Load-Reduction Capability Estimation for an Aggregator in Demand Bidding Program

H.T. Yang, J.T. Liao, and Jing-Yu Wang

National Cheng Kung University, Tainan, Taiwan

***Abstract* — In the recent decades, as a result of the increase in demand for electricity, it has been getting increasingly more frequent that the spinning reserve rate of the generators in Taiwan reaches lower level which reflects the emergency of power supply. The paper employs neural network (NN) to forecast the clearing price of the bidding through spinning reserve ratio and temperature data. Subsequently, the load-reduction of customers is forecasted through NN and fuzzy logic system. Fuzzy system is adopted for forecasting of low voltage LV customer to simulate the uncertainties of load reduction considering different situations during demand response (DR). In order to improve the forecasting accuracy when realistic data of DR is available, another procedure of correcting the customers' model for forecasting is proposed. Afterwards, the feasible contract capacity of load-reduction signed with Taiwan Power Company (TPC) is determined through an optimization algorithm. To actually assess the benefit, the real load data from Taiwan and Texas are used in the simulation.**

***Index Terms* — Demand response, demand-bidding, load-reduction forecasting.**

I. Introduction

In recent decades, the government has been promoting energy policies related to electric power, reflecting that the increase in demand for electricity has been an inevitable issue. In addition, along with the progress in living standards, the electricity demand grows up, which severely impacts the stability of electricity supply. The percent reserve margin of generators in Taiwan decreases year by year, which is also a symbol of the emergency of the power system. For the purpose of solving the crisis of energy shortage, initiative like promoting renewable energy resources such as photovoltaic power and wind power has arisen [1], and besides, smart grid [2] also emerges as a new paradigm in power grid. Combined with advanced communication technologies and control methodologies [3]-[5], smart grid has gradually become the mainstream trend of future electric industry owing to its ability of adjusting power generation, transmission, and distribution [6].

Among the features of smart grid, demand side management (DSM) is the modification of customer demand for energy through various methods such as adopting time of use tariff or even giving financial incentives [7]. Furthermore, there is another technique named automated demand response (ADR) cooperating with energy management system (EMS) which can automatically manipulate the appliances in houses or buildings through the advanced infrastructures installed for communication and control [8]. To sum up, both DSM and ADR are considerable approaches for peak shaving thus reducing the operating expense from expensive generators, and further deferring the capacity addition in the long run [9].

Subsequently, in order to encourage the involvement of more customers in the demand response (DR), a program called demand bidding is implemented in Taiwan. For the power utility, the main purpose of the program is to collaborate with the customers on DR, namely, each electricity customer can determine the available time of executing DR and bid the corresponding price, then the utility will judge whether the customer wins the bid or not. Similarly, the potential of participating in the demand-bidding program is worthy of assessment for the electricity customers.

As mentioned previously, the researches presented in [4], [5], [10]-[12] describe methods that improve the electricity consumption pattern for the industrial customer by means of adopting time-of-use (TOU) tariff. This way, the end-customers benefit from the kind of load management such as saving the electricity bills, and thereby the grid

[*] Corresponding author.
E-mail: z10408115@email.ncku.edu.tw

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obtains a smoother load curve. Additionally, applications of energy management for the residential customers have been considered [13]-[15].

Home energy management methods proposed in [6] and [16] focus on DSM. Instead of using traditional DSM strategy, [6] presents a strategy based on load shifting technique for a large number of devices of several types. In [16], the authors demonstrate load shifting applied to seven different customer load sectors and illustrate the effects of the various DSM measures on the load shapes and on the system reliability indices used in generating capacity adequacy assessment.

In addition to DSM, DR is a further mechanism for reshaping the load profile [17], [18]. In a narrow sense, the DR here refers to the direct control of end-customers' loads at times of high wholesale market prices or when system reliability is jeopardized, then the incentive is paid to the customers for their cooperation. Moreover, home energy management system (HEMS) plays an important role that enables the residential customers to execute DR programs and load scheduling autonomously in the smart grid [9]. In [19], up to 20% reduction in daily electricity cost is achieved through its proposed HEMS management algorithm according to TOU.

Thereafter, the concept named virtual power plant (VPP) emerges as a combination of various small size distributed generating units which form a "single virtual generating unit" that can act as a conventional one and capable of being visible or manageable on an individual basis [20]. Furthermore, reference [21] takes DR into consideration by proposing a novel scheme of DR implementation, which is done based on the customers' submissions of candidate load profiles ranked in the preference order. The result of costs minimization for DR participants is verified as well, nevertheless, the uncertainties of the customers are not considered according to the presented scheme. Research like [22] discusses the bidding problem of DR in the day-ahead and real-time markets, yet the recent demand-bidding structure in Taiwan is different from other countries like the USA.

However, it is valuable to assess the profitable potential of participating in the demand-bidding program. As a result, owing to the lack of literature discussing the demand bidding problem in Taiwan, this paper attempts to propose a procedure evaluating the overall effect for an aggregator who takes part in the program.

II. Problem description and system modeling

A. Overall System Structure

In order to assess the potential of being an aggregator which contains lots of electricity customers for participating in the demand bidding program in Taiwan, this paper attempts to propose a method which helps the aggregator develop the optimal strategy that maximizes the electricity incentive received from the power utility for

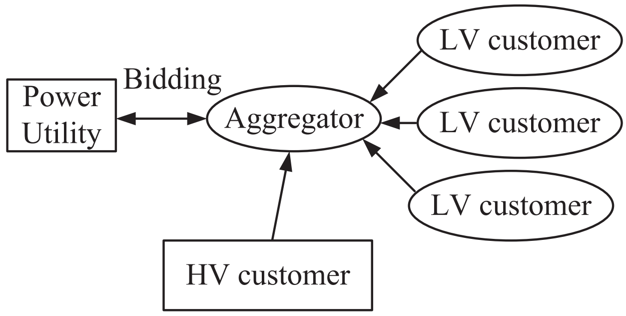


Fig. 1 Overall structure of the proposed Aggregator.

the bidding problem. Although LV customers cannot take part in DR in this stage, however, in this study, a future situation is mainly assumed that a HV customer serves as the aggregator who is able to cooperate with several LV customers on providing service like DR to the utility.

Fig. 1 illustrates the overall structure. In this structure, the smart meters, or advanced metering infrastructure

(AMI) known as the further form, are installed in each customer's house or building. By means of the smart meters, the electricity consumption can be monitored and be recorded along with time. The remote metering and the signal reception of electricity tariff or even DR can be implemented through the AMI as well. In the other words, it provides bidirectional communication between electricity customers and the power utility. In addition to AMI, another device called home energy management system (HEMS) which mainly comprises a gateway, controller for the appliances, and communication equipment, is necessary for a home to operate automated demand response (ADR) that involves automatic load shedding through program during DR events.

In the discussed structure, power consumption of equipment such as chiller can be adjusted by the energy management system for the HV customer during DR events. For the residential customer, air-conditioner and electric furnace are automatically controlled through HEMS during DR events. In addition, another function such as rescheduling the loads like clothes washer and clothes dryer is possible for the residential customers as well.

Finally, once the demand response is finished successfully, each customer and the aggregator are able to receive the corresponding incentive. In the proposed structure, it is reasonable for the aggregator to take commissions from the LV customers who take part in the DR program through the aggregator or even share the HEMS costs with the aggregator. To sum up, the aggregator can profit not only from the incentives of DR but also from the commissions taken from LV customers. On the other hand, the LV customers' profits consist of incentives of DR and the cost savings through load scheduling.

B. Demand bidding of Taiwan Power Company

It is undeniable that the spinning reserve rate, which represents the situation of electricity supply, has been lower and lower since 2012, especially on May 31, 2016, which has the lowest spinning reserve rate ever, about 1.64%. In order to improve the situation, a considerable way is to reduce the emergency of electricity supply from demand side, that is, to strengthen the DSM, and DR is one of the widely known terms. Furthermore, DR is completed by directly reducing the demand of the power customers during the peak period, and corresponding reward would be paid to the cooperative customers, thus for the utility, it is an issue to strike a balance between the cost of power generation and the payment for DR. As a result, the demand-bidding mechanism is utilized in Taiwan, which allows a lot of customers to decide their acceptable time to reduce their power consumption and bid a price for the reduction capacity to Taiwan Power Company (TPC), then TPC would determine which customers win the bid according to their concern of cost or others.

The business model of DR is a bidding process in Taiwan [23], [24], including the economical type, reliable type, and aggregated type. The general rule to evaluate a DR event is as follows:

1. Customer can decide the month of DR execution and the monthly minimum contract capacity of load-reduction.
2. Customer can decide the DR execution duration, which can last either 2 hours or 4 hours each day, and it cannot exceed 36 hours in total for the same month.
3. The bidding price per kWh cannot exceed 10 NT$/kWh.
4. The customer baseline load (CBL) is determined by the average value of the same period of DR execution time in previous five days except for load-reduction day, off-peak day, and weekends.
5. The actual reduction amount is determined by the difference between CBL and the maximum demand during the DR execution time. The amount is treated as 0 if it is less than the minimum contract capacity of load reduction.

More specifically, Fig. 2 presents an explanation.

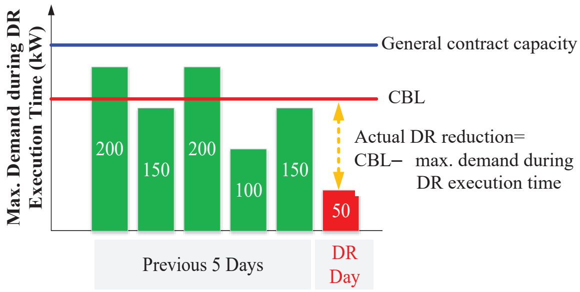


Fig. 2. Example for the calculation of actual load reduction.

III. Problem Formulation and the Proposed Bidding Strategy Optimization

In the proposed procedure, the forecasting of possible winning price for the demand-bidding program is firstly addressed, the load reduction for each role is then estimated through the designed models, and the last part deals with the bidding decision determining the capacity of load reduction. The entire flowchart is shown in Fig. 3.

A. Forecasting Models

The forecasting process in the proposed structure is executed for the demand-biddings of the forthcoming month, i.e. a month-ahead forecasting is designed, and besides, the decisions for the month are determined after each complete execution of the forecasting process. Additionally, the required inputs for the overall forecasting are mainly the spinning reserve rate and temperature data, which are predicted monthly and available from the official website of TPC and Central Weather Bureau (CWB) in Taiwan, and each residential customer's will for load reduction during DR.

1) Forecasting of Clearing Price for Demand-Bidding

In order to decide the bidding price, which is most probably winning for each DR event, a simple forecasting model of feed-forward artificial neural network (FNN) is proposed. The employed FNN uses the back-propagation algorithm to reach a better forecasting outcome [25].

For the mentioned neural network, its data inputs are designed as the forecasted temperature and the forecasted

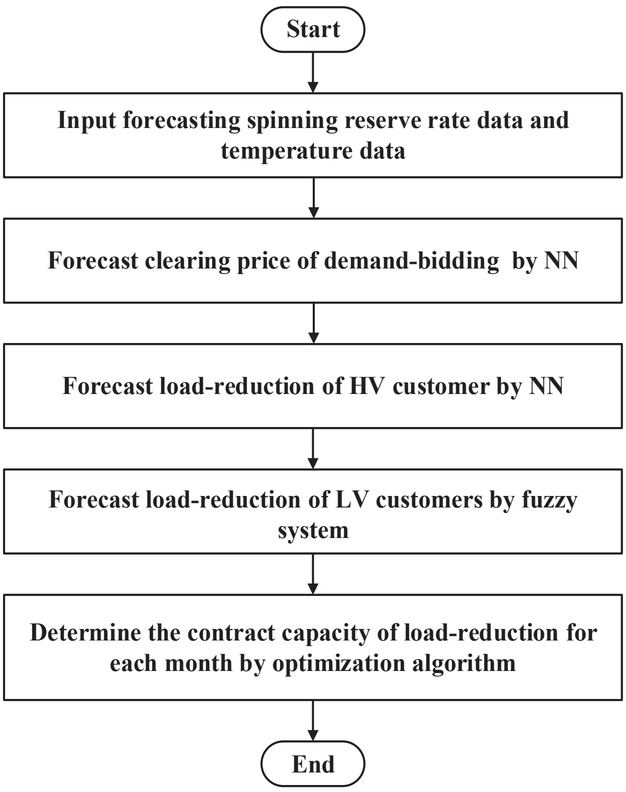


Fig. 3. Flowchart of proposed method.

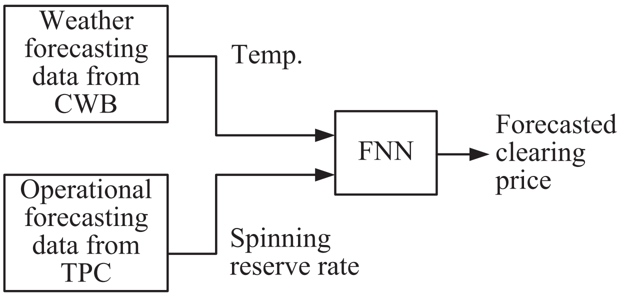


Fig. 4. Structure of the FNN for clearing price forecasting.

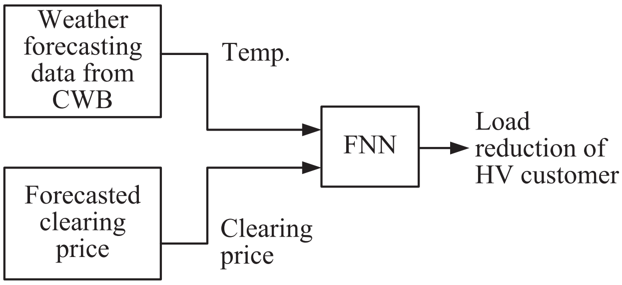


Fig. 5. Structure of the FNN for the forecasting of HV customer.

spinning reserve rate, which are available from the websites of CWB and TPC respectively, in the end, the data output of the neural network is the forecasting bidding price for the aggregator. The structure of the FNN used for the bidding price forecasting is shown in Fig. 4.

On the other hand, when it comes to the FNN training procedure, the historical data of the temperature and the spinning reserve rate corresponding to the past DR events are chosen as the training data. In spite of the fact that the historical data are similarly possible to be obtained from the websites of CWB and TPC, the historical data of the clearing prices for DR is another difficulty for the training procedure. In this case, the training output is replaced by the marginal cost of generation, which is estimated by the situation of generation for different generation units, since the marginal cost of generation is positively relevant to the clearing price.

2) Forecasting of Load Reduction for the High-Voltage Customers

For the aggregator who is going to participate in the demand-bidding mechanism, the estimation of the load-reduction amount for the forthcoming event is another important issue. Additionally, since the pattern of consuming electricity for HV customers, such as the industrial customers, is much more regular than the LV or residential customers, the load-reduction amount of the HV customer is forecasted by applying FNN, too.

Being similar to the forecasting of bidding price, the FNN is employed for the forecasting of the load reduction for the HV customer as well. The bidding price and the temperature, which are the two factors that influence the load reduction most likely, are adopted as the data inputs for this forecasting model, and the load-reduction amount is predicted. Fig. 5 depicts the forecasting model of the load-reduction estimation for the HV customer in the paper. Note that the input of bidding price is the clearing price produced from the previous forecasting FNN in the practical application. Besides, the training procedure can be accomplished by using historical data of temperature, the clearing price of the past demand-bidding events and the customer's load profile at the corresponding time.

3) Forecasting of Load Reduction for the Low-Voltage Customers

Being distinct from the HV customer, the pattern of power consumption for LV customers, which are residential customers here, is hardly to be predicted because each customer may have different habits or preferences for electricity consumption. For the sake of forecasting the load reduction for the LV customers considering the mentioned uncertainties, a fuzzy logic system is used here.

Three factors are selected as the inputs of the fuzzy logic system, the actual bidding price of the aggregator, customer's preference for the execution time of DR, and customer's preference for incentive, the output of fuzzy logic is the estimated percentage of load reduction for the appliances.

Regarding each factor, the bidding price decided by the aggregator impacts the final incentive for each customer, and the preference settings reflect the situation whether the load reduction is available or acceptable during the DR for each customer. The bidding price is normalized to represent its level, thus the three input factors' values of the fuzzy

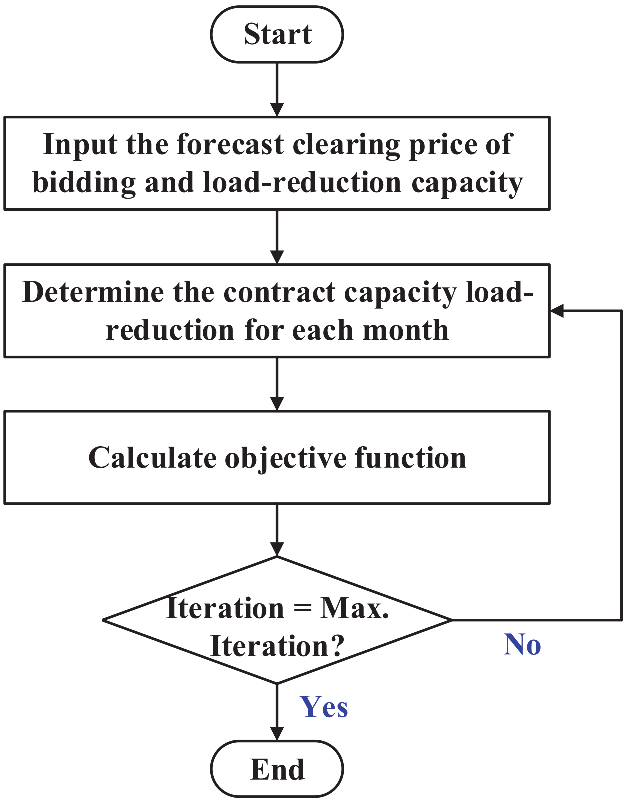


Fig. 6. Flowchart of proposed bidding strategy selection method.

system are all ranged from 0 to 1. For each of the three factors, a higher value would lead to a larger percentage of load reduction, which also means the customer is willing to reduce their electricity consumption under the situation.

Last but not least, the uncertainty of the power usage in the residential customers is an inevitable issue when forecasting the load-reduction amount. Therefore, for every residential customer, the uncertain characteristic is simulated by using random numbers that are generated according to the normal distribution as the inputs of the preference setting for the fuzzy logic system.

Moreover, considering the practicality, the preferences of every residential customer can be known through questionnaire surveys, then it would be possible to build up the normal distribution curve for each customer.

B. Formulation of Bidding Strategy Optimization

In the paper, the main purpose is to simulate an aggregator that takes part in the demand-bidding mechanism, maximizing the profit and finally evaluating the entire benefit for the discussed structure. As a result, in addition to the estimation of possible load reduction for the forthcoming DR, it is necessary to determine the contract capacity of minimal load reduction. Consequently, an optimization method is employed to maximize the profit based on the forecasting, the whole process is demonstrated in Fig. 6.

In the proposed structure, two types of the demand-bidding programs are discussed, i.e. reliable demand bidding and aggregated demand bidding. They can be described as follows:

1) Reliable Demand Bidding

According to the rule of the reliable DR, the overall objective function, which is to maximize the total incentive obtained from TPC is shown in (1). Equation (2)-(6) state the variables composing (1).

$$\max \sum_{m=1}^{12} IDC_m + \sum_{m=1}^{12}\sum_{d=1}^{n}(IEC_{m,d} + Pen_{m,d}) \tag{1}$$

$$IDC_m = p_{\text{contr},m} \times [P_{\text{IDC}} \times \frac{\sum_{d=1}^{n} b_{\text{s},m,d}}{n}(1-b_{\text{as},m}) + P_{\text{IDC,as}} \times b_{\text{as},m}] \tag{2}$$

$$IEC_{m,d} = P_{\text{bid},m,d} \times p_{\text{FLR},m,d} \times b_{\text{s},m,d} \tag{3}$$

$$Pen_{m,d} = 0.5 \times P_{\text{bid},m,d} \times (p_{\text{FLR},m,d} - p_{\text{contr},m}) \times (1-b_{\text{s},m,d}) \tag{4}$$

$$\begin{cases} b_{\text{s},m,d} = 1 & \text{if } p_{\text{FLR},m,d} - p_{\text{contr},m} \geq 0 \\ b_{\text{s},m,d} = 0 & \text{if } p_{\text{FLR},m,d} - p_{\text{contr},m} < 0 \end{cases} \tag{5}$$

$$\begin{cases} b_{\text{as},m} = 1 & \text{if } \sum_{d=1}^{n} b_{\text{s},m,d} = n \\ b_{\text{as},m} = 0 & \text{if } \sum_{d=1}^{n} b_{\text{s},m,d} < n \end{cases} \tag{6}$$

Where

- IDC_m is the incentive of demand charge for the month m (NTD).
- $IEC_{m,d}$ is the incentive of energy charge for the day d in the month m (NTD).
- $Pen_{m,d}$ is the penalty for the day d in month m (NTD).
- $P\text{contr},_m$ is the contract capacity of load reduction for the month m (kW).
- P_{IDC} is the incentive price for the demand charge, which equals 60 NTD/kW.
- P_{IDC},as is the incentive price for the demand charge particularly when all the DRs are executed successfully in the month m, which equals 72 (NTD/kW).
- $P_{\text{bid},m,d}$ is the forecasting clearing price for the day d in the month m.
- $P_{\text{FLR},m,d}$ is the total forecasting load-reduction capacity for the day d in the month m.
- $b_{\text{s},m,d}$ is the binary number of execution result, i.e. whether the DR on the day d in the month m succeeded or not.
- $b_{\text{as},m,d}$ is the binary number of monthly execution result, i.e. whether the DRs in the month m all succeeded or not.

$$0 < P_{\text{bid},m,d} \leq 10 \tag{7}$$

$$p_{\text{contr},m} \geq 50 \text{ kW} \tag{8}$$

The inequality constraints are listed in (7) and (8). Inequality (7) represents the allowable price of demand bidding. Inequality (8) describes the monthly minimal load reduction that should be signed with TPC, then there would be a penalty if there is any DR event with load reduction below $p_{\text{contr},m.}$

2) Aggregated Demand Bidding

According to the rule of the aggregated DR, the overall objective function is presented in (9). Equation (10), (11) state the variables composing (9)

$$\max \sum_{m=1}^{12}\sum_{d=1}^{n} IEC_{m,d} \tag{9}$$

$$IEC_{m,d} = P_{\text{bid},m,d}[1.05 p_{\text{FLR},m,d} \times b_{\text{er},md} + p_{\text{FLR},m,d} \times (1-b_{\text{er},m,d})] \tag{10}$$

$$\begin{cases} b_{\text{er},m,d} = 1 & \text{if } 0.6 \leq \dfrac{p_{\text{FLR},m,d}}{p_{\text{contr},m}} \leq 1.5 \\ b_{\text{er},m,d} = 0 & \text{if } \dfrac{p_{\text{FLR},m,d}}{p_{\text{contr},m}} < 0.6 \text{ or } \dfrac{p_{\text{FLR},m,d}}{p_{\text{contr},m}} > 1.5 \end{cases} \tag{11}$$

Where

- $\boldsymbol{IEC}_{m,d}$ is the incentive of energy charge for the day *d* in the month m (NTD).
- $\boldsymbol{P}_{\text{bid},m,d}$ is the forecasting clearing price for the day *d* in the month *m*.
- $\boldsymbol{p}_{\text{FLR},m,d}$ is the total forecasting load-reduction capacity for the day *d* in the month *m*.
- $\boldsymbol{b}_{\text{er},m,d}$ is the binary number of DR execution rate, i.e. the ratio of reduction capacity to the contract load-reduction capacity.

The inequality constraints are listed in (12) to state the monthly minimum load reduction required for each DR in month *m*.

$$p_{\text{contr,m}} \geq 100 \text{ kW} \tag{12}$$

It is used as a standard to evaluate the load-reduction capacity, if the amount is close to the contract capacity, then additional 5% of the bidding price would be paid as a reward. Note that the lower limit of the contract capacity for aggregated demand bidding is higher than that for reliable demand bidding. Besides, the limit of bidding price is the same as that of reliable demand bidding.

C. Cost Saving of Load Scheduling

The LV customers can save their electricity costs by rescheduling the schedulable loads in their buildings through HEMS according to different electricity tariffs.

Where

- $p_{s,d,h}$ is the total power consumption of schedulable loads at hour h on the day d (kWh).
- $p'_{s,d,h}$ is the total power consumption of schedulable loads after load scheduling at hour h on the day d (kWh).
- $P_{d,h}$ is the hourly electricity price at hour h on the day d (NTD/kWh).

D. Formulation Correction for Low-Voltage Customer

Considering the fact that there may be forecasting error when estimating the load reduction of LV customers, a correction method is proposed to improve the practicality of the model as long as the actual data of the load reduction for each customers is available in the future. The flowchart of the correction method is shown in Fig. 7.

In this part, the goal is to correct the preference settings through the historical data of DR. Specifically, by comparing the historical data with the results forecasted by the built fuzzy system and current preference settings, and tuning the preference settings to make the forecasting result of load reduction as close as possible to the historical one. That is to say, the objective is to minimize the mean absolute percentage error (MAPE) between the adjusted preference settings and the historical data, as shown in (13).

$$\min \frac{1}{n}\sum_{i=1}^{n}\left|\frac{LR_{\text{f},i} - LR_{\text{a},i}}{LR_{\text{a},i}}\right| \tag{13}$$

Firstly, in (13), $LR_{f,i}$ and $LR_{a,i}$ are the forecasted and actual load reduction respectively for each DR event. Secondly, the constraints are listed in (14) and (15).

$$0 \leq pref_{\text{inc},i} \leq 1 \tag{14}$$

$$0 \leq pref_{\text{time},i} \leq 1 \tag{15}$$

In these constraints, $pref_{inc,i}$ and $pref_{time,i}$ are the customer preferences for incentive and for execution time of the ith DR event, which are used as the inputs of the fuzzy logic system, and thus directly influence the prediction of load reduction. Note that the two preference indices are the decision variables in the optimization.

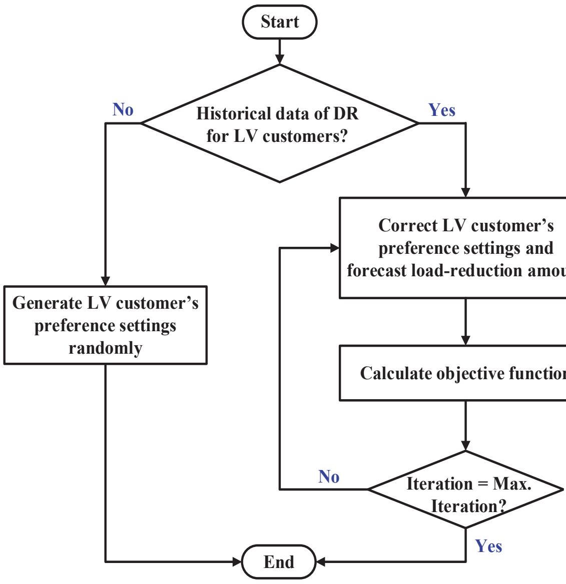


Fig. 7. Flowchart of proposed preference settings correction method.

IV. Simulation Results

A. Simulation Parameters

1) Load Profiles of the Customers

In this section, the daily load data of summer and winter are employed for demonstration. There are two types of customers, HV and LV customers, and their load patterns are discussed in the following part. Note that it is assumed in this paper that one HV customer serving as aggregator and one thousand LV customers join in the DR program.

- High-Voltage Customer

As mentioned previously, in this paper, the aggregator is composed of one HV customer and lots of LV residential customers. For the HV customer, its loads can be simply divided into controllable loads and non-controllable loads here. The daily load patterns of January and August are used to stand for winter and summer, as shown in Fig. 8 and Fig. 9.

The load profile is the actual electricity use data

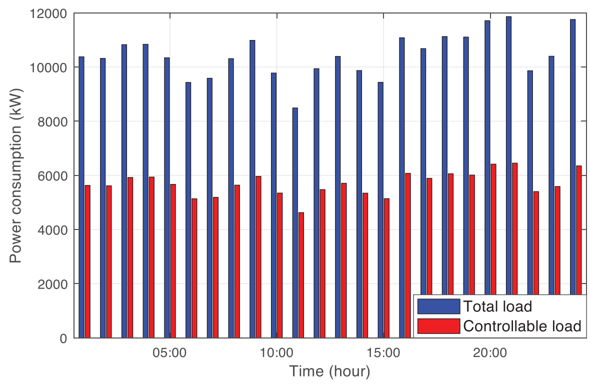


Fig. 8 Daily load profile of high-voltage customer (Jan. 2016).

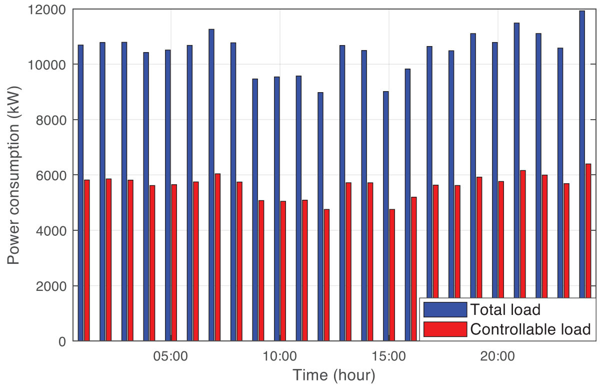


Fig. 9. Daily load profile of high-voltage customer (Aug. 2016).

measured from an industrial customer in Taiwan in 2016. Note that because of lack of actual controllable load data, the maximum of controllable loads, which are chillers here, is approximately assumed as half of the total load for load-reduction. Additionally, January and August of 2016 are chosen as winter and summer for the simulation, which will be scaled up to one year.

- Low-Voltage Customer

Subsequently, for the LV customers, which are the residential customers, two types of houses would be discussed in the paper, one is the apartment and the other is the single-house. The realistic data of about 260 LV customers comes from Austin, Texas [28]. In the simulation, the number of LV customers is scaled up to 1000.

Different from the HV customer, the house loads are further classified into controllable loads and schedulable loads, the former includes air-conditioner and electric furnace, and the latter includes dishwasher, clothes washer, clothes dryer, and electrical vehicle charger. For the same reason as the HV customer, Fig. 10 and Fig. 11 individually depict the daily load profiles of the apartment customers for summer and winter. Similarly, Fig. 12 and Fig. 13 illustrate the load profiles of the single-house customers.

2) Electricity Tariffs

To verify the effect of different tariffs on the cost saving for LV customers, two tariffs are used as example for a brief comparison. The first tariff is the 2-stage time of use tariff from TPC [26], and the second tariff [27] is actually the local marginal price of the day-ahead market from Electricity Reliability Council of Texas (ERCOT). The price is related to the situation of supply and demand, which reflects congestion.

Table 1. Simulation scenarios.

	HV customer	LV customers	
	DR type	DR type	Customer type
Scenario 1	Reliable	Aggregated	Apartment
Scenario 2	Reliable	Aggregated	Apartment
Scenario 3	Aggregated	Aggregated	Single-house
Scenario 4	Aggregated	Aggregated	Single-house

B. Forecasting of Load Reduction and Incentive

Firstly, the necessary term that must be assessed is the bidding price, thus the prediction result of the clearing price of demand bidding is simply demonstrated. Subsequently, there are four scenarios simulated in this section, as listed in Table 1 and the forecasting results are shown in the following section.

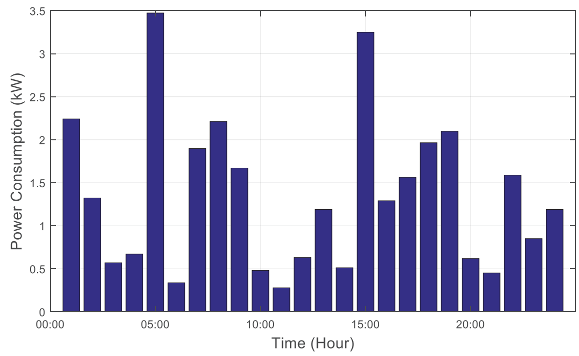
1) Forecasting Result of Clearing Price

The bidding prices are predicted through NN described previously, the inputs and output are presented in Fig. 14. Note that the forecasted bidding prices are regarded as the clearing prices, which means the maximum price accepted by TPC. There are 7 times and 8 times of DR, which lasts 4 hours each time, in January and August, respectively.

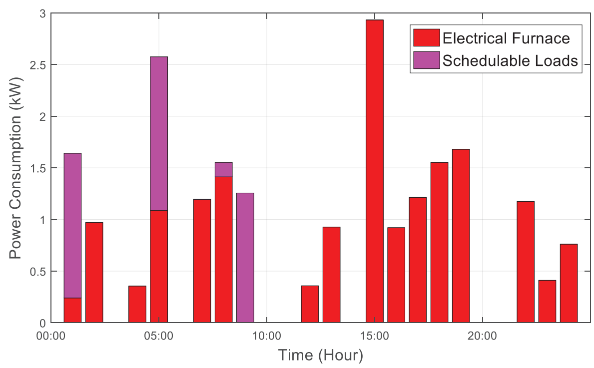
2) Forecasting Results of Scenario 1

For HV customer, the forecasting results of load-reduction and corresponding incentive are depicted in Fig. 15 - Fig. 17. In the presented results, the historical data of load reduction are used as actual load reductions, and the forecasting results come from the forecasting model. Note that the HV customer participates in reliable DR, thus it is reasonable for the penalty if the contract capacity of load reduction is not satisfied.

For LV customers, the forecasting results of load-reduction and corresponding incentive are illustrated in Fig. 18 and Fig. 19. However, due to lack of the historical data, only the forecasting results are presented in this stage.

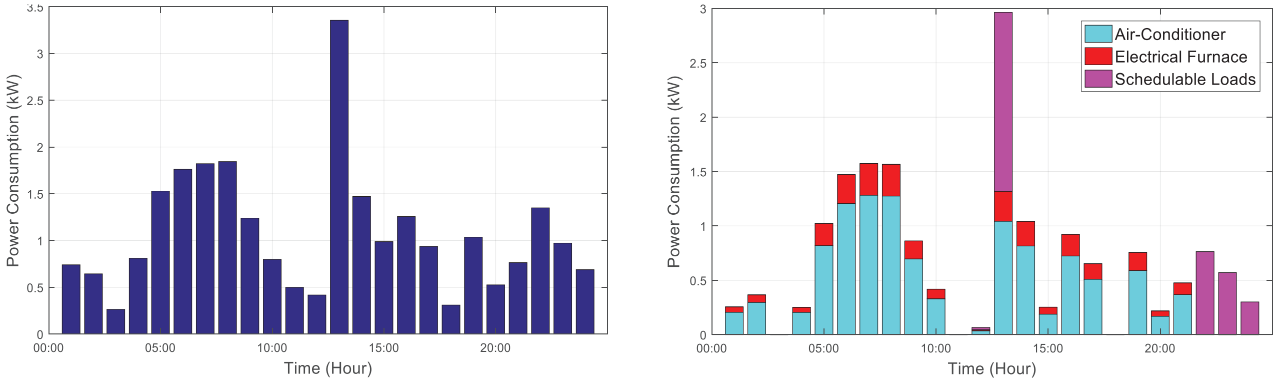


(a)



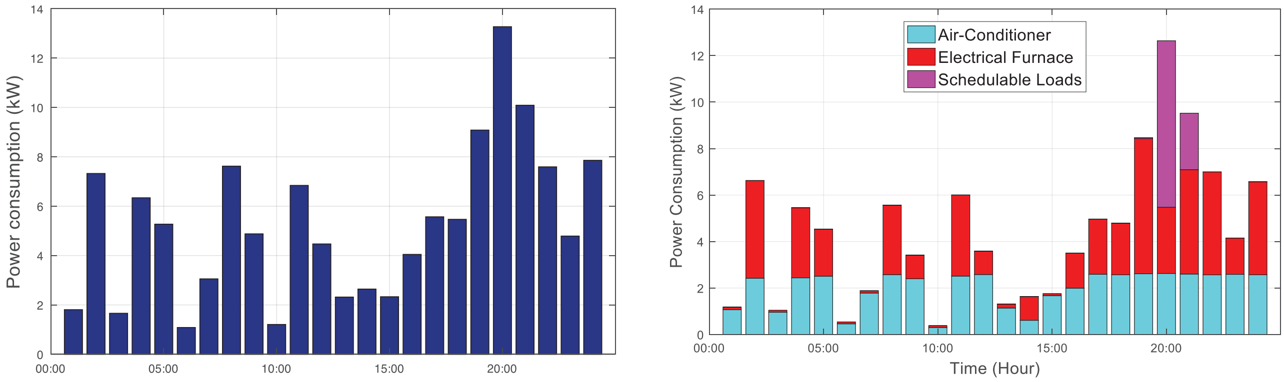
(b)

Fig. 10. Daily load profile of apartment customer (Jan. 2016) (a) Total load, (b) Schedulable loads.



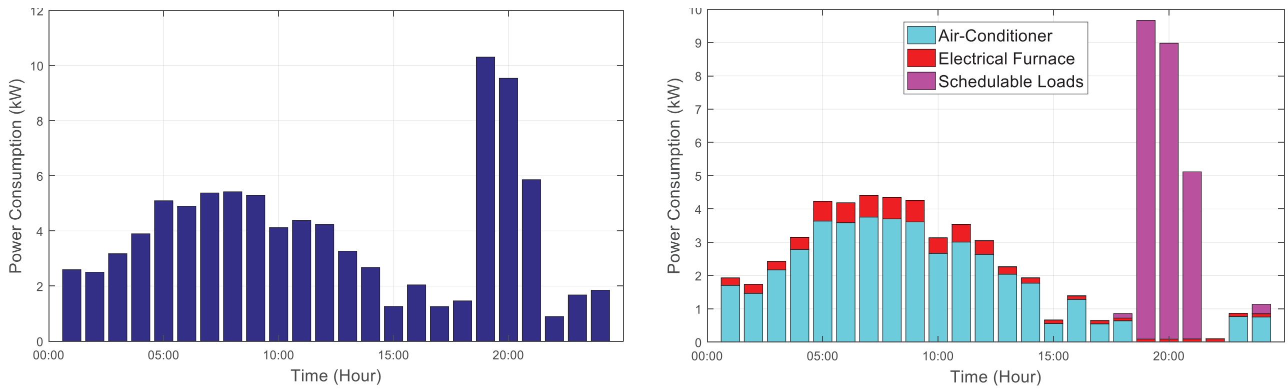
(a) *(b)*

Fig. 11. Daily load profile of apartment customer (Aug. 2016) (a) Total load, (b) Schedulable loads.



(a) *(b)*

Fig. 12. Daily load profile of single-house customer (Jan. 2016) (a) Total load, (b) Schedulable loads.



(a) *(b)*

Fig. 13. Discussed tariffs in the paper (a) 2-stage TOU tariff of TPC, (b) Real time price of ERCOT.

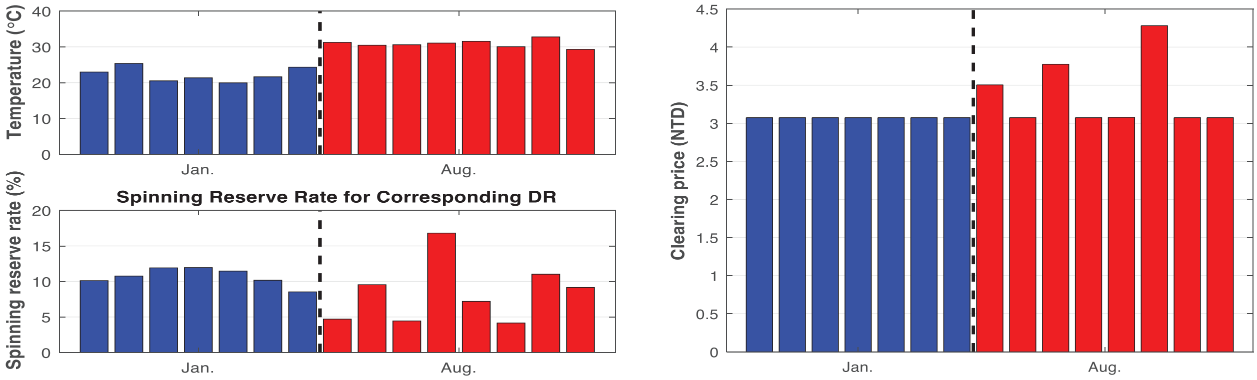
Note that the LV customers take part in the aggregated DR, hence the contract capacities of load reduction determined by the DR algorithm are feasible according to the demand bidding rule introduced previously.

In forecasting results, the dash lines represent the optimal contract capacities of load reductions determined by DR algorithm. For example, the blue dash lines in Fig. 15 and Fig. 16 are the optimal contract capacities of Load reduction for the actual load reductions; the red dash lines are the same but for the forecasted load reductions. If the red dash line is close to the blue dash line, then it means that the result of load reduction forecasting is close to actual one.

3) Forecasting Results of Scenario 2

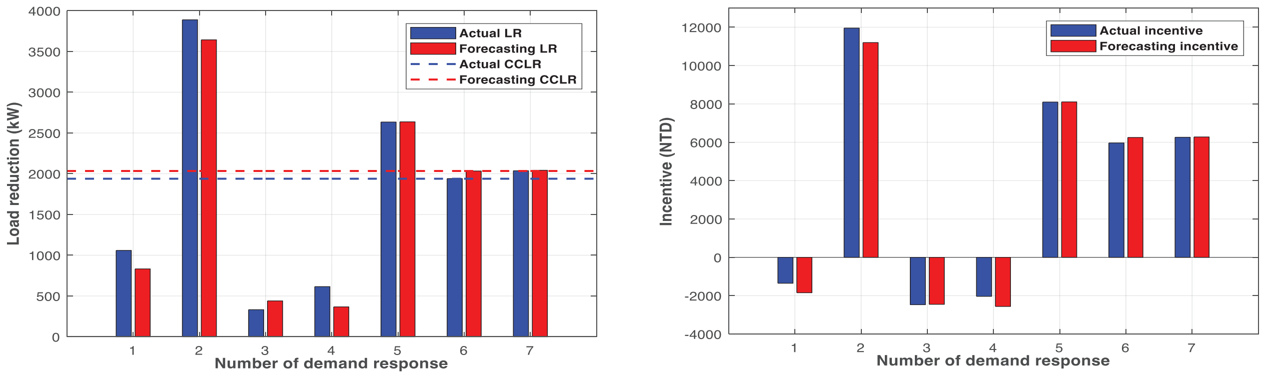
Similar to scenario 1, the main difference between scenario 1 and scenario 2 is the type of LV customers. Therefore, the forecasting for HV customer is totally the same as presented in scenario 1. The forecasting result of load reduction and incentive for the single-house customers are shown in Fig. 20 and Fig. 21.

According to the results, the overall incentives received by single-house customers apparently surpass those of apartment customers. The results are directly led by the total capacity of the controllable loads. However, the capacity of schedulable loads is another significant source



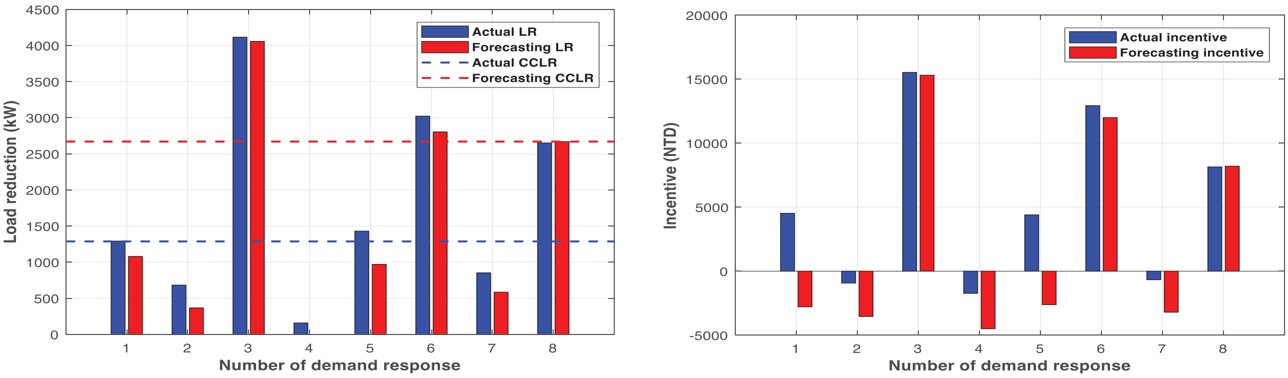
(a) (b)

Fig. 14. Forecasting result of bidding price (a) Inputs of the neural network, (b) Output of the neural network.



(a) (b)

Fig. 15. Forecasting result of HV customer in scenario 1 (winter) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.



(a) (b)

Fig. 16. Forecasting result of HV customer in scenario 1 (summer) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load-reduction.

that indirectly influences the load reduction during DR. Based on the calculation rule for actual load reduction, the load reduction for each DR can be raised up through technical manipulations of the schedulable loads. In other words, the schedulable loads are shifted to the same hours of DR execution during five days before DR event to heighten the baseline load, thus increasing the actual load reduction.

4) Forecasting Results of Scenario 3

Different from the previous scenarios, the HV and LV customers join the aggregated DR together. As a result, the historical load reduction data of the HV customer are used as the basis for the comparison of forecasting. Even though there are only the forecasting results for LV customers, the simulation results show the aggregated load-reduction capacity of HV and LV customers, as presented in Fig. 22 and Fig. 23.

Since it is much more stable for the HV customer to reduce electricity consumption during DR event than for the LV customers, there is no doubt that the success rate for execution DR would be higher through the aggregation of HV and LV customers. However, due to the absence of the incentive for demand charge in the aggregated DR, the overall incentive for the HV customer is accordingly less than that received in scenario 1 and scenario 2. Moreover, since there is no penalty in the aggregated DR, it is suitable for the HV customer even if the forecasting accuracy is not precise enough.

5) Forecasting Results of Scenario 4

As the comparison of scenario 1 and scenario 2, the simulation results here show the difference from scenario

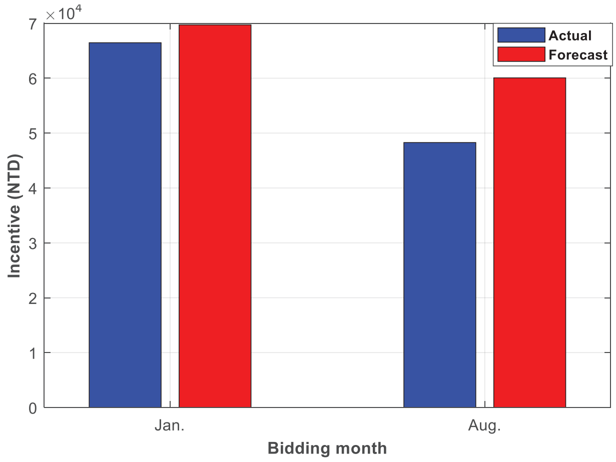


Fig. 17. Incentive of demand charge of HV customer.

3. In scenario 4, the HV customer cooperates with single-house customers on the aggregated DR as shown in Fig. 24 and Fig. 25. As discussed previously, with the larger controllable load capacity, the single-house customers have the potential to earn more incentive for DR execution. Besides, the HV customer chooses to take part in aggregated DR, which is a more conservative option.

In summary, by means of appropriately selecting the LV customers who have more potential in DR, the overall incentive received from TPC would be considerable even if the HV customer participates in the aggregated DR. In order to make a clearer comparison, the total incentives for the four scenarios are listed and discussed in the following section.

6) Summary for the simulation of the four scenarios

To sum up the four scenarios, Fig. 26 shows the effective annual incentive received. As the comparison in the Figure, it is obvious that the total incentive of scenario 2, where the HV customer participates in reliable DR and cooperates with the single-house customer, is the highest due to the additional incentives of demand charge for reliable DR and the incentives of energy charge earned through the large controllable load capacity of the single-house customers. Nevertheless, there is still an issue that is the risk for selecting reliable or aggregated DR, which is discussed in the later section.

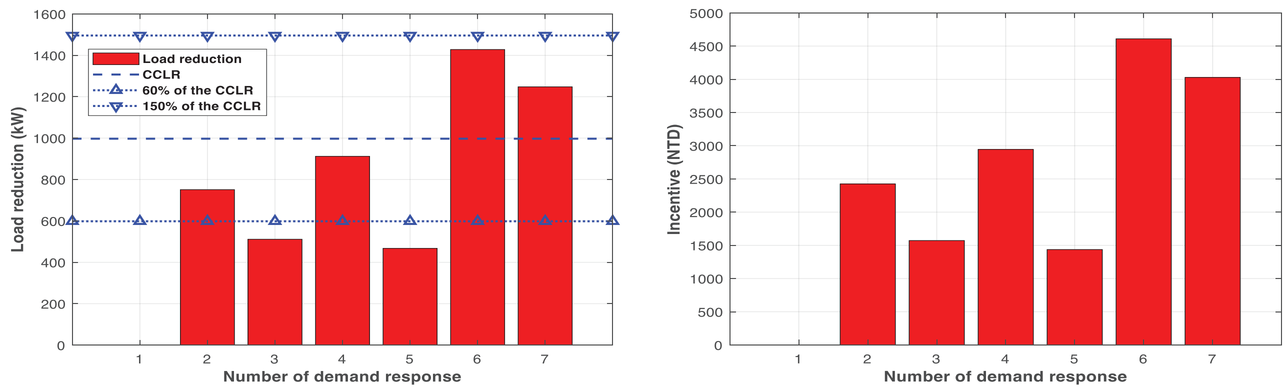


Fig. 18. Forecasting result of LV customer in scenario 1 (winter) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.

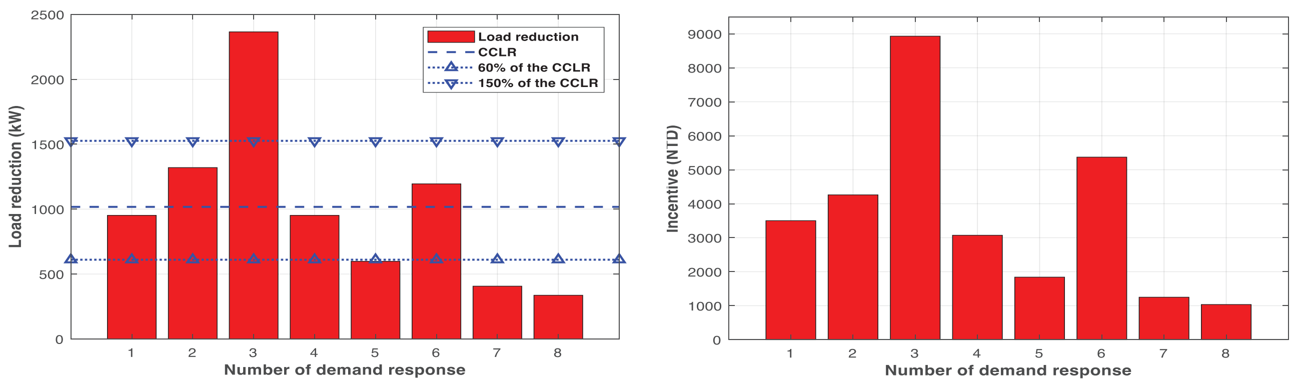
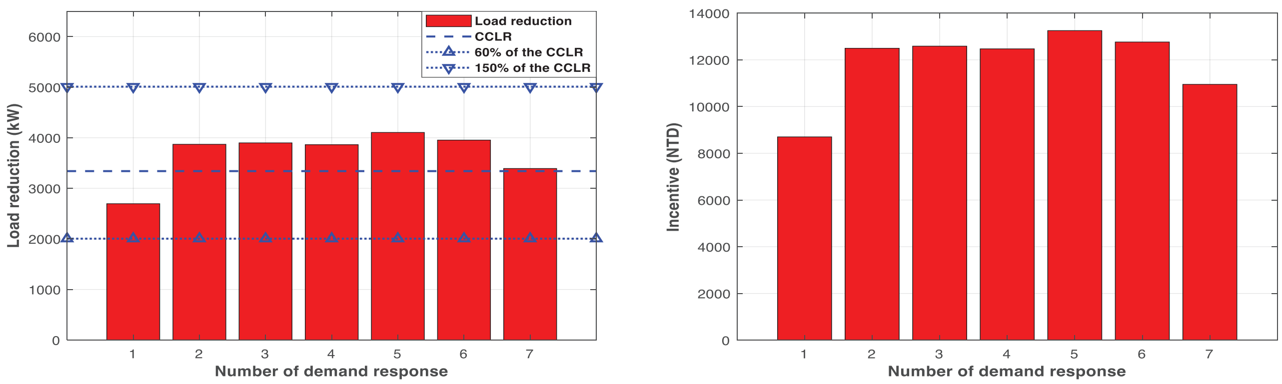
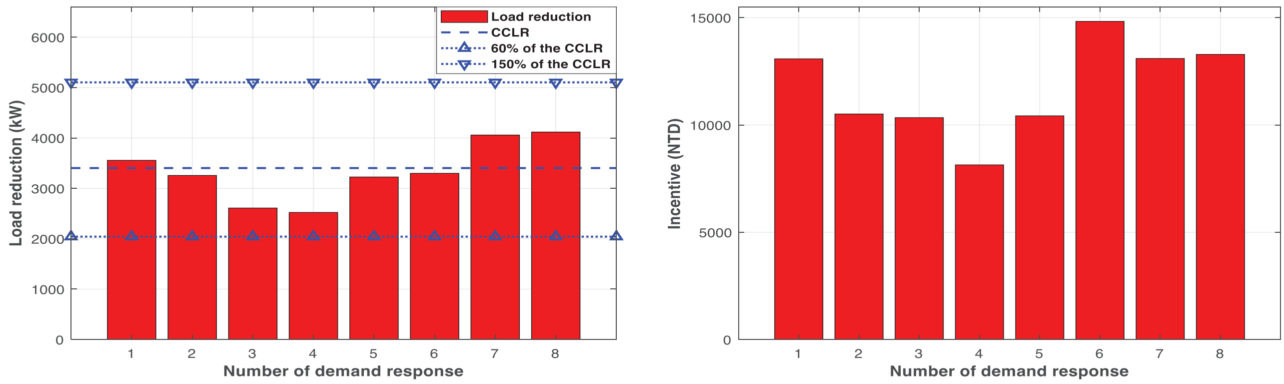


Fig. 19. Forecasting result of HV customer in scenario 1 (summer) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.



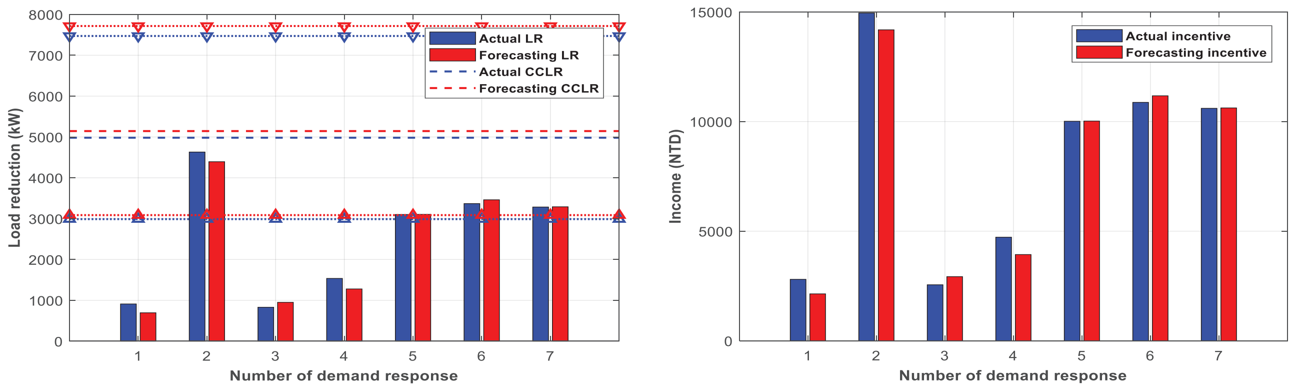
(a) (b)

Fig. 20. Forecasting result of LV customer in scenario 2 (winter) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.



(a) (b)

Fig. 21. Forecasting result of LV customer in scenario 1 (winter) (a) Load-reductions (LR) and contract capacity of load-reduction (CCLR), (b) Incentives of energy charge for the corresponding load-reduction.



(a) (b)

Fig. 22. Forecasting result of HV and LV customers in scenario 3 (winter) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.

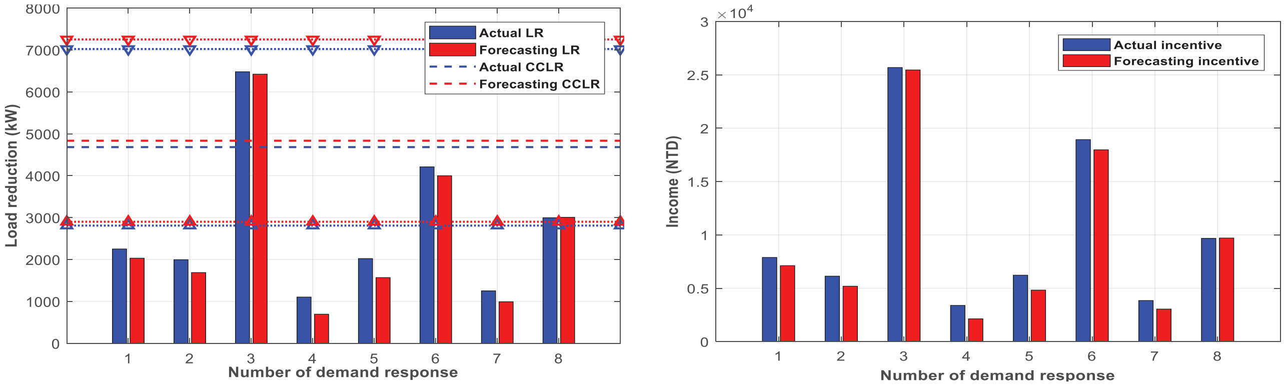
C. Cost Savings of Load Scheduling Considering Different Tariffs

For each LV customer who has established HEMS in house, the profit can be obtained not only from the DR program but also from the cost saving from daily power consumption. Therefore, a simple comparison of the cost saving by load scheduling for different kinds of customer is performed. In the meanwhile, two tariffs are compared for the reason that more and more tariffs may be published in the future.

It is apparent that the single-house customers have much greater saving than the apartment customers owing to the significant difference in their power consumption of schedulable loads. Besides, another noticeable point is that the effect of different tariffs, the real-time price of ERCOT brings the LV customers additional savings due to the larger price difference between hours in one day.

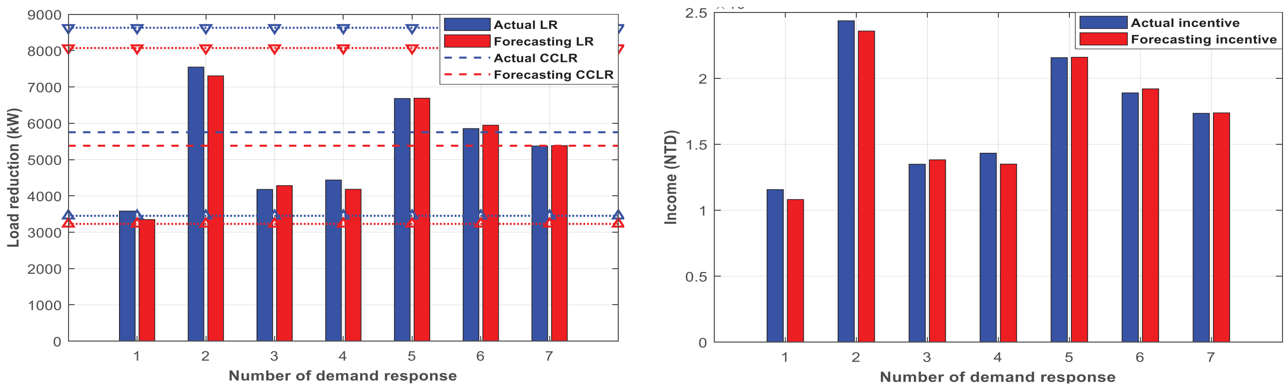
1) Cost-Benefit Analysis

In order to evaluate the profit, the hardware cost is taken into account. The recent costs of HEMS are approximately



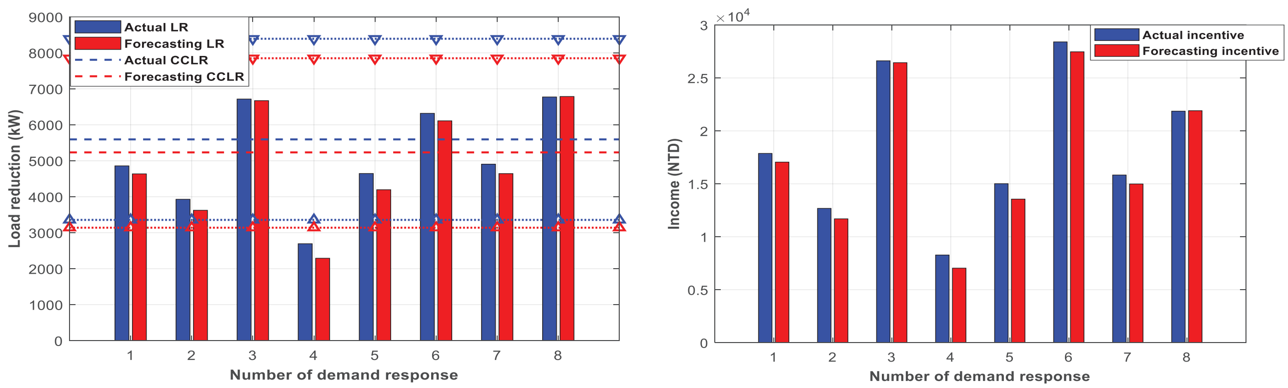
(a) *(b)*

Fig. 23. Forecasting result of HV and LV customers in scenario 3 (summer) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.



(a) *(b)*

Fig. 24. Forecasting result of HV and LV customers in scenario 4 (winter) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.



(a) *(b)*

Fig. 25. Forecasting result of HV and LV customers in scenario 4 (summer) (a) Load reductions (LR) and contract capacity of load reduction (CCLR), (b) Incentives of energy charge for the corresponding load reduction.

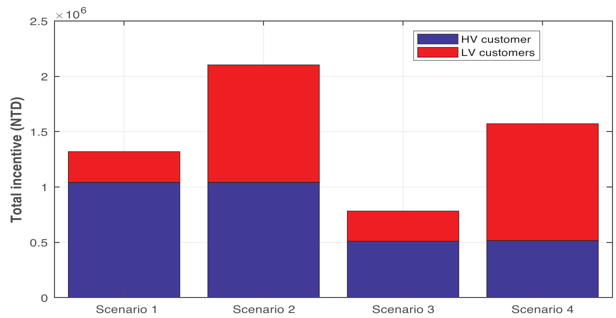


Fig. 26 Comparison of different scenarios

Table 2. Discussed cases for cost-benefit analysis.

	Hardware costs (NTD/customer)	Hardware lifetime (Year)
Case 1	50,000	2
Case 2	37,500	4
Case 3	25,000	6

NTD$50,000. Considering that the hardware cost may drop and its reliability may be improved in the future, as in case 2 and case 3 shown in Table II, the cost used in the simulation is the annually equivalent cost considering the interest rate of 3% and the life time of hardware for each case.

V. Conclusion

This paper has proposed a scheme to assess the potential of making profit for an aggregator to participate in the demand bidding in Taiwan. Techniques such as neural network and fuzzy logic system are employed for the forecasting of clearing price and load reduction, and the contract capacity of load reduction is decided through demand response algorithm. The simulation results have shown the evaluated effects for an aggregator to take part in two different types of DR and cooperate with two types of LV customer. The result has demonstrated the fact that the profit would be considerable when the aggregator signs reliable DR and aggregates single-house customers to execute aggregated DR.

However, there exists a different level of risk between reliable DR and aggregated DR. Based on the bidding rule, the aggregated DR has a larger tolerance for forecasting error than reliable DR, and it is verified in section 4. In addition, the cost-benefit analysis is performed to help the aggregator to make decision and evaluate the corresponding profit in a year. Finally, a correction process is proposed to improve the accuracy of the load reduction forecast for LV customers through realistic load-reduction data.

Acknowledgment

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