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Data-Driven Chance-Constrained Capacity Offering for Wind-Electrolysis Joint Systems

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ABSTRACT An alkaline water electrolyzer (AWE) that converts surplus electricity from fluctuating power of a wind farm (WF) is a promising technology for large-scale and cost-effective hydrogen production. By considering the complementarity of the AWEs and the WF in offering market services, this paper treats the AWE and the WF as a coalition and proposes a joint bidding strategy in the energy and regulation markets to maximize the coalition's revenue. To overcome the influence of wind and hydrogen uncertainties, we first establish a data-driven distributionally robust chance-constrained bidding model, which reduces market risks by observing uncertainty-related chance constraints for any distribution in the ambiguity set. Then, we use the Shapley value method to evaluate the marginal contribution of the AWE and the WF. Further we propose a game-theory-based bidding revenue allocation scheme. Eventually, case studies based on real-world market data demonstrate that the total profit of the proposed joint bidding strategy increases 27.4% if compared with individual bidding strategy. The average marginal cost of hydrogen production can be reduced by 5.1 \$/kg if compared with only participating in the energy market.

INDEX TERMS Alkaline water electrolyzer, joint bidding, distributionally robust chance-constrained optimization, revenue allocation, wind power.

NOMENCLATURE

A. INDICES AND SETS

w	Set of wind farms (WFs).
e	Set of alkaline water electrolyzers (AWEs).
t	Set of time periods.
$\mathbb{P}$	Probability distribution.
D_0	Ambiguity set.

B. PARAMETERS

$P_{\mathrm{w,t}}$	Predicted power of the WF [MW].
P_{w}^{rate}	The rated capacity of the WF [MW].
$P_{\mathrm{e}}^{\min/\max}$	The minimum/maximum operating power by the AWE [MW].
$P_{\mathrm{e,up/dn}}$	The maximum ramping up /ramping down power [MW].
$L_{H,\min/\max}$	The minimum/maximum hydrogen production [kg].
$\lambda_{\mathrm{t}}^{DA/RT}$	Day-ahead/ real-time energy price [\$/MWh].
$\lambda_{\mathrm{reg,t}}^{\mathrm{cap/perf}}$	Capacity/ mileage price in the regulation market [\$/MWh].
H_P	Hydrogen market price [\$/kg].
η_{e}	Efficiency of the AWE.
$R_{\mathrm{t}}^{\mathrm{mil}}$	Mileage multiplier.
S_{t}	Performance score.
k_1/k_2	The maximum ratio of the qualified wind power/ AWE capacity for regulation to the rated capacity.

C. VARIABLES

$C_{\mathrm{w,t}}^{\mathrm{fle}}$	The total capacity flexibility of WF [MW].
$P_{\mathrm{w,t}}^{DA/RT}$	Capacity flexibility of WF in the day-ahead/ real-time energy market [MW].

$C_{\text{w,t}}^{\text{reg}}$ Capacity flexibility of WF in the regulation energy market [MW].
$C_{\text{w,t}}^{\text{up/dn}}$ Up-regulation/down-regulation by the WF [MW].
$U_{\text{w,t}}$ A binary variable representing participation in up-regulation.
$C_{\text{e,t}}^{\text{fle}}$ The total capacity flexibility of AWE [MW].
$P_{\text{e},t}^{DA/RT}$ Capacity flexibility of AWE in the day-ahead/ real-time energy market [MW].
$C_{\text{e,t}}^{\text{reg}}$ Capacity flexibility of AWE in the regulation energy market [MW].
$C_{\text{e,t}}^{\text{up/dn}}$ Up-regulation/down-regulation by the AWE [MW].
$P_{\text{e},t}^{\text{act}}$ The consumed electricity by AWE [MW].
h_t Hydrogen production [kg].
$U_{\text{e,t}}$ A binary variable representing participation in up-regulation.
P_{t}^{DA} The biddable capacity of WEJS in the day-ahead energy market [MW].
$C_{\text{t}}^{\text{up/dn}}$ Up-regulation/down-regulation capacities of WEJS [MW].
ΔP_{t} Total imbalance in the real-time market [MW].
$\Delta P_{\text{t}}^{+/-}$ Sold/purchased power in the real-time marke [MW].
μ_{t} Up-regulation/down-regulation capacities of WEJS [MW].
ΔP_{t} A binary variable that indicates whether buying power.

I. INTRODUCTION

With the aggravation of the energy crisis, green hydrogen production has attracted much attention due to its zero-carbon-emission characteristics. Currently, the industry adopts alkaline water electrolysis technology to convert surplus electricity from fluctuating renewable energy such as wind power, realizing cost-effective and large-scale hydrogen production [1]. In this situation, integrated alkaline water electrolyzers (AWEs) and renewable energy farms become grid-connected coalitions that are capable of providing various market services. From the perspective of these newly developed coalitions, it is essential to investigate profitable offering or bidding strategies across different markets.

Recently, the joint participation of heterogeneous distributed energy resource (DER) aggregators has attracted interest from researchers in energy arbitrage [2], [3], primary [4], [5], and regulation ancillary service [6], [7]. In the modern power system, flexible DERs or concentrating resources reshape both the demand and supply side flexibility and can participate in various markets including the ancillary service markets (ASM) [8]. The flexibility, which characterizes a resource's capacity to cover fluctuating demand, can be allocated via interrelated market interaction [9]. Battery energy storage systems (BESS) are among the most promising DERs for offering multi-market capacity flexibility. Various researchers investigate how BESS supports renewable generation in multiple markets [10], [11], [12]. Emulating large-scale generation, DERs can form virtual power plants (VPP) or aggregators to participate in markets [13]. Consequently, the joint bidding for economic, environmental, and other goals is intensively studied for VPPs and aggregators [14], [15], [16].

Though various studies have addressed joint bidding of DER-based VPPs and aggregators, very few researchers consider how a wind-electrolysis joint system (WEJS) behaves in joint energy and regulation markets. Similar to VPPs or aggregators, WEJSs can also flexibly participate in both energy and regulation markets [17]. Specifically, a WEJS can sell the hydrogen produced by AWEs to obtain extra profits, meaning that the WEJS can cooperatively offer capacity flexibility among triple markets (i.e., energy markets, regulation markets, and hydrogen markets). In [18], a coordinated energy-trading and benefit-sharing strategy based on Nash bargaining theory is proposed for the decision-making of wind-hydrogen fueling stations in the energy market. By considering the inherent spatiotemporal imbalance between renewable energy and hydrogen demand, [19] investigate the optimal investment and operation of electrolyzers and storage to increase wind power absorption. Ref. [20] presents optimal rating and dispatch plans for renewable energy-hydrogen production stations in the ancillary market.

The inherent uncertainty of wind significantly impacts its use as a resource for AWEs. To address this, existing research primarily relies on stochastic programming (SP) [21] and robust optimization (RO) [22]. SP assumes that decision-making is guided either by known probability distributions or by large datasets of samples. However, exact probability distributions are often impractical to obtain, and relying on sample-based methods can lead to errors when the dataset is insufficient. For instance, [23] introduces a two-stage stochastic optimization model for integrated electric and hydrogen systems to manage the uncertainty of wind power generation effectively. In contrast, RO identifies optimal solutions under worst-case scenarios by defining an uncertainty set. Although this approach provides robust results, it often leads to overly conservative outcomes. For example, [24] presents a robust bidding optimization model for wind-electrolysis systems operating in energy and regulation markets, explicitly accounting for wind uncertainty. To overcome these limitations, distributionally robust chance constraints (DRCC) have emerged as a promising alternative. DRCC strikes a balance between the flexibility of SP and the caution of RO, leveraging partial distributional information to provide moderate robustness. A KL-divergence-based DRCC model, as proposed in [25], effectively handles wind uncertainty and enhances the performance of wind-hydrogen-storage systems. Nevertheless, to the best of the knowledge of the authors, few researcher has considered the joint bidding of WEJSs under multiple uncertainties, which cannot be ignored due to the stochasticity and intermittency of wind power. The upstream wind power uncertainty directly leads to the downstream hydrogen uncertainty. Further, the conversion efficiency of the AWE is uncertain at different load ratios and ambient temperatures, aggravating the uncertainty of hydrogen production. The resulting dual uncertainties of wind energy and hydrogen simultaneously affect both the electricity and hydrogen markets, incurring security risks. Therefore, it is necessary to develop new bidding strategies to handle these dual uncertainties.

In addition, a fair revenue allocation scheme is preferred for both the WF and the AWE of the WEJS. There are generally three main methods for revenue allocation in cooperative game theory: the Shapley value method [26], the Nucleolus method [27], and the Bargaining solution [28]. In [29], an improved Shapley-value-based profit allocation method is introduced for multiple DERs within a combined heat and power virtual power plant (CHP-VPP), aiming to achieve optimal profit distribution. Similarly, [30] employs a cost allocation method based on the Nucleolus to ensure fair cost sharing among members of a microgrid alliance, thereby maintaining the economic stability of the alliance. Furthermore, [31] proposes a profit allocation model grounded in the Nash-Harsanyi bargaining game theory, which accounts for the actual contributions of individual participants. In this paper, the Shapley-value method, known for its properties of global and coalitional rationality, is utilized to fairly quantify participants' payoffs within an integrated model.

In this paper, we treat AWEs and WFs as a coalition and propose a joint risk-averse bidding strategy based on the data-driven DRCC optimization method. The aim of this paper is to explore an optimal trading mechanism for the WEJS and to solve the revenue allocation problems between AWEs and WFs. According to the comparisons in Table 1, the main contributions are summarized as follows:

- A cooperative scheme in the regulation markets for a WEJS to maximize the revenue is proposed. By considering the complementarity of AWEs and WFs in offering regulation services, AWEs and WFs are coupled to respond to upward or downward regulation signals to increase the regulation trading revenue and reduce the hydrogen production marginal cost.
- A risk-averse bidding strategy based on the data-driven DRCC model that implements the cooperative scheme is developed. The dual uncertainties of wind and hydrogen, are explicitly modeled by observing uncertainty-related chance constraints for distributions in the ambiguity set.
- A game-theory-based bidding profit-sharing mechanism to reasonably distribute the market revenue among AWEs and WFs is proposed. The Shapley value method is employed to evaluate the marginal contributions of AWEs and WFs.

The remainder of the paper is organized as follows. Section II presents the detailed model of the capacity flexibility of WFs and AWEs; Section III addresses the optimal bidding strategies and profit-sharing mechanism, and case studies and relevant results are presented in Section IV. Section V concludes the paper.

TABLE 1. Comparisons of related literature.

Ref.	Market participation			Uncertainty modeling	Revenue allocation
	Energy	Regulation	Hydrogen		
[17]	Yes	Yes	Yes	No	No
[18]	Yes	No	Yes	Conditional value-at-risk (price)	Yes
[20]	No	Yes	Yes	SP (demand and price)	No
[23]	Yes	No	No	SP (wind)	No
[24]	Yes	Yes	Yes	RO (wind)	No
[25]	Yes	No	No	Distributionally robust optimization (wind)	No
[31]	Yes	No	Yes	Distributionally robust optimization (wind and demand response)	Yes
This paper	Yes	Yes	Yes	DRCC (wind and hydrogen)	Yes

II. CAPACITY FLEXIBILITY OF WIND-ELECTROLYSIS JOINT SYSTEM

In this section, We first describe the general framework of multi-market participation of wind-electrolysis joint system. Then separately formulate the capacity flexibility of WFs and AWEs for participating in different markets. Next, we quantify the integrated capacity flexibility of the WEJSs considering the complementarity of WFs and AWEs. Eventually, we deploy the Wasserstein-distance-based ambiguity set to characterize the uncertain capacity flexibility of the WEJSs, which lays a foundation for the joint bidding model and strategy design in section III.

A. GENERAL FRAMEWORK OF MULTI-MARKET PARTICIPATION OF WIND-ELECTROLYSIS JOINT SYSTEM

Fig. 1 presents the general framework of WEJS participating in energy, regulation, and hydrogen markets. When participating in the energy market, the WF can exchange energy flexibility with the AWE to increase the overall benefits. Thus, the AWE enables the utilization of surplus wind power to realize arbitrage by selling the produced hydrogen in the hydrogen market, which is beneficial for the WEJS when the price gap between electricity and hydrogen is large. For the regulation market, the regulation power is distributed to utilize the complementary capacity flexibility of the WFs and AWEs. When the down-regulation requirement is released, the output of wind will be reduced first, and then the consumption of the AWE will be increased. In contrast, while the up-regulation is required, the consumption of the AWE will be reduced first, and then the output of wind will be increased.

B. CAPACITY FLEXIBILITY OF WIND FARM

By dispatching power control orders to individual wind turbines, a WF can preserve capacity flexibility by flexibly allocating its capacity in different electricity markets (e.g.,

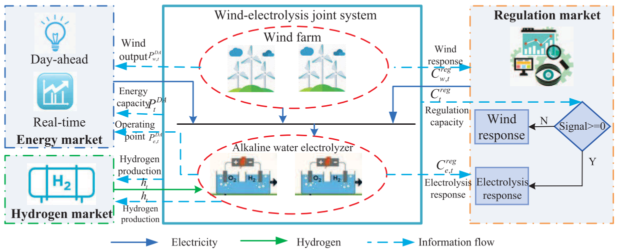

FIGURE 1. Frame of participating in energy, regulation, and hydrogen market.

energy and regulation markets). Eqs. (1)-(5) shows the capacity flexibility of a WF in the form of operating constraints. Eq. (1) represents the overall WF capacity flexibility, which contains the capacity flexibility in the day-ahead energy market and regulation market. Eq. (2) indicates that the regulation bid includes up-regulation and down-regulation. Due to the ramping limits of the wind generator, eq. (3) enforces that day-ahead energy market capacity flexibility minus the down-regulation capacity flexibility cannot be lower than zero. Eq. (4) enforces that day-ahead market capacity flexibility plus the up-regulation capacity flexibility cannot surpass the maximal available power. Eqs. (5)-(6) show maximal up-regulation and down-regulation capacity, in which κ_1 denotes the maximum ratio of the qualified wind power capacity for regulation to the rated capacity P_w^{rate} and $U_{\text{w},t}$ is a binary variable representing the state of wind.

$$C_{\text{w},t}^{\text{fle}} = P_{\text{w},t}^{\text{DA}} + C_{\text{w},t}^{\text{reg}} \tag{1}$$

$$C_{\text{w},t}^{\text{reg}} = C_{\text{w},t}^{\text{up}} + C_{\text{w},t}^{\text{dn}} \tag{2}$$

$$P_{\text{w},t}^{\text{DA}} - C_{\text{w},t}^{\text{dn}} \geq 0 \tag{3}$$

$$P_{\text{w},t}^{\text{DA}} + C_{\text{w},t}^{\text{up}} \leq P_{\text{w},t} \tag{4}$$

$$C_{\text{w},t}^{\text{up}} \leq \kappa_1 P_{\text{w}}^{\text{rate}} U_{\text{w},t} \tag{5}$$

$$C_{\text{w},t}^{\text{dn}} \leq \kappa_1 P_{\text{w}}^{\text{rate}} (1 - U_{\text{w},t}) \tag{6}$$

C. CAPACITY FLEXIBILITY OF ALKALINE WATER ELECTROLYZER

Currently, the commonly used electrolytic hydrogen production devices include alkaline water electrolysers and proton exchange membrane (PEM) electrolysers. This study focuses on AWE modeling; however, as demonstrated in [32], PEM electrolyzers can also be integrated into the proposed model if required. Specifically, AWEs can provide grid flexibility services by changing power consumption. Eq. (7) describes the overall capacity flexibility of the AWE across energy and regulation markets. Eq. (8) indicates that the regulation bid including up-regulation and down-regulation. The consumed electricity by the AWE is shown in (9). Eq. (10) enforces that the range of the consumed and purchased electricity by the AWE is constrained by the maximum operating power and minimum operating power of the AWE. Eq. (11) shows the ramping constraint for the AWE, $P_{\text{e,up}}$ and $P_{\text{e,dn}}$ represent maximum ramping up and ramping down power. Eq. (12) shows the constraints for the regulation capacity, $C_e^{\text{reg,min}}$ and $C_e^{\text{reg,max}}$ are the minimum and maximum regulation capacity. Upward and downward regulation capacities limits are presented in (13) and (14), respectively. $U_{\text{e},t}$ is a binary variable that indicates whether AWEs are participating in the up-regulation market. The relation between hydrogen production h_t and power consumption $P_{\text{e},t}^{\text{act}}$ is given in (15). $\eta_e\left(P_{\text{e,t}}^{act}\right)$ represents the efficiency of the AWE, which is affected by the consumed power $P_{\text{e},t}^{\text{act}}$. This is a nonlinear constraint, and we deploy the piecewise linear method to approximate it [33]. Considering the hydrogen load requirements, the output of the AWE should satisfy the boundary constraint, as shown in Eq. (16).

$$C_{\text{e},t}^{\text{fle}} = P_{\text{e},t}^{\text{DA}} + C_{\text{e},t}^{\text{reg}} \tag{7}$$

$$C_{\text{e},t}^{\text{reg}} = C_{\text{e},t}^{\text{up}} + C_{\text{e},t}^{\text{dn}} \tag{8}$$

$$P_{\text{e},t}^{\text{act}} = P_{\text{e},t}^{\text{DA}} + C_{\text{e},t}^{\text{dn}} - C_{\text{e},t}^{\text{up}} \tag{9}$$

$$P_{\text{e}}^{\text{min}} \leq P_{\text{e},t}^{\text{act}}, P_{\text{e},t}^{\text{DA}} \leq P_{\text{e}}^{\text{max}} \tag{10}$$

$$-P_{\text{e,dn}} \leq P_{\text{e},t}^{\text{DA}} - P_{\text{e},t-1}^{\text{DA}} \leq P_{\text{e,up}} \tag{11}$$

$$0 \leq C_{\text{e},t}^{\text{reg}} \leq \kappa_2 P_{\text{e}}^{\text{max}} \tag{12}$$

$$0 \leq C_{\text{e},t}^{\text{up}} \leq (P_{\text{e},t}^{\text{DA}} - P_{\text{e}}^{\text{min}}) U_{\text{e},t} \tag{13}$$

$$0 \leq C_{\text{e},t}^{\text{dn}} \leq (P_{\text{e}}^{\text{max}} - P_{\text{e},t}^{\text{DA}})(1 - U_{\text{e},t}) \tag{14}$$

$$h_t = \eta_e\left(P_{\text{e},t}^{\text{act}}\right) P_{\text{e},t}^{\text{act}} \tag{15}$$

$$L_{\text{H,min}} \leq \sum_{t=1}^{T} h_t \Delta t \leq L_{\text{H,max}} \tag{16}$$

D. COMPLEMENTARY CAPACITY FLEXIBILITY OF WIND FARM AND ALKALINE WATER ELECTROLYZER COALITION

WFs and AWEs have different flexibility characteristics. Specifically, on one hand, wind energy is generally considered a good candidate for regulation provision due to its fast response-ability. On the other hand, however, it is desired for wind plants of the WF to adopt maximum power point tracking (MPPT) mode to achieve full utilization of renewable energy. When offering down-regulation services, the WF can directly profit by reducing generation. However, in order to provide up-regulation services, the WF is forced to reduce power output to spare certain capacity for up-regulation need, which reduces the expected profit of offering this reduced power in the markets. Therefore, it is more profitable to use WFs to provide down-regulation than to provide up-regulation services.

Similar to WFs, directly controlling AWEs to participate in regulations will cause negative effects. To provide down-regulation services, the AWE needs to reduce the load ratio to reserve a considerable amount of power, which will lead to the reduction of the hydrogen production and extra power purchase to fill this hydrogen imbalance. Contrarily, when offering up-regulation services, the AWE can simply reduce consumption in response to automated signals. Therefore, it is more profitable to use AWEs to provide up-regulation than to provide down-regulation services.

Based on the analyses above, WFs and AWEs are highly complementary to each other in providing frequency regulation (FR) services. By taking advantage of this complementary flexibility, WFs and AWEs can operate in a cooperative mode to participate in FR. The up-regulation signals are primarily responded by reducing the power consumption of AWEs while the down-regulation signals primarily responded by reducing the power output of WFs. In the cooperative mode, both $P_{\mathrm{w},t}^{\mathrm{DA}}$ and $P_{\mathrm{e},t}^{\mathrm{DA}}$ can be close to the maximum power. The increase in $P_{\mathrm{w},t}^{\mathrm{DA}}$ and $P_{\mathrm{e},t}^{\mathrm{DA}}$ can reduce the reserved wind capacity and increase hydrogen production.

It should be noted that, in practice, the optimal utilization of these resources depends on a range of complex factors. On the one hand, technical aspects such as responsiveness, operating range, and efficiency play a critical role. On the other hand, economic considerations, including market prices, access to markets, wind profitability, and business models, significantly influence decision-making. Future research could further investigate the interactions between these factors and their impact on real-world outcomes.

E. UNCERTAINTY OF CAPACITY FLEXIBILITY OF WIND FARM AND ALKALINE WATER ELECTROLYZER

The WF capacity flexibility can be uncertain due to the uncertainty of wind power forecasting. In addition, the capacity flexibility of wind power-driven AWE is also uncertain. Therefore, characterizing the uncertainty capacity flexibility before proposing the bidding strategy is needed. It should be noted that the probability distribution function (PDF) of neither wind power nor hydrogen is known, and it is difficult to evaluate the PDF accurately. In this paper, we adopt the DRCC method and build a data-driven ambiguity set to characterize the uncertainties in the capacity flexibility model. Instead of using the moment ambiguity set which may lead to overly conservative solutions, we adopt the Wasserstein-metric-based ambiguity set for more flexible representation. Wasserstein-metric-based ambiguity set measures the distance between probability distributions, allowing the ambiguity set to capture complex distributions that may not be well-represented by a simple geometric shape in the traditional box or ellipsoidal ambiguity sets. Let $\xi = \left[P_{\mathrm{w},t}, P_{\mathrm{e},t}\right]$ denote the set of random parameters in the capacity flexibility model. Based on the sample set $\left\{\xi_i^1, \xi_i^2, \ldots, \xi_i^N\right\}_{i=1,2}$, the empirical distribution $\mathbb{P}_i^N$ which can be regarded as an estimation of the true distribution is formulated as follows:

$$\mathbb{P}_i^N = \frac{1}{N}\sum_{j\in N}\delta_{\xi_i^j} \tag{17}$$

where $\delta_{\xi_i^j}$ represents the Dirac measure on ξ_i^j and N denotes the value of independent samples.

The distance between two discrete distributions of $\mathbb{P}$ and $\mathbb{P}_i^N$ is formulated by:

$$W\left(\mathbb{P}, \mathbb{P}_i^N\right) = \inf\left\{\int d\left(\xi_i^1, \xi_i^2\right)\prod\left(d\xi_i^1, d\xi_i^2\right)\right\} \tag{18}$$

$$d\left(\xi_i^1, \xi_i^2\right) = \left\|\xi_i^1 - \xi_i^2\right\| \tag{19}$$

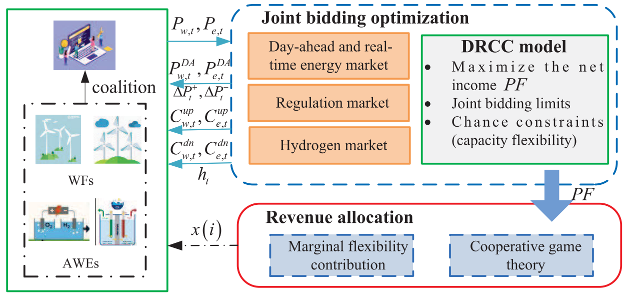

FIGURE 2. The proposed framework for the joint bidding and revenue allocation of WEJS.

where, $\prod\left(d\xi_i^1, d\xi_i^2\right)$ denotes the joint distribution of ξ_i^1 and ξ_i^2 with marginal distribution $\mathbb{P}$ and $\mathbb{P}_i^N$, respectively; d is a 1-norm function.

The ambiguity set is defined as:

$$D_0 = \left\{\mathbb{P} \in M(\Xi) \,\middle|\, W\left(\mathbb{P}_i^N, \mathbb{P}\right) \le \rho\right\} \tag{20}$$

where, $M(\Xi)$ is a Wasserstein ball centered on the empirical distribution with radius ρ. The radius ρ controls the degree of the conservativeness of the model, which can be expressed as:

$$\rho = D\sqrt{\frac{2}{N}\log\left(\frac{1}{1-\beta}\right)} \tag{21}$$

where β represents the prescribed confidence level and D denotes the constant coefficient.

III. OPTIMAL JOINT BIDDING STRATEGY OF WIND-ELECTROLYSIS JOINT SYSTEM

This section presents the proposed joint bidding strategy for the WEJS. In this study, it is assumed that hydrogen generated by AWEs can be stored indefinitely in a hydrogen tank without degradation or loss. Moreover, both wind energy and AWEs are treated as price-takers, submitting bids in the day-ahead market and clearing deviations in the real-time market [34]. The overall optimization framework is presented in Fig. 2, which includes an optimal bidding strategy and a revenue allocation mechanism. Furthermore, we formulate a risk-averse bidding model based on the DRCC method to deal with the uncertainties associated with WF and AWE capacity flexibility.

A. JOINT BIDDING OPTIMIZATION MODEL: DETERMINISTIC CASE

The objective of the optimal bidding strategy, as expressed in Eq. (22), is to maximize the revenue PF. Here, PF represents the total profit, which encompasses the combined revenue from the energy, regulation, and hydrogen markets. Eq. (23) defines the revenue PF^{E} from the energy market, which consists of two components: 1) the revenue from the day-ahead energy market, and 2) the imbalance cost resulting from deviations between day-ahead commitments and real-time deliveries, settled at the real-time market price. This two-settlement structure ensures that the WEJS accounts for both commit and actual energy schedules. Eq. (24) describes the revenue PF^{R} from the regulation market, modeled using a performance-based regulation scheme inspired by the PJM market [35]. The regulation revenue includes two parts: 1) the capacity payment (the first term in (24)), which compensates for the reserved regulation capability, and 2) the performance payment (the second term in (24)), which rewards the actual mileage provided during regulation service. Eq. (25) represents the revenue PF^{H} from the hydrogen market, where participants submit hydrogen production offers to the system operator (SO). The SO optimizes these offers and clears the market to determine the accepted hydrogen production quantities, which are settled at the hydrogen market price H_{P}.

$$PF = PF^{\mathrm{E}} + PF^{\mathrm{R}} + PF^{\mathrm{H}} \tag{22}$$

$$PF^{\mathrm{E}} = \sum_{t}^{T} (\lambda_t^{\mathrm{DA}} P_t^{\mathrm{DA}} + \lambda_t^{\mathrm{RT}} \Delta P_t^{+} - \lambda_t^{\mathrm{RT}} \Delta P_t^{-}) \tag{23}$$

$$PF^{\mathrm{R}} = \sum_{t}^{T} (\lambda_{\mathrm{reg},t}^{\mathrm{cap}} C_t^{\mathrm{reg}} S_t + \lambda_{\mathrm{reg},t}^{\mathrm{perf}} C_t^{\mathrm{reg}} R_t^{\mathrm{mil}} S_t) \tag{24}$$

$$PF^{\mathrm{H}} = H_{\mathrm{P}} \sum_{t}^{T} h_t \tag{25}$$

$$P_t^{\mathrm{DA}} = P_{\mathrm{w},t}^{\mathrm{DA}} + P_{\mathrm{e},t}^{\mathrm{DA}} \tag{26}$$

$$C_t^{\mathrm{up}} = C_{\mathrm{w},t}^{\mathrm{up}} + C_{\mathrm{e},t}^{\mathrm{up}} \tag{27}$$

$$C_t^{\mathrm{dn}} = C_{\mathrm{w},t}^{\mathrm{dn}} + C_{\mathrm{e},t}^{\mathrm{dn}} \tag{28}$$

$$(3) - (6), (9) - (16) \tag{29}$$

$$\Delta P_t = P_{\mathrm{w},t}^{\mathrm{DA}} - P_{\mathrm{w},t}^{\mathrm{RT}} + P_{\mathrm{e},t}^{\mathrm{DA}} - P_{\mathrm{e},t}^{\mathrm{RT}} \tag{30}$$

$$\Delta P_t = \Delta P_t^{+} - \Delta P_t^{-} \tag{31}$$

$$0 \leq \Delta P_t^{+} \leq \mu_t P_{\mathrm{im}}^{\max} \tag{32}$$

$$0 \leq \Delta P_t^{-} \leq (1 - \mu_t)\, P_{\mathrm{im}}^{\max} \tag{33}$$

The constraints of the optimal bidding strategy of the WEJS are described in (26)-(30). Eq. (26) indicates the day-ahead supply of energy. Eqs. (27)-(28) indicate the up-regulation and down-regulation capacities that are supplied by the aggregated flexibility of the WEJS. The up-regulation capacity is mainly offered by the AWE, whereas the down-regulation capacity is provided by the WF. The constraint for wind farms and the AWE participating in the energy and regulation market is stated in (29). Eqs. (30)-(33) show the constraints for system imbalance.

B. JOINT BIDDING OPTIMIZATION MODEL: STOCHASTIC CASE

This section studies how the WEJS achieves the risk-averse bidding strategy under uncertainties. We use chance constraints to formulate the bidding limits of WEJS, thus enhancing the system reliability under ambiguous sets:

$$\inf_{P \in D_0} \mathrm{E}_{\mathrm{P}} \left(P_{\mathrm{w},t}^{\mathrm{DA}} + C_{\mathrm{w},t}^{\mathrm{up}} \leq P_{\mathrm{w},t} \right) \geq 1 - \varepsilon \tag{34}$$

$$\inf_{P \in D_0} \mathrm{E}_{\mathrm{P}} \left(L_{\mathrm{H,min}} \leq \sum_{t=1}^{T} h_t \Delta t \leq L_{\mathrm{H,max}} \right) \geq 1 - \varepsilon \tag{35}$$

where $\varepsilon \in (0, 1)$ represents the risk tolerance of the chance constraint, which specifies the maximum allowable probability of constraint violation. A smaller ε reflects a more risk-averse approach, ensuring stricter adherence to the constraint, while a larger ε indicates a higher tolerance for risk, allowing for a greater probability of constraint violation. The complete optimization model is formulated as follows:

$$\max\ (22) \tag{36}$$

$$s.\ \mathrm{t.:}\ (3), (5),(10)\text{-}(15),(23)\text{ - }(28), (30) - (35) \tag{37}$$

The non-convex nature of chance constraints often poses significant challenges in deriving a tractable reformulation. In this paper, we address this issue by employing a Conditional Value-at-Risk (CVaR) approximation method, which offers a more practical and efficient approach for handling the complexity of such constraints.

The general formulation of DRCCs can be expressed as follows:

$$\inf_{\mathbb{P} \in \mathcal{D}} \mathbb{P} \left\{ \alpha_k(x)\, \tilde{\xi}_i \leq \beta_k(x) \right\} \geq 1 - \varepsilon \tag{38}$$

where the chance constraint is indexed by k. α_k and β_k represent affine mappings. Based on the CVaR constraints, Eq. (38) is approximated by:

$$\sup_{\mathbb{P} \in D_0} \mathbb{P} - CVaR_{\varepsilon} \left\{ \alpha_k(x)\, \tilde{\xi}_i \leq \beta_k(x) \right\} \leq 0,\ \forall k \leq K \tag{39}$$

Based on the polyhedron set $\Xi = \left\{ H\tilde{\xi}_i \leq h \right\}$, Eq. (39) can be further formulated as the explicit conic form:

$$\inf_{\mathbb{P} \in \mathrm{D}_0} \mathbb{P} \left\{ \alpha_k(x)\, \tilde{\xi}_i \leq \beta_k(x) \right\} \geq \varepsilon$$
$$= \begin{cases} \lambda_k \rho + \dfrac{1}{N} \displaystyle\sum_{n=1}^{M} s_{ik} \leq 0 \\ \tau_k \leq s_{ik} \\ \alpha_k(x)\, \tilde{\xi}_i - \beta_k(x) + (\varepsilon - 1)\, \tau_k + \varepsilon \gamma_{ik}^{T} \left(h - H\tilde{\xi}_i \right) \\ \leq \varepsilon s_{ik} \\ \left\| \varepsilon H^{T} \gamma_{ik} - \alpha_k \right\|_{*} \leq \varepsilon \lambda_k \end{cases} \tag{40}$$

where λ_k, s_{ik} and τ_k denote auxiliary variables. γ_{ik} is a decision variable. N represents the sample sizes.

C. COOPERATIVE GAME-THEORY-BASED PROFIT ALLOCATION METHOD

Due to the complementary capacity flexibility of WFs and AWEs, they can obtain more revenue from cooperation. Thus, the surplus profits demand a reasonable payoff allocation to share between the WF and the AWE. In this section, considering the flexibility performance of each participator, we employ the cooperative game theory method to fairly distribute the revenue. The collaborative revenue v is formulated

TABLE 2. Parameters of alkaline water electrolyzers.

Electrolysis system	Rated power (MW)	Minimum power(MW)	Maximum power(MW)
AWE1	50	10	50
AWE2	50	20	50

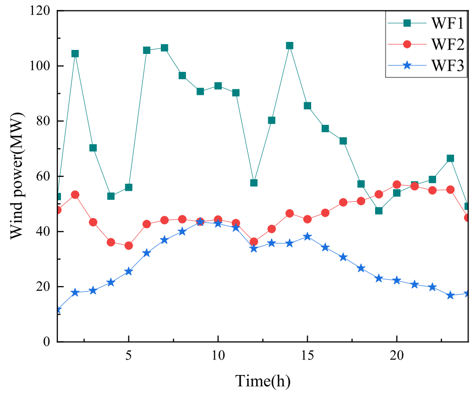

FIGURE 3. Wind power data for a sample day.

in (41). The Shapley value of each participator can represent its flexibility performance and marginal contribution in the coordinated bidding behavior, which can be determined by (42) [27].

$$v = \sum_{i=1}^{n} x_i \forall i \in n \tag{41}$$

$$x_i(v) = \sum_{S \subseteq N\backslash i} \frac{m!\,(n-m-1)!}{n!}\left[v\left(S \cup \{i\}\right) - v\left(S\right)\right] \tag{42}$$

where, x_i represents the allocated revenue of the ith participator, and $v(\cdot)$ denotes the revenue of each possible coalition. The set of all coalitions is denoted as S, and $S \subseteq N\backslash i$ is the set of all sub-coalitions without ith participator. $x_i(v)$ represents the Shapley value of ith participator, which is calculated based on the weighted average of its marginal contributions to each sub-coalition.

IV. CASE STUDY

In this section, we test the performance of the proposed bidding strategy using real market data. All simulations are implemented on a laptop with 2.50 GHz, Intel Core i7-7200 CPU using Gurobi and Matlab.

A. DATA INFORMATION

Three WFs and two AWEs are selected with different capacity flexibility to verify the performance of the proposed strategy. Fig. 3 shows the average wind power curve for a sample day. Parameters of the AWEs are listed in Table 2. The maximum ratio of the capacity flexibility of WFs and AWEs to regulation capacity (κ_1 and κ_2) is 30% and 50%, respectively.

We use historical WF data in Fig. 3 from the PJM market to build the ambiguity set [36]. The expected energy prices, including day-ahead, real-time market prices, regulation market capacity clearing prices, and regulation market performance clearing prices are obtained from the PJM market [36] and presented in Fig. 4. The average mileage ratio of RegD and performance score are calculated based on their historical performance. The hydrogen price is set at 6 $\$/kg$ [37].

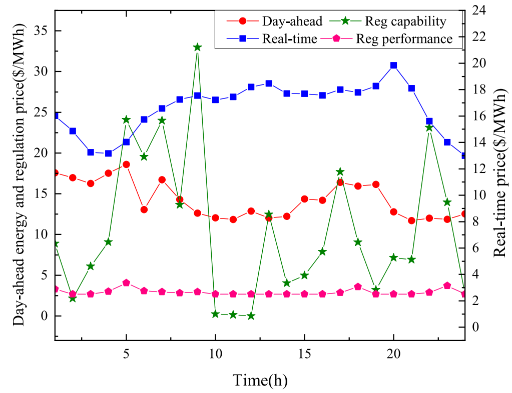

FIGURE 4. Expected hourly energy prices and capacity/ performance regulation prices.

TABLE 3. Economic benefit comparison of different cases.

Case No.	Energy revenue($)	Regulation revenue($)	Hydrogen revenue($)	Total revenue($)
Case 1	24,513	9,021	2,449	35,983
Case 2	38,758	12,688	3,300	54,746
Case 3	30,323	0	2,160	32,483

B. COMPARISON OF STOCHASTIC BIDDING AND REVENUE ALLOCATION RESULTS

We study the following three bidding cases:

Case 1: Individual bidding strategy, in which WFs and AWEs participate in the joint markets separately, without any coordination or cooperation.

Case 2: Coordinated bidding strategy I, in which WFs and AWEs participate in the joint markets cooperatively.

Case 3: Coordinated bidding strategy II, in which WFs and AWEs only bid in the energy market cooperatively.

Fig. 5 shows stochastic bidding results on a typical day. Fig. 5 (a) presents the bidding results of WFs and AWEs participating in the joint markets separately. Fig. 5 (b) shows the bidding results of the WEJS in the joint markets, and Fig. 5 (c) presents the bidding results of the WEJS participating only in the energy market. Compared with the individual bidding strategy in Fig. 5 (a), the WFs provide less capacity in the up-regulation market under the cooperative strategy. The average wind power excess shown in Fig. 5 (b) is reduced by approximately 4% of the rated wind power. Most of the AWE capacity is submitted to the down-regulation market and the hydrogen production is increased by 10.6 %.

Table 3 compares the economic profits for the three cases. Compared with the individual bidding strategy in case 1, the

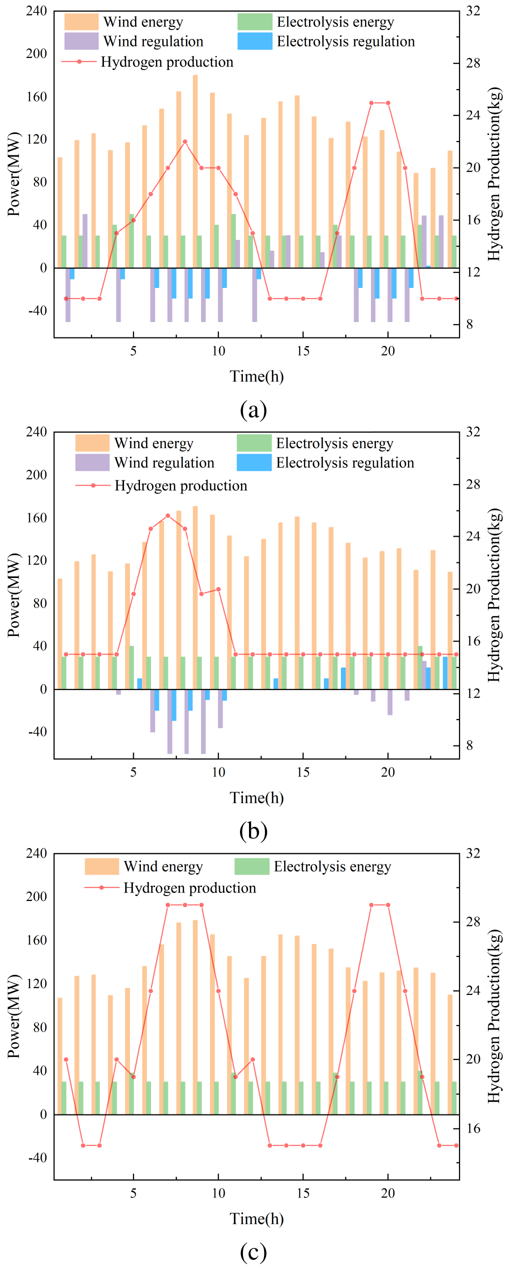

FIGURE 5. DRCC bidding results (a) Case 1 (b) Case 2 (c) Case 3.

regulation revenue of the WEJS in case 2 gives an increase of 28.9 %, which indicates that the proposed cooperative strategy can effectively improve regulation bidding profits by taking advantage of the complementarity of AWEs and WFs in offering FR services. It can also be observed that the hydrogen revenue of the WEJS in case 2 increases from \$2,449 to \$3,300, and the total revenue increases 34.3%, which further demonstrates the benefits of cooperative strategy for the joint markets bidding. In case 1, the total cost of the AWE for purchasing electricity is \$5,504, while the revenue for selling hydrogen is \$2,449. It indicates that the AWE can hardly benefit from converting electricity into hydrogen in the energy market. This is reasonable since the purchasing price is generally higher than that of hydrogen and the efficiency of the electrolysis is relatively low. Meanwhile, the AWEs can profit from providing regulation services, which is \$4,061. The revenue of the AWEs can be significantly improved by considering regulation services, which makes the total payoff of the AWE positive. The marginal benefit of the AWE from participating in the regulation market can be formulated as:

TABLE 4. Comparison of results of allocated profits based on the game-theory methods.

Player	Uncoordinated profits (\$)	Shapley-value method	
		Profit (\$)	Surplus profit (\$)
WF1	6,073	8,896	2,823
WF2	7,011	10,367	3,356
WF3	11,756	16,364	4,608
AWE1	5,854	9,251	3,397
AWE2	5,289	9,867	4,578

$$\begin{aligned}\Delta Income_t = \eta_e H_p \left(P_{e,t}^{DA} - S_t C_t^{reg}\right) \\ \times C_t^{reg}\left(\lambda_{reg,t}^{cap} + \lambda_{reg,t}^{perf} R_t^{mil}\right) \\ - \eta_e H_p P_{e,t}^{DA}\end{aligned} \tag{43}$$

Then the reduced marginal cost of hydrogen production by participating in the frequency market is:

$$\Delta Cost = \Delta Income/h = \frac{\lambda_{reg,t}^{cap} + \lambda_{reg,t}^{perf} R_t^{mil}}{\eta_e \left(1 - S_t\right)} - \frac{H_p S_t}{1 - S_t} \tag{44}$$

Under case 2, the average marginal cost of hydrogen production is reduced by 5.1 $\$/kg$, which shows that the WEJS participating in the regulation market can effectively reduce the cost of hydrogen production. When comparing Case 2 with Case 3, the total revenue in Case 2 is 40.6% higher, highlighting the significant economic benefits derived from regulation market participation. While the total cost in Case 3 is lower than in Case 1, the results clearly demonstrate that mere participation in the energy market does not yield the expected economic benefits. Instead, it is the inclusion of regulation market participation that drives substantial improvements in overall performance. This highlights the strategic importance of leveraging both energy and regulation markets to maximize profits. Therefore, it is advantageous for market participants to engage in both the energy and regulation markets simultaneously.

Through the Shapley allocation method, the payoffs of WF and the AWE are reallocated based on their contributions to the coalition, which is presented in Table 4. The results indicate that the reallocated profit for the WFs in case 2 is \$35,627, which shows a 30.3% increase compared with case 1. In addition, it can be observed that the surplus profits are not equally distributed among WFs and AWEs. For WFs, more profits is allocated to the WF3, while for AWEs, more profit is allocated to AWE2. The total surplus profit can reach \$18,763, which further demonstrates that the coordination of the WFs and the AWES can bring more profits.

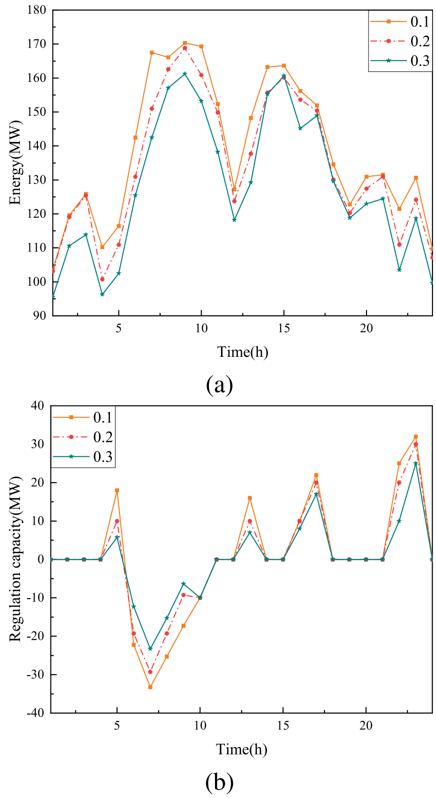

FIGURE 6. Comparison among bidding results with different Wasserstein radius (a) WFs (b) AWEs.

C. ANALYSIS OF ROBUSTNESS

1) IMPACT OF WASSERSTEIN RADIUS

We conduct a sensitivity analysis of the Wasserstein radius to verify its impact on the bidding results. When the Wasserstein radius ranges from 0.1 to 0.3, the bidding results in case 1 are shown in Fig. 6. From Fig. 6, it can be observed that with the increase of the value of the Wasserstein radius, energy arbitrage and regulation bids will decrease, leading to lower profits. The reason is that the Wasserstein radius measures the distance between the true distribution and the empirical distribution. A large Wasserstein radius introduces higher uncertainty and thus leads to a more conservative bidding strategy and a decrease in wind utilization and revenue. In contrast, a small Wasserstein radius may cause high penalty costs due to disqualified market performance. The result illustrates that a compromise between economic benefit and robustness can be prescribed and regulated by the Wasserstein radius.

Furthermore, Fig. 7 illustrates the impact of the Wasserstein radius ρ on CVaR and expected profit in case 2 (joint market) and case 3 (energy market). The Wasserstein radius ρ quantifies the range between the possible distribution and the empirical distribution, with larger values of ρ indicating higher levels of uncertainty. As depicted in Fig. 7, an increase in the Wasserstein radius leads to a decrease in profit and an increase in risk (CVaR). By comparing Fig. 7 (a) and (b), it is evident that participation in the joint market yields higher profits and lower risks compared to the single energy market. Additionally, the results demonstrate that the single market is more susceptible to uncertainty. Specifically, in the energy market, CVaR nearly reaches its peak at a certain value of $\rho = 0.3$, while in the joint market, CVaR continues to decline as ρ increases, demonstrating the greater resilience of the joint market to uncertainty.

TABLE 5. Economic benefit comparison under the different value of ε.

ε	Energy revenue($)	Regulation revenue($)	Hydrogen revenue($)	Total revenue($)
$\varepsilon = 0.1$	37,952	12,838	3,398	54,188
$\varepsilon = 0.15$	38,379	12,913	3,422	54,715
$\varepsilon = 0.2$	38,592	13,051	3,434	55,078

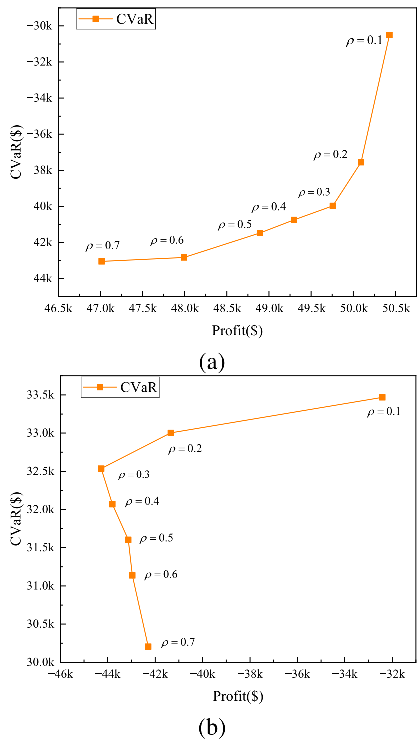

FIGURE 7. Impact of uncertainty on expected profit and CVaR: (a) Case 2 (b) Case 3.

2) IMPACT OF RISK PARAMETERS

Fig. 8 presents the bidding results in case 2 under different violation probability ε. Total market profits in stochastic cases are shown in Table 5. We can observe that the regulation capacity and corresponding market profits increase with the increase of ε (decrease of confidence level $1 - \varepsilon$), indicating that the bidding results are sensitive to the choice of ε. Since a larger ε tolerates a certain degree of probability in constraint violation, the total market revenue will increase. The system operators can obtain a trade-off between the operational risk and economic benefits by considering the confidence level.

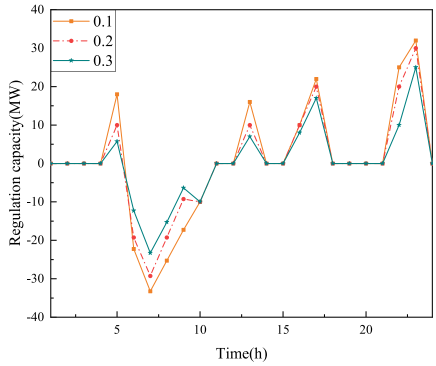

FIGURE 8. **Comparison among bidding results with different risk parameters.**

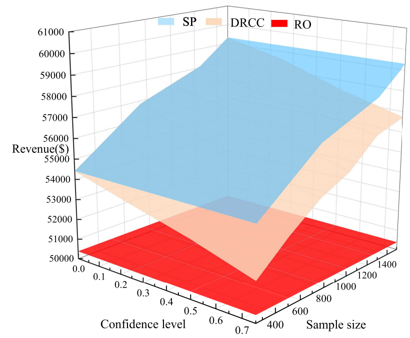

FIGURE 9. **Comparison among bidding results with different optimization methods.**

D. BENCHMARK WITH OTHER OPTIMIZATION METHODS

To investigate the performance of the proposed method, the scenario-based SP and RO models are compared. Fig. 9 shows the optimal market profits obtained from SP, RO, and the proposed method. The result indicates that the profits of the proposed method are between RO and SP. RO and SP have the lowest and highest market profits, respectively. This is because RO ignores the distribution information of the uncertain parameters and considers the worst-case scenario, which makes RO too conservative to get optimal results. SP optimization is implemented based on the predefined probability distribution, which leads to an overly aggressive solution. The proposed method, by contrast, adapts effectively to uncertainty, offering a tradeoff that integrates the strengths of both SP and RO.

Additionally, Fig. 9 demonstrates the influence of the historical data sample size on system revenues. As the number of samples increases, the ambiguity set shrinks, allowing the probability distribution of forecast errors to converge more closely to the true distribution. This reduces the conservativeness of the data-driven uncertainty set and the associated costs for WEJS to address uncertainty, resulting in higher revenues. Notably, as sample size grows, the revenue of the proposed method gradually approaches that of SP, further showcasing its adaptability and potential for enhancing economic efficiency while maintaining robustness. These findings highlight the importance of leveraging extensive historical data to optimize system performance.

E. SUMMARY

Overall, we can summarize results of the aforementioned case studies as follows:

1) The coalition (i.e., WEJS) where the members (i.e., the wind and the AWE) possessing inter-complementary characteristics in offering in a specific market (i.e., the frequency regulation market) can make more profits compared with the separate participation of each member in this market (e.g., the wind farm participates in the frequency regulation market). Besides, joint participation in multiple markets, where prices vary across markets, could yield more profits than unilateral participation in just one market. It inspires market engineers to incorporate complementary resources into an aggregator and make this aggregator offer in multiple markets to elevate profits.
2) The DRCC-based approach enables the trade-off between profitability and risk for the market participators. Different risk parameters will result in varying degrees of conservatism. Compared with SP (over-optimistic) and RO method (too conservative), the DRCC-based approach could provide appropriate suggestions for the market participator who pays attention to both the expected profits optimization and risk reduction by controlling the risk parameter.

V. CONCLUSION

In this paper, an optimal risk-averse bidding strategy and profit-sharing mechanism for WFs and AWEs to participate in the energy, frequency regulation, and hydrogen markets is proposed based on the data-driven distributionally robust chance-constrained method. We quantify the capacity flexibility of the WEJS and propose a cooperative bidding strategy based on the complementary capacity flexibility of WFs and AWEs. Moreover, to deal with both uncertainties of the wind capacity flexibility and hydrogen energy, a data-driven DRCC model is formulated for WEJS in the day-ahead and real-time market. Day-ahead imbalances resulting from uncertainties are restrained by chance constraints with worst-case distributions and provided by real-time scheduling eventually. This model can effectively balance the WEJS's economic benefit and risk of uncertainty according to its risk preference. Furthermore, Shapley value-based profit-sharing mechanism is developed to fairly distribute the benefits among participants according to their flexibility contributions. Numerical studies demonstrate the effectiveness and flexibility of the proposed model in terms of the tradeoff between optimality and robustness. By utilizing the complementary capacity flexibility of WF and the AWE, the profit of the proposed cooperative bidding strategy is increased by 27.4 % if compared with the individual bidding strategy. In addition, compared with the SP and RO, the proposed DRCC model has better risk-aver performance.

In future work, we plan to explore prediction methods for market prices to further enhance the accuracy and reliability of the bidding strategy.

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