Strategic Bidding in Distribution Network Electricity Market Focusing on Competition Modeling and Uncertainties

Mehrdad Mallaki, Mehdi S. Naderi, Mehrdad Abedi, Saeed D. Manshadi, and Gevork B. Gharehpetian

Abstract—**Developing the electricity market at the distribution level can facilitate the energy transactions in distribution networks with a high penetration level of distributed energy resources (DERs) and microgrids (MGs). However, the lack of comprehensive information about the marginal production cost of competitors leads to uncertainties in the optimal bidding strategy of participants. The electricity demand within the network and the price in the wholesale electricity market are two other sources of the uncertainties. In this paper, a day-ahead-market-based framework for managing the energy transactions among MGs and other participants in distribution networks is introduced. A game-theory-based method is presented to model the competition and determine the optimal bidding strategy of participants in the market. Robust optimization technique is employed to capture the uncertainties in the marginal cost of competitors. Additionally, the uncertainties in demand are modeled using a scenario-based stochastic approach. The results obtained from case studies reveal the merit of considering competition modeling and uncertainties.**

Index Terms—**Competition modeling, bidding strategy, distribution network electricity market, microgrid, uncertainty, robust optimization.**

NOMENCLATURE

β	New auxiliary variable
Γ	Parameter indicating risk-taking level in robust optimization (RO)
δ	Constant to control updating step of k_j
λ_w	Wholesale electricity market price
μ_D	Average value in demand prediction
π_j	Local energy price for the j^{th} participant
π_{js}	Local price for the j^{th} participant in scenario s
ρ_j	Bidding price of the j^{th} participant
σ_D	Standard deviation in demand prediction
a_j, b_j, c_j	Generation cost coefficients of the j^{th} participant
C_j	Generation cost of the j^{th} participant
D	Total demand in electricity market
$D^{forecast}$	Forecasted demand
DS	Set of scenarios that should be removed
D_s	Demand in scenario s
ΔD_s	Demand forecasting error in scenario s
$DT_{s,s'}$	Distance between scenarios s and s'
$Iter$	Game iteration counter
j	Index for electricity market participants
k_j	Strategic factor of the j^{th} participant
$k_j^{\min}$, $k_j^{\max}$	Boundary limits for k_j
k_j^{new}, k_j^{old}	Updated and old values of k
K_{DRA}	Strategic factor of demand response aggregator
K_{DG}	Strategic factor of distributed generator
K_{EB}	Strategic factor of energy broker
K_{MG}	Strategic factor of microgrid
MC_j	Marginal cost of the j^{th} participant
$MC_j^{\min}$, $MC_j^{\max}$	Limits for MC_j
$\widetilde{MC}_j$	Marginal cost of the j^{th} participant considering uncertainty
$\overline{MC}_j$	Average estimated value for MC_j
MCP	Electricity market clearing price
N_d	Reduced number of scenarios
N_s	Initial number of scenarios
P_{DRA}	Electricity market share of demand response aggregator
P_{DG}	Electricity market share of distributed generator
P_{EB}	Electricity market share of energy broker
P_j	Scheduled power of the j^{th} participant
$P_j^{\min}$, $P_j^{\max}$	Power limits of the j^{th} participant

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P_{MG}	Electricity market share of microgrid
P_{js}	Electricity market share for the j^{th} participant in scenario s
pr_s	Probability of scenario s
pr_s^{norm}	Normalized probability of scenario s
r	Scenario index with the minimum distance from scenario s
R_j	Profit of the j^{th} participant
s	Index for demand scenarios
S	Initial set of scenarios
w_j	Auxiliary variable in interval between 0 and 1
y_j	Dual variable of w_j

I. Introduction

IN recent years, the growth in the penetration level of distributed energy resources (DERs) has led to major changes in the electricity industry, particularly in distribution networks. Although the economic considerations and environmental concerns are attractive motivations, the uncoordinated utilization of DERs may have destructive effects on the secure operation of power systems [1].

It is an important issue to manage the financial transactions related to the purchase and sale of energy in the distribution network. The energy transactions among microgrids (MGs) and other participants in a distribution network could be handled in a distribution network electricity market (DNEM). To forecast the electricity market price, each participant requires a reliable prediction of the behavior of competitors in the electricity market to simulate the competition process. However, in reality, the accurate information about the marginal cost (MC) of opponents is not available; therefore, the optimal bidding strategy problem is faced with uncertainties. The demand in the distribution network and the wholesale electricity market (WEM) price are other uncertain parameters that affect the bidding strategy of participants in the DNEM.

At the distribution level, the electricity market is an emerging topic and the related details defining the structure are still in progress. Several works have addressed the topic in the literature trying to propose a practical structure for trading energy and ancillary services such as reserve or reactive power in a DNEM environment [2]-[4]. The current methods of modeling the participation of players in a day-ahead electricity market are divided into two classes: game-based and non-game-based methods [5]. In non-game-based methods, the electricity market clearing process is modeled as a price forecasting procedure without modeling the electricity market operator functions [6]. However, in game-based methods, the performance of all participants and the electricity market model are analyzed considering the factors that affect the decision-making process [7].

Several methods are introduced to solve the bidding strategy of participants in the WEMs [8]-[10]. The bidding strategy is also investigated for demand-side or distribution network participants in some limited works. Reference [11] proposes an optimal bidding scheme for a demand-side resource aggregator based on the conditional value-at-risk. A stochastic operation model for coordination of demand response aggregators and wind power producers is presented in [12] based on day-ahead electricity market concepts. The bidding problem of an electric vehicle aggregator in a day-ahead electricity market is analyzed in [13], which is formulated using a hybrid stochastic-robust optimization (RO) approach. In [14], a look-ahead technique is proposed to optimize the bi-level bidding strategy problem of an energy storage agent considering the electricity market prices.

In all discussed works, uncertainty modeling plays an important role in making the approach more practical. Generally, uncertainty modeling methods are divided into two main groups: probabilistic and non-probabilistic methods. In probabilistic methods, the input parameters of the model are random variables with a known probability density function (PDF) [15]. Monte Carlo simulation and scenario generation are the most recognized probabilistic methods [16]. The main drawbacks of these methods are the large computation burden and accurate estimation requirement of the PDF for the uncertain variables [17]. The information gap decision technique (IGDT) and RO are the most recognized non-probabilistic methods for uncertainty modeling. In the former method, the uncertainty is modeled as an interval around the forecasted quantity, where the interval is maximized while setting the optimization variables [18]. In the latter method, an uncertain interval is supposed around the forecasted parameter (obtained from the historical data) instead of estimating the probability of the uncertainty. The uncertainty of the forecasted parameter is modeled in these methods without making any assumption on its PDF [19].

In this paper, a day-ahead electricity market framework is proposed to facilitate the integration of participants in energy transactions within distribution networks operated by distribution system operator (DSO). The bidding strategy problem is formulated as a bi-level optimization problem. An incomplete information game-theory based approach is presented to model the competition. The uncertainty in demand is modeled by a scenario-based stochastic optimization problem and the RO technique is utilized to consider the uncertainty in the MC of competitors and model the incomplete information game.

The uncertainty in the MC of participants in a DNEM is not yet thoroughly addressed in the literature. Hence, the main contributions of this paper are highlighted as follows.

1) A market-based framework facilitating the energy transactions within distribution networks is proposed.

2) The bidding strategy problem of participants in a DNEM under uncertainties is formulated considering the competition modeling.

3) An RO formulation to model the uncertainty in the behavior of competitors is presented.

The rest of this paper is organized as follows. Section II demonstrates the proposed electricity market framework and the formulation of the bidding strategy problem. Section III describes the uncertainty modeling and the incomplete information game. In Section IV, a case study is presented and the simulation results are illustrated. Finally, concluding remarks are presented in Section V.

II. Structure Modeling and Problem Formulation

In this section, a framework is proposed to facilitate the contributions of participants in a DNEM. In the proposed model, the independent DERs, MGs and loads directly participate in the market, subject to the minimum capacity condition. The retailers and other aggregators such as demand response aggregators (DRAs) are also eligible to participate in the DNEM. In this model, the energy brokers (EBs) are intermediate agents between the DNEM and the WEM, where export/import energy from/to the DNEM [20]. The independent DERs, MGs, and EBs are the energy providers in DNEM. Their bids are submitted to the electricity market in the form of "bidding price-bidding quantity" pairs. Besides, customers in this electricity market are the retailers, independent loads, MGs, and EBs that serve their demands in the DNEM. The proposed DNEM clears before the starting time of the day-ahead WEM process.

A game-based approach is utilized to model the bidding strategy analysis. This approach models the problem as a non-cooperative game with incomplete information. The competition among the participants in DNEM is modeled using the supply function equilibrium method, which enables a electricity market participant to link its bidding price with the bidding quantity of its product using a supply function. Generally, the cost of a power supplier C_j is described as a function of its generated power P_j as:

$$C_j = a_j P_j^2 + b_j P_j + c_j \tag{1}$$

The generation MC for each supplier is obtained from the derivative of its cost function. It is assumed that all suppliers choose their bidding price using a decision variable, i.e., the strategic factor, according to the following linear supply function as:

$$\rho_j = k_j \cdot MC_j = k_j\left(2a_j P_j + b_j\right) \tag{2}$$

Each participant has the knowledge about its own generation costs, but this information about other participants is unavailable. Hence, the competition among participants is modeled as an incomplete game [21]. In this paper, the competition is first modeled as a complete game. Then, the uncertainty modeling techniques are utilized to compensate for the lack of information on the opponents' behavior and model the incomplete information game.

In a complete information game, each player's payoff function, is commonly known to all players. Each participant tries to maximize its profit by adopting the optimal strategic factor. The game converges to a Nash equilibrium, where no participant is willing to change its strategy. An iterative algorithm is utilized to find the equilibrium point. First, an initial bid is considered using initial strategic factors. Then, each participant updates its strategic factor to achieve the maximum profit. This process continues until the change of the strategic factor does not increases the profit for any of the participants. The flowchart of the iterative algorithm is shown in Fig. 1 [21].

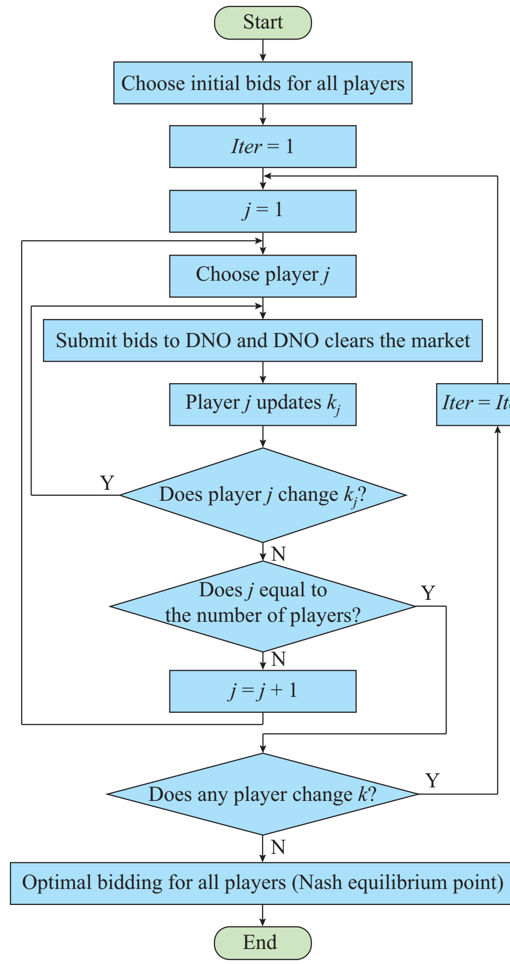

Fig. 1 Flowchart of iterative algorithm for complete game.

The rest of this section will present the problem formulation for the deterministic case. For each participant in DNEM, the profit is gained by subtracting the generation cost from the revenue of sold energy as:

$$R_j = \pi_j P_j - C_j P_j \tag{3}$$

The DSO aims to serve the power demand of customers with the minimum cost. Here, the DSO electricity market clearing problem is a linear problem as:

$$\begin{cases} \min\limits_{P_j} \sum\limits_j \rho_j P_j \\ \text{s.t.} \quad \sum\limits_j P_j = D \\ \qquad P_j^{\min} \le P_j \le P_j^{\max} \end{cases} \tag{4}$$

It should be noted that the linear formulation of the DSO electricity market clearing problem is utilized in this paper to focus on the competition and uncertainty within the market. Therefore, we ignore other aspects of distribution network such as loss and AC power flow in this paper. Therefore, the price is the same all over the distribution network and is named as the electricity market clearing price (MCP).

The optimal bidding strategy is a bi-level problem. At the upper level, each participant wants to maximize the profit through the optimal strategic factor. At the lower level, the DSO wants to minimize the cost of energy supply in the network. This bi-level problem is presented as:

$$\begin{cases} \max\limits_{k_j} R_j \\ \text{s.t.}\;\; k_j^{\min} \le k_j \le k_j^{\max} \\ \qquad \min\limits_{P_j} \sum\limits_j \rho_j P_j \\ \qquad \sum\limits_j P_j = D \\ \qquad P_j^{\min} \le P_j \le P_j^{\max} \end{cases} \tag{5}$$

A sensitivity-based solution method is used in each iteration to solve the optimization problem for each participant. First, each participant chooses an initial strategic factor k_j^{init} and determines its initial bidding price ρ_j^{init} using its supply function presented in (2). The electricity market clearing problem is solved using an estimation of strategic factors of other participants to find the electricity market price and the market share of all participants. Then, the participant calculates its own profit and its sensitivity to the strategic factor $\partial R_j / \partial k_j$. If the value of this sensitivity is not zero, the optimal solution has not been reached yet. Therefore, the value of the strategic factor is updated using (6), and the process is repeated again up until the optimal point is reached.

$$k_j^{new} = k_j^{old} + \delta \frac{\partial R_j}{\partial k_j} \tag{6}$$

According to (3), the sensitivity of the profit to the strategic factor for each participant is obtained as:

$$\begin{cases} \dfrac{\partial R_j}{\partial k_j} = \dfrac{\partial R_j}{\partial P_j}\dfrac{\partial P_j}{\partial k_j} + \dfrac{\partial R_j}{\partial \pi_j}\dfrac{\partial \pi_j}{\partial k_j} \\ \dfrac{\partial R_j}{\partial P_j} = \pi_j - \dfrac{\partial C_j}{\partial P_j} = \pi_j - MC_j \\ \dfrac{\partial R_j}{\partial \pi_j} = P_j \end{cases} \tag{7}$$

The terms $\partial P_j / \partial k_j$ and $\partial \pi_j / \partial k_j$ are calculated using dual theory and Karush-Kuhn-Tucker (KKT) conditions according to the formulation described in details in [20]. However, the MC of EB is equal to its purchasing price from WEM or DNEM (λ_w or π_j), depending on its role as an energy importer or exporter. It is not affected by the amount of exchanging power in DNEM. Therefore, the payoff function and the bidding price of an EB are formulated as (8) and (9), respectively.

$$R_j = \pm\left(\pi_j - \lambda_w\right) P_j \tag{8}$$

$$\rho_j = \begin{cases} k_j \lambda_w & \text{EB is an importer} \\ k_j \pi_j & \text{EB is an exporter} \end{cases} \tag{9}$$

The sensitivity of the EB profit to k_j is calculated as:

$$\begin{cases} \dfrac{\partial R_j}{\partial k_j} = \dfrac{\partial R_j}{\partial P_j}\dfrac{\partial P_j}{\partial k_j} + \dfrac{\partial R_j}{\partial \pi_j}\dfrac{\partial \pi_j}{\partial k_j} \\ \dfrac{\partial R_j}{\partial P_j} = \pm\left(\pi_j - \lambda_w\right) \\ \dfrac{\partial R_j}{\partial \pi_j} = \pm P_j \end{cases} \tag{10}$$

Here, the plus/minus sign implies the EB role in DNEM as an importer/exporter. An EB is a connector between WEM and DNEM and acts depending on the price difference between these two markets. Therefore, in order to specify the role of EB, it is firstly required to analyze the price of two electricity markets separately in the absence of this connector. Considering the large size of WEM compared with DNEM, it is supposed that the WEM price is not considerably affected by EB transactions. Thus, in order to specify the role of EB, the DNEM is cleared without EB and then the EB role is determined by comparing the DNEM price with the forecasted WEM price.

Generally, the sensitivity-based solvers are faced with two major issues in finding the solution of optimization problems: ① procuring a local optimal solution; ② consuming long computation time. In order to resolve these two issues, two techniques are used in this study, i.e., passing MCP and dynamic step size, which are introduced and described in detail in [22]. These techniques are briefly discussed here.

In the past MCP method, the search for the optimal solution begins from the lower limit of each player's strategic factor $k_j^{\min}$. Each time the search stopping criteria is met, the player's bidding price at the local optimum point is compared with the MCP value. If the bidding price is lower than the MCP, a new value will be chosen for k_j so that the bidding price be slightly higher than the MCP. Therefore, the search continues with a jump from the local optima. Also, if the proposed price is higher than the MCP, the new value for k_j will be chosen to be slightly lower than the MCP. This trend continues until the search reaches the upper limit of the player's strategic factor $k_j^{\max}$. The search space is explored entirely in this method to find the optimal solution. Therefore, the possibility of falling into local optima and losing the global optimal point is diminished.

In the dynamic step size technique, the value of δ is dynamically changed proportional to the searching condition. First, a small initial value δ_{init} is selected for δ. Then, in each update of k_j, if the value of $\partial R_j / \partial k_j$ remains unchanged, compared with the previous update, the value of δ is doubled. In the event of observing a change in $\partial R_j / \partial k_j$, the value of δ is restored to its initial value. This technique potentially accelerates the search process while maintaining the accuracy of solutions.

III. Uncertainty Modeling

The uncertain variables in the bidding strategy include demand, WEM price and the MC of participants. The demand uncertainty is modeled using a scenario-based stochastic approach. The WEM price is the MC of the EB and its uncertainty is modeled along with the uncertainty of the MC of other participants using the RO technique.

A. Modeling of Demand Uncertainty

The uncertainty in demand is realized using a scenario-based technique. Scenarios are generated by Monte Carlo simulation and roulette wheel mechanism (RWM) [23]. The load demand can be represented as:

$$D_s = D^{forecast} + \Delta D_s \tag{11}$$

The probability distribution of a random variable is represented by a finite set of scenarios with associated probabilities. In this study, the Gaussian distribution is used to model the demand uncertainty as [2]:

$$f_D(D)= \frac{1}{\sqrt{2\pi}\,\sigma_D} \exp\left(- \frac{\left(D-\mu_D\right)^2}{2\sigma_D^2} \right) \tag{12}$$

The distribution function for demand forecasting error is divided into some intervals. A typical PDF for the demand forecasting error discretized to seven intervals is shown in Fig. 2. Each interval determines one standard deviation error σ wide [24]. The probability for interval l is β_l. Then, RWM is utilized to generate the scenarios. In this regard, the probabilities are normalized in a way that their summation comes to be unity. As shown in Fig. 3, each interval is linked with an accumulated normalized probability [23].

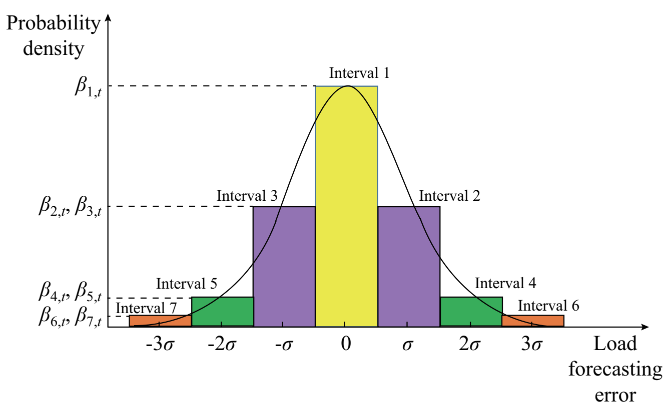

Fig. 2. Discretization of PDF for demand forecasting error.

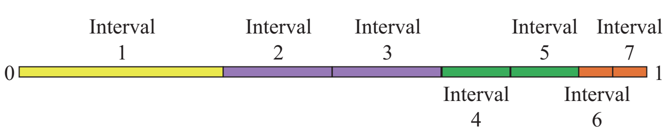

Fig. 3. Accumulated normalized probabilities of forecasting error intervals.

Then random numbers between 0 and 1 are produced for random variables in the scenarios. The first interval whose accumulated probability is less than or equal to this random number is chosen. Then, the scenario associated to this interval is selected. This process is repeated until the anticipated number of the scenarios is created. The normalized probability of the remaining scenarios is calculated as follows:

$$pr_s^{norm} = \frac{pr_s}{\sum_{s=1}^{N_d} pr_s} \tag{13}$$

The solutions attained from the remaining scenarios are accumulated according to their normalized probability to find the expected results [23]. The expected values for the final electricity market price and the electricity market shares can be evaluated as:

$$\begin{cases} \pi_j = \sum_s \left(pr_s^{norm} \cdot \pi_{js} \right) \\ P_j = \sum_s \left(pr_s^{norm} \cdot P_{js} \right) \end{cases} \tag{14}$$

The simultaneous backward technique is applied to minimize the number of the scenarios [23]. The process includes the following steps.

Step 1: consider an initial set of the scenarios S, and a set of the scenarios that should be removed DS, which is initially null; calculate $DT_{s,s'}$ for all scenario pairs as: $DT_{s,s'} = \left| D_s - D_{s'} \right|$, where $s, s' = 1, 2, \ldots, N_s$.

Step 2: for each scenario s, calculate $DT_{s,r} = \min DT_{s,s'}$ where $s, s' \in S, s' \neq s$.

Step 3: calculate $PD_s = pr_s \cdot DT_{s,r}$ for each s. Then, select scenario d in which $PD_d = \min PD_s, s \in \boldsymbol{S}$.

Step 4: $S = S - \{d\}, DS = DS + \{d\}, pr_r = pr_r + pr_d$.

Step 5: repeat *Steps 2-4* until the number of the scenarios meet the desired criteria $|S| = N_d$.

B. Uncertainty in MC of Opponents (Modeling Incomplete Information Game)

As mentioned in Section II, each participant calculates its own MC using the derivative of its cost function, but the cost function information of other opponents is confidential. Therefore, an incomplete information game needs to be considered in a real practical case. Consequently, an estimation of opponents' MC is essential to find the equilibrium point of the game using the solution algorithm, and this is a source of uncertainty and error.

Reference [21] presents a method for modeling incomplete information game in a pool-based WEM. In this way, all possible types of each competitor in terms of cost function coefficients are specified, and a probability distribution function is determined for each type. Then the problem is solved for all possible types and the equilibrium point of the game is extracted for all the combinations of types. The final equilibrium point is the weighted sum of the values obtained in each case, where the weighting factor of each type is equal to the occurrence probability. The idea is similar to stochastic optimization and scenario generation techniques in uncertainty modeling. The major disadvantage of this method is the need to determine the PDF for the cost function coefficients of opponents which is very difficult to obtain and may have relatively high error. In addition, by increasing number of participants, a lot of computation burden will be added to the problem-solving algorithm.

In this paper, the RO formulation is applied to the problem in order to model the incomplete information game and compensate the lack of information on the cost function of opponents. In this regard, an initial guess for MC of opponents is estimated. The uncertain parameter is supposed to change in a known interval around the average forecasted value of the parameter obtained from historical data [16]. The key advantage of this approach is that there is no need for a PDF for the MC of opponents. The RO technique adds linear terms to the problem formulation and offers the opportunity for simultaneous consideration of several uncertain parameters without a significant increase in computation burden [19]. The original incomplete game is now interpreted as a complete game with imperfect information, in which each participant can follow a similar procedure to find its optimal bidding strategy based on the Nash equilibrium point of this complete game.

Generally, all accepted offers in a pool electricity market are paid by MCP, independent of their offered prices. Thus, we can assume that participants offer at their predicted MCP values [25]. On the other hand, in a fully competitive market, the energy price in each node reflects the generation MC in that node [26]. Therefore, the historical data for energy price in each bus could be an initial estimation for the MC of the participant connected to the bus. It is supposed that these predictions are available and are the sources of uncertainties.

The uncertain value of MC can be formulated as:

$$\begin{cases} \widetilde{MC}_j = \overline{MC}_j + w_j\left(\Delta MC_j^+ - \Delta MC_j^-\right) \\ MC_j^{\min} \le \widetilde{MC}_j \le MC_j^{\max} \\ \Delta MC_j^+ \cdot \Delta MC_j^- = 0 \\ \Delta MC_j^+ = MC_j^{\max} - \overline{MC}_j \\ \Delta MC_j^- = \overline{MC}_j - MC_j^{\min} \end{cases} \tag{15}$$

$\overline{MC}_j$ is obtained using an estimation of energy price with historical data. Since the RO considers the worst uncertainty, the electricity market clearing problem can be rewritten as:

$$\min_{P_j, w_j} \left\{ \sum_j k_j \cdot \overline{MC}_j \cdot P_j + \max \sum_j k_j w_j \Delta MC_j^+ P_j \right\} \quad 0 \le w_j \le 1, \sum_j w_j = \Gamma \tag{16}$$

The interior maximization problem could be replaced with its dual minimization form:

$$\min_{P_j, y_j, \beta} \left\{ \sum_j \left(k_j \cdot \overline{MC}_j \cdot P_j\right) + \min\left(\sum_j y_j + \beta\Gamma\right) \right\} \quad y_j + \beta \ge \Delta MC_j^+ \cdot P_j \tag{17}$$

Since the worst case is considered in RO, the electricity market clearing problem is finally formulated as:

$$\min_{P_j, y_j, \beta} \left\{ \sum_j \left(k_j \cdot \overline{MC}_j \cdot P_j\right) + \left(\sum_j y_j + \beta\Gamma\right) \right\} \quad y_j + \beta \ge \Delta MC_j^+ \cdot P_j \tag{18}$$

The budget of the uncertainty will derive the level of conservatism for the decision-makers. Therefore, one can adjust the risk willingness by setting the parameter Γ that changes the budget of the uncertainty, without changing the model. Once the budget of the uncertainty is zero, the problem is deterministic. With the increase in the budget of the uncertainty, the conservatism increases to the level at which it becomes an interval optimization problem, where the worst deviation for all uncertain value will occur.

In each iteration of the game, each player solves this linear minimization problem shown in (22) for several times in order to optimize its strategic factor and bidding price, as shown in Fig. 1. The main equality constraint in electricity market clearing problem is the supply-demand balance constraint. The MCP, which is the bidding price of the marginal supplier in the market, is equal to the Lagrange multiplier of the supply-demand equality constraint. This multiplier is calculated as an auxiliary variable along with the main primary variables in the problem. This approach is identical in both deterministic (without RO) and non-deterministic (with RO) states. Therefore, the electricity MCPs can be determined.

IV. Simulation Results

The DNEM participants in our case study include an MG, an EB, a DRA, and an independent distributed generator (DG). Demand response is considered in the form of interruptible load. The quadratic cost function coefficients and the power supply limits for all participants are presented in Table I. The electricity market data is extracted from [20] and [27] with some modifications. In order to prevent participants from bidding at extremely higher or lower prices than their MC, the top and bottom boundary values for strategic factors are assumed to be 2 and 0.8, respectively. The MC of DG, DRA, and MG are 40 \$/MWh, 80 \$/MWh and 44 \$/MWh respectively, based on their cost functions and generation limits. The EB MC is variable and equal to the WEM price each hour.

TABLE I
Parameters of Electricity Market Participants

Generation limit		Cost function			Participant	
P_{max} (MW)	P_{min} (MW)	C (\$)	B (\$/MW)	A (\$/MW^2)	Name	Index
40	0	0	30	0.125	DG	1
20	0	0	70	0.250	DRA	2
60	0	0	20	0.200	MG	3
40	0	0	λ_w	0.000	EB	4

The forecasted values for DNEM demand and WEM price in a typical day is shown in Fig. 4. The demand curve is obtained from the average daily load during a summer day for a residential area [28]. The hourly prices are obtained from the weighted average of accepted offering prices during summer days in the associated service area [28].

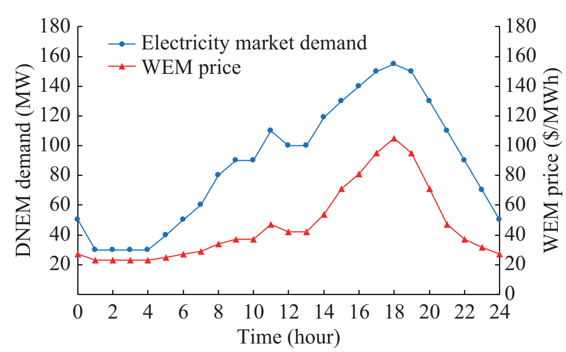

Fig. 4. Forecasted values for DNEM demand and WEM price.

To determine the role of EB in the DNEM, the electricity market is firstly cleared without EB.

Figure 5 shows the results in this case. The DNEM prices are higher than the WEM prices for all day hours. Therefore, the EB acts as an importer or seller in the DNEM. At 11:00, the DRA is the marginal producer and increases the price to its top boundary level. Also, since the demand at the time between 15:00 and 20:00 is higher than the total capacity of remaining electricity market participants, i. e. DG, DRA, and MG, the DNEM clearing price in these hours could be extremely higher than any other hour. However, it is limited by $k_j^{\max}$ and is fixed at 160 \$/MWh.

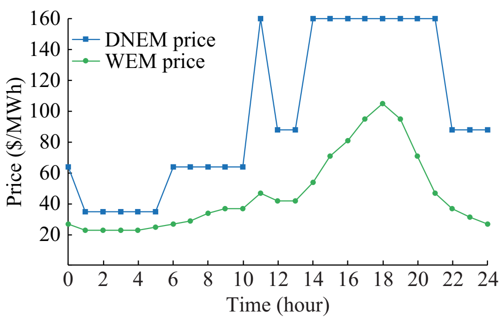

Fig. 5. DNEM clearing price in absence of EB.

In the following subsections, the numerical results are presented and discussed in four different cases. First, the deterministic bidding strategy is analyzed in Case 1. Then in Case 2 and Case 3, the bidding strategy problem is solved considering the demand uncertainty and MCs, respectively. Finally, the bidding strategy is analyzed considering all uncertainties in Case 4.

A. Deterministic Bidding Strategy (Case 1)

In this subsection, the results are presented without considering the uncertainties. Figure 6 shows the final DNEM clearing prices at the equilibrium point for different demand values. The forecasted WEM prices are also shown in the figure for better comparison. It is evident that after the introduction of EB, the DNEM prices are moderated compared with Fig. 5, but are still higher than the WEM prices. This verifies our prediction in the previous section on the role of EB as an importer in the DNEM.

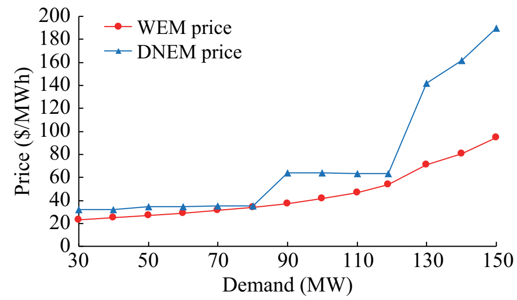

Fig. 6. DNEM prices at equilibrium point in Case 1.

Table II shows the final values obtained for the strategic factor and electricity market share of participants at the equilibrium point for different demand and WEM price levels. For $D \le 40$ MW, EB is the marginal producer, because it has the smaller MC value, and the network demand is less than its total capacity. For $40 < D \le 60$ MW, initially, the EB capacity is completely occupied. On the other hand, the lower limit for k_j prevents MG from reducing its bidding price. Therefore, DG becomes the marginal producer and determines the MCP by adjusting its strategic factor at 0.87.

TABLE II
BIDDING STRATEGY RESULTS FOR CASE 1 (DETERMINISTIC)

P_{EB} (MW)	P_{MG} (MW)	P_{DRA} (MW)	P_{DG} (MW)	K_{EB}	K_{MG}	K_{DRA}	K_{DG}	MCP (\$/MWh)	λ_w (\$/MWh)	D (MW)
30	0	0	0	1.39	0.80	0.80	0.80	31.97	23.0	30
40	0	0	0	1.27	0.80	0.80	0.80	31.92	25.0	40
40	0	0	10.0	0.80	0.80	0.80	0.87	34.80	27.0	50
40	0	0	20.0	0.80	0.80	0.80	0.87	34.80	29.0	60
40	17.1	0	12.9	0.80	0.80	0.80	0.88	35.20	31.5	70
40	22.3	0	17.7	0.80	0.80	0.80	0.88	35.20	34.0	80
40	10.0	0	40.0	0.80	1.45	0.80	0.88	63.80	37.0	90
40	20.0	0	40.0	0.80	1.45	0.80	0.88	63.80	42.0	100
40	60.0	0	10.0	0.80	0.80	0.80	1.59	63.60	47.0	110
40	60.0	0	19.0	0.80	0.80	0.80	1.59	63.60	54.0	119
10	60.0	20	40.0	2.00	0.80	0.81	1.60	142.00	71.0	130
20	60.0	20	40.0	2.00	2.00	0.82	0.80	162.00	81.0	140
30	60.0	20	40.0	2.00	0.80	2.00	0.80	190.00	95.0	150

For $60 < D \le 80$ MW, the DG has to fix its strategic factor at $k = 0.88$. This is because by increasing k to higher levels, the DG will force to leave its total electricity market share to MG. Also, reducing the bidding price leads to lower profit for the DG. Both DG and MG are the marginal producers with equal bidding prices in this area and determine the final MCP.

For $80 < D \le 100$ MW, the MG increases its offering price and loses part of its share to become the marginal producer. This allows the MG to determine the MCP at higher prices and earn more profit even by less electricity market share.

This trend is reversed in $100<D<120$ MW where the DG increases its k_j and becomes the marginal producer to increase the MCP. For $D\geq 120$ MW, the network demand is higher than the total capacity of the DG, MG, and EB. Therefore, the capacity of DRA is called to satisfy the demand. The EB bids at its maximum allowable price according to the k_j limits. This leads to higher MCP values and increases the profit for all electricity market participants, although the EB leaves part of its market share for others.

B. Demand Uncertainty (Case 2)

Seven PDF intervals are considered in this case for generating 200 demand scenarios according to the PDF segmentation presented in Fig. 2. Then the number of demand scenarios is trimmed down to seven, indexed by d_1 to d_7, using the simultaneous backward scenario reduction method. The aggregated results from solving the bidding strategy for different demand and WEM price levels are presented in Table III considering the demand uncertainty.

TABLE III
BIDDING STRATEGY RESULTS CONSIDERING DEMAND UNCERTAINTY

P_{EB} (MW)	P_{MG} (MW)	P_{DRA} (MW)	P_{DG} (MW)	K_{EB}	K_{MG}	K_{DRA}	K_{DG}	MCP ($/MWh)	λ_w ($/MWh)	D (MW)
30.0	0	0	0	1.39	0.80	0.80	0.80	31.97	23.0	30
39.2	0	0	0.8	1.20	0.80	0.80	0.80	32.38	25.0	40
40.0	0	0	10.0	0.80	0.80	0.80	0.87	34.80	27.0	50
40.0	0	0	20.0	0.80	0.80	0.80	0.87	34.80	29.0	60
40.0	17.1	0	12.9	0.80	0.80	0.80	0.88	35.20	31.5	70
40.0	22.3	0	17.7	0.80	0.80	0.80	0.88	35.20	34.0	80
38.4	11.8	0	39.8	0.81	1.42	0.80	0.88	58.94	37.0	90
40.0	20.0	0	40.0	0.80	1.45	0.80	0.88	63.80	42.0	100
40.0	60.0	0	10.0	0.80	0.80	0.80	1.59	63.60	47.0	110
40.0	60.0	0	19.0	0.80	0.80	0.80	1.59	63.60	54.0	119

The demand uncertainty in bidding strategy changes the results obtained at two demand levels ($D=40$ MW and $D=90$ MW). In order to observe the effect of the demand uncertainty on the bidding strategy results, the obtained results in all seven scenarios for these two cases are shown in Table IV. In both cases, d_4 represents the deterministic case.

TABLE IV
RESULTS OBTAINED IN 7 DEMAND SCENARIOS WITH $D=40$ MW AND $D=90$ MW

D (MW)	λ_w ($/MWh)	D Scenario	MCP ($/MWh)	K_{DG}	K_{DRA}	K_{MG}	K_{EB}	P_{DG} (MW)	P_{DRA} (MW)	P_{MG} (MW)	P_{EB} (MW)
40	25	d_1	31.75	0.80	0.8	0.80	1.27	0	0	0	37.4
		d_2	31.75	0.80	0.8	0.80	1.27	0	0	0	38.0
		d_3	31.75	0.80	0.8	0.80	1.27	0	0	0	38.8
		d_4	31.92	0.80	0.8	0.80	1.27	0	0	0	40.0
		d_5	34.80	0.87	0.8	0.80	0.80	1.2	0	0	40.0
		d_6	34.80	0.87	0.8	0.80	0.80	2.0	0	0	40.0
		d_7	34.80	0.87	0.8	0.80	0.80	2.6	0	0	40.0
90	37	d_1	35.20	0.88	0.8	0.80	0.96	33.3	0	50.8	0
		d_2	35.20	0.88	0.8	0.80	0.96	33.9	0	51.6	0
		d_3	35.20	0.88	0.8	1.45	0.80	40.0	0	7.3	40.0
		d_4	63.80	0.88	0.8	1.45	0.80	40.0	0	10.0	40.0
		d_5	63.80	0.88	0.8	1.45	0.80	40.0	0	12.7	40.0
		d_6	63.80	0.88	0.8	1.45	0.80	40.0	0	14.5	40.0
		d_7	63.80	0.88	0.8	1.45	0.80	40.0	0	15.8	40.0

C. MC Uncertainty (Case 3)

According to (22), Γ and ΔMC_j^+ are effective parameters in the RO method considering the uncertainty of competitors' behavior. In this section, the sensitivity of results to these two parameters is separately analyzed. The allowed margin for MC variation is assumed proportional to the forecasted MC of competitors ($\Delta MC_j^+=\alpha\overline{MC}_j$).

The MC of the DG, DRA and MG are 40 $/MWh, 80 $/MWh and 44 $/MWh, respectively. The MC of EB is equal to the WEM price or λ_w. Table V shows the effect of Γ on the results for several demand samples. The value of α is fixed to be $\alpha=0.3$.

The results obtained for $\Gamma=0$ represent the deterministic case. The results presented in Table V show that considering the MC uncertainty leads to major changes in the outcomes of the bidding strategy in all cases. For $D=40$ MW and $D=$

80 MW, this change appears when $\Gamma=1$. For $D=119$ MW and $D=130$ MW, the results remain unchanged until $\Gamma=2$. For $\Gamma>2$, there is usually no change in the results compared with $\Gamma=2$. Therefore, $\Gamma=2$ seems to be a proper value for considering the MC uncertainty. Table VI shows the sensitivity of results to ΔMC_j^+ (or α) considering the uncertainty of competitors' behavior. Here, the value of Γ is constant and equal to 2 in all cases. The value of α is changed between 0 and 0.2. The results obtained for $\alpha=0$ represent the deterministic case.

TABLE V
EFFECT OF Γ ON BIDDING STRATEGY RESULTS

D (MW)	λ_w (\$/MWh)	Γ	MCP (\$/MWh)	K_{DG}	K_{DRA}	K_{MG}	K_{EB}	P_{DG} (MW)	P_{DRA} (MW)	P_{MG} (MW)	P_{EB} (MW)
40	25	0	31.93	0.80	0.80	0.80	1.27	0	0	0	40
		1	53.88	1.62	0.82	1.47	2.00	0	0	0	40
		2	53.88	1.62	0.82	1.47	2.00	0	0	0	40
		>2	53.88	1.62	0.82	1.47	2.00	0	0	0	40
80	34	0	35.20	0.88	0.80	0.80	0.80	17.7	0	22.3	40
		1	69.74	1.14	0.91	1.83	2.00	40.0	0	0	40
		2	69.74	1.14	0.91	1.83	2.00	40.0	0	0	40
		>2	69.74	1.14	0.91	1.83	2.00	40.0	0	0	40
119	54	0	63.60	1.59	0.80	0.80	0.80	19.0	0	60.0	40
		1	63.60	1.59	0.80	0.80	0.80	19.0	0	60.0	40
		2	80.00	2.00	1.29	0.80	0.80	40.0	0	60.0	19
		>2	80.00	2.00	1.29	0.80	0.80	40.0	0	60.0	19
130	71	0	142.00	1.59	0.80	0.80	2.00	40.0	20	60.0	10
		1	142.00	1.59	0.80	0.80	2.00	40.0	20	60.0	10
		2	88.00	0.80	0.93	2.00	0.80	40.0	20	30.0	40
		>2	88.00	0.80	0.93	2.00	0.80	40.0	20	30.0	40

TABLE VI
EFFECT OF ΔMC_j^+ ON BIDDING STRATEGY RESULTS

D (MW)	λ_w (\$/MWh)	α	MCP (\$/MWh)	K_{DG}	K_{DRA}	K_{MG}	K_{EB}	P_{DG} (MW)	P_{DRA} (MW)	P_{MG} (MW)	P_{EB} (MW)
40	25	0	31.93	0.80	0.80	0.80	1.27	0	0	0	40
		0.05	50.85	1.31	0.80	1.19	2.00	0	0	0	40
		0.10	51.47	1.37	0.80	1.24	2.00	0	0	0	40
		0.15	52.11	1.43	0.80	1.30	2.00	0	0	0	40
		0.20	52.72	1.49	0.80	1.36	2.00	0	0	0	40
80	34	0	35.20	0.88	0.80	0.80	0.80	17.7	0	22.3	40
		0.05	69.96	1.83	0.92	1.59	2.00	0	0	40.0	40
		0.10	74.36	2.00	0.94	1.69	2.00	0	0	40.0	40
		0.15	77.88	2.00	0.88	1.77	2.00	0	20	20.0	40
		0.20	68.00	1.05	0.80	1.74	2.00	40.0	20	0	20
119	54	0	63.60	1.59	0.80	0.80	0.80	19.0	0	60.0	40
		0.05	80.00	2.00	1.04	0.80	0.80	19.0	0	60.0	40
		0.10	80.00	2.00	1.09	0.80	0.80	19.0	0	60.0	40
		0.15	80.00	2.00	1.14	0.80	0.80	19.0	0	60.0	40
		0.20	80.00	2.00	1.19	0.80	0.80	19.0	0	60.0	40
130	71	0	142.00	1.59	0.80	0.80	2.00	40.0	20	60.0	10
		0.05	142.00	1.67	0.88	0.80	2.00	40.0	20	60.0	10
		0.10	142.00	0.80	0.80	1.59	2.00	40.0	20	60.0	10
		0.15	142.00	0.80	0.82	1.71	2.00	40.0	20	60.0	10
		0.20	82.28	0.80	0.86	1.87	0.80	40.0	20	30.0	40

D. Uncertainties of Demand and MC (Case 4)

Table VII shows the solution of the bidding strategy considering the uncertainty of demand and MC simultaneously. For the MC uncertainties of competitors, the RO parameters are set to be $\Gamma=2$ and $\alpha=0.2$ based on the results obtained in Case 3.

To show how capturing uncertainties in the bidding strategy affects the results, the outcomes of Case 1 and Case 4 are graphically compared in Figs. 7-9. In Fig. 7, the DNEM price at the equilibrium point is shown for Case 4 and Case

1, for five different hours of the day. The results show that the uncertainty might have a significant effect on the final electricity market price. The difference between the results obtained for definite and uncertain cases depends on the demand level, the WEM price, and the MC of competitors. This difference is observed for $D=40$ MW, $D=80$ MW, and $D=119$ MW in Fig. 7.

TABLEVII
BIDDING STRATEGY RESULTS CONSIDERING ALL UNCERTAINTIES

D (MW)	λ_w (\$/MWh)	MCP (\$/MWh)	K_{DG}	K_{DRA}	K_{MG}	K_{EB}	P_{DG} (MW)	P_{DRA} (MW)	P_{MG} (MW)	P_{EB} (MW)
40	25	53.43	1.49	0.83	1.36	2.00	0.2	0	0	39.8
80	34	69.95	1.14	0.91	1.83	2.00	40.0	0.4	0	39.6
100	42	63.80	0.80	0.80	1.45	0.80	40.0	0	20.0	40.0
119	54	76.14	0.80	1.14	1.45	1.41	40.0	0	60.0	19.0
130	71	142.00	0.80	2.00	0.80	2.00	40.0	0	60.0	30.0

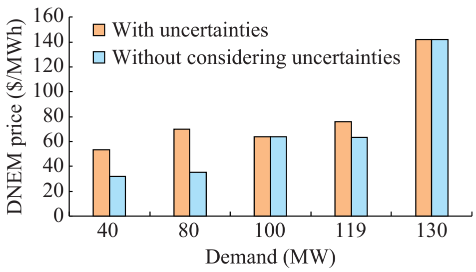

Fig. 7. Effect of uncertainties on DNEM clearing price.

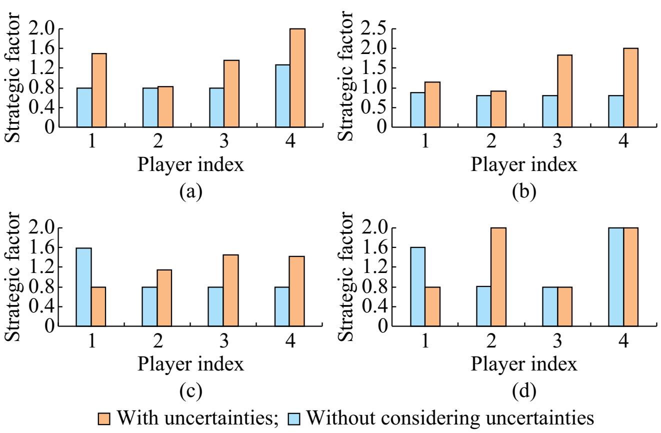

Fig. 8. Effect of uncertainties on final strategy of DNEM participants. (a) $D=40$ MW. (b) $D=80$ MW. (c) $D=119$ MW. (d) $D=130$ MW.

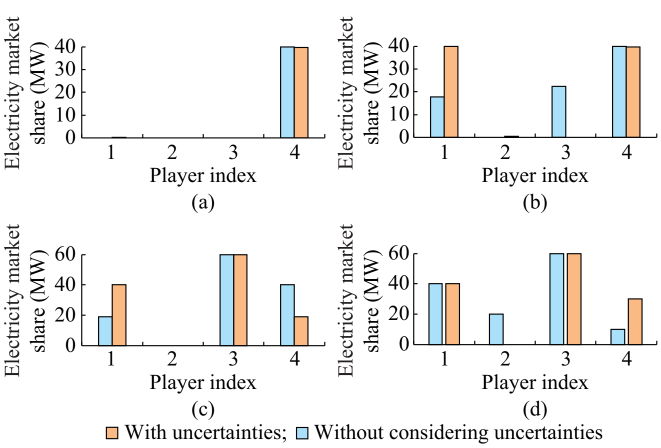

Fig. 9. Effect of uncertainties on final share of DNEM participants. (a) $D=40$ MW. (b) $D=80$ MW. (c) $D=119$ MW. (d) $D=130$ MW.

In addition to the effect of the demand uncertainty, by adopting a conservative strategy by participants considering the MC uncertainty, the expected electricity market prices will increase. To clarify this, the results obtained for the final strategic factor of participants at the equilibrium point with and without considering the uncertainties are compared in Fig. 8.

For $D=40$ MW, $D=80$ MW, and $D=119$ MW in the figure, the risk-averse nature of the RO method usually forces the participants to estimate the MC of opponents in higher values compared with the deterministic case. This increases the bidding prices for all participants and leads to higher MCP levels in the DNEM. The difference in strategic factors and bidding prices will change the electricity market share of players. The effect of considering uncertainties on the final market share of DNEM participants is illustrated in Fig. 9. For $D=40$ MW, there is no difference in the electricity market share results, because the entire electricity market is at the disposal of the EB considering the MC and market demand. However, the results obtained for $D=80$ MW, $D=119$ MW, and $D=130$ MW verify that by taking uncertainties into account, the final expected electricity market shares can be changed.

V. CONCLUSION

In this paper, a game-theory-based method is utilized to determine the optimal bidding strategy of participants in a DNEM under uncertainties. The RO method is applied to capture the uncertainties in the WEM price as well as the MC of participants. In addition, a scenario-based stochastic approach is used to model the demand uncertainty. The bidding strategy is modeled as a bi-level problem. An iterative algorithm is implemented to find the Nash equilibrium of the game. A sensitivity-based solution methodology is formulated in detail to solve the bi-level optimization problem of each participant in each iteration of the algorithm. The simulation results presented in four different cases have verified the merit of the proposed approach in modeling the competition among electricity market participants in the presence of uncertainties. It is shown that considering uncertainty in the behavior of competitors and demands will cause fundamental changes in the competition process and lead to totally different outcomes. In fact, adopting a conservative strategy and risk averse nature in the RO method leads to an increase in strategic factors and bidding prices, which increases the expected electricity market price and will in turn change the electricity market shares of participants compared with the deterministic case.

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