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Optimal use of incentive and price based demand response to reduce costs and price volatility☆

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ABSTRACT

There are two general categories of demand response (DR): price-based and incentive-based DR programs. Each one has its own benefits taking advantage of different aspects of flexible demand. In this paper, both categories of DR are modeled based on the demand-price elasticity concept 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. Time of use (TOU) programs are considered for a price-based scheme designed using a monthly peak and off-peak tariff. For the incentive-based DR, a novel optimization is proposed that in addition to calculation of an adequate and a reasonable amount of load change for the incentive, the best times to realize the DR is found. This optimum threshold maximizes benefit considering the comfort level of customers as a constraint. Results from a reduced model of the WECC show the proposed DR program leads to a significant benefit for both the load serving entities (LSEs) and savings in customer's electricity payment. It also reduces both the average and standard deviation of the monthly locational marginal price (LMP). The proposed DR scheme maintains simplicity for a small customer to follow and for LSEs to implement.

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 control down to the customer level. Among the many innovations related to these developments, a key component is effective demand side management [1,2].

The U.S. Department of Energy (DOE) defines demand response (DR) 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" [3].

The literature broadly shows two types of DR: price-based (PB) and incentive-based (IB) [4]. 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. PBDR schemes typically considered include: time-of-use pricing, critical peak pricing, peak load pricing and real-time pricing [5,6], 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 resulting a powerful approach to avoid capacity upgrades by peak shaving.

IB programs include Direct Load Control, Interruptible service, Demand Bidding/Buy Back, Emergency Demand Response Program, Capacity Market Program and various Ancillary Service Markets. These programs offer customers incentives in addition to their retail electricity rate, which may be fixed or time-varying for their load reduction. 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 [7]. 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 [8,9]. Peak time rebate is another type of IBDR program [10]; however, the rebate paid to consumers is typically very high and does not reflect the actual supply-demand market conditions.

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Nomenclature

α	load variation economic weight
β	percentage of affordable load reduction for TOU 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 at bus b and time t in response to TOU program
Δp_b^{OPT}	retail load tariff in change in off peak time
Δp_b^{PT}	retail load tariff in change in peak time
$\Delta \bar{D}_{bt}$	load change at bus b and time t in response to IBDR program
ε_j	elasticity of customer type j
ε_{tt_1}	elasticity of time t respect to time $t1$
ε_{tt_2}	elasticity of time t respect to time $t2$
CB_b	customer benefit at bus b
d_{bt}	new load at bus b and time t after TOU program
d_{bt}^0	demand at bus b and time t in base case with no DR
D_T	type of customer
LMP_{bt}	locational marginal price at time t and bus b
LSE_b	LSE benefit at bus b
N_B	total number of buses
NT	number of time in study period
p_{bt}^{inc}	incentive payment to customer at bus b and time t
p_b^0	retail load tariff at bus b in base case with no DR
p_b^{OPT}	retail load tariff in off peak time
p_b^{PT}	retail load tariff in peak time
T	study time period
T_d	daily period of study
T_h	hourly period of study
T_m	monthly period of study
DR	demand response
IBDR	incentive based demand response
LSEs	load serving entities
M	total number of time that IBDR implement
OPT	off peak time
PBDR	price based demand response
PT	peak time
TOU	time of use DR program
WECC	Western Electricity Coordinating Council

Each category of DR has its own benefits and takes advantage of different aspects of the potential for flexible demand. In this paper, both categories of DR measures are modeled based on the demand-price elasticity concept to design an optimum scheme for realizing the maximum potential of DR benefit. The main objective is to reduce costs and improve reliability. In addition, we suggest high price volatility negatively impacts both 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 IBDR 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 [11,12]. Psychologists mainly believe, in most societies, the reward may cause more considerable improvement for habit development relative to punishment [13,14]. In this paper, a different elasticity value is considered for each DR program to emphasize this variable response from customers. IBDR as a reward-based system should lead to higher elasticity. Note that the DR discussed in this paper is more related to small customers who cannot participate in a wholesale market directly. As will be detailed in Section 3.2, customers in this study are divided into three groups: small commercial, small industrial and residential.

Price volatility over a period of time reflects the uncertainty of prices. Power markets, especially in terms of hourly prices and peak loads, are often volatile. Several elements lead to price volatility or price spikes [15]. Price spikes may occur when the demand side has no response to electricity prices so generators completely determine price, e.g., when the market lacks sufficient competition to constrain GenCo bids. In addition, price spikes might occur when generation reserves are lower during peak demand hours. To compensate for generation shortages at peak hours, generators with high marginal costs must supply peak demands, which results in a significant under-utilization of such generators at off-peak periods [16]. In some cases, electricity prices can vary by several multiples, e.g., from less than \$20 per MWh to several hundred dollars per MWh [17].

In a competitive electricity market where all generators are paid the market clearing price (MCP) under a uniform price auction structure, even a small reduction in demand can result in considerable reduction in the system marginal costs of production [18]. Although these peak price events may be short in duration, they still add significantly to the average cost per kWh for a consumer. Allowing DR in a constrained electricity grid can significantly lower these peak energy costs and potentially act as a check against the exercise of market power by GenCos [19,20].

2. Literature review

There is extensive literature on PBDR. Jia et al. [21] propose an application of on-line learning theory tailored to the problem of pricing for retail load customers who participate in a demand response program. This work considers thermal dynamic loads for which electricity is consumed to maintain the temperature near preferred comfort settings. In [22], an optimum time-of-use pricing scheme for use in monopoly utility markets is developed. The optimal pricing strategy maximizes the societal benefit. Vivekananthan et al. [23] propose an improved real time pricing 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 utility benefit from this scheme. In [24], a novel demand response program for optimizing power systems electric vehicle charging load is introduced. A demand response program which includes multiple tariffs for different groups of customers is proposed. Three scenarios are considered, i.e., standard tariff, single-tariff and multi-tariff programs. The results show that a multi-tariff program could help utilities reduce daily cost by 1.5% and help customers reduce electricity bills by 7% compared to the standard tariff. Kamyab et al. [25] used the idea of transferring market price via smart meter in smart grid to design PBDR program for residential customers. They address the interaction among multiple utility companies and multiple customers in smart grid by modeling the DR problem as two non cooperative games: the supplier and customer side games.

The literature on IBDR is also extensive. Research by Yu et al. focused on the price elasticity of electricity demand where the loads are managed using energy management controller units (EMC). 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 [26]. 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 [27]. Mallette and Venkataramanan investigate financial incentives necessary to encourage plug in hybrid electric vehicle (PHEV) owners to participate in DR program [28]. Zhang et al. demonstrate the potential benefits of coupon IBDR programs using numerical experiments. When there is a potential price spike in the wholesale market based on the ISO/RTO information, load serving entities (LSEs) would set the initial coupon price. After the LSE distributes coupon information to the consumers, these consumers reduce their demand. The LSEs then bid to the ISO/RTO with this response and ISO/RTO determines the LMP based on the demand reductions [29]. In [30], demand curve flattening and nodal voltage profile impacts are investigated for an IBDR program based on a practical load curve of Punjab State Transmission Corporation Limited in India.

It is possible to use both types of DR programs in various combinations. In [31], it was found that PB programs would only be effective if a small new 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 adequate 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 [32]. Shu et al. investigate that with properly analyzing the energy procurement cost and user elasticity, a dynamic incentive strategy can be considered in a dual-tariffs system where flat pricing (FP) and time dependent pricing (TDP) co-exist. The dynamic incentive strategy gives appropriate incentive to the users who are involved into the TDP program, and guarantee the utility profit at the same time [33]. Wang et al. research presents and analyzes case studies in North America of different electric utility programs, including enabling technologies and incentives for smart grid demand response. The program results are evaluated in terms of reduction in peak load and/or customer energy usage and customer satisfaction. It is shown how various incentives can affect the success and scalability of smart grid demand response programs [34]. Some researchers suggest load modeling enhancement to improve results of DR. Alami et al. [35] discussed in their studies that there are many different alternatives of DR programs for improving load profile characteristics and achieving customers' satisfaction. Regulator should find the optimal solution which reflects the perspectives of each DR stakeholder. They used Multi Attribute Decision Making (MADM) to handle such an optimization problem.

Despite extensive research on various approaches to demand response, there remains a lack of understanding for retail customers who do not participate directly in the electricity market. The ability for each LSE to effectively design and implement DR programs remains limited. The proposed model in this paper attempts to develop a simple framework to consider customer benefits and convenience. Both DR programs in this paper focus on retail customers. In general, the main contribution of this study is designing specific TOU and IBDR program for small customers considering their behavior model and their comfort constraint. Considering the restrictions and limitations for designing DR for small customers, the proposed programs in this study are as close to the reality as possible and practical for almost all the current market infrastructure and regulations in U.S. For TOU program, load variation and economic concern are both simulated which could be weighted by the designer based on their priority. The load variation is especially needed to achieve the market goal which is harnessing the price volatility. Without this part, considering the region based design of DR, there is good chance that load variation becomes worse or remain unchanged. IBDR is also designed in novel format that would calculate required load change, adequate incentive payments and more importantly appropriate time to implement DR. Different type of customers, residential, small commercial and small industrial are simulated in DR program that gives this capability to model their various behavior model, including their load change limit, elasticity value and so on. The design of IBDR program was first proposed by authors in [36] with the main focus on WECC application. In this paper, IBDR is developed to consider customer behavior in more complex format, and in addition combination of TOU and IBDR program is discussed and shows how they could perform together to bring the maximum amount of benefit for all participants. To simulate a more accurate model of customers in IBDR program, the load change threshold for each customer type is derived based on bottom-up model at each load bus. Devices at each sector divided into three parts of the critical, shiftable and reducible load. Using the hourly load profile for each appliance, the maximum hourly amount of reducible and shiftable part of the load is calculated for the entire year. In addition, the sensitivity of LSEs benefit to customer type share in total load signal is discussed to emphasize on the necessity of customer classification in DR programs. The structure of proposed DR in this study is shown in Fig. 1.

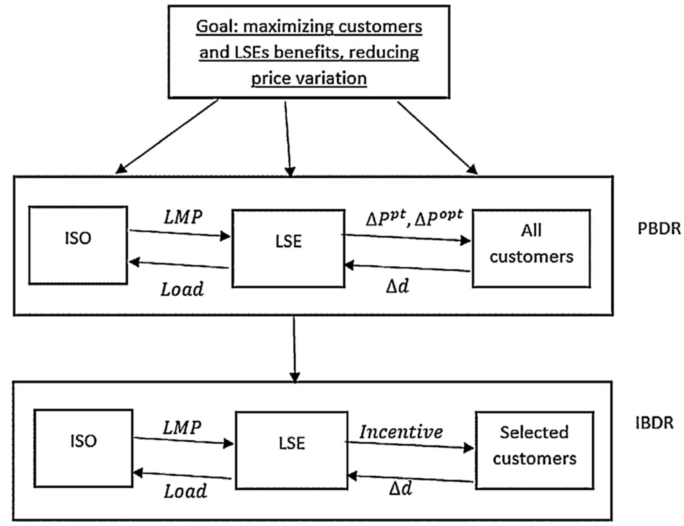

Fig. 1. Structure of proposed DR program in this paper.

3. Methodology

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.

3.1. TOU design

LSEs, or similarly load aggregators, supply electricity for retail load customers, such as, residential or small commercial and industrial from the wholesale market. LSEs purchase electricity from the market at a variable price while selling it to their customers at a retail load tariff. LSE's benefit is related to the difference of market price and customer price. If we assume the retail tariff is fixed, the LSE's objective function is as follows:

$$\max \sum_{b=1}^{N_B} \sum_{t=1}^{T_y} d_{bt}^0 (p_b^0 - \mathrm{LMP}_{bt}) \tag{1}$$

Under this objective function, the LSEs 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 work, a tariff with a peak and an off-peak price is considered that changes every month, which provides reasonable transparency and simplicity for the customer.

The optimal monthly peak and off-peak tariffs are proposed based on the competing objectives of the customer and the LSE. The customer benefit is considered in objective function since TOU DR program is mandatory based and it should be guaranteed that both customers and LSEs gain benefit and it is a fair program for both sides. In addition, reducing load variation is also addressed in the objective function. The motivation is to not only improve the economical operation of the system using DR but also enhance the efficiency of market generation and reduce the stress of the system due to high load variation. Coefficient α is introduced to represent dolor value of load change in (2) and more importantly to weight priority of each objective. In some cases, like high penetration of renewable resource, LSEs could emphasize more on load change objective to use the potential of renewable generation at the off-peak period.

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 the 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:

$$\min_{\Delta d_{bt},\Delta P_b^{\mathrm{PT}},\Delta P_b^{\mathrm{OPT}}} \alpha\left(\sum_{b=1}^{N_B}\left(\sum_{t_2\in \mathrm{PT}} d_{bt_2}-\sum_{t_1\in \mathrm{OPT}} d_{bt_1}\right)\right) - \left(\sum_{b=1}^{N_B} CB_b+\sum_{b=1}^{N_B}\mathrm{LSEB}_b\right) \tag{2}$$

with the following constraints:

$$-\beta\sum_{t=1}^{T_d} d_{bt} \le \sum_{t=1}^{T_d}\Delta d_{bt} \le 0 \tag{3a}$$

$$\Delta d_{bt} = d_{bt}^0\left(\sum_{t_1\in OPT}\varepsilon_{tt_1}\frac{p_b^{\mathrm{OPT}}-p_b^0}{p_b^0}+\sum_{t_2\in \mathrm{PT}}\varepsilon_{tt_2}\frac{p_b^{\mathrm{PT}}-p_b^0}{p_b^0}\right) \tag{3b}$$

$$\Delta d_{bt}^{\min} \le \Delta d_{bt} \le \Delta d_{bt}^{\max} \tag{3c}$$

In (2), customer benefit is represented as:

$$CB_b = p_b^0\sum_{t=1}^{NT} d_{bt}^0 - p_b^{\mathrm{OPT}}\sum_{t_1\in \mathrm{OPT}} d_{bt_1} - p_b^{\mathrm{PT}}\sum_{t_2\in \mathrm{PT}} d_{bt_2} \tag{4}$$

LSE benefit at each bus is calculated as:

$$\mathrm{LSEB}_b = \sum_{t_1\in \mathrm{OPT}}(d_{bt_1}p_b^{\mathrm{OPT}} - d_{bt_1}\mathrm{LMP}_{bt_1}) + \sum_{t_2\in \mathrm{PT}}(d_{bt_2}p_b^{\mathrm{PT}} - d_{bt_2}\mathrm{LMP}_{bt_2}) - \sum_{t=1}^{NT}(d_{bt}^0 p_b^0 - d_{bt}^0\mathrm{LMP}_{bt}) \tag{5}$$

In the above formulation 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:

$$d_{bt} = d_{bt}^0 + \Delta d_{bt} \tag{6}$$

$$p_b^{\mathrm{OPT}} = p_b^0 + \Delta p_b^{\mathrm{OPT}} \tag{7}$$

$$p_b^{\mathrm{PT}} = p_b^0 + \Delta p_b^{\mathrm{PT}} \tag{8}$$

TOU design formula is quadratic optimization with linear constraints that could be solved using any quad solver. In this paper, the interior-point-convex algorithm is used to solve this optimization. The input variables of (2) are hourly load and LMP, self and cross elasticity, peak and off-peak period, and customer fixed tariff (p^0). The value of p^0 is not critical since optimization has to find the deviation from this fixed tariff in each period of the day. In this paper, average of LMP in each month is considered as p^0.

The critical points for the TOU tariff design are both the load and LMP variations. 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.

3.2. Incentive-based DR design

As is clear in (1), the LSE loses money when the market price is greater than the flat rate price, i.e., during a peak hour with a price spike in the wholesale market. The IBDR programs can help the LSE minimize this loss by paying incentives to reduce demand during these times. The IBDR program can be seen as a reward based plan for customers. Reward based programs tend to have a longer lasting effect on customer behavior [10,11]. TOU strikes most customers as punishment since typically only a small fraction of the load can be reduced but the price applies to the full load. Consequently, an IBDR program may be more attractive to customers, especially since it typically has a short duration and is required only a few hours each month.

The LSE objective function for an optimum incentive payment with the needed load reduction is as follows:

$$\max_{\Delta\bar{D}_{bt},\, p_{bt}^{inc}} \sum_{b=1}^{N_B}\sum_{t=1}^{M}(d_{bt}-\Delta\bar{D}_{bt})p_b^{\mathrm{PT}} - (d_{bt}-\Delta\bar{D}_{bt})\mathrm{LMP}_{bt} - \Delta\bar{D}_{bt}p_{bt}^{inc} \tag{9}$$

with the following constraints:

$$\Delta\bar{D}_{bt} = \sum_{j=1}^{D_T}\Delta D_{bt_j} \tag{10a}$$

$$\Delta D_{bt}^{\min} \le \Delta D_{bt_j} \le \Delta D_{bt}^{\max} \tag{10b}$$

$$\Delta D_{bt_j} = g_{tj}(p_{bt}^{inc}) \tag{10c}$$

We separate total load reduction at each hour into three types of customers: residential, commercial and small industrial. Each category has a different elasticity and allowable load change at each hour. During the daytime, industrial and commercial sectors tend to have higher elasticity whereas residential loads tend to have more flexibility in the evenings. The function $g_j(p_{bt}^{inc})$ reflects the response of the consumer when offered an incentive payment. Under the assumption of linear demand curves, g_j can be explicitly expressed as:

$$\Delta D_{bt_j} = \varepsilon_{tj}(p_{bt}^{inc}) \tag{11}$$

The unknown variables in this optimization are incentive payment and load reduction at each hour. As a result, the optimization leads to a quadratic optimization program with linear constraints.

3.3. Optimum threshold to trigger incentive-based DR

One important question for designing an IBDR is to determine when is the best time to be implemented, i.e., when is it worthwhile to offer payments to the customer to encourage load change. This question directly relates to total benefit for both the customer and LSEs, as well as important implementation factors such as simplicity, total allowable hours of reduction in a given time period, and so on. Regarding just the simplicity of method, a constant threshold above retail load tariff could be considered. For example, the LSE could ask for DR whenever the LMP in the wholesale market exceeds their selling price by some increment, say \$10/MWh. The increment acts as a trigger point for the IBDR program. A constant increment has some disadvantages. One of which is that the total hours of DR in a day cannot be controlled. It is expected that most reductions will need to occur on hot Summer days and might put too great an inconvenience on the customer resulting in a reduction of the number of the volunteer participants. Consequently, an optimum threshold above the market price to trigger a DR programs is proposed considering both benefit and limitation from the customer side. We propose the following objective for the optimum threshold:

$$\min_{u_t,\, \Delta \bar{D}_{bt}} \left[\sum_{b=1}^{N_B} \sum_{t=1}^{T_y} u_t \left(\Delta \bar{D}_{bt}(p_b^{\mathrm{PT}} - \mathrm{LMP}_{bt}) + \Delta \bar{D}_{bt} \frac{\Delta \bar{D}_{bt}}{\varepsilon} \right) \right] \tag{12}$$

Subject to:

$$\Delta \bar{D}_{bt} = \sum_{j=1}^{D_T} \Delta D_{bt_j} \tag{13a}$$

$$\Delta D_{bt_j}^{\min} \le \Delta D_{bt_j} \le \Delta D_{bt_j}^{\max} \tag{13b}$$

$$\Delta D_{bt_j} = \varepsilon_{tj} P_{bt}^{inc} \tag{13c}$$

$$T_d^{\min} \le \sum_{i=1}^{T_d} u_i \le T_d^{\max} \tag{13d}$$

$$T_m^{\min} \le \sum_{i=1}^{T_m} u_i \le T_m^{\max} \tag{13e}$$

$$u_t \in \{0, 1\} \tag{13f}$$

In the above formulation, the total hours requesting response are limited. The incentive payment substitutes load change for elasticity in order to simplify. N is an arbitrarily large number used to represent conditions when the constraint is not enforced. Eq. (12) is mix integer quadratic optimization with linear constraints. In this paper branch and bound method is applied to binary variable u_t and quadratic part is solved by the interior-point-convex algorithm. The inputs for (12) are peak time tariff, hourly load and LMP and elasticity of each customer type. Results are load change and required incentive payment signal if IBDR is applied and u_t is equal to 1.

Table 1
Regions of WECC-240 bus system.

Region name	# of buses	Region name	# of buses
Southwest	12	PG&E	21
San Diego	2	Northwest	14
LADWP	17	Rocky Mt.	19
San Francisco	4	Idaho	3
Bay Area	11	Nevada	4
Fresno	4	SMUD	3
Cnt. Coast	4	SCE	11

4. Results

For a case study, representative data from the WECC 240 reduced bus system model from the year 2004 is chosen [37]. This system consists of 11 load areas within California ISO (CAISO) and aggregated sub-regions outside of CAISO. There are 16 wind and 4 solar farm areas, 50 aggregated gas-fired generators, 17 coal plants, 4 nuclear base-loaded plants, 27 hydro, 6 geothermal and 3 biomass power plants [37]. Network and generator parameters, including cost function, nominal power, line impedance and hourly load profile are available for this system, so the hourly locational marginal price (LMP) can be calculated for the entire year. MATPOWER is used to solve a DCOPF problem at each hour [38]. The details of DC power flow formulation could be found in [39]. While the analysis is specific to this data, the methodology for optimizing the tariff is general and the regions covered by the data diverse.

The interaction between retail load customer and load serving entities (LSE) is an important concept in this paper, so the 129 load buses are divided into 14 regions. For simplicity, 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. The name of each region with the number of buses within their authority is listed in Table 1.

4.1. Load characteristic and elasticity

The affordable load reduction at each hour is limited due to the types of loads. Devices in the residential and commercial sector can be divided into three groups: (1) reducible loads, whose consumption can be interrupted at a specific time and will not need to be supplied in the future; (2) shiftable loads, whose consumption can be shifted to another time of day; and (3) firm loads that are so important for the customer. For this group of devices, no manipulation on the pattern of consumption is acceptable.

Making the assumption that 10% of the demand of each device is reducible and using the load profiles for each device from [40,41] maximum affordable limit of load reduction at each hour would be calculated. The RELOAD database, as used by the Electricity Module of the National Energy Modeling System (NEMS), consists of a variety of 1486 representations of load shapes for the residential, commercial, and industrial demand sectors. A load shape typically consists of a sequence of hourly electricity loads over the period of one year. The full load shape, consisting of a set of 8760 separate values for electricity loads, can be summarized or represented by using average or typical days instead of all the days of the month. The 28–31 days of each month can be summarized or represented by using a typical or average weekday, a typical or average weekend day, and a peak day. Fig. 2 shows on example of load profiles for space heating in western regions in February.

In Table 2 summary of elasticity value that is used in TOU and IBDR program is shown. For each customer type, the lowest reported value for elasticity is used to reflect lower uncertainty in customers response. As it showed before, the proposed IBDR program has this capability to consider any form of customers comeback to incentive signal. In this paper, constant elasticity is

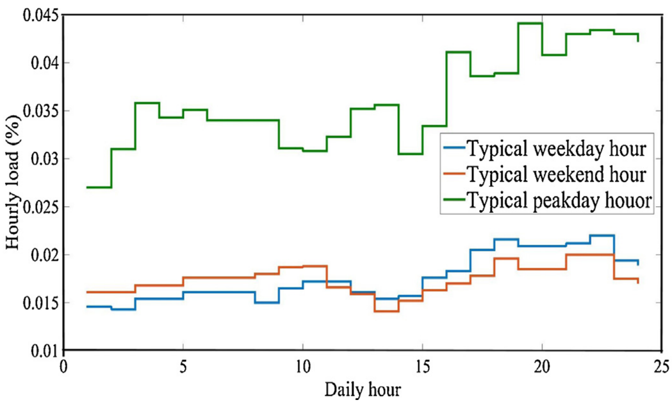

Fig. 2. Example of load profile for space heating in February [40].

considered for each customers type. However, the sensitivity of IBDR program toward variation of elasticity is discussed in details in other studies of the authors [44,45].

4.2. Peak and off-peak tariffs results

As explained in Section 2, a monthly peak and off-peak retail load tariffs 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 is calculated based on shiftable appliance according to Section 4.1. The main focus in this section is on the shiftable load for this DR program, and small portion of 1% for reducible load is modeled in TOU program. According to the output of the TOU optimization from Eq. (2), the peak and off-peak tariffs difference can be calculated using hourly load profile and LMP for the entire year. For case study α is considered to be 1$/MWh to reflect more less emphasize. Results for the San Francisco and PG&E region are shown in Fig. 3. 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 and it could reach to as much as $20/MW.

In PG&E, there is no difference between the peak and off- peak tariffs in January, March and April and little difference in February. As mentioned in Section 3.1, TOU demand response programs are more suitable if there exists a 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 TOU in these months. An exception is the Northwest region. The LMP has small standard deviation (less than 0.5) and the day and night average are close. For the Northwest only in January does the cold weather make some sense for TOU. For other months, IBDR is required to reduce peak prices.

Load change threshold for IBDR program is found according to controllable device in Section 4.1. Load and retail load selling price are found by TOU program. To find the optimum threshold in Eq. (12), the maximum hours that IB can be activated in each day is set to three. The maximum number of monthly hours is limited as well. 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 18% (1621 h) in the SCE region, but on average just 8% of the year (699 h) requires IBDR. Thus by shifting load less than 5% and reducing 10% of the total load for 8% time of year, a large saving and significant effect on LMP curve can be achieved.

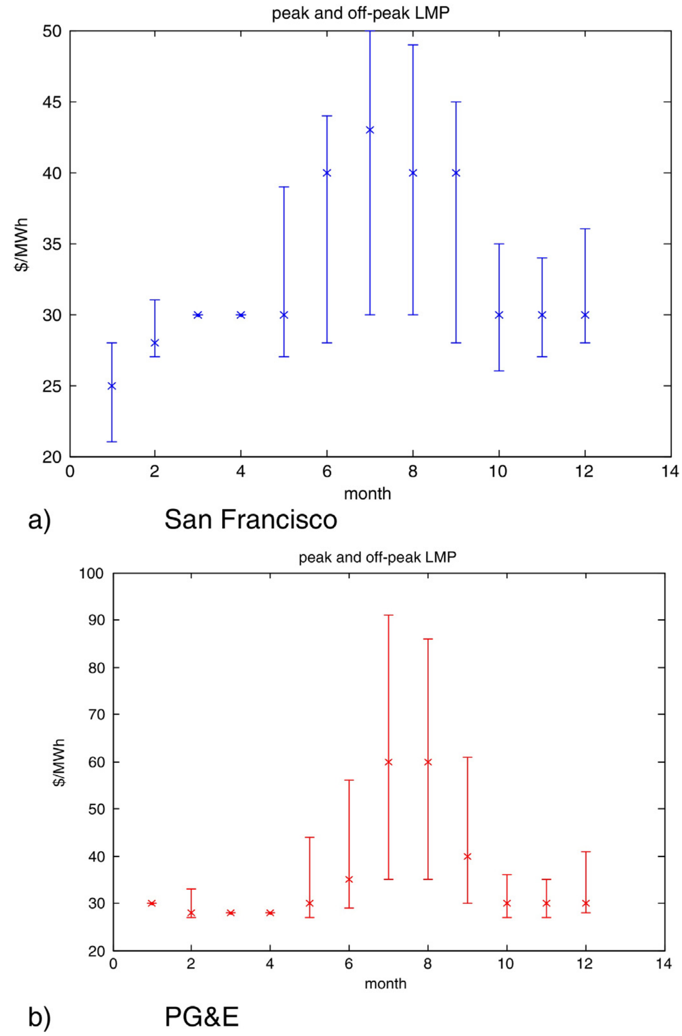

Fig. 3. Peak and off-peak tariffs.

4.3. Effects of DR programs on LSEs net revenue

Both TOU and IB need to bring an acceptable amount of benefit for the customer and LSE to be acceptable. Table 3 shows LSEs net

Table 2
Elasticity value for each DR program [42,43].

Price based program	
Self elasticity	−0.1
Cross elasticity	0.07
Incentive based program	
Residential	0.15
Commercial	0.1
Industrial	0.05

Table 3
LSE net revenue change by each DR program.

	Net revenue by TOU	Net revenue by IB	Total net revenue
High benefit region			
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%

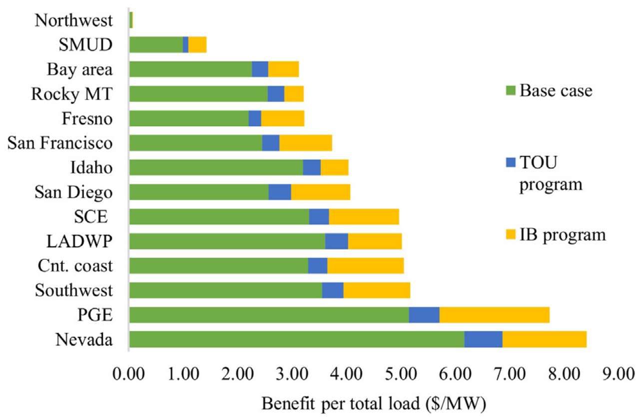

Fig. 4. LSE net revenue per total load by different program.

revenue change for each program based on the optimization procedure and then combined for low and high beneficial regions. Base case in this table is the LSE total net revenue without any DR programs calculated according to (1) as the difference between market price and the flat rate tariff. Notice TOU benefit tends to be uniform for most regions while IB 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 not be much benefit to the IB program.

LSE net revenue per total load ($/MW) for the base case, after TOU and after IB is shown in Fig. 4. Base case in this figure means with no demand response program but with the optimized tariff. Fig. 5 shows the LSE total net revenue relation by average LMP during high price periods. Regions with higher average LMP have higher revenue by demand response programs.

4.4. Effects of DR programs on customer electricity payment

Customer reduction in electricity costs is shown in Table 4. The base case is the customer payment without any DR which is assumed to be on the flat rate price based on 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, which is a small fraction of total demand. Customers who participate in the program earn $2.86/MW on average for their load change. Fig. 6 shows the customer saving and LSE net revenue change exclusively through the TOU demand response program. Relative benefits are similar, which suggests a fairness in the program.

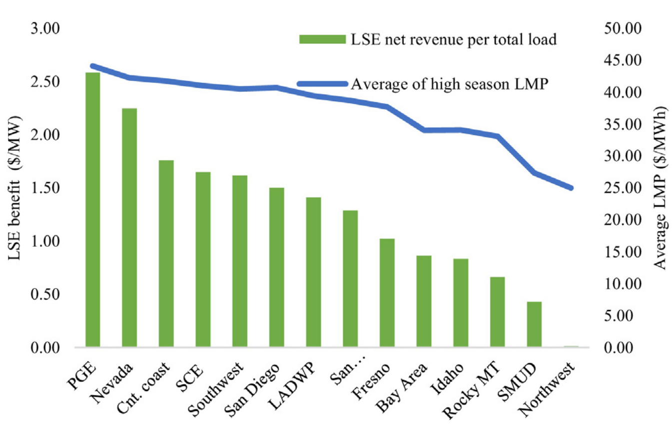

Fig. 5. Total LSE net revenue in compare with average LMP.

Table 4
Customer saving in each region.

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

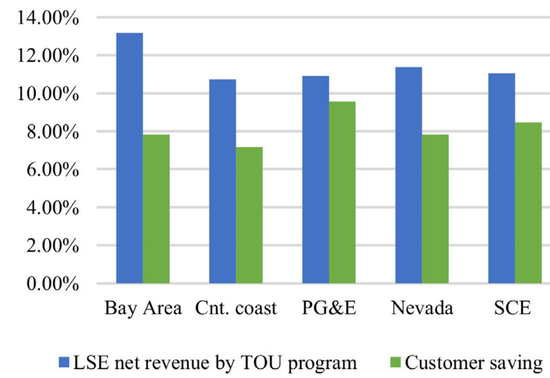

Fig. 6. Customer saving and LSE net revenue by TOU program.

Customer saving and LSE net revenue after both DR programs are shown in Fig. 7 sorted based on regions with the highest benefit. The revenue for LSE and customer savings remains comparable. Thus, the results here for the proposed DR program appear to adequately benefit both the customer and LSE.

4.5. Effects of DR programs on LMP

In Figs. 8 and 9, the monthly average LMP and standard deviation are shown before and after the DR programs in two example regions. LMP average and volatility is relatively small in the Winter and higher during the Summer peak period as expected. The optimum DR tariff proposed here does reduce both average costs and volatility.

4.6. Customer type effects on DR results

As it explained before, the proposed IBDR formula in this papers designed based on different customer type, e.g., residential, commercial and industrial. This option gives this possibility to LSEs to

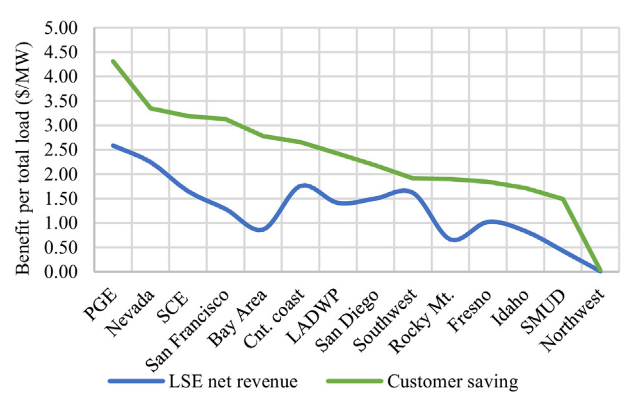

Fig. 7. Customer saving and LSE net revenue per total load.

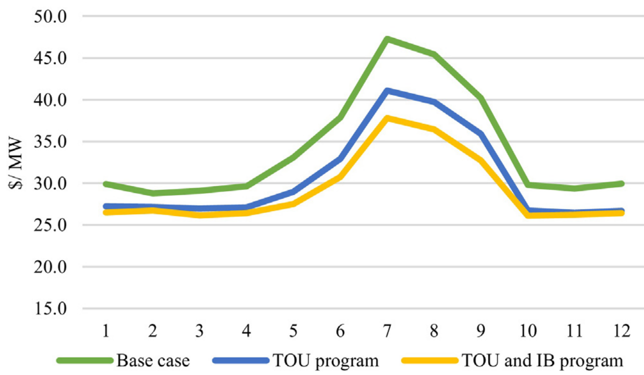

Fig. 8. Average monthly LMP in San Diego.

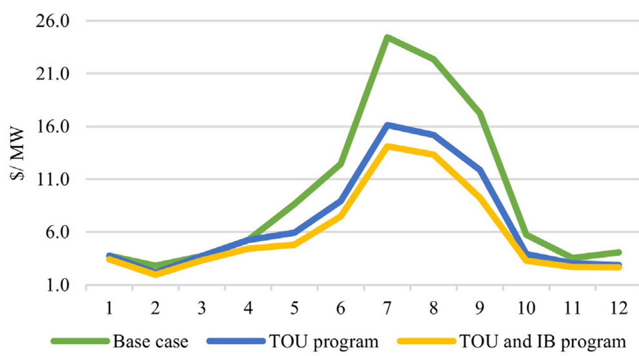

Fig. 9. Monthly standard deviation of LMP in LADWP.

simulate diversity of customers behavior and make their DR program more accurate and realistic. In this paper results are reported based on equal share for each customer type at each load bus. Since the case study is done on WECC 240 reduce model, which each bus is aggregated of various small neighborhood regions, this assumption is reasonable and would not cause large error. However, to emphasize more on necessity of customer classification in DR design, sensitivity of LSEs benefit toward customer grouping is shown in this section.

Fig. 10 example of LSEs sensitivity to share of each customer type for PG&E region in July. On the horizontal axis, the first row is the ratio of industrial demand to the total load and the second row is the summation of the residential and commercial demand in percentage. As it shown, when the population of residential and commercial increase the LSEs revenue using DR is also increased. The reason is higher elasticity and more flexibility for load change from this group of customers in compare with industrial loads. However, for higher residential/commercial load share (bigger than 60%), LSE benefit is less sensitive to the customer type even though it continues to gain benefit.

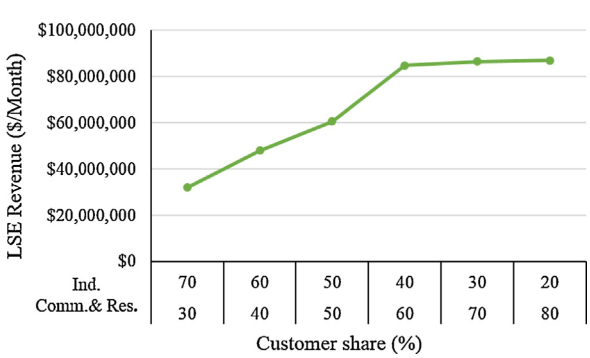

Fig. 10. Sensitivity of LSE benefit to customer type share- PG&E region – July.

5. Conclusion

In this work, a demand response model combining TOU and IBDR programs is analyzed. The model considers both single and multi-period loads using concepts of demand-price elasticity. The comprehensive model explores the potential of both reward and punishment in DR tariffs. A method to design optimum peak and off-peak customer tariffs is developed, which calculates the load change using self- and cross-elasticity. A novel formulation for the optimal tariff is proposed. The optimization determines not only the appropriate incentive payment and load reduction but also when to activate the IBDR program. 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 demand peak power using both load shifting and load shedding. It shows that in Summer, which is peak season of consumption, average LMP could reduce more than 15$/MW and standard variation would decrease as much as 10$/MW. Consequently, total generation cost reduces significantly and all participants in the market, including LSEs, benefit. Customer savings consists of the incentives received and lower prices that together bring significant savings. Case study n WECC shows, customers could save up to 10% on their monthly bill and LSES could have up to 50% more revenue using the proposed DR scheme in this study.

References

[1] T.F. Garrity, Getting smart, IEEE Power Energy Mag. 6 (2) (2008) 38–45.
[2] M. McGranaghan, D. Von Dollen, P. Myrda, E. Gunther, Utility experience with developing a smart grid roadmap, in: IEEE PES General Meeting, Pittsburg, July 200-24, 2008, pp. 1–5.
[3] U.S. Department of Energy, Benefit of Demand Response in Electricity Market and Recommendation for Achieving, 2006.
[4] M.H. Albadi, E.F. El-Saadany, A summary of demand response in electricity markets, J. Electr. Power Syst. Res. 78 (11) (2008) 1989–1996.
[5] B. Severin, J. Michael, R. Arthur, Dynamic Pricing, Advanced Metering and Demand Response in Electricity Markets, University of California Energy Institute, Berkeley, 2002.
[6] C. Kang, W. Jia, Transition of tariff structure and distribution pricing in China, in: IEEE PES General Meeting, Detroit, July 24–29, 2011, pp. 1–5.
[7] H. Zhong, L. Xie, Q. Xia, Coupon incentive-based demand response: theory and case study, IEEE Trans. Power Syst. 28 (2) (2013) 1266–1276.
[8] C.S. Chen, J.T. Leu, Interruptible load control for Taiwan power company, IEEE Trans. Power Syst. 5 (1990 May) 460–465.
[9] M.H. Amini, J. Frye, M.D. Llic, O. Karabasoglu, Smart residential energy scheduling utilizing two stage mixed integer linear programming, in: IEEE North American Power Symposium, Charlotte, NC, October 4–6, 2015, pp. 1–5.
[10] F.A. Wolak Frank, Residential Consumer Response to Real-Time Pricing: The Anaheim Critical Peak Pricing Experiment, Department of Economics, Stanford University, 2006.
[11] J.D. Dodson, Relative values of reward and punishment in habit formation, Psychobiol. J. 1 (3) (1917 Nov) 231–276.
[12] M.A. Hoge, R.J. Stocking, A note on the relative value of punishment and reward as motives, J. Anim. Behav. 2 (1) (1912) 43–50.
[13] F.W. Finger, The effect of varying conditions of reinforcement upon a simple running response, J. Exp. Psychol. 30 (1) (1942 Jan) 53–68.
[14] J. Luft, Bonus and penalty incentives contract choice by employees, J. Account. Econ. 18 (2) (1994 Sep) 181–206.
[15] C. De Jonghe, L. Meeus, R. Belmans, Power exchange price volatility analysis after one year of trilateral market coupling, in: 5th European Energy Market Conference, Lisbon, Portugal, May 28–30, 2008, pp. 1–6.
[16] A. Khodaei, M. Shahidehpour, S. Bahramirad, SCUC with hourly demand response considering inter temporal load characteristics, IEEE Trans. Power Syst. 2 (3) (2011) 564–571.
[17] R. Walawalkar, S. Blumsack, J. Apt, S. Fernands, Analyzing PJM's economic demand response program, in: IEEE PES General Meeting, Pittsburg, July 20–24, 2008, pp. 1–9.
[18] S. Blumsack, J. Apt, L.B. Lave, Lessons from the Failure of U.S. Electricity Restructuring, Electricity Industry Center, Carnegie Mellon University, 2006.

[19] D. Violette, R. Freeman, C. Neil, DRR Valuation and Market Analysis, vol. I, Overview Report for the International Energy Agency (IEA) DRR Task XIII, 2006.
[20] D. Violette, R. Freeman, C. Neil, DRR Valuation and Market Analysis, vol. II, Assessing the DRR Benefits and Costs, A report prepared for International Energy Agency (IEA) DRR Task XIII, 2006.
[21] L. Jia, Q. Zhao, L. Tong, Retail pricing for stochastic demand with unknown parameters: an online machine learning approach, in: 51th Annual Allerton Conference, University of Illinois, Illinois, October 2–3, 2013, pp. 1353–1358.
[22] S. Datchanamoorthy, S. Kumar, Y. Ozturk, G. Lee, Optimal time-of-use pricing for residential load control, in: IEEE Smart Grid Common Conference, Brussel, Belgium, October 7–10, 2011, pp. 375–380.
[23] C. Vivekananthan, Y. Mishra, G. Ledwich, A novel real time pricing scheme for demand response in residential distribution systems, in: 39th Annual IEEE Industrial Electronics Society Conference, Vienna, Austria, November 10–13, 2013, pp. 1956–1961.
[24] P. Zhang, K. Qian, C. Zhou, D.M. Hepburn, Demand response for optimization of power systems demand due to EV charging load, in: Asia-Pacific Power and Energy Engineering Conference, Shanghai, China, March 27–29, 2012, pp. 1–4.
[25] F. Kamyab, M.H. Amini, S. Sheykhha, M. Hasanpour, M.M. Jalali, Demand response program in smart grid using supply function bidding mechanism, IEEE Trans. Smart Grid 7 (3) (2016) 1277–1284.
[26] R. Yu, W. Yang, S. Rahardja, Optimal real-time price based on a statistical demand elasticity model of electricity, in: 1st IEEE Workshop on Smart Grid Modeling and Simulation, Brussel, Belgium, October, 2011, pp. 90–95.
[27] P. Simone, L.I.B. Matteo, R. Barry, G. Madeleine, L. Kling, Capacity Assessment of Residential Demand Response Mechanisms, in: 46th International IEEE Universities Power Engineering Conference, Sorest, Germany, September 5–8, 2011, pp. 1–6.
[28] M. Mallette, G. Venkataramanan, Financial incentives to encourage demand response participation by plug-in hybrid electric vehicle owners, in: IEEE Energy Conversion Congress and Expo Conference, Atlanta, Georgia, September 12–16, 2010, pp. 4278–4284.
[29] H. Zhong, L. Xie, Q. Xia, Coupon incentive-based demand response (CIDR) in smart grid, in: IEEE PES General Meeting, San Diego, CA, July 22–26, 2012, pp. 1–6.
[30] C.P.S. Gill, Y.S. Brar, K. Singh, Incentive based demand response program: an effective way to tackle peaking electricity crisis, in: 25th IEEE Canadian Conference on Electrical and Computer Engineering, Montreal, Quebec, April 29–May 2, 2012, pp. 1–6.
[31] K. Kuroda, T. Ichimura, R. Yokoyama, An effective evaluation approach of demand response programs for residential side, in: 9th IET International Advances in Power System Control, Operation and Management Conference, Hong Kong, China, November 18–21, 2012, pp. 1–6.
[32] W. Yang, R. Yu, M. Nambiar, Quantifying the benefits to consumers for demand response with a statistical elasticity model, IET Gen. Transm. Distrib. 8 (3) (2014) 503–515.
[33] H. Shu, R. Yu, S. Rahardja, Dynamic incentive strategy for voluntary demand response based on TDP Scheme, in: Asia-Pacific signal and Information Processing Association Annual Summit and Conference, Hollywood, CA, December 3–6, 2012, pp. 1–6.
[34] J. Wang, M. Biviji, W. Wang, Case studies of smart grid demand response programs in North America, in: IEEE PES Innovation Smart Grid Technology Conference, Anaheim, CA, July 17–19, 2011, pp. 1–5.
[35] H.A. Aalami, M.P. Moghaddam, G.R. Yousefi, Modeling and prioritizing demand response programs in power markets, J. Electr. Power Syst. Res. 80 (4) (2010) 426–435.
[36] A. Asadinejad, K. Tomsovic, M.G. Varzaneh, Examination of Incentive Based Demand Response in Western Connection Reduced Model, in: IEEE North American Power Symposium, Charlotte, NC, October 4–6, 2015, pp. 1–5.
[37] J.E. Price, J. Goodin, Reduced network modeling of WECC as a market design prototype, in: IEEE PES General Meeting, Detroit, July 24–29, 2011, pp. 1–6.
[38] http://www.pserc.cornell.edu/matpower/.
[39] M.H. Amini, R. Jaddivada, S. Mishra, O. Karabasoglu, Distributed security constrained economic dispatch, in: IEEE PES Innovation Smart Grid Technology Conference, Bangkok, Thailand, November 3–6, 2015, pp. 1–5.
[40] RELOAD Database Documentation and Evaluation and Use in NEMS, 2009.
[41] California Commercial End-Use Survey, Itron, Inc., 2006.
[42] U.S. Government Accountability Office, Electricity Markets: Consumers Could Benefit from Demand Programs, But Challenges Remain, Report to Senate Committee on Governmental Affairs, 2004.
[43] The Brattle Group, Quantifying Demand Response Benefits in PJM report for PJM Interconnection and Mid Atlantic Distributed Resource Initiative (MADRI), 2007.
[44] A. Asadinejad, K. Tomsovic, Ch.F. Chen, Sensitivity of incentive based demand response program to residential customer elasticity, in: IEEE North American Power Symposium, Charlotte, NC, September 16–20, 2016.
[45] A. Asadinejad, M.G. Varzaneh, K. Tomsovic, Ch.F. Chen, R. Sawhney, Residential customers elasticity estimation and clustering based on their contribution at incentive based demand response, in: IEEE Power and Energy Society General Meeting, Boston, MA, July 17–22, 2016.