Coupon-Based Demand Response Considering Wind Power Uncertainty: A Strategic Bidding Model for Load Serving Entities

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***Abstract*—With the growing development in demand response, load serving entities (LSEs) may participate in electricity market as strategic bidders by offering coupon-based demand response (C-DR) programs to customers. However, due to customers' versatile electricity consumption patterns under C-DR programs as well as the increasing penetration of wind power generation, obtaining the deterministic bidding decision becomes unprecedented complex for LSEs. To address this challenge, a new strategic bidding model for an LSE is proposed in which the primary objective is to maximize the LSE's profit by providing optimal C-DR considering high wind power penetration. The proposed strategic bidding is a bi-level optimization problem with the LSE's net revenue maximization as the upper level problem and the ISO's economic dispatch (ED) for generation cost minimization as the lower level problem. This bi-level model is converted to a stochastic mathematic program with equilibrium constraints (MPEC) by recasting the lower level problem as its Karush-Kuhn-Tucher (KKT) optimality conditions. Then, the stochastic MPEC is transformed to a mixed-integer linear programming (MILP) problem, which is solvable using available optimization software, based on strong duality theory. In addition, the effectiveness of the proposed method has been verified with simulation studies of two sample systems.**

***Index Terms*—Coupon-based demand response (C-DR), electricity market, load serving entity (LSE), mathematic program with equilibrium constraints (MPEC), mixed-integer linear programming (MILP), strategic bidding, wind power.**

NOMENCLATURE

N	Number of buses.
M	Number of lines.
c_i	Generation bidding price at bus i (\$/MWh).
G_i	Generation dispatch at bus i (MWh).
G_i^{max}, G_i^{min}	Maximum and minimum generation output at bus i.
D_i	Demand at bus i (MWh).
GSF_{l-i}	Generation shift factor to line l from bus i.
$Limit_l$	Transmission limit of line l.
π_i	Locational marginal price at bus i.
$\eta_{i,k}$	Electricity retail price for customer k at bus i (\$/MWh).
$r_{i,k}$	Coupon price offered to customer k at bus i (\$/MWh).
$D_{i,k}$	Energy consumption of customer k at bus i.
$D_{i,k}^0$	Energy consumption baseline of customer k at bus i.
A	Bus set of the LSE strategic bidder.
B_i	Customer set at bus i belong to the LSE strategic bidder.
λ	Dual variable associated with the power balance equation in economic dispatch.
μ_l^{min}, μ_l^{max}	Dual variables associated with the lower and upper limits of transmission line l.
$\omega_i^{min}, \omega_i^{max}$	Dual variables associated with the lower and upper limits of the generator at bus i.
Ψ	Lagrangian function of ISO's ED problem.
s	Index of wind power scenario (in superscript).
p_s	Probability of wind power scenario s.
$P_{W,i}^s$	Power output of wind farm at bus i in wind power scenario s.
$p_{j,d}$	Probability of the dth demand reduction block under the jth coupon price.

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I. INTRODUCTION

THE increasing demand-side participation in electricity market has presented new challenges and opportunities for the market participants [1], [2]. For power system operators, various demand response (DR) programs have been deployed as potential resources to balance supply and demand, reduce peak-hour loads, and enhance the generation efficiency [3]. For end customers, the electricity consumption is expected to be responsive to the fluctuant pricing signals to reduce their electricity payments [4]–[11]. In a fully competitive electricity market, load serving entities (LSEs) play a critical role to fill the gaps between end customers and wholesale market operators to connect them into an optimal operation framework [12].

As a profit-seeking organization, the objective for LSEs is to maximize the expected payoff considering the uncertainty from both wholesale market and end customers. The majority of customers pay electricity bills with flat rates [13], while LSEs purchase electricity with time-varying rates from wholesale market. Naturally, LSEs will have the motivation to induce the end customers' inherent elasticity by offering DR programs [14], [15], especially when the system is under stress or close to the next binding constraint, which is termed as a critical load level (CLL) in [16] and [17]. Further, this can be even more interesting with the consideration of the uncertainty due to high wind power penetration.

Coupon based demand response (C-DR) attempts to induce the demand flexibility in retail customers (such as small/medium size commercial, industrial, and residential customers) on a voluntary basis [15]. In practice, LSEs have been adopting various methods, such as peak time rebate (PTR) and critical peak pricing (CPP), to realize the demand side management. However, C-DR holds its unique features. In PTR, the rebate rates during critical periods are pre-determined and fixed whereas the coupon price in C-DR is an optimization variable. In CPP, mandatory high prices are utilized to motivate customers to adjust their electricity consumption whereas the customers are voluntary to participate in C-DR.

Fig. 1 demonstrates the impact of C-DR and wind power uncertainty to both electricity supply curve and elastic demand curve. As shown in Fig. 1, (D_1, π_1) is the intersection between expected supply curve and original demand curve, and (D_2, π_4) denotes the intersection between expected supply curve and the new demand curve with coupons. Considering the wind power output, LMP π_1 is greater than flat rate price η at system demand level D_1. If the wind power output is lower than forecasted, the LMP goes higher at π_3; meanwhile, if the wind generates more power than forecasted, the LMP becomes lower at π_2. Under demand level D_1, the expected net revenue for the LSE considering wind uncertainty $(\eta - \pi_1)D_1$, is negative. When a coupon is provided, the elastic demand curve changes from $\mathrm{D}_1(\mathrm{P})$ to $\mathrm{D}_2(\mathrm{P})$. With the new demand curve, the corresponding LMP will be π_4 which is lower than flat rate η. Consequently, as long as the net revenue $(\eta - \pi_4)D_2 - r(D_1 - D_2)$ is greater than $(\eta - \pi_1)D_1$, the LSE will have incentive to offer coupon price r to customers in C-DR. Therefore, the C-DR program with proper coupon prices can help LSEs increase their profits by mitigating the price volatility due to wind uncertainty in wholesale market.

In competitive wholesale markets, there are two ways to implement C-DR: 1) C-DR is administered by LSEs to maximize their own profit; or 2) C-DR is administered by ISOs to maximize social welfare. Here, this paper discusses the former one. In other words, the customers' demand can be dispatched through C-DR by LSEs for the sake of LSEs' profit maximization.

To study the operation of an LSE under this new perspective, a strategic bidding approach considering C-DR and the wind power uncertainty is proposed in this paper. In the proposed method, the LSE offers C-DR program to customers. Then, the range of corresponding demand reduction under certain coupon is modeled. Next, the LSE aggregates all customers' demand reduction information and mimics ISO's electricity market-clearing procedure considering wind power uncertainty. Hence, the LSE can obtain the optimal bidding strategy with the maximal possible expected net revenue. The final decision variables of LSEs are the coupon prices and the corresponding optimal load dispatches.

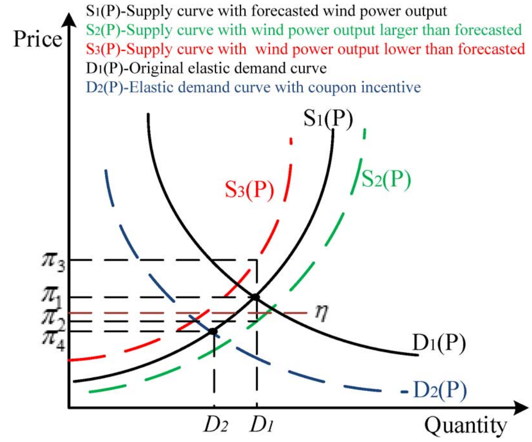

Fig. 1. Impact of C-DR and wind power on supply and demand curves.

The rest of this paper is organized as follows: Section II presents the overall bi-level model of strategic bidding for LSEs considering C-DR. Section III discusses the baseline load and the probabilistic demand reduction models. Section IV proposes the solution to solve the stochastic bi-level model including the procedure of transforming it into MPEC problem, and the conversion from MPEC to MILP. Section V demonstrates the simulation results and numerical analyses of PJM 5-bus system and IEEE 118-bus system to verify the proposed method. Section VI presents the summary and conclusion.

II. Strategic Bidding Model for LSEs

A. Procedure of LSEs' Strategic Bidding

The three-layer electricity market structure is shown in Fig. 2. The generation companies provide electricity offers including available generation quantities and prices to the corresponding independent system operator (ISO), then LSEs provide demand bids to the ISO, and finally the ISO clears the market to maximize the social welfare. The illustration of LSEs' strategic bidding under this market structure will be discussed in the following Sections II-B, II-C, and II-D. Most ISOs in the U.S. implement the two-settlement system [18]: day-ahead (DA) market and real-time (RT) market. The energy cleared in real-time markets is around 2%–8% [19], which represents a considerable with respect to the possible DR amount. With the expectation that DA price reflects the expected RT price, the DA market can be viewed as part of RT. Therefore, only the RT market is modeled for LSEs' strategic bidding for simplicity such that this work can focus on the discussion about C-DR.

Fig. 3 is the flowchart of the proposed strategic bidding for LSEs. First, LSE obtains LMPs information from ISO's DA market. Then, the LSE broadcasts the coupon price for the hours

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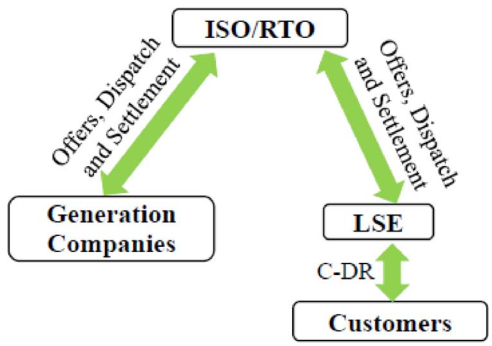

Fig. 2. Structure of the electricity market.

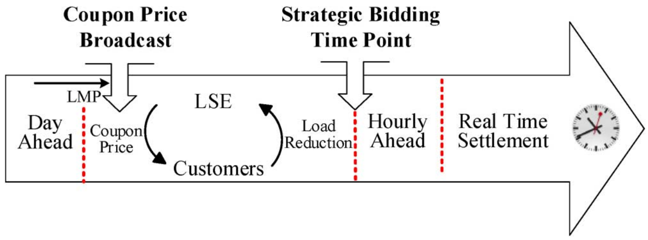

Fig. 3. Flowchart of the proposed strategic bidding.

in which the LSE wants to perform C-DR to stimulate customers to reduce their demand (i.e., the hours when LMP exceeds or likely to exceed the electricity flat rate). After gathering all the information of potential demand reduction, the LSE mimics ISO's economic dispatch (ED) process to identify the optimal demand reduction. Finally, the LSE performs bidding with the revised demand.

In the above procedure, the LSE can broadcast, and then update the coupon price several times through communicating with customers to obtain the optimal coupon price iteratively. While in practice, the information exchange between LSEs and customers cannot be performed many times due to the huge data processing burden from numerous customers. Therefore, before broadcasting the coupon price, LSEs should find a method to estimate a rough range of the optimal coupon price [20] such that the iterations between LSEs and customers can be reduced and the actual updating process of coupon price can be implemented in a shorter term. To determine this initial optimal coupon price, LSE can model customers' probabilistic electricity consuming pattern under different coupon prices, then perform the strategic bidding for each coupon price, and finally obtain the optimal coupon price. The probabilistic demand reduction model will be presented in Section III.

B. Net Revenue of LSEs

The LSE receives a gross revenue from each customer $k(k \in B_i)$ at bus $i(i \in A)$, as shown in k_4 to k_7 of LSE A in Fig. 4. This revenue is calculated as the product of the retail price $\eta_{i,k}$ and the electricity consumption $D_{i,k}$. Then, the payment (i.e., the product of spot price π_i and the electricity consumption $D_{i,k}$) is subtracted, since the LSE purchases electricity from ISOs in wholesale market at volatile nodal prices. Finally, the financial incentives that the LSE pays to customers

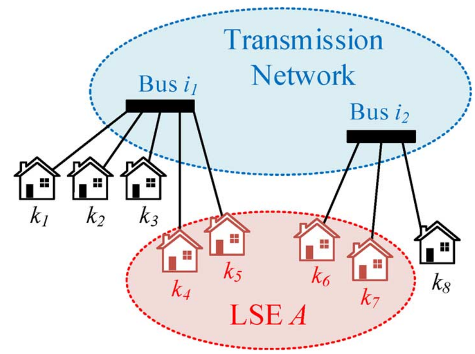

Fig. 4. Illustrative figure of an LSE and its customers.

should be subtracted as well, which is the product of coupon price $r_{i,k}$ and the deviation between actual electricity demand and baseline electricity consumption. Therefore, the LSE's net revenue, represented by R_n, should be expressed as (1):

$$R_n = \sum_{i \in A} \sum_{k \in B_i} \left[(\eta_{i,k} - \pi_i) \times D_{i,k} - r_{i,k} \times \left(D^0_{i,k} - D_{i,k} \right) \right]. \tag{1}$$

The LMP π_i in (1) is obtained from ISO's ED [16], [17], and the LMP formulation will be discussed in Section II-C.

C. ISO's Economic Dispatch

ED is carried out by ISOs to clear the market as well as determining LMPs and generation dispatches. As C-DR program is between LSEs and customers, the demands in the ISOs' ED model holds no elasticity.

Here, a fixed transmission network is assumed with a linearized, lossless DC model, and generations are considered fully competitive and rational in bidding at their marginal costs [21], [22]. This is aligned with various DC optimal power flow (DCOPF) models utilized by many ISOs [21]. Also, wind and DR are considered in terms of modeling the uncertainty, while other sources of uncertainty can be added if needed [22].

Hence, the DCOPF approach is employed to model the electricity market and estimate LMPs. While the actual models in practice are more complex, due to the need of computation robustness and efficiency, the ED based on DCOPF is utilized to illustrate the main point of the proposed work. The DCOPF is essentially a linear programming (LP) problem given by

$$min \sum_{i=1}^{N} c_i \times G_i \tag{2a}$$

$$s.t. \sum_{i=1}^{N} G_i = \sum_{i=1}^{N} D_i : \lambda \tag{2b}$$

$$D_i = \sum_{k \in B_i} D_{i,k}, \; \forall i \in A \tag{2c}$$

$$- Limit_l \leq \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \leq Limit_l : \mu_l^{\min}, \; \mu_l^{\max}, \; \forall l = 1, 2, \ldots, M \tag{2d}$$

$$G_i^{\min} \leq G_i \leq G_i^{\max} : \omega_i^{\min}, \; \omega_i^{\max}, \; \forall i = 1, 2, \ldots, N. \tag{2e}$$

After obtaining the optimal solution of the above ED, the LMP π_i can be calculated with the Lagrangian function. This function and LMP can be written as

$$\begin{aligned}\psi = &\left(\sum_{i=1}^{N} c_i \times G_i\right) - \lambda\left(\sum_{i=1}^{N} G_i - \sum_{i=1}^{N} D_i\right)\\ &- \sum_{l=1}^{M} \mu_l^{\min}\left(\sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) + Limit_l\right)\\ &- \sum_{l=1}^{M} \mu_l^{\max}\left(Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i)\right)\\ &- \sum_{i=1}^{N} \omega_i^{\min}\left(G_i - G_i^{\min}\right) - \sum_{i=1}^{N} \omega_i^{\max}\left(G_i^{\max} - G_i\right)\end{aligned} \tag{2f}$$

$$\pi_i = \frac{\partial\psi}{\partial D_i} = \lambda + \sum_{l=1}^{M} GSF_{l-i}\left(\mu_l^{\min} - \mu_l^{\max}\right). \tag{2g}$$

D. Bi-Level Model of Strategic Bidding

In the bidding process, the decision variables are the coupon prices $(r_{i,k})$ and the corresponding demand dispatches $(D_{i,k})$. Since the LMPs depend on ISO's ED in (2a)–(2e), the strategic bidding problem is formulated as a bi-level problem. The upper level is to maximize the LSE's profit in (1), and the lower level is to minimize the generation cost to model ISO's market-clearing process [23]–[25]. The bi-level strategic bidding model is given by

$$max \sum_{i\in A}\left(\sum_{k\in B_i}\left(\eta_{i,k} \times D_{i,k} - r_{i,k} \times \left(D_{i,k}^0 - D_{i,k}\right)\right) - \pi_i \times D_i\right) \tag{3a}$$

$$s.t.\ D_{i,k}^{\min} \le D_{i,k} \le D_{i,k}^{\max},\ \forall i \in A,\ k \in B_i \tag{3b}$$

where

$$\pi_i,\ \forall i \in \arg\left\{(2a) - (2e), (2g)\right\} \tag{3c}$$

where $D_{i,k}^{min}$ and $D_{i,k}^{max}$ are the minimum and maximum demand values, respectively, of demand k at bus i. B_i is the set of customers on bus i which have the C-DR with this LSE. The LMP π_i from the ED depends on the demand, $D_{i,k}$, as well as the bid prices/quantities of generators.

Note that both coupon price and LSE's demand are decision variables in the bidding process, and the objective function is nonlinear. To solve the strategic model in (3a) to (3c), it is necessary to discuss the demand model first. Therefore, Section III covers the baseline model and a probabilistic demand reduction model that gives the probability distribution of demand reduction under a specific coupon price. Since $r_{i,k} \times (D_{i,k}^0 - D_{i,k})$ is linear with a specific (given) coupon price, $D_{i,k}$ in (3a)–(3c) can be solved for a specific $r_{i,k}$ using the mathematic algorithm presented in Sections IV-A to IV-C, with different wind scenarios considered. Then, Section IV-D discusses the overall process to choose the optimal coupon price.

III. Baseline Demand and Probabilistic Demand Reduction

A. Baseline Demand Model

The C-DR programs are critically dependent on customers' demand baseline [26] from which the demand reduction in DR can be calculated. Due to the strong cyclic pattern of customers' electricity consumption over time [27], demand baseline can be obtained from historical data. For instance, Southern California Edison (SCE) employs an approach called "10-Day Average Baseline" [28]. More details concerning the baseline calculation have been introduced in [29], though it is out of the research scope of this paper to discuss the pros and cons of various consumer demand baseline methods.

B. Probabilistic Residential Demand Reduction Model

As previously discussed, the uncertainty of customers' demand reduction is typically modeled as follows in C-DR based strategic bidding: 1) LSE offers a coupon price to its customers; 2) the customers provide the range of corresponding demand reduction to the LSE; 3) the LSE calculates its expected net revenue through bidding this revised demand in ISO's electricity market; and 4) by repeating steps 1)–3) with different coupon prices, the optimal coupon price, which brings the LSE the maximum net revenue, can be found.

However, there are two potential challenges for this process: 1) it is rarely feasible to keep frequently updating customers' demand reduction data; and 2) interaction with numerous customers makes it too time-consuming to serve as an online implementation. Therefore, a practical probabilistic model of demand reduction under different coupon prices is established in this paper. The schematic information flow is shown in Fig. 5, where the inputs of the model are coupon price, C-DR's location and time length. The figure also shows that the output is the corresponding probability distribution of demand reduction. The procedure to generate this model can be summarized as follows:

Step 1) Based on the given location to be studied, the residents will be categorized into several groups $(G_1, G_2 \ldots\ldots G_N)$ based on their demographic information. For each group of residents, step 2) to 5) will be performed.

Step 2) For group G_i, the types and ratings of their appliances can be obtain by analyzing Residential Energy Consumption Survey [30] (RECS) by the U.S. Energy Information Administration (EIA).

Step 3) For group G_i, the American Time Use Survey [31] (ATUS) by the U.S. Department of Labor can provide what are the current activities of residents.

Step 4) In order to study customers' reactions to financial incentives, the Center for Ultra-wide-area Resilient Electric Energy Transmission Networks (CURENT) [32] has collected self-reported data from 711 U.S. residents across 48 states in 2013. This study estimated the adopting rates of major DR behaviors as a

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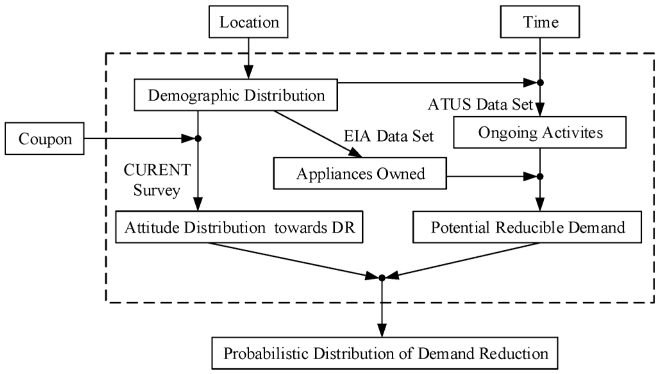

Fig. 5. Schematic figure of information flow for residential demand reduction model.

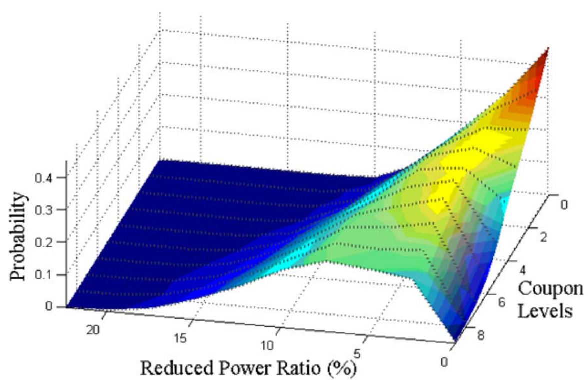

Fig. 6. Probability distribution of RPR under different coupon prices.

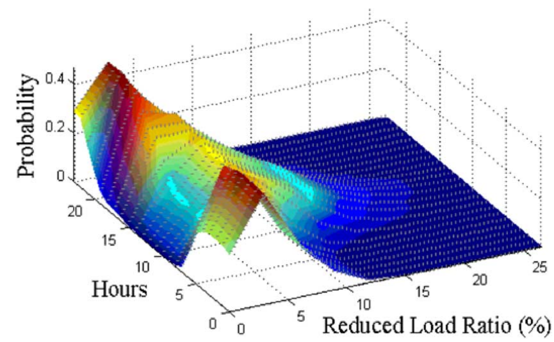

Fig. 7. Probability distribution of 24-hour RPR.

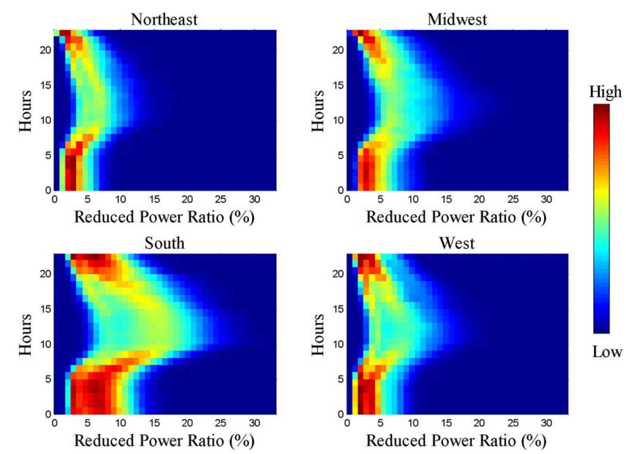

Fig. 8. Probability distribution of 24-hour RPR in different areas.

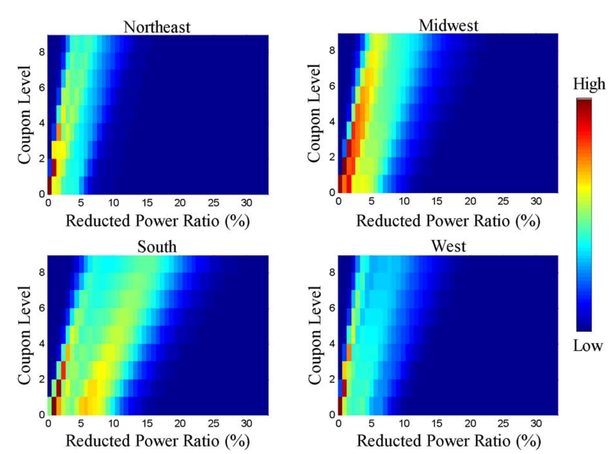

Fig. 9. Probability distribution of RPR under different coupon prices in different areas.

function of the demanded financial rewards.[1] Therefore, based on the results of this survey, the attitude of group G_i towards DR with given coupon price can be estimated.

Step 5) With the integration of the appliances information and the activities that those residents are performing, the potential demand reduction can be obtained.

Step 6) Given the residents' attitude towards different coupons, their possible demand reduction activity can be modeled. As long as the residents' attitude distribution and the potential reducible demand of all the groups are known, it is easy to obtain the probability distribution of the demand reduction.

In summary, the model proposed above evaluates the characteristics of residential demand reduction under C-DR programs based on the residents' portfolios and provides the probability distribution of demand reduction for given times, locations, and coupon prices.

Here, several simulation results of a typical scenario have been tested to demonstrate the model features. Fig. 6 shows the probability distribution of reduced power ratio (RPR) with various coupon prices. The characteristics of residential loads at a given coupon price for 24 hours are illustrated in Fig. 7. Furthermore, the residential load model varies with different resident portfolios. For example, the probability distribution of RPR for 24 hours is significantly different for Northeast, Midwest, South, and West regions, as shown in Fig. 8. According to Fig. 9, the customers' responses towards different coupon prices vary as well.

The aforementioned results of the preliminary study regarding residential demand modeling are reasonable, and they can verify the effectiveness of the proposed model. Therefore, this model has been implemented to simulate the uncertainty of

[1]This survey study was conducted through Amazon's Mechanical Turk (MTurk). MTurk is a crowdsourcing Internet market place that enables researchers to collect data. MTurk has received great popularity among social scientists as a useful research tool to collect data [45].

customers' behaviors to further formulate the strategic bidding model.

IV. Mathematical Solution of the Proposed Model

As introduced in Section II, the strategic bidding problem in (3a) to (3c) is a bi-level optimization problem. Because of the existence of dependent variables in each level, these two optimization problems are coupled. For instance, the LMP in the upper level problem is decided by the lower level problem of ISO's market clearing, while the demands at load buses of LSE bidders in the lower level market clearing problem depends on the upper level. In this paper, DCOPF is implemented to clear the ISO's market. Due to the linearity of DCOPF [21], [33], its optimal solution should be unique and satisfies the Karush-Kuhn-Tucher (KKT) optimality conditions. Consequently, the bi-level optimization problem is formulated as a mathematical program with equilibrium constraints (MPEC) by integrating the lower level problem into the upper level problem using its KKT conditions as the extra complimentary constraints [22], [34], [35]. According to the strong duality theory [35]–[37], this MPEC model can be converted to a MILP that is solvable by available software.

A. Formulation as a MPEC

Given that the lower level ED is a LP problem, the bi-level strategic bidding model can be transformed to a MPEC by re-casting the lower level problem as its KKT optimality condition, then adding them into the upper level problem as a set of additional complimentary constraints:

$$max \ (3a) \tag{4a}$$

$$s.t. \text{ Constraint in } (2b),\ (2c),\ (2g) \text{ and } (3b) \tag{4b}$$

$$c_i = \lambda + \sum_{l=1}^{M} GSF_{l-i} \times \left(\mu_l^{\min} - \mu_l^{\max}\right) + \omega_i^{\min} - \omega_i^{\max} \tag{4c}$$

$$0 \le \mu_l^{\min} \perp Limit_l + \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \ge 0 \tag{4d}$$

$$0 \le \mu_l^{\max} \perp Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times (G_i - D_i) \ge 0 \tag{4e}$$

$$0 \le \omega_i^{\min} \perp G_i - G_i^{\min} \ge 0 \tag{4f}$$

$$0 \le \omega_i^{\max} \perp G_i^{\max} - G_i \ge 0. \tag{4g}$$

B. Mixed-Integer Linear Programming (MILP)

The MPEC model in (4a)–(4g) is nonlinear due to the product term $\pi_i D_{i,k}$ in the objective function and the complementarity constraints (4d)–(4g). The linearization for them is presented below.

According to the strong duality theory, the objective of the primal problem is equal to the objective of the corresponding dual problem. For the ED problem, the relationship between the objectives of the dual and primal problems can be expressed as follows:

$$\begin{aligned}
&\lambda \times \sum_{i=1}^{N} D_i + \sum_{l=1}^{M} \mu_l^{\max} \times \left(-Limit_l - \sum_{i=1}^{N} GSF_{l-i} \times D_i\right) \\
&+ \sum_{l=1}^{M} \mu_l^{\min} \times \left(-Limit_l + \sum_{i=1}^{N} GSF_{l-i} \times D_i\right) \\
&+ \sum_{i=1}^{N} \omega_i^{\max} \times \left(-G_i^{\max}\right) + \sum_{i=1}^{N} \omega_i^{\min} \times \left(G_i^{\min}\right) \\
&= \sum_{i=1}^{N} c_i \times G_i.
\end{aligned} \tag{5}$$

From the LMP expression in (2f), the product term $\pi_i D_{i,k}$ in (3a) can be transformed as (6):

$$\sum_{i\in A} \pi_i \times D_i = \lambda \times \sum_{i\in A} D_i + \sum_{l=1}^{M} \sum_{i\in A} GSF_{l-i} \left(\mu_l^{\min} - \mu_l^{\max}\right) \times D_i. \tag{6}$$

Note that (6) describes $D_i (i \in A)$ which is about the demand at the bus within the LSE bidder, while (5) is about all buses in the system. Taking (6) into (5), we have

$$\begin{aligned}
&\sum_{i\in A} \pi_i \times D_i + \lambda \times \sum_{i\notin A} D_i + \sum_{l=1}^{M} \mu_l^{\max} \\
&\times \left(-Limit_l - \sum_{i\notin A} GSF_{l-i} \times D_i\right) + \sum_{l=1}^{M} \mu_l^{\min} \\
&\times \left(-Limit_l + \sum_{i\notin A} GSF_{l-i} \times D_i\right) + \sum_{i=1}^{N} \omega_i^{\max} \\
&\times \left(-G_i^{\max}\right) + \sum_{i=1}^{N} \omega_i^{\min} \times \left(G_i^{\min}\right) = \sum_{i=1}^{N} c_i \times G_i
\end{aligned} \tag{7}$$

where $D_i (i \notin A)$ is the demand on the bus which does not belong to the LSE bidder and it is assumed that the demands on these buses are constant for simplicity. Also, a strategic bidder can include a set of probabilistic scenarios to represent the other LSEs' demand uncertainty.

Therefore, based on (7), we can replace the $\sum_{i\in A} \pi_i \times D_i$ item in the objective function (3a) to form (8a), which is shown below. Thus, the MPEC problem is converted to a MILP problem given by

$$\begin{aligned}
max &\sum_{i\in A} \sum_{k\in B_i} \left(\eta_{i,k} \times D_{i,k} - r_{i,k} \times \left(D_{i,k}^0 - D_{i,k}\right)\right) \\
&- \sum_{i=1}^{N} c_i \times G_i + \lambda \times \sum_{i\notin A} D_i \\
&+ \sum_{l=1}^{M} \mu_l^{\max} \times \left(-Limit_l - \sum_{i\notin A} GSF_{l-i} \times D_i\right) \\
&+ \sum_{l=1}^{M} \mu_l^{\min} \times \left(-Limit_l + \sum_{i\notin A} GSF_{l-i} \times D_i\right)
\end{aligned}$$

$$+\sum_{i=1}^{N}\omega_i^{\max}\times(-G_i^{\max})+\sum_{i=1}^{N}\omega_i^{\min}\times\left(G_i^{\min}\right) \quad (8a)$$
$$s.t.\ \text{Constraints in (4b) and (4c)} \quad (8b)$$
$$0\le\mu_l^{\min}\le M_\mu^{\min}\nu_{\mu,l}^{\min} \quad (8c)$$
$$0\le Limit_l+\sum_{i=1}^{N}GSF_{l-i}\times(G_i-D_i)\le M_\mu^{\min}\left(1-\nu_{\mu,l}^{\min}\right) \quad (8d)$$
$$0\le\mu_l^{\max}\le M_\mu^{\max}\nu_{\mu,l}^{\max} \quad (8e)$$
$$0\le Limit_l-\sum_{i=1}^{N}GSF_{l-i}\times(G_i-D_i)\le M_\mu^{\max}\left(1-\nu_{\mu,l}^{\max}\right) \quad (8f)$$
$$0\le\omega_i^{\min}\le M_\omega^{\min}\nu_{\omega,i}^{\min} \quad (8g)$$
$$0\le G_i-G_i^{\min}\le M_\omega^{\min}\left(1-\nu_{\omega,i}^{\min}\right) \quad (8h)$$
$$0\le\omega_i^{\max}\le M_\omega^{\max}\nu_{\omega,i}^{\max} \quad (8i)$$
$$0\le G_i^{\max}-G_i\le M_\omega^{\max}\left(1-\nu_{\omega,i}^{\max}\right) \quad (8j)$$

where $M_\mu^{\min}$, $M_\mu^{\max}$, $M_\omega^{\min}$, and $M_\omega^{\max}$ are large enough constants, and $\nu_{\mu,l}^{\min}$, $\nu_{\mu,l}^{\max}$, $\nu_{\omega,i}^{\min}$, and $\nu_{\omega,i}^{\max}$ are the auxiliary binary variables [38].

C. Model Extensions to Integrate Wind Power

In this subsection, the extensions of the above model, including the uncertainty of wind power, is discussed. The forecasted wind power production is expressed as a set of probabilistic scenarios ($s = 1 \sim S$) with a probability set of $\{p_s\}$. The model below in (9a)–(9f) is an example of an ED model that includes wind power for one scenario:

$$min\ \sum_{i=1}^{N}c_i\times G_i^s \quad (9a)$$
$$\text{s.t.}\ \sum_{i=1}^{N}\left(G_i^s+P_{W,i}^s\right)=\sum_{i=1}^{N}D_i:\lambda^s \quad (9b)$$
$$D_i=\sum_{k\in B_i}D_{i,k},\ \forall i\in A \quad (9c)$$
$$-Limit_l\le\sum_{i=1}^{N}GSF_{l-i}\times\left(G_i^s+P_{W,i}^s-D_i\right)\le Limit_l:\ \mu_l^{s,\min},\mu_l^{s,\max},\ \forall l=1,2,\ldots,M \quad (9d)$$
$$G_i^{\min}\le G_i^s\le G_i^{\max}:\omega_i^{s,\min},\omega_i^{s,\max},\forall i=1,2,\ldots,N \quad (9e)$$

where G_i^s is the generation dispatch at bus i (MWh) under the sth wind scenario.

The LMP is given by

$$\pi_i^s=\lambda^s+\sum_{l=1}^{M}GSF_{l-i}\left(\mu_l^{s,\min}-\mu_l^{s,\max}\right). \quad (9f)$$

Therefore, the LSE's net revenue can be formulated as (10a) and then transformed to (10b). The constraints are modeled in (10c) to (10l):

$$max\ \sum_{i\in A}\left(\sum_{k\in B_i}\left(\eta_{i,k}\times D_{i,k}-r_{i,k}\times\left(D_{i,k}^0-D_{i,k}\right)\right)-\sum_{s=1}^{S}p_s\times\pi_i^s\times D_i\right) \quad (10a)$$

$$\begin{aligned}max\sum_{i\in A}\sum_{k\in B_i}&\left(\eta_{i,k}\times D_{i,k}-r_{i,k}\times\left(D_{i,k}^0-D_{i,k}\right)\right)-\sum_{s=1}^{S}p_s\\&\times\Bigg\{\sum_{i=1}^{N}c_i\times G_i^s-\lambda^s\times\left(\sum_{i\notin A}D_i-\sum_{i=1}^{N}P_{W,i}^s\right)-\sum_{l=1}^{M}\mu_l^{s,\max}\\&\times\left[-Limit_l+\sum_{i=1}^{N}GSF_{l-i}\times P_{W,i}^s-\sum_{i\notin A}GSF_{l-i}\times D_i\right]\\&-\sum_{l=1}^{M}\mu_l^{s,\min}\times\left[-Limit_l-\sum_{i=1}^{N}GSF_{l-i}\times P_{W,i}^s+\sum_{i\notin A}GSF_{l-i}\times D_i\right]\\&-\sum_{i=1}^{N}\omega_i^{s,\max}\times(-G_i^{\max})-\sum_{i=1}^{N}\omega_i^{s,\min}\times\left(G_i^{\min}\right)\Bigg\}\end{aligned} \quad (10b)$$

$$s.t.\ \text{Constraints in (3b), (9b), and (9c)} \quad (10c)$$
$$c_i=\lambda^s+\sum_{l=1}^{M}GSF_{l-i}\times\left(\mu_l^{s,\min}-\mu_l^{s,\max}\right)+\omega_i^{s,\min}-\omega_i^{s,\max} \quad (10d)$$
$$0\le\mu_l^{s,\min}\le M_\mu^{\min}\nu_{\mu,l}^{s,\min} \quad (10e)$$
$$0\le Limit_l+\sum_{i=1}^{N}GSF_{l-i}\times\left(G_i^s+P_{W,i}^s-D_i\right)\le M_\mu^{\min}\left(1-\nu_{\mu,l}^{s,\min}\right) \quad (10f)$$
$$0\le\mu_l^{s,\max}\le M_\mu^{\max}\nu_{\mu,l}^{s,\max} \quad (10g)$$
$$0\le Limit_l-\sum_{i=1}^{N}GSF_{l-i}\times\left(G_i^s+P_{W,i}^s-D_i\right)\le M_\mu^{\max}\left(1-\nu_{\mu,l}^{s,\max}\right) \quad (10h)$$
$$0\le\omega_i^{s,\min}\le M_\omega^{\min}\nu_{\omega,i}^{s,\min} \quad (10i)$$
$$0\le G_i^s-G_i^{\min}\le M_\omega^{\min}\left(1-\nu_{\omega,i}^{s,\min}\right) \quad (10j)$$
$$0\le\omega_i^{s,\max}\le M_\omega^{\max}\nu_{\omega,i}^{s,\max} \quad (10k)$$
$$0\le G_i^{\max}-G_i^s\le M_\omega^{\max}\left(1-\nu_{\omega,i}^{s,\max}\right). \quad (10l)$$

D. Demand Uncertainty Under Different Coupon Prices

The optimization models (4a)–(4g), (8a)–(8j), and (10a)–(10l) above give the LSE's net revenue and optimal demand dispatch under specific coupon price and demand reduction level $[D_i^{min}, D_i^{max}]$. However, the LSE still need to obtain the optimal coupon price. Based on the probabilistic model of demand reduction presented in Section III, the customers will have different behavior patterns responding to different coupon prices in C-DR program. Here, the expected net revenue (ENR) is defined as an indicator for the LSE bidder to determine the most profitable coupon price. The ENR under the jth coupon price is

$$ENR_j = \sum_{d=1}^{N^d} p_{j,d} \times R_{n,j,d} \tag{11}$$

where $R_{n,j,d}$ is the LSE's net revenue in the dth demand reduction block under the jth coupon price which can be obtained through the model (10b)–(10l) presented in previous sections. When all ENR under different coupon prices are obtained, the LSE can choose the optimal coupon price with the maximum ENR and the corresponding demand dispatch. It should be noted that although the demand uncertainty under a specific coupon price can be model in the optimization model (10b)–(10l) using the similar approach to wind uncertainty, however, the model established in that way will be dimensionally more complex. For instance, if n wind scenarios and m demand reduction blocks under a coupon price are considered, the whole model contains $n \times m$ sets of variables and constraints for the lower level ISO's ED problem. Therefore, the discretized decomposition using (11) and the optimization algorithm in (10b)–(10l) is straightforward and easy to solve.

E. Overall Procedure

To better illustrate the proposed strategic bidding model for LSE, the flowchart of the overall procedure is shown in Fig. 10 and described next. According to the probabilistic demand reduction model proposed in Section III, the demand reduction is subject to a probability distribution with different coupon prices as shown in Figs. 6 and 9. For any given coupon price, the proposed model generates a set of discretized range of demand reduction and the corresponding probability. Then, the optimization model in (10b)–(10l) can provide the amount of profit under a specific demand reduction range with multiple probabilistic wind scenarios considered. Hence, the LSE's expected profit can be obtained by summing up the profits under different demand reduction ranges multiplied by corresponding probability weights, as shown in (11). Finally, the optimal coupon price can be found with a comparison of the LSE's ENR profits at different coupon prices to find the best ENR.

It should be noted that if more than one LSE behave strategically in the market according to the model proposed in this paper, the resulting model will become an equilibrium problem with equilibrium constraints (EPEC) [39]. Another concern associated with multiple LSEs performing DR is that the LSEs may implement different types of DR programs such that it may not be realistic to perform this C-DR based strategic bidding for all LSEs in the electricity market. However, these still could be the future research topics on C-DR.

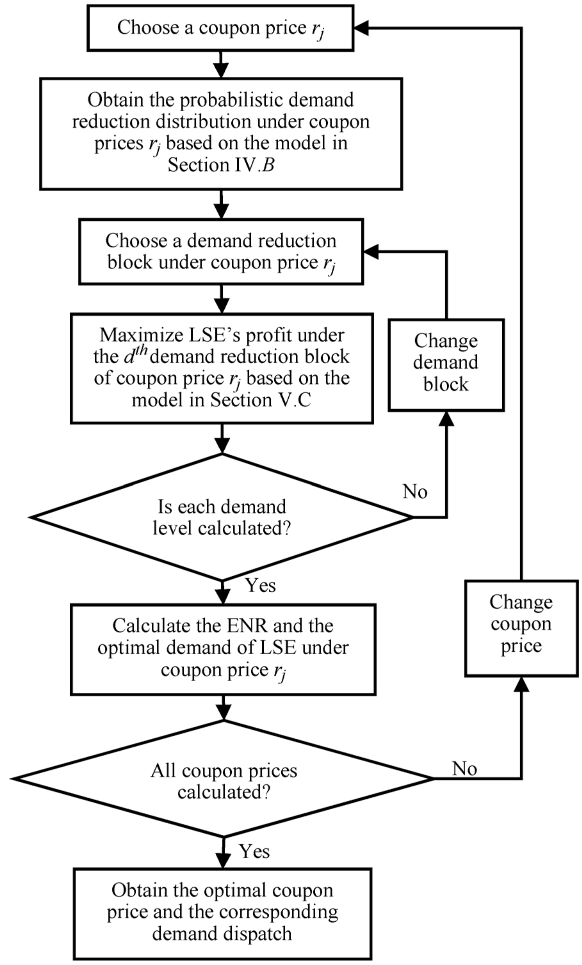

Fig. 10. Flowchart of the proposed strategic bidding model.

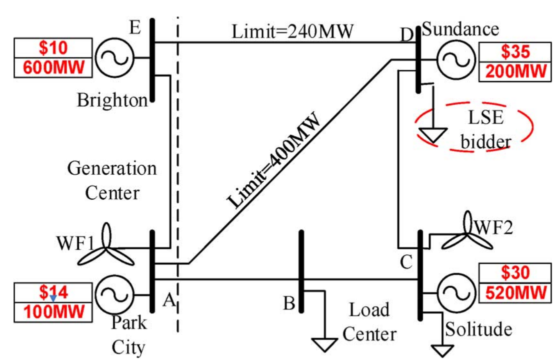

Fig. 11. PJM 5-bus system with two wind farms.

V. Case Studies

In this section, the proposed strategic bidding approach is performed on the modified PJM 5-bus system [40], which is chosen for the easiness to illustrate the concept and to verify by the audience. Another case study is performed on the IEEE 118-bus system to further verify the proposed method. The MILP problem is solved by CPLEX 12.6 [41] under GAMS [42] on a DELL laptop with dual Core-i5 processors clocking at 2.6 GHz and 4 GB of RAM.

A. PJM 5-Bus Test System

The test system is modified from the PJM 5-bus system. The system parameters are from [21]. Two wind power plants (WF1 and WF2) with the same generation capacity are added into the system at buses A and C, while one of two original generators at bus A is removed. The total load is equally distributed between buses B, C, and D. The modified system is depicted in Fig. 11.

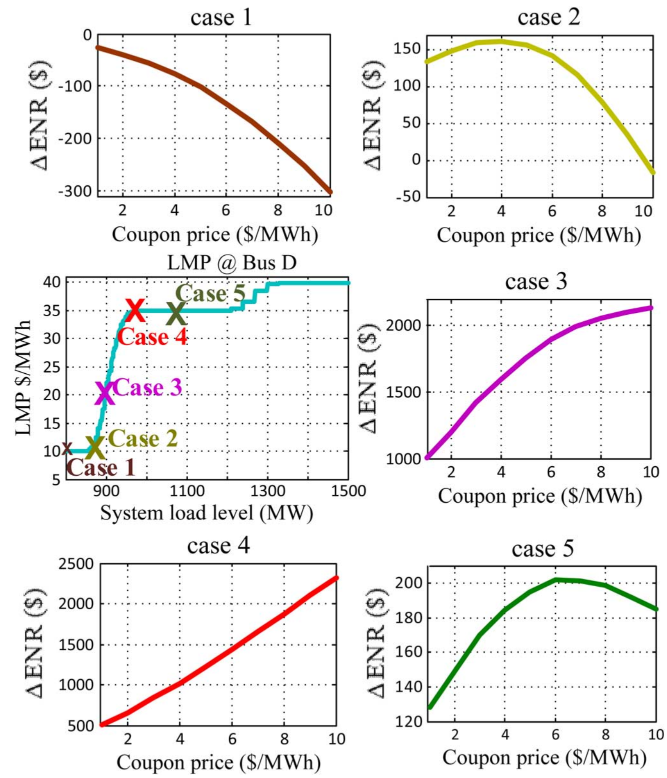

Fig. 12. ΔENR versus coupon price on five typical operating points.

TABLE I
DR RESULTS UNDER DIFFERENT OPERATING POINTS

Cases	Load at Bus D (MW)	ENR w/o DR	Exp LMP w/o DR	ENR w/ DR	Exp LMP w/ DR	Coupon ($/MWh)	Dispatched Load (MW)
Case 1	266	2660	10	2660	10.00	0	266.0
Case 2	290	2510	11.346	2670	10.40	4	281.3
Case 3	300	-61.4	20.205	2089	11.60	10	276.6
Case 4	320	-4684	34.638	-2358	26.80	10	290.9
Case 5	350	-5250	35	-5048	34.99	6	327.7

In the case study, the LSE bidder is located at bus D. The flat electricity rate offered to the customers at bus D by the LSE is set as $20/MWh. This study also assumes that the highest coupon price is no more than 50% of the flat electricity rate. Hence, the coupon price varies between $0/MWh to $10/MWh with $1/MWh as the incremental step. Hence, there are 11 different levels which are aligned with the 11 probabilistic levels of demand reduction in the survey data obtained in [30]–[32].

B. Implication at Different Load Levels

In this subsection, five representative operating points (cases 1–5) at different system load levels (CLLs) are chosen to investigate the implication for DR at different load levels. The wind power generation model in [43] is implemented in the case study.

The five load levels are chosen based on the critical load level concept which represents a binding constraint at a particular system load level [21], [33]. As shown in Fig. 12, the left-center diagram shows the five cases at different load levels with the "X" symbols in the LMP versus load curve, which is obtained with probabilistic wind power scenarios. The corresponding demand dispatches under the optimal coupon price for each operating point are listed in Table I.

The curves of changed ENR (or ΔENR) with C-DR for the five case studies are shown in Fig. 12. Again, the coupon range is between $1/MWh and $10/MWh corresponding to the ten probabilistic demand reduction levels.

It can be observed that the patterns of five case studies are different. Case 1 demonstrates that when the current operating point is not close to a CLL (i.e., the next binding constraint when the load increases) and the corresponding LMP is lower than the flat rate, the ΔENR is negative which implies that LSE has no incentive to implement C-DR at this operating point.

In contrast, the ΔENR is positive for each of the other four cases, which means an increased profit of LSE with C-DR. Meanwhile, the pattern of ΔENR versus coupon price varies for these four cases 2–5. In Cases 3 and 4, ΔENR versus coupon price continuously increases in the range of [1], [10] $/MWh, while ΔENR versus coupon price in Cases 2 and 5 increases and then decreases. The pattern is analyzed as follows. First, the ENR is related to the LSE's payment to ISO, which is the product of price and demand (i.e., $\pi \cdot D$). Therefore, when the operating point is considerably greater than the previous CLL as in Cases 2 and 5, any reduction of demand does not give much reduction in the price, as also shown in Table I. In contrast, in Cases 3 and 4, a reduction in demand will lead to considerably reduction in price as well, so the total reduced payment to ISO or ΔENR is somewhat quadratic to coupon price and dominates the coupon paid to customers. So, the ΔENR versus coupon price curve is monotonically increasing in Cases 3 or 4; however, in Cases 2 and 5, the curves increase when the coupon price is low, and then decrease when the coupon price is high which implies the coupon is too costly if compared with demand reduction because the price does not change much.

C. Impact From Wind Power Capacity

Various scenarios have been simulated to investigate the impacts of wind power from two aspects: 1) wind power capacity, and 2) wind power forecast uncertainty. This subsection discusses the wind power capacity, and the next subsection discusses about the impact from wind power uncertainty.

As illustrated in Fig. 13, the simulation results with total wind power capacity from 0 to 600 MW show that the staircase curve of LMP holds the same pattern while the CLLs vary. Consequently, the typical operating points for each specific case change in accordance with wind power capacities. The results of ΔENR versus coupon price under three different wind capacities (320, 360, and 400 MW) are graphed in Fig. 14.

It can be observed from Fig. 14 that in the same case, the curves of ΔENR versus coupon price hold similar patterns to the previous case study in Section V-B, despite the differences in wind capacities. Therefore, the wind penetration does not change the ΔENR versus coupon price pattern with respect to a specific case. As a matter of fact, the operating point with respect to CLL will determine the pattern of ΔENR versus coupon price.

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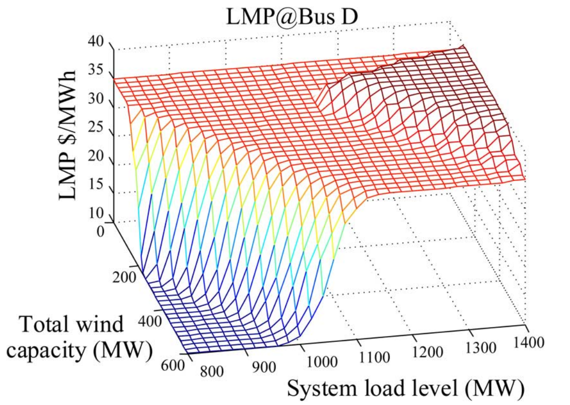

Fig. 13. LMP versus different load levels with various wind capacity integrated into PJM 5-bus system.

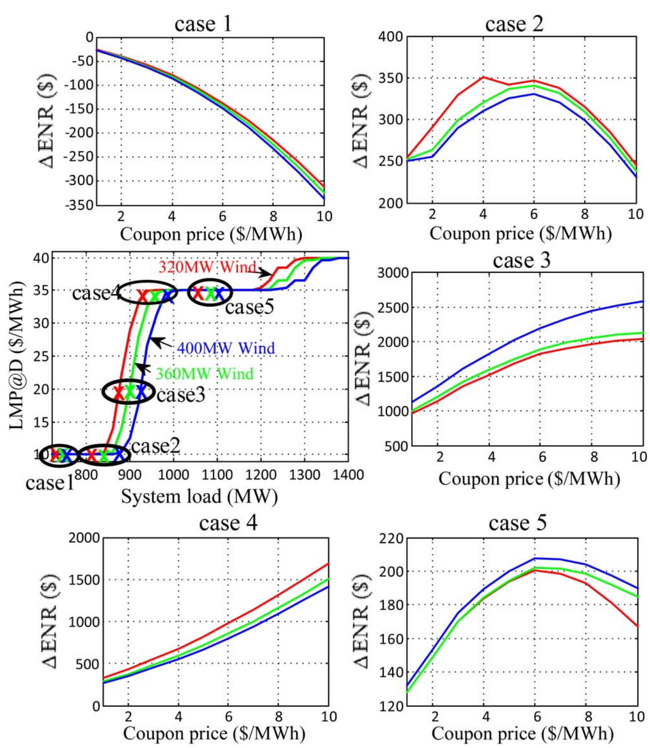

Fig. 14. ΔENR versus coupon price with different wind power capacities.

D. Wind Power Forecast Uncertainty

Fig. 15 shows the impact of wind power forecast uncertainty to the ΔENR by implementing C-DR program at five load levels (LL1–LL5). Table II shows the simulation parameters. Fig. 16 is the staircase LMP curves under various wind power forecast uncertainty.

According to Fig. 15, at LL3 and LL4, C-DR helps the LSE to gain a significant amount of ΔENR when σ is low; however, ΔENR decreases when σ, the indicator of wind power forecast uncertainty, increases. The reason is that the LMP sensitivity at LL3 and LL4 decreases when uncertainty increase demonstrated in Fig. 16 (i.e., the slope of LMP decreases when σ increases). Consequently, a higher uncertainty leads to lower LMP variations and smaller values of ΔENR.

In contrast, in LL2 and LL5, ΔENR has a moderate increasing trend when σ increases. The reason is that the LMP

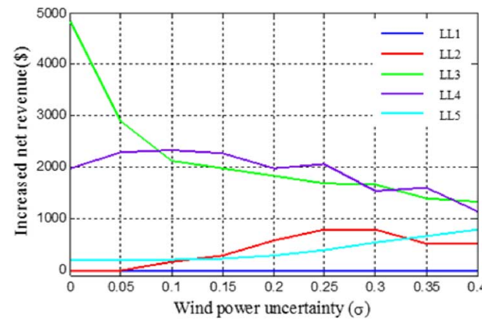

Fig. 15. Impact of wind power forecast uncertainty on ENR on five typical operating points.

TABLE II
PARAMETERS IN WIND UNCERTAINTY TEST

Wind Speed Model	***Normal Distributed***
WF1 Wind Power Mean (MW)	180
WF2 Wind Power Mean (MW)	180
σ , Wind Speed Standard Deviation Range (p.u.)	0~0.4

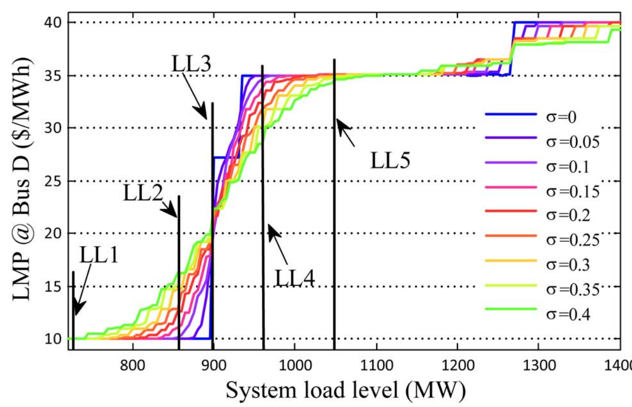

Fig. 16. LMP against load level under various wind forecast uncertainty.

sensitivity in LL2 and LL5 rises when uncertainty increases. Consequently, a higher uncertainty may lead to a higher LMP sensitivity and then greater values of ΔENR.

Further, when the operating point is extremely low, as in LL1, ΔENR may stay at zero because it is preferred to not active the C-DR program. This is aligned with the results in Case 1 in Section V-B.

Thus, we can conclude that when the LMP at a specific load level is sensitive at that load level (e.g., LL3 and 4), ΔENR decreases with wind uncertainty; otherwise, ΔENR may increase with wind uncertainty.

E. IEEE 118-Bus System

The IEEE 118-bus system [44] is applied to demonstrate applicability of the proposed method to large systems. The system, as shown in Fig. 17, has 4242 MW load and 9966 MW generation capacity and consists of 118 buses, 54 generators, and 186 branches.

The generator bidding data are similar with that in [16]: 20 low-cost generators with bids $5, $5.5 and from $11 to $19.5 with $0.5 increment; 20 expensive generators with bids from

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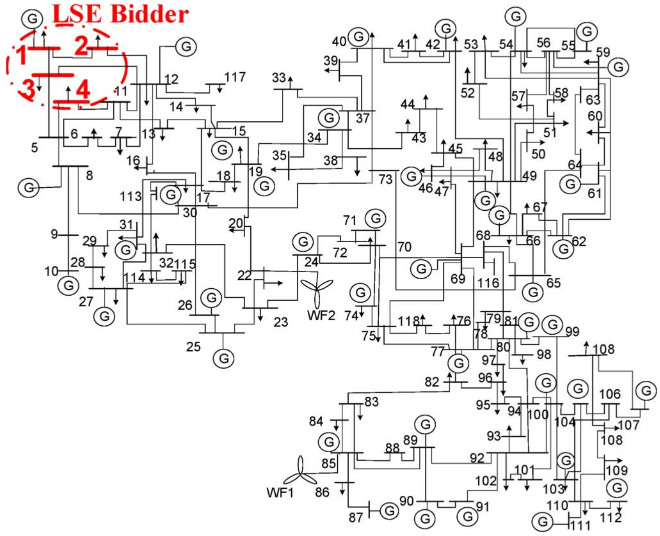

Fig. 17. LSE bidder in IEEE 118-bus system integrated with two wind farms.

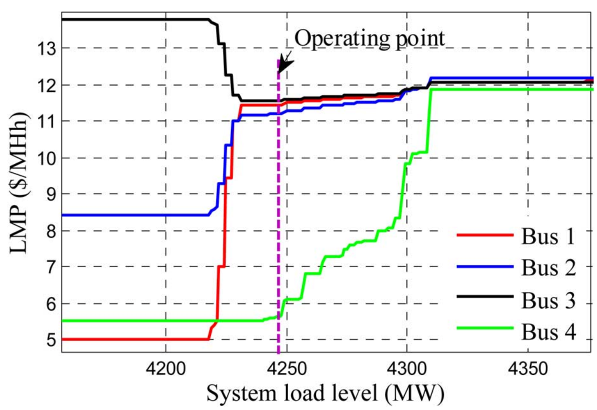

Fig. 18. LMPs of LSE's buses in IEEE 118-bus system.

$30 to 49 with $1 increment; and 14 most expensive generators with bidding from $70 to 83 with $1 increment. Seven thermal limits are applied to the transmission system: 100 MW for line 1–3 and 6–7, 175 MW for line 3–12 and 46–47, 150 MW for lines 15–33, 300 MW for line 71–72, and 250 MW for line 70–75.

Two wind power farms are connected at bus 85 (WF1) and bus 22 (WF2). At the bidding hour, the mean power from each wind farm is set as 300 MW with a 10% standard deviation (σ).

The LSE performing the strategic bidding is located at the northwestern part of the system covering the demands on Bus 1, Bus 2, Bus 3, and Bus 4. LMPs on Bus 1 to Bus 4 versus the system load level is shown in Fig. 18. The coupon prices are set in the range between $0/MWh and $2.5/MWh with $0.5/MWh as the increment step. Therefore, there are six different levels, which are aligned with the six probabilistic levels of demand reduction from the survey data obtained in [26] and [27]. The demands at each bus of this LSE and the corresponding flat electricity rates are shown in Table III. The load dispatched by the LSE for each bus and the ENR under different coupon prices are in Table IV. Also, Table V shows the LSE's Bus LMPs.

The results in Table IV reflect that the LSE can obtain a considerable revenue increment from $-\$237.882$ to $59.283 through C-DR with coupon price $0.5 MW/h. However, the LSE's ENR decreases with the coupon price larger than $0.5 MW/h. Two factors are related to this result:

1) Under this operation condition, a small demand reduction can cause the LMP drop to the lower level due to its step change pattern. Meanwhile, the change of LMP is not obvious with the further increasing the coupon price. As shown in Table V, LMP on Bus 1 decreases from $11.441/MWh to $5.000/MWh when the coupon price changes to $0.5/MWh.
2) Higher coupon price increases the payment from LSE to customers.

Moreover, it can be observed that the impacts of LSE's strategic behavior to the LMPs may vary at different buses. As demonstrated in Table V, the LMP on Bus 3 increases while the LMPs on the other buses decrease. This observation is reasonable, because the objective of LSE is to maximize its total payoff gathered from all the customers on different buses. Therefore, it is possible that the LMP at a specific bus may increase with the LSE's strategic behavior, while the LSE's overall profit is maximized.

TABLE III
LOAD AND FLAT ELECTRICITY RATE ON LSE BIDDER'S BUSES

Bus	Base Load (MW)	Flat Electricity Rate ($/MWh)
1	51	7.5
2	20	9.5
3	39	11.5
4	39	5.5

TABLE IV
DISPATCHED LOAD ON BUSES AND LSE'S ENR UNDER DIFFERENT COUPON PRICES

Coupon	Dispatched Load (MW)				ENR
	Bus 1	Bus 2	Bus 3	Bus 4	
0	51.000	20.000	39.000	39.000	-237.9
0.5	49.904	19.744	36.945	38.501	59.3
1.0	49.494	19.542	36.380	38.106	55.8
1.5	49.121	19.304	36.126	37.643	50.5
2.0	48.403	19.002	35.160	37.053	42.0
2.5	47.631	18.686	36.437	36.437	31.0

TABLE V
LMP ON BUSES UNDER DIFFERENT COUPON PRICES

Coupon	LMP ($MW/h)			
	Bus 1	Bus 2	Bus 3	Bus 4
0	11.441	11.179	11.552	5.532
0.5	5.000	8.417	13.798	5.500
1.0	5.000	8.417	13.798	5.500
1.5	5.000	8.417	13.798	5.500
2.0	5.000	8.417	13.798	5.500
2.5	5.003	8.415	13.789	5.497

VI. CONCLUSIONS

In this paper, a strategic bidding approach for LSE with C-DR is proposed with the consideration of wind power uncertainty and customers' behavior patterns toward different coupon prices. The contributions of this work can be summarized as follows:

1) A strategic bidding model for LSEs using bi-level optimization for C-DR is proposed by recasting the lower-level problem into the KKT optimality condition. Thus, this bi-level problem is transformed to a MPEC problem, then further converted into a MILP problem that is easy to solve by available software tools.
2) A probabilistic model of residential demand is applied to mimic customers' behavior patterns toward different coupon prices. Therefore, the time-consuming interacting process with numerous customers can be avoided, which makes online implementation of C-DR feasible.
3) The strategic bidding is studied at five typical operating points representing different load levels. The simulation results demonstrate that change of expected net revenue (i.e., ΔENR) is closely related to the CLL, because this determines whether there will be a considerable price change or not if the load is reduced.
4) The wind power capacity does not change the patterns of ΔENR versus coupon prices, while the wind uncertainty may have an impact to ΔENR. ΔENR may either decrease with wind uncertainty when LMP is sensitive to load level or increase when LMP is not that sensitive to load level.

Furthermore, it should be noted that although the discussion in this paper focuses on the strategic bidding in RT market, similar mechanism or approach can be applied to DA market as long as some price incentives are offered to encourage customers to participate in DA market such as TOU tariff, which can be roughly viewed as different C-DR at different time windows.

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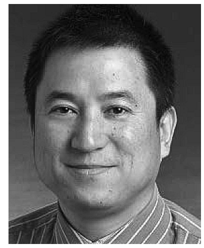

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