designed considering market price and elasticity uncertainty.

Third, a comprehensive study to estimate residential load elasticity in an IBDR program. A key component in all demand response programs design is elasticity, which implies customer reaction to LSEs offers. Due to limited information, PB elasticity is

used in IBDR as well. Customer elasticity is calculated using data from two nationwide surveys and integrated with a detailed residential load model. In addition, IB elasticity is reported at the individual appliance level, which is more effective than one for the aggregate load of the feeder. Considering the importance of HVAC in the aggregate load signal, its elasticity is studied in greater detail and estimated for different customer groupings.

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Nomenclature

α Load variation economic weight in PBDR objective function.

β maximum percentage of allowable load reduction by PBDR program.

ΔD_{bt_j} Load change of customer type j in time period t and bus b due to IBDR program.

Δd_{bt} Load change of customer in time period t and bus b due to PBDR program.

$\Delta \bar{D}_{bt}$ Load change of customer in time period t and bus b due to IBDR program.

$\Delta \bar{D}_{bt}^{C}$ Load change of commercial customer in time period t and bus b due to IBDR program.

$\Delta \bar{D}_{bt}^{I}$ Load change of industrial customer in time period t and bus b due to IBDR program.

$\Delta \bar{D}_{bt}^{R}$ Load change of residential customer in time period t and bus b due to IBDR program.

μ Average of observations.

ρ Level of conservativness.

ρ_s PRobabiloty of scenario s.

σ Standard deviation of observations.

θ Safety parameter.

$\triangle p$ Change of price in elasticity estimation.

$\triangle q$ Change of demand in elasticity estimation.

ε^C Elasticity of commercial customers.

ε^I Elasticity of industrial customers.

ε_j Elasticity of customer type j.

ε_{kg}^R Elasticity of residential customer for appliance k and contribution group g.

ε_k^R Elasticity of residential customer for appliance k.

a_i Random vector of matrix A.

b_i Random vector of matrix b.

B_L Conductance matrix of transmission line.

C_i Capacity cost offer of unit i

CB_b Customer benefit at bus b by PBDR program.

D_{bt} Orignial demand at time period t and bus b before IBDR program.

d_{bt}^0 Orignial demand at time period t and bus b before PBDR program.

D_{jt} Power consumption of demand j during time period t.

D_T Customer type of T.

$e_i(x)$ Expectation for constraints of linear programming optimization.

F_k Transmission limit of line k.

G_{it} Generation output schedule from unit i during period t

g_j Customer response function to incentive payments

GSF_{ki} Generator shift factor to line k from unit i.

GW_{it_s} Generation of wind turbine i at time t and for scenario s

LMP_{bt} LMP of market at time period t and bus b.

LSE_b LSE benefit at bus b by PBDR program.

n Number of observations in DOE analysis.

N_B Number of buses in each region.

N_D Number of runs for each factor.

ND Number of demand buses.

NG Number of generator buses.

NT Number of time periods of study.

NWG Number of wind turbine generator.

OPT Off peak of time period.

p Number of factors.

p_0 Initial value of price in elasticity estimation.

P_{bt}^{inc} Incentive payments at bus b and time period t.

P_b^0 LSE fix selling tariff for customers at bus b.

p_b^{OPT} LSE selling tariff for customers at bus b in off peak period time.

p_b^{PT} LSE selling tariff for customers at bus b in peak period time.

PT Peak of time period.

q_0 Initial value of demand in elasticity estimation.

q_{it} Capacity cost of spinning reserve of generator i during period t.

R_{it} Scheduled spinning reserve for unit i during time period t.

R_L Resistance matrix of transmission line.

RD_i Down-ramping rate of unit i.

RU_i Up-ramping rate of unit i.

S_i Start-up cost function of generator i

T_d Daily time period.

T_m Monthly time period.

T_y Yearly time period.

u set of uncertainty of parameters.

u_{it} 1 if unit i is scheduled on during time priod t and 0 otherwise

u_t 1 if DR is implemented and 0 otherwise.

V_i Covariance matrix.

$v_i(x)$ Standard deviation for constraints of linear programming optimization.

X Design matrix in DOE analysis.

$X'X$ Information matrix in DOE analysis.

X_i Set of observations.

x_i Factors for coded value in DOE analysis.

X_L Reactance matrix of transmission line.

CPP Critical Peak Pricing program.

DA Day ahead market

DCOPF DC optimal power flow.

DOE Design of expriement.

DR Demand Response.

EDPR Emergency demand response program.

HVAC Heating ventilation and air conditioner.

IBDR Incentive based demand response.

ISO Independent system operator.

LMP Locational marginal price.

LP Linear programming optimization.

LSE Load serving entitie.

PBDR Price based demand response.

RER Renewable energy resource.

RTP Real time pricing.

TOU Time of use pricing program.

WECC Western electricity coordinating council.

1 Introduction

Ongoing developments in the so-called Smart Grid promise a future power system that is more economically efficient, environmentally friendly, fault resilient and operationally flexible. This future system will depend on new digital communications, computing, monitoring and controls down to the customer level. Among the many innovations related to these developments, a key component is effective demand side management.

In a conventional electric power system, the main objective is to control the supply to meet the demand. However, the demand side could change its passive role in a new modern grid via Demand Response (DR). Note that DR is not energy efficiency. Energy efficiency refers to actions taken to permanently reduce the energy consumption of goods and services, for example insulating a home, switching to more efficient appliances, and

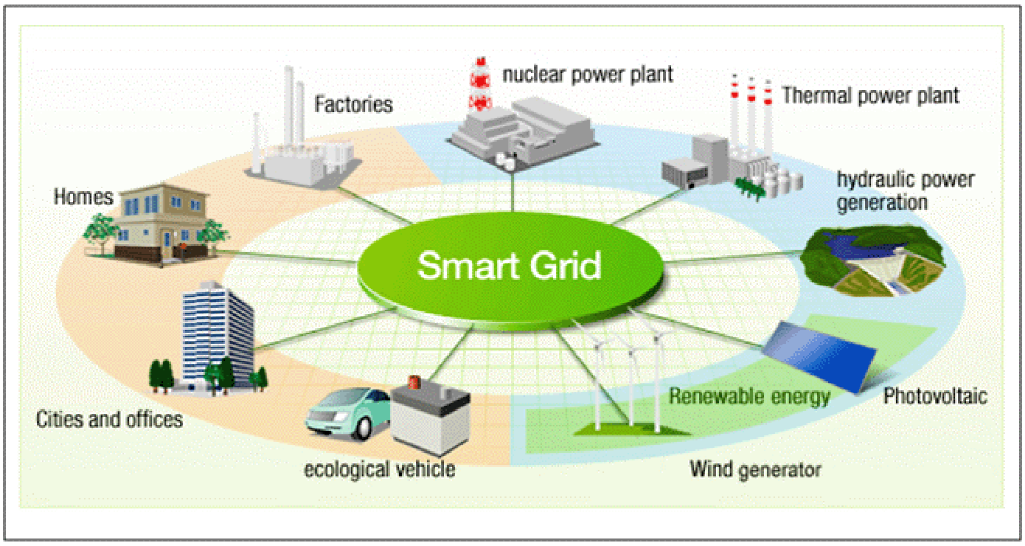


Figure 1.1: Schematic of smart grid system

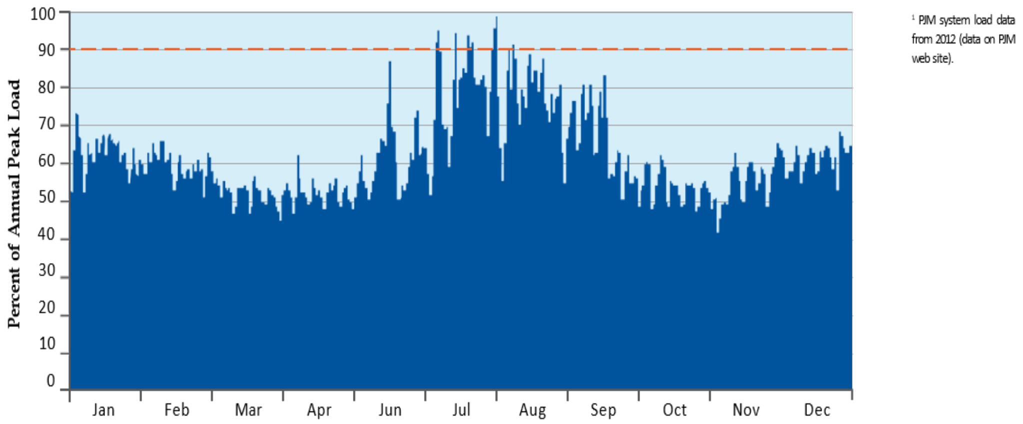


Figure 1.2: Design capacity of power grid in compared with yearly load

tuning a commercial heating, air conditioning, and ventilation (HVAC) system [3].

The electric power gird is typically designed with large margins to support the peak period of energy consumption, which only happens for a few hours each year [1, 2]. Generator owners or utility companies have been required to increase their generation capacity at all times only to meet these infrequent peak demands. Generally, around 20% of the power generation capacity is only for supplying the peak demand, for say,, approximately 5% of the time [4]. Fig. 1.2 shows this concept graphically. The red line in this figure is the design capacity of generation in grid vs. the load variation in whole year using data of PJM in 2012.

To overcome these issues, there are three main options available: building new power plants, developing new storage technologies, or developing DR programs [5, 6].

Building new conventional power plants is not always appropriate due to the added costs and increasing environmental pollution by using fossil fuel based peaker units [1, 2]. In addition, adding new generators only solves the problem over a short period of time considering the growth rate of the demand [7]. Energy storage could be one of the most important aspects of the future smart grid that could supply peak load as well as by providing new functions, such as, ancillary services [8]. The most popular forms of energy storage are pumped storage, flywheel, compressed air, electrical vehicle batteries, and large thermal storage tanks. However, the technology for most of these energy storage types remains at the research level with high costs or other restrictions limiting large scale deployment [9, 10].

Both of the above solutions are based on the traditional idea of controlling supply to match the demand. DR on the other hand is trying to reach to the same goal by managing the demand. DR helps utilities and market operators to reduce peak demand instead of increasing generation. It will allow customers to play an active role in the market that was impossible historically [11, 12].

Design and implementation of DR connect to two other important concepts: power markets and demand elasticity. These are explained in more detail in the following subsections. In addition, as one of the main application of DR is under high penetration of renewable energy resource (RER), characteristics of RERs are reviewed.

1.1 Background

1.1.1 Power Market

In a regulated market, utilities own or control the entire flow of electricity from generation to end-user. States with this type of market in the U.S. include Idaho, Kentucky, Florida, Colorado, and Tennessee [24]. Deregulation began in the 1970s after the passage of the public utilities regulatory act. The real market was opened in 1992 after the energy policy act, which canceled the limitation on the price that would be charged by the wholesale market. Deregulation has continued to expand since then but has slowed down in recent years [24]. In a deregulated market, utilities are generally only responsible for:

- distribution, operations, and maintenance from the interconnection at the grid to the meter,
- billing customers; and
- acting as the provider of last resort.

In deregulated markets, Independent System Operators (ISOs) administer the wholesale market to guarantee the reliability and economic operation of systems. In the U.S. several states have joined the deregulated market over the last 20 years, mainly in the Northeast, Mid-Atlantic, Texas, and California [25]. From economic point, electricity is a commodity that could be bough, sold, and traded. The electricity market is a structure which enables this trade in short term and long term through the bids and offers from sellers and buyers. Bids and offers use supply and demand convention to set the price [13]. The transactions in the wholesale market are typically cleared by ISOs which try to keep the balance of supply and load while maintaining the economic efficient of market operation as well.

The market for energy products trading is normally cleared by ISOs in 5, 15 and 60 minutes intervals [14, 15]. Power related products are also traded in wholesale market in order to ensure the reliability of the system. These commodities are normally traded in the ancillary service pool and could include various products, such as, spinning and non spinning reserve, operating reserve, and regulation up / down reserve [16, 17, 18]. While energy and power products are the major components of the electricity market, there are also some other products, including those for transmission congestion, electricity futures and options. Recently, California ISO is running a market to trade imbalance of renewable energy and power.

To estimate the price of the market at each delivering point, the method that most ISOs use is called Locational Marginal Price (LMP). In this method, an optimization is designed to find the price for supplying one additional kWh demand at a bus using a hypothetical incremental cost of the re-dispatch of available generators, considering the network constraints [19, 20]. In the market based on above pricing structure, generators and customers should submit their bids and offers one day in advance and ISO would run a security constraint optimization to find the least cost dispatch arrangement which ensures *n-1* security as well. The ISOs must always ensure reliability of the system as the first priority and then consider economic aspects. It means that if there is transmission line congestion, ISOs cannot allow more power flow on the line, although there could be cheaper generation on the lower cost side. This restriction will result in different prices at two ends of a congested line. Unusual patterns can emerge, including where energy is flowing from the expensive node to the low cost node. If there was no transmission limit, then nodal price of all neighbors would be the same. [21, 22].

1.1.2 Demand Response

The U.S Department of Energy defines demand response as “a tariff or program established to motivate changes in electric use by end-use customers in response to changes in the price of electricity over time, or to give incentive payments designed to induce lower electricity use at times of high market prices or when grid reliability is jeopardized” [26]. In a competitive wholesale market where there is a unique pricing structure for everyone, even a small reduction in demand can result in significant change in the total production cost of the system [39]. The main example of this condition is during peak load. Although peak periods are short in duration, they force the ISOs to use the most expensive generators of the system to maintain the load and supply balance and therefore, they cause significant price change. DR can reduce the load at peak time and not only reduce the market clearing price, but also limit the exercise of market power by generator owners [40, 41].

DR entails either shifting electricity use, for example, off peak, resulting in no net energy savings, or shedding (i.e., curtailing) electricity use temporarily, for example, during peak hours, resulting in net energy savings but only for a small portion of the hours in a year. DR programs can take a number of forms . Some examples are listed below [33, 35, 60]:

- DR can reduce wholesale energy prices and their volatility. In systems without DR, demand is inelastic. Additionally, when a power system nears its generation capacity, supply becomes increasingly inelastic. The result is extreme wholesale electricity price volatility on days when system demand is high.

- DR can reduce the need for power system infrastructure expansion. Power systems are sized to provide electricity during the peak hours. Through DR, the peak is reduced and new investments in power plants and transmission can be delayed.

- DR can limit the use of peaking power plants, i.e., peakers. The peakers are only used a small number of hours per year, and have high marginal costs, are generally less efficient than other power plants and have higher emissions.

- DR can improve grid reliability. For example, DR can provide emergency response to grid contingencies via ancillary services such as spinning reserve.

- DR can provide power system flexibility. Similar to generators and energy storage devices, it can be viewed as a resource that can provide energy (via demand reductions) or provide services (via demand reductions and increases) to the grid.

- DR may be able to provide fast energy balance service, which is specifically important in a system with high levels of renewable resources.

The literature broadly shows two types of DR: price based (PB) and incentive based (IB) [26]. PBDR programs pass on the variation of wholesale market electricity price directly to customers so that they pay for the value of electricity at different times of the day[27]. PBDR schemes typically considered, include: Time-Of-Use pricing (TOU), Critical Peak Pricing (CPP), Peak Load Pricing (PLP) and Real-Time Pricing (RTP) [28, 29], although there are many other possible PB schemes. The main idea behind all PBDR is that a significant difference between prices in different hours leads customers to adjust timing of their flexible loads in order to take advantage of lower price periods. From the load aggregator or utility point of view, peak shaving results in a powerful approach to peak shave and avoid capacity upgrades.

IB programs include Direct Load Control (DLC), Interruptible/curtail-able service (I/C), Demand Bidding/Buy Back (DB), Emergency Demand Response Program (EDRP), Capacity Market Program (CAP) and various Ancillary Service Markets (A/S). These

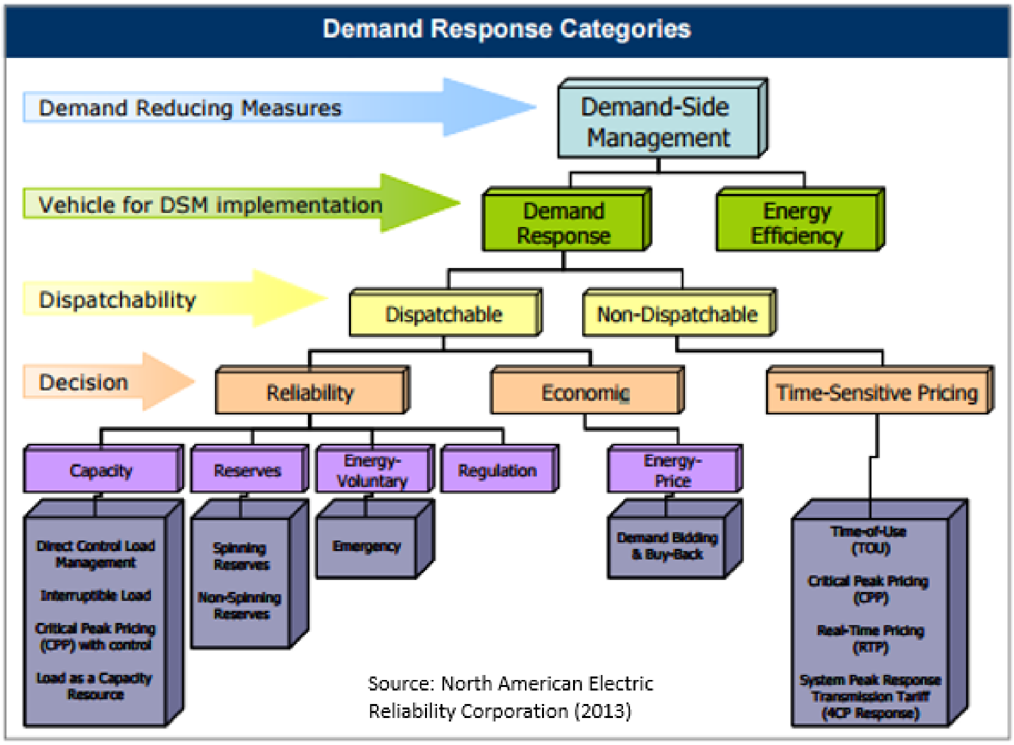


Figure 1.3: Different categories of demand response programs

programs offer customers incentives in addition to their retail electricity rate, which may be fixed or time-varying. Demand reductions are needed either when required for system reliability or when prices become too high. In percentage terms, IBDR programs provide about 93% of the peak load reduction from existing DR resources in the U.S. today [30]. Among all IBDR programs, the interruptible load contract (ILC) is the most common approach for controlled demand reduction. Utilities and regulators have encouraged ILC for larger loads since 1980s [31]. Peak Time Rebate (PTR) is another type of IBDR program [32]; however, the rebate paid to consumers is typically very high and does not reflect the actual supply-demand market conditions. Recently, IBDR becomes more attractive to researchers and market operators due to the man barriers that face full implementation of PB programs (see Fig. 1.4).

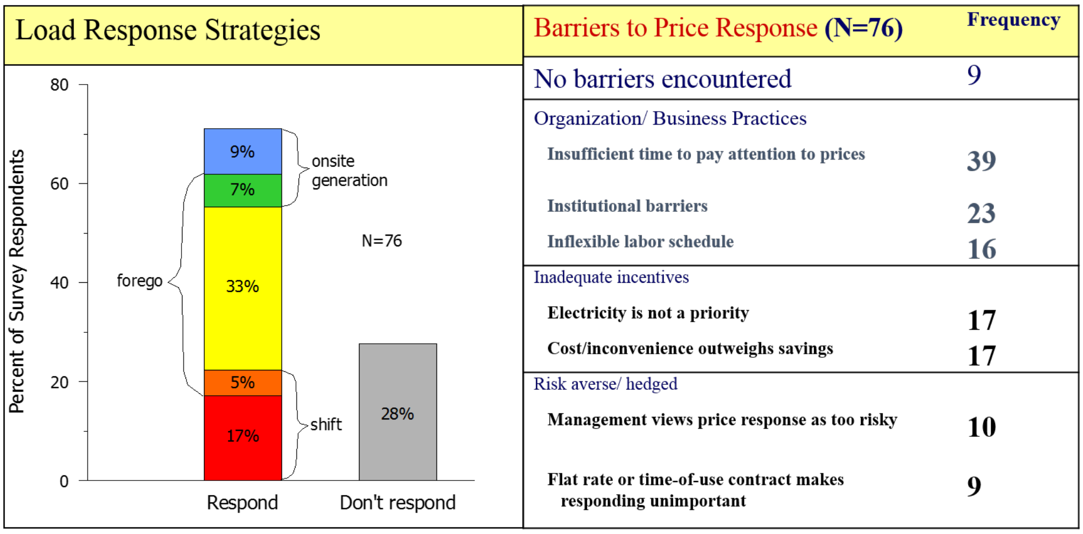


Figure 1.4: Barriers to RTP program, source :www.demandresponseresources.com

1.1.3 Demand Elasticity

Deregulation of electricity market in most developed countries, unstable oil prices and continuing global warming concern have rekindled interest in energy conservation and demand management to reduce electricity consumption [42]. Demand side management interest has increased in most electricity markets in recent years due to the considerable promise for demand modification through DR different programs [43]. A key factor in proper design of DR programs is the elasticity. Elasticity is a measure of the customer response to a tariff or incentive signal. Due to the complexity of human behavior, demand elasticity remains poorly understood but the socio-economic importance of electric consumption supports deeper investigation [45]. Fig. 1.5 shows the price vs. demand curve. Slope of this curve represents elasticity of demand.

According to economic theory, demand for energy is less responsive to price changes in compare to the other products. Price elasticity for most of the commodities, including electricity is negative. Thus, if the price for electricity increases, the demand for it would be decreased. There are two ranges for price elasticity of the products: elastic and inelastic. In general, if the absolute value of the elasticity is between 0 to 1, the demand is called inelastic and if it is more than 1, it considered to be elastic toward price changes

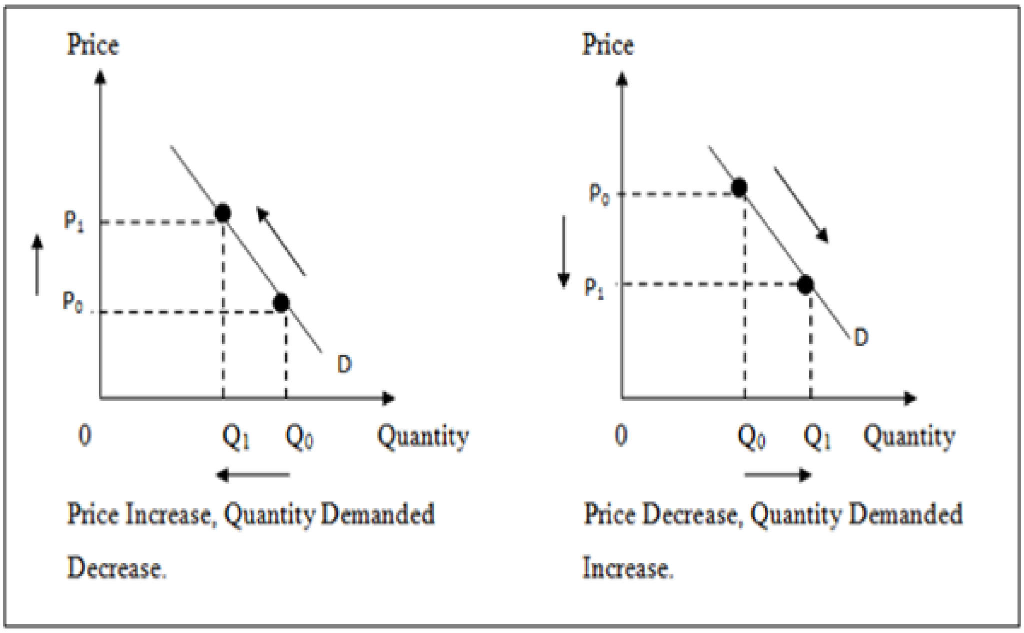


Figure 1.5: Price-demand curve

[46]. In an inelastic range, a commodity demand change ratio to a given change in the price is less than 1. The elasticity for electricity is generally inelastic. For example, if the price of electricity increases by 10 percent with a price elasticity of –0.10, then one expects demand to decrease by only 1 percent. As an example of elastic demand, home decoration accessories elasticity is around –2.5, so demand for them would drop by 25 for price increase by 10 percent. This relationship is pictured in Fig. 1.6.

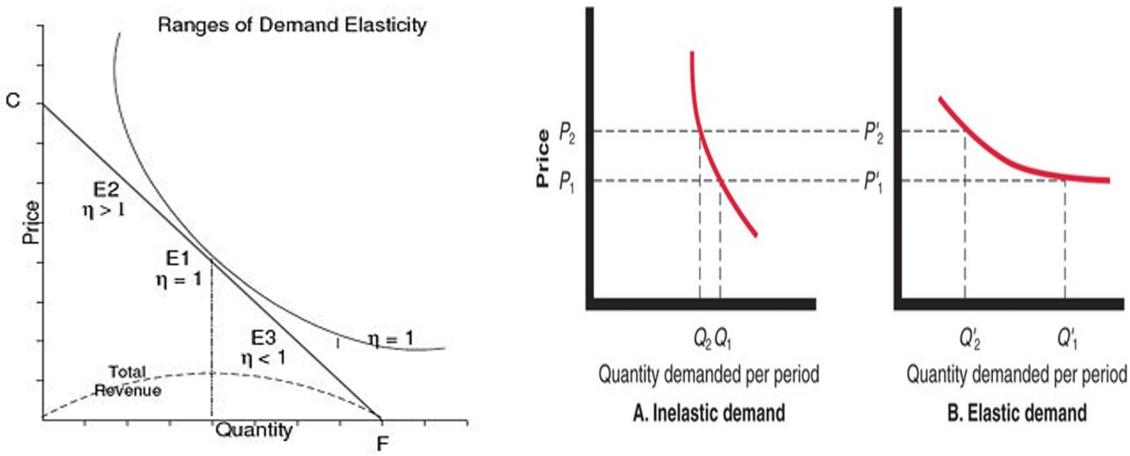


Figure 1.6: Relation between price and demand for elastic and inelastic demand

There are generally two types of elasticity coefficients that are used: own and cross elasticity of a commodity. Own price elasticity of a good is an index of how much customers would change their demand in response to price changes of that commodity. The own price elasticity is specifically useful for investigation of long term adjustment of the product demand toward price changes. Own elasticities are normally negative which shows the reciprocal relation between the price and demand. Cross elasticity shows how the customers would substitute one commodity for another, or change consumption due to that price change. For electricity, cross elasticity is useful to calculate the amount of load change from an expensive to a cheaper time. Cross elasticities are typically positive values [47, 48].

The incentive based elasticity of electricity contains important information on the demand response of consumers to financial incentives. Despite the importance, empirical estimates of the incentive based elasticity are difficult to find. Elasticity is mainly reported for different customer types, such as, residential, commercial and industrial sectors. However, aggregating all customer responses may lose valuable information and lead to inaccurate estimation of response to incentives. This may be one explanation for the wide range of elasticity values found for electricity. Generally speaking, elasticity can be modeled in two ways: through statistical evaluation using historical data or by direct query of customers with surveys [44]. There have been some attempts to find a more detailed value for elasticity. For example Guardia et al. [44] clusters residential customer load profile based on their similarity and report elasticity for each group. There are also some studies on segmenting elasticity based on demographic information, including: income of customers, urban or rural area and so on [45, 49].

1.1.4 Renewable Energy Resources

There are variety forms of generation resource classified as "alternative" energy. Generally, alternative energy divides into two main forms: Renewable Energy Resource (RER), such as, wind and solar; and single use resource like biomass and uranium. The use of RERs has a long history dating back many centuries as people used wind and solar for much of their energy demand. After the industrial revolution, the extensive use of fossil fuels widely replaced RERs. Nowadays, due to the environmental damage caused by fossil fuels, interest has returned to RERs [50]. Utilities and grid operators around the world are adopting RERs [53, 54]. There are significant advantages to using RERs. The main one is decreasing the environmental pollution. The nuclear power plants are not considered fully renewable due to their toxic and radioactive waste product. Still, nuclear power has its proponents and some consider it much cleaner than coal power plants [51].

Another advantage of RERs is their availability in isolated and remote areas where delivering fossil fuels is expensive. Wind, solar and biomass are available in almost all rural areas and producing energy from them is more convenient than building infrastructure for transport of gas and oil. For populated city areas, using conventional power sources is still more economic than RERs. Still, considering the harmful effects of fossil fuels, even urban areas will move toward more clean energy. Recently, roof top photo-voltaic panels has been growing rapidly with excess energy sold at parity back to the grid [52, 55].

Unfortunately, despite continuing advances in technology, there are still significant financial barriers against the extensive deployment of RERs. One of the important drawbacks is large investment cost of wind and solar in comparison with expansion or maintaining the current conventional power plants. In addition, installing large solar panels or wind farms to produce a huge amount of energy needs a great area of land which is a challenge in large cities [56]. Another major barrier for RERs is intermittent output. Wind power can be predicted with fairly limited accuracy. Typically, the standard deviation of forecast error for a wind farm power is close 10% in the hour-ahead forecast, 15% for 12 hour-ahead and 20% and more in the day-ahead forecasting as in shown in Fig. 1.7 [57, 58, 59, 60]. Therefore, the integration of wind power introduces additional uncertainty and a great challenge to system operators.

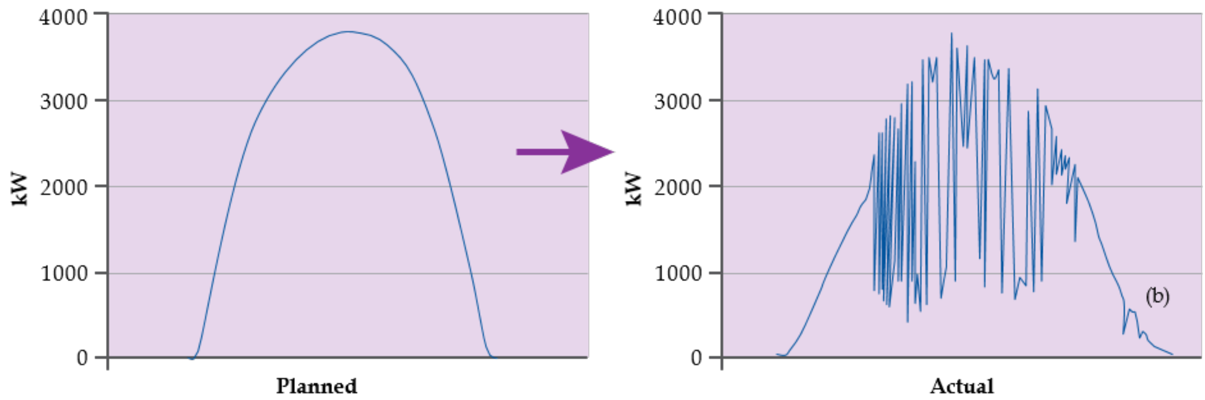


Figure 1.7: Comparison of planned renewable output to its actual, day-ahead

1.2 Motivation

The work in this dissertation is inspired by two facts in today's power system. Firstly, the large scale integration of RERs especially wind is advancing rapidly. Secondly, demand response plays an increasingly important role in reliable and economic operation of power systems and electricity markets. Demand response in this dissertation is mainly focused on retail customers who can not participate directly in the market. Small customers are buying electricity from the utility at a constant price. Therefore, they are not aware of the price variation in wholesale market. Customers flat price vs. market price is shown in Fig. 1.8. RTP program was proposed based on idea of transferring variation of market price to retail customers. However, this DR programs faces many practical barriers and cannot achieve the full potential of DR.

The objective of this research is to design an appropriate DR scheme for small customers that can capture maximum potential of load modification, brings benefits for all participants, reduces market price variation but remains sufficiently simple and practical for typical customers.Specifically, this research focuses on the IBDR program because due to disadvantages with PBDR for retail load costumers, including:

- Most customers will need new metering and communication equipment to participate fully in RTP.

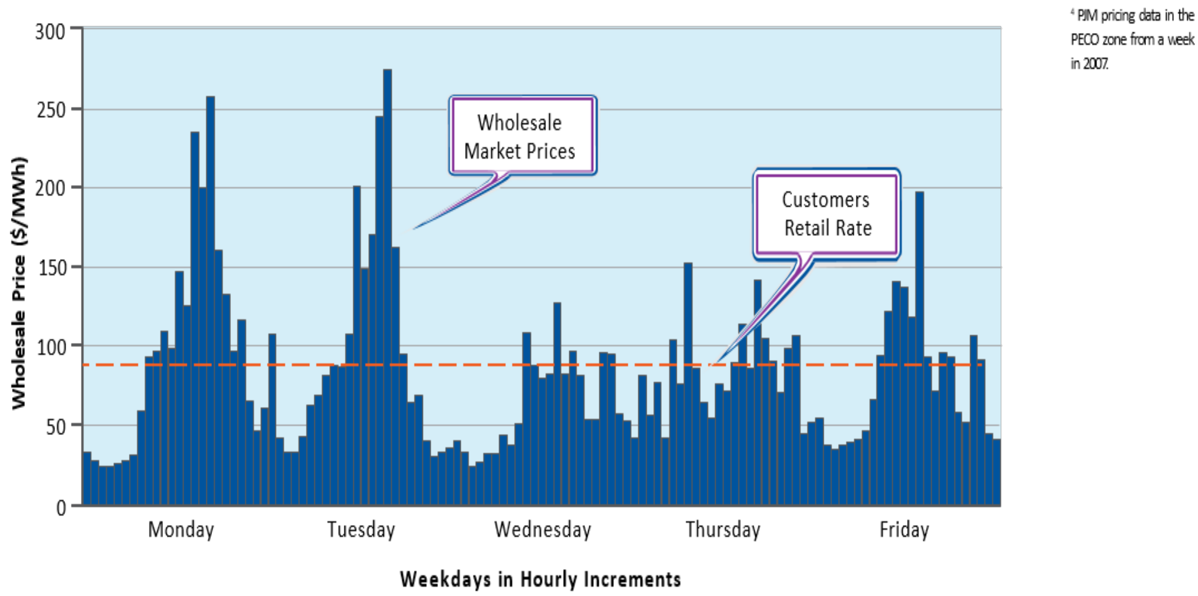


Figure 1.8: Retail customers flat rate price vs. market variable price

- Many customers and regulators fear that real time pricing will result in increases in monthly electricity bills.
- Volatility of real-time prices can make it difficult for customers to plan personal or small business budgets.
- Evidence that when costumers face sudden and significant changes in their monthly bill, they reduce their consumption temporarily; however over time, periodic fluctuations in prices are likely to cause consumers to ignore the savings and return to traditional consumption patterns.

Although the effect of PB programs is also investigated in this research, the main concentration is on IBDR. For example, as will be shown in chapter 6 and 7, IBDR can be particularly effective under situations of generator outage and high penetration of RERs. The key element in well-designed of demand response programs is elasticity. The term elasticity is representing customers behavior toward price signals (for PBDR) or incentive payment (for IBDR). According to many psychological studies, customer reaction toward price increases is different than from incentive offers. PB approaches tend to be viewed as punishment, while IB approaches tend to be viewed as reward based. Due to lack of information, PB elasticity is normally used in investigation of IBDR program design; however, optimum design of IBDR requires a good customer behavior model. The main motivation for elasticity estimation in this research is incorporating the correct model of customers response to the DR design.

1.3 Contribution

Contributions of this dissertation are as follows:

1. A novel optimization is proposed for IBDR design that calculates load change and incentive along with an optimum threshold for the DR program. This framework maximizes LSE benefit while satisfying customer comfort constraints. The main advantage of the optimum threshold estimation is that it eliminates the need for communication between customers and LSEs and simplifies the planning process.

2. Customer response in IBDR program is carefully modeled, including different load types (industrial, commercial and small industrial) and allows the possibility to model diverse customer behavior.

3. TOU optimization is proposed not only based on economic objectives but with load variation considered as a separate goal. This gives the ability to control priority of economic or load variation concerns in DR program design.

4. Application of IBDR for small customers during emergency situations is proposed considering time scale criteria. It is shown that appropriate design of IBDR can effectively diminish economic impact of generator outages. To overcome variation in speed of response for small customers, a new approach generator ranking based on their economic effect is proposed. Generator outage ordering allows more time for operators to implement DR.

5. IBDR is designed for a high penetration of RERs considering uncertainty of market price and elasticity of demand.

6. Incentive based elasticity of residential customers is estimated using data of two nation wide surveys and residential modeling toolbox. This elasticity is specifically designed for IBDR programs to reflect customers behavior toward reward based programs.

7. Residential elasticity is calculated for the main appliances in a household, considering the role and share of each appliance in the aggregated load signal. The concept of distributed elasticity is introduced to the load scheduling problems to allow more precise IBDR.

8. Residential customers classification is proposed for IBDR program. Customers segmentation is done using both load level and incentive expectation criteria. This classification could help utilities to design an appropriate DR program for each group to increase participation and achieve greater response for lower cost.

1.4 Dissertation Outline

The chapters of dissertation are as follows:

Chapter 2 reviews the literature on demand response and elasticity estimation as well as a discussion of customers segmentation toward different DR programs.

Chapter 3 gives information on the test bed system. WECC 240-bus reduced model is used as test system in this research to investigate effect of DR programs. Hourly LMP for one year is calculated and reported in this chapter for two condition, low and high penetration of RERs.

Chapter 4 concerns IBDR design under various customer flat rate tariffs. Two trigger points methods are used for implementation of the DR program, constant threshold and optimum threshold above customers flat rate tariff.

Chapter 5 introduces a combination of PB and IB program to fully use the advantages of both. These two programs could perfectly fulfill each other limitation and make optimum scheme of DR program.

Chapter 6 investigates the effect of IBDR during emergency situations. Although small customers are normally not participant during emergency conditions like generator outage, this work shows that they could be an effective resource.

Chapter 7 estimates LMP uncertainty due to wind forecast error. Scenario based economic dispatch is used to find various value of market price corresponding to forecast error. For scenario reduction, a Design Of Experiment (DOE) approach is used to find the range of price uncertainty.

Chapter 8 proposes a robust DR model to manage market price and customer response uncertainty. As shown in this chapter, the TOU program is not appropriate due to high variation of LMP, but the IBDR could effectively reduce much of the volatility. Strategy for renewable biding is also discussed in this chapter.

Chapter 9 builds a model for estimation of IB elasticity. Elasticity in this chapter is reported based on different customer segmentation, first based on consumption level, and second based on incentive expectation. It is calculated for main appliance usage among residential sectors.

Chapter 10 discusses the effect of appliance and incentive based elasticity of residential sector on DR in both low and high renewable production. Using customer grouping would improve the design of IBDR and brings more benefit for all participants. In high penetration of RERs, using potential of load shift would diminish the variation of price.

Chapter 11 provides conclusion and future research.

2 Literature Review

In this chapter available literature on analysis and modeling of different demand management programs is reviewed and summarized. First section is an overview of incorporating DR programs in power market. Different type of DR programs for both large and small customers would be discussed in this section, following various purpose that each DR is pursuing. In second part, studies that have been done to estimate elasticity of electricity are summarized. Last part would be summery of research for customer clustering based on different objectives of DR programs.

2.1 Overview of Demand Response

DR can play a significant role in maintaining the supply and demand balance using the flexible part of the load instead of increasing the power plant generation. There are many players in the market who can benefit from DR, including the transmission system owners (TSO), distribution system owners (DSOs), retailers and end-customers. DR is not a new concept, but has been discussed since the deployment of the first electricity grids in the 1890s, especially with respect to time differentiated electricity rates [138]. Other DR concepts such as interruptible load management, mainly for industrial customers, and direct load control, mainly for residential customers, became popular in the 1970s [139, 140, 141]. Around the same time, international energy crises lead to increased interest in demand side management and integrated resource planning, in which DR can play an active part [139, 140].

In the 1990s, many electricity systems in the U.S. started the process of deregulation/ restructuring, moving from vertical integration to utility divestment in generation resources and competitive wholesale electricity markets. As the 2000-2001 California Energy Crisis showed, a competitive wholesale electricity market with an unresponsive demand side can lead to problems of generation market power [61]. This spurred further interest in DR, for example,Lawrence Berkeley National Laboratory (LBNL) Demand Response Research Center (DRRC) began several research and pilot projects in 2004 [61].

At a high level, there are three different scenarios for customers to participate in DR program each with its own benefits and costs. First, customers can reduce their load consumption at peak time when the price is higher. For example, they could adjust their thermostat setting during peak times and leave it unchanged during off-peak periods. This option would save money for the customer but results in some comfort loss [148, 149, 150]. Second, customers can shift part of their demand from peak to off-peak when the price is cheaper. For example, they could schedule their washing devices for off peak period. In residential sector, this scenario tends to have less impact on customer comfort [133, 134, 135]. In the industrial sector, this second scenario is more challenging, since it requires changes in work schedule and perhaps higher labor costs in order to work outside normal business hours [137, 142, 143, 144]. Third, customers can use their own distributed generation, such as, roof top photo-voltaic panels or microturbines. In this situation, customers have to make the least amount of change in their consumption pattern but utilities see a significant change in net demand [145, 146, 147]. The first and second approaches are expanding as costs to implement PB and IB programs have decreased. Fig. 2.1 shows the comparison between PB and IB programs according to the appropriate time frame for implementation.

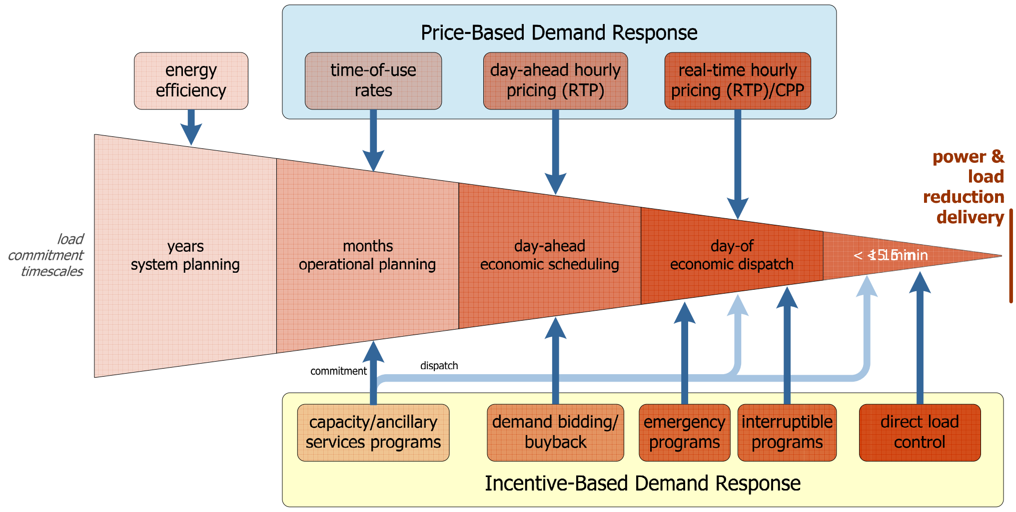


Figure 2.1: Comparison of DR programs across time frames

2.1.1 Price Based DR Programs

There is extensive literature on PBDR. Jia et al. [62] propose an application of on-line learning theory tailored to the problem of pricing for retail load customers who participate in a DR program. Their work considers thermal dynamic loads for which electricity is consumed to maintain temperature near preferred comfort settings. In [63], an optimum TOU pricing scheme for use in monopoly utility markets is developed. The optimal pricing strategy maximizes the societal benefit. C. Vivekananthan et al. [64] propose an improved RTP scheme for residential customers using smart meters and in-home display units to broadcast the price and appropriate load adjustment signals. Application of this program manages overloading problems and voltage issues and ensures both customers and utilities benefit. In [65], a novel DR program for optimizing power systems electric vehicle charging load is introduced. In this work, a DR program is proposed based on three tariff scenarios for different customer groups: standard, single and multi-tariffs. The results show that using a multi-tariff scheme could save up to 1.5% on utility cost and 7% on customer monthly bills. Gyamfi et al. [66] highlighted customer responsiveness to TOU, RTP, and CPP programs by considering behavioral issues. They applied these PB programs in three different countries and show how results vary across regions. In

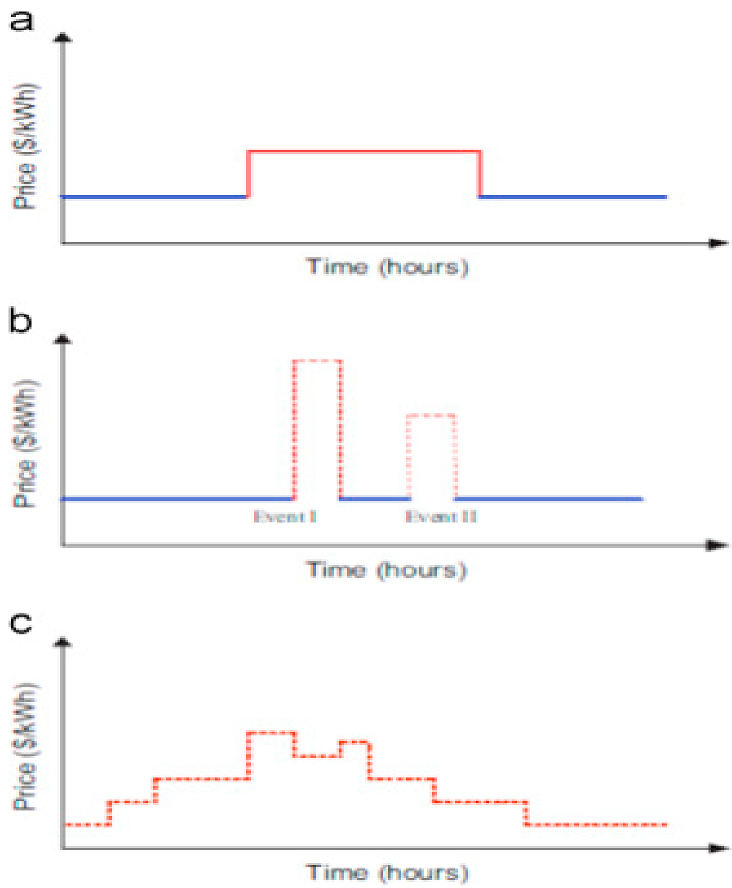


Figure 2.2: Time varying price schemes (a) TOU , (b) CPP and (c) RTP

[74], price uncertainty is modeled through robust optimization techniques. They use a linear optimization to find the hourly load change of the customer in response to hourly variable electricity price. The objective function is to maximize customer benefit considering constraints of minimum energy needed, ramping limits at each load level and so on. Work in [75] argues that price prediction is essential part of any RTP program for residential load management. Therefore, they propose a simple weighted average price prediction filter to find the optimal decision coefficient for each hour of a day for the customers. They test their price prediction algorithm on data from an Illinois power company from January 2007 to December 2009. Fig. 2.2 shows graphical difference between three important categories of PB program, TOU, CPP and RTP.

2.1.2 Incentive Based DR Programs

The literature on IB program is also extensive. Research by R. Yu et al. focused on the price elasticity of electricity demand where the loads are managed using energy management controller units. The purpose of the study is to maximize benefit of users by considering both load and the corresponding real time electricity prices in the wholesale market [67]. The main goal of research conducted by Pagliuca et al. is to present a new approach to modeling flexible loads to understand the potential of residential demand response. The selected demand response option is based on interruptions of appliances for short periods [68]. Mallette and Venkataramanan investigate financial incentives necessary to encourage plug in hybrid electric vehicle owners to participate in DR programs [69]. Zhang et al. demonstrate the potential benefits of coupon based DR programs using numerical experiments. When there is a potential price spike in the wholesale market based on the ISO information, LSEs would set the initial coupon price. After the LSE distributes coupon information to the consumers, these consumers can reduce their demand. The LSEs then bid to the ISO with this response and ISO determines the LMP based on the demand reductions [70]. X. Fang et al [136] used coupon based DR in conjunction with wind power plants in the system. They present an optimum bidding strategy model for LSEs considering coupon based DR. In [71], demand curve flattening and nodal voltage profile impacts are investigated for an IBDR program based on a load curve from the Punjab State Transmission Corporation Limited in India. Farahani et al. [72] discuss the effect of DR potential and incentive level to model customer response in DLC program. They propose six scenarios based on different incentive level at peak time and DR potential for flat DLC rates. The results show that increasing the incentive payments increase the percentage of peak reduction and load modification; however, increasing the demand potential has the antithetical effect because of load shifting. Babar et al. [73] focus on maximizing customer comfort using a demand reduction-bidding IBDR programs. They use a dynamic programming approach to balance the benefit of customers and utilities while managing peak energy consumption. The objective is to find the least aggregated reduction bids of the customers, which retains reduction of peak load while bringing benefits to all participants.

2.1.3 Combinations of Price Based and Incentive Based DR Programs

It is possible to combine PR and IB DR programs in various ways. In [83], it was found that PB programs would only be effective if an electricity supplier had more customers than its electric supply capability and could acquire electricity from other power companies/markets. The research shows that the way to gain the most benefits is through combinations of DR programs to various arrangements in targeted markets. The main focus of the work by Yang et al. is to quantify the benefits of DR. To conduct this analysis, a hybrid market structure with different pricing schemes is assumed [84]. Shu et al. [85] proposed a dynamic incentive strategy in a dual tariff system based on user elasticity and energy procurement cost analysis. The objective of dynamic incentive strategy is to give the opportunity to the people who want to participate while guaranteeing profit. The research by Wang et al. [86] explores the effect of incentive payments over different smart grid technologies in several utility companies in North America. It is shown how various incentives affect the success and scalability of smart grid demand response programs. In Fig. 2.3 summary of DR programs in the literature is shown. This figure illustrates the impact of DR on market participants, system reliability, market performance and market operations.

2.1.4 Residential Load Programs

There are several studies that show the residential sector does not respond well to PB programs. The main reason is that residential customers care more about their comfort than a small saving on their monthly bill. These also may not fully understand the pricing

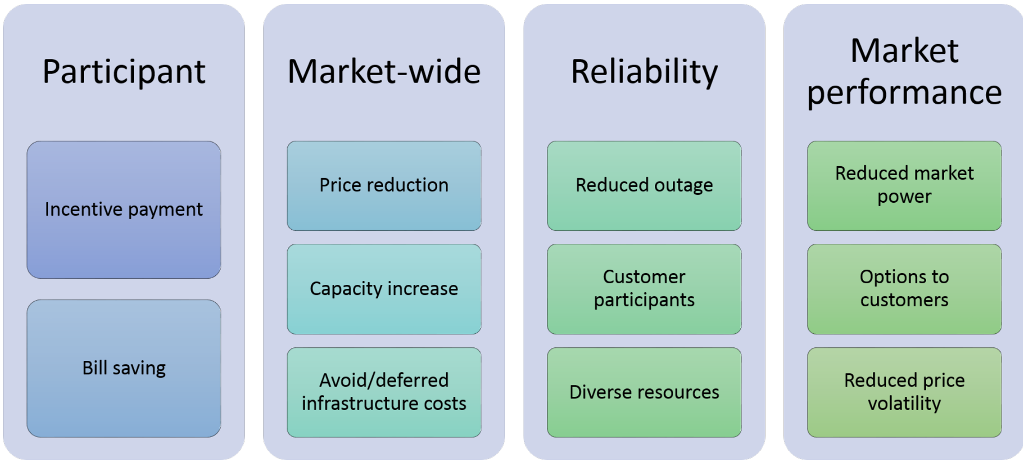


Figure 2.3: Summary of DR benefit according to available literature

scheme in order to react properly. These considerations has lead to specific design of DR for residential areas.

Hamidi et al. [87] studied DR programs in residential sector to investigate the effectiveness of each PB program. They propose a generic approach based on the appliance load profile to measure the responsiveness level of customers to various electricity tariffs. There are only certain types of household appliance whose consumption pattern can be modified in DR programs. In [76] and [77], this fact is used to design a specific DR for residential sector. The authors in [77] propose a load management algorithm based on controllable appliances to adjust the customer's hourly consumption. The effect on the network is neglected. If each house tries to maximize its own benefit, the market operator could face new peak load since every one schedules consumption independently. This issue is addressed in [78] where authors trie to avoid gaming by household and control appliances by considering the network. They use a Nash equilibrium approach to obtain the price and energy usage for each time period in order to minimize the overall energy cost. Customer satisfaction and comfort level is not included in the formulation. In [79] and [80], a decentralized optimization based on dual decomposition and sub-gradient multipliers is used to maximize social welfare. Although customer satisfaction is considered, these efforts fail to model different types of loads in the customer utility function. In [81],

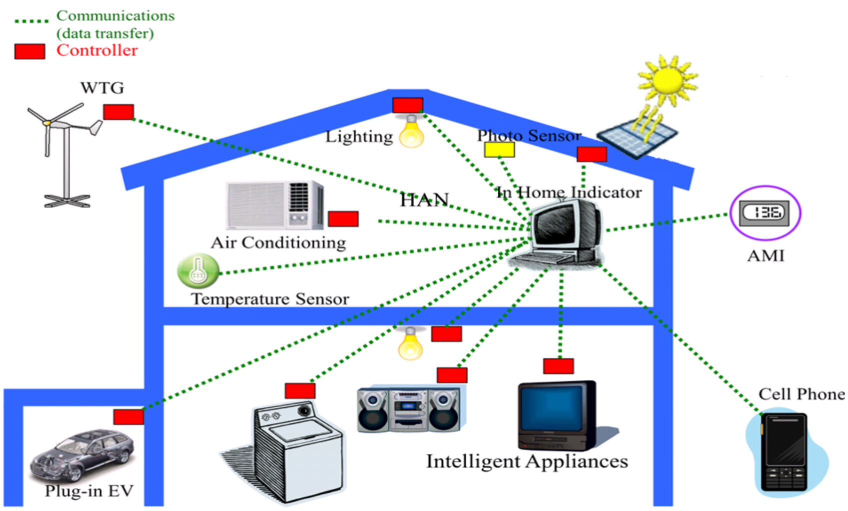


Figure 2.4: Schematic of smart home [76]

a message-passing approach is used to develop a decentralized optimization for residential energy management. The decentralized optimization is based on the alternating direction method of multipliers.

The authors in [82] present a coordinated home energy management system (HEMS) scheme where individual houses coordinate with each other for a real-time DR program. In this study, the economic motivation for both utilities and customers to participate in HEMS program is evaluated in detail. The proposed HEMS is a dynamic programming problem solved using a convex optimization based on dual decomposition. The main focus of this study is on shiftable appliances, such as, washing device and plug-in electric vehicles. Much of this literature in this area works on the design and control of the Smart Home. An example schematic of HEMS is shown in Fig. 2.4. In contrast, there is little effort to understand the impact on the wholesale market. From the market point of view, there is surprising limited study of retail customers who cannot participate directly in market. It means the available data and technology for an LSE to design and implement DR is limited. Therefore real time pricing, customer bidding and dynamic incentives are difficult to successfully implement for residential customers.

2.2 Overview of Elasticity Estimation

Numerous studies on price elasticity of electricity have been conducted over the years, especially during the 1980s and early 1990s when energy prices were rising rapidly and concerns about energy conservation increased. Electricity demand modeling has been one of the most heavily studied in energy and has been the subject of a number of surveys over the last four decades; elasticity estimation is almost always a part of these studies. Fig. 2.5 shows the frequency of various elasticity values that have reported in different literature. This figure shows both price elasticity (P) and income elasticity (Y) for long term (P_{lr}, Y_{lr}) and short term (P_{sr}, Y_{sr}). It also shows the values of elasticity from papers that used a statistical method to estimate elasticities of customers (P_{stat}, Y_{stat}). Note the wide variation in estimates.

One of the oldest studies was done by Houthakker [88] estimating demand in the residential sector for 42 towns in U.K. in 1951. He finds price elasticity not far from unity. On the other hand, Fisher and Kaysen [89] estimate price elasticity for residential demand as almost inelastic and close to zero in 1962. The range of estimation for elasticities various significantly depending on the data set, modeling technique, location, time and so on. Short run price elasticity range from -2.01 to -0.004 with a mean of -0.35 and median of -0.28. Long run elasticities estimates vary between -2.25 to -0.04 with a mean of -0.85 and median of -0.81 [42]. According to empirical estimates, there are three types of electricity elasticity: long term, short term (less than one year) and real-time (from TOU studies). In the short term, residential price elasticity is small but it is still greater than larger customer who have zero price elasticity in short term [45].

Alfaris [90] and C.T. Jones [91] both report short term elasticity around -0.04 in 1990s using an error correction model and log-linear method, respectively. Jones found higher elasticity using translog technique on its time series data from 1960-1992. Long term elasticity reported by Alferis is about -0.82 and it's -0.207 using both methods in Jones work. Beenstock et al. [92] estimates long term elasticity in households -0.6 using time

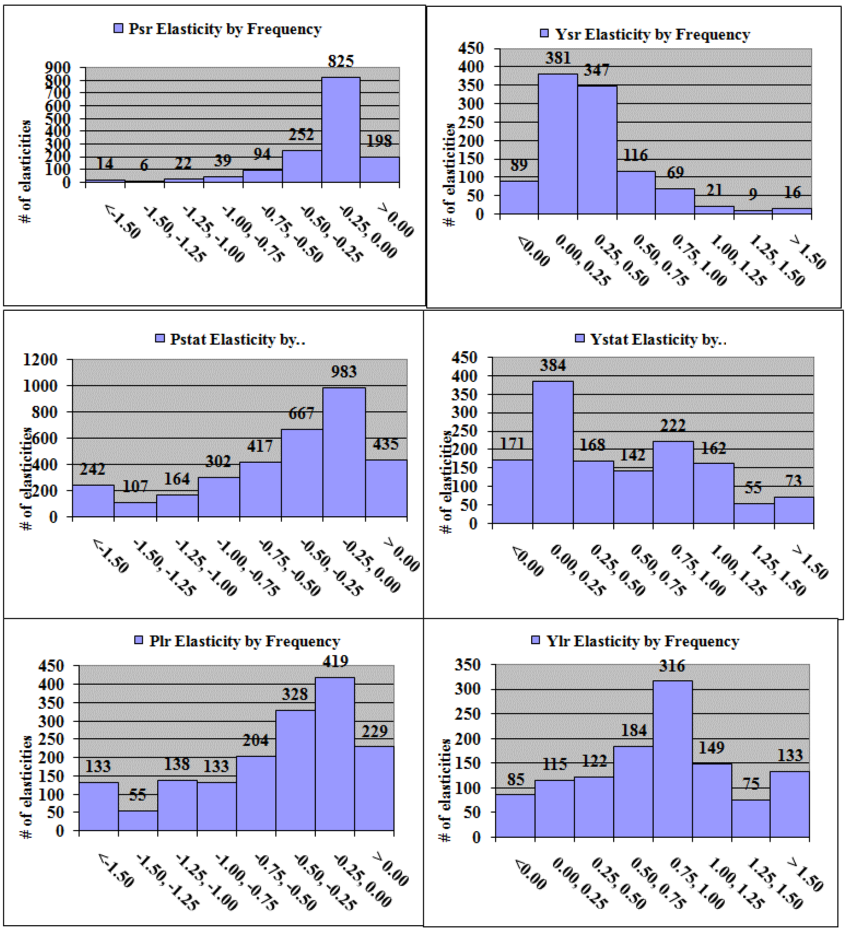


Figure 2.5: Frequency of values for short term and long term elasticity [42]

series data from 1973 to 1994. Walters et al. [93] found two different long term elasticities using log-linear or translog method, one -0.26 and -0.1. Houthakker and Taylor [94] estimate long run elasticity of United States in the 1970s around -1.89. Holtedahl and Louts [95] report household long term elasticity in Taiwan around -0.16 using time series data from 1955 to 1996. The common point between these studies is their estimation for short run elasticity of about -0.15. M. Filippini [96] and Narayan et al. [97] do not report separate elasticity for short term and long term but both estimate average elasticity around -0.3 for Switzerland and Australia, respectively. Bose et al. from India data [98] and Baker et al. from the U.K. [99] also just estimate on total elasticity for residential sector that is around -0.7. Flippini and Pachauri studied [103] in 2004 in India estimates elasticity for urban area in different season, they found less elasticity (-0.29) in summer and highest one in monsoon months (-0.51). Lebandeira et al. [45] also found that there is relation between outdoor temperature and short term elasticity, it shows their short term elasticity of residential sector which is about -0.25 would change at least by 5% from hot to cold days. There are also several studies that show price elasticity of electricity close unity, e.g., Houthakker et al. [100] in 1974 and Kamerschen et al. [101] in 2004 both for United States residential electricity demand. Halversen [102] found elasticity more than -1 in Unites States in 1975. Note there are very few papers investigating elasticity for IBDR. Cabera et al. [104] is one of the few such studies considering different incentive payments and levels of customer willingness to participate. They do not report any specific elasticity value.

2.3 Customer Segmentation

Customer classification for addressing appropriate DR signal has been discussed in some papers. Dam et al. [107] propose a heuristic based approach to select an optimal DR program from the customer viewpoint. In this study, customers collect information of different DR program signals and price rates as well as energy supply constraints and decide whether to accept the DR signal or not. The main barrier against this approach is the amount of the information that needs to be collected and analyzed by customers. Aalami et al. [108] develop another approach to select the best DR program based on multi-attribute decision-making. The model simulates the customers behavior toward different electricity prices, incentives and penalties. They used this model to prioritize DR signals using similarity to the ideal solution. The priority list helps the utility and customers to select the best DR program. Three DR programs were tested in this study, IBDR programs, PBDR programs, and a combination of both programs.

Gomes et al. [105] proposed a multi-objective evaluation approach to optimize electric load groups. They grouped the load based on physical and geographical parameters to control the peak demand at three levels: residence, aggregated feeder and substation.

The results show that demand could be reduced up to 4.39%, 3.91%, and 7.49% at each level, respectively, while increasing the average unit profit per kWh by 3.07%. Beal et al. [106] attempted to improve the load grouping based on a power color algorithm for stochastic-constraint satisfaction. In this approach, customers can define the flexibility of different appliances in the house by choosing a color code. Despite various research on customer segmentation, there is very little work that classifies customers based on behavior toward incentive signals; however, this kind of classification could greatly help utilities to design DR for targeted groups.

2.4 DR with High Levels of RERs

A major economic barrier against the large-scale deployment of RERs is the high investment cost that is needed for backup reserve to ensure the reliable operation of the system. Stochastic optimizations are one approach to quantifying reserve requirements and evaluating effect of RER integration on operation costs. Numerous renewable integration studies based on unit commitment have been performed recently by Ruiz et al. [109] , Sioshansi and Short [110], Wang et al. [112], Contantinescu et al. [114], Tuohy et al. [115], Morales et al. [116], Bouffard et al., Papavasiliou et al. [117] and Papavasiliou and Oren [118]. The study of Ansari et al. [119] presents a new stochastic security-constrained unit commitment for hydro-thermal units considering the uncertainty of load forecast, prediction of inflows to hydro reservoirs and unavailability of units. The proposed unit commitment is based on AC model of network. A novel hybrid decomposition strategy composed of generalized Benders decomposition and outer approximation/equality relaxation is also proposed in this study to deal with mix integer and non linearity nature of the model. Still, these studies mainly focus on the impact of renewable output uncertainty on the power system operation and integration of DR and its valuable potential is not discussed.

Sioshansi and Short [110] modify the unit commitment model based on the effect of

DR on uncertainty. Borenstein and Holland [120] and Joskow and Tirole [121]-[122] use the same approach to see the impact of real time pricing and renewable uncertainty on unit commitment results. The main portion of flexible demand belongs to deferrable loads, such as, plug-in electric vehicles, washing devices, and so on. The shiftable load acts as a storage from the system operator viewpoint. Some research focuses on the unit commitment formulation to include this flexible part of load. Sioshansi [123] proposes a unit commitment formula based on co-optimization of electric vehicles and generators. The proposed model does not reflect the uncertainty of RERs output.

There are fundamental barriers against using DR schemes discussed previously. As shown in [124] and [125], the demand side bidding needs a real time pricing scheme at retail level. There is strong opposition against exposing retail customers to the volatility of market prices. In addition, due to non-convexity of system operating cost, real time pricing often fails to reflect the true economic value of demand response. Researchers in [110] show that non-convexity along with dispatch of deferrable resources lead to excessive start up and minimum load costs. An alternative demand response program is discussed by Hirst and Kirby [126, 127], where flexible loads are used to deliver services to the ancillary services market. In this DR scheme, load aggregators submit bids on behalf of the loads in an ancillary service market. The load aggregator runs the DR program under both IB and PB strategies. The possibility of using demand side management as spinning reserve under high penetration of RERs has also been analyzed [128]. The current market regulations are not amenable for this kind of DR and regulatory changes are needed to allow flexible load to provide high reliability products.

3 Reduced Model of WECC as a Demand Response Prototype

In this chapter, a reduced model of WECC is described in detail. The WECC 240-bus model is used as test system throughout this thesis to evaluate different demand response schemes.

3.1 WECC System Information

Resource characteristics for WECC 240-bus model have been derived from a published California ISO (CAISO) transmission study data and WECC's Transmission Expansion Planning Policy Committee (TEPPC) as follows:

- Hourly time variable loads for 11 areas within the CAISO are derived from [151, 152].
- Hourly time variable output for wind and solar resources, which is aggregate in the 240-bus model, are derived from TEPPC studies. There are three wind farm areas and one solar power plant in CAISO, as well as 13 wind power plants and four solar resource outside of CAISO.
- Hourly time variable output for geothermal resources in the CAISO have also been derived from [151, 152] and are aggregated by utility controlled vs. non utility controlled geothermal resources. They are placed in the North Bay/Geysers area, which is the largest concentration of geothermal resources in the CAISO. The output

of the four geothermal areas outside CAISO are assumed to be constant at 80% of the maximum capacity based on their average performance.

- Hourly time variable output of biomass generations come from [151, 152]. The biomass generators are aggregated at three buses in CAISO and it is assumed they are all under utility control. There are very few biomass generators outside the CAISO and they are modeled as generic RERs.

- Gas fired power plants have a large share of generation capacity in WECC. They are modeled as dispatchable resources using their heat rate data derived from the published CAISO transmission study and TEPPC online data. The required information to run a full unit commitment is not available but basic assumptions in CAISO are made. For example, the minimum output of gas generator is assummed to be 5% of maximum capacity.

- Coal power plants in CAISO area assumed to be at 85% of their maximum output constantly based on overall performance data.

- There are two nuclear power plants in CAISO area and two outside. All are assumed to run at 100% of capacity since they are based-loaded; however, their output can be reduced to 90% if needed for congestion management.

- Generation capability of hydro power plants mainly depend on available water storage, which changes month by month. Scheduling and dispatching of hydro units also depends on environmental requirements limiting ramping and release due to criteria , such as, fishing management, recreation, irrigation rand so on. These considerations make the process of hydro optimization complex. In this study based on actual data in [152], hydro power plants are modeled as dispatchable units with maximum capacity of 87% after accounting for reserves and a minimum output of 20%. The maximum hourly ramping is considered to be 10% of capacity.

3.2 Load Serving Entities within WECC

In this thesis, target customers are primarily residential. Therefore, the regulatory structure for LSEs and their retail customers is critical. There are different types of LSE structures and different terminology used including, load aggregator, electricity utility, distribution company and so on. In any case, an LSE main functional is to supply electricity t

o customers. In general, an LSE participates in the market to serve either an entire distribution area or groups of customers through an arrangement with the actual distribution company. Distribution companies operate the physical infrastructure incluiding the lines, metering and so on. For purposes of this thesis, the main characteristics of an LSE is:

- An LSE operates within a territory, although they may operate in in more than one area.
- An LSE has tariffs (rate plans), which are central and unified for most of their customers.
- An LSE purchases power in the power markets for the individual customers.

The 129 load buses in the WECC model are divided into 14 regions. It is assumed that each region belongs to one LSE that serves all buses in the region with the same tariff and each load bus is an aggregator for the retail load customers served by the bus. Geographical positions of these regions are shown in Fig. 3.1.

3.3 Unit Commitment in WECC

Unit commitment process at wholesale power market determines the status of each generator and their scheduled output for the next market window. Unit commitment is essentially an optimization problem to minimize production cost considering operational

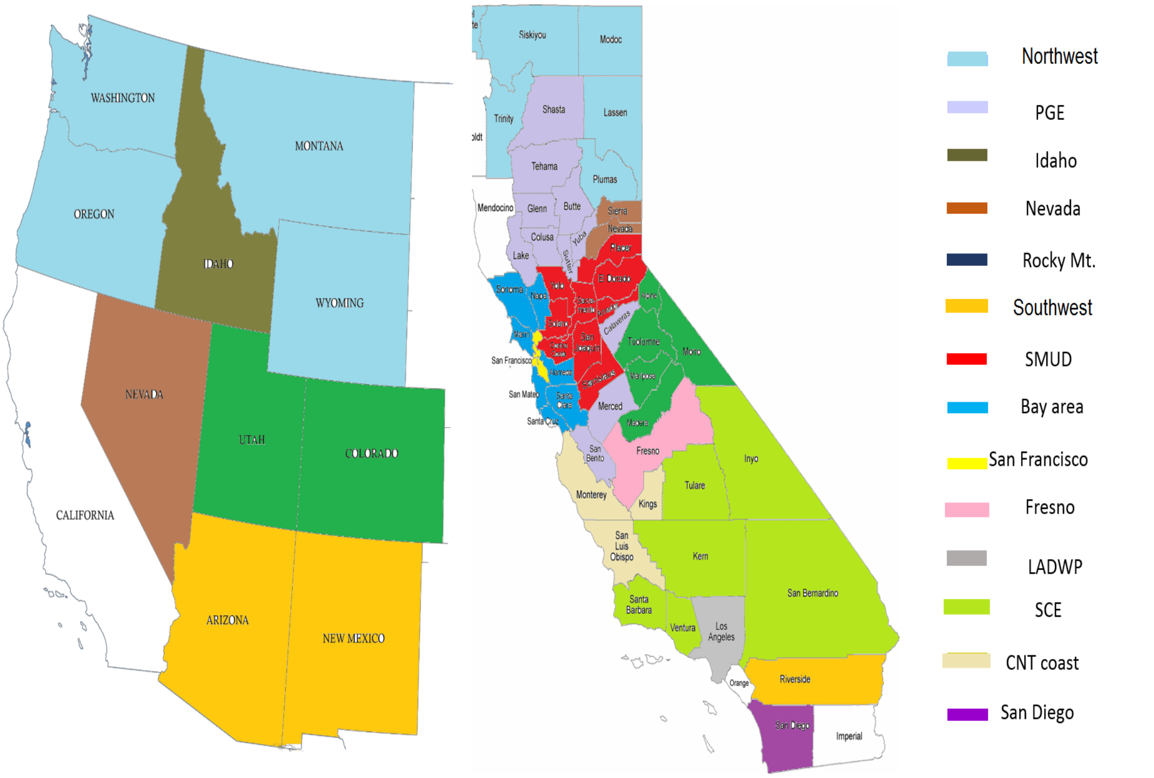


Figure 3.1: Geographical map of WECC regions

constraints of the power grid. The general formulation of unit commitment problem is [153]:

$$\min_{G_{it},u_{it},R_{it}} \left\{ \sum_{t=1}^{NT} \sum_{i=1}^{NG} [C_i(G_{it}, u_{it}) + S_i(u_{it}) + q_{it}R_{it}] \right\} \tag{3.1}$$

$$\sum_{i=1}^{NG} G_{it} = \sum_{j=1}^{ND} D_{jt} \tag{3.2a}$$

$$G_i^{\min} u_{it} \leq G_{it} \leq G_i^{\max} u_{it} \tag{3.2b}$$

$$G_{it} + R_{it} \leq G_i^{\max} \tag{3.2c}$$

$$0 \leq R_{it} \leq u_{it}(RU_{i\Gamma}) \tag{3.2d}$$

$$\sum_{i=1}^{NG} R_{it} \geq R_t^{\min} \tag{3.2e}$$

$$G_{it} - G_{i,t-1} \leq RU_i u_{i,t-1} + R_i^{\text{start}}(u_{it} - u_{i,t-1}) \tag{3.2f}$$

$$G_{it} - G_{i,t-1} \geq -RD_i u_{i,t-1} - R_i^{\text{shut}}(u_{it} - u_{i,t-1}) \tag{3.2g}$$

$$R_i^{\text{start}} = \max RU_i, G_i^{\min} \tag{3.2h}$$

$$R_i^{\text{shut}} = \max RD_i, G_i^{\min} \tag{3.2i}$$

$$\sum_{i=1}^{NG} GSF_{ki} G_{it} - \sum_{j=1}^{ND} GSF_{kj} D_{jt} \leq F_k^{\max} \tag{3.2j}$$

The objective of unit commitment problem is to minimize the system operation cost, which consists of fuel cost, start up cost and reserve cost. The constraint (7.2) ensures the balance between supply and demand. The generation capacity constraints (4.3a) and (10.2f) limit the amount of power and reserves that can be supplied by a generator. The constraint (10.2g) reflects the maximum spinning reserve from a generator. The constraint (3.2e) requires at least certain amount of spinning reserve to be provided for the system. Constraint (3.2f) and (8.5) are the ramp rates of generators. The transmission flow limits are approximated by the DC power flow (3.2j).

There are limitations in performing a complete unit commitment on the WECC data in this thesis. Primarily, limitations arise as the ramp rate and start up and shut down costs for all generators is not known. Thus, the unit commitment in this study depends more on the generator cost functions. Still since the units are aggregates in any case, this is probably a reasonable approximation. The main impact would be on coal and nuclear power plants since they have lower ramp rates and hydro since here is assumed hydro is highly constrained by other factors. The reserve requirement is assumed to be a constant 5% of load at each hour to be provided by gas turbines with their high ramp rate. As a result, coal, nuclear and hydro power plants are essentially base loaded. Gas turbines can be shut down or started up to adjust load-power balance and provide reserve requirements. These assumptions are consistent with the original data that has a unit commitment solution for each hour from the actual data.

3.4 Economic Dispatch in WECC

Economic dispatch is performed by the market operator in various time windows, e.g., next 5 or 15 minute interval. In this process, the status of generator defined by unit commitment does not change, but instead scheduled MW is updated using more accurate load forecast data. The general formulation of economic dispatch without considering reserve is as follows [154]:

$$\min_{G_{it}} \left\{ \sum_{t=1}^{NT} \sum_{i=1}^{NG} C_i(G_{it}) \right\} \tag{3.3}$$

$$\sum_{i=1}^{NG} G_{it} = \sum_{j=1}^{ND} D_{jt} \tag{3.4a}$$

$$G_i^{\min} \leq G_{it} \leq G_i^{\max} \tag{3.4b}$$

$$\sum_{i=1}^{NG} GSF_{ki} G_{it} - \sum_{j=1}^{ND} GSF_{kj} D_{jt} \leq F_k^{\max} \tag{3.4c}$$

Economic dispatch determines the optimal dispatch of a set of committed generating units to supply the forecasted load. The objective function is to minimize the operating cost of generators. The constraint (7.5a) ensures the balance between supply and demand.

The generation capacity constraint (8.14) limits the amount of power that can be supplied by a given generator. The transmission flow limits are approximated using DC power flow in (8.15). Economic dispatch as formulated here is a continuous convex problem and can be solved efficiently by various nonlinear programming techniques.

In this thesis, the problem is solved using the MATPOWER toolbox. MATPOWER is a package of MATLAB M-files for solving power flow and optimal power flow problems. MATPOWER is initially designed for researchers and educators in academic level considering its simplicity and capability of modification by end user. MATPOWER was developed by Ray D. Zimmerman, Carlos E. Murillo-Sánchez and Deqiang Gan of PSERC at Cornell University under the direction of Robert Thomas [155].

3.5 Renewable Resources in WECC

There are several factors that impact the future wholesale power market, including: the price of natural gas, any costs for carbon dioxide (CO_2) emissions and RERs development. Such factors effectively change the variable cost of the generator operations and thus, the market price. Consequently, market price analysis under renewable expansion is one of the main concerns of this thesis.

3.5.1 Current potential of Renewable Power Plants

In 2004 (the year for which the base data was known), there were 8000 MW of installed RERs including wind, solar, geothermal and biomass in the WECC model. This represents less than 10% of the total energy required to serve load in the WECC controlled Grid. Wind resource has the biggest share in the total renewable generation and led to the greatest operational challenges. The output of the wind generators is extremely variable. In California, the highest wind output was during the off peak period. Tab. 3.1 shows information of RERs potential in 2004, including their geographical location and maximum capacity.

Table 3.1: Information of Renewable power plants in WECC

Bus number	Generator	Category	Max Capacity (MW)	Region
126	BRIDGER	Wind	248	Rocky Mt.
130	COLOEAST	Wind	597	Colorado
133	CORONADO	Wind	240	Southwest
136	COULEE	Wind	240	Northwest
138	DALLES21	Wind	375	Northwest
144	FULTON	Geothermal	965	Geysers
157	HUMBOLDT	Biomass	53	Humboldt
158	HANFORD	Wind	174	Northwest
161	IMPERIAL	Solar	117	Imperial
166	JOHN DAY	Wind	976	Northwest
169	MALIN	Wind	240	Northwest
174	MESA CAL	Wind / solar	1660	PG&E
178	MIDPOINT	Wind	236	Idaho
191	MONTA G1	Wind	190	Bay area
201	PITSBURG	Wind	690	Northwest
206	ROUND MT	Biomass	314	PG&E
216	TESLA	Biomass / wind	472	PG&E
220	VALMY	wind	50	Nevada
223	WCASCADE	Wind	215	Northwest
227	CMAIN GM 20	Wind	420	BC

3.5.2 Expansion of Renewable Power Plant

Under California's existing renewable portfolio standard, utilities must supply at least 30 percent of all electricity for retail customers from approved renewable resources by 2030. The majority of required renewable generation to meet the portfolio standards will come from wind farms and solar. The intermittent output of these resource will make the operation of electric power system more challenging. Coal power plants are the main source of CO_2 emission, and therefore, they are the first target of retirement from renewable expansion. In the WECC 240-bus reduced model, there are 7 buses that have both coal and renewable power plants. In this study, RERs at these buses is expanded to reduce coal power plant capacities. Current and expanded capacity of RER on these buses is shown in Fig. 3.2.

Expansion of renewable power plants is proportional to their current capacity with

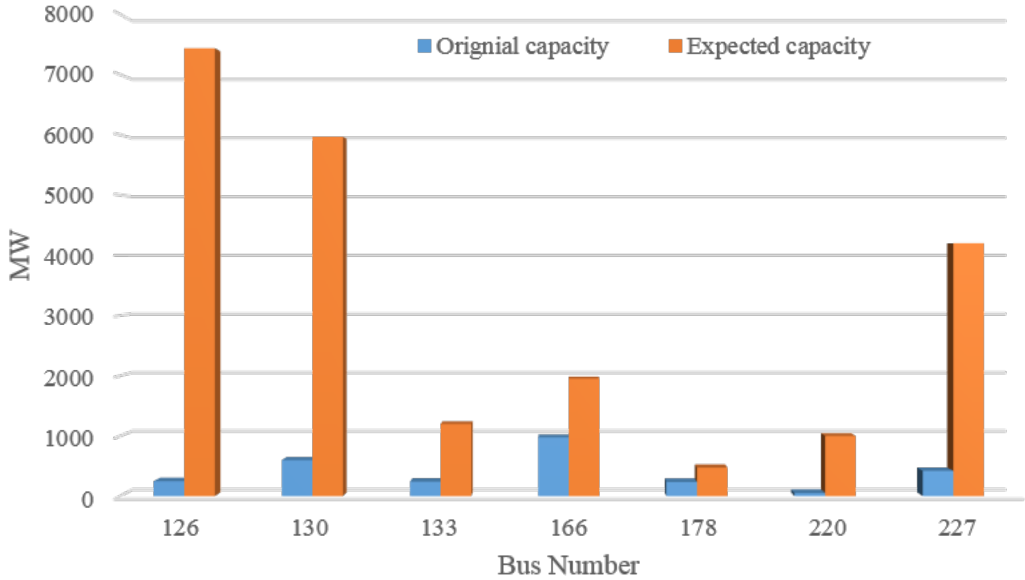


Figure 3.2: Capacity of RERs before and after expansion

the same hourly variation within one year. This means higher production in off peak and less production at peak. In Fig. 3.3 and Fig. 3.4, new renewable capacity compares with previous coal production is shown for Feb. and July, respectively. During Feb. and similar winter months, expanded output of RER generally exceeds earlier coal power production. This means, in these hours, LMP will decrease because of higher availability of cheap power. In the July and similar summer months, on the other hand, expanded renewable output is less than the existing coal production. Therefore, it is expected that LMP will increase at these hours due to reduced power capacity.

3.6 LMP Characteristics in the WECC Model

LMP in the various regions of WECC are investigated under two different scenarios: 2004 reference and high penetration of RERs. The reference case is the original load and production data of 2004 while high penetration of renewable case is as detailed in sec. 3.5.2. In the reference case, most regions have a summer peak. Thus, summer months LMPs are higher on average with a greater standard deviation. A few regions have winter

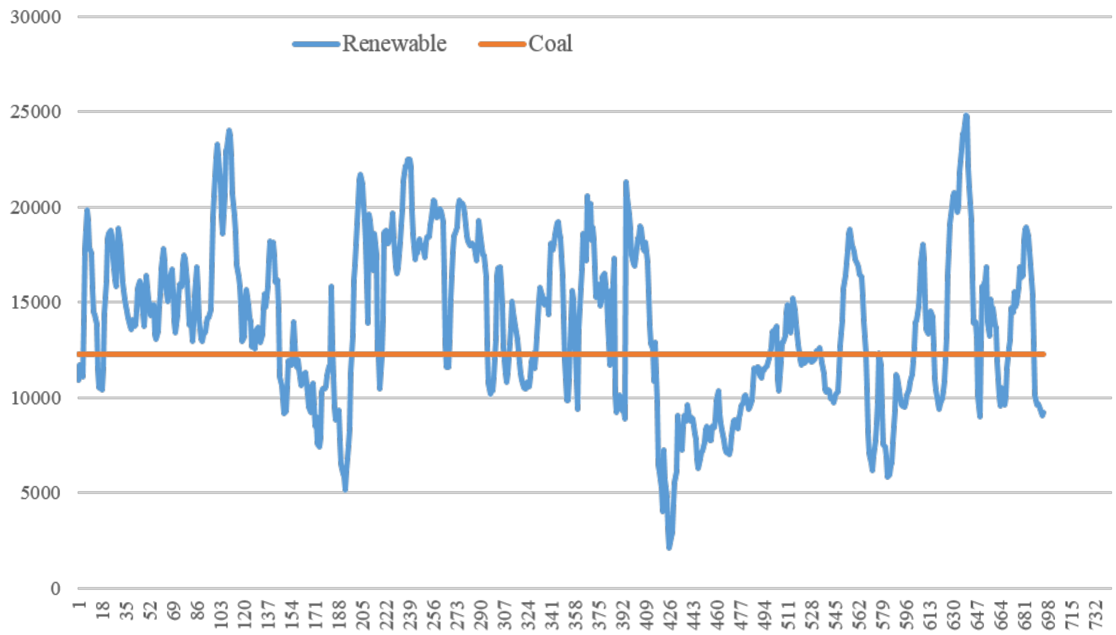


Figure 3.3: Renewable expanded capacity in compare with Coal in Feb.

peak load, such as, Rocky mountain and Northwest. However, the variation of LMP in these regions, especially in the Northwest, is relatively small. The main reasons are the relatively high industrial loads and reliance on coal power production. After renewable expansion, LMP changes depend on time of the year, region, location of congested lines and higher residential load. Generally, we observe three various particular periods:

- High load and low RER production: this occurs for most of the regions in summer especially during peak hours that lead to higher LMP relative to pre-retirement of coal units.
- Low load and high RER production: this relates to moderate weather conditions in spring and fall where residential load is considerably reduced but wind power is significantly higher. Since the RERs are modeling as "must take," this condition leads to considerably lower LMP and at times negative during off-peak hours.
- Moderate load and moderate RER production: while this condition may arise in any season, it occurs most frequently on winter days. Effect on market price depends

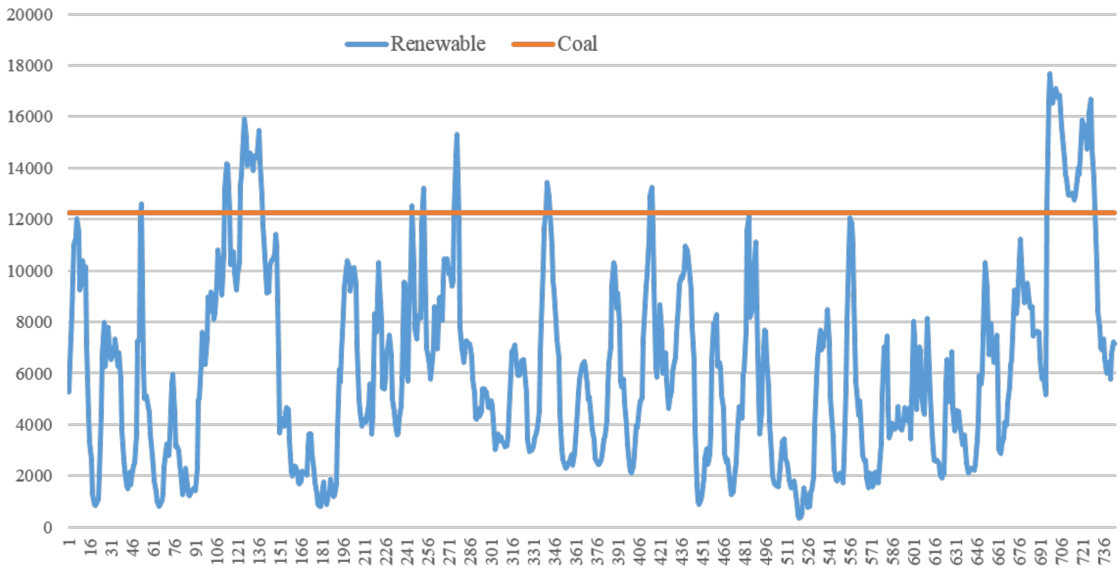


Figure 3.4: Renewable expanded capacity in compare with Coal in July

on the similarity of RERs output to the old coal capacity. For some regions in winter months, the average LMP increases after RERs expansion and for others it decreases.

LMP variation in all regions and during the whole year increase after renewable expansion due intermittent output of RERs. LMP changes in east regions of WECC, that are closer to renewable power plants, are greater relative to western regions. In general, LMP variation becomes correlated with renewable generation profile rather than load profile. In Tab. 3.2 monthly average and standard deviation of LMP are shown for several regions. Case 1 refers to renewable expansion and case 2 is the reference case.

In Fig. 3.5, Fig. 3.6 and Fig. 3.7, LMP of one bus of LADWP, Nevada and San Diego is plotted to show more detail. In August for most of the hours, LMP increases after renewable expansion and is more salient at peak hours. As another example, Idaho in February is selected since it is close to RERs and has light load in winter. Mainly LMP decreases in this situation. Still, the LMP has a significant number of hours with negative LMP due to over-generation. In chapter 7, it will be shown how to overcome this problem if renewable bid into the market instead of deployed as “must take” resources.

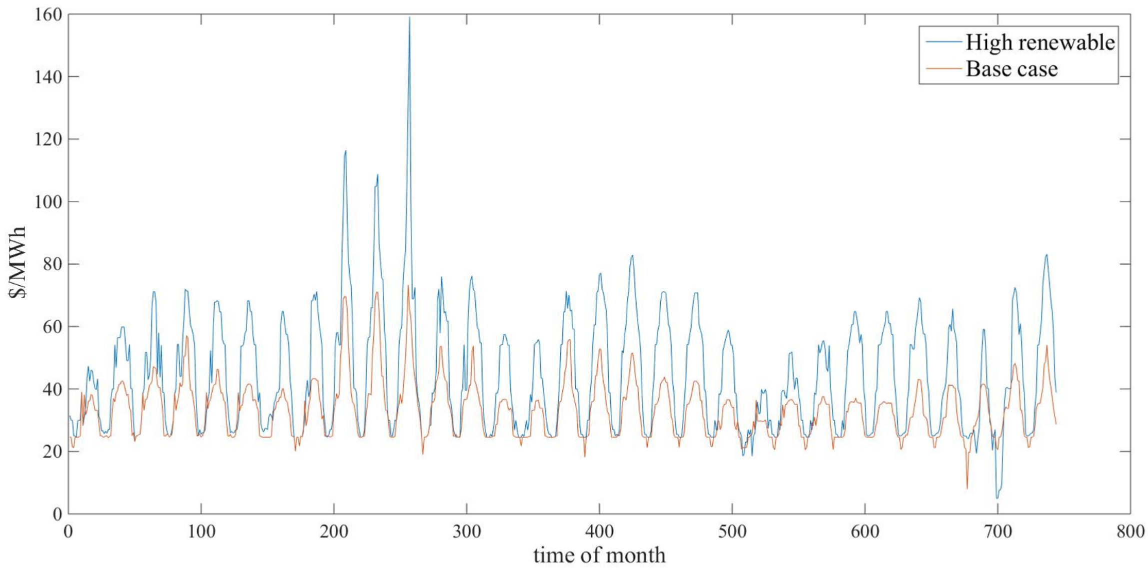


Figure 3.5: LMP variation in LADWP during August

3.6.1 Renewable Bidding Strategy

As of today, most power systems operate under a "use all available wind generation" policy - the so-called " must take" strategy. This approach can result in increased volatility in market prices, as shown in previous sections. Another challenge is over generation leading to negative LMP. Some researchers have proposed bidding strategies for wind generation. This should help with both negative LMP and high volatility of prices while it may lead to wasting some amount of RERs production. Fig. 3.8 shows market price variation for the two cases of "must take" and bidding. The bids are assumed for simplicity to be 0 for all MW output of wind. Thus, the main effect of bidding is to avoid negative prices due to over generation Results are plotted for April which has highest amount of excess wind power and consequently highest number of hours with negative LMP.

3.6.2 Effect of Congestion on LMP

Most research considers renewable expansion in conjunction with transmission expansion due the necessity of having sufficient capacity to transfer renewable power to other areas. Two examples are shown in Fig. 3.9 for October. During this month, price differences are

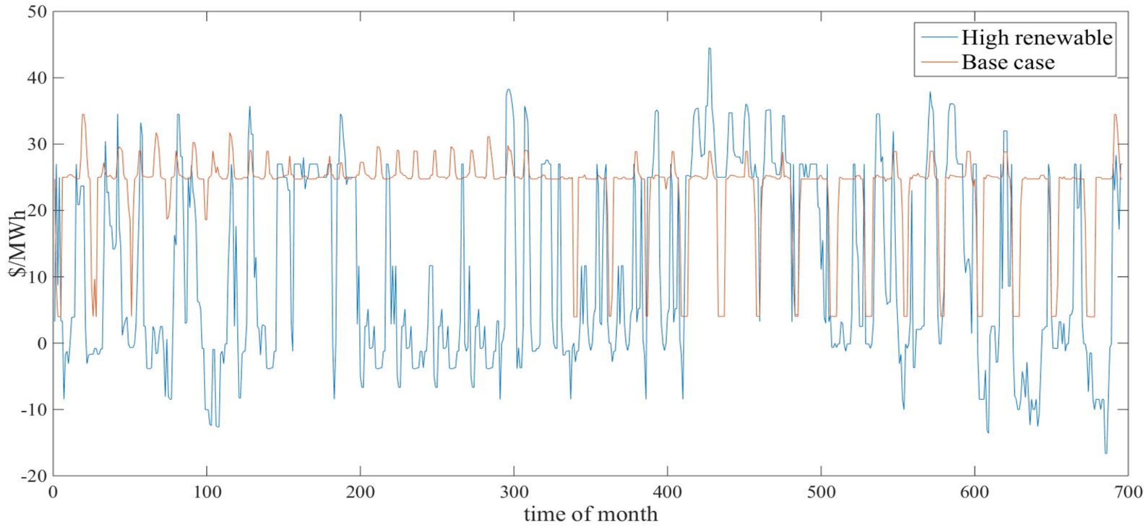


Figure 3.6: LMP variation in Nevada during Feb.

significant. There are regions which have negative LMP most of the time, while other regions have very high LMP. As shown in Fig. 3.9, the buses with significant price difference are located across two sides of a congested line. Effect of transmission congestion on market price is not specific to renewable expansion; however, if renewable output increases in the system, transmission limits will likely be more of a concern. This thesis does not explore impact of transmission impact in detail except to illustrate how DR may help alleviate such problems.

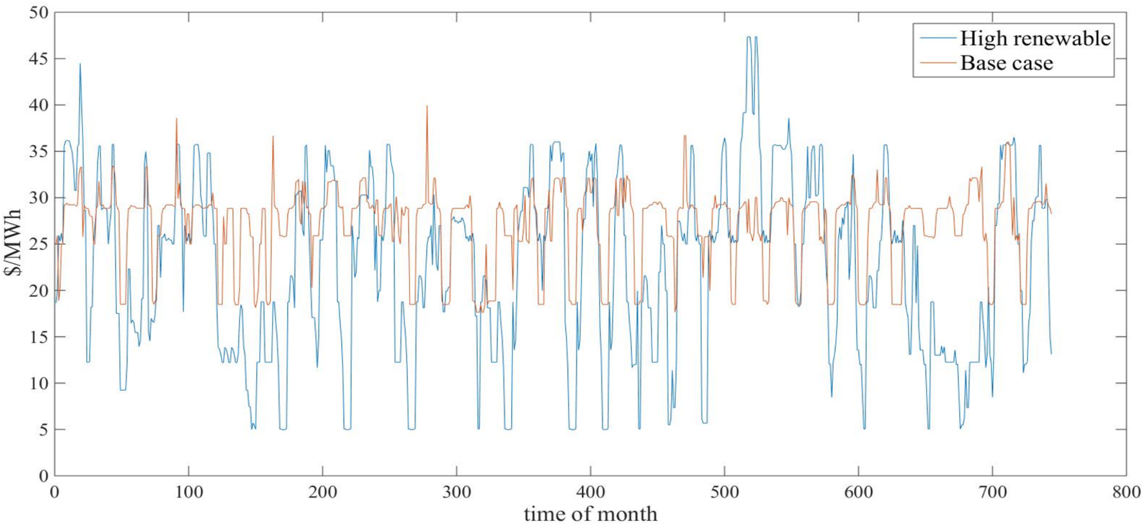
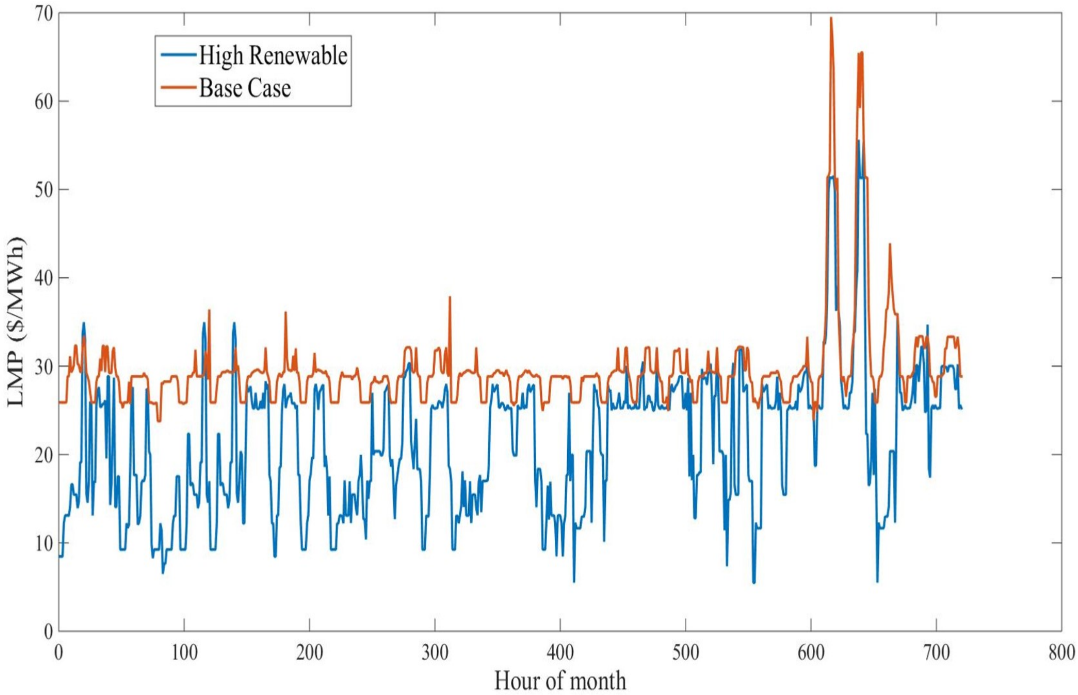


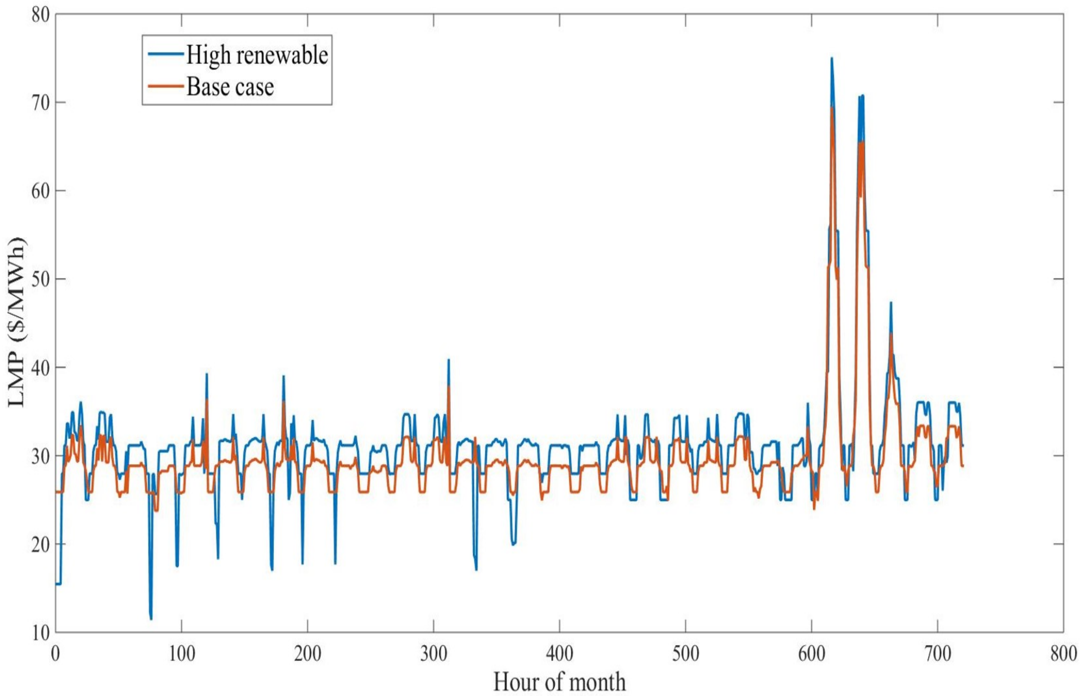
Figure 3.7: LMP variation in San Diego during March

Table 3.2: LMP change in some regions before and after renewable expansion

Southwest	Jan.	Feb.	March	April	May	June	July	Aug.	Sept.	Oct.	Nov.	Dec.
average 1	20.5	20.8	20.1	18.3	31.6	34.2	44.0	44.0	36.2	21.9	23.2	25.1
average 2	25.2	23.7	22.3	22.4	28.0	33.9	43.3	41.1	35.6	23.4	26.2	29.3
std 1	9.8	8.3	10.9	9.1	11.8	11.9	21.5	21.5	15.2	8.3	11.3	13.7
std 2	4.6	3.8	5.0	5.9	9.1	11.9	15.7	15.8	11.2	7.1	4.9	5.0
Bay Area												
average 1	31.9	30.2	30.5	28.2	34.8	36.1	41.7	41.7	36.6	29.1	34.1	36.6
average 2	30.6	27.4	28.3	28.7	30.4	32.0	36.0	35.3	32.9	28.4	28.4	29.4
std 1	7.1	6.6	7.6	7.5	7.2	8.1	13.7	13.7	11.1	5.5	8.9	11.0
std 2	6.6	3.4	4.9	4.8	6.4	6.7	8.9	10.1	8.3	4.9	4.2	4.9
PG&E												
average 1	34.9	33.8	34.2	28.0	51.1	53.1	70.4	70.4	50.6	29.3	36.5	44.5
average 2	29.3	26.7	26.2	26.3	30.9	36.7	51.4	49.2	38.6	27.9	27.1	29.1
std 1	13.1	13.8	13.4	10.3	25.7	28.8	40.1	40.1	31.3	6.4	12.8	18.7
std 2	5.2	4.2	3.0	3.6	7.9	14.9	25.4	38.0	20.9	5.4	4.3	5.8
Northwest												
average 1	29.7	26.5	25.7	25.5	25.3	25.4	25.3	25.3	25.5	26.2	51.9	44.2
average 2	28.5	25.1	25.2	25.3	25.0	25.0	24.9	25.0	24.9	25.1	25.1	25.2
std 1	13.9	2.4	1.8	3.6	0.7	1.1	1.6	1.6	1.1	1.1	45.3	34.1
std 2	12.3	0.3	0.8	1.2	0.2	0.3	0.3	0.2	0.2	0.3	0.2	1.3
Rocky Mt.												
average 1	16.6	16.2	22.7	15.8	32.7	36.6	46.2	46.2	33.8	19.5	20.0	25.5
average 2	25.4	23.7	21.2	21.1	26.1	29.3	36.7	34.1	32.3	22.2	22.8	25.1
std 1	14.4	12.5	14.8	12.0	14.1	16.0	21.2	21.2	23.6	11.6	15.2	17.1
std 2	5.5	5.9	7.6	7.9	8.5	7.9	17.6	10.7	13.2	8.9	7.3	5.9
Idaho												
average 1	8.0	9.1	17.8	9.3	29.0	32.4	41.1	41.1	28.2	15.0	14.4	19.5
average 2	24.9	23.0	19.9	19.7	24.5	26.1	31.6	29.0	29.7	20.6	21.7	24.1
std 1	18.7	15.8	17.0	17.2	14.5	13.2	16.1	16.1	17.8	15.4	19.7	22.4
std 2	6.3	7.3	9.6	9.8	9.1	6.7	12.3	6.2	11.2	10.4	9.0	6.6
Nevada												
average 1	21.4	21.2	26.3	18.5	41.6	45.1	59.6	59.6	42.0	22.2	24.6	32.2
average 2	26.3	24.9	22.6	22.6	28.5	33.4	45.0	41.9	36.6	24.3	24.4	27.1
std 1	13.2	12.6	14.2	10.9	20.4	22.0	30.5	30.5	25.3	10.2	14.0	17.0
std 2	5.4	5.8	6.5	7.0	9.3	11.6	25.2	20.2	18.4	8.7	7.1	6.7

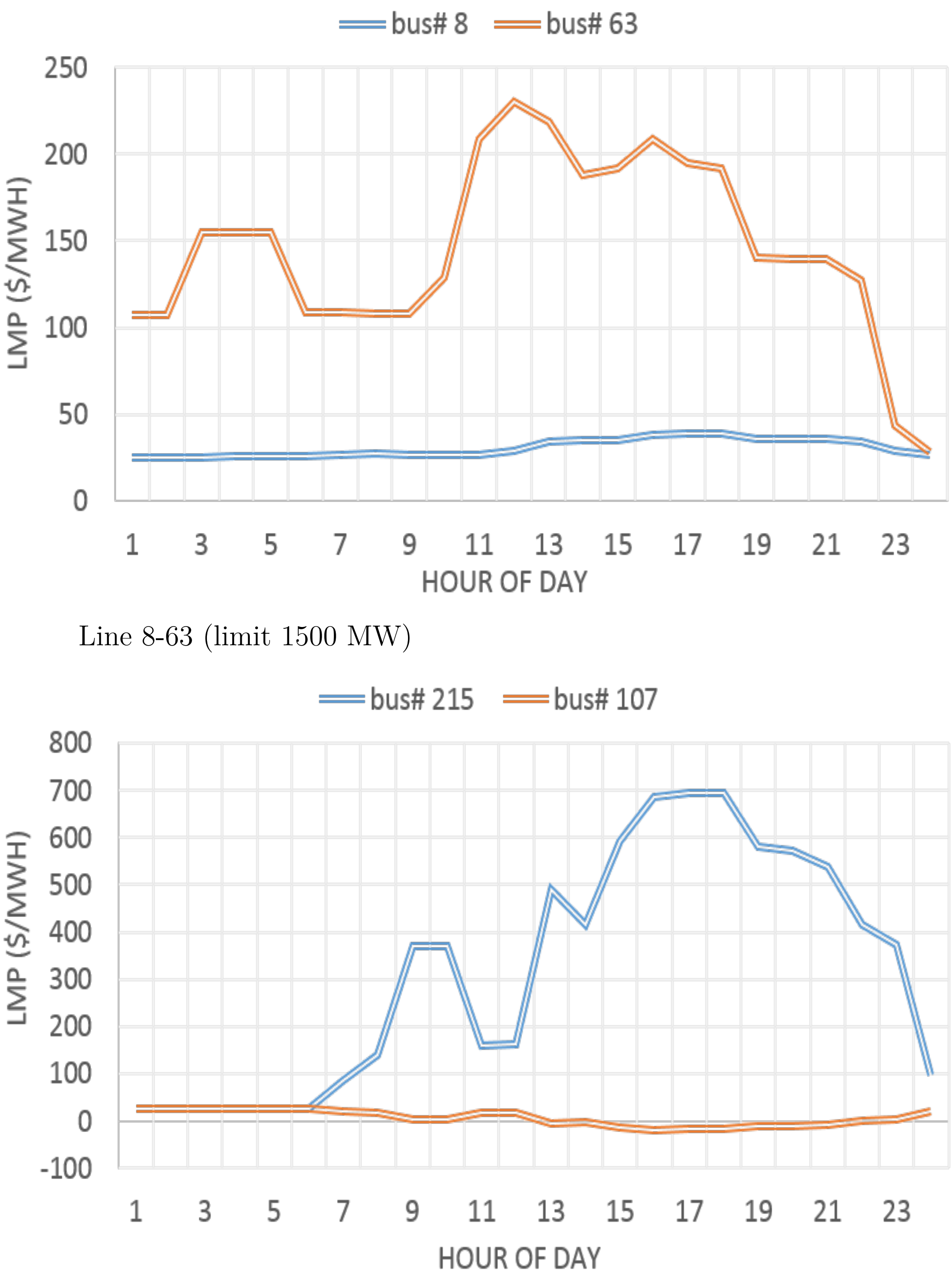


a) “Must take”



b) Bidding

Figure 3.8: LMP variation in San Diego



a) Line 8-63 (limit 1500 MW)

b) Line 215-107 (limit 840 MW)

Figure 3.9: LMP on two edge of congested lines - October 15th

4 Optimal Incentive Based Demand Response

In this chapter, the design and formulation of an optimal IBDR is developed relative to real time prices so that the full benefits of DR can be achieved. Specifically, we propose a method to design the optimal IB program considering historical generation and load patterns. The objective is ensuring reliability of the grid and reducing the generation cost, as well as, increasing the customer acceptance for DR programs. While there has been increasing interest in PB programs with the installation of smart meters, residential customers have generally not welcomed these programs. On the other hand, IB programs struggle to realize a specific objective, e.g., reduced generation costs or improved reliability. Instead, the incentives are an indirect method that hopefully improves system performance under a variety of metrics. The main concept of IBDR is straightforward, a customer would simply be offered a specific incentive payment at a high price time for a small change in their consumption. Still, there are some fundamental questions in order to design an appropriate IBDR scheme. The load change required at each time and appropriate incentive need to be determined. We formulate this as an optimization problem in this chapter.

4.1 LSE Objective for DR Design

LSEs main responsibility is to provide electricity for retail customers, such as, residential, small commercial or industrial loads. They can participate in the various wholesale market trading pool on behalf of their customers and purchase electricity with time varying price, although they mainly sell it to their customer through a set of relatively fixed tariffs or flat rate prices. LSEs benefit is defined according to the difference wholesale market price and their flat rate price. Therefore, the LSE objective function is:

$$\max \sum_{b=1}^{N_B} \sum_{t=1}^{T_y} D_{bt}(P_b^0 - LMP_{bt}) \tag{4.1}$$

LSEs profit depends on the flat rate price that it can charge (carefully regulated) so as to cover LSEs fixed and variable expenses. In sec. 4.4 we will explain more about various possible tariff scheme for customers. It is easy to see directly from (9.1) that LSE earns profit whenever the charged price is higher than market price and loses money at other times, but this does not account for the demand response. Technically, DR programs achieve benefits by changing the loads. Thus, the LSE objective function to design an incentive payment and the needed load reduction becomes:

$$\max \sum_{b=1}^{N_B} \sum_{t=1}^{M} [(D_{bt} - \Delta\bar{D}_{bt})(P_b^0 - LMP_{bt}) - \Delta\bar{D}_{bt} P_{bt}^{inc}] \tag{4.2}$$

$$\Delta\bar{D}_{bt} = \sum_{j=1}^{D_T} \Delta D_{bt_j} \tag{4.3a}$$

$$\triangle D_{bt_j}^{\min} \leq \Delta D_{bt_j} \leq \triangle D_{bt_j}^{\max} \tag{4.3b}$$

$$\Delta D_{bt_j} = g_j P_{bt}^{inc} \tag{4.3c}$$

As it shown in (4.3a), total load change at each time is the summation of different customer types: residential, commercial and industrial. This segmentation helps to reflect different characteristics of these groups. The parameter g_j reflects the response of the customer when offered an incentive payment. Under the assumption of linear demand curves, equation (10.2g) can be explicitly expressed as:

$$\Delta D_{bt_j} = \varepsilon_j P_{bt}^{inc} \tag{4.4}$$

4.2 Optimum IBDR Design

The important design parameter to address is the appropriate time to implement DR. LSEs lose money whenever market price is higher than the flat rate price, but in our approach we also seek not to ask for frequent load changes. We select a specific value above market price to serve as a trigger point for requesting DR. This threshold could be either fixed for the year or seasonal or optimally calculated for each period of study. A constant threshold has some merit, not least of which is transparency and simplicity, but this approach may put too much burden on customers in more expensive periods. Consequently, it's better to find a variable threshold that provides benefit for all participants and also maintains customer's comfort convenience [156]. We formulate this as:

$$\max \sum_{b=1}^{N_B} \sum_{t=1}^{T_y} u_t[(D_{bt} - \Delta\bar{D}_{bt})(P_b^0 - LMP_{bt}) - \Delta\bar{D}_{bt} P_{bt}^{inc}] \tag{4.5}$$

$$\Delta\bar{D}_{bt} = \sum_{j=1}^{D_T} \Delta D_{bt_j} \tag{4.6a}$$

$$\triangle D_{bt_j}^{\min} \leq \Delta D_{bt_j} \leq \triangle D_{bt_j}^{\max} \tag{4.6b}$$

$$\Delta D_{bt_j} = \varepsilon_j P_{bt}^{inc} \tag{4.6c}$$

$$T_d^{\min} \leq \sum_{i=1}^{T_d} u_i \leq T_d^{\max} \tag{4.6d}$$

$$T_m^{\min} \leq \sum_{i=1}^{T_m} u_i \leq T_m^{\max} \tag{4.6e}$$

$$u_t \in \{0, 1\} \tag{4.6f}$$

In (4.5), the binary variable u_t indicates whether DR is needed. The main advantage of this method is that we could consider customer comfort as a constraint at in any level that is desired. In our formulation, the number of hours that IBDR occurs is limited both daily and monthly.

4.3 Load Characteristics

The affordable load reduction at each hour is limited due to the types of loads. Devices in the residential and commercial sectors can be divided into three groups: (1) interruptible devices, whose consumption can be interrupted at a specific time and will not need to be supplied in the future; (2) controllable devices, whose consumption can be transferred to another time of day; and (3) critical devices that are so important that no manipulation of the consumption is generally acceptable.

Based on Tab. 4.1, the main reducible load consists of air conditioning and electric heating, water heating and lighting. Assuming that 10% of the demand for each device is reducible and using the load profiles for each device from [157, 158], the maximum affordable limit of load reduction at each hour can be calculated. The National Energy

Table 4.1: Classification of common residential electric devises

Interruptible device	Controllable device	Critical device
Air conditioner	Rechargeable tools	Oven/ microwave
Space heater	Clothes washer	TV/DVD player/Games
Water heater	Clothes Dryer	PC/ laptop/Wifi/ modem
Lighting	Dishwasher	Coffee maker
pool/ hot tub/ spa heater	EHV batter	Refrigerator/freezer
	Pool filter / pump	Printer/fax machine

Modeling system provides a database which is representative of more than 1,486 loaf profiles for residential, commercial, and industrial sectors (called the RELOAD database). The database reports based on three types of day for each month, average weekday, average weekend and a peak day. Using this data an entire year of 8,760 hourly values can be generated since each day of month typically falls in to one of these three types.

The key component in DR programs, either PB or IB, ones is of demand against price change or incentive payments. Accuracy of anticipated load reduction and adequacy of incentive design are highly dependent on elasticity of demand. Full understanding of electricity demand elasticity remains an open problem. In chapter (8) and (9) explore estimated elasticity in greater detail. In this chapter, the average elasticity value of 0.1 for residential and commercial sector and 0.05 for residential one is used [159, 160].

4.4 Retail Load Tariff Plans

LSE profit depends on the flat rate price that it can charge so as to cover fixed and variable expenses. The important question is what's the best retail load tariff strategy for implementing DR programs that supports the overall market. There are several schemes considering various design factors. A constant price for the whole year is the simplest and similar to a traditional residential rate. Given the large variation between average LMP in each season though, another simple approach would be to offer a seasonal tariff. Similarly, a tariff that takes into account the wide differences in prices between day and night or between weekends and weekdays could be beneficial. Incentive schemes

Table 4.2: Seasonal and yearly customer tariff in WECC regions

Tariff ($/MWh)	Spring	Summer	Fall	Winter	Yearly fixed
Southwest	31	51	28	26	35
San Diego	36	54	32	31	40
LADWP	33	54	29	28	35
San Francisco	36	46	34	32	35
Bay area	34	43	33	31	34
Fresno	31	47	28	28	35
Cnt. Coast	33	53	29	28	35
PG&E	38	71	34	31	40
Northwest	25	25	25	26	26
Rocky Mt.	28	38	27	26	28
Idaho	27	34	27	26	26
Nevada	35	63	32	28	40
SMUD	29	44	28	27	35
SCE	33	55	30	28	35

with hourly price variations may also encourage customers to reduce consumption in ways not possible with seasonal pricing. Some of these tariffs would require greater communication infrastructure and need more initial investment; however, other schemes, such as, seasonal or day/nigh tariff could lead to useful consumption modification with existing infrastructure.

In this chapter, IBDR effect on LSE benefit and customer saving, under various retail electricity tariff is illustrated. Tab. 4.2 shows seasonal vs. yearly fixed tariff in different regions of WECC. Since most of the regions have a summer peak, the biggest tariff difference is between summer and other seasons. For some regions that have higher residential load, the summer tariff is much higher relative to other seasons, like PG&E. In other regions with light residential load and more coal power or little seasonal variation in load, there is not a significant difference between the tariffs, e.g., the Northwest.

4.5 IBDR Evaluation with Fix Trigger Threshold Value

In this section, the effect of IBDR on both customers and LSEs in the WECC 240-bus model is discussed. The trigger point to implement IBDR in this section is set to be

Table 4.3: LSEs benefit of IBDR program

Region	Seasonally fixed	Seasonal d/n	Yearly fixed	Yearly d/n
Low benefit Region (% of benefit change after DR)				
SMUD	13.15	26.70	234.85	614.30
Cnt. coast	21.11	62.70	66.06	153.88
Southwest	22.37	74.79	30.91	123.41
SCE	21.12	147.82	119.86	632.31
LADWP	25.72	73.98	157.35	192.49
San Diego	32.62	145.18	24.81	64.11
High benefit Region				
Idaho	38.22	186.45	378.18	693.96
Bay area	40.88	236.32	459.44	306.72
Rocky Mt.	41.56	390.38	344.18	539.87
Northwest	52.10	200.52	11.47	115.89
Nevada	63.35	227.13	121.73	360.48
Fresno	85.41	273.59	96.64	371.67
PG&E	86.92	229.00	503.30	612.61

\$10/MWh above the fixed price. This means whenever market price is 10\$/MWh more than customer flat rate tariff, LSEs would run a DR program to reduce load. While numerous approaches for pricing could be designed, we look at for four schemes: fixed tariff for whole year (yearly fixed), day and night tariff (yearly d/n), seasonal tariff (seasonally fixed), day and night tariff for each season (seasonal d/n).

Equation (10.1) can be solved to find the desired load change and incentive at each hour. By reducing the demand, the market price will decrease, so LSEs will benefit from both a lower price in market and lower demand within their region at expensive hours. In Tab. 4.3, the benefit for LSEs after DR under various tariffs is shown. The regions are divided into high and low benefit groups. In this table, the schemes are ordered from lowest to highest benefit, a fixed tariff for each season brings the lowest benefit for LSEs while a day/night tariff for the whole year leads to the greatest benefits.

In Fig. 4.1, LSEs net revenue per total load in the high benefit group is shown. Relative to Tab. 4.3, although there is high difference in terms of benefit percentage between various tariffs, revenue per total load is relatively comparable. This could justify that either a yearly fixed or yearly day/night tariff will not bring significant revenue increase

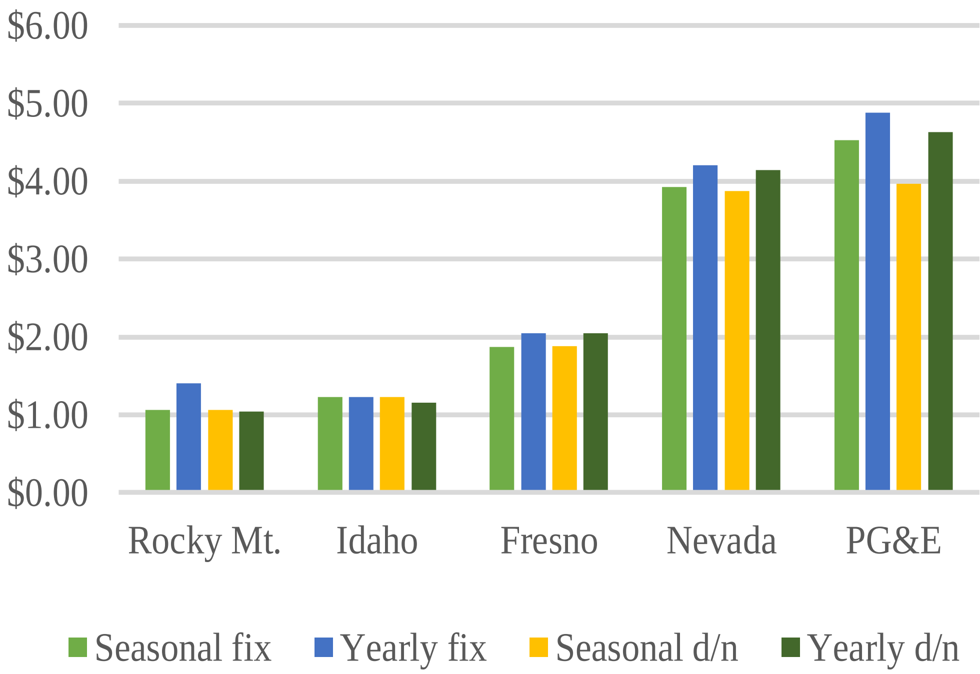


Figure 4.1: LSEs net revenue per total load after DR in high benefit region

for LSEs, therefore, the DR is not showing much impact under these schemes.

Customer saving after IBDR for the two groups of high and low saving regions are shown in Tab. 4.4 and the saving per total load change is shown in Fig. 4.2. Customer saving is only calculated for those who participate in the DR program and receive incentive payment. As shown in Fig. 4.2, a seasonal fix tariff ranks second order for customer saving as it was for LSE net revenue per total load. In this case study of WECC, it can be concluded that a seasonal tariff is appropriate structure of IBDR for both customers and LSE. The result could be different for different test systems and relates to the LMP variation at various time scales. In the next section, seasonal tariff is chosen to measure the effect of threshold and to unify a tariff strategy under both DR plans.

Table 4.4: Participating customer saving after DR

Region	Seasonal fix	Seasonal d/n	Yearly fix	Yearly d/n
Low Saving Region (% of saving on total bill)				
PG&E	35.31	14.08	35.50	0.47
SMUD	45.18	37.13%	46.03	5.67
Nevada	47.83	26.85	50.83	0.73
Fresno	49.44	34.56	54.87	1.44
Cnt. coast	55.46	35.79	61.48	0.21
High Saving Region				
SCE	57.40	33.52	63.25	0.23
LADWP	57.74	30.08	63.49	0.11
Southwest	58.44	38.78	65.47	0.08
San Diego	59.37	38.67	67.61	1.76
Rocky Mt.	60.52	48.19	56.76	1.14
Idaho	67.27	69.15	56.78	17.46
Bay Area	71.34	70.83	69.61	3.55

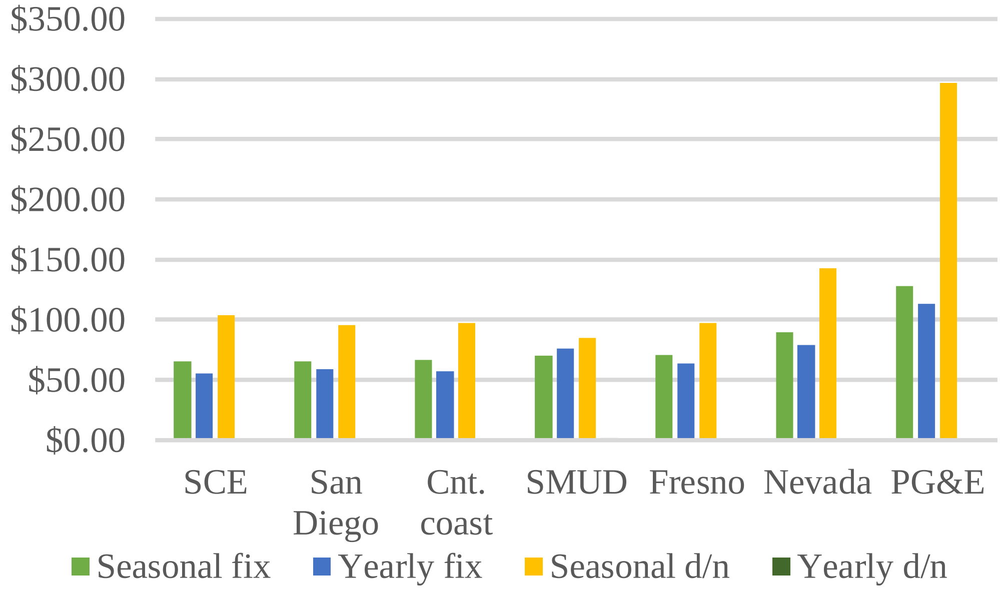


Figure 4.2: Saving per total load change in high benefit region

Table 4.5: Optimum threshold value in some regions of WECC

Month	Southwest	Idaho	Bay area	Fresno	PG&E	Rocky Mt.
Jan.	3	3.5	7.5	5.5	5	4
Feb.	2.5	2.5	2	1	4	4
March	2.5	1	3.5	1.5	2	2
April	3	1.5	2.5	1	1.5	1.5
May	5	4	2	5	13	5.5
June	17	3.5	3.5	10	15	6.5
July	14	7	5	22	25	13
Aug.	3	6	5	19	20	8
Sept.	3	7	3.5	12	17	5
Oct.	7	3.5	3	4.5	14	5.5
Nov.	1.5	2.5	2.5	3.5	13	3.5
Dec.	5	3.5	1	5.5	10	5.5

4.5.1 Optimum vs. Constant Trigger Threshold

An optimum threshold for requesting IBDR is investigated in this section using (4.5). The threshold varies by region from month to month. In Tab. 4.5, results for some regions are shown. According to these results it can be seen that a constant threshold results in many DR requests in summer and very few in winter. This unbalance of DR, while bringing benefits for LSEs, puts a greater burden of inconvenience on customers.

In Fig. 4.3 and Fig. 4.4, the LSEs benefit and customers saving are shown for constant vs. optimum threshold based on overall utility. The constant threshold brings higher benefit for LSEs but less saving for customers.

To show that the optimum threshold is in fact the better option in this case, the total number of hours that DR is requested is shown in Tab. 4.6. As desired, the optimum threshold limits the number of requests of DR both daily and monthly.

4.5.2 Effect of IBDR on Market Price

In this section, it is shown how each method could help reduce price variations and peak LMP in the wholesale power market. Fig. 4.5 and Fig. 4.6 shows the LMP monthly standard deviation and average, respectively.

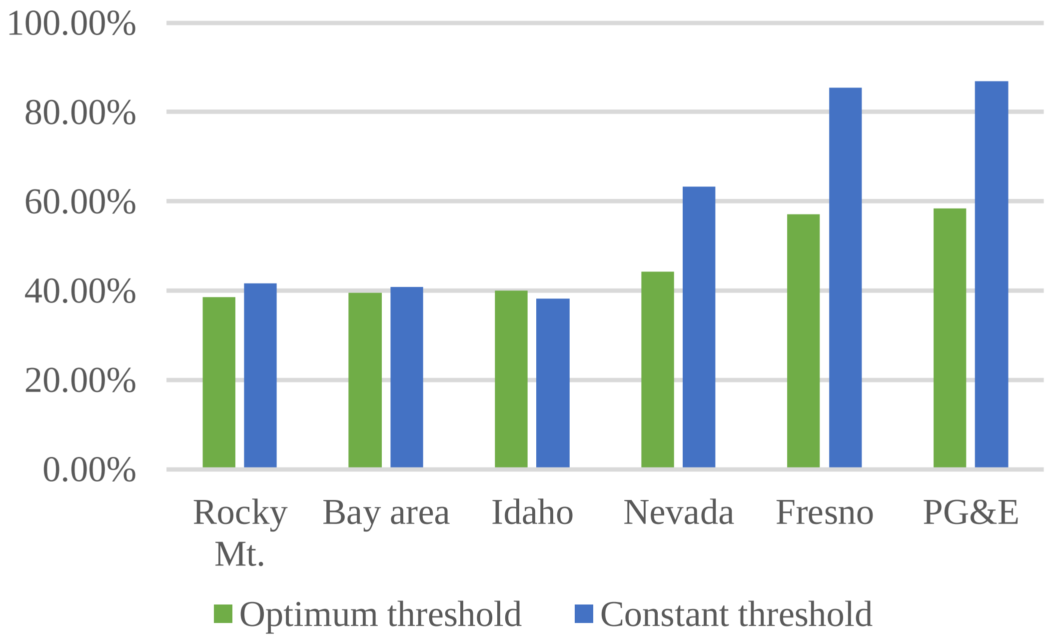


Figure 4.3: LSEs benefit of IBDR in high benefit region

As shown in Fig. 4.5 and Fig. 4.6, using the optimum threshold has a greater effect on the monthly average and standard deviation of LMP in the non-peak summer months. Fig. 4.7 and Fig. 4.8 show the worst day for summer in Nevada as one of the hot regions and for winter in Rocky Mountain as a colder region.

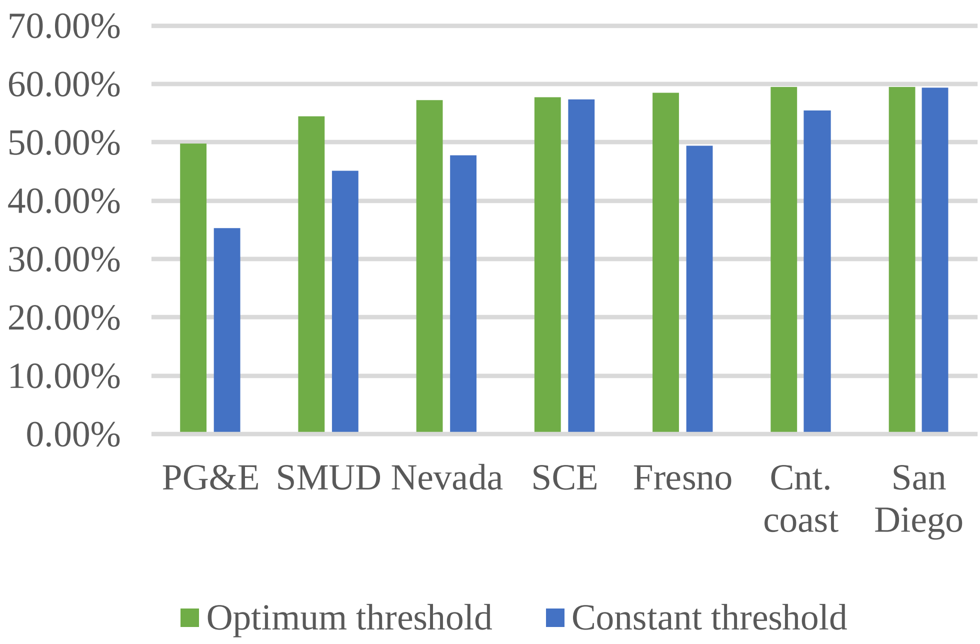


Figure 4.4: Participating customers saving in low benefit region

Table 4.6: Number of hours of load change in some regions of WECC

Total hour of DR	Constant threshold		Optimum threshold	
Region	Summer	Year	Summer	Year
San Diego	308	547	290	900
LADWP	311	573	303	947
Fresno	454	784	270	911
Cnt. coast	389	675	292	917
PG&E	1128	2616	836	2540
Rocky Mt.	346	532	328	852
Idaho	175	194	240	783
Nevada	632	1708	510	1539
SCE	310	570	307	809

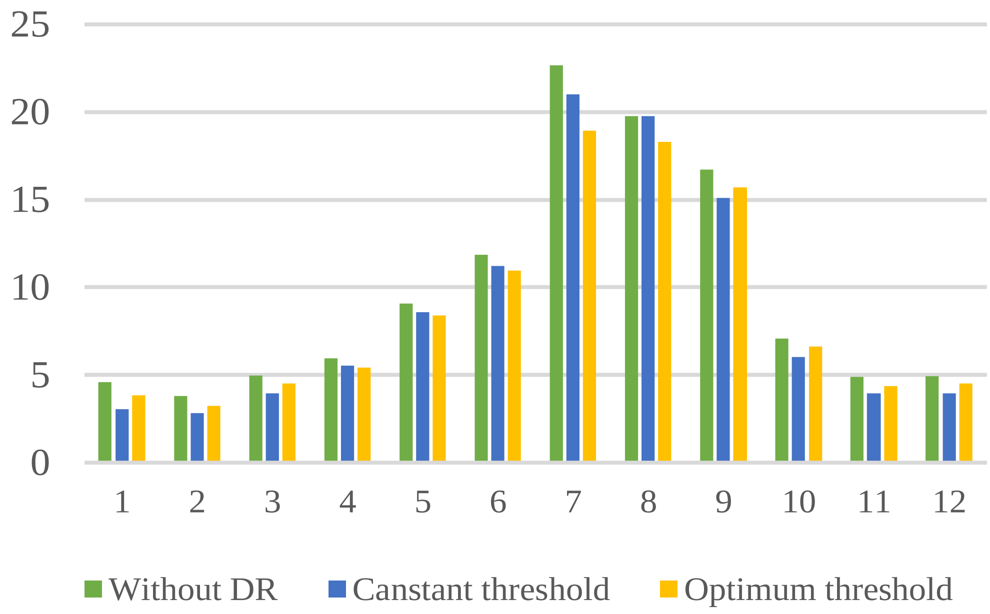


Figure 4.5: LMP monthly standard variation in Southwest

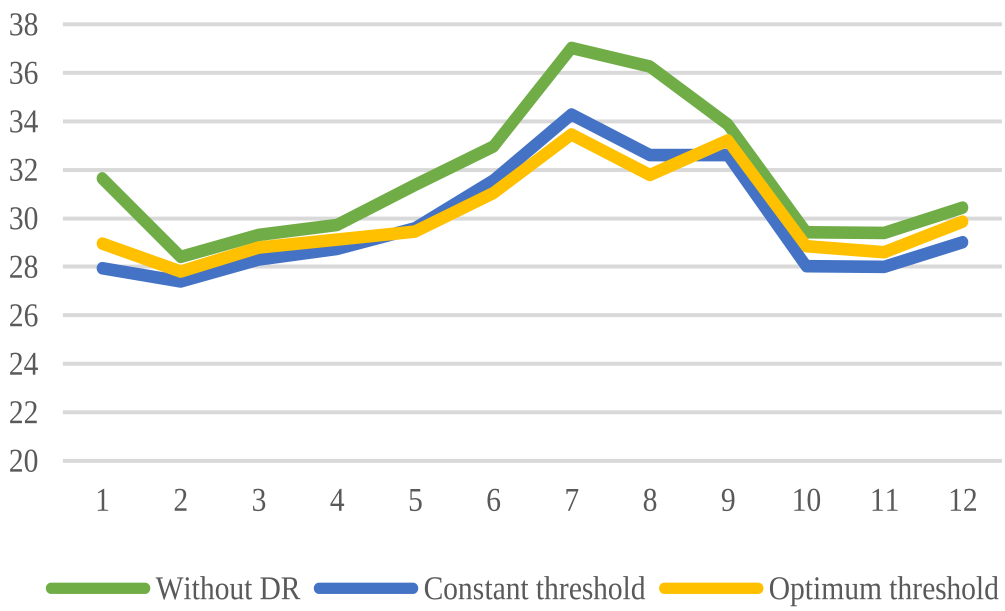


Figure 4.6: LMP monthly average in Bay area

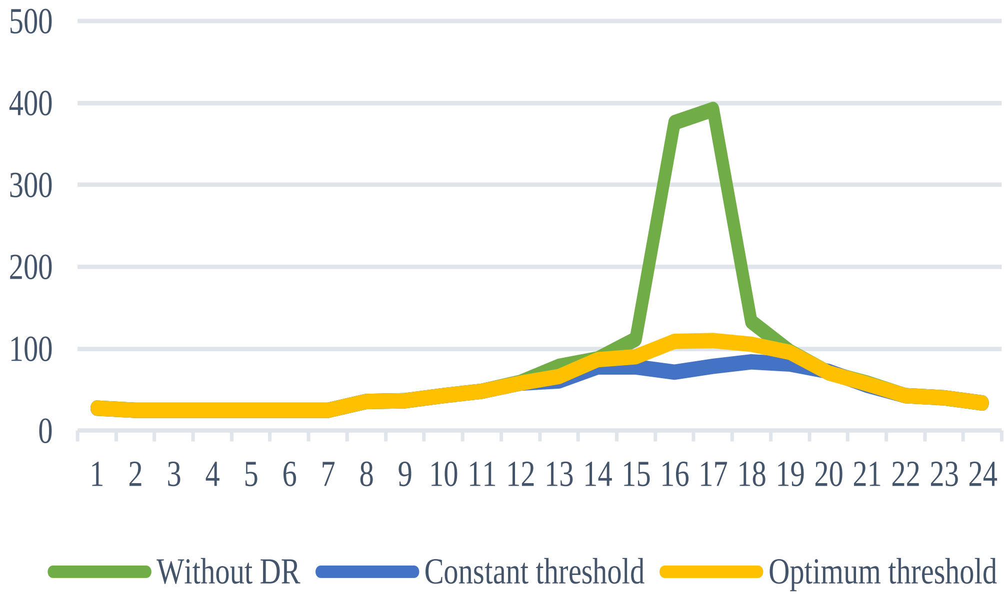


Figure 4.7: Worst day in summer in Nevada region

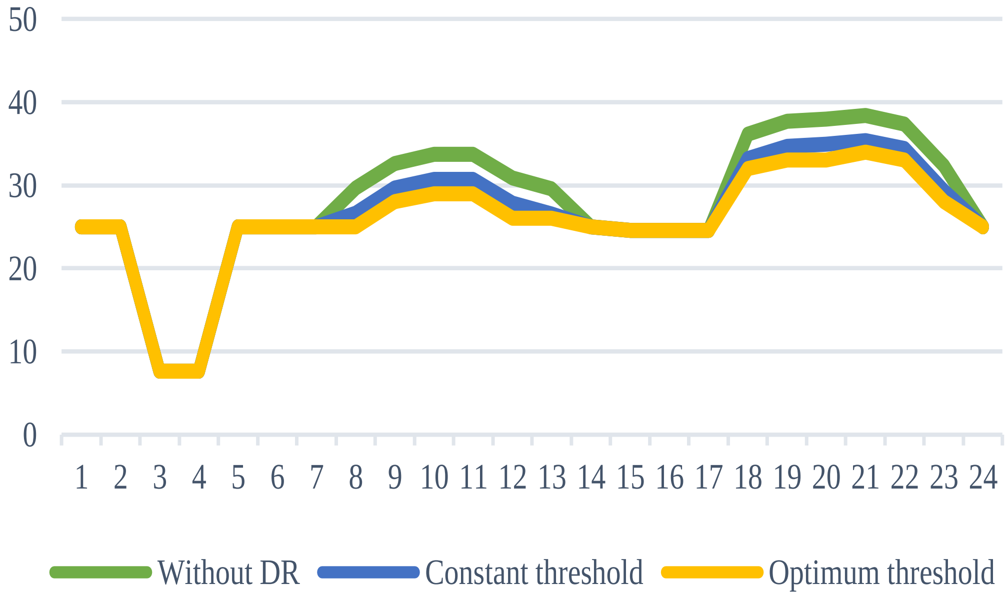


Figure 4.8: Worst day in winter in Rocky MT region

5 Optimal Use of Incentive Based and Price Based DR

Each category of DR, incentive based and price based, has its own benefits and takes advantage of different aspects of the potential for flexible demand. In this chapter, a combination of both DR categories is proposed as an optimal scheme to achieve the maximum benefit for DR programs. The goal is to reduce the production cost and improve the reliability of the network by reducing price volatility. In addition, we suggest high price volatility negatively impacts residential customer satisfaction and may be indicative of overall system stress. Thus, DR can be used both to mitigate price volatility and reduce overall costs.

It has been shown that customers' attitudes toward PB and IB programs are not similar. From the perspective of human behavior, "there are two main reinforcement conditions: reward and punishment, which lead to some significant changes in the subject's behavior" [161, 162]. Psychologists mainly believe, in most societies, reward may result in more considerable improvement for habit development relative to punishment [164, 165]. In this chapter, a different elasticity value is considered for each DR program to emphasize this variable response from customers. IBDR as a reward-based system should have higher elasticity.

The following proposes a combined DR program consisting of both PB and IB programs. A voluntary IBDR program would supplement the mandatory TOU program to increase response as needed for reducing peaks that remain after some load shift from pricing. Both of these DR programs are regional based, so each region would implement its DR program individually considering market conditions. Note while load change in each region may be small, the cumulative effect on prices could be considerable.

5.1 Time Of Use Design

LSEs, or similarly load aggregators, supply electricity for retail load customers, such as, residential or small commercial and industrial from the wholesale market. LSE's benefit is related to the difference of market price and customer price. The LSE selling price must be regulated since the customer is captive and increasing price always increases profit. The important question here is what the best retail load tariff strategy is specifically for implementing a DR program that supports the overall market. This not only affects the LSE and customer benefits but also directly relates to overall electricity consumption. Different TOU retail tariffs include peak, off-peak, valley, and so on, each of which could vary daily, weekly, monthly or seasonally based on the desired simplicity. In this chapter, a tariff with a peak and off-peak price is considered that changes every month, which provides reasonable transparency and simplicity for customers.

The optimal monthly peak and off-peak tariff is proposed based on the competing objectives of the customer and the LSE. Specifically, the objective considers the change in customer payment, the LSE overall profit and load variation. A coefficient α is introduced to represent dollar value of load change in (7.2) and more importantly to weight priority of each objective. The output of this optimization is the deviation from fixed price in the peak and off-peak period as well as new hourly load. Load change at each hour depends on two variables: self-elasticity of demand, which represents change of demand at each time because of price change at that same time, and cross-elasticity, which shows the effect of price change at other times on the load change. This is detailed below:

$$\min \left[\alpha(\sum_{b=1}^{N_B}(\sum_{t_2\in PT} d_{bt_2} - \sum_{t_1\in OPT} d_{bt_1})) - (\sum_{b=1}^{N_B} CB_b + \sum_{b=1}^{N_B} LSEB_b) \right] \tag{5.1}$$

with the following constraints:

$$-\beta\sum_{t=1}^{T_d} d_{bt} \le \sum_{t=1}^{T_d} \Delta d_{bt} \le 0 \tag{5.2a}$$

$$\Delta d_{bt} = d_{bt}^0 (\sum_{t_1\in OPT} \varepsilon_{tt_1} \frac{p_b^{OPT} - p_b^0}{p_b^0} + \sum_{t_2\in PT} \varepsilon_{tt_2} \frac{p_b^{PT} - p_b^0}{p_b^0}) \tag{5.2b}$$

$$\Delta d_{bt}^{\min} \le \Delta d_{bt} \le \Delta d_{bt}^{\max} \tag{5.2c}$$

In (7.2), customer benefit is represented as:

$$CB_b = p_b^0 \sum_{t=1}^{NT} d_{bt}^0 - p_b^{OPT} \sum_{t_1\in OPT} d_{bt_1} - p_b^{PT} \sum_{t_2\in PT} d_{bt_2} \tag{5.3}$$

LSE benefit at each bus is calculated as:

$$LSEB_b = \sum_{t_{1\in OPT}} (d_{bt_1} p_b^{OPT} - d_{bt_1} LMP_{bt_1}) +$$
$$\sum_{t_2\in PT} (d_{bt_2} p_b^{PT} - d_{bt_2} LMP_{bt_2}) - \sum_{t=1}^{NT} (d_{bt}^0 p_b^0 - d_{bt}^0 LMP_{bt}) \tag{5.4}$$

In the above formulation, the superscript 0 indicates the flat rate condition where a price is fixed for the whole month, whereas OPT and PT represent off-peak time and peak time, respectively. Note we can write the deviations from nominal as:

$$d_{bt} = d_{bt}^{0} + \Delta d_{bt} \tag{5.5}$$

$$p_b^{OPT} = p_b^{0} + \Delta p_b^{OPT} \tag{5.6}$$

$$p_b^{PT} = p_b^{0} + \Delta p_b^{PT} \tag{5.7}$$

The critical points for the TOU tariff design are both the load and LMP variation. The main objective of the TOU DR program is to reduce load during peak times and consequently the LMP variation should decrease. Note though that at some times during the year the load variation between peak and off-peak may not be significant. In this case, implementing an aggressive TOU could inadvertently result in a new peak and possibly introduce greater price volatility. These times vary with region but mainly occur during mild weather months, such as the spring months of March and April in the Western US.

5.2 TOU Program Results

As explained , a monthly peak and off-peak retail load tariff is considered for the TOU scheme. Peak time is assumed from 10 a.m. to 10 p.m. and off-peak from 10 p.m. to 10 a.m. A constant retail load tariff for the TOU program design corresponds to the average monthly LMP in each region. Maximum load change at each hour considered is 5% with 1% that is reducible and the remaining 4% shiftable. Self-elasticity is set to be -0.1 and cross-elasticity is 0.07. According to the output of the TOU optimization from (7.2), the peak and off-peak tariff difference can be calculated. For current case study, α is considered to be $1 per MWh to reflect relatively less emphasis. Results for the San Francisco and PG&E region are shown in Fig. 5.1 and Fig. 5.2, respectively. A constant price is indicated by (*) whereas upper and lower lines provide the peak and off peak tariffs in each month. The difference between peak and off peak is greater in summer months reaching as much as $20 per MW.

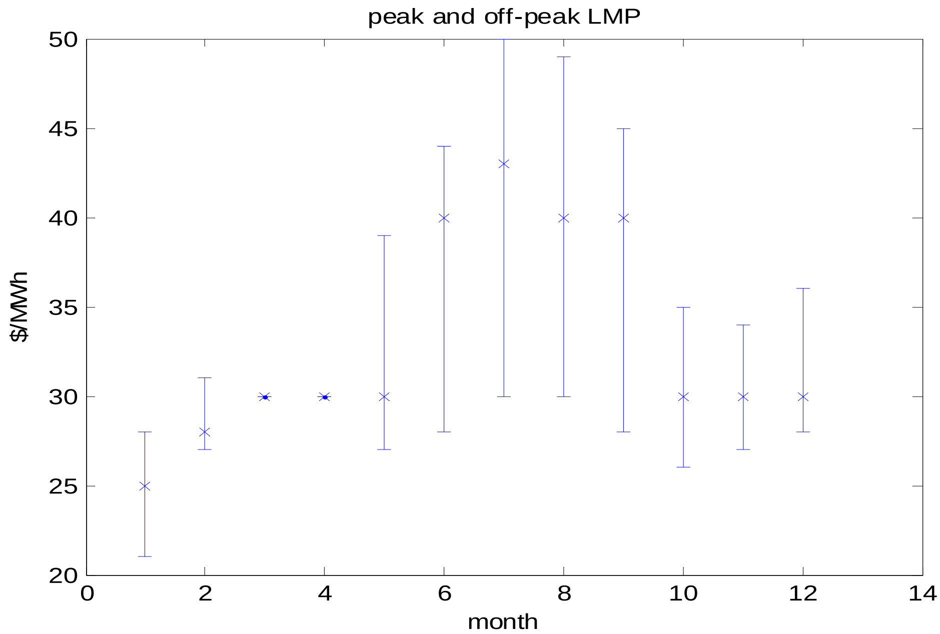


Figure 5.1: Peak and off peak tariff in San Francisco

In PG&E, there is no difference between the peak and off peak tariff in January, March and April and little difference in February. As mentioned in sec. 5.1, TOU DR programs are more suitable if there exists considerable difference between peak and off peak time prices and loads. In most regions in the WECC model during these months, the LMP curve has a low standard deviation and a small difference between day and night. As a result, there is little benefit to implementing TOU in these months. The Northwest has a different LMP curve pattern relative to other regions. The LMP has a small standard deviation (less than 0.5) and the day and night average are close in most of the months. For the Northwest, only in January does the cold weather make some sense for a TOU rates. For other months, IBDR is more acceptable as a method to reduce peak prices.

Tab. 5.1 shows the LSEs benefit and customers saving after TOU DR program. LSEs benefit after DR is approximately the same in all regions; however relative to the IBDR program, this benefit is much less. Customers saving varies by each region but it is comparable with LSE benefit reflecting a fairness to the tariff design. Also despite the IBDR program, a TOU mandatory is for all customers so it brings saving for everyone as

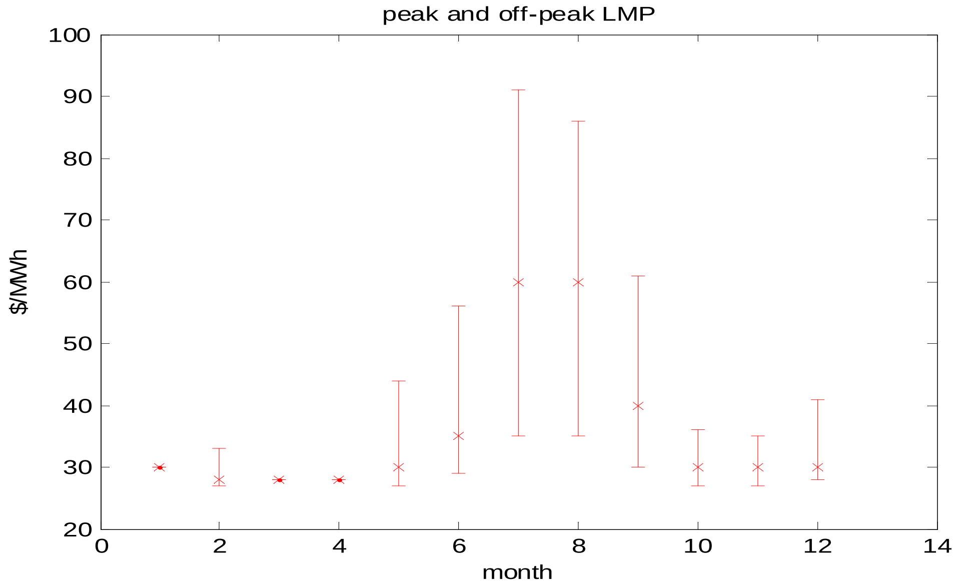


Figure 5.2: Peak and off peak tariff in PG&E region

long as they modify their consumption, accordingly. Fig. 5.3 shows the customers saving and LSEs net revenue change exclusively through the TOU DR program. Again, relative benefits are similar.

Table 5.1: LSEs benefit and customers saving after TOU program

Region	LSEs benefit	Customers saving
San Diego	16.07%	5.54%
Bay area	13.18%	7.79%
Rocky Mt.	11.87%	6.31%
LADWP	11.61%	6.54%
Nevada	11.38%	7.74%
SCE	11.05%	8.45%
Southwest	11.01%	5.34%
Fresno	10.63%	5.23%
Cnt. Coast	10.73%	7.11%
Idaho	10.21%	5.93%

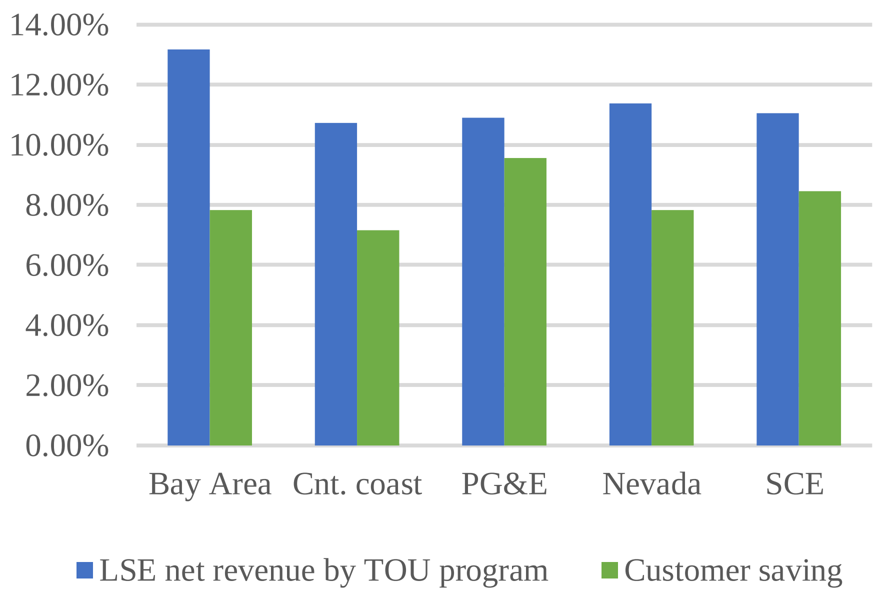


Figure 5.3: Customers saving and LSEs net revenue by TOU program

5.3 Impact of DR Programs on LSE Benefit

IBDR and TOU] as individual programs was discussed previously. Each has its own advantages. In this section, we want to combine these program to see whether further benefits can be realized. The IBDR program maximum threshold of load reduction is set to 10% of total load. Retail prices are found for TOU program. To find the optimum threshold for IBDR, the maximum hours that DR can be activated in each day is three. Since the TOU program decreases the number of price spikes, the need for the incentive program is also reduced. Results show the maximum percentage of time that DR activates yearly is at most case 18% (1621 hours) in the SCE region, but on average just 8% of the year (699 hours) requires IBDR. Thus by shifting less than 5% of the load and reducing 10% of the total load for 8% time of year, a large costs savings and significant impact on LMP is realized. The main reason is the region based design for DR programs. The accumulation of small load modification across all regions results in significant price changes.

Table 5.2: LSEs net revenue change by each DR program

High benefit region	Net revenue by TOU	Net revenue by IBDR	Total net revenue by both DR
San Diego	16.07%	36.36%	58.27%
Cnt. Coast	10.73%	38.46%	53.32%
San Francisco	13.12%	34.83%	52.52%
PG&E	10.89%	35.40%	50.15%
Low benefit region			
Idaho	10.21%	14.33%	26.00%
Rocky Mt.	11.87%	12.50%	25.85%
Northwest	1.08%	13.86%	15.09%

Both TOU and IBDR need to bring benefits for both the customers and LSEs to be acceptable. Tab. 5.2 shows LSEs net revenue change for each program based on the optimization procedure and then for the combined program in both low and high beneficial regions. Base case in this table is the LSE total net revenue without any DR programs. Notice TOU benefit tends to be uniform for most regions while IBDR varies more. This is due to the nature of the original LMP spikes variation in each region. If the TOU program can eliminate most of the higher values of LMP, then there may be little benefit to the IBDR program.

LSEs net revenue per total load ($/MW) for base case, after TOU and after IBDR is shown in Fig. 5.4. Base case in this figure means with no demand response program.Fig. 5.5 shows the LSEs total net revenue relation with average LMP during high price periods. Regions with higher average LMP have higher revenue by DR programs. Thus, the Northwest that has the smallest price spikes and price variation has the least benefit of DR. PG&E has highest residential load in WECC, so it has the highest LMP peak, especially in summer, and consequently obtains the most benefit from DR programs.

5.4 Effect of DR Programs on Customer Savings

Customer savings after DR are shown in Tab. 5.3. The base case is the customer's monthly electricity payment without any DR, which is assumed to be the flat rate price based on

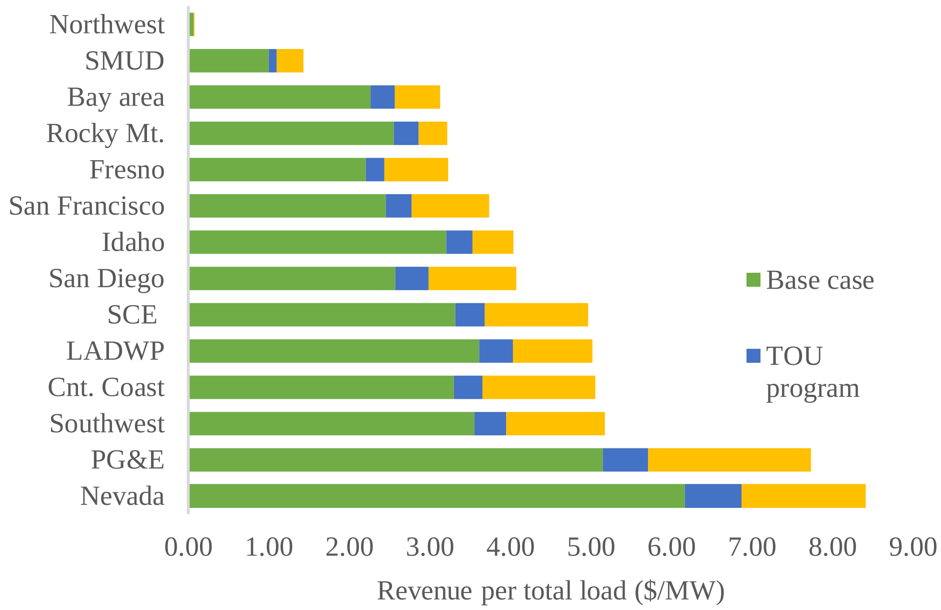


Figure 5.4: LSEs net revenue per total load by different DR program

Table 5.3: Customers saving in each region

High benefit region	Total reduction (%)	Low benefit region	Total reduction (%)
PG&E	9.56%	San Diego	5.58%
SCE	8.47%	Southwest	5.36%
Bay area	7.83%	Fresno	5.26%
Nevada	7.83%	SMUD	4.70%

the seasonal average of LMP in each region. This saving mainly arises from the TOU program since incentive payments are only for customers who participate in DR programs. Therefore, the customer saving for IBDR is less than 1% considering all customers. Customer savings and LSEs net revenue per total load, after both DR programs are shown in Fig. 5.6, sorted from high to low benefit. The revenue for LSEs and customer savings remains comparable in all regions. Thus, the results here for the proposed DR program appears to adequately benefit both the customers and LSEs.

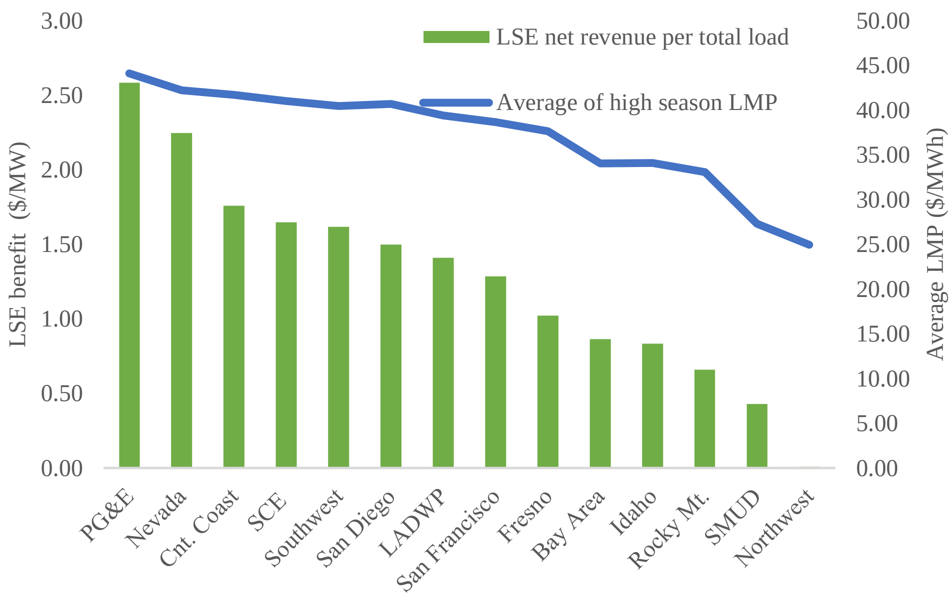


Figure 5.5: Total LSEs net revenue in compare with average LMP

5.5 Effect of DR Programs on LMP

In Fig. 5.7 and Fig. 5.8, the monthly average LMP and standard deviation are shown before and after the DR programs in San Diego and LADWP regions. LMP average and volatility is relatively small in the winter and higher during the summer peak period as expected. The optimum DR scheme reduce both average and variation of LMP.

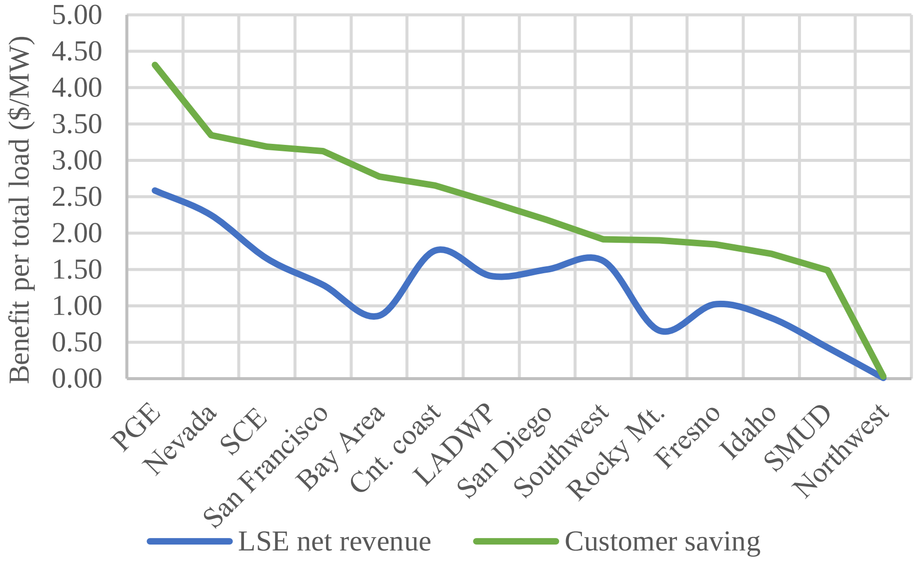


Figure 5.6: Customers saving and LSEs net revenue per total load

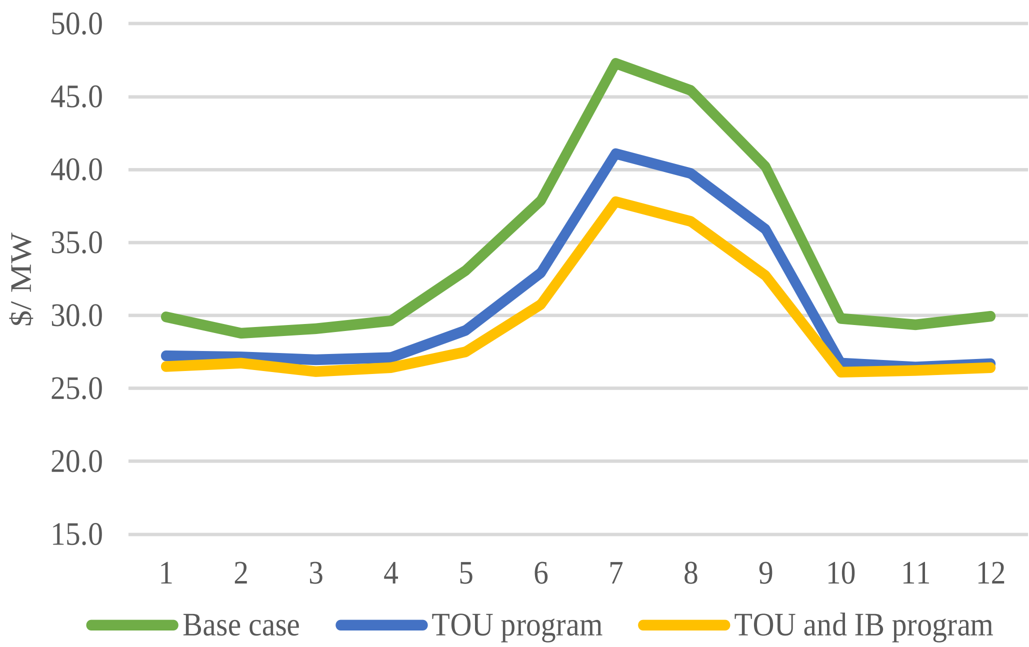


Figure 5.7: Average monthly LMP in San Diego

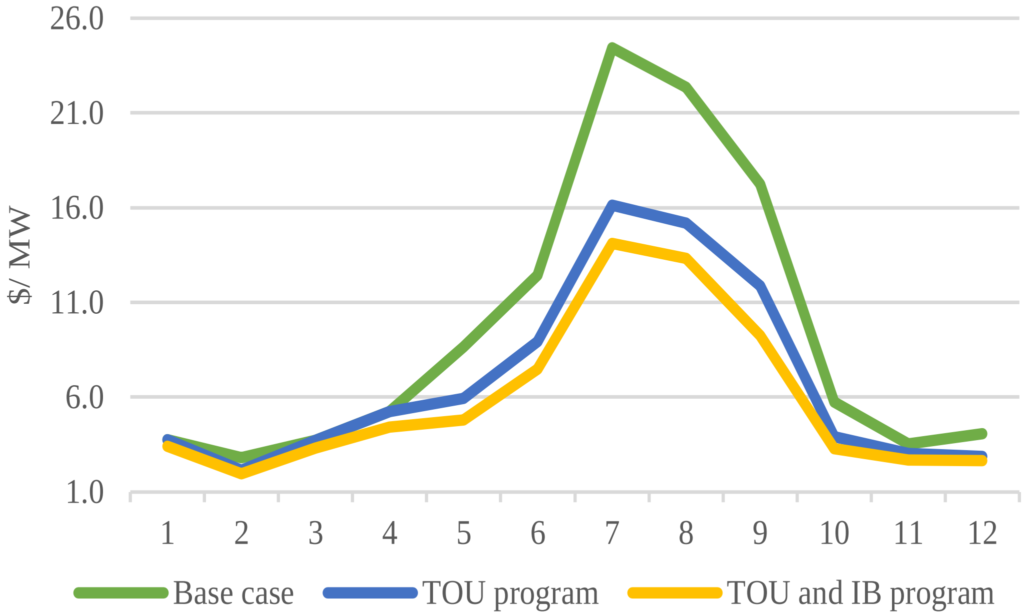


Figure 5.8: Monthly standard deviation of LMP in LADWP

6 Generator Outage and Using IBDR to Diminish Economic Impact

Transmission and distribution systems mainly face two broad types of reliability issues: insufficient capacity (generation or transmission) and resilience to faults. Insufficient capacity is a major threat for the system viability especially at the transmission level. In this case, ISOs call on capacity of available resources and emergency units first and then ask for DR for large customers [166]. Market operators using various types of emergency load relief programs during shortages. New York ISO (NYISO) offers emergency DR and distributed load relief programs for customers who can shed at least 100 kW and 50 kW, respectively. PJM ISO (Pennsylvania, Jersey, Maryland) has two levels of load response program during emergency, voluntary and mandatory program, which are implemented based on the severity of situation. CAISO has mandatory interruptible DR program which requires that customer shed at least 100 kW [167]. Most of these programs target large customers. The potential of small customers in these circumstances is underestimated. In this chapter, the effect of small customers on load reduction is investigated for outage conditions.

6.1 Effect of Generator Outage on Market Price

During a shortage of capacity, such as, a generator outage, the market operator must ask for more expensive generators to meet the demand. This can cause sharp and sudden changes in market price. Since unscheduled generator outage is a real time problem, the unit commitment result would not be changed and economic dispatch should be done using available reserve generators. After a generator outage, the LMP can be found using the following DC Optimal Power Flow (DCOPF) formulation:

$$\min \sum_{t=1}^{NT} \sum_{i=1}^{NG+NR} (C_i \times (G_{it} + R_{it})) \tag{6.1}$$

Subject to:

$$\sum_{i=1}^{NG+NR} G_{it} + R_{it} = \sum_{j=1}^{ND} D_j \tag{6.2a}$$

$$\sum_{i=1}^{NT} GSF_{ki} \times P_{it} \leq \text{limit}_k \tag{6.2b}$$

$$G_i^{\min} \leq G_{it} \leq G_i^{\max} \tag{6.2c}$$

$$R_{it}^{\min} \times \text{Ramp}_i^{\text{down}} \leq R_{it} \leq R_{it}^{\max} \times \text{Ramp}_i^{up} \tag{6.2d}$$

$$P_{it} = G_{it} - D_{jt} \tag{6.2e}$$

According to above formulation, after generator outage, market price found according to available generators and selected reserves to dispatch. For reserve generators, ramp rate of their output power and their start up cost should also be considered.

6.2 Using IBDR to Decrease Economic Consequence

Emergency DR in most of current literature is seen as that large enough to meet requirements of reserve market; however, aggregate of small customers could also be significant enough to meet shortage capacity, but they are rarely mentioned in literature. In this chapter, it will be shown that small customers, especially residential sector, could be effective enough to mitigate economic effect of outage in market. DR is viewed in this

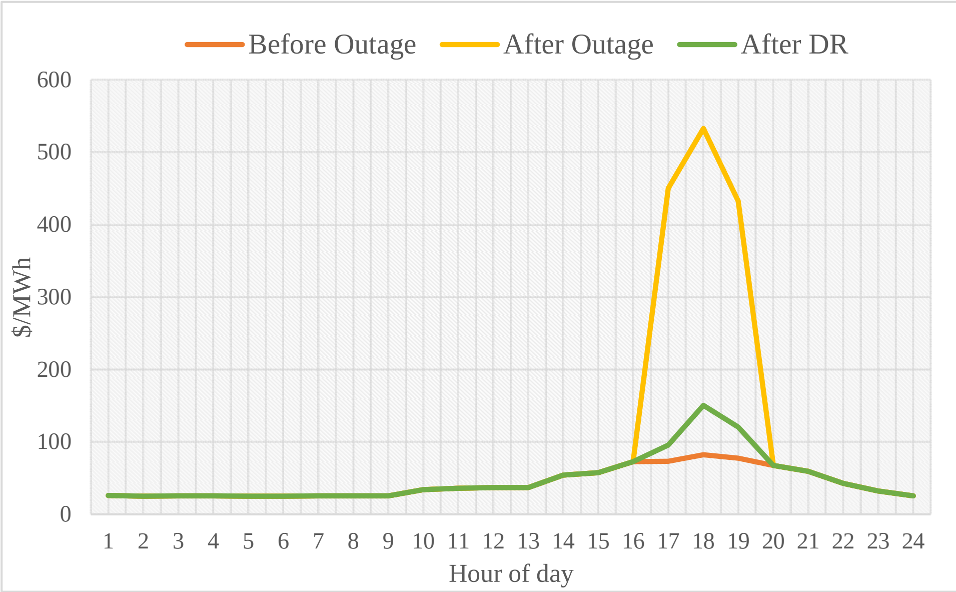


Figure 6.1: LMP on bus# 215-July 6th -100% of DR potential

chapter as an economic based program, which tries to decrease economic consequence of an element outage in the power system. This DR does not deal directly with reliability but the related economic effects [193].

In Fig. 6.1 and Fig. 6.2, a coal unit is considered to be out for two hours on July 6th. The generator outage is considered on peak time to simulate worst case situation in the system. During peak hours, most of the available generators are producing maximum output, and therefore, outage of one significantly effects market price. If the proposed IBDR in this chapter could be useful during peak hours, it should be effective in other hours with less price change as well.

As shown generator outage has considerable effect on LMP, but IBDR will significantly diminish sharp change in LMP. In Fig. 6.1, 100% of the estimated potential of DR is captured and in Fig. 6.2, only 70% of the estimated load change is achieved. Even with 70% of the forecast load reduction, DR has considerable impact on LMP. In other words, Fig. 6.2 shows that even if there is 30% error in estimation of load change potential (that is considerable), still IBDR effectively mitigates the economic impact of a generator outage.

The main point of the proposed DR program is that, although generator outages affect

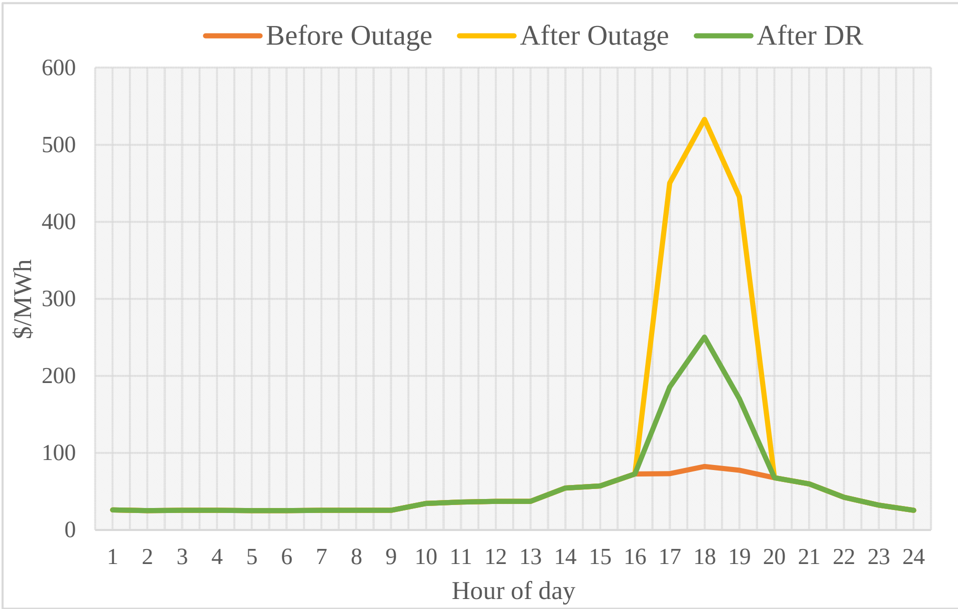


Figure 6.2: LMP on bus# 215-July 6th -70% of DR potential

the whole system and many regions would incur costs from a higher LMP; the DR only needs to be implemented in the region with the outage. This point is significantly helpful for practical implementation of DR program. When generator is out for unscheduled reasons in one region, there is no need to communicate with other regions for load modification. Fig. 6.3 show the results of LSE benefit loss after the outage and after DR. The generator outage results in significant costs increase, especially for the PG&E region where the generator is located. The, IBDR effectively reduces costs for all LSEs.

In Tab. 6.1, the load reduction and incentive payment at 5 p.m. of July 6th are shown for some of the load buses in the PG&E region. The load reduction is either small or the incentive amount is significant in response to the load change. Customers get more than $4 incentive in response to each MW change. This load change occurs rarely, i.e., only following an outage, so it is not a large impact on customer's comfort. In Fig. 6.4, another example of DR impact on prices is shown. In this case, a gas turbine is out for two hours on October 14th. Summary of savings for LSEs after DR is shown in Fig. 6.5. In this example, LADWP has highest benefit lost, since the gas turbine is located in this region. As in the previous example, IBDR effectively reduces the economic consequences

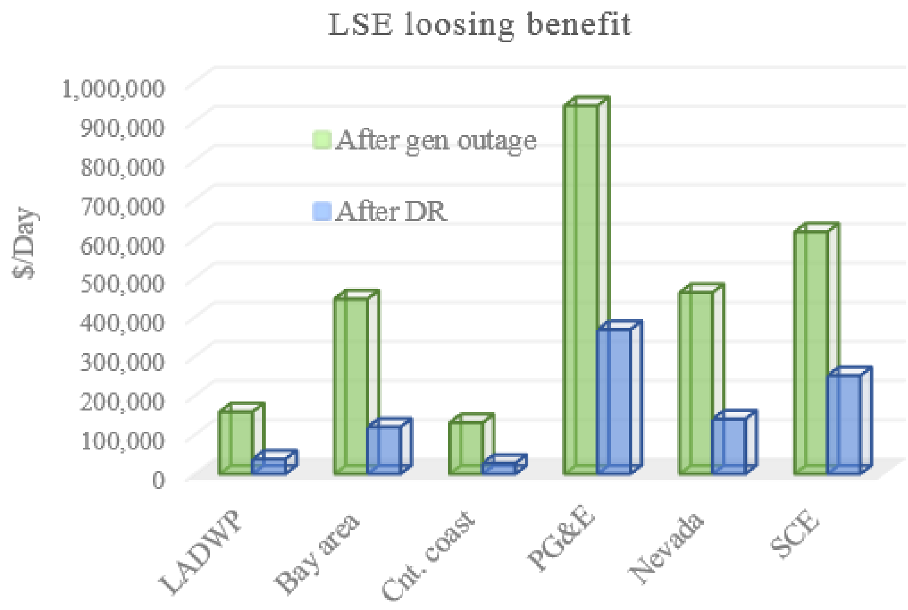


Figure 6.3: July 6th- LSEs benefit lost

of the generator outage.

6.3 Economic Rank of Generator Outage

A challenge for designing DR in outage condition is time constraints. Fast response is important in shortage condition since it could endanger reliability of system. On the one hand, small customers are one of the slowest responders for DR. To overcome this contrast, the novel idea of outage economic ranking is proposed. Economic ranking is ordering outage of each element based on their expected effect on market price. This helps operators to estimate economic consequence of generator outage faster than the market real time price window and allows time to implement appropriate DR.

The electrical distance approach is used to rank economic consequence of generator outage. When there is an outage, power is shifted among generators to different transmission paths. Distribution factors such as the power transfer distribution factor (PTDF) and line outage distribution factor (LODF) are used to estimate changes in line power

Table 6.1: Demand Response Report at 17 p.m. in PG&E region

Bus#	Load change (MWh)	Incentive ($/MWh)
14	25	100
19	13.68	74.24
20	11.68	63.4
35	20.9	89.91
36	3.14	12.57
45	2.22	8.88
50	1.11	6.68
75	12.61	68.42
83	11.76	63.97
215	17.32	93.98
217	6.15	24.6

flow and generator injection due to these faults. These factors, which are based on the DC power flow method, provide approximate but a quick solution for the change in power flows. Higher PTDF and LODF, means a larger change in system caused by the change in an injection, which means higher sensitivity and generally shorter electrical distance.

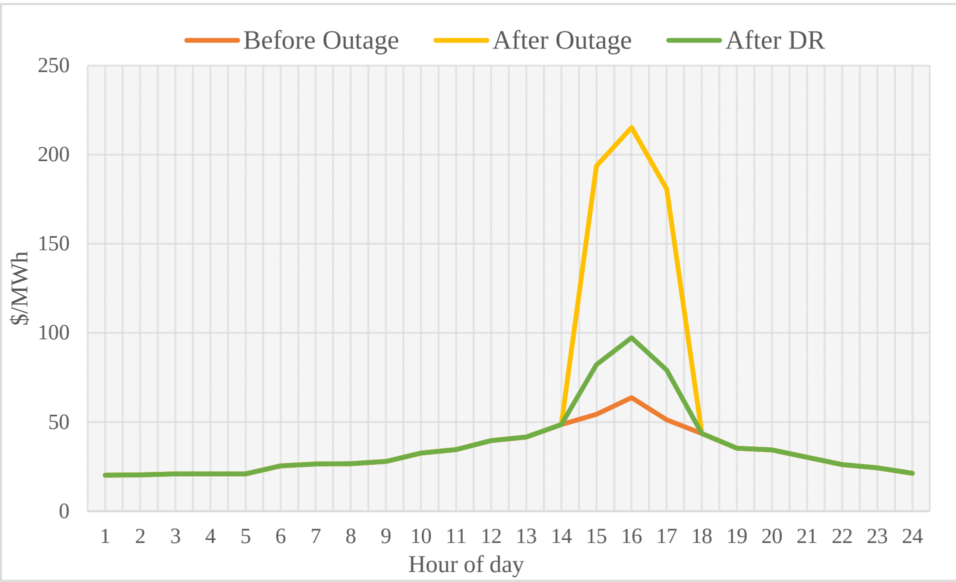


Figure 6.4: LMP on bus# 11- October 14th

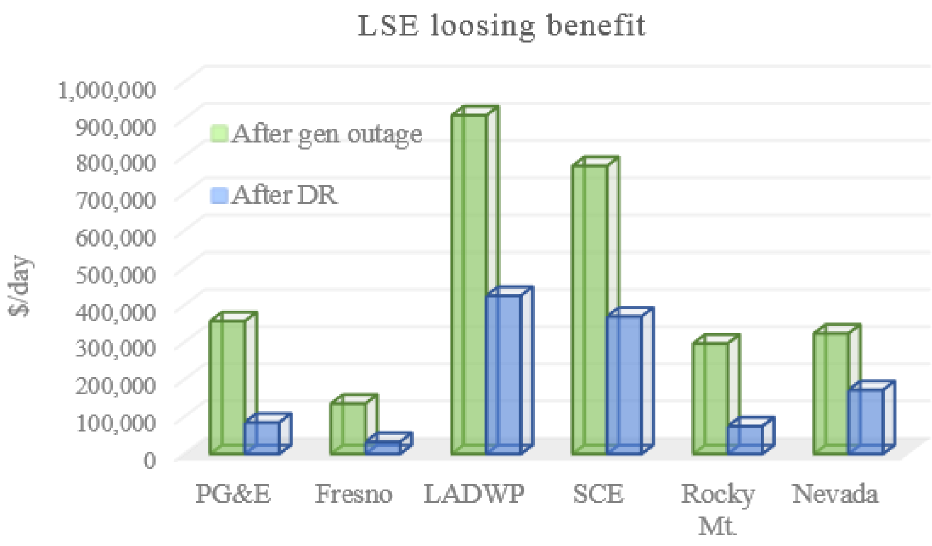


Figure 6.5: October 14th - LSEs benefit lost

The power flow on a transmission line is approximately calculated as following [168]:

$$P_{ij} = \frac{\delta_i - \delta_j}{x_{ij}} \tag{6.3}$$

This requires the angle value of the "from" and "to" buses, which is obtained from (10.3b)

.

$$\delta = B^{-1}P \tag{6.4}$$

where B is from the impedance matrix of system as follows:

$$B = Im(Y) = (\frac{-X_L}{R_L^2 + X_L^2}) \tag{6.5}$$

The inverse of B at the n^{th} bus without loss of generality is taken as the slack bus, a zero entry is inserted for the n^{th} row and column, so this new matrix is labeled as X. Therefor the PTDF matrix is as follows:

$$PTDF = B_{br} \times A \times X_L \tag{6.6}$$

where B_{br} is a $N_T \times N_T$ dimensional matrix and A is $N_T \times N_L$, the branch incidence matrix where 1 and -1 stand for the "for bus" and "to bus" respectively.

There are three important sets of elements in power market, marginal units which define market price at each time, expensive generators and congested lines which lead to different prices in various locations. Electrical distance from each of these sets give an appropriate measure for ordering economic consequence of each generator outage. Economic ranking is helpful for any corrective actions since the operator can immediately initiate appropriate DR without waiting for the next real time price market window to see its true effect.

In the following example, we investigate how generators can be ranked based on their economic impact. Three generators are chosen, which have similar power output but with different effects on LMP. Their economic impact is ordered as generators 208, 199 and 227. It means, an outage of gas turbine number 208 has the highest impact on price change and outage of generator 227 has the least effect. In the following tables, the distribution factor for these generators on congested lines, marginal units and expensive units is shown. These distribution factors act as a sensitivity where the higher values reflect a tighter relation and closer electrical distance. In Tab. 6.2 and Tab. 6.3, there is no clear pattern between the distribution factors that match with economic order of the generators. Still in Tab. 6.4, generator 208 has highest factor to the all expensive generators and unit 227 has the lowest factor. This trend matches with their economic ordering.

Table 6.2: Distribution factor of generators with congested lines

Congested line	Gen. 208	Gen. 199	Gen. 227
123-138	0.2249	0.1955	0.0705
57-172	0.2403	0.2108	0.1806
58-146	0.2164	0.187	0.2027
63-179	0.262	0.2336	0.1613
64-54	0.1441	0.1147	0.1513
77-196	0.0538	0.0414	0.2523
107-215	0.2027	0.1733	0.1072

Table 6.3: Distribution factor of generators with marginal units

Marginal unit	Gen. 208	Gen. 199	Gen. 227
209	0.2408	0.2113	0.277
139	0.1655	0.1361	0.1726
210	0.1319	0.0829	0.2473
126	0.2326	0.264	0.1917
140	0.1572	0.2075	0.2828
155	0.0826	0.06	0.2636
166	0.2216	0.1921	0.0793
178	0.2553	0.2413	0.169
197	0.2298	0.2004	0.0892
161	0.1053	0.0445	0.2502

Table 6.4: Distribution factor of generators to expensive units

Expensive Gen.	Gen. 208	Gen. 199	Gen. 227
190	0.2762	0.1507	0.0898
180	0.1692	0.162	0.1326
174	0.2457	0.1364	0.0829
201	0.2281	0.1986	0.1644
157	0.3442	0.3147	0.2472
216	0.2102	0.1608	0.1355
202	0.2995	0.2701	0.2399

7 Impact of Wind Forecast Error on Real Time Market Price

The real time market price is associated with uncertainty due to load or RER forecast error, unscheduled outage and so on. Various approaches to these forecasts are possible but weather is one of the key components and requires multiple source of data. For example, California ISO (CAISO) used neural network based forecasting software for its Day-Ahead (DA) forecast. To ensure the average load forecast error is minimized, CAISO continuously updates its DR forecast data based on updated weather information. CAISO also uses the scheduled energy data that each LSE would submit in the DA market. Each LSE has its own method of load forecasting for its offers in the market [170]. With the current state-of-the-art in forecasting tools, load forecast error for DA is typically less than 2%, which normally would not cause any major issues [169]. The main source of uncertainty in DA scheduling for RERs is due to two main reasons. First, RER are not required to submit bids in the DA market and moreover the forecast error for wind generators in DA is around 30%. Currently, the uncertainty associated with forecasting the output levels of intermittent resources in the DA time frame do not pose any reliability concerns as the levels are not great; however with expansion of RERs, this could lead to reliability issues as well as increased financial risk. In this chapter, a scenario based economic dispatch is introduced, using the DOE approach for scenario reduction, to simulate variation of real time market prices considering wind forecast error.

Table 7.1: Summary of wind forecast error statistics

	Average	Minimum	Maximum	Standard Deviation	Autocorrelation
Winter	0.00	-0.36	0.31	0.07	0.61
Spring	0.00	-0.43	0.31	0.09	0.71
Summer	0.00	-0.32	0.31	0.08	0.65
Fall	0.00	-0.32	0.4	0.08	0.59

7.1 Wind Forecast Error Distribution

The wind forecast error used in this study is based on information from the AWS TrueWind corporation. It is calculated by taking the difference between the actual and forecast production from June 2006 through May 2011 [170]. The forecast error for various time frames are shown in Tab. 7.1. The autocorrelation (R) is calculated to determine the time-dependence of forecast errors. If the R value is close to 1 it shows that there is strong positive relation between current and previous values. When the R value is close to -1, it expresses the negative dependency between the observations. An autocorrelation close to 0 indicates that the current value provides no information about the next value. In our study, the correlation between forecast errors of seven power plants is assumed to be negligible due to their significant geographic distance.

$$R = \frac{1}{(n-1)\sigma^2}\sum_{i=1}^{n-1}(X_i - \mu)(X_{i+1} - \mu) \tag{7.1}$$

The statistical distribution of the forecast error was analyzed in [170]. The forecast error distribution mainly follows a truncated normal distribution. A truncated distribution simply bounds the extreme points. This characteristic is more practical for physically constrained data. For example, we can not expect the wind forecast error to exceed plant capacity. The truncated normal distribution is represented in piece-wise function to ensure no value falls outside the boundary. It is re-scaled by the normal distribution

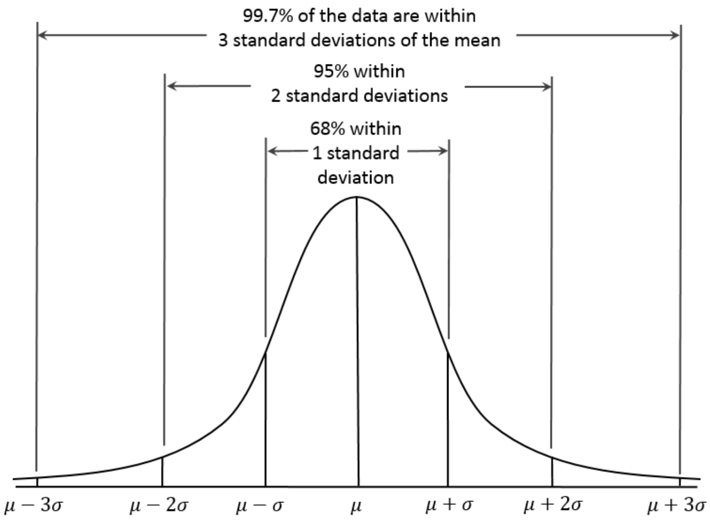


Figure 7.1: Tolerance intervals for normal distribution

as in Fig. 7.2.

$$PDF_{TND}(\epsilon) = \begin{cases} 0, & -\infty \leq \epsilon \leq \epsilon_{min} \\ \frac{PDF_N(\epsilon)}{\int_{\epsilon_{min}}^{\epsilon_{max}} PDF_N(\epsilon) d\epsilon} & \epsilon_{min} \leq \epsilon \leq \epsilon_{max} \\ 0, & \epsilon_{max} \leq \epsilon \leq +\infty \end{cases} \tag{7.2}$$

where n (7.2), the normal distribution is:

$$PDF_N(\epsilon) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{\frac{-1}{2}(\frac{t-t_0}{\sigma})^2}, \ -\infty \leq \epsilon \leq +\infty \tag{7.3}$$

Maximum and minimum of forecast error shown in Tab. 7.1 are equivalent to more than 3 standard deviations, which means, if we use these ranges, we cover about 99.7% of the data as shown in Fig. 7.1. A tolerance interval shows a statistical interval that a specific proportion of sampled data would fall within with some confidence level. Distribution of the wind forecast error in each season is shown in Fig. 7.2.

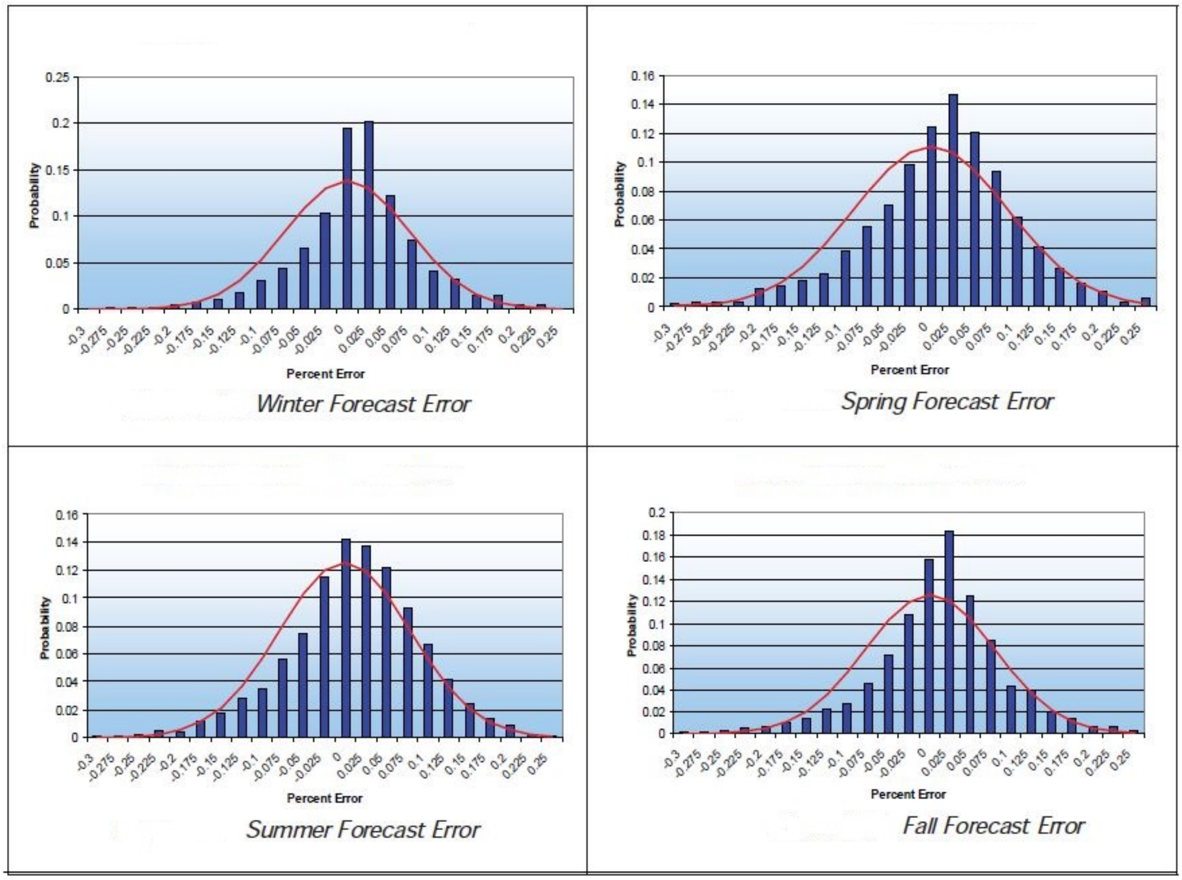


Figure 7.2: Day ahead wind forecast error by season

7.2 Scenario Based Economic Dispatch

There are many methods to address the uncertainty of variables in optimization problems. In this dissertation, a scenario based robust approach is chosen to estimate the effect of wind forecast error on market price. The scenario method or scenario optimization approach is a technique for finding the solutions to robust optimization and also chance-constrained optimization problems that have some random constraints. The technique has existed for decades as a heuristic approach and more recently a more systematic foundation has been developed. The goal of this section is to simply find a range of market prices due to wind forecast error. This range will be useful in our other analysis for robust DR design. Here, the scenarios are simply input to an economic dispatch since unit commitment results generally do not change if renewable output deviates from their scheduled value and available reserve generation can compensate for the imbalance.

$$\min_{G_{it}} \left\{ \sum_{t=1}^{NT} \sum_{i=1}^{NG} \rho_s C_i(G_{it_s}) \right\} \tag{7.4}$$

$$\sum_{i=1}^{NG} G_{it_s} + \sum_{i=1}^{NWG} GW_{it_s} = \sum_{j=1}^{ND} D_{jt_s}, \ \forall s \in S \tag{7.5a}$$

$$G_i^{\min} \leq G_{it_s} \leq G_i^{\max}, \ \forall s \in S \tag{7.5b}$$

$$\sum_{i=1}^{NG} GSF_{ki}(G_{it_s} + GW_{it_s}) - \sum_{j=1}^{ND} GSF_{kj} D_{jt_s} \leq F_k^{\max}, \ \forall s \in S \tag{7.5c}$$

In (10.2f), the cost of wind power is not considered since wind units are “must take” in the market. Index s in the above formulation refers to the different scenarios. Since the purpose is to find a range of prices, equal probability is considered for all scenarios. Each scenario in (10.2f) refers to a particular output of wind generation, considering various level of forecast error. After running all scenarios, the minimum and maximum market prices can be found. The main obstacle for this method is the size of scenario sets. Since the main objective is to find a range of prices, one appropriate method to deal with number of scenarios is the DOE approach as discussed in next section.

7.3 Price variation: DOE approach

The objective of this section is to find range of market prices using the minimum possible number of scenarios.

7.3.1 Fractional Factorial

With 7 wind farms, the full factorial model has $2^7 = 128$ combinations which is too large for the analysis over a full year. An alternative is to use a fractional factorial design

[171, 111]. In a full factorial design, we would build models with 7 variable interactions as follows:

$$y = a_0 + \sum a_i x_i + \sum a_{ij} x_i x_j + ... + \alpha x_1 x_2 ... x_7 \tag{7.6}$$

Using a fractional factorial instead of full factorial can be justified if the reduced model is efficient and the missing information is limited. Specifically:

- Efficiency of design: This criteria quantifies the goodness or efficiency of an experimental design. Common measures of the efficiency of an $(N_D \times p)$ design matrix X are based on the information matrix $X'X$. There are three major efficiency measures [172]:
  - A-efficiency is a function of the arithmetic mean of the eigenvalues (and the arithmetic average of the variances) is given by the trace $((X_0X)^{-1})/p$

    $$A - efficiency = 100 \frac{1}{N_D trace((X_0X)^{-1})/p} \tag{7.7}$$

  - D-efficiency is a function of the geometric average of the eigenvalues and it is given by $|(X_0X)^{-1}|^{1/p}$. Both D-efficiency and A-efficiency are based on the concept of average variance but using a different mean.

    $$D - efficiency = 100 \frac{1}{N_D |(X_0X)^{-1}|^{1/p}} \tag{7.8}$$

  - G-efficiency is based on σ_M which is the maximum standard error of prediction over the candidate set.

    $$G - efficiency = 100 \frac{\sqrt{p/N_D}}{\sigma_M} \tag{7.9}$$

Table 7.2: Design Efficiency

	full factorial	fractional factorial
A-efficiency	100%	100%
D-efficiency	100%	100%
G-efficiency	100%	100%

> There are no absolute values of the above inefficiencies that are given in the literature and could be used to measure the effectively of study approach and the observations. Instead, the efficiency values of different designs should be compared to each other to make an appropriate decision.

The proposed model is a fractional factorial model with 2^{7-3} treatment combinations. As give in Tab. 7.3, instead of 128 treatment combinations we now have $2^{7-3} = 16$ combinations. The first criteria for validity of fractional factorial model is efficiency. As seen in Tab. 7.2, switching from full factorial to fractional factorial is valid. The second criteria requires finding confounding pattern. The following formula shows the confounding pattern of fractional factorial model. As it can be seen, there is no ambiguity about definition of any main effect.

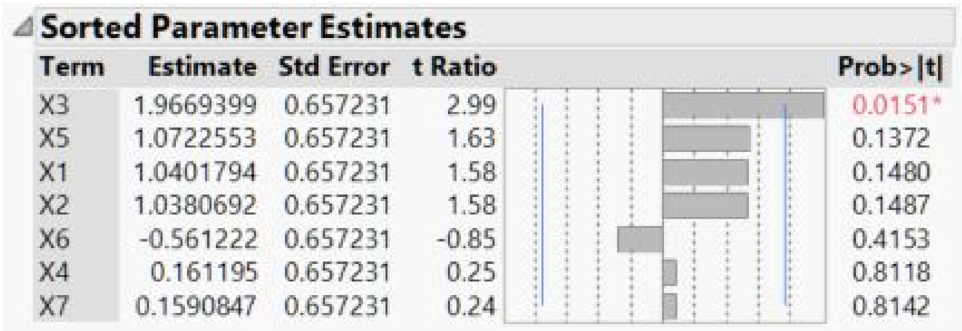
$$I = x_2x_3x_4x_5 = x_1x_3x_4x_6 = x_1x_2x_5x_6 = x_1x_2x_4x_7 = x_1x_3x_5x_7 = x_2x_3x_6x_7 = x_4x_5x_6x_7 \tag{7.10}$$

7.3.2 Results

Since the model has all factors at both low level and high levels as well as all two and three factor interactions, it is highly likely that we will capture the range of variation in LMP. Another possibility is anomaly in the data with the maximum/minimum somewhere between +1s and -1s. A point (0000000) is added to model to capture that situation. If surface analysis shows any significant, then a follow up design and analysis is necessary

Table 7.3: Treatment Combinations

	x1	x2	x3	x4	x5	x6	x7		x1	x2	x3	x4	x5	x6	x7
T1	-1	-1	-1	-1	-1	-1	-1	T9	+1	-1	-1	-1	-1	+1	+1
T2	-1	-1	-1	+1	+1	+1	+1	T10	+1	-1	-1	+1	+1	-1	-1
T3	-1	-1	+1	-1	+1	+1	-1	T11	+1	-1	+1	-1	+1	-1	+1
T4	-1	-1	+1	+1	-1	-1	+1	T12	+1	-1	+1	+1	-1	+1	-1
T5	-1	+1	-1	-1	+1	-1	+1	T13	+1	+1	-1	-1	+1	+1	-1
T6	-1	+1	-1	+1	-1	+1	-1	T14	+1	+1	-1	+1	-1	-1	+1
T7	-1	+1	+1	-1	-1	+1	+1	T15	+1	+1	+1	-1	-1	-1	-1
T8	-1	+1	+1	+1	1	-1	-1	T16	+1	+1	+1	+1	+1	+1	+1


Sorted Parameter Estimates

Term	Estimate	Std Error	t Ratio	Prob>|t|
X3	1.9669399	0.657231	2.99	0.0151*
X5	1.0722553	0.657231	1.63	0.1372
X1	1.0401794	0.657231	1.58	0.1480
X2	1.0380692	0.657231	1.58	0.1487
X6	-0.561222	0.657231	-0.85	0.4153
X4	0.161195	0.657231	0.25	0.8118
X7	0.1590847	0.657231	0.24	0.8142

Figure 7.3: Parameter estimates at hour 234 for bus 14

with points halfway inside the original design. Here the analysis shows that the given design is valid. For one example, analysis at hour 234 for bus 14 is shown in Fig. 7.3 and Fig. 7.4. Variable selection shows that LMP is dependent on the output of generator x_3. The prediction profile shows how the output of different generators will change the LMP on bus 14. The parameter x_3 has the highest slope and is the most effective predictor.

As another example, consider bus 8. The original LMP is categorized into \$5 intervals and the change in LMP is analyzed for each interval. In addition to surface analysis, the surface profile can confirm the small curvature assumption. For different price segments, the prediction profile is depicted in Fig. 7.5. Prediction profile shows how changes of each factor changes the model output. For example with the price of \$35, the slope of x_3 is greatest and is the most predictive. The interaction profile is depicted in Fig. 7.6. The variable interactions do not show any curvature and generally change linearly. The surface profile for different LMP prices is given in Fig. 7.7.

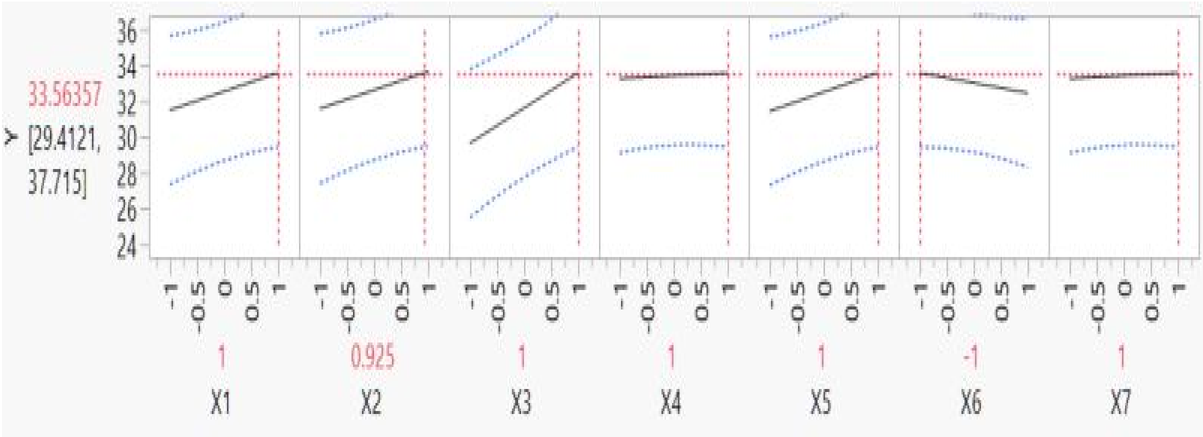


Figure 7.4: Prediction profile at hour 234 for bus 14

7.4 Market Price Range Results

Using the scenario based economic dispatch and DOE approach, the uncertainty range of price is now calculated. Selected examples during peak hours of different seasons are presented in the following graphs. Generally, a lower LMP has a smaller range of uncertainty since price is less sensitive to load or generation changes. If load is low and RER output is sufficient, then forecast error should not cause much variation in market price. While if demand is high and RER output is low, the forecast error could have significant effect on price. In other words, the range of price uncertainty depends primarily on load consumption and available RER production.

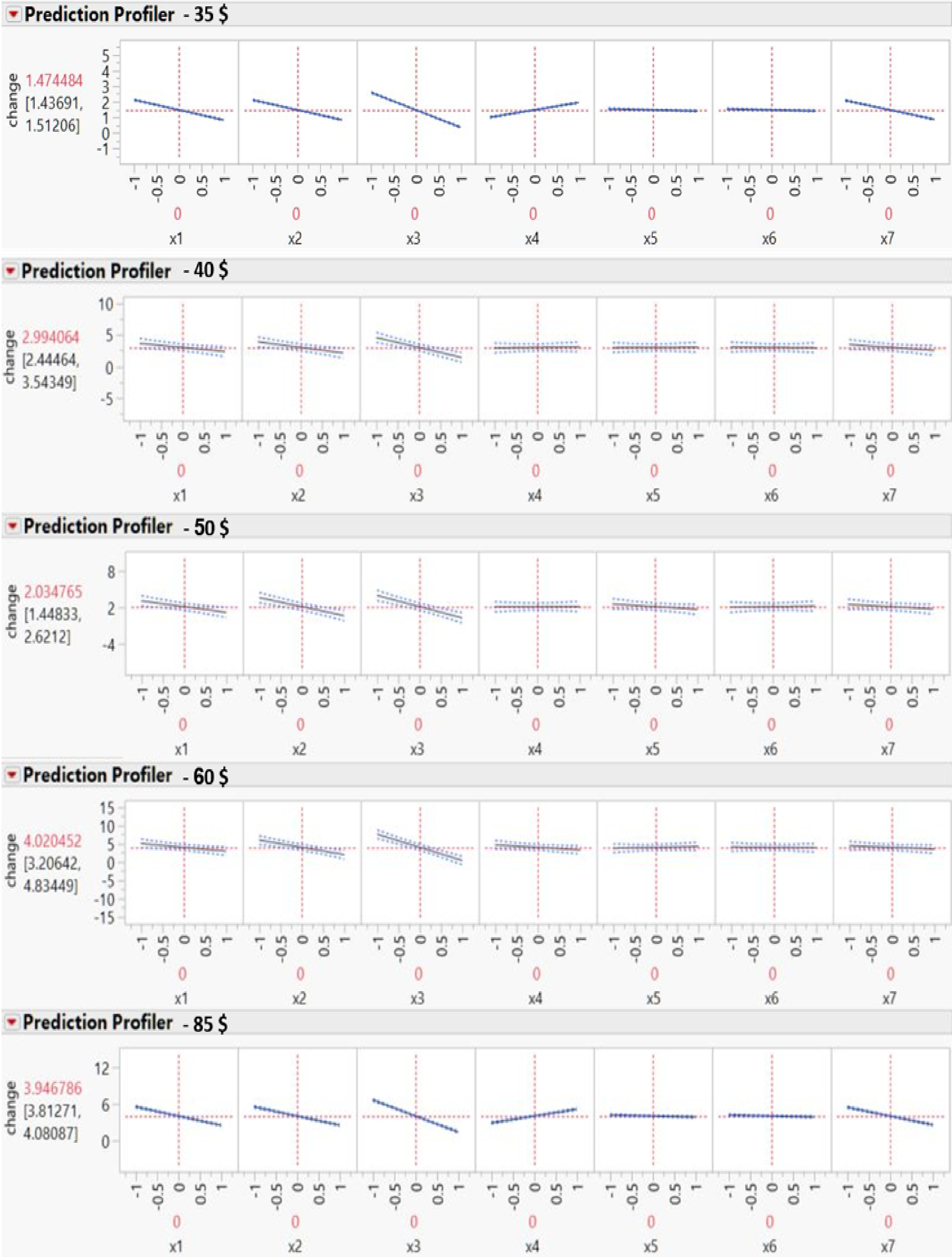


Figure 7.5: Prediction profiler for bus 8

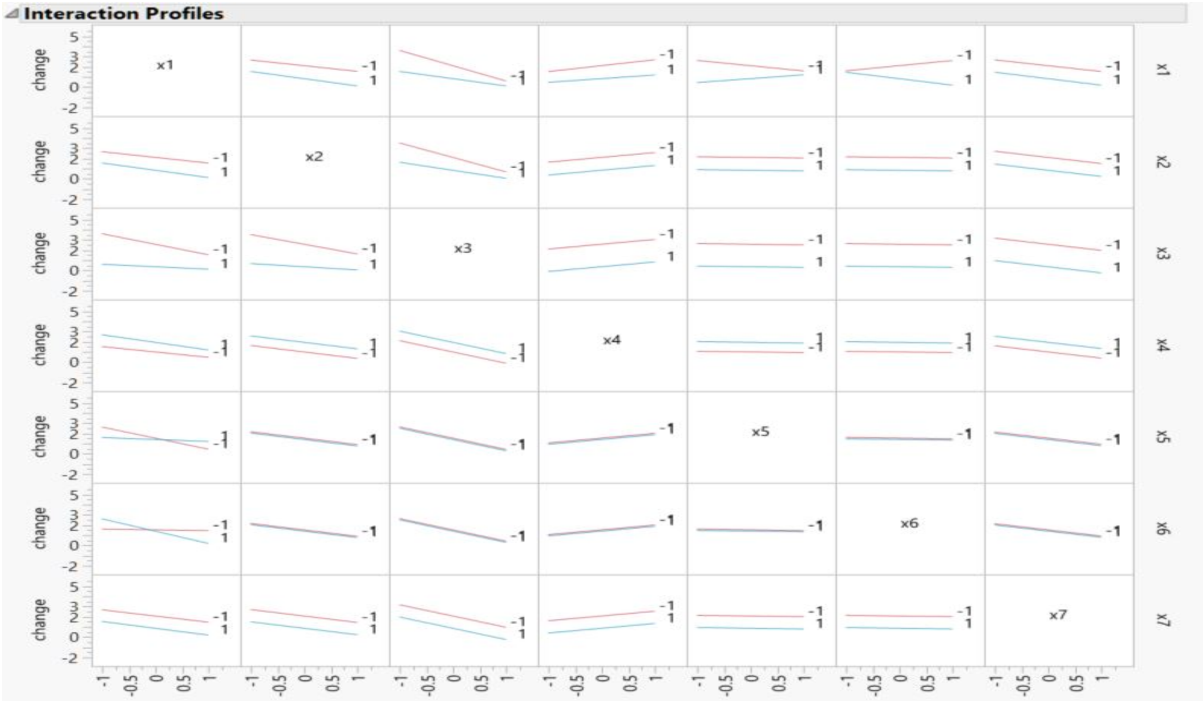


Figure 7.6: Interaction profile for bus 8

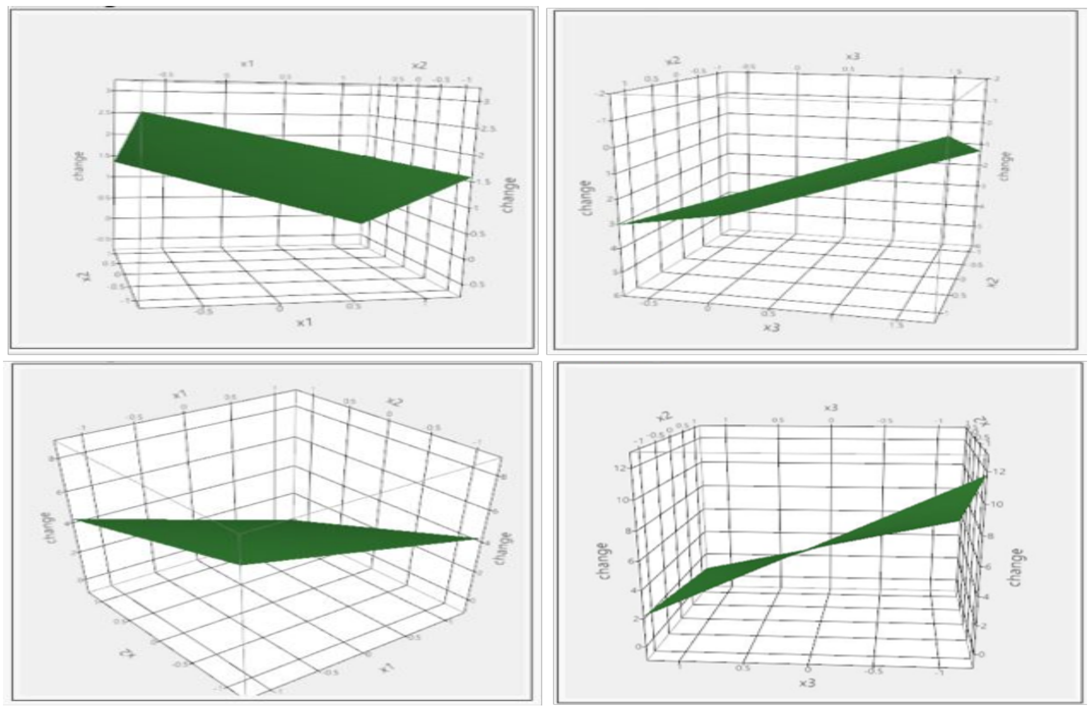


Figure 7.7: Surface profile for bus 8

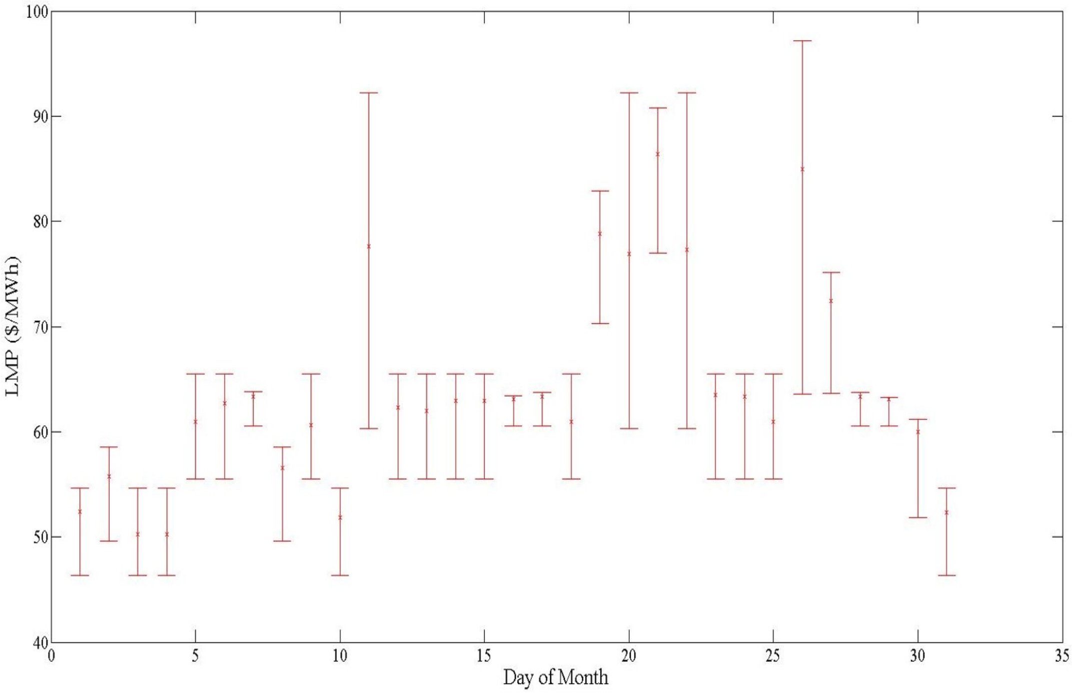


Figure 7.8: Range of prices at daily peak hour in July in San Francisco

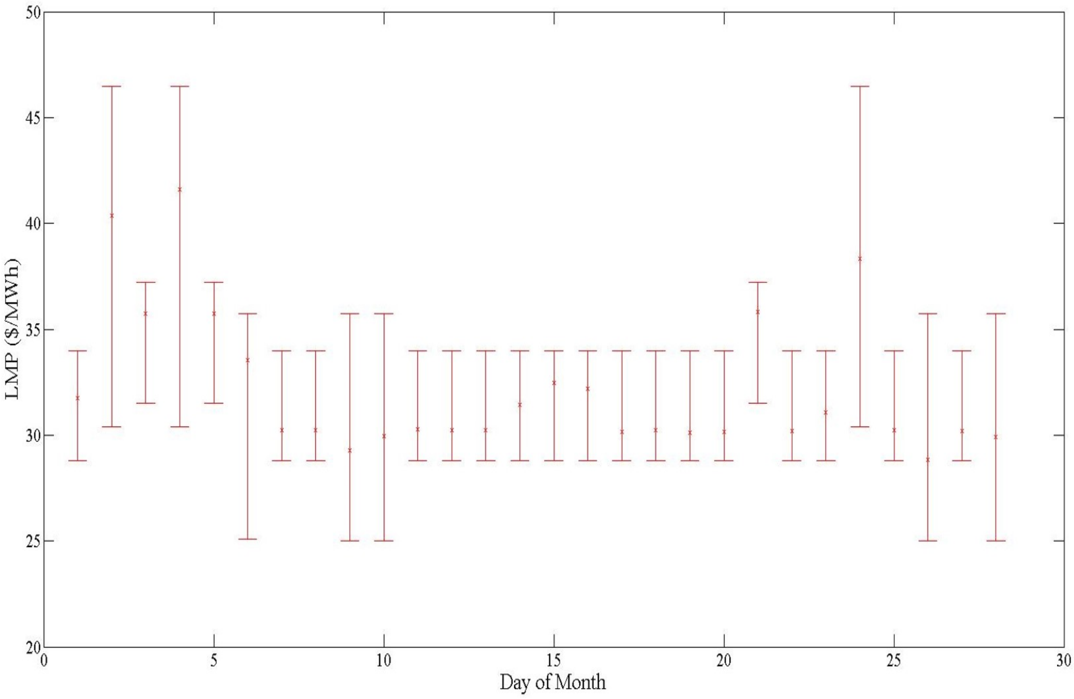


Figure 7.9: Range of prices at daily peak hour in March for SMUD

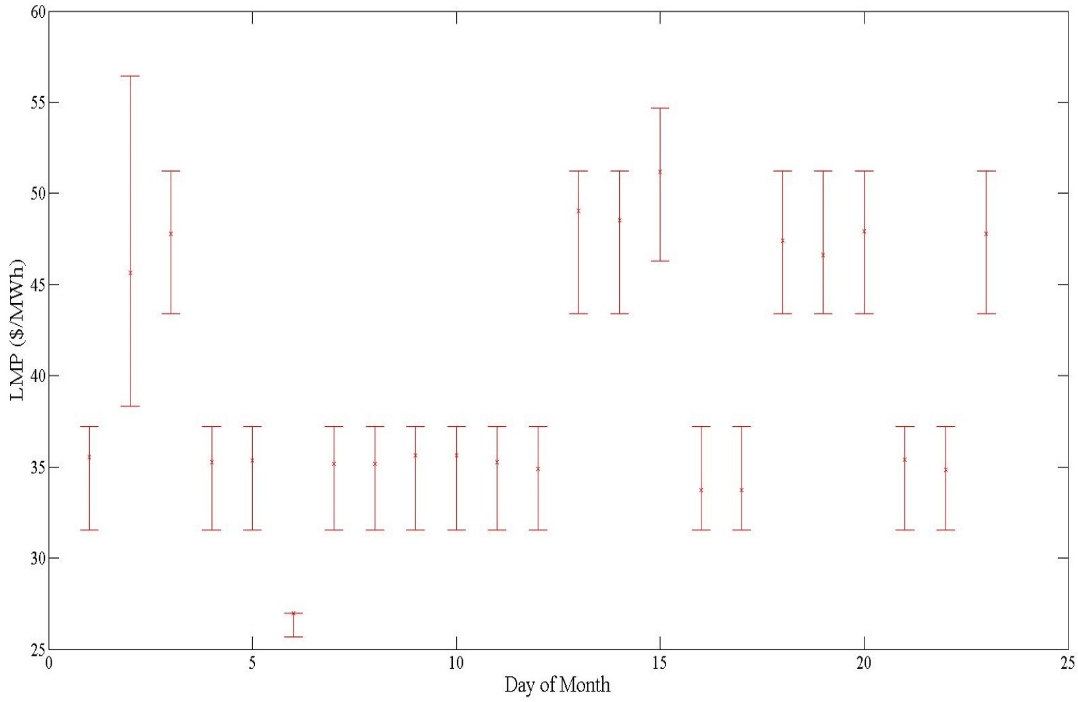


Figure 7.10: Range of prices at daily peak hour in November for Idaho

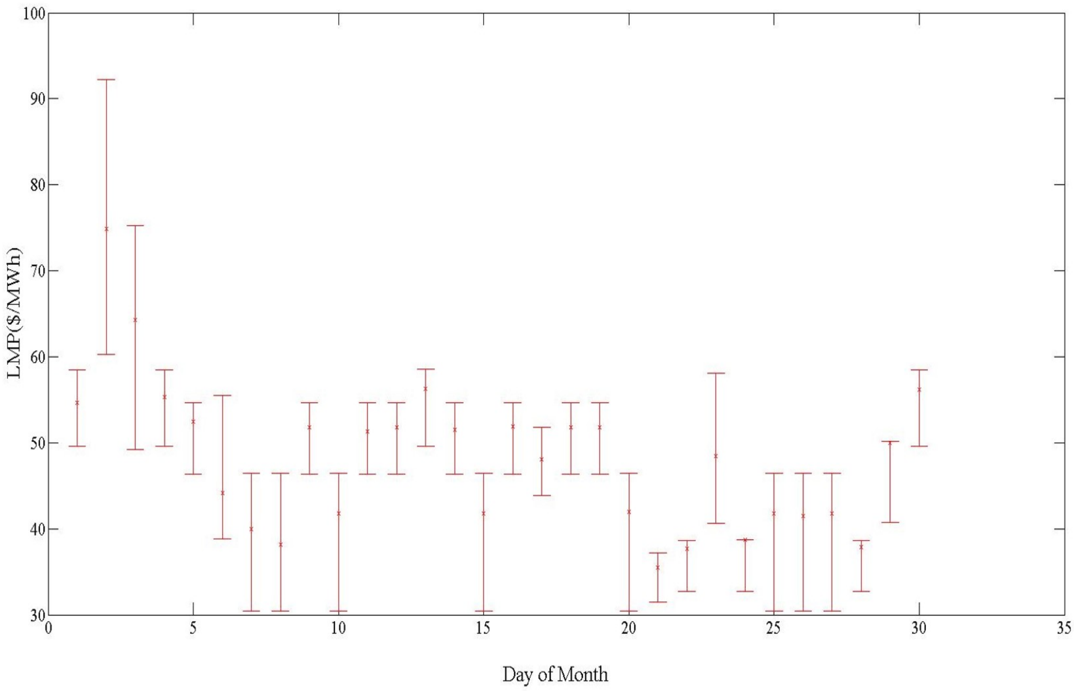


Figure 7.11: Range of prices at daily peak hour in May for Rocky Mt.

8 IBDR with High Penetration of RER

Global concerns of climate change and energy price have led to focused attention RERs. Among the RERs, wind power generation remains the dominant source. The uncertain nature of wind power and the relatively high investment costs create barriers to large scale grid adoption. Nevertheless, it is expected that 20% of the total consumption in U. S. will from wind power generation by 2030. The main research question is how best ISOs can overcome the negative impacts of wind power intermittency and facilitate grid integration. As of today, most power systems are operated under a "must take wind power" policy. The approach so far has been to manage the wind volatility and uncertainty through supply-side reserves. In this chapter, we show how the flexibility of the demand in terms of consumption modification could effectively mitigate the intermittency. An robust IBDR program considering real time market price forecast uncertainty is designed. In addition, customer behavior uncertainty is simulated in terms of an elasticity range [113].

8.1 Impact of RER Expansion on LSE benefit

The customer tariff prices are chosen as close to the monthly average of LMP based on the LSEs revenue objective function as in (4.1). Still, the LSE profit depends on the variation in market price. As LMP variation is related to time of year and RER output, the LSE benefit will also vary across regions and season. The impact of renewable expansion on profit is assessed based on both the average and standard deviation of the LMP. Two sets of examples are chosen: (1) PG&E and SMUD where LSE profit decreases after

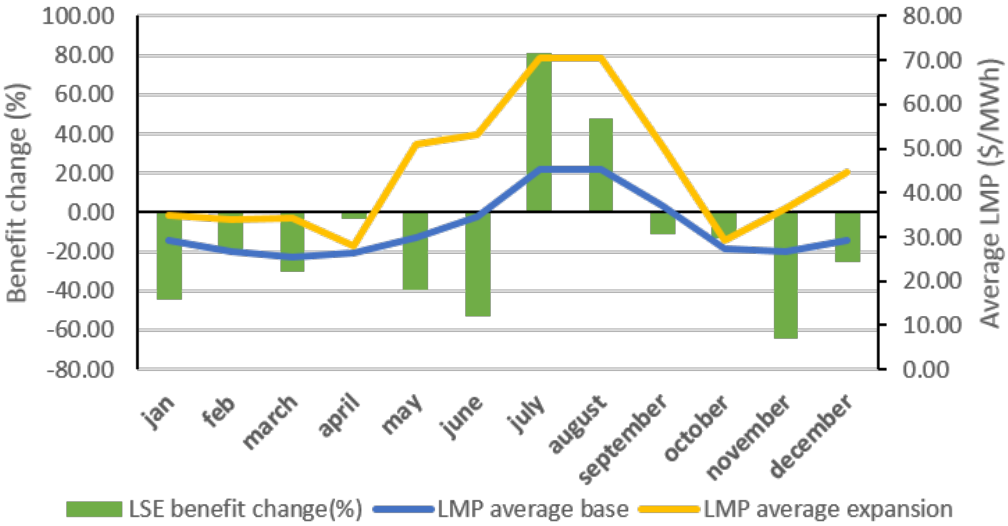


Figure 8.1: LSE benefit change in PG&E

expansion in all seasons, except summer; (2) Southwest, San Diego and LADWP where LSE profit is reduced in winter and fall but increases in summer and spring. Within the first set (Fig. 8.1), the monthly average of LMP and standard deviation increases for all months. Since the load in off peak is much lower than at peak, the LSEs lose profit relative to less price volatility. In summer, since standard deviation was high even before renewable expansion of renewable, the revenue change is minimal. Among the second group (Fig. 8.2), the change in average LMP is small and customer tariff remains relatively unchanged. As a result, LSEs lose profit in the summer and spring and increase profit in fall and winter.

In addition to above examples, there are three other regions where the impact of RERs on LSE profit is interesting to discuss. The Northwest loses throughout the year. The standard deviation of LMP in this region before expansion was small and so the price volatility increases greatly. This is an interesting example of how variation in market price can affect utility profit event if average costs remains approximately the same. In the Rocky Mt. and Idaho regions, the LSE profit increases throughout the year. These regions are closest to the location of large RERs and also have low load most of the year. Therefore, the average LMP decreases after expansion most of the year.

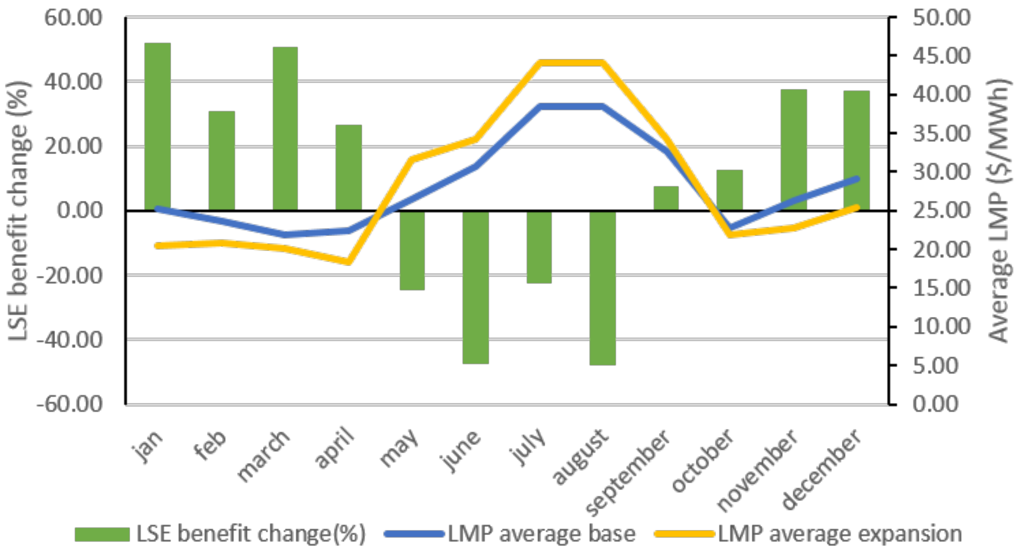


Figure 8.2: LSE benefit change in Southwest

8.2 Robust IBDR Optimization

In robust optimization, random variables are modeled as uncertain parameters that belong to a convex uncertainty set and primarily protect against worst case scenarios. In robust optimization, the uncertain quantities, either parameters or random variables, are modeled as parameters that belong to predefined intervals. One important concept in robust optimization is the level of conservativeness.

8.2.1 Ellipsoid Uncertainty

Ellipsoidal uncertainty sets are used in this study but they will increase the problem complexity. For example, the robust representative of a linear program is a second-order cone problem. Ellipsoidal uncertainty sets are deemed an appropriate choice here based on the Ben-Tal study [163]. Namely:

- A simple geometry of uncertainty is not mathematically interesting and provides little insight.

- An ellipsoid is a convenient entity as in can be represented in a simple parametric format and is well-behaved numerically.

- In many cases of stochastic uncertain data, probabilistic arguments allow one to replace stochastic uncertainty by an ellipsoidal deterministic uncertainty. For example, an uncertain Linear Programming (LP) problem with random entries in the constraint matrix. For a given x, the left hand side $l_i(x) = a_i^T x + b_i$ of the i^{th} constraint in the system, $A^T x + b_0 \geq 0$, is a random variable with expectation $e_i(x) = (a_i^*)^T x + b_i$, and standard deviation $v_i(x) = \sqrt{x^T V_i x}$. A typical value of the random variable $l_i(x)$ will therefore be $e_i(x) \pm O(v_i(x))$. For a light tail distribution of the random data, a likely lower bound on this random variable is $\hat{l}_i(x) = e_i(x) - \theta v_i(x)$ with "safety parameter" θ of order of one (cf. the engineers "3-rule" for Gaussian random variables). This bound leads to the "likely reliable" version:

$$e_i(x) - \theta v_i(x) \geq 0 \tag{8.1}$$

Note that the latter constraint is exactly the robust counterpart of the original uncertain constraint.

$$a_i^T x + b_i \geq 0 \ \forall a_i \in u_i \tag{8.2}$$

u_i is specified as the ellipsoid set as follows:

$$u_i = \{a : (a - a_i^*)^T V_i^{-1} (a - a_i^*) \leq \theta\} \tag{8.3}$$

8.2.2 Robust format of IBDR

To include elasticity uncertainty, the market price in (4.2) in chapter 4 is rewritten as:

$$\max \sum_{b=1}^{NB}\sum_{t=1}^{M}[-D_{bt}LMP_{bt} - \Delta\bar{D}_{bt}P_b^0 + \Delta\bar{D}_{bt}LMP_{bt} - \Delta\bar{D}_{bt}P_{bt}^{inc}] \tag{8.4}$$

$$\Delta\bar{D}_{bt} = \sum_{j=1}^{D_T} g_j P_{bt}^{inc} \tag{8.5}$$

$$\triangle D_{bt_j}^{\min} \leq \Delta D_{bt_j} \leq \triangle D_{bt_j}^{\max} \tag{8.6}$$

Substituting the equality constraint (8.5), we obtain:

$$\max \sum_{b=1}^{NB}\sum_{t=1}^{M}[-D_{bt}LMP_{bt} - \sum_{j=1}^{D_T} g_j P_{bt_j}^{inc} P_b^0 + \sum_{j=1}^{D_T} g_j P_{bt_j}^{inc} LMP_{bt} - \sum_{j=1}^{D_T} g_j P_{bt_j}^{inc} P_{bt_j}^{inc}] \tag{8.7}$$

$$\triangle D_{bt_j}^{\min} \leq \Delta D_{bt_j} \leq \triangle D_{bt_j}^{\max} \tag{8.8}$$

The equivalent minimization problem is:

$$\min \sum_{b=1}^{NB}\sum_{t=1}^{M}[D_{bt}LMP_{bt} + \sum_{j=1}^{D_T} g_j P_{bt_j}^{inc} P_b^0 - \sum_{j=1}^{D_T} g_j P_{bt_j}^{inc} LMP_{bt} + \sum_{j=1}^{D_T} g_j P_{bt_j}^{inc} P_{bt_j}^{inc}] \tag{8.9}$$

$$\triangle D_{bt_j}^{\min} \leq \Delta D_{bt_j} \leq \triangle D_{bt_j}^{\max} \tag{8.10}$$

Introducing the auxiliary variable Z, we simplify (8.9) to:

$$\min\ Z \tag{8.11}$$

subject to:

$$Z-[\sum_{b=1}^{NB}\sum_{t=1}^{M}\sum_{j=1}^{D_T} g_j P_b^0 P_{bt_j}^{inc}-\sum_{b=1}^{NB}\sum_{t=1}^{M}\sum_{j=1}^{D_T} g_j LMP_{bt} P_{bt_j}^{inc}+ \sum_{b=1}^{NB}\sum_{t=1}^{M}\sum_{j=1}^{D_T} g_j P_{bt_j}^{inc} P_{bt_j}^{inc}] \geq \sum_{b=1}^{NB}\sum_{t=1}^{M} D_{bt} LMP_{bt} \tag{8.12}$$

$$\triangle D_{bt_j}^{\min} \leq \Delta D_{bt_j} \leq \triangle D_{bt_j}^{\max} \tag{8.13}$$

In matrix representation, (8.12) is:

$$-P^0 G e^T P^{inc} + Z + GLMP^T P^{inc} - P^{inc^T} diag(G) P^{inc} \geq D^T LMP \tag{8.14}$$

And by adding uncertainty range of variable to (8.14), we have:

$$-P^0(G^0+u_1G^1)e^T P^{inc} + Z + (G^0+u_1G^1)(LMP^0+LMP^1)^T P^{inc} - P^{inc^T} diag((G^0+u_1G^1))P^{inc} \geq D^T(LMP^0+LMP^1) \tag{8.15}$$

$$\forall(u : \|u\|_2 \leq 1) \tag{8.16}$$

If there is a point in the ellipsoid $\|u\|_2 \leq \tau$ that cannot satisfy the constraint (8.15), the entire problem becomes infeasible. This possibility highly depends on the range of variation, which we can manipulate to gain insight into the problem. We first define conservativeness. In a linear problem, $\rho \geq 1$ is level of conservativeness $u = \{(A^0, b^0) + \rho(A^1, b^1)\}$. As ρ increases above 1, the feasible region shrinks and eventually fells inside the original feasible region. The smallest ρ for which this occurs is called the level of conservativeness. So we can increase the viable range by selecting a narrow range and increasing ρ. Conversely, we can start with a large range and decrease ρ to find the largest feasible set.

$$-P^0(G^0+u_1G^1)e^T P^{inc} + Z + (G^0+u_1G^1)(LMP^0+LMP^1)^T P^{inc} - P^{inc^T} diag((G^0+u_1G^1))P^{inc} - D^T(LMP^0+LMP^1) \geq 0 \tag{8.17}$$

$$\forall((u,\tau) : \|u\|_2 \leq \tau) \tag{8.18}$$

We want to make sure that if $\|u\|_2 \leq \tau$ then constraint (8.17) holds. If we replace the left hand side by w then we can write:

$$\tau - u^T u \geq 0 \Rightarrow w \geq 0 \ if \ \ \exists \lambda \geq 0 : w \geq \lambda(\tau - u^T u)$$

So if such a λ exists the problem is feasible. We can write this as another optimization problem as follows:

$$\max \tau \tag{8.19}$$

Subject to:

$$\|u\|_2 \leq \tau \tag{8.20}$$

$$\begin{aligned} &- P^0(G^0 + u_1 G^1)e^T P^{inc} + Z + (G^0 + u_1 G^1)(LMP^0 + LMP^1)^T P^{inc} - \\ &\qquad P^{inc^T} diag((G^0 + u_1 G^1))P^{inc} - D^T(LMP^0 + LMP^1)^T \geq \lambda(\tau - u^T u) \end{aligned} \tag{8.21}$$

$$\lambda \geq 0 \tag{8.22}$$

We use the τ as in the original model.

8.3 Robust IBDR Results

In this section, a deterministic and robust IBDR program are analyzed from different perspectives. The price uncertainty is obtained from chapter 7 with elasticity range is considered to be $[-0.05 \ -0.15]$ for small commercial and industrial customers and $[-0.1 \ -0.2]$ for the residential sector. An important component in this work is identifying risks that robust design can minimize.

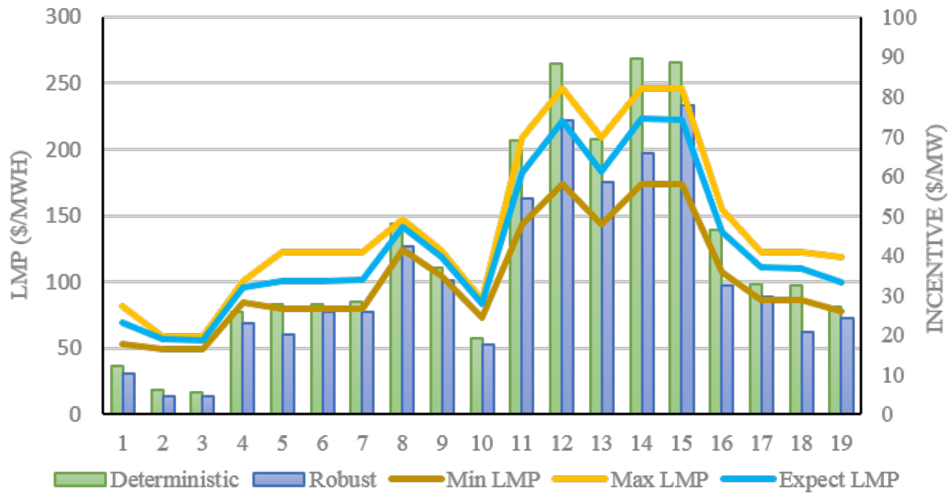


Figure 8.3: Hourly incentive payment vs. expected LMP in San Diego during July

8.3.1 Comparison of Deterministic and Robust Program

From the LSE point of view, an IBDR program faces risks due either unexpectedly high LMP or unexpectedly low LMP. For high LMP, LSEs should pay greater incentive and increase the demand response. In a deterministic solution, this situation leads under-payment for DR. For low LMP, the deterministic program results in over-payment of incentives.

As shown in chapter 3 for most times, the expected day-ahead LMP falls approximately midway between the lowest and highest possible LMP. In thess hours, robust and deterministic programs have similar results. This does not always though. In Fig. 8.3, an hourly incentive payment for deterministic and robust program vs. market price range are shown for peak hours in one week of July. When the expected LMP falls close to either the maximum on minimum LMP, then there is robust solution provides significantly different incentive payments. In Fig. 8.4, results are plotted in the Southwest region for one week in October. When risk of higher LMP is greater, e.g. hours 5, 6 and 7, robust pay greater incentive to the customers to take advantage of an “opportunity” in the market. For a lower price risk, e.g., hours 1, 2 and 3, robust pays less incentive to avoid unnecessary losses from over-payments.

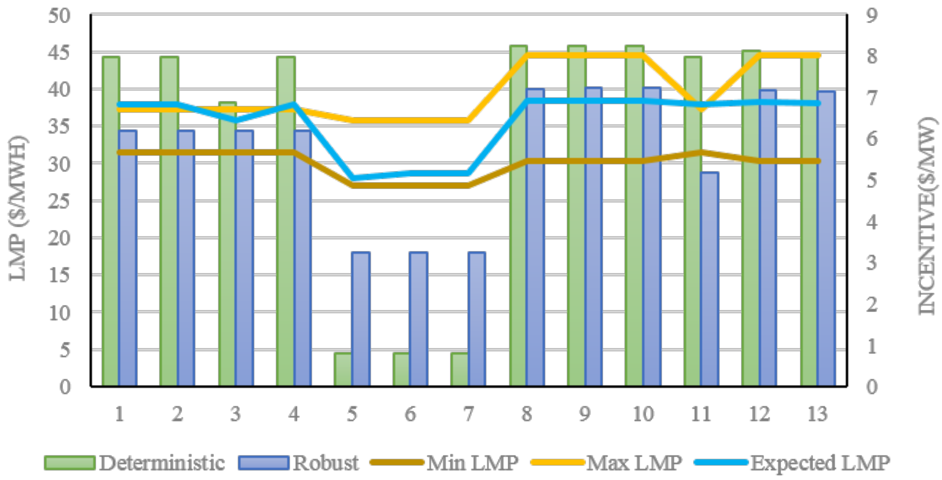


Figure 8.4: Hourly incentive payment vs. expected LMP in Southwest during October

If real time LMP deviates little the forecast value, then obviously the robust IBDR program has little benefit. Still, significant errors during only a few hours results in significant loss without the robust approach. Tab. 8.1 show LSE benefit under the two IBDR programs for expected case, low LMP and higher LMP cases. Note that profit loss the expected values covers an entire month but unexpected LMP reflects only an hour. Thus, the robust solution can cover lost profit with with just a few hours of unexpectedly high or low prices.

Another important comparison between robust and deterministic program is the effect on market price. Higher incentive payments will lead to greater DR. Therefore, considering low LMP concern, the robust solution pays less incentive, while for high LMP concern, the robust pays more incentive. Thus, the net effect should be less volatility in LMP. Fig. 8.5 shows LMP variation in one day at July for Bay area region. In hour 10, the robust solution lowers LMP but increases LMP during.

8.3.2 Effect of IBDR on LSE profit

Whether RER expansion results in profit loss or gain for LSEs, IBDR is an effective tool to reduce market peak prices and bring other benefits to all participants. IBDR

Table 8.1: Comparison of LSE profit by DR (different between robust and deterministic)

July			
Region	Expected	Low LMP	High LMP
Southwest	-$109,953	$55,277	$32,276
San Diego	-$10,022	$16,902	$6,362
LADWP	-$17,883	$7,307	$7,560
Bay area	-$20,152	$6,684	$2,939
Fresno	-$9,283	$3,480	$2,511
Rocky Mt.	-$43,855	$18,416	$16,077
Idaho	-$13,147	$5,130	$4,559
Nevada	-$9,387	$5,753	$6,038
SMUD	-$27,720	$8,722	$11,583
Feb.			
Region	Expected	Low LMP	High LMP
Southwest	-$160,336	$51,141	$47,221
San Diego	-$18,327	$4,410	$2,519
San Francisco	-$29,168	$2,134	$1,924
Bay area	-$193,073	$23,863	$20,679
Cnt. Coast	-$67,225	$7,434	$5,246
PG&E	-$267,146	$60,296	$80,058
rocky Mt.	-$209,917	$15,818	$14,758
Idaho	-$58,673	$11,492	$10,754
SCE	-$196,412	$19,161	$12,026

program design in this thesis is region based, so each region implements a DR program individually. Considering the total demand response, the LMP changes are considerable even with relatively small load changes in each region. Fig. 8.6 shows two examples of LSE profit change after RERs expansion and DR. In (a), several regions are shown that lose profit under RER expansion but DR decreases the percentage loss. In (b), several regions are shown that increase profit and under DR profit increases more. Fig. 8.7 shows the effect of DR on net revenue in regions where expansion has an overall negative impact on profit (part a) and an overall positive impact on profit (part b). In both cases, DR remains effective and helps compensate for economic consequence of high RERs.

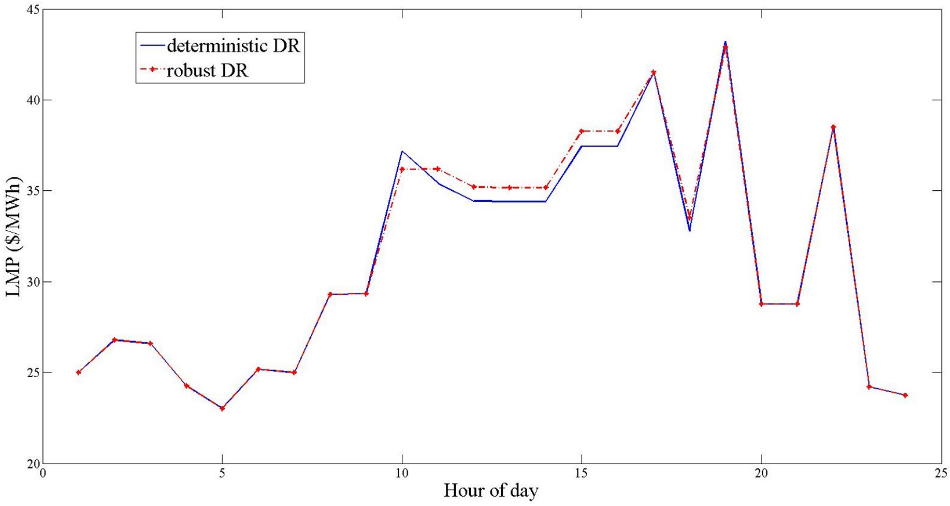


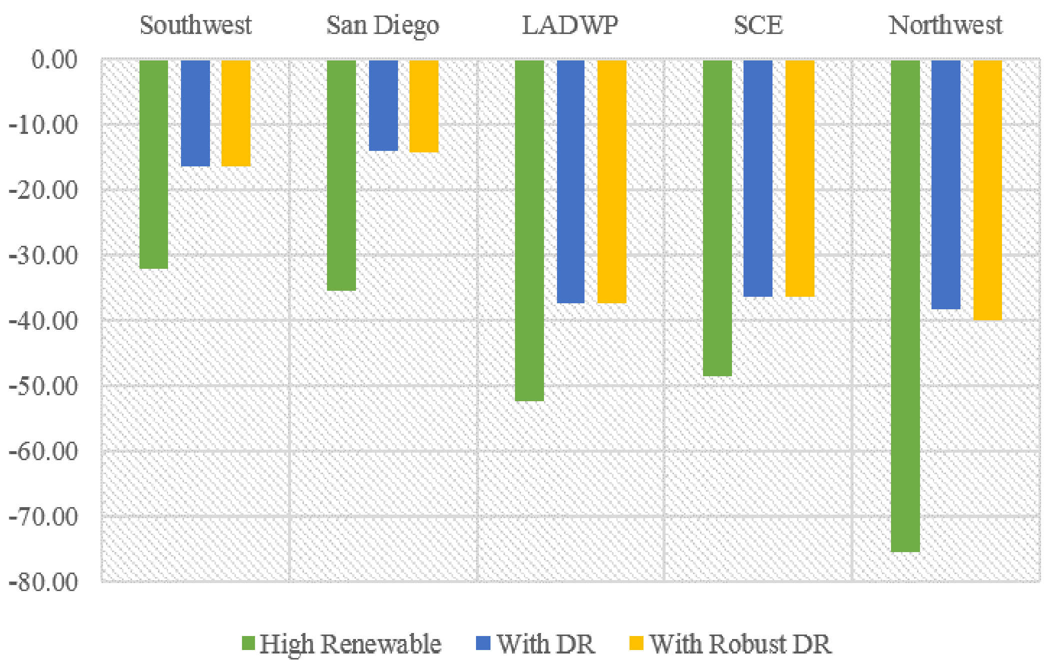
Figure 8.5: Effect of robust and deterministic program on LMP in Bay area during June

8.3.3 Customer savings under IBDR

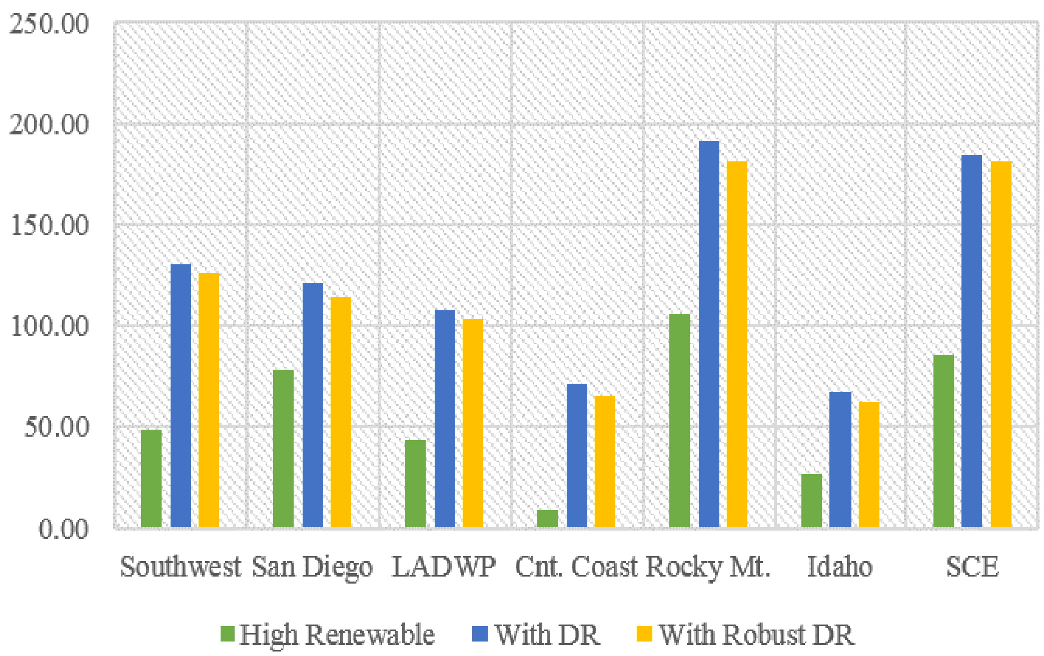
Fig. 8.8 shows customer saving per load change during summer and winter. As expected, summer has the greatest benefits for customers, since the load change in the peak season is more critical. The incentive payments shown in Fig. 8.8 indicate the proposed IBDR achieves acceptable saving for customers. The proposed IBDR in this thesis would be a voluntary program and would not change customers monthly tariff, but simply pay sufficient incentives to reward participants. That is, savings are only for customers who participate.

8.3.4 Effect of IBDR on LMP

In addition to benefits for load aggregators and customers, the proposed IBDR program will impact price, especially at peak times. In Fig. 8.9, Fig. 8.10 and Fig. 8.11, the LMP variation for the worss day of August, February and October is shown, respectively. The largest effect on LMP occurs during the summer higher sensitivity to load change at peak times and greater incentive payments from each LSE (Fig. 8.8). The effect of RER expansion on LMP variation can be seen in Fig. 8.11. While the LMP profile no longer simply follows load variation but follows RER generation profile. Still, DR reduces LMP

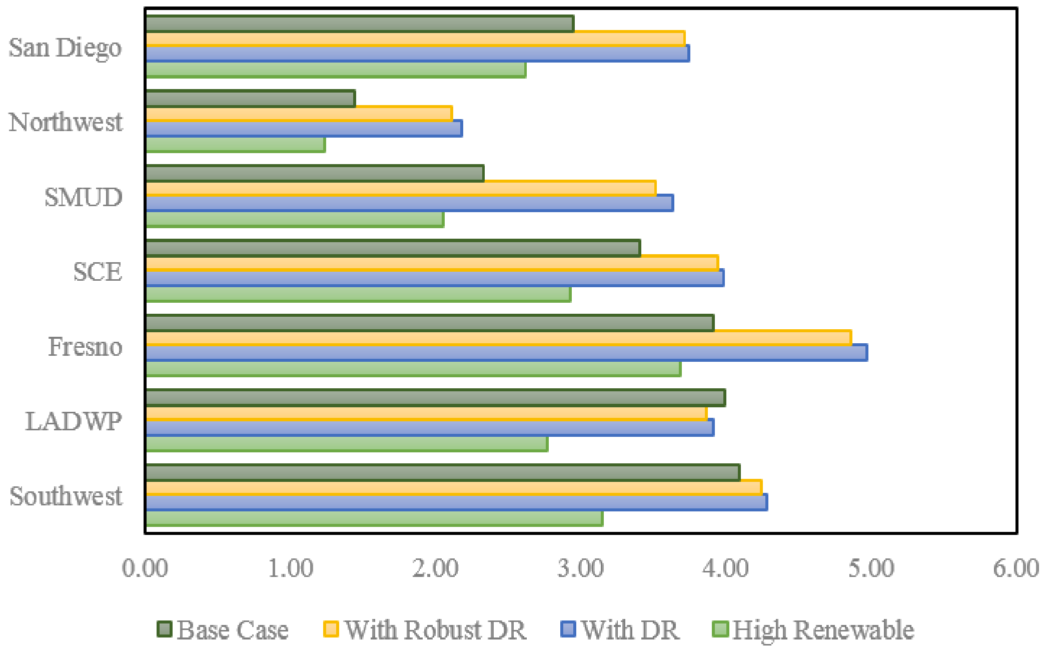


a) Profit loss (summer)

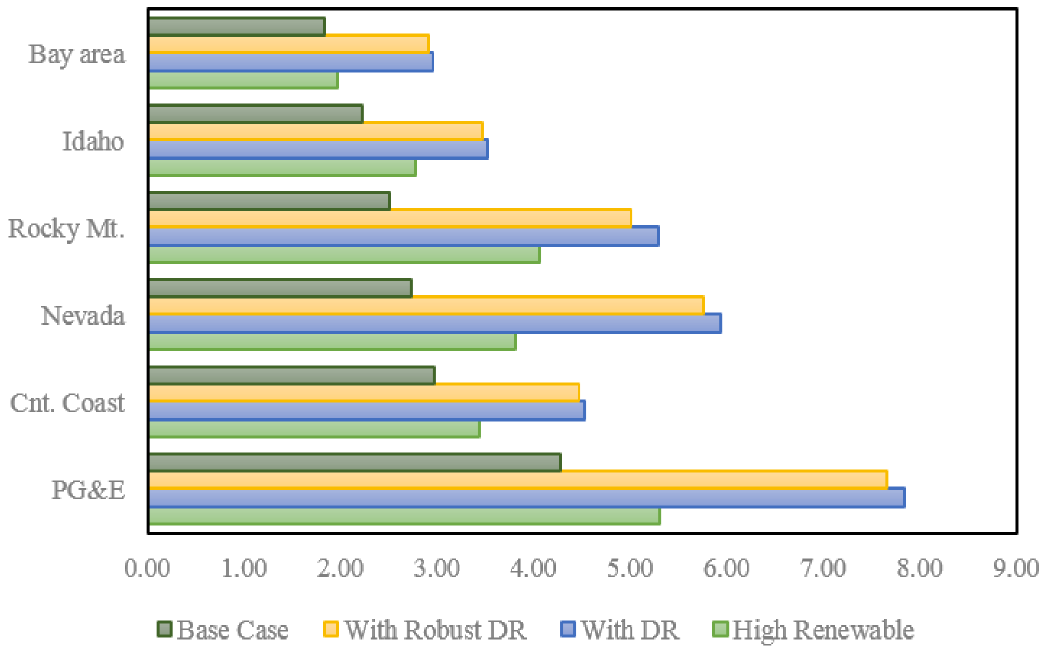


b) Profit gain (winter)

Figure 8.6: LSE benefit change under RER expansion and DR

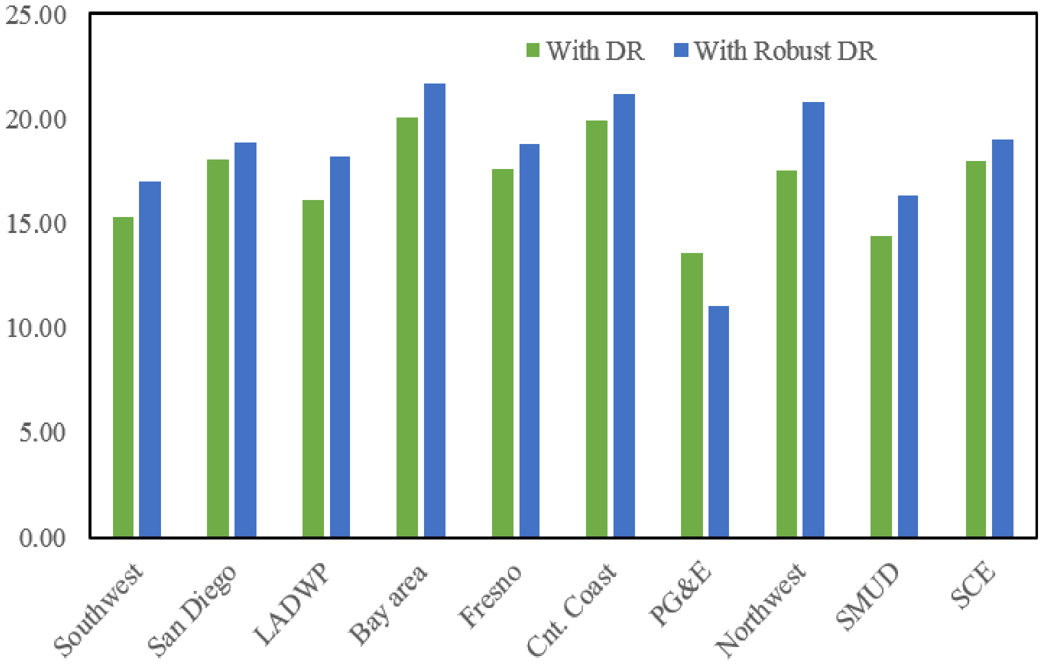


a) Profit loss

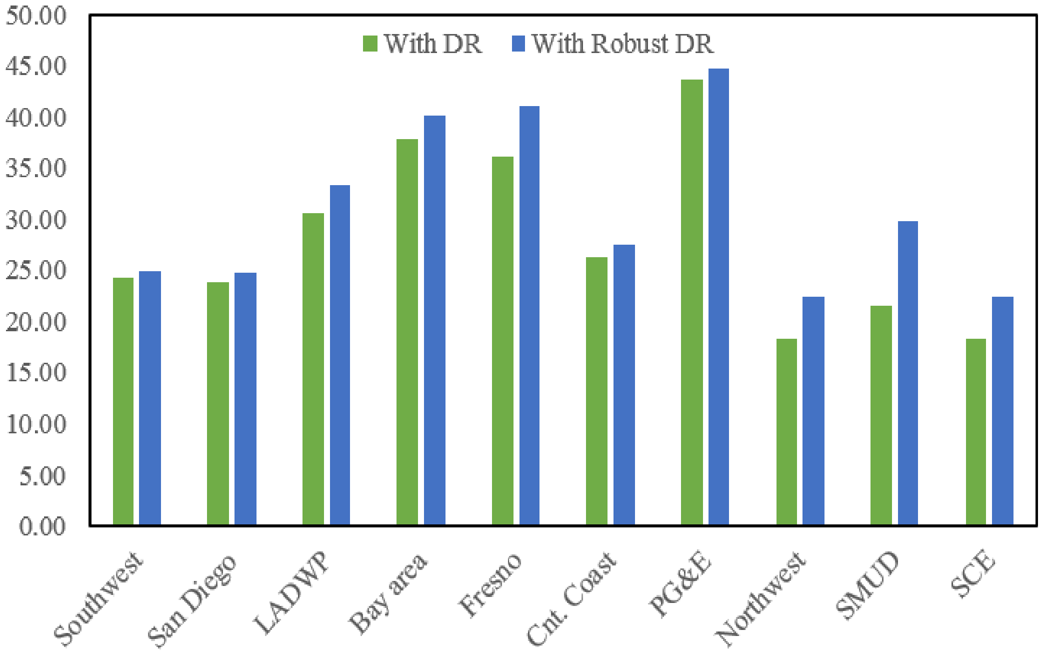


b) Profit gain

Figure 8.7: LSE net revenue change under RER expansion and DR



a) Winter



b) Summer

Figure 8.8: Customer saving under each IBDR program

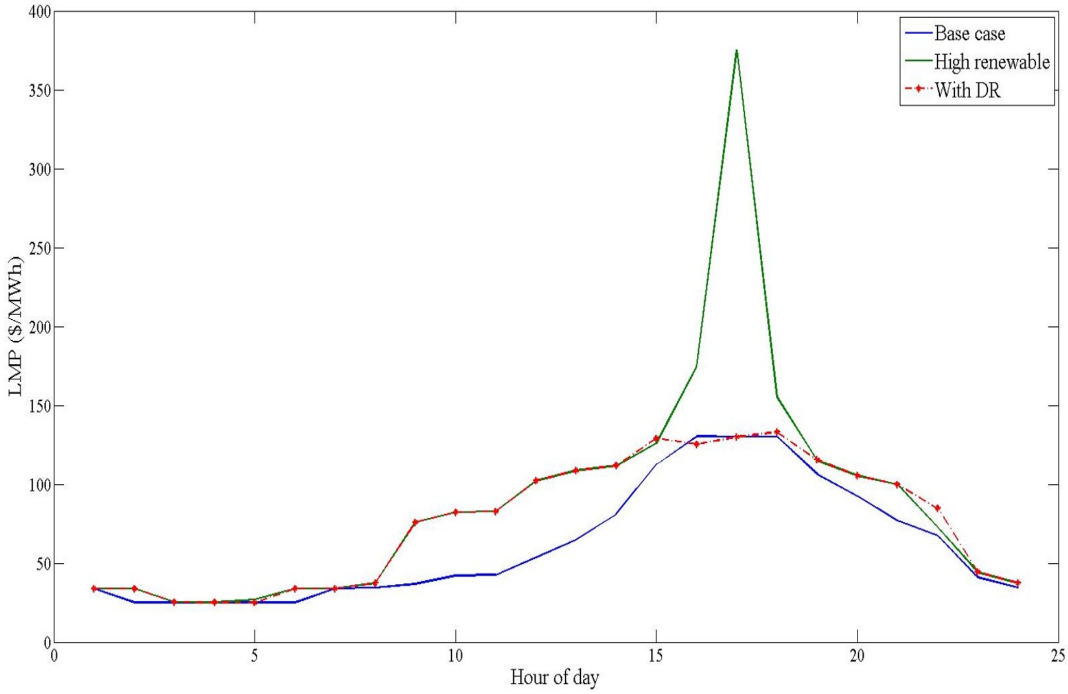


Figure 8.9: LMP variation in one day of August in Fresno

volatility.

8.4 Discussion on TOU Effectiveness

Implementation of an effective TOU program after RER expansion is challenging as the variation of LMP does not follow a regular pattern that customers could anticipate. Note the following situations:

- Low load and high RER production. The variation of price in one day will not match the typical specific peak and off peak hours, because LMP variation mostly follows the RER output instead of load profile. An example is show in Fig. 8.12 for Idaho during first four days of October.

- High load and low RER production. iWe can find peak and off peak period for each day individually but they will still vary across days. Even though RER output is low, the RERs still have the highest influence on LMP value. The peak prices

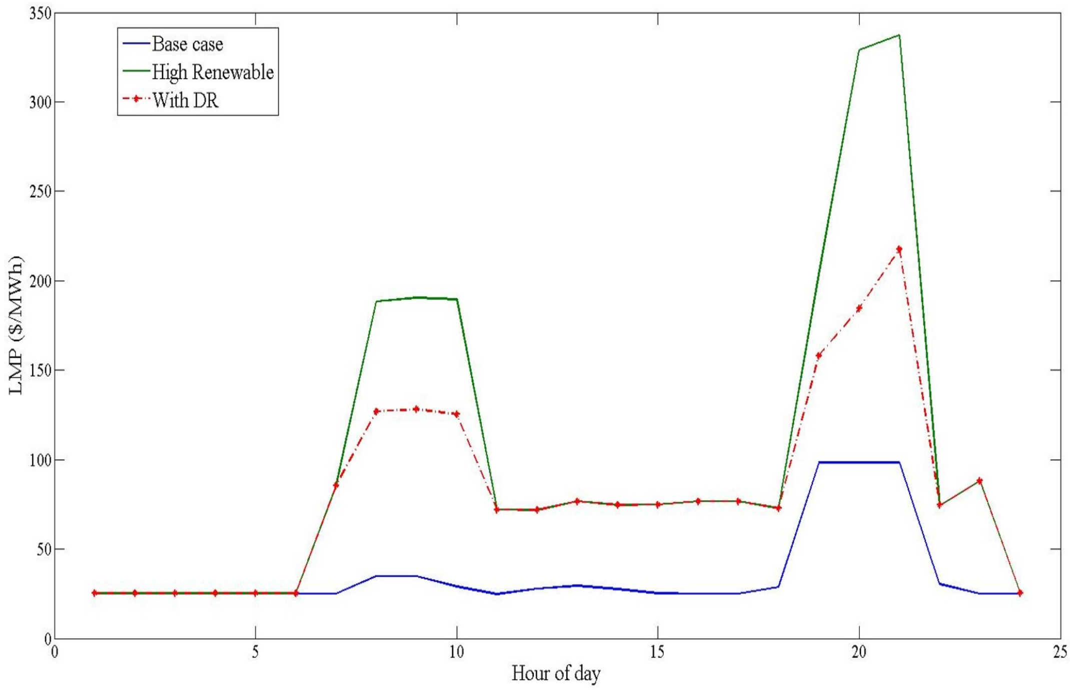


Figure 8.10: LMP variation in one day of Feb. in PG&E

occur during the lowest RER production. An example is shown in Tab. 8.2 for the San Diego area in March. The table compares day two and three as an example to variation in peak hours. To design an effective TOU program, the peak and off peak time period must be changed each day.

- Moderate load and moderate RER production. Peak and off peak time periods are relatively similar each day; however, the LMP value varies greatly. The TOU can be designed based on constant peak and off peak period with a varying tariff from day to day. An example is shown in Fig. 8.13 for Rocky Mt. during one week of January.

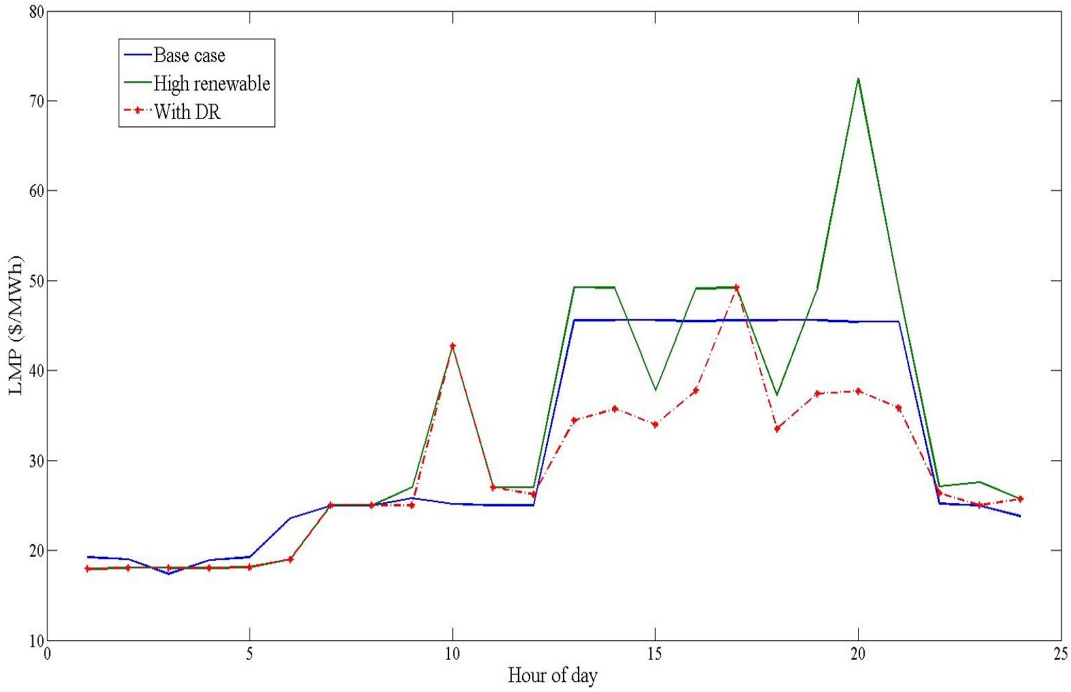


Figure 8.11: LMP variation in one day of October in Nevada

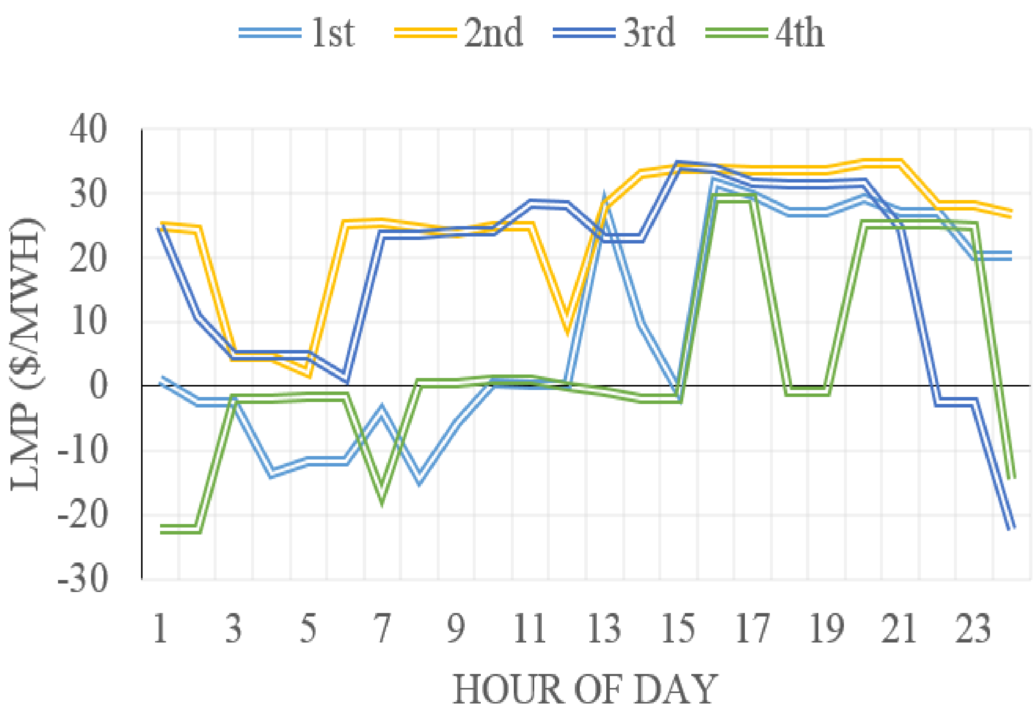


Figure 8.12: LMP variation during 4 days of October in Idaho

Table 8.2: Peak and off peak periods from March 8th to 14th in San Diego

Off peak hours						
Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
1	1	1	1	1	2	1
2	2	14	2	2	4	2
3	4	15	3	3	5	3
4	3	16	4	4	14	4
5	5	17	5	5	15	5
6	6	18	6	6	16	6
19	7	19	7	7	17	7
20	8	20	8	19	18	8
Peak hours						
Day 1	Day 2	Day 3	Day 4	Day 5	Day 6	Day 7
7	12	2	13	8	1	12
8	13	3	14	9	3	13
9	14	5	15	10	6	14
10	15	4	16	11	7	15
11	16	6	17	12	8	16
12	17	7	18	13	9	17
13	18	8	19	14	10	18
14	19	9	20	15	11	19

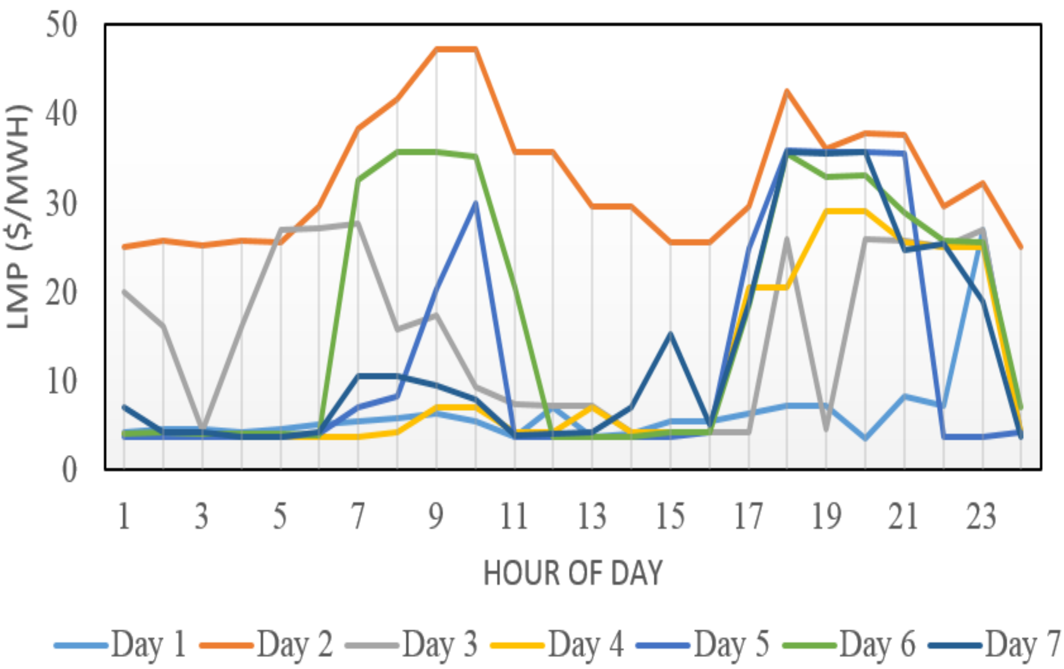


Figure 8.13: LMP variation in one week of January in Rocky Mt.

9 Estimation of IB Elasticity for Residential Customers

A key factor in the design of almost all demand response programs is the load elasticity. Elasticity is a measure of the customer response to a tariff or incentive. Due to the complexity of human behavior and corresponding electricity use, demand elasticity remains poorly understood. Many studies have been conducted over the years to estimate elasticity of electricity demand to price signals, particularly, during the 1980s and early 1990s when energy prices were rising rapidly and concerns about energy conservation increased [173]. The majority of these studies use an electricity demand modeling technique to calculate price and income elasticity of electricity; however, they almost exclusively focus on on PB elasticity. There is a need for further research on IB elasticity. This chapter explores this subject.

9.1 Problem Statement

The distinction between customer response to a price or incentive signal is the main motivation for this study. IBDR as a reward program should compare favorably to PBDR programs as customers tend to see PB approaches as a punishment. There are three components of elasticity explored in this chapter:

- elasticity of residential customers,
- elasticity toward an IBDR program, and

- elasticity specific to different household appliances.

9.1.1 Residential customer

The residential sector makes up about 40% of total electric energy consumption. At peak time, the share is higher and it can be as much as 50% of consumption. In addition, according to U.S. energy information administration, residential sector load is growing and demand is expected to increase at least 15% by 2040 [167]. Historically, industrial and large commercial loads are considered to be best candidates for DR programs due to the challenge of controlling large numbers of small residential loads. Still, residential loads can provide more reliable response in compare with small number of large loads [174]. Local controls in the residential sector can allow for faster response [175, 176]. Finally, smaller loads can effectively provide continuous response unlike larger loads [177]. Today, DR potential of residential sector remains untapped.

9.1.2 IBDR programs

IBDR is a reward system in contrast with PBDR programs that can be seen as a punishment (paying a penalty) program. Studies show that people subject to punishment type programs are more nervous, less happy and are less responsive [178]. People are more likely to accept incentive contract described in bonus terms than contracts that appear exactly the same except for being explained in penalty terms [179]. In addition, customer's preference for reward based programs increase with experience that makes IBDR programs more effective over the long term [180]. Other concerns about PBDR programs include the need for extensive infrastructure to implement on a large scale, social equity and price volatility [181, 182]. Generally, retail customers are risk-averse and not willing to make decisions about consumption on hourly basis as is required for PBDR programs, such as, TOU [183]. Precise evaluation of the IBDR program on other hand is highly related to elasticity.

9.1.3 Household appliance usage

Elasticity at household appliance level is similar to the concept of distributed control of different appliance in residential demand management programs [184, 185]. Residential load can be classified into two categories: controllable and critical. Critical loads that are very important in a customer's life with interruptions highly inconvenient or dangerous. Controllable loads are those that can be shifted in time without as great an impact on consumers lifestyle [186]. Space cooling and heating, water heating, lighting and washing device are generally considered controllable. HVAC has the main potential as a DR resource because of the relatively large power consumption. Overall, about 25% of total electric energy consumption belongs to air conditioners, ventilation and heating [167]. In addition, they are easily defer able since buildings have thermal inertia. Washing devices do not have much power consumption, but can be easily rescheduled without significant effect on comfort. Assessing elasticity at the appliance level can lead to more accurate estimation of the effectiveness of DR programs.

9.2 Methodology

Elasticity is generally the proportion of relative change in demand for a product that is caused by a change in the price of the product. Generally, the demand for most products decreases as the price of the commodity increases. This is true for electricity as well, therefore elasticity of electricity has a negative sign. In addition since electricity is so critical in today's life, price change would hardly effect consumption of customer. Therefore, elasticity of electricity is small and less than unity most of the times. Elasticity is formulated as follows:

$$\varepsilon = \frac{\frac{\partial q}{q_0}}{\frac{\partial p}{p_0}} = \frac{\frac{\partial (q' - q_0)}{q_0}}{\frac{\partial (p' - p_0)}{p_0}} \cong \frac{\frac{(q' - q_0)}{q_0}}{\frac{(p' - p_0)}{p_0}} = \frac{\frac{\triangle q}{q_0}}{\frac{\triangle p}{p_0}} \tag{9.1}$$

For IBDR , price change would substitute by incentives upon customer monthly electricity bill:

$$\varepsilon = \frac{\frac{(q^{'} - q_0)}{q_0}}{\frac{(b' - b_0)}{b_0}} = \frac{\frac{\triangle q}{q_0}}{\frac{\triangle b}{b_0}} \tag{9.2}$$

9.2.1 Approach

Approach for calculation of elasticity in (10.1) accordingly requires estimation of the load change and incentives.

9.2.1.1 Financial incentive calculation

There are different ways to estimate customer's financial incentives expectation. Process of estimation is both complicate and divers. Perhaps one of the best way is directly asking customers. This means a survey should design for each target customers to get information about their desired incentives. However, there is tight relation between incentive amount and load change that makes this step complex. Customers should know how much they should change their consumption to fill out their desired incentives, and in other hand, utility should know how much response they would be received to estimate their affordable incentives. To overcome this complexity, there is two ways. One is that utilities should ask several questions to cover different possibilities. This method, although would give more comprehensive vision of customers, but it makes survey too long and tedious. Alternative way is to ask about optimum situation that is acceptable for both customers and utility. In this chapter, second method is chosen.

9.2.1.2 Load change calculation

Another step of elasticity estimation is calculation of load change in response to financial incentives as illustrates briefly in Fig. 9.1. Since elasticity in this chapter is based on

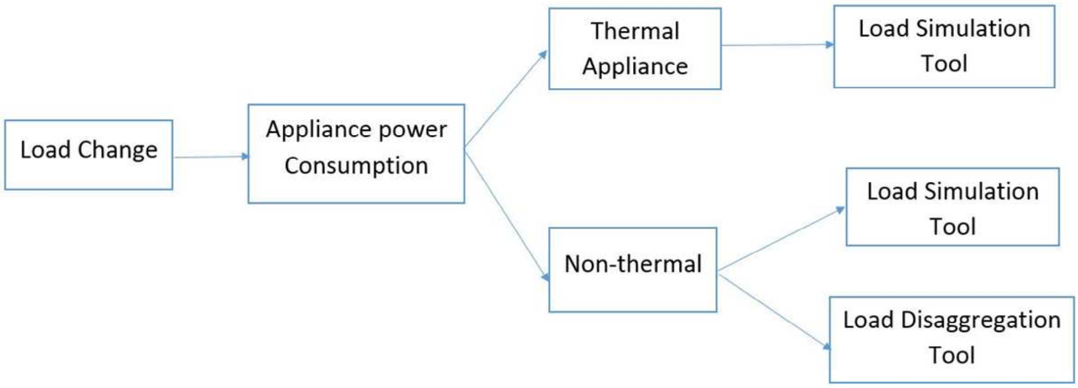


Figure 9.1: Methodology Diagram

appliance, so load change for each one should calculate separately. There is two ways to determine hourly power of each appliance, bottom up model and load disaggregation. In bottom up model, each individual house energy would calculate based on some basic information, like their life style, number of residence, area of house, outdoor temperature, parameter of their electric device and etc. In this method, power consumption of each appliance and load change could be both calculate with one tool. In case of lack of information, load disaggregation method could be useful. This method uses historical data to separate each device energy signal from aggregated one.

Controllable appliances divide into two groups, appliance with thermal setting and other devices with ON/OFF switch. For thermal appliance like HVAC, water heating and refrigerator, it's against customer's comfort to completely shut them down. One way to save energy of these devices is to change their thermostat setting temporarily. Therefore problem for these devices is converting the thermostat change to MW change during the DR hour and calculation of returning load after DR hours. For this type of device it is necessary to have access to appropriate toolbox to simulate their power in order to convert temperature changing to MW.

For other appliance that could stop their consumption, like lighting, or shift them to off peak hour like washing device, no conversion to MW is needed. Either load disaggregation method or load simulation tools could be helpful [191].

9.2.2 Data Estimation

In this subsection more details would be given on procedure of elasticity estimation by explaining following tools: survey for incentive expectation evaluation, and Matlab based toolbox for residential load modeling.

9.2.2.1 Survey Platform and Participants

The two survey studies were conducted through Amazon's Mechanical Turk (MTurk). MTurk is a crowd sourcing internet market place which enables researchers and companies to collect data on human intelligence tasks rapidly and inexpensively. Mturk has been received great popularity among social scientists as a useful research tool to collect data . To ensure the relevance and representatives of the data, only people who live in the U.S. were asked to take the surveys. Surveys ran on two different season, winter and summer respectively, to test customer's reaction at different outdoor condition.

For the first survey, valid responses were collected from 665 U.S. residents. Among the 711 respondents, 54.7% were females. Ages ranged from 18 to 75 (Medium = 30). The majority of participants were White (81.80%), followed by Asian (5.11%), Black (4.51%), and Hispanic (3.91%). Nearly half of the participants had at least a bachelor's degree or equivalent (47.14%). 60.16% participants had an annual household income higher than \$35,000, including a 21.63% having an annual household income higher than \$75,000. 35.49% identified themselves as democrats, while 15.04% identified themselves as republicans.

For the second survey, 754 valid responses were collected, and the demographic characteristics were similar: 58.2% were females. Ages ranged from 18 to 72 (Medium = 32). The majority of participants were White (83.82%), followed by Black (4.91%), Hispanic (4.38%), and Asian (3.58%). A little over half of the participants had at least a bachelor's degree or equivalent (52.24%). 67.02% participants had an annual household income higher than \$35,000, including a 27.10% having an annual household income higher than

$75,000. 40.05% identified themselves as democrats, while 28.25% identified themselves as republicans.

The two surveys were composed of similar parts as follow: first, respondents answered the type of heating and cooling devices that they use, source of energy, whether someone stays at home between 9 am and 5 pm, and the usual thermostat setting during the summer and winter. Second, respondents were proposed with a series of DR behaviors, and asked to choose the minimum amount of money (scaled as a percentage of average monthly bill) they would accept in exchange for adopting those behaviors. The major behaviors included:

1) Raising/lowering HVAC thermostat setting for 2-3F^0 during summer/winter when someone is at home.

2) Raising/lowering HVAC thermostat setting for $5F^0$ or more during summer/winter before everyone will be away for more than 4 hours.

3) Letting utility companies adjust HVAC thermostat setting for 2-3F^0 during summer/winter when someone is at home and the system load is high.

4) Shutting down HVAC devices for 10 minutes or 30 minutes as soon as receiving an emergency message from the utility company.

Fig. 9.2 shows the answers of survey 1 participants to second part of questions. As it shows, majority of customers need at least 10% incentives to modify their consumption. Another interesting point is that, number of people who don't change their load at all, would significantly increase if utility wants to automatically adjust thermostat setting. It shows people are concerned about their freedom and privacy. This could support this claim that people are better responding to volunteer program than automation DR programs.

Also, it is worth to point out, that during emergency situation, acceptable number of people are willing to change their load without any incentives. They only need appropriate message to informed them.

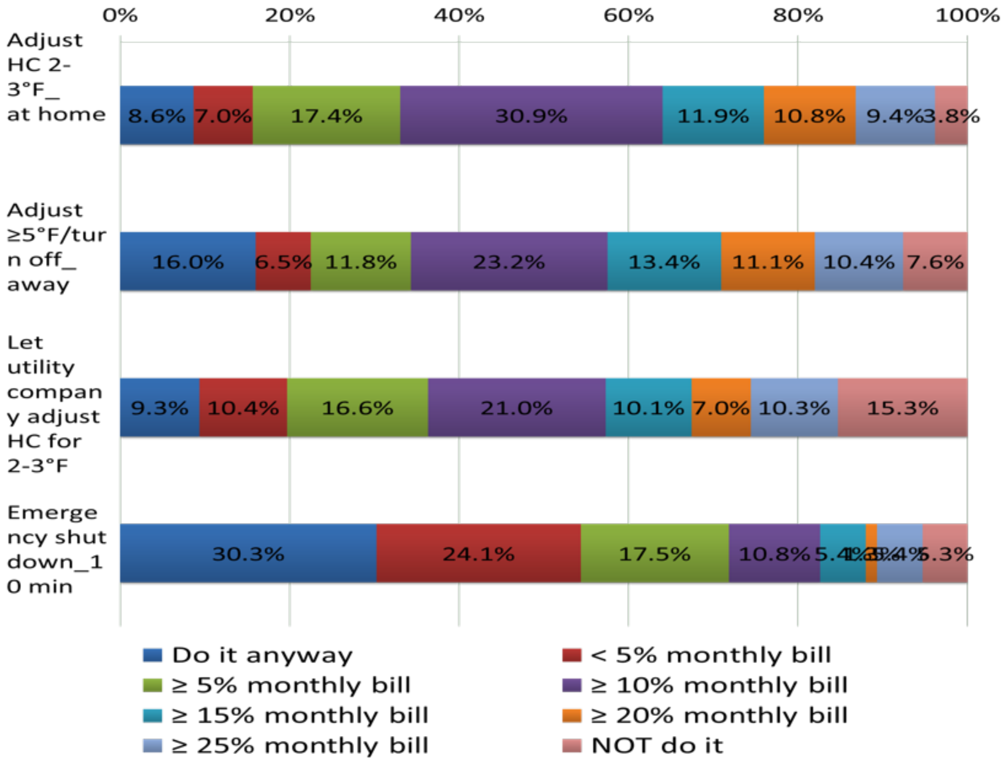


Figure 9.2: Participant response to different incentive value questions

Third, respondents were asked to rate their electricity saving habits, such as "turning off lights when not in use" and "raising/lowering the cooling/heating temperature when sleeping or away from home" on a Likert scale from 1 ("never") to 7 ("always"). At the end, social-psychological variables (such as concern for environmental impacts, bill/money consciousness, need for comfort, and trust in utility companies) were measured and demographic information was collected.

We could divide survey participants based on their response to incentive expectation to three groups. Low contribution groups which asks for more than 20% incentives, high contribution which request less than 10% and medium contribution group. Although there is not any dominant demographic characteristic between these groups, but still some statistical pattern are interesting in these groups. Fig. 9.3 and Tab. 9.1 show some statistical difference between low and high contribution groups.

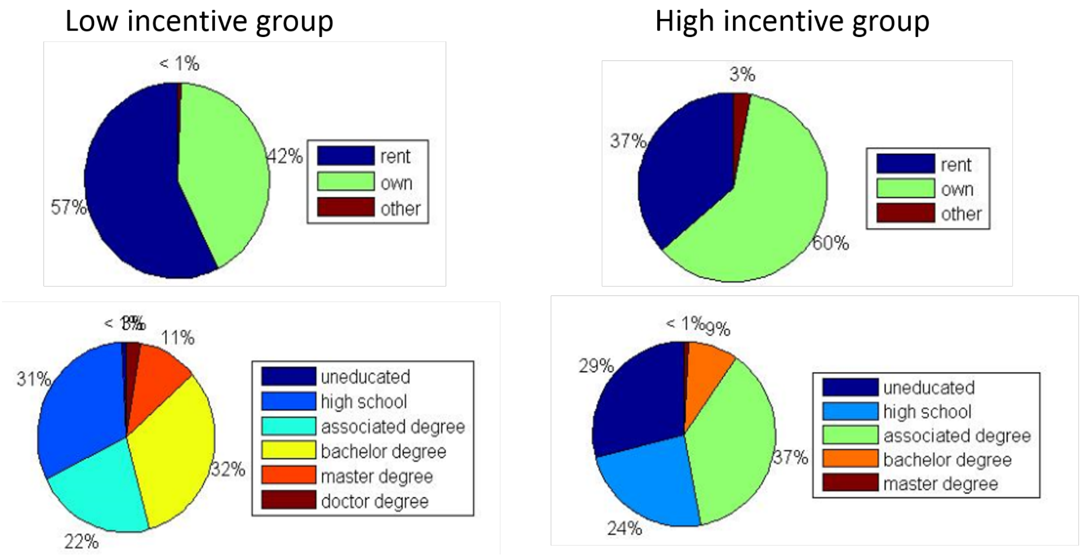


Figure 9.3: Education and rent/own distribution within different groups

Table 9.1: Demographic distribution in low and high contribution groups

characteristic	High cooperative	Low cooperative
Age	More younger	Less younger
Rent / own	More rental	Less rental
Education	Higher education	Even distribution
House occupant	Less occupant	More crowded
Income	Less income	Higher income
Male / female	Even distribution	More female
House area	Average house	Larger house

9.2.2.2 Residential load simulation

B. Johnson [187] develops Matlab based dynamic model for residential appliance including home's heating, ventilation, and air conditioning (HVAC) system, water heater, refrigerator, freezer, washer, dryer, dishwasher, lighting, cooking, television and computer. The dynamic model development is based on three items. First, occupant behavior and residential activity pattern for an appliance are developed using data from the American Time Use Survey (ATUS) [188]. Second, dynamic models for each appliance are built using available literature. Third, these models are combined to produce a model of residential power demand. This model is based on statistics of contribution of each appliance in residential load consumption, typical power rating of each of them and demographics of the overall population.

For model validation, multiple resources is used. The Oak ridge National Laboratory rotating shadow band radiometers is used for recording local environmental data [189]. Residential load power consumption data is collected from ten control house in TVA's Campbell Creek energy efficient homes project and occupied home in Atlanta, GA is used to validate individuals load models [190].

Residential appliance divide to four groups in this model, thermostatically controllable load, deferrable load, uninterruptible load and additional load power. Details on modeling of each appliance is given in reference [187, 188]. Using the information that is given in two surveys, this toolbox is used to estimate power consumption of people who participate before and after load change in Feb. and July of 2013.

9.3 Elasticity per appliance

For elasticity estimation of each device two values should calculate, load change and incentive expectation. In Tab. 9.2 these values are listed for main appliances at home, HVAC, lighting and washing device. Incentive amounts are derived from survey 1 and load change is calculated using toolbox that is introduced in sec. 9.2.2.2. Load modification is implemented for peak hour from 17:00 to 22:00.

Since in (10.1) both numerator and denominator must be in percentage, incentive expectation is divided by monthly bill of survey participants.

In both months, highest elasticity belongs to lighting. It seems that energy saving from lighting is relatively easy for most people to accept and they expect minimal incentives to turn off extra lights. Elasticity among the various washing device appears relatively and independent of season. HVAC depends highly on season as might be expected given the variable needs of the year and different tolerance of hot and cold temperature.

Another point that could be discussed in Tab. 9.2 is load change of each appliance in compare with total load change. This point could be more explained by Tab. 9.3 that

Table 9.2: Survey1- elasticity report

Survey 1 July (%)				
Appliance	Appliance change	Total change	Incentive	Elasticity
HVAC	4.77	2.71	13.01	0.21
Lighting	38.75	1.55	3.43	0.45
Dishwasher	35.57	0.65	5.46	0.12
Washer	28.32	0.11	6.05	0.23
Dryer	28.52	1.27		
Survey 1 Feb. (%)				
HVAC	2.15	1.2	10.96	0.11
Lighting	28.27	1.41	3.37	0.42
Dishwasher	41.81	0.71	5.24	0.13
Washer	30.95	0.13	5.88	0.27
Dryer	31.2	1.47		

Table 9.3: Share of each device in aggregate signal

July	Daily ratio (%)			Peak ratio(%)		
Appliance	Average	Min	Max	Average	Min	Max
HVAC	55.54	40.1	67.5	53.2	30.7	66.9
Lighting	4.7	3.4	6.9	6.2	4.1	12.4
Dishwasher	1.6	0.9	2.3	3.1	1.7	5.5
Washer	0.4	0.3	0.6	0.4	0.3	0.7
Dryer	4.6	3.1	7.1	5.4	3.3	8.9
Feb.						
HVAC	52.2	35.6	74.4	37.6	22.9	70.8
Lighting	5.8	3.1	7.8	10.8	5.5	14.2
Dishwasher	1.6	0.8	2.4	3.8	1.3	5.4
Washer	0.4	0.2	0.5	0.5	0.2	0.7
Dryer	4.6	2.1	6.4	6.1	2.4	8.2

shows share of each appliance in aggregated load signal. In this table, average, maximum and minimum contribution of each appliance power signal in monthly energy signal is shown.

In Tab. 9.3, HVAC has highest contribution in total load signal by consuming on average half of total load. For washing device, although customers contribution for load shift program is acceptable and about 30% are willing to delay their washing program from peak time to off peak, but since their power consumption is low, total load change is small for this appliance and therefore elasticity is not significant number.

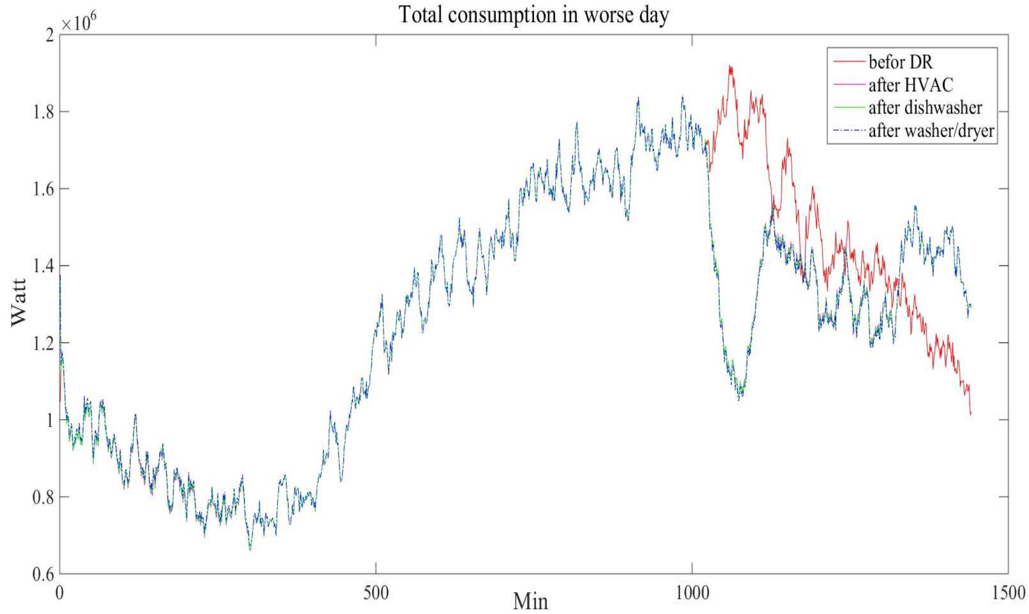


Figure 9.4: Load signal of survey2 participants- July 2013

In Fig. 9.4 aggregated load signal is shown after HVAC and washing device load change for hottest day in July 2013 considering survey 2 participants. Thermostat modification has significant effect on load signal at peak hour. However, effect of washing device load change is hardly noticeable on load profile. For washing device load is deferred form peak time to off peak, so in Fig. 9.4 it's shown at early morning that modified load curve is higher than original one. In addition for HVAC device, thermostat setting change should return to its original point for customer comfort after peak time, therefore load consumption after 22:00 is considerably higher than original load level. To avoid new peak load after 22:00, returning to original thermostat setting should be distribute in time. In this chapter, DR end signal is administered in two hours.

9.4 Elasticity for HVAC Device

Generally speaking, highest portion of residential electricity consumption belongs to air conditioner device (depending on the region), therefore its worth to study it in more details. Elasticity is load change divided by incentive asking; so customers could be

Table 9.4: Survey2- HVAC elasticity report

July	Total saving	Incentive	Average Energy (MWh/m)	Elasticity
≤64	1.36	9.05	1.261	0.151
65 -68	2.41	10.30	1.058	0.234
68 -70	2.7	11.12	0.904	0.242
70-72	2.92	10.85	0.791	0.269
72 -74	3.06	10.14	0.682	0.3013
74 - 76	3.16	12.88	0.575	0.246
76 - 78	3.22	10.44	0.479	0.308
78- 80	3.08	11.81	0.381	0.261
≥80	3	10.79	0.3	0.2782
Feb.				
≤64	0.64	9.39	1.196	0.069
65 -68	1.27	10.61	1.134	0.1195
68 -70	1.26	11.82	1.22	0.107
70-72	1.29	11.54	1.274	0.112
72 -74	1.2	10.5	1.435	0.1142
74 - 76	1.18	12.57	1.622	0.094
76 - 78	1.12	10.67	1.549	0.105
78- 80	1.19	9.4	1.979	0.126
≥80	0.98	9.75	2.308	0.101

divide based on their incentive requesting or their level of consumption.

9.4.1 Elasticity for Different Consumption Level

In this subsection customers segmentation based on different load levels is illustrated. HVAC consumption is highly related to its thermostat setting, so in this part customers are divided based on their thermostat settings. Load change and incentive needing for each group is summarized in Tab. 9.4 for July and Feb., using survey 2 participants.

In Tab. 9.4 although incentive requesting of different groups are similar, but energy saving and as a result elasticity is different in each group. Power saving is highly related to average power consumption of each house as it shown in Fig. 9.5. It's important to consider this point that elasticity variation is proportional to reward expectation that is based on survey participant's response and could include some noise, therefore elasticity could have smoother pattern and decrease more monopoly as average power consumption

Table 9.5: Survey2- HVAC elasticity report for combined groups

Feb. Temp.	Elasticity	Load Change	Incentive	Average Energy (MW/m)	Elasticity change (%)
≤70	0.106	1.187	11.195	72.289	-1.028
70-75	0.11	1.243	11.327	83.412	2.708
≥75	0.107	1.106	10.32	106.94	-0.093
July					
≤ 64	0.15	1.36	9.053	112.249	-41.950
65-70	0.239	2.58	10.812	95.867	-7.508
70-74	0.282	2.977	10.544	81.622	9.133
74-78	0.28	3.196	11.424	68.398	8.359
78-80	0.266	3.056	11.476	57.132	2.942

decrease.

Grouping customers based on their temperature settings would lead to more diverse elasticity values. In some group difference with average elasticity for whole customers is higher and for some is less. In winter the lowest elasticity belongs to temperature setting more than 80 degree and in summer the lowest elasticity is for group people of that put their thermostat on less than 60 degree. Considering this fact the comfort temperature for most of people is around 72 degree in both season, there is obviously high difference between comfort setting and mentioned ones. Both of these temperature shows that these people do care more about their comfort than money, so their elasticity is lower than other groups.

It may be seemed so hard to decompose total HVAC consumption to 9 distinct groups. Alternative way is to combine groups with each other and make less customer groups. In winter, since most of group's elasticity are close to each other, it is better to have only 3 groups, but in summer we try to keep more diversity since elasticity is higher in summer.

9.4.2 Elasticity for different incentive level

We can divide survey respondents into three groups based on their incentive expectation.

1. High contribution group: incentive expectation is less than 10% of monthly bill,

Table 9.6: Elasticity per customer cooperative segmentation

Device	Low contribution		Medium contribution		High contribution	
	winter	summer	winter	summer	winter	summer
HVAC	0.055	0.123	0.106	0.253	0.352	0.499
Lighting	0.326	0.316	0.426	0.458	0.618	0.653
Dishwasher	0.156	0.143	0.2	0.217	0.217	0.253
Washer/Dryer	0.209	0.197	0.297	0.297	0.381	0.379

2. Medium contribution group: incentive expectation is between 10%-15% of monthly bill,

3. Low contribution group: incentive expectation is more than 20% of monthly bill.

Elasticity for each group in summer and winter based on survey 2 data is listed in Tab. 9.6. There is considerable difference between the elasticity of each group for each appliance. For HVAC, this difference is critical. In the peak of summer (depending on region), HVAC may count for as much as 50% of total load. Targeting a group with elasticity of 0.5 at this time could make an important difference in the IBDR program design and implementation.

In Fig. 9.6, the load change for each customer group by IBDR is shown for one day. The DR program in all cases is the same, a two degree change in thermostat setting, turning extra lights off and shifting washing device from peak to off peak time in return for some incentive. Load change is close for each group since the same type of DR program is applied for each group; however, there is some differences between results. These differences arise from variations in parameters that are used to simulate load profile. Thermostat setting in the high contribution group is lower (in summer) than other groups. Therefore, the load reduction from a 2 degree thermostat setting change is higher in this group. The required incentive at each hour according to elasticity of each group is shown in Fig. 9.7.

As it is shown, there is significant difference between incentive expectation for similar load change. Fig. 9.7 could simply shows huge potential of saving, if appropriate customer clustering could be done. In other words, if we could target right group pf customers, with right amount of incentive, significant financial difference could be achieved.

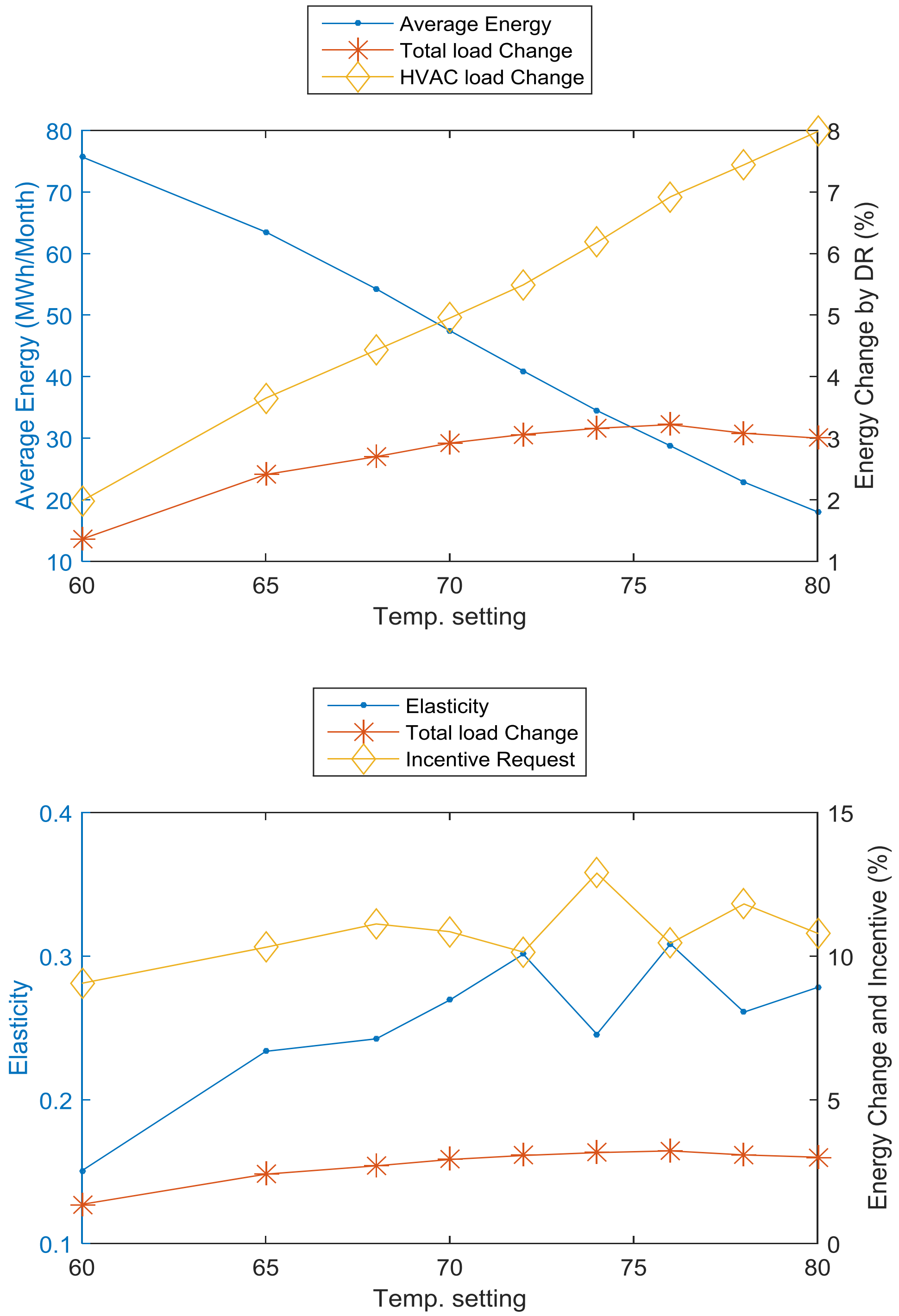


Figure 9.5: Comparison of elasticity and average power for survey2 participants- July 2013

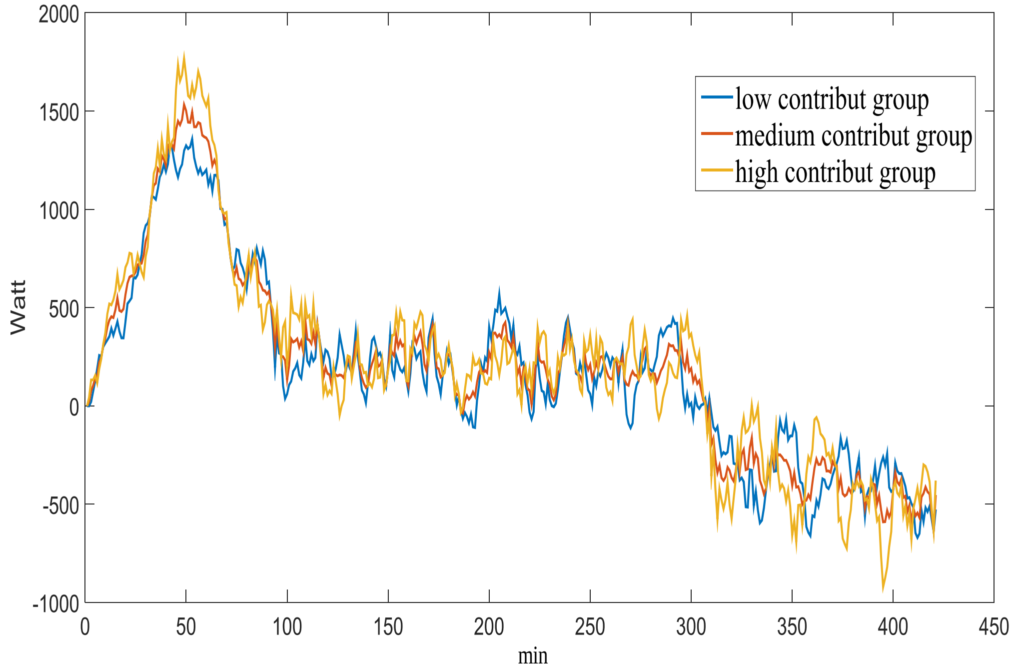


Figure 9.6: Load change in each customer group

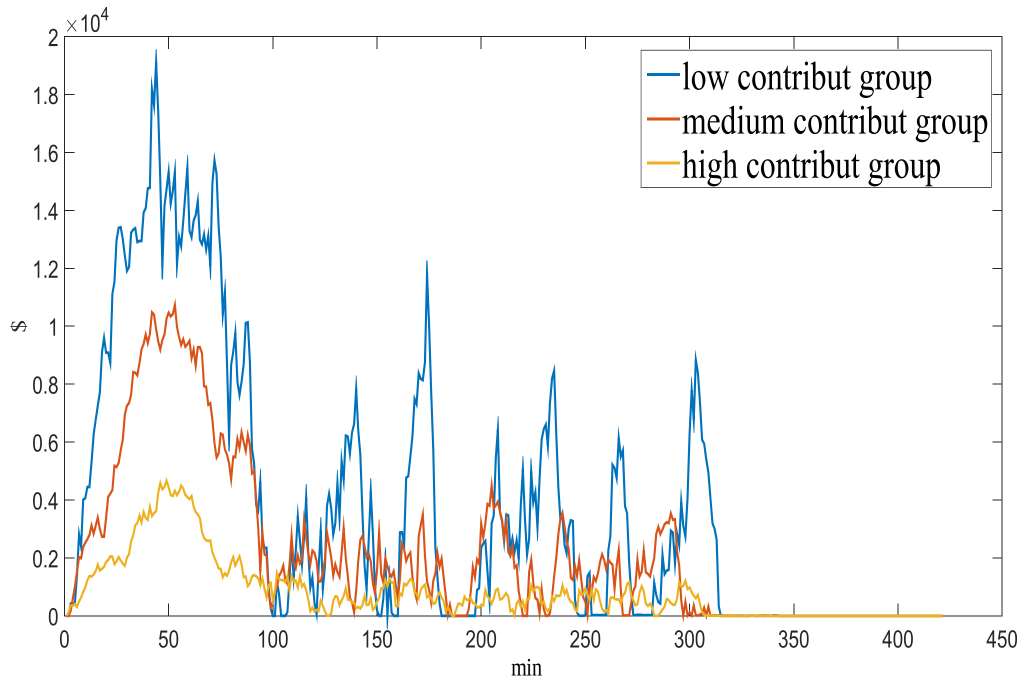


Figure 9.7: Required incentive for each customer group

10 Effect of Customer Classification on IBDR program

In this chapter, IB elasticity is considered for the proposed IBDR program to understand how elasticity estimation affects results. Estimated elasticity is specific to IBDR programs and is calculated based on the main appliances in each residence instead of aggregated across all residential customers. The motivation is to not only evaluate IB elasticity vs. PB elasticity but also to consider the individual importance load types. In addition, customer classification is used to improve modeling precision. Elasticity has been typically considered across broad customer groups only, such as, the residential, commercial and industrial sectors. This ignores potentially valuable information that could be used to improve accuracy. In this chapter, customers are classified based on surveys of their willingness to participate in IBDR programs and also their nominal HVAC thermostat settings. IB based elasticity is examined under both low and high penetration of RER scenarios.

10.1 IBDR Design using IB Elasticity

In this study, the proposed IBDR formula in chapter 3 is modified to consider individual appliance elasticity for the residential sector as follows [192]:

$$\max \sum_{b=1}^{N_B} \sum_{t=1}^{M} [(D_{bt} - \Delta\bar{D}_{bt})(P_b^0 - LMP_{bt}) - \Delta\bar{D}_{bt} P_{bt}^{inc}] \tag{10.1}$$

$$\Delta\bar{D}_{bt} = \Delta D_{bt}^{R} + \Delta D_{bt}^{C} + \Delta D_{bt}^{I} \tag{10.2a}$$

$$\Delta D_{bt}^{C} = \varepsilon^{C} P_{bt}^{inc} \tag{10.2b}$$

$$\Delta D_{bt}^{C\ \min} \leq \Delta D_{bt}^{C} \leq \Delta D_{bt}^{C\ \max} \tag{10.2c}$$

$$\Delta D_{bt}^{I} = \varepsilon^{I} P_{bt}^{inc} \tag{10.2d}$$

$$\Delta D_{bt}^{I\ \min} \leq \Delta D_{bt}^{I} \leq \Delta D_{bt}^{I\ \max} \tag{10.2e}$$

$$\Delta D_{bt}^{R} = \sum_{k=1}^{D_{app}} \Delta D_{bt_k}^{R} \tag{10.2f}$$

$$\Delta D_{bt_k}^{R} = \varepsilon_{k}^{R} P_{bt}^{inc} \tag{10.2g}$$

$$\Delta D_{bt_k}^{R\ \min} \leq \Delta D_{bt_k}^{R} \leq \Delta D_{bt_k}^{R\ \max} \tag{10.2h}$$

Equation (10.1) is valid over the time that IBDR is requested. The load change in (10.1) is a summation of the various customer responses. Each type has a range of load change and specific elasticity value. Elasticity represents the relation between the incentive payment and the load reduction. Parameter M indicates the time that DR is applied and can be either fixed or optimized as developed in chapter 3. In (10.2f), residential load change is a summation of the various appliances in the home and different thresholds for consumption modification are considered for each. The residential customer response can be model separately for each appliance using an appliance based elasticity as shown in (10.2g). Customer segmentation can also further segment response to achieve more accurate results. Equations (10.2f) and (10.2g) are modified to (10.3a) and (10.3b), respectively, to reflect customer change in demand.

$$\Delta D_{bt}^{R} = \sum_{g=1}^{D_{con}} \sum_{k=1}^{D_{app}} \Delta D_{bt_{gj}}^{R} \tag{10.3a}$$

$$\Delta D_{bt_{gk}}^{R} = \varepsilon_{gk}^{R} P_{bt}^{inc} \tag{10.3b}$$

Table 10.1: Elasticity values for scenario 1

Time Period/ Load Type	Residential	Commercial	Industrial
Day	0.1	0.15	0.15
Night	0.07	0.01	0.01

Table 10.2: Elasticity values for scenario 2

Time Period/ Appliance	HVAC	Lighting	Washing device
Winter	0.1	0.42	0.27
Summer	0.21	0.45	0.23

10.2 Residential Incentive Based Elasticity

To evaluate the effects of new elasticity values on IBDR performance under low penetration of RERs, three scenarios are examined. First, an average price based elasticity is used within the residential, commercial and small industrial sectors. Second, an appliance-incentive based elasticity is used for each season in the residential part. Third, the residential customers are classified based on their willingness to participate and ability to contribute toward the IBDR program. Elasticity values for each scenario are shown in Tab. 10.1 to Tab. 10.3.

For the case of high RER production, one more scenario is studied. Customers are divided based on their thermostat setting to three groups: thermostat settings below 70, between 70-75 and above 75 degrees in either summer or winter. The elasticity for each

Table 10.3: Elasticity values for scenario 3

Customer Group/ Appliance	HVAC	Lighting	Washing device
Winter			
Low contribution	0.055	0.38	0.4
Medium contribution	0.1	0.45	0.59
High contribution	0.35	0.48	0.7
Customer Group/ Appliance	HVAC	Lighting	Washing device
Summer			
Low contribution	0.12	0.28	0.35
Medium contribution	0.25	0.32	0.59
High contribution	0.65	0.35	0.65

Table 10.4: Elasticity values for scenario 4

Customer Group/ Appliance	HVAC	Lighting	Washing device
Winter			
Temp. Group 1	0.1	0.42	0.27
Temp. Group 2	0.11		
Temp. Group 3	0.09		
Customer Group/ Appliance	HVAC	Lighting	Washing device
Summer			
Temp. Group 1	0.17	0.45	0.23
Temp. Group 2	0.257		
Temp. Group 3	0.3		

grouping is shown in Tab. 10.4.

10.3 Results of IBDR for Base Case data of WECC

The appliance-incentive based elasticity of customers impact on the IBDR program is analyzed under low penetration of RERs with the base case data of WECC 240-bus system. Fig. 10.1 and Fig. 10.2 show load change and required incentive payments for each scenario in the various regions of WECC during the summer.

The required incentive for scenario 1 is higher than the others but results in significantly

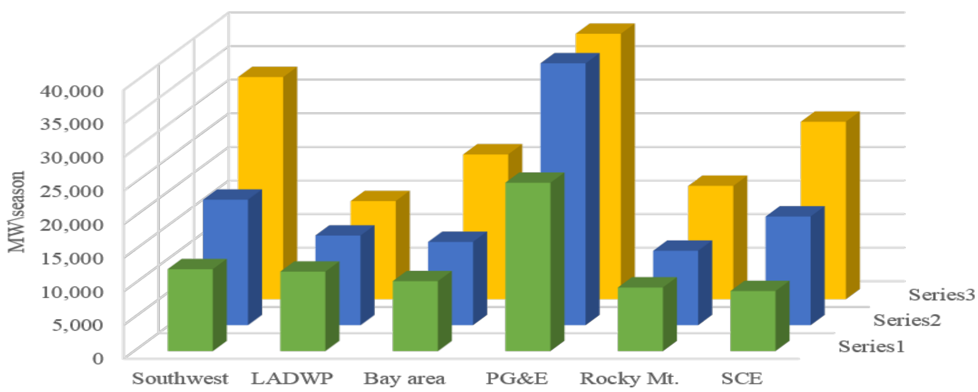


Figure 10.1: Load change for different scenarios in WECC

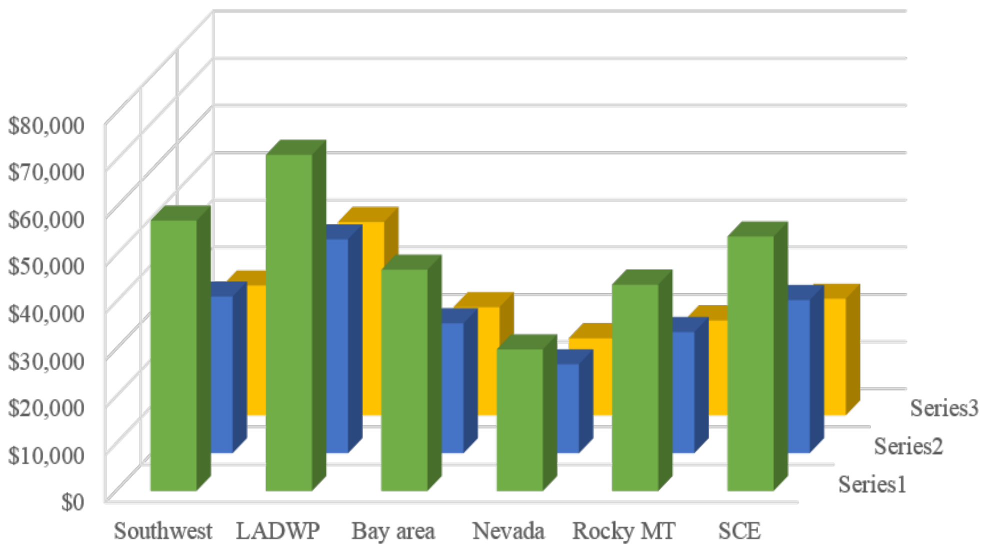


Figure 10.2: Incentive payment for different scenarios in WECC

lower load reduction. The reason is without targeting the incentive carefully the LSE has to provide greater incentives to more customers. Scenario 3 has the best performance as it obtains the most load change while paying the least incentive. This verifies the value of customer classification to target the most receptive group of customers to a DR program. The different in load changes under each scenario result in different benefits for both the LSEs and customers as shown in Fig. 10.3 and Fig. 10.4. Scenario 1 brings the least benefit and scenario 3 leads to the highest benefit for all participants. LSEs additional profit increases by as much as a factor 10 times in some regions under scenario 3. Customer saving is also significantly higher, which suggests all DR participants can gain using a more sophisticated IBDR design.

In addition to benefits for LSEs and customers, the proposed IBDR program has an considerable impact on peak prices. Fig. 10.5 shows the LMP profile during one week in August, including scenario 4 now. As shown, scenario 2 and 3 not only have better performance relative to case 1 but they can reduce the price to during the cheapest weak

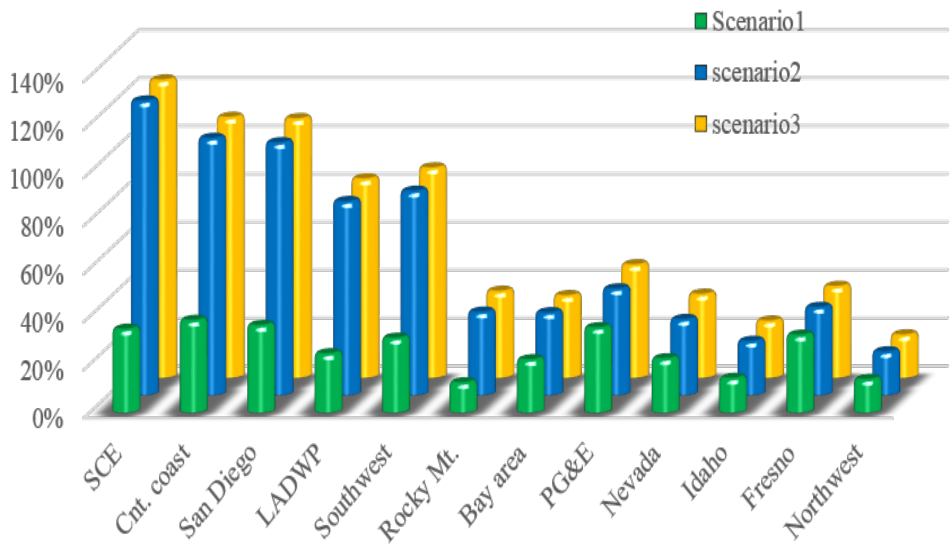


Figure 10.3: Percentage of LSE benefit by different IBDR scenario

of the month.

Fig. 10.6 shows LMP profile in one day of July after each IBDR scenario. Scenario 1 has the least effect and scenario 3 has the highest effect on market price as it was expected. These Figures verifies the effect of customer classification on DR design which could bring more benefit for all participants and in addition has better effect on peak shaving of price.

10.4 Sensitivity of LSE Benefit to Elasticity Values

An interesting point in Fig. 10.3 is that although there is a considerable difference in load change under scenario 2 or 3, LSEs benefits are similar in both cases. In other words, although scenario 3 has higher elasticity value (for the high and medium contribution group) and brings more load change with less incentive payments, it does not bring significantly higher benefit for LSEs. To illustrate, the sensitivity of LSE benefit to

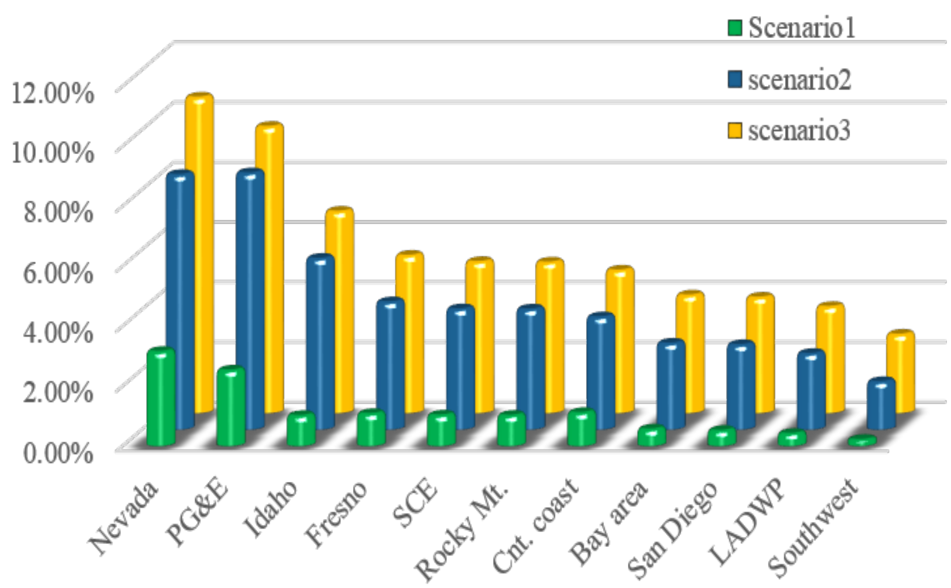


Figure 10.4: Percentage of Customer saving by different IBDR scenario

elasticity is calculated and plotted in Fig. 10.7 and Fig. 10.8 for summer and winter, respectively. Note for higher elasticity (larger than 0.3), LSE benefit is less sensitive to the elasticity value even though it continues to gain some benefit from higher elasticity. The advantage of customer grouping is more clear when the ability to pay incentives is limited. In this case, targeting the high contribution of customers could lead to significantly more load modification with the same amount of incentive relative to average elasticity for all customers.

10.5 Results of IBDR under High Level of RER

In this section, effects of customer classification and using appliance-incentive based elasticity are studied assuming high penetration of RER. Fig. 10.9 and Fig. 10.10 show the effect of each DR scenario on LSE benefit in spring and fall for 4 regions in California. The results are shown based on the percentage of benefit change compare with low renew-

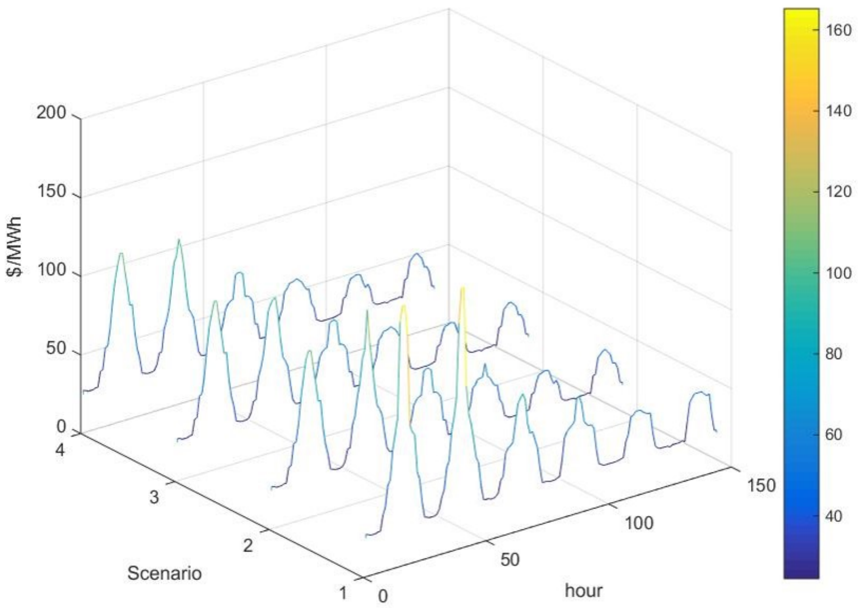


Figure 10.5: LMP profile in one week of August after each DR scenario

able production and no DR. The greatest benefit arises under scenarios 3 and 4. DR of scenario 3 group customer based on incentive expectation has the most benefit followed closely by grouping considering thermostat setting. These results verify the need and effect of customer classification on IBDR design. Customer grouping should lead to higher profit for participants under either low or high RER production. Customer segmentation is helpful to design right type of DR for each customer group and consequently increase benefits.

Tab. 10.5 shows the LSE's net revenue per total load in winter and summer for selected regions. Revenue after renewable expansion and by using different DR scenarios is compared. LSEs would have the highest revenue if they classify customers based on their incentive request and contribution level to IBDR program. The revenue gain for scenario 3 is as much as 3 times higher relative to using a simple average price based elasticity as in scenario 1.

To illustrate LSE benefit change under each DR scenario, Tab. 10.6 shows the total

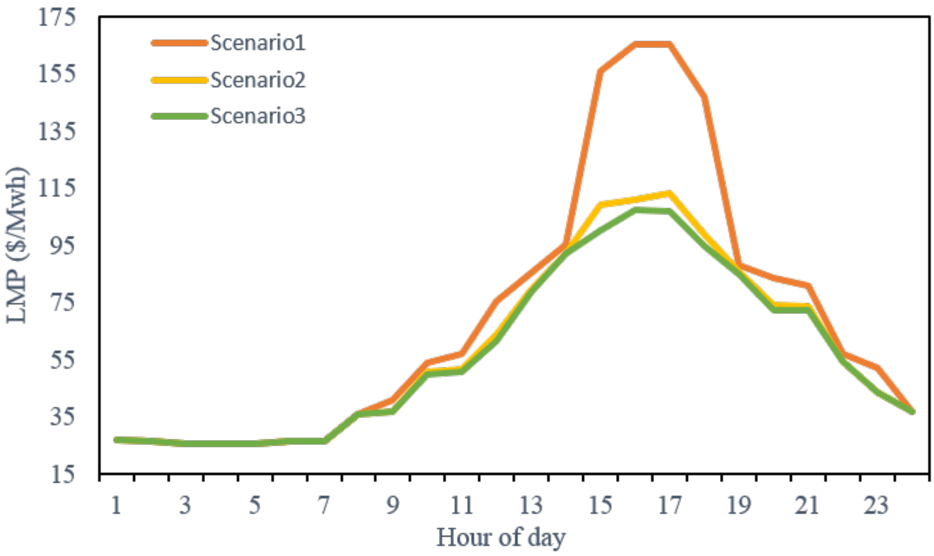


Figure 10.6: LMP profile in one day of July under each DR scenario

Table 10.5: LSE net revenue per unit load under different DR scenarios

Winter	After expansion	DR 1	DR 2	DR 3	DR 4
Fresno	$4.33	$8.46	$8.60	$15.98	$10.11
Cnt. Coast	$5.00	$7.79	$10.06	$17.31	$12.33
PG&E	$6.90	$15.62	$22.81	$33.60	$24.94
Northwest	$2.18	$4.08	$6.09	$24.37	$18.82
Summer					
PG&E	$46.27	$52.82	$59.77	$136.58	$62.34
LADWP	$12.68	$16.69	$15.08	$26.45	$22.25
SCE	$14.42	$17.87	$19.80	$30.11	$22.69
SMUD	$16.08	$15.32	$15.78	$39.72	$32.51

amount of incentive payments and load change in different seasons of the year. In general, scenario 1 requires highest incentive for each MW of load change. Using appliance-incentive based elasticity allows a little bit of improvement. The best scenarios are again scenario 3 and 4. This table provides some insight on how the scenarios benefit LSEs.

In addition to the more benefit that using incentive-appliance based elasticity and customer grouping could bring for utilities and customers, another motivation for using these types of DR under high penetration of RERs is reducing price variation. The easiest way to reduce price variation is load shifting, which is easier with an understanding of customer appliance use. Washing devices are the primary shiftable loads, which can

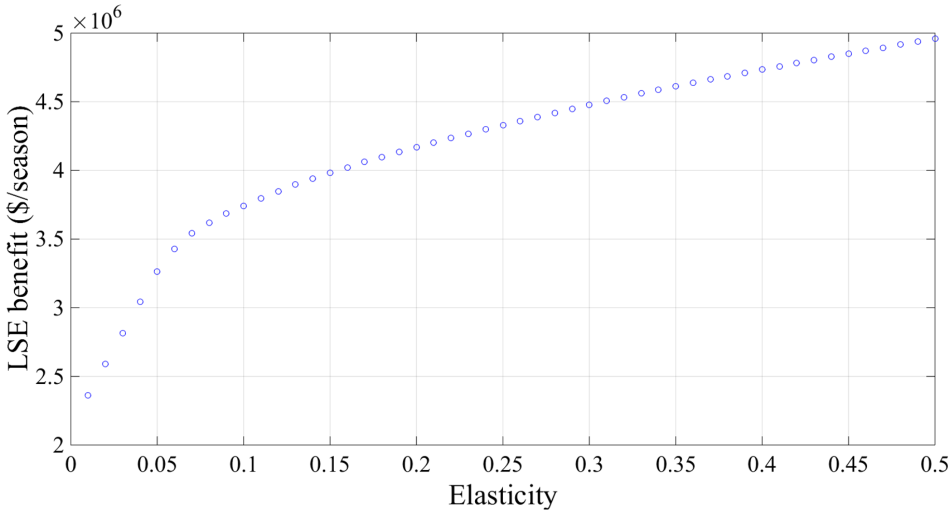


Figure 10.7: LSE benefit as a function of demand elasticity during summer

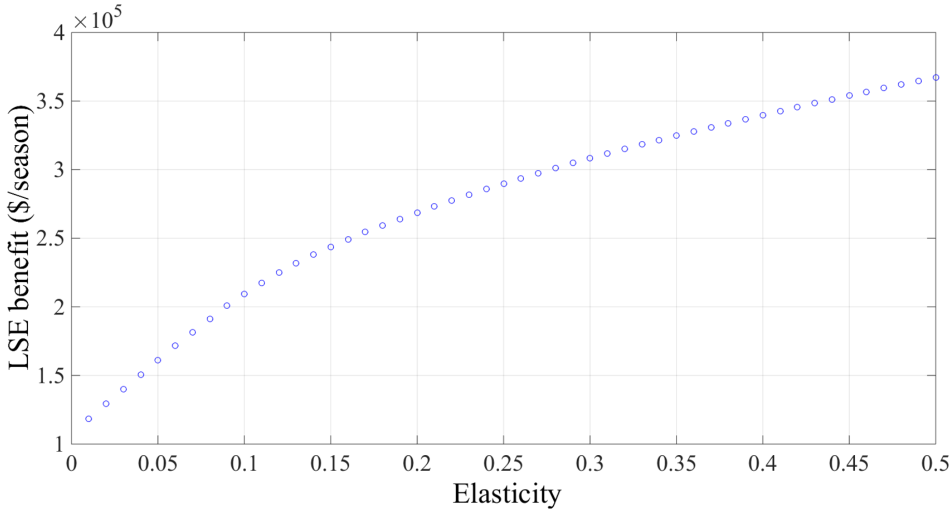


Figure 10.8: LSE benefit as a a function of demand elasticity during winter

easily be shifted to the cheaper times of the day. Knowing the elasticity of customers and their incentive expectation allows these loads to be targeted. HVAC consumption is both reducible and shiftable. People can change their thermostat setting during peak times to reduce consumption. Still, one they return to a normal setting, HVAC would consume more electricity for some time. This extra needed power is called "return of load" and acts as shiftable load in the system. In this study, the return of load for HVAC is calculated based on temperature data for different regions in the WECC. In Fig. 10.11 and Fig. 10.12, the effect of proposed DR scenarios are shown for one day in summer and

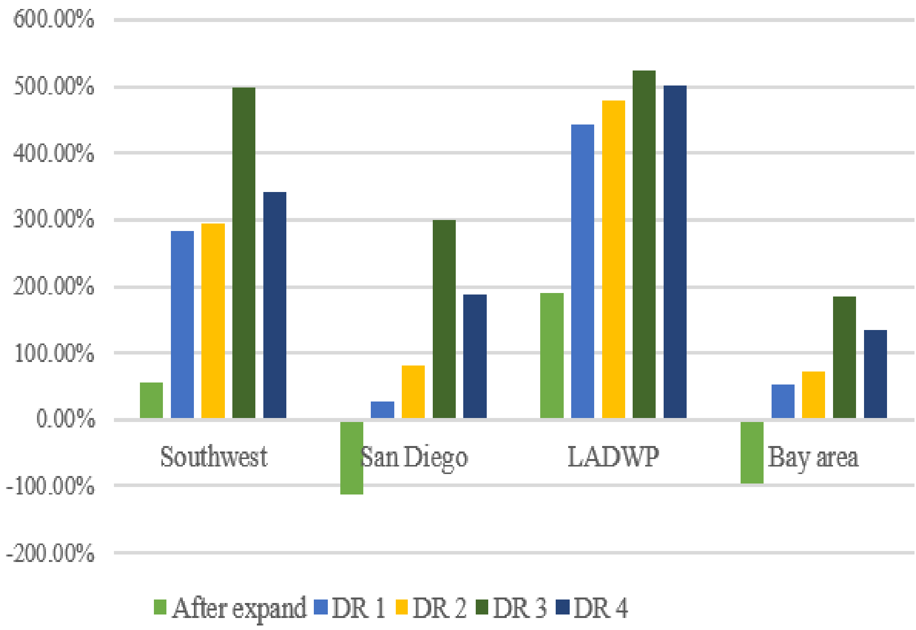


Figure 10.9: LSE benefit change under different DR scenarios in spring

fall, respectively.

As shown, using appliance based elasticity, and more importantly customer classification, not only reduces price at peak hours but also increases the cheaper price during off peak period. Notably in the fall, when renewable expansion leads to many negative LMP hours, load shifting eliminates many such hours and could allow better use of wind turbine generators. This effect is shown in Fig. 10.12.

Tab. 10.7 shows statistical variation of LMP in San Diego area for different months of the year. Customer classification and load shifting, under scenarios 3 and 4, has considerable impact on reducing peak prices and volatility.

Table 10.6: Total load change and incentive payments in each season

Region	Winter				Spring			
	DR 1	DR 2	DR 3	DR 4	DR 1	DR 2	DR 3	DR 4
Southwest	5,219	5,649	10,020	7,795	5,887	5,830	10,519	7,757
	$13,085	$10,284	$8,789	$10,363	$15,444	$14,414	$11,273	$14,706
Bay area	4,532	3,763	5,108	4,912	5,496	3,597	5,070	4,917
	$16,067	$11,329	$9,081	$12,958	$18,291	$13,739	$9,632	$15,034
Fresno	2,133	1,412	1,522	1,450	2,922	1,591	1,901	1,757
	$6,812	$5,956	$3,840	$5,163	$8,089	$7,459	$4,518	$6,391
Nevada	3,493	1,778	2,088	1,972	3,807	1,751	2,087	2,017
	$10,772	$7,708	$6,379	$6,772	$13,521	$7,686	$7,873	$7,214
Region	Summer				Fall			
Southwest	12,452	11,315	20,706	15,682	5,528	4,719	8,095	6,727
	$31,435	$29,161	$21,600	$28,187	$13,832	$12,680	$10,391	$12,980
Bay area	7,674	5,624	9,125	8,835	6,019	3,696	4,195	4,008
	$20,656	$18,513	$12,119	$18,313	$19,182	$15,047	$9,847	$14,183
Fresno	5,005	3,114	3,897	3,630	1,713	1,026	1,086	1,023
	$14,835	$12,513	$7,835	$11,326	$8,450	$6,358	$4,288	$6,642
Nevada	7,701	3,399	4,336	4,209	2,000	1,111	1,321	1,271
	$20,938	$16,655	$12,942	$16,708	$7,567	$5,417	$4,787	$6,044

Table 10.7: Monthly variation of LMP in San Diego area under different DR scenarios

Month	May			June		
Price variation	Min.	Max.	STD	Min.	Max.	STD
After expansion	4.52	86.60	11.74	8.31	86.60	13.09
DR 1	4.52	65.32	10.81	8.31	60.29	10.95
DR 2	5.04	72.07	10.11	10.74	63.89	10.08
DR 3	15.32	67.72	8.01	17.50	58.24	7.78
DR 4	15.78	68.34	8.97	15.80	61.72	8.97
Month	November			December		
Price variation	Min.	Max.	STD	Min.	Max.	STD
After expansion	8.26	58.20	10.68	8.33	76.48	13.87
DR 1	8.26	49.90	9.01	8.33	56.73	10.82
DR 2	8.32	53.00	8.86	12.21	60.48	9.20
DR 3	17.39	48.42	4.65	18.81	57.84	8.78
DR 4	17.39	50.42	5.50	18.81	56.18	8.26

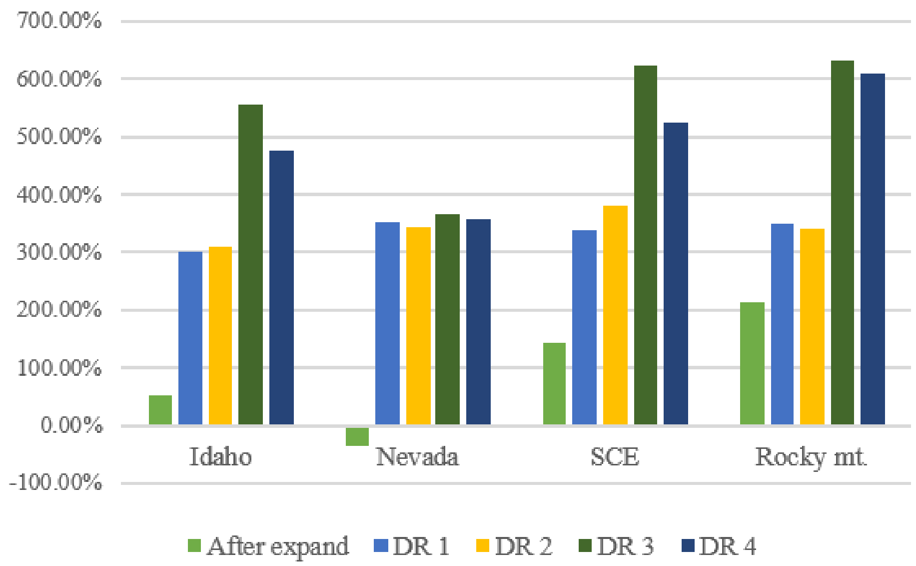


Figure 10.10: LSE benefit change by different DR scenarios in fall

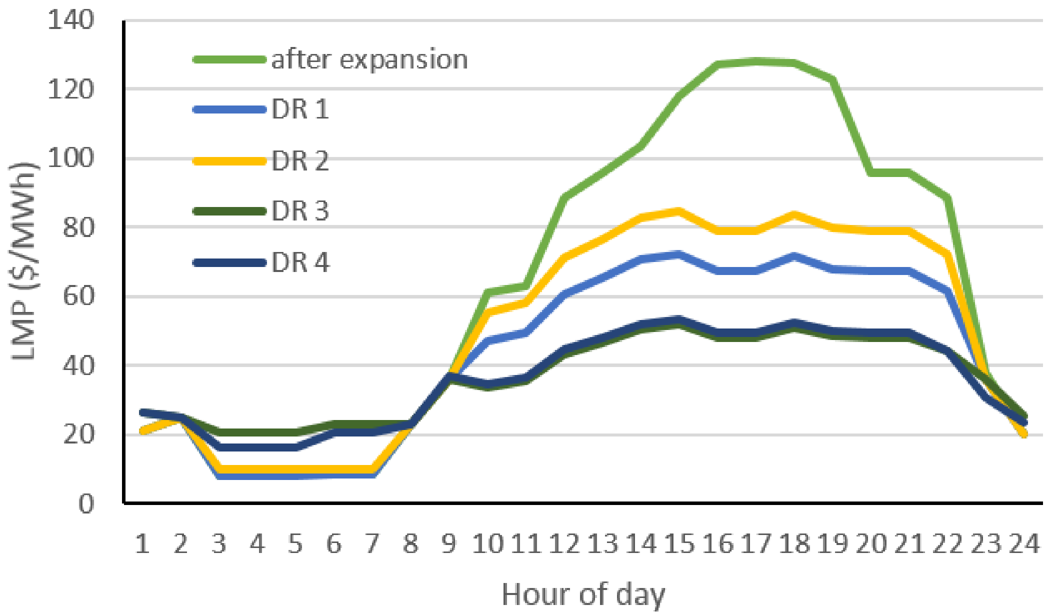


Figure 10.11: LMP variation after different DR scenarios in Southwest region, July

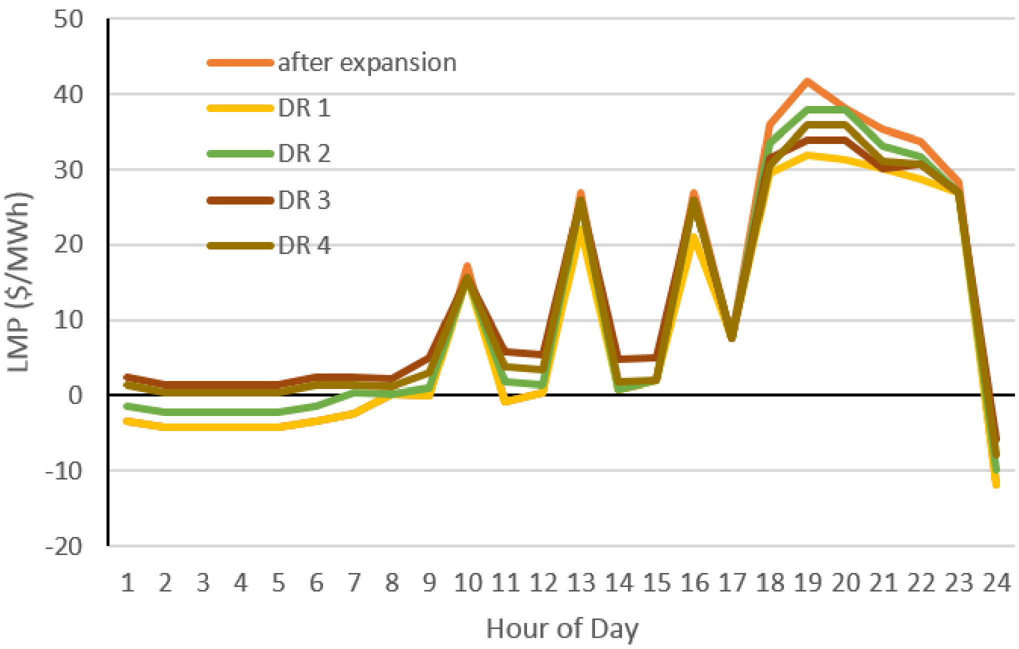


Figure 10.12: LMP variation after different DR scenarios in Idaho during November

11 Conclusions

In this work, a demand response framework combining TOU and IBDR programs has been developed. The comprehensive model explores the potential of both reward and punishment in DR tariffs. A method to design optimum peak and off peak tariffs utilizing self and cross elasticity is developed. For the IBDR program, a novel formulation for the optimal reward is proposed. The optimization determines not only the appropriate incentive payment and load reduction but also when to activate the IBDR program. Two different types of thresholds for requesting load response are considered: a constant level above the market price and an optimal threshold. Results show that while the constant threshold performs well at high load times, the variable threshold is more effective under more normal conditions. Customer satisfaction should be a determining factor since not only total savings is important but also the frequency for which they need to change their consumption relates closely to their convenience. From this point-of-view, the variable threshold with appropriate constraints is more desirable.

A successful demand response program can significantly reduce electricity prices, improve system reliability and reduce price volatility. A case study using representative data from the WECC 240-bus reduced model demonstrates the effects of the proposed DR programs on reducing price variation and peak demand considering both load shifting and load reduction. Consequently, total generation cost reduce significantly and all participants in market benefit. Customer savings consists of both the incentives received and the resulting lower prices, which together yield significant savings. From the ISO point-of-view, an interesting point is that although the percentage of time for DR requests is less than 10% in each region, there is considerable reduction in price volatility and average LMP across all regions.

Application of the IBDR in emergency situations is also analyzed. During generator outages, the LMP may increase with system wide effects. In order to avoid price changes, LSEs can implement an IBDR over a short period of time to decrease load. The proposed IBDR program tests on the WECC model shows significant LMP reduction during outages. An important aspect of the program is that the DR program only needs to be implemented in a few regions and for a small portion of customers to result in significant savings. During outage conditions, time may be a key factor, therefore, an economic ranking of generators was introduced to quickly identify needed DR. Results show that electrical distance between a generator to the more expensive generators can act as proxy for the price impact of an outage.

The effect of small customer's DR under high penetration of RERs is analyzed. LMP variation after renewable expansion becomes highly correlated with renewable intermittent. As a result, a TOU program is difficult to successfully implement; however, results show IBDR can diminish most sharp price changes during peak load. To model the risk that is associated with renewable forecast uncertainty, a robust optimization is designed considering market price and elasticity variation. A DOE approach is used to analyze different scenarios of market price according to renewable forecast errors. Analysis of the associated market risk using a deterministic approach shows two possible concerns: unexpected high LMP leading to opportunity loss and unexpected low LMP causing economic loss. A comparison between robust and deterministic results shows that although the LSE loses some benefit using the robust design under normal conditions, even a few hours of large price deviations can render the robust approach valuable.

Elasticity of residential customers toward IBDR was calculated for different appliances and for different HVAC thermostat settings, using two nation wide surveys and a Matlab based load modeling toolbox. Results show customer incentive expectation for lighting and washing device is far less than HVAC. Still since HVAC generally has the highest share of the aggregate load, the resultant load reduction from the HVAC thermostat changes is higher than from other devices. Due this important role of HVAC load, especially at peak hours, the HVAC elasticity is analyzed for different thermostat settings. Incentive expectation across temperature groups are close, based on survey data, therefore, elasticity mainly depends on load change. Considering the relationship between load change and average power consumption, the elasticity of HVAC decreases as average power increases. In addition, customers are clustered based on their incentive expectation. Elasticity of each group is calculated and compared with the average. There is a significant difference between the elasticity of low and high contribution classes. This type of classification could help utilities and load aggregators target customers with the appropriate incentive to achieve required load response. This type of approach could also help achieve higher levels of response at lower cost while motivating greater customer participation.

Next, it was demonstrated how the right information about incentive based elasticity of customers can improve DR performance. Two cases of incentive based elasticity are compared with a standard price based elasticity assumption. An appliance based elasticity is considered for residential customers in order to reflect the various roles of each device daily use. Second, customers are classified according to their contribution to IBDR. These scenarios are tested on data from the WECC 240-bus reduced model for the whole year. Results show the necessity of accurately accessing IB elasticity with detailed information of customers, such as, targeted appliances and customers classes. More information means greater benefit for participants and reductions in peak market prices. In summary for efficient and economical design of IBDR program, it is necessary to have appropriate data to allow detailed and accurate information about customer response to IB programs.

Effect on customer classification and incentive based elasticity on high penetration of renewable resource is also evaluated. For high renewable generation, four scenarios are compared. The effect of using average price based elasticity, appliance and incentive based elasticity, incentive based elasticity and customer classification based on people incentive request, and finally customer grouping based on temperature setting at each house. Using the customer clustering improves the results of load reduction at the peak time and by using the potential of shiftable appliance, price variation also decreases.

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Vita

Ailin Asadinejad was born in beautiful city in southern part of Iran, called Shiraz, in 1985. She lived in her hometown for 18 year. In univerityies exam entrance she ranked 110 among more than 200,000 competent and she then moved to capital city Tehran to peruse her bachelor's degree in one of the top universities. She got her bachelor degree in electrical engineering field with major of power system from Polytechnic university, which it best college of Iran in power and energy field, in 2007. Few months later she started her graduate program in the same university in the energy management field and she got her master degree in 2009.

Ailin Asadinejad worked for 2 years after her master graduation as power plant substation design supervisor but she find out that need more adventure and perhaps higher education. She started her PhD program in university of Tennessee in 2011 with concentration on market engineering modeling and optimization. Her research interest include but not limited too power system modeling and optimization, residential demand response and residential elasticity.