Robust Optimization Model for Photovoltaic Power Producer’s Bidding Decision-Making in Electricity Market

Lifeng Liu,1 Huisheng Gao,2 Yuwei Wang3, and Wei Sun3

1Shaoxing Power Supply Company of State Grid Zhejiang Electric Power Co. LTD., No. 58 Electric Power Building, Shengli East Road, Yuecheng District, Shaoxing City, Zhejiang Province, China
2School of Electrical and Electronic Engineering, North China Electric Power University, Baoding, Hebei 071003, China
3Department of Economic Management, North China Electric Power University, Baoding, Hebei 071003, China

Correspondence should be addressed to Yuwei Wang; wangyuwei2010@126.com

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With the deepening of electricity market (EM) reform and the high penetration of photovoltaic (PV) energy in power system, the uncertainties of a PV power output and fluctuation of EM prices would bring substantial financial risks for PV power producers (PPPs). This paper proposed a robust optimization model for PPP’s power bidding decision-making. Specifically, the random PV power outputs are modeled by the uncertainty set, which need no probabilistic information and can fully depict the continuous range of uncertainties. Subsequently, with respect to any scenario for day-ahead EM prices, PPP’s optimal power bidding strategy is obtained under the worst-case realization within the uncertainty set, which guarantees the robustness in resisting the negative impact of random PV power outputs on PPP’s profit. Moreover, a reformulation approach was introduced for equivalently transforming our model into a tractable framework. Simulation was implemented to validate the feasibility and effectiveness of applying our proposed model.

1. Introduction

It is considered that the global climate changes and energy depletion, most serious threats to sustainable development, result from the overexploitation and utilization of fossil fuels [1–3]. Renewable energy, an alternative to fossil fuels, has been regarded as an effective way to fight against the energy shortage and environmental issues [4]. Photovoltaic (PV) power, which is an important part of renewable energy, has a promising future due to its emission-free, mature technology and low cost [5, 6].

In China, according to the latest statistics of China’s electric power industry, the installed capacity of PV power is up to 174.63 million kilowatts, accounting for about 10% of national total capacity, and the PV power generation was 177.5 billion kilowatt/hour (kWh) at the end of 2018 [7]. A promising target has been set by the Chinese government for further expanding the installed capacity to 200 GW by 2020 [8]. The Chinese government has launched a series of policies and plans to support the development of the PV industry. However, the intermittency and instability (randomness) of solar energy resources, which are influenced by weather, season, and terrain, are gradually becoming a bottleneck that restricts the utilization of PV power. Especially, with the deepening of the electricity market (EM) reform and the high penetration of PV power in EM, the uncertainties of the PV power output and fluctuation of EM prices would bring substantial financial risks for PV power producers (PPPs). Therefore, it is a valuable and tough research issue for PPPs to optimize their power bidding strategies in EMs.

Apparently, quantitative analysis of the uncertainties is the important base for optimizing a bidding strategy for PPPs and other renewable energy sources (RESs). Gomes et al. [9] proposed a scenario-based stochastic optimization (SO) model for a PPP participating in the day-ahead market, where the uncertainties of PV power and EM prices are simulated by multiple stochastic scenarios. Gomes et al. [10]
established a two-stage SO model for an integrated wind-photovoltaic system to obtain its optimal day-ahead offering strategy. In [11], the SO-based PV power bidding model was modified by introducing a risk-aversion term in a form of conditional value at risk (CVaR) to additionally provide flexibility in finding a trade-off between profit maximization and risk management. The SO approaches should generate a large number of probabilistic scenarios according to the uncertainties, which would require considerable computational effort [12] or may result in nonconvex nonlinear optimization problems [13].

Robust optimization (RO) has been verified as another brilliant method to account for uncertainties. Thatte et al. [14] proposed a RO-based day-ahead bidding strategy for a wind power plant in combination with an ESS device, given the inherent uncertainties in spot EM prices and the wind power output. In [15], an uncertainty set for wind and PV power outputs was constructed, and then a RO model was proposed for optimal dispatch of power system. Thatte and Xie [16] developed a RO-based model predictive control (RMPC) scheme to determine the optimal offering strategies of an integrated wind farm-energy storage system, given the uncertainties in spot EM prices. In the RO model proposed by Wang et al. [17] for the day-ahead scheduling of a microgrid, conservative parameters were introduced in the uncertainty set of distributed wind and PV power outputs. With the introduction of RO, multiple stochastic scenarios in SO are replaced with the continuous uncertainty set, which shows advantages of robustness improvement and relatively lower computational complexity [18].

Recently, some hybrid approaches with the RO method or idea have been introduced in the operation optimization issues of various energy systems. Wang et al. [12] proposed a stochastic-robust-based day-ahead bidding strategy for a wind-ESS system. By applying the similar modeling approach with [12], Wang et al. [19] established the optimal operation model for a combined cooling, heating, and power (CCHP) system based on the stochastic-robust hybrid optimization. In [20], with the help of the information gap decision theory (IGDT), both the robust and opportunity approaches are more desirable than SO due to the advantages mentioned above. However, as far as this paper can tell, the RO-related studies for the optimal bidding strategy of a PPP in EM are still scarce at present. Apparently, due to the differences in system structures, models for other energy systems cannot be directly applied to the field of photovoltaic power plant. Therefore, the main contributions of this paper can be summarized as follows:

1. A RO-based model is proposed and customized for solving the problem of PPP’s power bidding decision-making in day-ahead EM. On one hand, the random PV power outputs are modeled by an (budget parameter embedded) uncertainty set, which need no probabilistic information and can fully depict the continuous range of uncertainties; on the other hand, with respect to any scenario for day-ahead EM prices, PPP’s optimal power bidding strategy is obtained under the worst-case realization within the uncertainty set, which guarantees the robustness in resisting the negative impact of random PV power outputs on PPP’s profit.

2. A reformulation approach is proposed for equivalently transforming our proposed model into a tractable framework which can be easily solved by using the C&CG method.

3. Simulations are designed and implemented to validate the effectiveness of our proposed model in terms of profit optimization, computational time, and the ability of resisting uncertainties. Moreover, with the help of sensitivity analysis, the robustness of our proposed model is deeply studied, which is a necessary prerequisite for practical applications.

The rest of this paper is organized as follows. In Section 2, formulations for the PV power uncertainty set, a RO model for PPP’s day-ahead bidding decision-making, and a reformulation approach for model solving are proposed, respectively. Simulations are implemented in Section 3 for verifying the feasibility and rationality of our method, and Section 4 concludes the paper.

2. Methodology

2.1. Relevant Explanation and Hypothesis. In this section, the robust optimization model is mathematically formulated for a PPP to make bidding decisions in spot EM. For the sake of simplicity and without loss of generality, we make some assumptions and explanations listed as follows before conducting any further research:

1. Similar to [21], this paper considers the PPP as a “price taker” participating in spot EMs. This is equivalent to that the behaviors of PPP will not affect EM clearing prices.

2. Operation cost of PV is neglected because obtaining radiation from the sun is for free.

2.2. Formulations for PV Power Producer’s Power Deviation. For time period \( t \) (\( 1 \leq t \leq T \)), let \( P_{D,t} \) be the day-ahead scheduled power output of PPP and \( \bar{P}_{R,t} \) be its real-time power output. Then, the power output deviation \( \Delta_t \) can be formulated as

\[
\Delta_t = \bar{P}_{R,t} - P_{D,t} = \Delta_t^+ - \Delta_t^-, \quad \forall t
\]

where \( \Delta_t^+ \) stands for the positive deviation and \( \Delta_t^- \) represents the negative deviation, which can be further formulated as

\[
\Delta_t^+ = \max\{\bar{P}_{R,t} - P_{D,t}, 0\}, \quad \forall t
\]

\[
\Delta_t^- = \max\{P_{D,t} - \bar{P}_{R,t}, 0\}, \quad \forall t
\]
2.3. Uncertainties of PV Power Producer’s Real-Time Power Outputs. This paper proposes an uncertainty set for modeling the stochastic feature of PPP’s real-time power output. In an uncertainty set, there is no need to estimate the probabilistic information, which makes the corresponding uncertainty model easy to be constructed and tractable. A typical uncertainty set for PPP’s real-time power outputs is formulated as

$$U = \left\{ \bar{P}_R = (\bar{P}_{R_1}, \bar{P}_{R_2}, \ldots, \bar{P}_{R_T}) : \text{s.t. } \bar{P}_{R_t} \in [P_{M_t} - \bar{P}_{R_t}, P_{M_t} + \bar{P}_{R_t}], \sum_{t=1}^{T} \frac{|\bar{P}_{R_t} - P_{M_t}|}{\bar{P}_{R_t}} \leq \Gamma \right\},$$

(4)

where $P_{M_t}$ is the forecasted value of PPP’s real-time power output for time period $t$ and $\bar{P}_{R_t}$ denotes the radius of uncertainty interval for $\bar{P}_{R_t}$. Moreover, $\Gamma$ is a budget parameter for controlling the conservativeness of decision-making. Specifically, a larger $\Gamma$ corresponds to a larger uncertainty set $U$, which means more uncertain scenarios should be considered and leads to more conservative in decision-making.

2.4. Robust Optimization Model for PV Power Producer’s Power Bidding Decision-Making. In this paper, due to the lack of flexible sources (e.g., energy storage devices), PPP cannot control its real-time power output in the stage of balancing markets. That is to say, on the one hand, PPP can only strategically participate in the day-ahead EM; on the other hand, real-time deviations from this participant’s day-ahead scheduled power outputs are often inevitable and may cause extra cost. Hence, the key problem to be solved in this paper is how to optimally make the day-ahead power bidding decisions for PPP under uncertainties.

For a delivery day, PPP pursues the maximization of its own profit:

$$\max R = \sum_{t=1}^{T} \left[ \lambda_{DA} P_{D,t} - \lambda_{E} (\Delta_{t}^d + \Delta_{t}^e) \right],$$

(5)

where $R$ stands for the daily profit of PPP participating in spot EMs; $\lambda_{DA}$ means revenue obtained from selling $P_{D,t}$ in day-ahead EM; $\lambda_{E}$ represents extra cost caused by deviation $\Delta_{t}^d$ or $\Delta_{t}^e$ in the real-time stage; and $\lambda_{DA}$ and $\lambda_{E}$ are day-ahead and balancing prices, respectively.

For time period $t$ ($1 \leq t \leq T$), the day-ahead scheduled power output should not exceed its maximum limitation:

$$0 \leq P_{D,t} \leq P_{\text{max}}, \quad \forall t,$$

(6)

where $P_{\text{max}}$ can be deemed as the rated capacity of the PV unit.

It should be noted that PPP cannot maximize its profit by neglecting the impact of its stochastic real-time power outputs. Hence, this paper applies the robust optimization approach in modeling the optimal day-ahead power bidding problem for PPP.

The goal of the robust optimization approach is to obtain the optimal decision under the worst-case realization of uncertainties. Therefore, when PPP makes its power bidding decisions using robust optimization, it is necessary to clarify what is the worst impact of uncertainties on profit. Although this worst impact may not be happened in reality, PPP still needs to focus on it to avoid the potential risk of profit loss caused by the worst-case realization of uncertainties.

Based on the robust optimization approach, our proposed model for PPP’s power bidding decision-making can be formulated as follows:

$$\max \min_{P_{D}} \sum_{t=1}^{T} \left[ \lambda_{DA,t} P_{D,t} - \lambda_{E,t} (\Delta_{t}^d + \Delta_{t}^e) \right],$$

(7)

s.t. equations (2) and -(3) and (6)

$$\bar{P}_{R} \in U.$$  

(8)

Evidently, the inner min item in objective function equation (7) equals to find out the worst-case realization of $\bar{P}_{R}$ which minimizes PPP’s profit; the outer max item in objective function equation (7) equals to obtain the optimal day-ahead power bidding strategy $P_{D} = (P_{D,1}, P_{D,2}, \ldots, P_{D,T})$ which maximizes PPP’s profit under the worst-case realization of $\bar{P}_{R}$. 

**Table 1: Literature summary.**

| Reference | Research object | Modeling method | Characteristic | Limitation |
|----------|----------------|----------------|---------------|------------|
| [9–11, 13] | Wind power plant, PV power plant or electric energy retailer, etc. | SO approaches | A large number of stochastic scenarios are generated to depict the uncertainties | Considerable computational effort, etc., would be caused. |
| [12, 14–17, 19, 20] | Wind-storage system, power system (with wind and PV penetrations), microgrid, CCHP, energy hub, etc. | RO and RO-related approaches | Stochastic scenarios are replaced with the continuous uncertainty set, which shows advantages of robustness improvement and relatively lower computational complexity | The RO-related studies for the optimal bidding strategy of a PPP in EM is still scarce at present |
2.5. Model Reformulation. To facilitate model solving, model equations (2),(3), and (6)–(8) should be further reformulated. Because the item $\lambda_{DA}^t$, $\lambda_{DI}^t$ is not directly related to $P_R$, objective function equation (7) can be rewritten as

$$\max_{P_D} \left\{ \sum_{t=1}^{T} \lambda_{DA,t} P_{DI,t} + \min_{P_A} \sum_{t=1}^{T} \left[ -\lambda_{RI}^t (\Delta_+^t + \Delta_-^t) \right] \right\}. \quad (9)$$

By introducing an auxiliary variable $C$, equation (9) can be further rewritten as

$$\max_{P_D,C} \left\{ \sum_{t=1}^{T} \lambda_{DA}^t P_{DI,t} + C \right\}, \quad \text{s.t.} \quad C \leq \min_{P_A} \sum_{t=1}^{T} \left[ -\lambda_{RI}^t (\Delta_+^t + \Delta_-^t) \right]. \quad (10)$$

Evidently, equations (10) and (11) are equivalent to equation (9).

Based on equations (2), (3), and (9), the relationship among $\Delta_+^t$, $\Delta_-^t$, and $P_{RI,t}$ can be reformulated as

$$\min \max \left\{ \lambda_{DA}^t \Delta_+^t, \Delta_-^t \right\}, \quad \text{s.t.} \quad \Delta_+^t \geq P_{RI,t} - P_{DI,t}, \quad \forall t, \quad \Delta_-^t \geq 0, \quad \forall t, \quad \Delta_+^t \geq P_{DI,t} - P_{RI,t}, \quad \forall t, \quad \Delta_-^t \geq 0, \quad \forall t. \quad (13)$$

Accordingly, the reformulation of model equations (2), (3), and (9)–(16) can be summarized as model equations (6), (8), (10), (11), and (13)–(16). The robust optimization model equations (6), (8), (10), (11), and (13)–(16) is mathematically an NP-hard problem. Therefore, this paper further decomposes model equations (6), (8), (10), (11), and (13)–(16) into a main problem (MP) and a subproblem (SP).

The MP, with $P_D$ and $C$ as the decision variables, determines the optimal power bidding strategy in all the worst-case realizations generated by the SP:

$$\max_{P_D,C} \left( \sum_{t=1}^{T} \lambda_{DA,t} P_{DI,t} + C \right), \quad \text{s.t.} \quad C \leq \sum_{t=1}^{T} \left[ -\lambda_{RI}^t (\Delta_+^t + \Delta_-^t) \right], \quad \forall k \in K, \quad (17)$$

where $k$ and $K$ represent the index and index set of the worst-case realizations generated by the SP.

The SP, with $\Delta_+^t, \Delta_-^t$, and $P_{RI,t}$ as the decision variables, determines the worst-case realizations under an optimal power bidding strategy generated by the MP:

$$\min \max_{k} \left\{ \lambda_{RI}^k (\Delta_+^k + \Delta_-^k) \right\} d \quad \text{s.t.} \quad \text{equations (8) and (13)–(16).} \quad (18)$$

In summary, the final obtained MP and SP are equivalent to model equations (2), (3), and (6)–(8) and can be directly solved by using the following C&CG method [22]:

1. $k \leftarrow \phi, \ k \leftarrow 1, \ \Psi \leftarrow +\infty$, define feasibility tolerance $\Delta$;
2. while $\Psi \geq \Delta$ do
3. solve (MP), obtain optimal solution of (MP) $P_{DI,t}$;
4. solve (SP) with $P$, get solution $\Delta_+^{t,k}, \Delta_-^{t,k}$, and $P_{RI,t,k}$;
5. $k \leftarrow k \cup k, \ k \leftarrow k + 1$;
6. end while.

3. Simulation and Comparisons

3.1. Case Design. In this subsection, for the purpose of demonstrating our simulation results more lucidly, we introduce an experimental case design concretely. In our case, a PPP, with a capacity of 100 MW, participates as a “price taker” in the day-ahead electricity market. A delivery day is discretized into 24 time units with 1 hour for the duration of each time unit. The uncertainty set for real-time PV power outputs is constructed based on historical data. Specifically, the historical hourly PV power output data were generated by using the power curve function in [23] and the hourly mean radiation data in a Chinese city from July 1st to July 30th, 2018 [24]. Our model is solved based on the uncertainty set of PV power outputs and different scenarios for day-ahead and real-time EM clearing prices. The scenarios, as listed in Table 2, were obtained from historical prices data from the DK-West area in the Nord Pool market during July 20th to July 30th, 2018 (because the Nord Pool market is of a two-price balancing market, up/downregulation prices are different and one or the other of them is equal to the day-ahead one at any specific time unit. Hence, we take the different one as the balancing price in the one-price balancing market).

All simulations are implemented by utilizing the MATLAB R2014a software on a PC laptop with an Intel Core i7 at 2.1 GHz and 8 GB memory.

Moreover, the constructed uncertainty set (with $\Gamma = 24$) is depicted in Figure 1. Besides, in Figure 1, PM is composed of 24 hourly average PV power outputs, with each one calculated by historical data for the same period; PMAX represents 24 hourly maximum PV power outputs, with each one obtained by comparing historical data for the same period.

3.2. Calculation Results Analysis. In this subsection, simulation of our proposed model is implemented to obtain the PPP’s optimal day-ahead power bidding strategy. Relevant parameters are set as $\Gamma = 20$ and $\Delta = 0.000001$. The obtained strategies under scenarios 1, 6, and 10 are demonstrated in Figures 2–4, respectively.

It can be found in Figures 2–4 that in the day-ahead stages, PPP usually offers larger power outputs when the
| H  | Scen. 1 | Scen. 2 | Scen. 3 | Scen. 4 | Scen. 5 | Scen. 6 | Scen. 7 | Scen. 8 | Scen. 9 | Scen. 10 |
|----|---------|---------|---------|---------|---------|---------|---------|---------|---------|---------|
| 1  | 218.4   | 202.3   | 163.8   | 179.9   | 134.4   | 133.4   | 191.4   | 168.2   | 222.7   | 148.6   |
| 2  | 183.6   | 183.6   | 151.5   | 179.9   | 69.3    | 69.3    | 169.1   | 169.7   | 200.9   | 148.8   |
| 3  | 174.2   | 174.2   | 144.2   | 179.3   | 58.6    | 58.6    | 165.6   | 176.2   | 189.4   | 145.1   |
| 4  | 163.1   | 163.1   | 127.1   | 179.9   | 51.8    | 51.8    | 161.8   | 180.2   | 177.7   | 148.9   |
| 5  | 150.2   | 150.2   | 124.8   | 179.9   | 90.9    | 74.3    | 161.3   | 180.2   | 174.3   | 144.7   |
| 6  | 166.9   | 166.9   | 123.3   | 123.3   | 90.3    | 74.3    | 173.8   | 184.2   | 188.3   | 152.3   |
| 7  | 196.7   | 186     | 133     | 133.8   | 111.3   | 64.8    | 237.5   | 237.5   | 225.3   | 197.2   |
| 8  | 234.4   | 267.8   | 149.2   | 149.2   | 134.1   | 185.9   | 261.8   | 275.2   | 260.1   | 260.1   |
| 9  | 244.1   | 279     | 159.4   | -141.3  | 135.6   | 180.2   | 282.2   | 297.5   | 271.2   | 271.2   |
| 10 | 178.5   | 212.5   | 176.3   | 127.9   | 148.8   | 176.1   | 249.5   | 200.8   | 260.2   | 221.7   |
| 11 | 175.8   | 205     | 163.9   | 137.7   | 160.2   | 184.2   | 244.8   | 200.8   | 242.5   | 138.5   |
| 12 | 173.5   | 203.3   | 163.8   | 163.8   | 161.7   | 184.2   | 235.7   | 223.1   | 234.1   | 213.6   |
| 13 | 167.8   | 203.3   | 162.6   | 162.6   | 159.9   | 184.2   | 223    | 222.9   | 212.8   | 212.3   |
| 14 | 164.3   | 203.3   | 155.1   | 155.1   | 157.9   | 184.2   | 218.2   | 218.1   | 197.5   | 197.5   |
| 15 | 164.3   | 164.3   | 144.2   | 144.2   | 153.2   | 176.2   | 221.3   | 221.2   | 181.1   | 181.13  |
| 16 | 165.3   | 165.3   | 137.7   | 137.4   | 151.2   | 151.2   | 217.7   | 217.6   | 165.8   | 165.8   |
| 17 | 166.2   | 166.2   | 133.5   | 133.5   | 136.8   | 136.8   | 226.7   | 221.6   | 164.7   | 164.7   |
| 18 | 169.5   | 135.5   | 148.5   | 148.5   | 134.2   | 134.8   | 244.7   | 213.7   | 171.3   | 249.3   |
| 19 | 171.3   | 171.3   | 171.8   | 171.8   | 163.8   | 163.7   | 267.7   | 213.7   | 183.6   | 261.8   |
| 20 | 173.5   | 173.5   | 188.3   | 199.9   | 199.1   | 199.4   | 285.7   | 223.1   | 205.6   | 245.5   |
| 21 | 183.9   | 183.9   | 189.5   | 199.9   | 208.1   | 215.7   | 287.5   | 287.4   | 200.8   | 223.2   |
| 22 | 184.2   | 184.2   | 186.1   | 199.9   | 226.8   | 238.2   | 264.5   | 264.5   | 272.1   | 219.9   |
| 23 | 184.2   | 184.2   | 191.5   | 199.9   | 235.3   | 240.9   | 260.1   | 274.4   | 200.8   | 191.4   |
| 24 | 166.7   | 166.7   | 166.6   | 127.9   | 218.5   | 168.2   | 252.8   | 260.3   | 141.9   | 204.8   |

Note. "Da" means day-ahead and "Re" means real-time.
day-ahead prices are relatively high and offers smaller power outputs when the day-ahead prices are relatively low. Reasons for this is that the strategies of “selling more at relatively high prices” and “selling less at relatively low prices” in the day-ahead market help to profit improvement. However, exceptions still exist. For example, in Figure 4, day-ahead offerings at the 10th to 15th time periods are relatively large although the corresponding day-ahead prices are relatively low. It is obvious that uncertainties of PV power outputs often cause power deviations which will bring excess costs in the presence of real-time EM prices. Therefore, the robust day-ahead strategy based on our proposed model disobeys the abovementioned “selling more at relatively high prices” and “selling less at relatively low prices” rules sometimes for avoiding the potential risk of cost increase. Moreover, by implementing our simulation in this subsection, it takes an average of 11.7 seconds for obtaining our strategy. It is generally known that the day-ahead market starts at least 12 hours before the delivery day and the balancing market begins few minutes to half an hour in advance; that is to say, low computational time makes our proposed model feasible in practice.

In order to facilitate the description, the strategy obtained by our proposed model is called strategy 1 in the rest of this paper. Moreover, a strategy obtained by a deterministic model is called strategy 2, and it is taken here for comparison. The difference between a deterministic model and our proposed model is that the former one is solved not based on the uncertainty set but only based on PM as presented in Figure 1. The obtained profits under 10 scenarios of these two strategies are demonstrated in Figures 5–7.

It can be found in Figures 5–7 that in Figure 5, the obtained profits by strategy 2 are generally higher than that by strategy 1. Conversely, in Figures 6 and 7, the obtained profits by strategy 1 are generally higher than that by strategy 2. Strategy 2 is obtained based on PM. Given that the real-time PV power outputs are presented by PM (as depicted in Figure 5), the obtained profits by strategy 2 are certainly the highest ones. In practice, the occurrence of PM in real-time is nearly impossible, which means the deviations of real-time PV power outputs from PM may cause substantial cost for strategy 2. However, strategy 1 is obtained based on the uncertainty set, which guarantees the robustness of PPP’s power bidding schedules in avoiding substantial cost brought by real-time PV power deviations. Hence, the obtained profits by strategy 1 are generally higher than that by strategy 2 in most realizations of real-time PV power outputs except for PM. In summary, by utilizing our proposed model for power bidding decision-making, PPP’s obtained profits can be further increased in the face of random fluctuations in PV power outputs.

3.3. Sensitivity Analysis. Parameter $\Gamma$ will significantly influence the result of our proposed model. In this subsection, the sensitivity analysis for $\Gamma$ is presented for further studying the performance of our proposed model, which is shown in Figure 8.

In Figure 8, the average profit equals to the mean value of the obtained profits under different prices scenarios. The range of the uncertainty set increases with the increase of the $\Gamma$ value and decreases with the decrease of the $\Gamma$ value. In extreme cases,
the uncertainty set will shrink into PM when $\Gamma = 0$ and will expand into a largest one as presented in Figure 1 when $\Gamma = 24$. A larger uncertainty set corresponds to a more conservative and robust strategy which obtains less profit when there is no real-time PV power deviation but guarantees less excess cost when there exist real-time PV power deviations. A smaller uncertainty set corresponds to a more aggressive strategy, which obtains more profits when there is no real-time PV power deviation, but brings more excess costs when there exist some real-time PV power deviations. Therefore, as shown in Figure 8, the average profit decreases with the increase of the $\Gamma$ value, given that the real-time PV power outputs are presented by PM. Conversely, the average profit increases with the increase of the $\Gamma$ value, given that the real-time PV power outputs are presented by the worst-case realization.

4. Conclusions

This paper proposed a robust optimization model for a PPP in determining the day-ahead power bidding schedules under EM circumstances. In our proposed model, the stochastic feature of real-time PV power outputs is modeled as an uncertainty set. The optimal power bidding schedules are determined under the worst-case realizations within the uncertainty set, which guarantees the robustness in resisting the impact of real-time PV power deviations on profit. Moreover, a model reformulation approach based on dual theory was introduced for transforming our model into a MP-SP problem which is tractable and easy to be solved by the C&CG method. Simulations have presented some interesting conclusions:

(1) Our proposed model can make PPP strategically bids in day-ahead EM according to prices signals (“selling more at relatively high prices” and “selling less at relatively low prices”).

(2) By implementing our simulation, it takes an average of 11.7 seconds for obtaining our strategy. That is to say, low computational time makes our proposed model feasible in practice.

(3) By utilizing our proposed model for power bidding decision-making, PPP’s obtained profits can be further increased in the face of random fluctuations in PV power outputs.

(4) With increasing the values of the budget parameter in the uncertainty set, a more conservative and...
robust strategy can be obtained, which obtains less profit when there is no real-time PV power deviation, but guarantees less excess cost when there exist real-time PV power deviations.

Our future work will release the “price taker” assumption and focus on the “price maker” strategies of PPP. Moreover, extending the PPP to some hybrid energy systems such as microgrid, virtual power plant, and integrated energy system will also be the topic that we will focus on in the future.

Data Availability
No data were used to support this study.

Conflicts of Interest
The authors declare no conflicts of interest.

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