Bidding Curve Design for Hybrid Power Plants with Uncertain Solar Forecast

Preprint

Yue Chen,[1] Yashen Lin,[1] Mia E. Moore,[2] Xiaoge Huang,[3]
Xi Chen,[3] and Ziang Zhang[3]

1 National Renewable Energy Laboratory
2 Colorado School of Mines
3 Binghamton University - SUNY

Presented at the 50th Annual Conference of the IEEE Industrial Electronics Society (IECON)
Chicago, Illinois
November 3–6, 2024

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00- 90787
November 2024

Bidding Curve Design for Hybrid Power Plants with Uncertain Solar Forecast

Preprint

Yue Chen,[1] Yashen Lin,[1] Mia E. Moore,[2] Xiaoge Huang,[3]
Xi Chen,[3] and Ziang Zhang[3]

1 National Renewable Energy Laboratory
2 Colorado School of Mines
3 Binghamton University - SUNY

Suggested Citation
Chen, Yue, Yashen Lin, Mia E. Moore, Xiaoge Huang, Xi Chen, and Ziang Zhang. 2024. *Bidding Curve Design for Hybrid Power Plants with Uncertain Solar Forecast: Preprint*. Golden, CO: National Renewable Energy Laboratory. NREL/CP-5D00-90787. https://www.nrel.gov/docs/fy25osti/90787.pdf.

© 2024 IEEE. Personal use of this material is permitted. Permission from IEEE must be obtained for all other uses, in any current or future media, including reprinting/republishing this material for advertising or promotional purposes, creating new collective works, for resale or redistribution to servers or lists, or reuse of any copyrighted component of this work in other works.

NREL is a national laboratory of the U.S. Department of Energy
Office of Energy Efficiency & Renewable Energy
Operated by the Alliance for Sustainable Energy, LLC

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

Contract No. DE-AC36-08GO28308

Conference Paper
NREL/CP-5D00- 90787
November 2024

National Renewable Energy Laboratory
15013 Denver West Parkway
Golden, CO 80401
303-275-3000 • www.nrel.gov

NOTICE

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office Agreement Number DEEE0009341. The views expressed herein do not necessarily represent the views of the DOE or the U.S. Government.

This report is available at no cost from the National Renewable Energy Laboratory (NREL) at www.nrel.gov/publications.

U.S. Department of Energy (DOE) reports produced after 1991 and a growing number of pre-1991 documents are available free via www.OSTI.gov.

Cover Photos by Dennis Schroeder: (clockwise, left to right) NREL 51934, NREL 45897, NREL 42160, NREL 45891, NREL 48097, NREL 46526.

NREL prints on paper that contains recycled content.

Bidding Curve Design for Hybrid Power Plants with Uncertain Solar Forecast

Yue Chen, Yashen Lin
Power Systems Engineering Center
National Renewable Energy Laboratory
Golden, CO, USA.
{yue.chen, yashen.lin}@nrel.gov

Mia E. Moore
Advanced Energy Systems
Colorado School of Mines
Golden, CO, USA.
mia_moore@mines.edu

Xiaoge Huang, Xi Chen, Ziang Zhang
Electrical and Computer Engineering
Binghamton University - SUNY
Binghamton, NY, USA.
{xhuang98, xchen18, ziang.zhang}@binghamton.edu

***Abstract*—This paper presents a novel bidding curve design algorithm tailored for hybrid power plants (HPPs) to participate in the wholesale electricity market. Utilizing forecasts for photovoltaic (PV) generation and available battery power, our algorithm strategically computes the bidding curve to maximize HPP profit while adeptly managing the inherent uncertainty associated with PV power generation. In addition, the introduction of the penalty cost in HPP bidding curves provides the system operator a tool to effectively manage the system-level uncertainty that caused by HPPs. Numerical analysis through Monte Carlo simulations confirms that our bidding curve methodology outperforms the benchmark across various scenarios.**

***Index Terms*—hybrid power plant, bidding curve, day-ahead market, economic dispatch.**

I. Introduction

The rapid transformation of the global energy landscape is underscored by the increasing integration of renewable energy sources into the power grid. Renewable energy, such as wind and solar power, is known for its volatile generation, which introduces uncertainty between forecast and actual generations. This uncertainty can lead to power fluctuations in the real-time market and may increase price volatility [1]. Hybrid Power Plants (HPPs), which combine renewable energy generation with energy storage, represent a significant advancement in sustainable and resilient energy systems [2]. They mitigate the intermittency of sources like solar and wind by storing surplus energy when production is high and releasing it during low production. The U.S. Department of Energy (DOE) has recognized the essential role of HPPs in advancing the future of renewable power plants and advocates for their research and development and integration into the energy market [3].

This paper investigates HPPs that integrate photovoltaic (PV) panels with battery storage systems. Recently, market participation for PV generation is fast evolving, and it varies with different system operators in current power grid operations. Some PV generations are included in day-ahead net load forecasting. Grid operators predict the next day's load and renewable energy generation, then calculate the day-ahead net load to inform economic dispatch decisions. In some regions, PV resources can participate in the day-ahead and real-time electricity market: in the day-ahead market, they are treated as all other generators, and in the real-time market, PV owners are compensated based on real-time electricity prices [4]. All these methods introduce the inherent uncertainty of PV generation into the real-time market. While they are suited to current market conditions where PV penetration remains relatively low, these methods can introduce significant fluctuations in the real-time electricity market as PV penetration increases, potentially compromising grid reliability.

To efficiently manage the growing PV generation, it is crucial to address their uncertainty beyond the real-time market; for example, in the day-ahead market. Both system operators and the research community have proposed potential solutions, such as additional reserves [5], market enhancement [6]–[8], or new market products [9]. However, central management of this uncertainty by grid operators is becoming increasingly challenging due to the substantial accumulated uncertainty at the system level. A more suitable strategy is to decentralize the management of this uncertainty, assigning it to individual HPPs, thereby requesting these units to manage their specific renewable uncertainties.

Participation in the day-ahead market requires a well-defined bidding strategy for HPPs. The existing literature on HPP bidding strategies can be generally divided into two categories: price-taker and price-maker strategies. Price-taker strategies operate under the assumption that HPP bids do not influence the market clearing price, with bidding decisions highly dependent on the forecast of the market clearing price; examples include [10]–[12]. However, when the number of HPPs increases significantly, this assumption may no longer be valid. Conversely, price-maker strategies acknowledge that HPP bids can affect the market price. To effectively capture the interactions among the market participants and their influence to the market dynamics, formulation of complex optimization

This work was authored in part by the National Renewable Energy Laboratory, operated by Alliance for Sustainable Energy, LLC, for the U.S. Department of Energy (DOE) under Contract No. DE-AC36-08GO28308. Funding provided by U.S. Department of Energy Office of Energy Efficiency and Renewable Energy Solar Energy Technologies Office Agreement Number DE-EE0009341. The views expressed in the article do not necessarily represent the views of the DOE or the U.S. Government. The U.S. Government retains and the publisher, by accepting the article for publication, acknowledges that the U.S. Government retains a nonexclusive, paid-up, irrevocable, worldwide license to publish or reproduce the published form of this work, or allow others to do so, for U.S. Government purposes.

This report is available at no cost from the National Renewable Energy Laboratory at www.nrel.gov/publications.

problems is often required, as seen in studies like [13]–[15]. Furthermore, when a large portion of the market participants behave strategically, the implication to the system volatility, cost, and social welfare could be complex [16], [17]; this impact could also be negative in some cases [18].

In this paper, we propose a novel approach to construct the bidding curve for HPPs under the price-maker strategy. The proposed bidding curve mimics the cost curve of traditional generators and is suitable for deployment in today's wholesale electricity market. A key distinction between HPPs and traditional generators is the inherent uncertainty in HPP power generation due to the variability of PV output. To address this, we incorporate a penalty cost into the bidding curve design to penalize HPPs that fail to meet their committed generation. Then, the cost curve is obtained by integrating the power costs associated with the PV, battery, and under-generation penalty. Consequently, HPPs can submit hourly-based bidding curves to the system operator for economic dispatch, similar to traditional generators.

The contributions of this paper are summarized below. Firstly, we develop a novel bidding curve design methodology that enables HPPs to effectively manage their generation uncertainty and participate in the electricity market. Secondly, we incorporate the penalty price into the HPP cost curve design, providing grid operators with a tool to balance local HPP profits and overall system reliability and cost. Lastly, we conducted comprehensive simulations to demonstrate the efficacy of the proposed bidding curve solution and its impact on grid operations. Note that although the focus of this paper is on the day-ahead market, the proposed HPP bidding curve is also applicable to other electricity markets.

The remainder of this paper is organized as follows. Section II introduces the HPP modeling. Section III describes the derivation of the bidding curve and formulates the economic dispatch problem with HPPs. Section IV provides numerical results to evaluate the effectiveness of the proposed bidding curve strategy. Finally, conclusions and directions for future research are discussed in Section V.

II. HPP Modeling

This section presents the modeling of the PV generation and battery storage in an HPP system. Although the focus is primarily on the PV+battery configuration, the methodologies and results discussed in this paper are applicable to a broader range of HPP configurations with any uncertain power generation paired with an energy storage solution.

A. PV Model

The PV system is characterized by its power generation and the associated cost of generation. In the day-ahead market, the power from the PV system is characterized by the forecast. We represent the day-ahead forecast of PV power by a cumulative density function (cdf):

$$\phi(P) = \text{prob}\{P^{\text{pv}} < P\}, \tag{1}$$

where P^{pv} represents the power generated from the PV. Additionally, we use λ^{pv} (\$/MW) to denote the cost associated with PV generation.

B. Battery Model

The battery within the HPP system is characterized by its energy level E_t (MWh) and the associated power cost, λ_t^{bt} (\$/MW). Denoting the battery charging power by P_t^{bt}, the following equations describe the updates of the battery energy and the associated power cost, according to its charge/discharge behavior:

$$E_{t+1} = \begin{cases} E_t + (1/\alpha^-)P_t^{\text{bt}}\Delta t, & \text{if } P_t^{\text{bt}} \le 0 \\ E_t + \alpha^+ P_t^{\text{bt}}\Delta t, & \text{if } P_t^{\text{bt}} > 0 \end{cases} \tag{2}$$

and

$$\lambda_{t+1}^{\text{bt}} = \begin{cases} \lambda_t^{\text{bt}}, & \text{if } P_t^{\text{bt}} \le 0 \\ \frac{\lambda_t^{\text{bt}}(E_t/\Delta t) + \lambda_t^{\text{chg}} P_t^{\text{bt}}}{E_t/\Delta t + P_t^{\text{bt}}}, & \text{if } P_t^{\text{bt}} > 0 \end{cases} \tag{3}$$

where $\Delta t = 1$ hour (assumes hourly market), α^- and α^+ in (2) represent the battery's discharge and charge efficiencies, respectively, and λ_t^{chg} (\$/MW) in (3) is the battery power charge price, which can be derived from the grid electricity price, the cost of PV generation, or a combination of the two, depending on the battery's charging sources. Equation (3) describes two aspects of the battery cost update: 1) when the battery discharges power ($P_t^{\text{bt}} \le 0$), the cost remains the same; 2) conversely, when charging the battery ($P_t^{\text{bt}} > 0$), the cost is computed as the "average" of pre-existing and newly charged power.

In addition, the battery is subject to operational constraints:

$$\underline{P}^{\text{bt}} \le P_t^{\text{bt}} \le \bar{P}^{\text{bt}} \tag{4a}$$

$$0 \le E_t \le \bar{E} \tag{4b}$$

where $\underline{P}^{\text{bt}}$ and $\bar{P}^{\text{bt}}$ denote the minimum and maximum charge/discharge power limits of the battery, respectively, and $\bar{E}$ indicates the maximum energy capacity of the battery.

III. Economic Dispatch with HPP

In the paper, we consider the wholesale market based on the uniform clearing-price (UCP) auction. In this framework, generators are dispatched in ascending order of bid prices until the total demand is met. All generators whose bids are accepted receive the market clearing price, which is the highest bid needed to meet demand. This UCP framework incentivizes generators to bid their incremental cost to increase their chance of being dispatched and maximizing profitability. While conventional generators operate with a consistent generation cost function, the cost function for an HPP depends on its available power within the system. Given that PV power is based on a forecast, the cost associated with an HPP inherently carries uncertainty. In the subsequent section, we will present the design of the HPP bidding curve in the presence of such uncertainty in PV power.

This report is available at no cost from the National Renewable Energy Laboratory at www.nrel.gov/publications.

A. HPP Bidding Curve Design

We introduce $\lambda^{\text{hpp}}(P)$ to denote the incremental cost of HPP associated with power generation P. Given the inherent uncertainty in the generation of PV power, $\lambda^{\text{hpp}}(P)$ appears as a random variable. However, under the constraints of the current market, bidding with an uncertain cost function is not permissible. To address this challenge, we formulate the following optimization problem aimed at deriving a deterministic cost function that seeks to minimize the distance to the uncertain cost $\lambda^{\text{hpp}}(P)$, quantified by the mean squared error:

$$\underset{z(P)}{\text{minimize}} \quad E\left[\left(z(P)-\lambda^{\text{hpp}}(P)\right)^2\right]. \tag{5}$$

To solve the optimization problem, we expand the expected function as follows:

$$\begin{aligned} & E\left[\left(z(P)-\lambda^{\text{hpp}}(P)\right)^2\right] \\ & = E\left[z^2(P)+\left(\lambda^{\text{hpp}}(P)\right)^2-2z(P)\lambda^{\text{hpp}}(P)\right] && \text{(6a)} \\ & = z^2(P)+\left(E\left[\lambda^{\text{hpp}}(P)\right]\right)^2+Var\left(\lambda^{\text{hpp}}(P)\right) \\ & \quad -2z(P)E\left[\lambda^{\text{hpp}}(P)\right] && \text{(6b)} \\ & = \left(z(P)-E\left[\lambda^{\text{hpp}}(P)\right]\right)^2+Var\left(\lambda^{\text{hpp}}(P)\right). && \text{(6c)} \end{aligned}$$

Using equation (6c), the optimal solution to (5) is obtained as $z^*(P)=E\left[\lambda^{\text{hpp}}(P)\right]$. This suggests bidding the uncertain HPP incremental cost by its expected value.

To calculate the expected value of an HPP's incremental cost, we introduce a penalty price, denoted as λ^{pen} ($/MW), which is applied to any HPP that fails to meet its bid power. This penalty serves two critical functions:

1) It acts as a link between the day-ahead market and the real-time market, addressing potential under-generation by HPPs.
2) It acts as a regulatory mechanism that incentivizes HPPs to properly manage their uncertainty in power generation.

A detailed numerical analysis of the impact of the penalty price on HPP operations and market dynamics can be found in Section IV.

Assuming that $\lambda^{\text{pv}} \leq \lambda^{\text{bt}} \leq \lambda^{\text{pen}}$, the expected incremental cost is calculated as follows:

$$\begin{aligned} & E[\lambda^{\text{hpp}}(P)] \\ & = \text{prob}\{P \leq P^{\text{pv}}\}\lambda^{\text{pv}} + \text{prob}\{P^{\text{pv}} < P \leq -\underline{P}^{\text{bt}}+P^{\text{pv}}\}\lambda^{\text{bt}} \\ & \quad + \text{prob}\{P > -\underline{P}^{\text{bt}}+P^{\text{pv}}\}\lambda^{\text{pen}} && \text{(7a)} \\ & = (1-\phi(P))\lambda^{\text{pv}} + [\phi(P)-\phi(P+\underline{P}^{\text{bt}})]\lambda^{\text{bt}} \\ & \quad + \phi(P+\underline{P}^{\text{bt}})\lambda^{\text{pen}} && \text{(7b)} \end{aligned}$$

where the cdf $\phi(*)$, as defined in (1), is obtained from the PV forecast, and $-\underline{P}^{\text{bt}}$ represents the maximal battery discharge power. Equation (7a) decomposes the expectation by considering three possible ranges of power generation, according to their cost prices; equation (7b) rearranges these terms, representing them in terms of cdf $\phi(*)$.

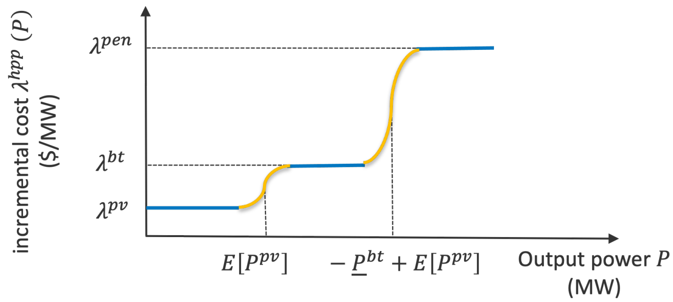

Fig. 1. Illustration of the proposed HPP bidding curve.

An illustration of the cost curve (7b) for a typical HPP is provided in Fig. 1. The curve features three relatively flat segments representing the PV price, battery price, and penalty price, respectively. Additionally, two transition segments (colored yellow) reflect the PV uncertainty. In the absence of PV uncertainty, such as during nighttime, these yellow segments disappear.

Furthermore, the cost curve can be extended to incorporate pre-determined battery arbitrage operations. For example, when the battery is scheduled to charge using PV power, the cost curve illustrated in Fig. 1 is shifted to the left by the arbitrage charging power from the PV system. Conversely, to incorporate the arbitrage discharge power into the HPP bid, the maximum battery discharge power $-\underline{P}^{\text{bt}}$ in Fig. 1 is replaced by the arbitrage discharge power.

B. Economic Dispatch

Consider a power system with N_f traditional fossil-fuel plants and N_h HPPs. The day-ahead economic dispatch is formulated below:

$$\underset{\boldsymbol{P}^f,\, \boldsymbol{P}^{\text{hpp}}}{\text{minimize}} \quad \sum_{t=1}^{24}\left(\sum_{k=1}^{N_f} c_{k,t}^f(P_{k,t}^f)+\sum_{i=1}^{N_h} c_{i,t}^h(P_{i,t}^{\text{hpp}})\right) \tag{8a}$$

$$\text{subject to} \quad \sum_{k=1}^{N_f} P_{k,t}^f + \sum_{i=1}^{N_h} P_{i,t}^{\text{hpp}} = P_t^d \tag{8b}$$

$$\underline{P}_{k,t}^f \leq P_{k,t}^f \leq \bar{P}_{k,t}^f \tag{8c}$$

where $c_{k,t}^f$ and $c_{i,t}^h$ are the generation cost associated with traditional fossil-fuel plants and HPPs, respectively. The cost associated with traditional fossil-fuel plants is usually described by a quadratic equation:

$$c_{k,t}^f(P) = a_k + b_k P + c_k (P)^2. \tag{9}$$

The HPP cost function is the integral of the expected incremental cost:

$$c_{i,t}^h(P) = \int_{P=0}^{P} E\left[\lambda_{i,t}^{\text{hpp}}(P)\right] dP. \tag{10}$$

Equation (8b) maintains the system's power balance, with P_t^d representing the power demand at time t. Equation (8c) sets the power limits for traditional plants. It's worth noting that constraints related to the HPP power limits are not explicitly

This report is available at no cost from the National Renewable Energy Laboratory at www.nrel.gov/publications.

defined, as they are inherently incorporated within the bidding curve design, where a penalty cost is imposed for under-generation.

There are two possible approaches for grid operators to perform the economic dispatch. The first approach involves collecting day-ahead generator bidding curves and finding the most cost-effective solution. This method requires each HPP to submit 24 hourly bidding curves at once. The second approach performs economic dispatch on an hourly basis, where each generator provides a bidding curve for one hour at a time. This allows generators to adjust their bidding curves based on the results of the previous hour's economic dispatch, which is particularly beneficial for HPPs that need to reschedule their battery operations based on committed power. In this paper, since the focus is on the bidding curve design, we adopt the first approach for demonstration, assuming that battery arbitrage is determined before the day-ahead economic dispatch process.

IV. Numerical Study

To demonstrate the proposed work, we conducted a numerical study of a 24-hour day-ahead economic dispatch problem with five HPPs and five traditional generators. The parameters for five fossil generators are summarized in Table I, which includes coefficients of the quadratic cost function (9) and the minimum/maximum generation power. For HPPs, note that the methodologies for PV forecasting and day-ahead battery power scheduling are beyond the scope of this paper; in this numerical study, these elements are assumed to be predetermined and are provided as inputs. We assumed the day-ahead PV forecast follows the Gaussian distribution $\mathcal{N}(\mu_{i,t}, \sigma_{i,t}^2)$ for HPP$_i$ at time t. The mean of the PV power forecast was given as Fig. 2, and the standard deviation was assumed linear to the mean value, i.e., $\sigma_{i,t} = \beta\mu_{i,t}$. This study will explore the impact of various levels of PV uncertainty by adjusting the parameter β. To ensure practicality, we constructed the PV distribution by truncating the Gaussian distribution to range between 0 and the 95^{th} percentile. In addition, the batteries were assumed to have a predetermined schedule to charge power at a rate of 2.5 MW from the PV generation during 10:00-13:00 and discharge power at 10 MW at time 18:00. Table II provides the associated PV and battery power costs of HPPs in simulation.

Based on the day-ahead PV and battery information, we designed hourly bidding curves for each HPPs. Fig. 3 shows bidding curve examples of HPP$_1$ at various times of the day, considering penalty cost $\lambda^{\text{pen}} = \$60/\text{MW}$ and PV uncertainty level $\beta = 0.5$. Those HPP bidding curves, together with cost curves of fossil fuel plants, were considered for the hourly day-ahead economic dispatch problem (8), to meet the day-ahead load curve that shown at bottom of Fig. 2.

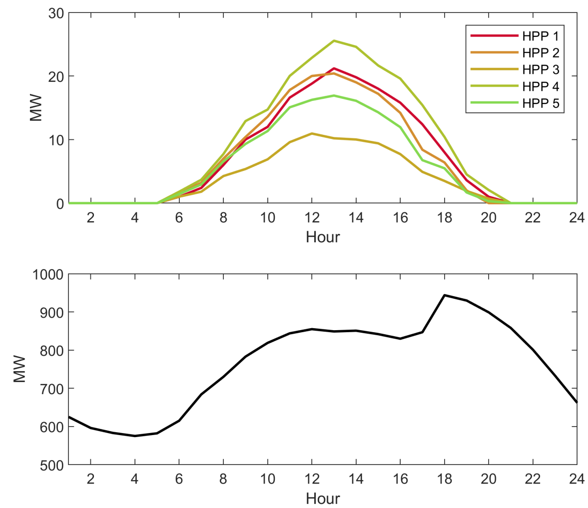

Fig. 2. Numerical study inputs. Top: PV generation forecast (mean) for each HPP; bottom: load profile used in the economic dispatch problem.

In this numerical study, we are interested in: **i) HPP profitability** and **ii) system operation cost** to meet daily demand. As a reference point, we compare the results of the *proposed bidding curve (proposed BC)* methodology to a *benchmark* strategy which always bids the expected value of HPP power output without considering the uncertainties. The performance of the proposed bidding curve is affected by several key factors, which are outlined below and detailed in Table III.

1) **Penalty cost**. This cost is imposed by the system operator to penalize generators for generating less than their day-ahead bidding power. Generally, a higher penalty cost is expected to result in less profitability for HPPs.
2) **PV uncertainty**. The uncertainty in the day-ahead PV forecast is quantified by the standard deviation of the Gaussian distribution (recall $\sigma_t = \beta\mu_t$ where μ_t is the

TABLE I
Traditional Generator Parameters

Generator	Min (MW)	Max (MW)	a_k	b_k	c_k
FF$_1$	40	300	22	25	0.02
FF$_2$	30	250	17	27	0.01
FF$_3$	40	200	81	13	0.10
FF$_4$	40	350	32	18	0.03
FF$_5$	50	400	42	22	0.02

TABLE II
HPP Cost Parameters

Generator	PV cost ($/MW)	Battery cost ($/MW)
HPP$_1$	5.417	10.18
HPP$_2$	5.720	10.598
HPP$_3$	5.000	9.418
HPP$_4$	5.302	9.908
HPP$_5$	5.417	9.931

TABLE III
Numerical Study Parameters

Parameter	Values Investigated
Penalty price: λ^{pen} ($/MW)	[40, 60, 80, 100]
PV uncertainty parameter: β	[0.1, 0.3, 0.5]
Real-time factor k	[1.0, 1.5, 2.0]

This report is available at no cost from the National Renewable Energy Laboratory at www.nrel.gov/publications.

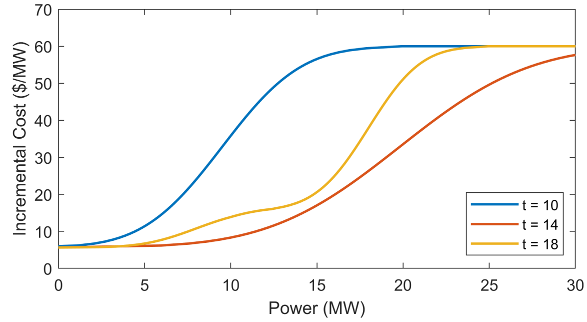

Fig. 3. Example of the proposed bidding curves for HPP 1 at different hours.

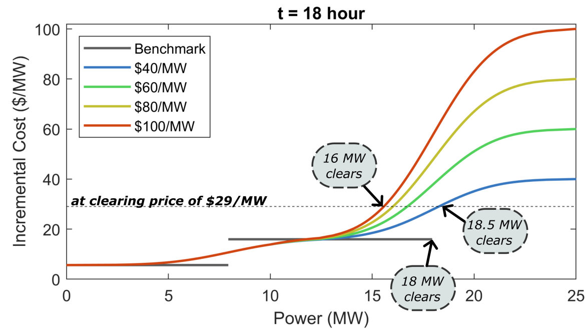

Fig. 4. Comparison of bidding power between the proposed and benchmark bidding curves, assuming the same clearing price.

PV forecst mean). Accurate PV forecasting is expected to enhance profitability for HPPs and reduce overall costs for the system operator by decreasing the financial risks associated with generation shortfalls.

3) **Real-time market cost**. This refers to the cost incurred to the system operators to compensate for deficient generation in the real-time market. It represents how expensive the under generation is to the system operators.

Fig. 4 illustrates the bidding power profiles for different strategies, distinguished by the penalty costs. A high penalty cost encourages HPPs to adopt a conservative bidding strategy to minimize the risk of significant penalties, whereas a low penalty cost motivates HPPs to pursue a more aggressive bidding strategy to maximize profits. In contrast, the benchmark strategy does not adjust for variations in penalty costs, which can lead to suboptimal financial outcomes.

Fig. 5 shows the hourly clearing price obtained after solving the economic dispatch problem, with the PV uncertainty level set at $\beta = 0.5$. It compares the results of the proposed bidding curve approach with the benchmark across various penalty costs. The benchmark strategy always bids the mean value of the HPP power and thus has the same clearing price for different penalty costs. In contrast, with the proposed bidding curve, the clearing prices become higher as the penalty cost increases due to the HPPs's strategy to bid less power, as shown in Fig. 5. The explanation for this bidding power adjustment is illustrated in Fig. 4. Additionally, the notable bidding spike at time 18 hour in Fig. 5 is caused by the scheduled battery discharge behavior.

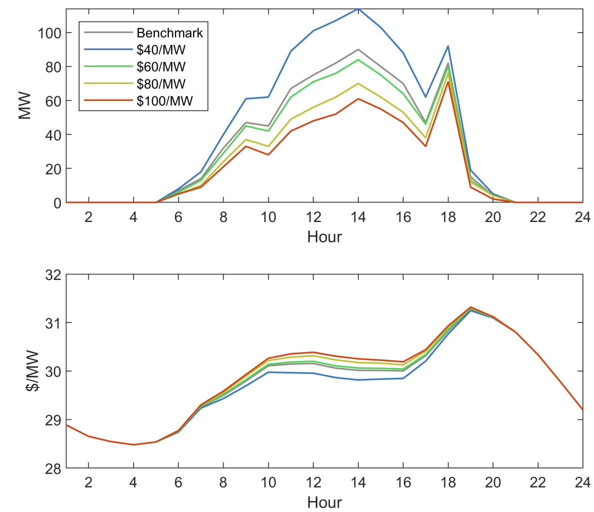

Fig. 5. Economic dispatch results. Top: sum of all HPP accepted power bids; bottom: hourly clearing price.

Based on the results of the economic dispatch, we next analyze the HPP profit and the system operation costs. The following results were obtained from 1,000 Monte Carlo simulations, where each simulation scenario was distinguished by each HPP's PV generation, which was randomly sampled from its probability distribution.

A. HPP Profit

To compute the HPP profit, we assumed that 1) the HPP is paid for the bidding power with the clearing price, and 2) the HPP is penalized with the penalty price if the available HPP generation is less than the bidding power. Let non-negative $\check{P}^{\text{bt}}_{i,t}$ and $\hat{P}^{\text{bt}}_{i,t}$ denote the battery charge and discharge power, respectively. Define $P^{\text{ava}}_{i,t,n} := P^{\text{pv}}_{i,t,n} - \check{P}^{\text{bt}}_{i,t} + \hat{P}^{\text{bt}}_{i,t}$ as the available HPP power, where n is the index of Monte Carlo simulation number. Then we apply the following formula to compute the profit for HPP i at time t:

$$\text{profit}_{i,t,n} = \begin{cases} \pi^{\text{clr}}_t P^{\text{bid}}_{i,t} - \lambda^{\text{pv}}_i (P^{\text{bid}}_{i,t} - \hat{P}^{\text{bt}}_{i,t}) - \lambda^{\text{bt}}_i \hat{P}^{\text{bt}}_{i,t}, & \text{if } P^{\text{ava}}_{i,t,n} \geq P^{\text{bid}}_{i,t} \\ \pi^{\text{clr}}_t P^{\text{bid}}_{i,t} - \lambda^{\text{pv}}_i (P^{\text{pv}}_{i,t,n} - \check{P}^{\text{bt}}_{i,t}) - \lambda^{\text{bt}}_i \hat{P}^{\text{bt}}_{i,t} \\ \qquad - \lambda^{\text{pen}}_t (P^{\text{bid}}_{i,t} - P^{\text{ava}}_{i,t,n}), & \text{if } P^{\text{ava}}_{i,t,n} < P^{\text{bid}}_{i,t} \end{cases} \tag{11}$$

The first case calculates profit when available power meets or exceeds the bid power, while the second case calculates profit when available power is less than the bid power, including the under-generation penalty.

We first examine the impact of solar forecast accuracy on HPP profitability. Given that individual results for each HPP follow similar patterns, we devote this part of our analysis to one plant, HPP_1. Fig. 6 illustrates the 1,000 Mente Carlo simulation results for the HPP's daily profit under three solar uncertainty levels. The results indicate that increasing PV uncertainty negatively impacts HPP profitability under both methodologies. This decline in profit is mainly due to the increased penalties associated with power deficiencies, which

This report is available at no cost from the National Renewable Energy Laboratory at www.nrel.gov/publications.

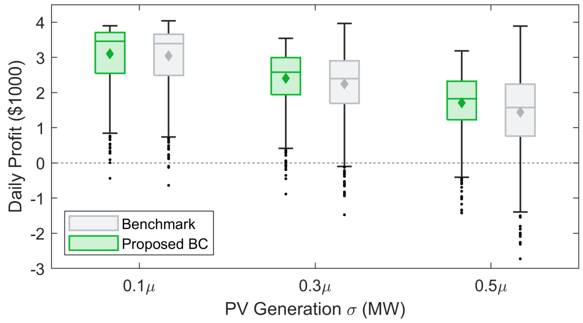

Fig. 6. HPP Profits under different solar uncertainty levels.

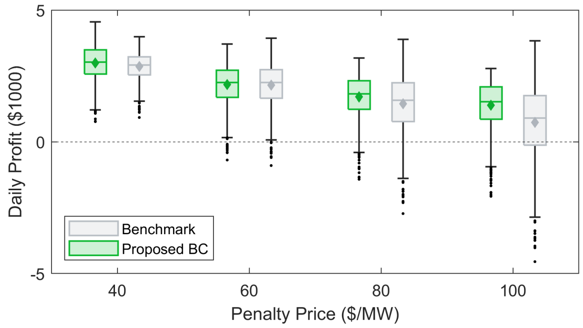

Fig. 7. HPP profits under different penalty prices.

become more noticable as PV forecast uncertainty increases. Furthermore, the results suggest that the proposed method consistently outperforms the benchmark method in managing the PV uncertainty in the sense that 1) the HPP expected profit is higher (this benefit is more significant when uncertainty is large), and 2) the width of the profit distribution (risk metric) is smaller and less sensitive to increasing penalty price.

We next explore the impact of penalty price on HPP profitability. Setting the solar uncertainty level $\beta = 0.5$, Fig. 7 illustrates HPP's daily profit under four penalty price scenarios, comparing the outcomes between the proposed bidding curve and the benchmark methods. It shows that, under both methods, the HPP profit decreases as the penalty price increases. However, using the bidding curve methodology, the HPP's profit is less sensitive to increasing penalty price than that uses the benchmark methodology. In the benchmark case, the HPP is bidding the same amount regardless of the penalty price and thus incurs more penalties for deficient generation when the penalty is higher.

In summary, the proposed bidding curve method consistently outperforms the benchmark across all examined PV uncertainty levels and penalty prices, in terms of the HPP profit. However, it is important to note the implications of aggressive bidding under low penalty prices. As illustrated in Fig. 8, overly aggressive bids can lead to a significant risk of unmet load in real time, potentially compromising system reliability. To understand these dynamics, the following subsection will investigate the overall system operation cost, providing a balanced view of the financial and operational impacts of the bidding strategies under different conditions.

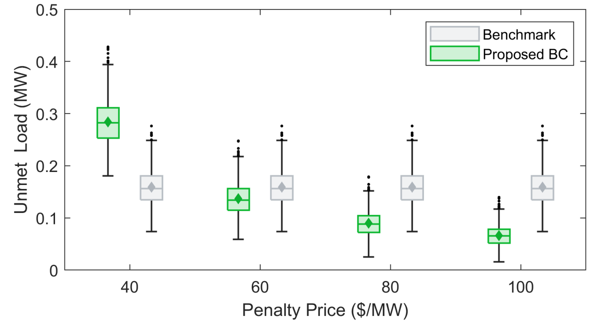

Fig. 8. Unmet load under different penalty prices.

B. System Operation Cost

A simple estimate of the daily operation cost can be calculated by multiplying each hour's clearing price by the corresponding load demand. However, this does not necessarily reflect the actual cost of meeting daily demand, as it overlooks the situation that any generation scheduled in the day-ahead market that is not fulfilled will have to be settled in the real-time market. In this market, electricity prices are volatile and can reach multiples of those in the day-ahead market [19]. To assess the system cost, we introduce a new parameter denoted as k, representing the ratio of clearing price in the day-ahead to the price in real time. This is applied to the portion of the demand that is not met by the generators. Therefore, the system operation cost to meet the load demand is calculated as follows:

$$c_{t,n}^{\text{op}} = \sum_{i=1}^{N_h} \sum_{t=1}^{24} \pi_t^{\text{clr}} \left(P_{i,t,n}^{\text{met}} + k \cdot P_{i,t,n}^{\text{unmet}} \right) \tag{12}$$

where

$$\begin{cases} P_{i,t,n}^{\text{met}} = P_{i,t}^{\text{bid}}, P_{i,t,n}^{\text{unmet}} = 0 & \text{if } P_{i,t,n}^{\text{ava}} \geq P_{i,t}^{\text{bid}} \\ P_{i,t,n}^{\text{met}} = P_{i,t,n}^{\text{ava}}, P_{i,t,n}^{\text{unmet}} = P_{i,t}^{\text{bid}} - P_{i,t,n}^{\text{ava}} & \text{if } P_{i,t,n}^{\text{ava}} < P_{i,t}^{\text{bid}} \end{cases}$$

The results of applying (12) with k = 1, 1.5, and 2.0 are presented in Fig. 9. It is evident that the system cost increases as the k increases. For a specific k, the system cost associated with the benchmark method remains the same across different penalty prices because its bidding strategy does not adapt to variations in penalty price. In contrast, the system cost under the proposed method decreases with increasing penalty prices, yielding different costs compared to the benchmark method. For the case of $k = 1$, the system does not incur additional cost to serve the unmet generation, so the uncertainty in PV generation does not affect the system cost, and the system cost is determined by the market clearing price. This is an unlikely case in practice, but it might serve as a reference case for comparison. For the case of $k = 1.5$, both the clearing prices and the unmet generation affect the system cost, and they both change with the different penalty prices. When the penalty price increases, the clearing price increases, and the unmet generation decreases. The net impact on the total system cost is not very significant, as observed from Fig. 9. For the case of $k = 2$, the cost to compensate for the unmet generation increases, emphasizing the importance of

This report is available at no cost from the National Renewable Energy Laboratory at www.nrel.gov/publications.

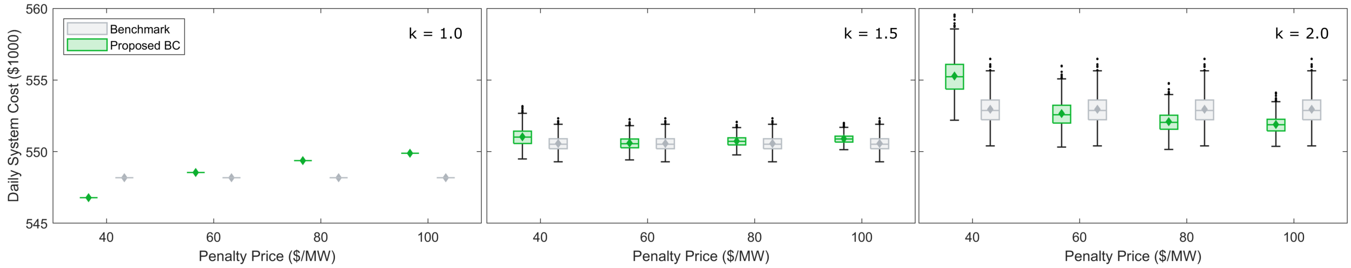

Fig. 9. System operation cost concerning different k values and penalty prices.

managing the uncertainty in the bidding strategy. In this case, the proposed bidding curves show more significant benefits, especially when the penalty prices increase. This suggests that system operators can employ the penalty price as a tool to lower system costs by discouraging overly aggressive HPP bidding strategies.

Discussion. The proposed bidding curve is designed to maximize an HPP's individual profit, and it could potentially compromise grid reliability if HPPs bid over aggressively to take advantage of the low penalty price. Meanwhile, as a way to prevent such grid reliability issues, it justifies the introduction of the penalty mechanism for the future high renewable penetration market to regulate the HPP bidding strategy. Generally, there is a tradeoff between maximizing HPP profit and minimizing system operation cost. The careful design of the penalty price is crucial to balance the HPP profit and the overall system operation cost to maintain grid efficiency and reliability.

V. Conclusions

The paper introduces a novel bidding curve for HPPs in the electricity market. The proposed bidding curve incorporates the PV uncertainty in the bidding power cost calculation, making it highly adaptable to fluctuating market conditions and varying levels of PV uncertainty. Through numerical study, we demonstrate the efficacy of the proposed bidding curve, showing the potential of this methodology to enhance both economic and operational performance in energy markets.

Several directions are considered for future research. We are particularly interested in investigating the penalty price in the future energy market with high renewable penetration. Understanding and optimizing penalty prices will provide grid operators with a valuable tool to enhance grid reliability and manage operational costs effectively. Additionally, we aim to develop new algorithms that treat battery scheduling as a control variable within the HPP bidding curve design. This will enable a more interactive and integrated bidding strategy between PV systems and battery storage, optimizing both energy utilization and economic returns.

References

[1] C. Brancucci Martinez-Anido, G. Brinkman, and B.-M. Hodge, "The impact of wind power on electricity prices," *Renewable Energy*, vol. 94, no. C, pp. 474–487, 2016. [Online]. Available: https://ideas.repec.org/a/eee/renene/v94y2016icp474-487.html

[2] C. Murphy, P. Brown, and V. Carag, "The roles and impacts of PV-Battery hybrids in a decarbonized U.S. electricity supply," National Renewable Energy Laboratory, Golden, CO, Technical Report NREL/TP-6A40-82046, 2022.

[3] K. Dykes, J. King, N. DiOrio, R. King, V. Gevorgian, D. Corbus, N. Blair, K. Anderson, G. Stark, C. Turchi, and P. Moriarty, "Opportunities for research and development of hybrid power plants," 2020.

[4] New York Independent System Operator, *Intermittent Power Resources: FAQ*. [Online]. Available: https://www.nyiso.com/documents/20142/20259596/Intermittent-Power-Resources-FAQ.pdf

[5] James Friedrich, "An imbalance reserve product to manage uncertainty between the day-ahead and real-time markets," https://tinyurl.com/26zcfkea, California Independent System Operator, 2024.

[6] California Independent System Operator, "Initiative: Day-ahead market enhancements," https://tinyurl.com/sk32frr8, accessed: 2024.

[7] ——, "Initiative: Extended day-ahead market," https://tinyurl.com/5t5bdyhs, accessed: 2024.

[8] D. Zhao, A. Botterud, and M. Ilic, "Uniform pricing vs pay as bid in 100%-renewables electricity markets: A game-theoretical analysis," in *Proceedings of the 14th ACM International Conference on Future Energy Systems*, 2023, pp. 236–241.

[9] E. Spyrou, R. B. Hytowitz, B. F. Hobbs, M. Al-Ashery, M. Cai, E. Ela, and Y. Zhang, "Flexibility auctions: A framework for managing imbalance risk," National Renewable Energy Lab.(NREL), Golden, CO (United States), Tech. Rep., 2022.

[10] H. Mohsenian-Rad, "Optimal bidding, scheduling, and deployment of battery systems in california day-ahead energy market," *IEEE Transactions on Power Systems*, vol. 31, no. 1, pp. 442–453, 2015.

[11] A. Attarha, N. Amjady, and S. Dehghan, "Affinely adjustable robust bidding strategy for a solar plant paired with a battery storage," *IEEE Transactions on Smart Grid*, vol. 10, no. 3, pp. 2629–2640, 2018.

[12] X. Huang, Z. Zhang, Y. Lin, and Y. Chen, "Arbitrage and capacity firming in coordination with day-ahead bidding of a hybrid pv plant," in *2022 IEEE Power & Energy Society General Meeting (PESGM)*. IEEE, 2022, pp. 1–5.

[13] C. Ruiz and A. J. Conejo, "Pool strategy of a producer with endogenous formation of locational marginal prices," *IEEE Transactions on Power Systems*, vol. 24, no. 4, pp. 1855–1866, 2009.

[14] S. Bhattacharjee, R. Sioshansi, and H. Zareipour, "Energy storage participation in wholesale markets: The impact of state-of-energy management," *IEEE Open Access Journal of Power and Energy*, vol. 9, pp. 173–182, 2022.

[15] S. Shafiee, H. Zareipour, and A. M. Knight, "Developing bidding and offering curves of a price-maker energy storage facility based on robust optimization," *IEEE Transactions on Smart Grid*, vol. 10, no. 1, pp. 650–660, 2017.

[16] G. De Vivero-Serrano, K. Bruninx, and E. Delarue, "Implications of bid structures on the offering strategies of merchant energy storage systems," *Applied energy*, vol. 251, p. 113375, 2019.

[17] J. R. Cruise, L. Flatley, and S. Zachary, "Impact of storage competition on energy markets," *European Journal of Operational Research*, vol. 269, no. 3, pp. 998–1012, 2018.

[18] R. Sioshansi, "When energy storage reduces social welfare," *Energy Economics*, vol. 41, pp. 106–116, 2014.

[19] R. Das, R. Bo, H. Chen, W. Ur Rehman, and D. Wunsch, "Forecasting nodal price difference between day-ahead and real-time electricity markets using long-short term memory and sequence-to-sequence networks," *IEEE Access*, vol. 10, pp. 832–843, 2022.

This report is available at no cost from the National Renewable Energy Laboratory at www.nrel.gov/publications.