Arbitrage and Capacity Firming in Coordination with Day-Ahead Bidding of a Hybrid PV Plant

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Abstract— **A hybrid PV plant (HPP) combines a photovoltaic (PV) plant with a battery energy storage system (BESS), which is considered a promising step towards the future of renewable power plants by the U.S. Department of Energy. When the renewable penetration reaches a significant level, a hybrid PV plant can bid in as a controllable thermal plant in the future electricity market. In this study, a bidding and BESS scheduling model is proposed for the HPP. The robust optimization (RO) technique has been utilized to identify the worst-case scenario of uncertainties during the bidding process. To address the overly conservative issue of the single-stage RO, we have decoupled the BESS schedule for arbitrage and PV capacity firming by a two-stage RO formulation. By comparing the output of single-stage RO and two-stage RO, the two-stage RO bids and schedules in a more aggressive manner, which increases the income of HPP. Also, the penalty of under-generation is considered in our model so that the day-ahead bidding decision and arbitrage schedules can be adjusted based on the potential UNDER-GENERATION penalty. Because the proposed model is non-convex and contains multi-stages, the Column-and-Constraint Generation (C&CG) algorithm is applied to the model as the solution. The proposed model has shown better economic performance compared to a state-of-art single-stage bidding method in case studies.**

Index Terms— **Hybrid PV plant, bidding model, BESS scheduling, two-stage robust optimization, C&CG algorithm**

I. Introduction

To have a seamless transformation towards a carbon-free energy system, the number of thermal power plants needs to be significantly reduced. Future renewable generation plants must also take some responsibility for system balancing. A key difference between traditional thermal plants and PV plants is their generation reliability. The output of a thermal power plant is usually viewed as deterministic if a schedule has been made. On the contrary, the output of a PV plant still contains uncertainty, and therefore more likely to encounter an under-generation penalty. The constant uncertainty poses a great challenge for PV plants in achieving optimum market behavior. The concept of A hybrid PV plant (HPP) combines a plant-controlled BESS with a PV plant to eliminate the generation uncertainty [1]. Under this context, this paper studies the day-ahead bidding method of an HPP, and the BESS scheduling method cooperates with the bidding decision.

In this study, the HPP is considered a price-taker in the power market, which assumes its limited capacity compared to the thermal power plants. As a price-taker, the major difficulty in achieving optimal bids and schedules comes from the uncertainties of the day-ahead market information and the PV generation.

One feasible approach to address uncertainties is to use the stochastic programming technique, which characterizes uncertainties with prepared scenarios. Stochastic programming-based bidding methods calculate the bidding incomes of a set of uncertainty scenarios and maximize those incomes' expectations [2]-[4]. This approach considers uncertainties in the modeling process to some extent, but its performance relies heavily on the quality of prepared scenarios [5]. An alternative roadmap uses RO to characterize the uncertainty as a prepared uncertainty set. The formulation methodology of robust bidding models has been introduced [6]-[9]. The main idea is to maximize the income of a power plant under the worst-case scenario of the market uncertain set. However, the solution of RO-based methods is often considered overly conservative. While this issue may be addressed by reducing the conservative level of uncertainty sets, the uncertainty set's representativeness to uncertainties will decrease.

In addition, hybrid PV power plants also need to conduct scheduling for the BESS operation. The BESS schedule should cooperate in the bidding decision. We consider two BESS applications in an HPP: arbitrage and PV capacity firming. These two applications are generally executed within two days in the following time sequence. During the bidding day, the arbitrage schedule will be first determined. For example, a BESS will be scheduled to store energy when the electricity price is low and discharge the stored energy when the price goes high. Based on the arbitrage schedule, the day-ahead bid decision for the HPP can be made and sent to Independent System Operator (ISO). During the transaction day, the under-generation will be revealed, which is based on the bid. Then, capacity firming can be conducted by discharging stored power to compensate for the under-generation.

In our problem, a bidding model is expected to output the next day's hourly bidding strategy for the HPP and operational schedule for BESS by taking the forecasted day-ahead PV

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generation and market price as inputs. Ref. [8], [9] proposed robust bidding models that considered day-ahead BESS scheduling. However, they are based on the single-stage RO formulation, which assumes the capacity firming and arbitrage are scheduled at the same time in the day-ahead market. The solution of the single-stage RO tends to be overly conservative [10]. To address this issue, a bidding model based on the two-stage robust formulation is proposed in this study. BESS schedules of arbitrage and PV capacity firming are decoupled. We also assume capacity firming is conducted after the arbitrage is scheduled and the uncertainty is revealed. Based on this assumption, the worst-case scenario of PV uncertainties can move to a more aggressive point [10]. Thus, our model can increase the HPP's income without changing the conservative level of the PV uncertainty set. Moreover, we notice that the execution of arbitrage and capacity firming have different objectives. To merge them within one model, we involve the calculation of the under-generation penalty to bridge their multi-objectives. Thus, the day-ahead bidding decision and arbitrage schedules can be adjusted based on the under-generation penalty received on the transaction day.

Our contributions can be summarized as follows: A two-stage robust bidding (TSRB) model is proposed for HPP to simulate the bidding operation process from arbitrage to PV capacity firming, and integrate the under-generation penalty into the day-ahead scheduling. The proposed TSRB model increases the income of HPP compared to a state-of-art single-stage bidding model.

The rest of this paper is structured as follows: The formulation of the TSRB model is introduced in Section II. Then, the C&CG algorithm is applied to solve the proposed TSRB model in Section III. Case studies to verify the proposed model are demonstrated in Section IV. Finally, we conclude our work in Section V.

II. Problem Formulation

This section introduces the two-stage model (TSRB) to calculate BESS's optimal bidding decisions and schedules for the HPP. To provide a more intuitive view, a proposed two-stage operation for future HPPs is as shown in Fig. 1. Then, the TSRB model is formulated to simulate this operational process. And the solution method of the TSRB will be described in the next section.

The flow chart in Fig. 1 demonstrates the process from submitting bids to delivering power to the grid. The simulated process lasts for two days; the first day is the bidding day and the second day is the power transaction day. On the first day, the PV generation and market pricing uncertainty sets are collected as the initial conditions. The HPP first schedules the charge/discharge of the plant-controlled BESS for arbitrage during the power transaction. A bidding decision will then be submitted to the ISO based on the arbitrage schedule. At this point, the first day's bidding income can be calculated. We simulate the transaction day to capture the possible under the generation charge. The RO technique is applied to identify the worst-case scenario of PV generation, which will lead to the heaviest under-generation penalty. Capacity firming is scheduled to reduce the under-generation penalty by reserving power in BESS for the next-day operation. Therefore, the

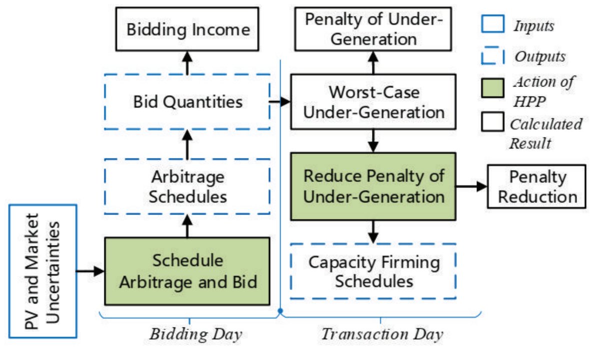

Fig. 1. Proposed two-stage operation for future HPPs. The TSRB model is to simulate this operation and maximize {Bidding Income - Penalty of Under-Generation + Penalty Reduction}.

penalty reduction based on the original under-generation penalty can also be calculated. By merging the arbitrage and capacity firming schedules, we can obtain the total BESS schedules.

A proposed two-stage model captures the two-day bidding and operation process. The objective of the model is to maximize the income of the HPP. The detail of the proposed model is as follows:

A. Bidding Day Calculations (Stage I)

The output of the model includes optimal hourly bid power P_t^{bid} and schedules of BESS. BESS schedules have been decoupled into two application-oriented variables. For each hour t in a day, $P_{B,t}^{arb+}/P_{B,t}^{arb-}$ denote the arbitrage-oriented charge/discharge of BESS, and $P_{B,t}^{firm+}/P_{B,t}^{firm-}$ denote the firming-oriented charge/discharge. In parallel, we also decouple the energy level of BESS E_t into two variables, E_t^{arb} and E_t^{firm}, which have the following relationship:

$$E_t = E_t^{arb} + E_t^{firm}. \tag{1}$$

We assume the power generated by PV can be used for selling to the market $P_{PV,t}^{sell}$ or charging the BESS. Therefore, on the bidding day, we have the following:

$$0 \leqslant P_{PV,t}^{sell} + P_{B,t}^{arb+} \leqslant \overline{P}_{PV,t}, \tag{2}$$

where $\overline{P}_{PV,t}$ is the upper boundary of PV generation. We also assume the hourly bid power P_t^{bid} can come either from PV generation or the discharge of BESS:

$$P_t^{bid} = P_{PV,t}^{sell} + P_{B,t}^{arb-}. \tag{3}$$

The BESS has its rated power P_B^{Rate}. In line with [6], [9], binary variables u_t^+ and u_t^- are used to control the charge/discharge mode of the BESS:

$$0 \leqslant P_{B,t}^{arb+} \leqslant P_B^{\mathrm{Rate}} \cdot u_t^+, \tag{4}$$

$$0 \leqslant P_{B,t}^{arb-} \leqslant P_B^{\mathrm{Rate}} \cdot u_t^-, \tag{5}$$

$$u_t^+ + u_t^- \leqslant 1,\ u_t^+, u_t^- \in \{0,1\}. \tag{6}$$

The energy level of BESS has the following constraints:

$$E_t^{arb} = E_{t-1}^{arb} + P_{B,t}^{arb+} \cdot \eta_c - P_{B,t}^{arb-} \cdot \frac{1}{\eta_d}, \tag{7}$$

$$0 \leqslant E_t^{arb} \leqslant E^{\max}. \tag{8}$$

where η_c/η_d denote the charge/discharge efficiency of the BESS, and $E^{\max}$ is the capacity of the BESS.

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The first-day bidding income under the worst-case price uncertainty can be calculated as follows:

$$income_1 = \min_{\lambda_t \in \Xi_t^{\lambda}} \sum_{t\in T} \lambda_t \cdot P_t^{bid} - \sum_{t\in T} c_B \cdot (P_{B,t}^{arb+} + P_{B,t}^{arb-}) \tag{9}$$

where λ_t is the uncertain price (\$/MW) within the uncertainty set Ξ_t^{λ}. We also consider the operational cost of BESS in (9), c_B is the coefficient of BESS operational cost (\$/MW).

B. Power Transaction Day Calculations (Stage II)

In the simulated transaction day, we introduced the slack variables $P_{B,t}^{adjust}$ and $P_{PV,t}^{UG}$ to balance the scheduled PV output and actual PV generation $P_{PV,t}$.

$$(P_{PV,t}^{sell} - P_{PV,t}^{UG}) + (P_{B,t}^{arb+} - P_{B,t}^{adjust}) + P_{B,t}^{firm+} \leqslant P_{PV,t}. \tag{10}$$

$P_{PV,t}^{UG}$ denotes the under-generation of the HPP, which has:

$$P_{PV,t}^{UG} \leqslant P_{PV,t}^{sell}. \tag{11a}$$

$P_{B,t}^{adjust}$ denotes the adjustment to the arbitrage schedule (charge curtailment) based on worst-case under-generation, which has:

$$P_{B,t}^{adjust} \leqslant P_{B,t}^{arb+}. \tag{11b}$$

The firming-oriented charge/discharge of BESS is also and controlled by u_t^+ and u_t^-, because a BESS is unable to charge and discharge simultaneously at time t:

$$0 \leqslant P_{B,t}^{firm+} \leqslant P_B^{\text{Rate}} \cdot u_t^+ \tag{12}$$

$$0 \leqslant P_{B,t}^{firm-} \leqslant P_{PV,t}^{UG} \tag{13}$$

$$0 \leqslant P_{B,t}^{arb+} - P_{B,t}^{adjust} + P_{B,t}^{firm+} \leqslant P_B^{\text{Rate}} \tag{14}$$

$$0 \leqslant P_{B,t}^{arb-} + P_{B,t}^{firm-} \leqslant P_B^{\text{Rate}} \cdot u_t^- \tag{15}$$

Constraints (14)-(15) guarantee the charge/discharge of BESS are limited by the rated power. Also, the energy level of BESS is limited by its capacity:

$$E_t^{firm} = E_{t\text{-}1}^{firm} + (P_{B,t}^{firm+} - P_{B,t}^{adjust}) \cdot \eta_c - P_{B,t}^{firm-} \cdot \frac{1}{\eta_d}, \tag{16}$$

$$0 \leqslant E_t \leqslant E^{\max}. \tag{17}$$

The worst-case under-generation penalty that considers the capacity firming and the operational cost can be calculated as follows:

$$penalty_2 = \max_{\rho_t \in \Xi_t^{\rho}} \sum\nolimits_{t\in T} \rho_t \cdot (P_{PV,t}^{UG} - P_{B,t}^{firm-}) + \sum\nolimits_{t\in T} c_B \cdot (P_{B,t}^{firm+} + P_{B,t}^{firm-} - P_{B,t}^{adjust}). \tag{18}$$

where ρ_t is the uncertain under-generation penalty (\$/MW) within the uncertainty set Ξ_t^{ρ}. The total under-generation penalty is calculated based on the difference of under-generation power and the reserved power by BESS for capacity firming. The under-generation power is all caused by PV as the BESS discharge is not uncertain.

C. The Objective Function Bridges Two-Stage

The objective is to maximize the worst-case net income:

$$\max_{\substack{P_{PV,t}^{sell},\, P_{B,t}^{arb+},\, P_{B,t}^{arb-},\\ E_t^{arb},\, u_t^+,\, u_t^-,\, P_t^{bid}}} income_1 + \min_{P_{PV,t} \in \Xi_t^{PV}} \max_{\substack{P_{PV,t}^{UG},\, P_{B,t}^{adjust},\, P_{B,t}^{firm-},\\ P_{B,t}^{firm+},\, E_t^{firm},\, E_t}} - penalty_2 \tag{19}$$

D. The Proposed Two-Stage Robust Bidding Model

The two-stage bidding model is formulated as follows. For ease of expression, the model is written in a compact form:

$$\min_{\boldsymbol{q}} \mathbf{k}^{\mathrm{T}}\boldsymbol{q} + \max_{\boldsymbol{P_{PV}} \in \Xi^{PV}} \min_{\boldsymbol{x} \in \mathcal{F}(\boldsymbol{q}, \boldsymbol{P_{PV}})} \mathbf{c}^{\mathrm{T}}\boldsymbol{x} \tag{20a}$$

$$\text{s.t. } \mathbf{N}\boldsymbol{q} \geq \mathbf{g}, \tag{20b}$$

$$\mathcal{F}(\boldsymbol{q}, \boldsymbol{P_{PV}}) = \{\boldsymbol{x}\text{: } \mathbf{G}\boldsymbol{x} \geq \mathbf{h} - \mathbf{E}\boldsymbol{q} - \mathbf{M}\boldsymbol{P_{PV}}\}. \tag{20c}$$

where $\boldsymbol{x} = [\boldsymbol{P_{PV}^{UG}}, \boldsymbol{P_B^{adjust}}, \boldsymbol{P_B^{firm-}}, \boldsymbol{P_B^{firm+}}, \boldsymbol{E^{firm}}, \boldsymbol{E}]^{\mathrm{T}}$, and $\boldsymbol{q} = [\boldsymbol{P_{PV}^{sell}}, \boldsymbol{P_B^{arb+}}, \boldsymbol{P_B^{arb-}}, \boldsymbol{E^{arb}}, \boldsymbol{u^+}, \boldsymbol{u^-}, \boldsymbol{P^{bid}}]^{\mathrm{T}}$. (20b) is used to denote constraints (2)-(8). (20c) is the matrix expression of constraints (1), (10)-(18). Note that we have $\boldsymbol{x} \in \mathcal{F}(\boldsymbol{q}, \boldsymbol{P_{PV}})$, which assumes when solving the second-stage variable $\boldsymbol{x}$, the first-stage variable $\boldsymbol{q}$ is determined, and the uncertain variable $\boldsymbol{P_{PV}}$ is revealed. This assumption is the key to addressing the overly conservative issue of the single-stage RO formulation.

III. Solution Method

This section applies C&CG algorithm [10] to solve the proposed model (20). While (20) is a two-stage model, the two-stage decision variables $\boldsymbol{q}$ and $\boldsymbol{x}$ are not independent. The C&CG algorithm is to obtain a combination of $[\boldsymbol{q}, \boldsymbol{x}]^{\mathrm{T}}$ that achieves the objective in (20a) and subjects to (20b)-(20c).

To this end, the C&CG algorithm decomposes (20) as a master problem (MP) and a subproblem (SP). MP searches the optimal two-stage solution in the solution space, and SP conducts the optimal cut by generating constraints for MP, which progressively narrows the solution space. The optimal two-stage solution can be reached by alternately solving MP and SP [10]. The MP of (20) is as follows:

$$\text{(MP)} \quad \min_{\boldsymbol{q},\, \eta \in \mathbb{R}_+,\, \boldsymbol{x}^k} \mathbf{k}^{\mathrm{T}}\boldsymbol{q} + \eta \tag{21a}$$

$$\text{s.t. (20b)}, \tag{21b}$$

$$\eta \geq \mathbf{c}^{\mathrm{T}}\boldsymbol{x}^k, k \in K \tag{21c}$$

$$\mathbf{G}\boldsymbol{x}^k \geq \mathbf{h} - \mathbf{E}\boldsymbol{q} - \mathbf{M}\boldsymbol{P_{PV}}^{*k}, k \in K \tag{21d}$$

where η is introduced to characterize the optimal solution of the second-stage model. $k \in K$ is the iteration index of the solution. $\boldsymbol{P_{PV}}^{*k} \in PV$ is the critical scenario of PV generation identified by solving SP in k-th iteration. With the optimal $\boldsymbol{q}^*$ searched from MP, SP can be written as follows:

$$\text{(SP)} \quad \mathcal{Q}(\boldsymbol{q}^*) = \max_{\xi \in \Xi^{PV}} \min_{\boldsymbol{x}} \mathbf{c}^{\mathrm{T}}\boldsymbol{x} \tag{22a}$$

$$\text{s.t.} \quad \mathbf{G}\boldsymbol{x} \geq \mathbf{h} - \mathbf{E}\boldsymbol{q}^* - \mathbf{M}\boldsymbol{P_{PV}}, \tag{22b}$$

The "max-min" objective can be transferred to a "min" objective in (22a) using Karush–Kuhn–Tucker (KKT) method.

The solution process of the C&CG algorithm is as shown in Fig. 2. The iteration in Fig.2 ensures that the first-stage schedule can be adjusted according to its impact on the second stage, even though we assume the first-stage schedule is determined when solving the second-stage model.

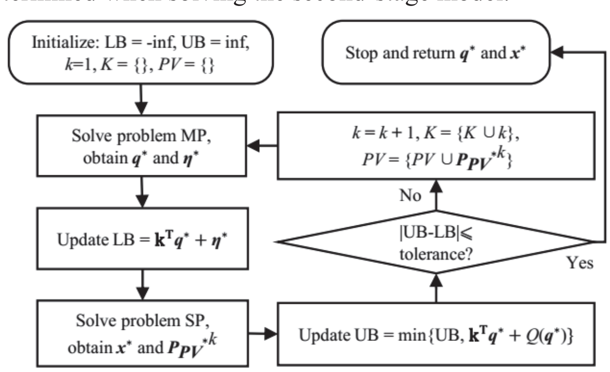

Fig. 2. Solve the TSRB model using C&CG algorithm.

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IV. CASE STUDIES

A. General Setting and Assumptions of the Experiments

In the following case studies, PV and market information datasets have been used. We assume the tested HPP locates near the New York Metropolitan area. The PV data of the corresponding location is from the NREL's Solar Power Data (six-month, 184 days) [11]. The market data is downloaded from NYISO [12]. We understand the current PV systems bid in the market with zero cost and no under- generation charge, which is likely to change in the future market. Without going too far into the future market design topic, we use the under-generation charge from the NYISO service tariff [13] for thermal power plants in our study. The HPP is assumed to have a PV farm rated 21 MW and a 10 MW/ 10 MWh BESS on site. The setting of related parameters mentioned in the modeling section is given in Table I. To maintain the initial storage level, the BESS is assumed to be recharged at midnight using the energy from the forward market with an affirmatory and constant charging cost. Because the amount of recharge is constant, we do not show this recharge in the following figures. The uncertainty sets in this work are generated using the same method as ref. [9].

B. Study of a Representative One-Day Case

We selected a partially cloudy day to explain the results of the algorithm. The input of the proposed model is as shown in Fig. 3, which includes one-day uncertainty sets of PV generation and market information. Based on these uncertainty sets as input, the proposed model outputs bids and the self-schedule of the HPP, as shown in Fig. 4. The outputs contain the schedule of selling PV-generated power and stored power in BESS for arbitrage. Combining these two items, we can obtain the bid decision submitted to the ISO. To achieve the maximum income, BESS is scheduled to charge at 8:00-9:00 and 14:00-15:00, which are the points with the lowest market prices within hours of nonzero PV production. Also, the stored power is scheduled to sell at 10:00-11:00 and 19:00-20:00, which are the points with the highest market prices within hours of nonzero PV production. In parallel, BESS also has 6.9 MW reserved power for capacity firming at 10:00-11:00. Also, the TSRB model guarantees the energy level of BESS is within the feasible range. In this one-day case, we found that the lowest energy level decreases to 0 at 19:00-20:00.

TABLE I. PARAMETERS SETTING

	Meaning of Parameters	Value
η_c/η_d	Charge/discharge efficiency of BESS	98%
E_1	The initial BESS storage level	50%
c_B	Rate of BESS operational cost ($/MW)	0.5 [14]
tolerance	Tolerance of |UB-LB| in C&CG	10^{-6}

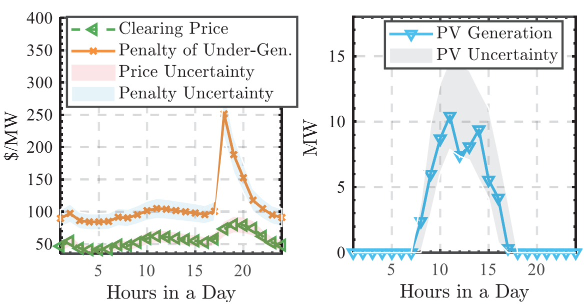

Fig. 3. Market (left) and PV (right) data and uncertainty sets in the representative day.

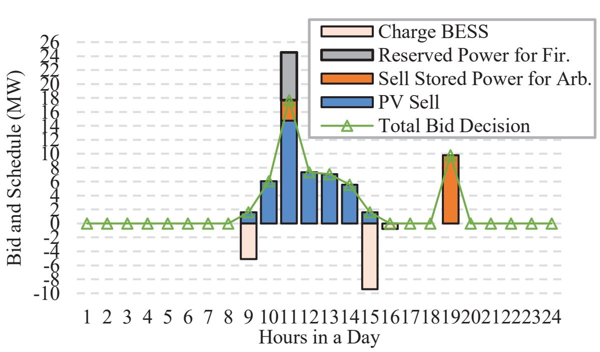

Fig. 4. Bid and schedule results of the representative day.

To study the performance of the proposed TSRB model, our problem is also formulated as a single-stage robust bidding (RB) model based on the similar formulation in [7]-[9]. The TSRB model and the single-stage RB model have been compared based on the same input; the result is as shown in Fig. 5.

Because the two-stage formulation in the TSRB model is designed to weaken the overly conservative issue that appeared in single-stage RB models, we plotted out the worst-case PV output as identified by the single-stage RB model and TSRB model in Fig.5 (top). It is observed that the worst-case scenario of PV uncertainty identified by the TSRB model is more aggressive compared to the result identified by the single-stage RB model at 8:00-9:00, 10:00-11:00, and 14:00-15:00. Because RO calculates the optimal solution under the worst-case scenario of uncertainties, the worst-case PV outputs are equal to the scheduled PV outputs in the solution. Therefore, the worst-case PV output can be calculated as follows:

$$P_{PV,t}^{output} = P_{PV,t}^{sell} + P_{B,t}^{arb+} - P_{B,t}^{adjust} + P_{B,t}^{firm+}. \tag{23}$$

The worst-case PV output is aggressive at 10:00-11:00 because the BESS has reserved power for firming at this time, and this is a point with one of the highest market prices within hours of nonzero PV production. Also, the worst-case PV output is aggressive at 8:00-9:00 and 14:00-15:00 because these are the best time to charge the BESS (with the lowest under-generation penalties within hours of nonzero PV production).

Fig.5 (bottom) shows the hourly bids by the single-stage RB and the TSRB models, respectively. It can also be observed that the TSRB model bids more power at 8:00-9:00, 10:00-

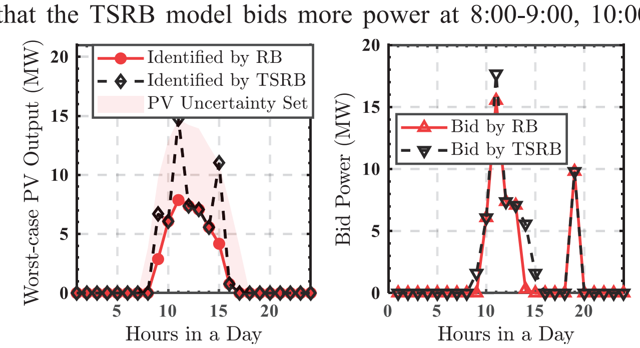

Fig. 5. Scheduled PV outputs (left) and hourly bids (right) of the representative day.

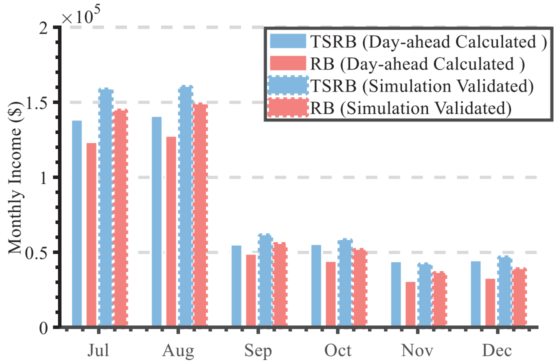

Fig. 6. Six Months Incomes of the HPP.

11:00, and 13:00-15:00, respectively. The TSRB model bids more power at 8:00-9:00 and 13:00-15:00 are simply because the single-stage RB model schedules to charge the BESS with all PV generation at these three points. Because the worst-case PV output is elevated at 10:00-11:00, the TSRB model bids more power at this time.

C. Economic Performance in Six-Month Case

This subsection compares the economic performance of the proposed TSRB model and single-stage RB model. To this end, the two models were applied to conduct continual bids based on six-month PV and market datasets [11], [12]. The day-ahead calculated incomes and the simulated transaction day incomes earned by the HPP each month are shown in Fig. 6. For both methods, the day-ahead calculated incomes are the minimum guaranteed incomes. As observed in Fig. 6, simulation validated incomes are higher than their corresponding day-ahead calculated incomes. Apart from this, the significant economic advantage of the proposed TSRB model was observed each month in both day-ahead calculated and simulation validated incomes, compared to the single-stage RB model.

To sum up, the total six-month incomes of the TSRB model and single-stage RB model are compared in Table II. It is observed that the TSRB model has achieved 17.23% (day-ahead calculated) and 10.88% (simulation validated) income improvement compared with the single-stage RB model.

V. Conclusion

In this study, a two-stage robust bidding and scheduling model is proposed for future HPP operation. Different from other works, the BESS schedule for arbitrage and PV capacity firming are decoupled. A two-stage formulation is used to simulate the execution of arbitrage and capacity firming that follows their time sequence. Using the proposed formulation, we observed that the worst-case scenario of uncertainties can be moved to a more aggressive point from the case studies. As a result, the income can be increased based on the more aggressive worst-case uncertainties. To bridge the multi-objectives of BESS arbitrage and capacity firming, the calculation of the under-generation penalty is also included in our model. The C&CG algorithm is applied to calculate the optimal solution that applies to two-stage objectives in the proposed TSRB model. In case studies, we have shown the proposed TSRB model can achieve over 10% improvement compared with a state-of-art robust bidding model.

TABLE II. Compare Six-Month Incomes

	Day-ahead Calculated Income	Simulated Income After the Transaction Day
RB ($)	408,669.3	475,745.1
TSRB ($)	479,061.5	527,510.6
Outperform	17.23%	10.88%

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