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Dynamic Demand Response using Customer Coupons Considering Multiple Load Aggregators to Simultaneously Achieve Efficiency and Fairness

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***Abstract*—This paper discusses the feasibility of using customer coupon demand response in meshed secondary networks. Customers are rewarded by coupons to achieve the objective of optimal operation cost during peak periods. The interdependence of the locational marginal price and the demand is modeled by an artificial neural network. The effect of multiple load aggregators participating in customer coupon demand response is also investigated. Because load aggregators satisfy different proportions of the objective, a fairness function is defined that guarantees that aggregators are rewarded in correspondence with their participation towards the objective. Energy loss is also considered in the objective as it is an essential part of the distribution system. A dynamic coupon mechanism is designed to cope with the changing nature of the demand. To validate the effectiveness of the method, simulations of the proposed method have been performed on a real heavily-meshed distribution network in this paper. The results show that customer coupon demand response significantly contributes to shaving the peak, therefore, bringing considerable economic savings and reduction of loss.**

***Index Terms*—Customer coupon demand response, fairness, load aggregator, locational marginal price, meshed secondary network.**

I. NOMENCLATURE

ANN	Artificial Neural Network
CCDR	Customer Coupon Demand Response
CPP	Critical Peak Pricing
CPR	Critical Peak Rebates
ISO	Independent System Operator
LMP	Locational Marginal Price
LSE	Load Serving Entity
RTP	Real-Time Pricing
SVM	Support Vector Machine
TOU	Time-of-Use

II. INTRODUCTION

IN the context of the smart grid, demand response has received great attention in recent years as it can shave the peak using financial incentives [1]-[3]. Demand response programs provide opportunities to balance the supply and demand during the peak period [4]-[7]. Most Load Serving Entities (LSEs) are companies that purchase electricity at real-time Locational Marginal Price (LMP) from the wholesale market and supply electricity at a flat rate to the customers. The risk for an LSE mainly comes from the uncertainty with the wholesale LMP. Under the scheme of demand response, the risk of the fluctuating wholesale LMP can be largely transferred from the LSE to the customers.

Several kinds of time-based rate demand response programs have been investigated, such as Time-of-Use (TOU) pricing, Real-Time Pricing (RTP), Critical Peak Pricing (CPP), and Critical Peak Rebates (CPR) [8]-[13]. CPR has been implemented in several pilot experiments. However, the rebates paid to the customers are pre-determined fixed value, which cannot satisfy different operating conditions. Therefore, there are some papers proposing another demand response program called Customer Coupon Demand Response (CCDR), in which the coupon value can be an optimization variable [14]-[15]. Under CCDR, LSEs broadcast the coupon value to the customers. Customers are rewarded by the reduction of their demand with a coupon. Note that LSEs have flexibility issuing a dynamic coupon at the peak period. Customers participating in CCDR program still pay the residual demand at a flat rate to be compatible with the existing electricity bill design.

As with other demand response techniques, LSEs would implement the CCDR program only when the marginal price exceeds the flat rate. LMP is the price of electricity at different locations and consists of three components: energy, congestion, and loss [16]. The LMP represents the marginal cost of electric demand at different locations, accounting for the patterns of demand [17]-[18]. When implementing CCDR, the demand will be reduced which may have influence on the LMP. Therefore, the interdependence between the LMP and the demand cannot be neglected in the CCDR program.

References [14] and [15] calculate the LMP using dc optimal power flow. They provide a straightforward way to model the relationship between LMP and demand based on the known network topology. However, in some areas, the network topology cannot be directly accessed and merely demand bid data is published by the Independent System Operator (ISO). Therefore, machine learning algorithms have been developed to model the LMP and demand without knowing the network topology. Among them, Neural Networks (NNs) have received great attention because of their good resolution to model complex nonlinear relationships [19]-[20]. It is known that LSE bids and LMP are mutually dependent [21]-[22]. There exists a nonlinear relationship between LSE bids and

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LMP. Hence, an Artificial Neural Network (ANN), as a powerful machine learning method, is applied to estimate the LMP based on the demand data because of its improved accuracy and good performance. Most of the studies estimate the LMP based on the demand of the specific region and neglect that the LMP of the specific region can be influenced by other regions. The above issues are discussed in this paper using an ANN to estimate the LMP based on the demand bid from several LSEs.

Due to the weak ability of individual customers to reduce demand, customers are encouraged to apply CCDR through aggregators unless they are able to reduce 50 kW or more [23]. Therefore, load aggregators are necessary participants in CCDR programs. Today, there is no research studying CCDR with multiple load aggregators. Additionally, the aggregators take different proportions of the operation cost of the LSE because of the location diversity. Therefore, the coupon for each aggregator should be differentiated. It would be fair for the aggregators to be rewarded in accordance to their contribution to the reduction of the operational cost. In this paper, a fairness function is defined to determine the coupon values for multiple load aggregators.

Previous CCDR publications [14]-[15] have not paid attention to the energy loss of the distribution system. Since the CCDR is implemented in a distribution system, the energy loss should be taken in account because of the relatively high resistance to inductance ratio of low voltage distribution systems. Most of the demand response programs are implemented in metropolitan areas which consist of numerous residential and commercial customers. Meshed networks are commonly used in metropolitan areas in North America because of the necessary high level of reliability [25]-[26]. Therefore, it is essential to investigate the impact of the demand response program on meshed networks. In this paper, the energy loss has been considered in a real meshed secondary network.

The main contributions of the paper are: (1) to consider the case when multiple load aggregators participate in the CCDR program. A fairness function is defined to determine the coupon values for different aggregators; (2) to perform simulations of the proposed method on a real heavily-meshed distribution network, in which the energy loss is also considered. Existing papers on CCDR have not taken the energy loss into account; (3) to design a dynamic coupon mechanism considering the changing behavior of the demand within one day. Existing publications on CCDR have not discussed the coupon value according to the variation of the demand. Therefore, none of the methods in exiting publications can determine the dynamic value of the coupon for an entire day.

Numerical results show that the presented method greatly contributes to shaving of the peak, which brings significant saving to the operation cost.

III. Problem Formulation

In the real-time wholesale market, the price of electricity is determined by the ISO in a clearing auction. Suppliers provide the exact amount of electricity for a given price. LSEs choose how much electricity they want to purchase based on their own load forecast. Then the ISO selects the suppliers with least cost to meet the hourly load demand with requirements of reliability and efficiency. For the LSEs, the ISO establishes the price at the specific locations, the so-called Locational Marginal Price (LMP). LMP can be used to reflect the value of electricity at different locations considering the cost of loss and congestion under the operating circumstances.

As shown in Fig. 1, the ISO collects the demand bids from different LSEs and determines the LMP for each LSE. Normally, power plants have their own bilateral contracts with fuel companies to hedge the risk of price variation. Thus, we can assume that the coefficients for the generation cost are flat in the short time forecast. We assume that all the LSEs in the specific region have been included and considered. Under this assumption, the LMP of the specific LSE is mainly correlated with its own demand and the demand bid from other LSEs which can be formulated as follows:

$$C_{RT}^{m}(t) = f\left(P_{LSE}^{1}(t), P_{LSE}^{2}(t), \cdots, P_{LSE}^{m}(t)\right) \tag{1}$$

where $C_{RT}^{m}(t)$ and $P_{LSE}^{m}(t)$ are the real-time LMP for LSE m at time t and demand bid for LSE m at time t.

Note that, although LSE may have a minor impact on the LMP, for completeness, the model of the marketing clearing process of the ISO is provided.

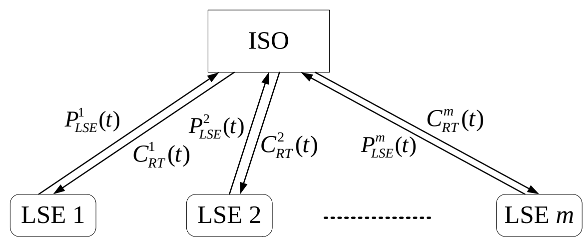

Fig. 1. Operation procedure of the electricity market.

A. Data Classification

It is a fact that the CCDR program can only be implemented when real-time LMP is greater than the flat rate during the peak period [14]. Therefore, it is necessary to distinguish between the peak period and off-peak period before the LMP estimation. Due to the different characteristics between peak period and off-peak period, we can estimate the peak period based on the load data. In this paper, Support Vector Machine (SVM) is used to estimate the peak period based on the load characteristic. SVM is a supervised learning model which is widely applied for classification analysis [27].

B. LMP-Demand Model

Customers participating in the CCDR program would reduce the system demand depending on the coupon value which may decrease the LMP as a consequence. As a result, the relationship between the demand and LMP should be taken into consideration in the coupon optimization problem. LMP is mostly related to the network topology of power systems, load bid data, and generator bid data. However, some operators do not have direct access to the information of the network topology. They have to depend on data published by the ISO. Therefore, machine learning algorithms have been developed to model the LMP and demand without knowing the network topology.

To calculate LMP after CCDR, we should first build the LMP-Demand model. In this paper, an ANN is trained to build the LMP-Demand model rather than a market simulation. We

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collect the training data from one of the sub-regions served by PJM Interconnection LLC (PJM). This sub-region of PJM includes eight LSEs (LSE 1 to LSE 8). For the LMP estimation, the input is the demand from several LSEs at time t and output is the real-time LMP for LSE m at time t based on (1). Hourly demand bid data of different LSEs are available online from PJM. We collect the training data from one of the sub-regions served by PJM [28]. This sub-region of PJM includes eight LSEs in total. Fig. 2 shows the recorded demand data of these LSEs from July 1st to August 31st of 2015. For simplicity, we assume that CCDR is implemented in only one of the eight LSEs (LSE m). After applying CCDR, the demand bid from LSE m will change when compared to the recorded data. Other LSEs are still operating independently and bidding as per recorded data. Therefore, the ANN method provides the updated LMP after applying CCDR for LSE m.

As discussed previously, the CCDR program is operated only during the peak period. After data classification, 74 among the 1488 hours can be considered as peak period which becomes the training set. Fig. 3 provides estimated results of the LMP for LSE 5 during the peak period. It proves that a well-trained ANN model is accurate enough to model the relationship between demand and LMP.

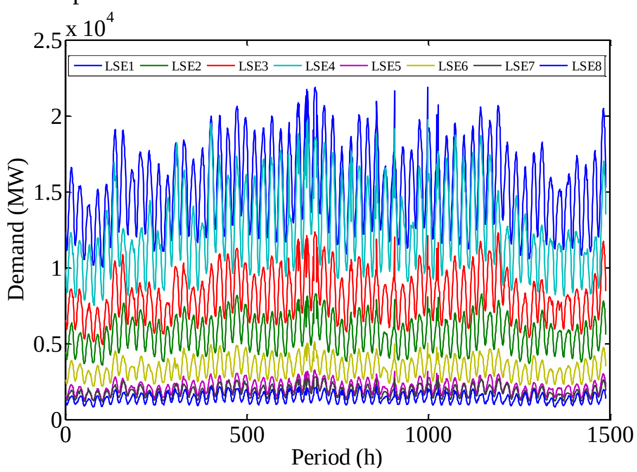

Fig. 2. Actual demand of eight LSEs served by one sub-region of PJM from July 1st to August 31st, 2015 [28]. The top line corresponds to LSE_1, the second from the top to LSE_2, and so forth.

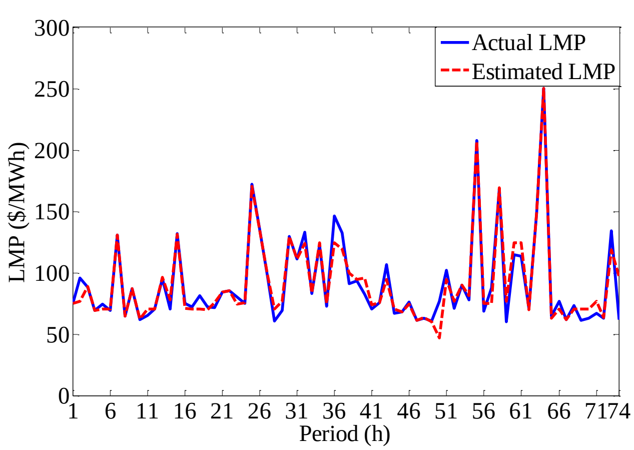

Fig. 3. Comparison between the actual LMP and the estimated LMP during the peak period.

C. Minimization of the LSE Net Loss

The LSE sells electricity at a flat rate to customers and pays for the time-varying LMP purchasing price from the wholesale market. Therefore, the purchasing cost has more fluctuation than the selling revenue due to the variation of the wholesale LMP. During the peak period, the wholesale LMP exceeds the flat rate, which leads to a loss for the LSE. The LSE net loss equals the purchasing cost minus the selling revenue. LSE net cost minimization can be formulated as follows:

$$\min_{C_C^k(t)} \sum_{t=1}^{T}\Big[C_{RT}^m(t)\Big(\sum_{k=1}^{K}\big(P_0^k(t)-\Delta P^k(t)\big)+P_{NP}(t)+P_{loss}(t)\Big)-C_{FR}^m\Big(\sum_{k=1}^{K}\big(P_0^k(t)-\Delta P^k(t)\big)+P_{NP}(t)\Big)+\sum_{k=1}^{K}C_C^k(t)\Delta P^k(t)\Big] \quad (2)$$

where $P_0^k(t)$, $\Delta P^k(t)$, and $C_C^k(t)$ are the original demand, demand reduction based on coupons, and coupon value for load aggregator k at time t. $P_{NP}(t)$, C_{FR}^m, K, and T represent the time-varying demand which does not participate in the CCDR program, flat rate for LSE m, total number of aggregators, and total amount of time periods.

In this paper, power flow results are obtained using OpenDSS, which is a comprehensive electrical power system simulation tool for electric utilities. The distribution system is fully modeled and analyzed with OpenDSS. For simplicity, the power loss in the distribution system at time t is denoted as a nonlinear function G, where the residual demands after CCDR are taken as input and power flow results are provided as the output. The updated G function is provided as follows:

$$P_{loss}(t) = G\left[\left(\boldsymbol{P_0^1(t)}-\Delta\boldsymbol{P^1(t)}\right),\cdots,\left(\boldsymbol{P_0^k(t)}-\Delta\boldsymbol{P^k(t)}\right),\boldsymbol{P_{NP}(t)}\right] \quad (3)$$

where $\boldsymbol{P_0^k(t)}$ is a vector that denotes the original demand of the aggregator k, which includes the original demand of every end-user within the aggregator k. $\Delta\boldsymbol{P^k(t)}$ is a vector that denotes the demand reduction of the aggregator k, which includes the demand reduction of every end-user within the aggregator k. $\boldsymbol{P_{NP}(t)}$ is a vector that includes the demand of every end-user not participating in the aggregators.

Fig. 4 gives the hourly purchasing cost and selling revenue without CCDR for the entire day based on the recorded data of LSE 5 on July 20th in 2015 by PJM [28]. The shaded region in Fig. 4 shows the total net loss during the peak period.

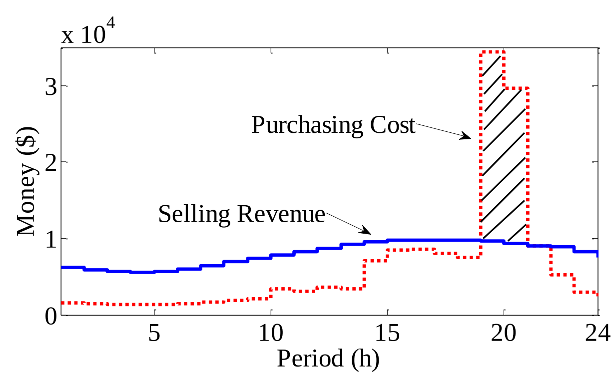

Fig. 4. Illustration of the purchasing cost and selling revenue for LSE; data from [28].

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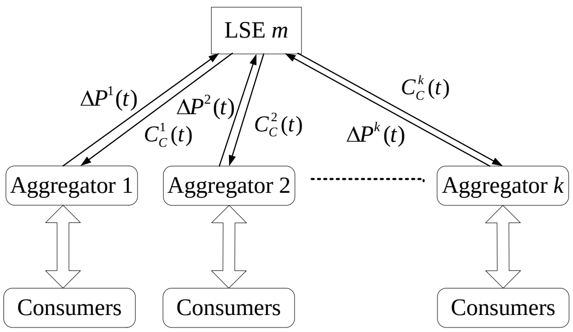

Fig. 5. Interaction between the LSE and load aggregators.

D. Fairness among Multiple Load Aggregators

Electric load aggregator is an organization which clusters customers together to increase the market power of individual customers. As shown in Fig. 5, the LSE *m* broadcasts the coupons to different load aggregators to minimize its net loss. Customers adjust the load consumption pattern and post the demand reductions to the aggregators. The load aggregators collect the total demand reduction and submit to the LSE. For simplicity, the CCDR program is assumed to be implemented in the area served by one LSE and the competition among multiple LSEs is neglected.

Most research papers related to coupon demand response focus on achieving a system-level optimization objective. However, they neglect the factor of fairness, which is important for policy makers [24]. In other words, the rewards that customers can get are not proportional to their contribution towards the system-level objective. The aggregators take different proportions of the operational cost of the LSE because of the location diversity. Intuitively, the contribution is largely dependent on size and location of the load aggregators. In order to measure the impact in a mathematical way, we employ Shapley Value in a cooperative game model. Note that, the CCDR is a top-down scheme and aggregators can be seen as cooperative participants from the perspective of the LSE.

Without the CCDR program, the net loss of the LSE at time t is derived from (2) as:

$$V(t) = C_{RT}^{m}(t)\left(\sum_{k=1}^{K}\left(P_0^k(t) - \Delta P^k(t)\right) + P_{NP}(t) + P_{loss}(t)\right) - C_{FR}^{m}\left(\sum_{k=1}^{K}\left(P_0^k(t) - \Delta P^k(t)\right) + P_{NP}(t)\right) \quad (4)$$

Our definition of fairness is that each aggregator gets coupons according to its impact on $V(t)$. The fairness function is defined as:

$$\boldsymbol{C_C^k(t) \propto \frac{\varphi^k(t)}{\sum_{j=1}^{N}\varphi^j(t)}} \quad (5)$$

where $C_C^k(t)$ is the coupon value for load aggregator k, $\varphi^k(t)$ and $\varphi^j(t)$ denote the impact of load aggregators k and j on $V(t)$, and N is the total number of aggregators. When large customers participate independently (not aggregated), they are treated as other aggregators. In this paper, (5) is proposed as an axiomatic index to measure fairness. We assume that it is fair to distribute the coupon value for each aggregator using (5). Under this assumption, the coupons that customers get are proportional to their impact on the system-level objective (4).

To calculate the $\varphi^k(t)$, we model the coupon allocation as a cooperative game. Therefore, the Shapley value can be used to distribute the net loss to the players in a fair way [24]. In the Shapley method, $\varphi^k(t)$ can be determined from two scenarios. First, is the case when aggregator k is not part of the grid. Second, is the case when aggregator k is within the grid. Then we can calculate the Shapley value as:

$$\varphi^k(t) = \frac{1}{N!}\sum_{S\in N\setminus\{k\}} S!\,(N-S-1)!\left[V_{S\cup\{k\}}(t) - V_S(t)\right] \quad (6)$$

where S is a subset of N not containing aggregator i. $V_{S\cup\{k\}}(t)$ and $V_S(t)$ are the net loss function of subset S with aggregator and without aggregator k, respectively.

E. Maximizing the Customer Utility Function

In economics, utility function is used to measure welfare or satisfaction of the customers over a set of goods and services. In this paper, we assume that the customers of CCDR choose to reduce the demand with the objective of maximizing their own utility function [14]. The electric load aggregator is an organization that clusters customers together to increase their market power. We assume that the customers make commitments with their aggregator. To keep fairness among customers within one aggregator, the amount of demand reduction of customers is assigned in proportion to their size with the same coupon value.

Economists use the demand curve to model the relationship between price and quantity demanded [30]. The quantity demanded is the amount of the good that customers are willing to purchase. Fig. 6 shows the typical elastic demand curve. C_w^k, $P^k(t)$, P_{min}^k, $P_x^k(t)$, and $P_0^k(t)$ are the price that customer k is charged, quantity demanded of customer k at time t, the minimum demand value of customer k which is the inelastic demand amount, the optimal demand value of customer k at time t under the CCDR program, and the initial demand value of customer k at time t without the CCDR program, respectively. Based on theory of economics [30], the CCDR will shift the demand curve to the left because it gives the customer incentive to reduce the demand. Therefore, the LSE will have less demand while keeping the flat rate. It has been demonstrated that the CCDR is effective in encouraging customers to reduce load voluntarily [14].

Price elasticity of load aggregator ε^k is defined as the relative change in demand that results from a relative change in the price [31]-[32]. In general, measuring price elasticity ε^k is a complex task and includes large uncertainties. Reference [33] defines short-run and long-run price elasticity. In this paper, only short-run elasticity is considered which can be expressed as follows:

$$\varepsilon^k = \frac{\Delta P^k / P_{ref}^k}{\Delta C^k / C_{ref}^k} \quad (7)$$

where ΔP^k, ΔC^k, P_{ref}^k, and C_{ref}^k denote the variation of demanded quantity of aggregator k, price variation for aggregator k, reference demand of aggregator k, and reference price for aggregator k, respectively.

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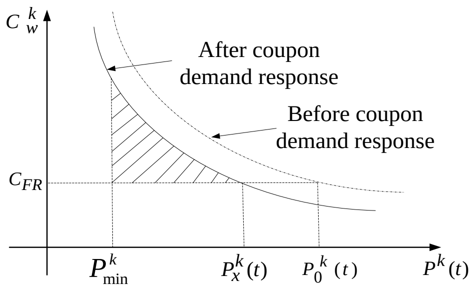

Fig. 6. Impact of CCDR on the price elastic demand curve.

From [33], the function of demand curve can be formulated as follows:

$$P^k(t) = a^k \cdot (C_w^k)^{\varepsilon^k} \tag{8}$$

where a^k is the coefficient for the demand curve that can be calculated by putting reference values P_{ref}^k and C_{ref}^k into (8).

From the view of an economist [30], the area below the demand curve and above the price measures the customer surplus in a market (see the shaded region in Fig. 6). Besides, the customers get the reward from the demand reduction which should be also taken into account. Note that, the coupon should be greater than the specific value (flat rate of electricity), otherwise customers will not give up the comfort for less than the flat rate they consume. In this paper, the customers' utility function is defined as the sum of the surplus and the coupon reward. Maximizing the utility function can be formulated as follows:

$$\max_{P_x^k(t)} \left[\int_{P_{min}^k}^{P_x^k(t)} \left(\frac{P^k(t)}{a^k}\right)^{1/\varepsilon^k} dP - C_{FR}^m\left(P_x^k(t) - P_{min}^k\right) + \left(C_c^k(t) - C_{min}\right)\left(P_0^k(t) - P_x^k(t)\right)\right] \tag{9}$$

$$\text{subject to: } P_x^k(t) = P_0^k(t) - \Delta P^k(t) \tag{10}$$

$$P_{min}^k \le P_x^k(t) \le P_0^k(t) \tag{11}$$

$$C_{min} \le C_c^k(t) < C_{max}(t) \tag{12}$$

where C_{min} and $C_{max}(t)$ are the flat rate of electricity and the wholesale electricity prices at time t, respectively. This is because the LSEs would not pay for the demand reduction at a price that is more expensive than the wholesale price.

Due to the convexity of (9), (11), and (12), the global optimal solution can be found by the Karush-Kuhn-Tucher (KKT) condition [34]:

$$P_x^k(t) = a^k \cdot (C_{FR}^m + C_c^k(t) - C_{min} + \lambda_1 - \lambda_2)^{\varepsilon^k} \tag{13}$$

$$\lambda_1 \cdot \left(P_x^k(t) - P_0^k(t)\right) = 0 \tag{14}$$

$$\lambda_2 \cdot \left(P_{min}^k - P_x^k(t)\right) = 0 \tag{15}$$

$$\lambda_1, \lambda_2 \ge 0 \tag{16}$$

where λ_1, λ_2 are Lagrange multipliers.

Hence, the optimal demand value of customer k at time t under the CCDR program is determined as follows:

$$P_x^k(t) = \begin{cases} a^k \cdot (C_{FR}^m + C_c^k(t) - C_{min})^{\varepsilon^k} & \lambda_1, \lambda_2 = 0 \\ P_{min}^k & \lambda_1 = 0, \lambda_2 \ne 0 \\ P_0^k(t) & \lambda_1 \ne 0, \lambda_2 = 0 \\ \emptyset & \lambda_1 \ne 0, \lambda_2 \ne 0 \end{cases} \tag{17}$$

F. Overall Procedure

As discussed in previous sections, the objective of the CCDR program is to minimize the net economic loss of the LSE and maximize the utility function of customers. The objectives of the co-optimization (or bi-level optimization) problem can be formulated as (2) and (9), subject to (10), (11), and (12).

As shown in Fig. 5, the LSE broadcasts the coupon value $C_c^k(t)$ to the aggregators. As a result, the consumers within aggregators reduce demand $\Delta P^k(t)$. The demand reduction $\Delta P^k(t)$ in (2) is decided by the utility function of customers (9), however, the coupon value $C_c^k(t)$ depends on the net economic loss function of LSE (2). Therefore, (2) and (9) form a bi-level optimization problem with correlated variables in both levels. Note that, the real-time LMP for LSE $C_{RT}^m(t)$ depends not only on its own demand bid but also demands on bids from other LSEs, which is illustrated by Fig. 1. Therefore, $C_{RT}^m(t)$ in (2) could be obtained from a well-trained ANN, as (1). The demand bid $P_{LSE}^m(t)$ of LSE m in (1) can be calculated by:

$$P_{LSE}^m(t) = \sum_{k=1}^{K}\left(P_0^k(t) - \Delta P^k(t)\right) + P_{NP}(t) + P_{loss}(t) \tag{18}$$

In this paper, the bi-level optimization problem is regarded as a mathematical program with equilibrium constraints (MPEC). First, we solve the lower level optimization (9) with KKT optimality condition and then we can obtain an analytic solution using (17). Subsequently, the solution is employed in the upper level optimization (2). Therefore, the multi-objective optimization problem is converted into a single-objective optimization problem, as follows:

$$\min_{C_C^k(t)} \sum_{t=1}^{T}\left[C_{RT}^m(t)\left(\sum_{k=1}^{K}\left(P_x^k(t)\right) + P_{NP}(t) + P_{loss}(t)\right) - C_{FR}^m\left(\sum_{k=1}^{K}\left(P_x^k(t)\right) + P_{NP}(t)\right) + \sum_{k=1}^{K} C_C^k(t)\left(P_0^k(t) - P_x^k(t)\right)\right] \tag{19}$$

By replacing $P_x^k(t)$ in the objective function (2), the coupon value $C_C^k(t)$ has become the only decision variable of the optimization problem (19). To reduce the search space, practical conditions are established: (1) the lower bound is set to the flat rate ($100/MWh) and the upper bound is set to the wholesale price. This is because the LSEs would not pay for a demand reduction at a price that is cheaper than the flat rate or more expensive than the wholesale price; (2) the coupon value is set to be an integer variable. Therefore, the step size of the coupon ΔC_C^k is chosen as $1/MWh. To solve the optimization problem, we use an exhaustive method: Increase coupon value by fixed increment ΔC_C^k and then calculate the objective (19) iteratively until the maximum value is reached. Finally, we can get the optimal value of coupons for the load aggregators that maximize the objective function of the LSE.

Several main steps are involved as follows:

Step 1: For a given coupon value of load aggregator k, the fair distribution of coupon for the other aggregators can be determined. Initial coupon value is C_{min}.

Step 2: Customers participating in the CCDR program choose to reduce their demand to the optimal value to maximize their utility function.

Step 3: Based on the residual demand, the LSE employs SVM to estimate whether it is still peak period. If it is still peak period, it is possible for LSE to distribute more coupons. Then, proceed to step 4. If not, the LSE would not distribute more coupons and stop iterating. The coupon of this iteration is chosen as optimal coupon value.

Step 4: ANN is applied to estimate the LMP based on the characteristics of load. To highlight the effect of CCDR, we assume that the program is only implemented by one LSE and other LSEs remain with the original demand profiles.

Step 5: Calculate the objective function of the LSE under the given coupon value.

Step 6: Increase coupon value by fixed increment ΔC_C^k and then iterate from step 1 to step 6 until reaching the maximum value C_{max}. Finally, we can get the optimal value of coupons for the load aggregators that maximize the objective function of the LSE.

The steps above are executed based on one hour of the day. Hourly CCDR can be determined by repeating the above steps. The flowchart of the above steps is illustrated in Fig. 7.

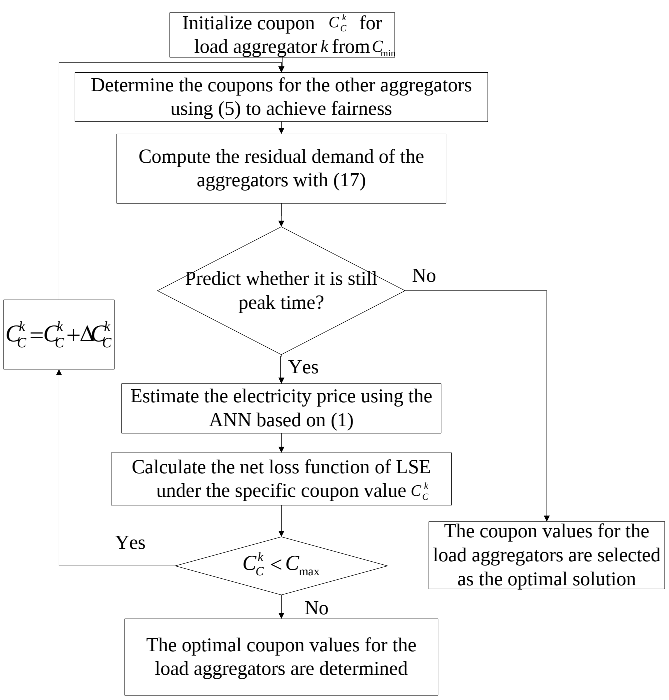

Fig. 7. Flowchart of the proposed method.

G. Practical Implementation

The two-settlement mechanism, which includes day-ahead market and real-time market, is widely used in North American electricity markets. Most LSEs would lock the energy price in forward or day-ahead markets to hedge the risk of real-time price variation. However, due to the space limitations, this paper focuses on CCDR under real-time markets. As references [14] [15] point out, the energy cleared in the real-time market is around 2% to 8%. Although the percentage seems small, it is significant for a demand response program. To diminish the risk of real-time price volatility, the LSEs would encourage the consumers to reduce demand by financial incentives such as CCDR when real-time price spikes occur. With the smart grid technology such as smart meters, the consumers' response to the CCDR could be realized close to real-time.

Fig. 8 gives a better illustration on the time scale of the proposed coupon based operation. First, the LSE prepares to broadcast the coupon to the consumers when a wholesale price spike occurs according to the updated report by ISO. Due to the huge data processing pressure in practice, it is impossible for LSEs to interact with consumers to determine the optimal coupon value iteratively. Hence, LSEs should be aware of the approximated optimal coupon value so that the iterations between LSEs and consumers can be minimized. The pre-operating interval of the real-time markets is set to 60 minutes by the Electric Reliability Council of Texas (ERCOT)[14][15][35]. Therefore, if the peak period is one hour long, there will be approximately one hour for the consumers to adjust their electricity usage. In addition, facilitated by enhanced communication technologies, consumers' response to the coupon price could be realized in near real-time (e.g. 10-15 min).

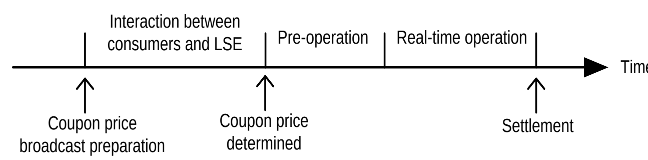

Fig. 8. Timeline of the CCDR implementation.

IV. Simulation Results

Simulations of the proposed method have been performed on a real heavily-meshed distribution network that has 1905 buses, 5 substation transformers, and 210 secondary transformers (4 transformer connected with spot loads at 480 V and 206 transformers connected with secondary network at 208 V, see Fig. 9. The peak demand is 97.9 MW at 0.91 power factor (lagging). The substation supplies power through several MV radial feeders. The secondary network is fed by the radial feeders through network transformers. Most regular loads are connected to the secondary network at 208 V and a few large customers (so-called spot loads) are supplied at 480 V.

The method is illustrated when three load aggregators are present with percentage of the total load given in Table I. Note that the situation that some customers are not willing to participate in the CCDR is also considered.

LSE 5 is assumed to be the only one that participates in the CCDR program. However, estimation of the LMP for the LSE 5 needs the demand data from other seven LSEs. To evaluate the effectiveness of the proposed method, the load profile and the LMP curve of the LSE served by PJM is investigated [28]. We pick July 20th of 2015 as our study period which has a typical summer load pattern. The load profile and the LMP pro-

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file for the LSE 5 on that day are presented in Figs. 10 and 11. The demand data of the other seven LSEs can be found in Fig. 2. As shown, the LMP and the demand behave in a similar manner during the day. The peak of the LMP is almost coincidental with the peak of demand (around 7:00 PM). Since the LMP has direct and positive correlation with demand, the LMP has good possibilities to be reduced when the demand is stimulated to decrease under the implementation of CCDR. This will largely relieve the burden of purchasing electricity at peak period for the LSE, which gives the CCDR great potential to be implemented.

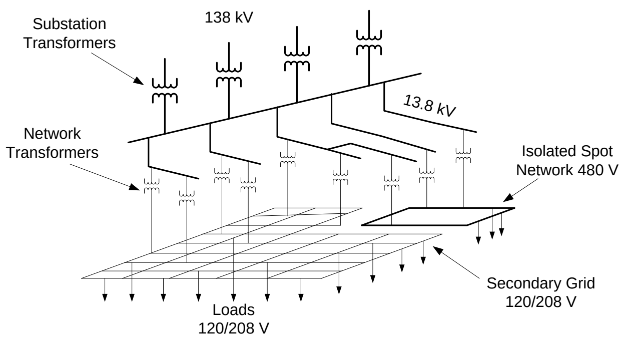

Fig. 9. Structure of the meshed network used in the study.

TABLE I
CHARACTERISTICS OF THE LOAD AGGREGATORS

Load Type	Aggregator 1	Aggregator 2	Aggregator 3	Others not in CCDR
Percentage	24.58%	31.20%	21.19%	23.03%

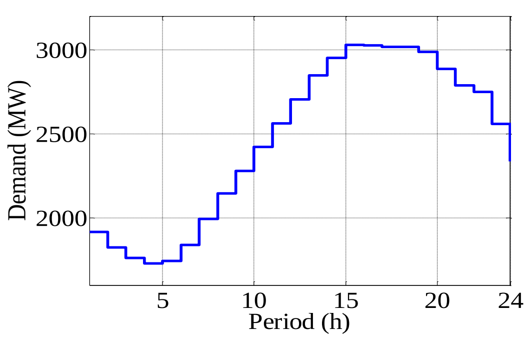

Fig. 10. Demand profile on July 20th, 2015 [28].

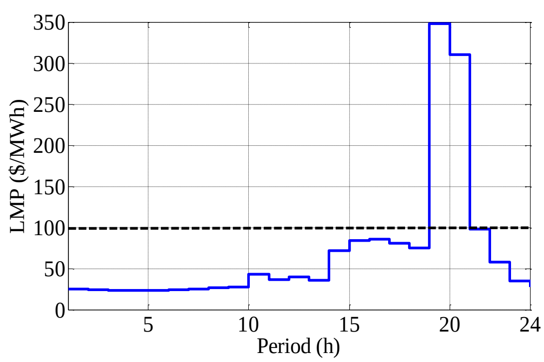

Fig. 11. LMP profile on July 20th, 2015 [28].

A. Base Case

A system operating under flat rate without the CCDR program is chosen as base case. The electricity retail rate is set to $100/MWh [29]. As shown in Fig. 11, the peak period lasts 2 hours from hour 19 to hour 20. As expected, the peak of demand is coincidental with the peak of LMP. Therefore, the LSE will suffer a great economic loss by charging customers less than the purchasing cost.

Table II gives the hourly system operation cost for the peak period. The demand has a smooth variation during the peak period. However, the LMP has a large spike at hour 19 which expands the gap between the purchasing cost and selling revenue. One can find that the LMP rather than the demand is the key factor to the purchasing cost. Yet, electricity selling revenue has a strong relationship with the demand as the LSE charges the customers a flat rate regardless of peak or off-peak period. The calculations of the operation cost during peak period and the entire day are shown in Tables III and IV. At peak, the average wholesale LMP ($329/MWh) has exceeded the flat rate ($100/MWh) which causes a net loss of $45,071.06. Because of the short-lasting peak, the profit made during the off-peak period can fully compensate for the loss during peak, which leads to $40,202.96 of net profit.

TABLE II
OPERATION COST FOR THE BASE CASE AT EACH HOUR OF PEAK PERIOD

Hour	19	20
Total Demand (MWh)	96.33	93.01
Wholesale LMP ($/MWh)	348	310
Electricity Purchasing Cost ($)	34,409.43	29,594.78
Electricity Selling Revenue ($)	9,632.54	9,300.61
Energy Loss ($)	883.08	757.96
Net Loss ($)	24,776.89	20,294.17

B. CCDR

As shown above, the LSE suffers losses because of the gap between the LMP and flat rate at peak period. This leads to the CCDR program implementation. In this case, hour 19 to 20 are considered as the valid CCDR implementation interval. The coupon value C_C^1 for aggregator 1 changes from flat rate ($100/MWh) to wholesale price with $1/MWh incremental steps. As discussed previously, coupon value should satisfy (5) to achieve fairness. Thus, the coupon value for aggregators 2 and 3 can be calculated once C_C^1 is known. The price elasticity reflects the peoples' willingness to adjust their demand pattern based on the price variation. In general, measuring the elasticity is a complex and uncertain task. Therefore, the price elasticity of load aggregators 1, 2, and 3 are chosen as: -0.35, -0.25, and -0.22 based on experience [33].

Fig. 12 provides the relationship between the coupon value C_C^1 and six factors including demand, coupon payment, energy loss, purchasing cost, selling revenue, and total cost at hour 20. As coupon value increases, the customers are more willing to reduce the demand which also leads to the growth of coupon payment as shown in Figs. 12 (a) and (b). This will result in a decrease of energy loss and purchasing cost, see Figs. 12 (c) and (d). However, it also leads to a reduction of selling revenue as the consequence of losing a part of demand as illustrated in Fig. 12(e). Therefore, the net loss curve of the LSE will

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have a minimum. Fig. 12(f) shows that the net loss reaches the optimal point, when the coupon value is $147/MWh.

The system optimal operation cost for the peak period is shown in Table V. One can find that the optimal coupon value keeps increasing with the increase of LMP. This is because the LSE has the motivation to give out higher coupon values when the wholesale LMP is much higher than the flat rate. The calculations of operation cost during peak period and the entire day are shown in Tables III and IV. At peak period, the demand and average LMP have been reduced by 12.58% and 0.61% compared to the base case, which brings 4.88% reduction of the net loss including 13.32% reduction of energy loss. The comparisons of demand between the base case and the CCDR at peak period are shown in Figs. 13. Because the LSE would not implement the CCDR program at off-peak period, the total demand and the average LMP reduction is 1.25% and 0.24% for the entire day. Note that, the LSE can have a greater profit ($42,403.95) than net profit ($40,202.96) of base case due to the large reduction of losses at peak period (4.88%).

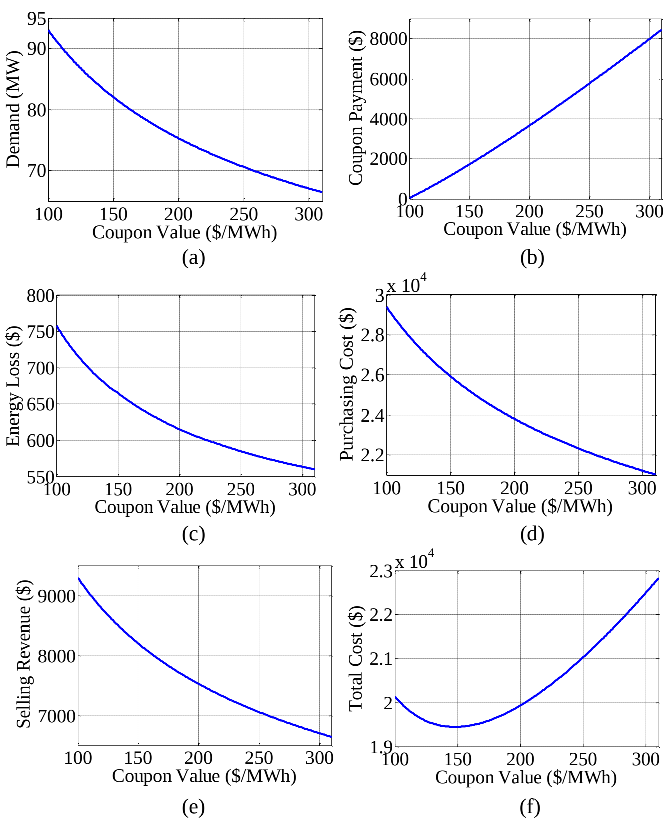

Fig. 12. Six factors of the operation cost versus coupon value; (a) relationship between the demand and coupon value; (b) relationship between the coupon payment and coupon value; (c) relationship between the energy loss and coupon value; (d) relationship between the purchasing cost and coupon value; (e) relationship between the selling revenue and coupon value; (f) relationship between the total cost and coupon value.

TABLE III
COMPARISON OF THE OPERATION COST BETWEEN BASE CASE AND CCDR FOR PEAK PERIOD

	Without CCDR	With CCDR	Reduction Rate
Total Demand (MWh)	189.33	165.52	12.58%
Average Wholesale LMP ($/MWh)	329.00	327.00	0.61%
Electricity Purchasing Cost ($)	64,004.21	55,557.25	13.20%
Electricity Selling Revenue ($)	18,933.15	16,552.22	12.58%
Energy Loss ($)	1,641.04	1,422.51	13.32%
Net Loss ($)	45,071.06	42,870.07	4.88%

TABLE IV
COMPARISON OF THE OPERATION COST BETWEEN BASE CASE AND CCDR FOR THE ENTIRE DAY

	Without CCDR	With CCDR	Reduction Rate
Total Demand (MWh)	1,910.96	1,887.15	1.25%
Average Wholesale LMP ($/MWh)	68.80	68.64	0.24%
Electricity Purchasing Cost ($)	150,893.33	142,446.36	5.60%
Electricity Selling Revenue ($)	191,096.29	188,715.35	1.25%
Energy Loss ($)	3,901.86	3,683.33	5.60%
Net Loss ($)	-40,202.96	-42,403.95	-5.47%

* Negative means net profit instead of net loss

TABLE V
OPERATION COST OF THE CCDR CASE AT EACH HOUR OF PEAK PERIOD

Hour	19	20
Coupon for Aggregator 1 ($/MWh)	162	147
Coupon for Aggregator 2 ($/MWh)	176	160
Coupon for Aggregator 3 ($/MWh)	151	137
Demand Reduction within Aggregator 1 (MWh)	5.00	3.95
Demand Reduction within Aggregator 2 (MWh)	5.44	4.43
Demand Reduction within Aggregator 3 (MWh)	3.17	2.38
Total Demand Reduction (MWh)	13.61	10.76
Residual Demand (MWh)	83.00	82.52
Wholesale LMP ($/MWh)	346	308
Coupon Payment ($)	2,249.44	1,615.60
Electricity Purchasing Cost ($)	29,471.70	26,085.54
Electricity Selling Revenue ($)	8,299.77	8,252.44
Energy Loss ($)	754.50	668.01
Net Loss ($)	23,421.37	19,448.70

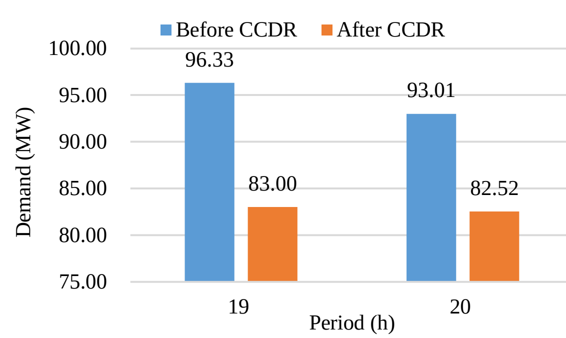

Fig. 13. Impact of CCDR on the demand variation at peak period.

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V. Conclusions

This paper has investigated the economic aspects of the CCDR program to encourage customers to reduce their demands at peak periods by coupon incentives. The connection between the LMP and demand has been modeled using an ANN algorithm. For the first time multiple load aggregators have been considered. The proposed method guarantees fairness among the different aggregators. Energy loss of the LSE has also been considered. Customers are encouraged to reduce the demand to the optimal value to maximize their utility function.

The objective of the study is to minimize the net loss of the LSE during the peak period and maximize the utility function of the customers. Simulation results show that the customers participating in the CCDR program would voluntarily reduce their demand by the coupon incentives. This reduction has a significant effect on shaving peak, decreasing energy loss, and reducing the operation cost. Therefore, the CCDR program has the potential to help LSEs save money by reducing the demand at peak periods and the ability to defer construction of power plants intended for use during peak periods.

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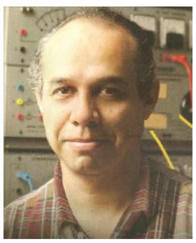

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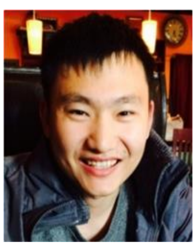

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