Optimal Bidding Strategy for a Wind-Storage System Considering Self-Owned and Shared Energy Storage

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***Abstract*—The coordinated operation of wind power and energy storage can mitigate forecast deviations and enhance the market performance of wind generation. However, a single storage unit faces scheduling conflicts between arbitrage and fluctuation mitigation due to the mutually exclusive nature of charging and discharging. This paper proposes an optimal bidding strategy for a wind-storage system (WSS) under wind power uncertainty considering both self-owned storage and external capacity leasing. A bilevel optimization model is established, where the upper level maximizes net profit by considering market revenues, penalties, and leasing costs, and the lower level represents the joint clearing of energy and reserve markets. Based on the KKT optimality conditions, the bilevel problem is reformulated into a single-level mixed-integer linear program (MILP) using strong duality and Big-M linearization. Case studies on a modified IEEE 39-bus system validate the method's effectiveness in enhancing flexibility and profitability.**

***Index Terms*--electricity market, wind-storage system, wind power uncertainty, energy storage capacity leasing, bilevel model**

I. INTRODUCTION

With the rapid growth of wind and photovoltaic power, the penetration of renewables in power systems has continued to rise. However, the anti-peaking characteristics and uncertainty of wind power hinder revenue stability. Forecast deviations affect both profit realization and deviation settlement, reducing overall economic efficiency [1]. As a key flexibility resource, energy storage systems (ESS) can smooth renewable fluctuations through energy shifting and power regulation, enhancing system flexibility [2]. Integrating storage with wind generation to form a wind-storage system (WSS) improves the output controllability and market participation efficiency [3].

Conventional WSS designs typically rely on a single storage unit to serve multiple economic and technical functions. A primary function is price arbitrage: charging during low-price periods and discharging when prices are high to capture the price differential. Reference [4] proposed an arbitrage optimization model for a WSS that schedules charging and discharging to exploit price fluctuations. Another key function involves using the storage to mitigate short-term fluctuations of the wind power output. Reference [5] developed a power-smoothing and penalty-minimization model, verifying storage effectiveness in improving wind dispatchability. However, operational conflicts may arise in a single storage unit when it is required to simultaneously perform price arbitrage, fluctuation mitigation and other services such as reserve provision. Limited capacity and the mutually exclusive nature of charging and discharging make it hard to meet all the objectives, causing trade-offs and profit loss-known as the operational competition problem [6]. Although multiple independent storage units could decouple functions, high investment and diminishing returns make this approach uneconomical.

To address these limitations, the shared energy storage (SES) concept has been introduced. Centralized storage facilities are jointly utilized through capacity leasing, achieving value complementarity and improving resource utilization. Reference [7] proposed an optimal shared-storage allocation framework based on power and capacity-sharing mechanisms under a leader-follower game, demonstrating improved allocation efficiency and lower investment. Reference [8] further established a multi-regional shared-storage framework coordinated by multi-regional energy operators, enabling efficient cross-regional resource sharing. However, excessive reliance on leased storage may cause cost volatility, dependence on market availability, and reduced scheduling flexibility [9]. Thus, while SES alleviates investment pressure, it cannot fully replace the autonomy of self-owned storage. In practice, energy storage leasing is subject to region-specific contractual and market rules: long-term, project-lifetime arrangements prevail in Guangdong, and day-ahead procurement with daily settlement has been explored in some shared-storage markets. Spatial distribution and network deliverability may also constrain leasing decisions. Accordingly, this paper focuses on coordinated day-ahead leasing and bidding under short-term or rolling leasing arrangements, assuming leased storage is electrically co-located with the wind farm. Based on the above analysis,

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this paper proposes a day-ahead (DA) optimal bidding strategy for a WSS that jointly optimize the use of self-owned and externally leased storage. The main contributions are as follows:

1) Proposes a DA bidding strategy for a WSS with both self-owned storage and shared storage leasing, achieving a flexible profit-risk balance under different penalty environments through coordinated operation.

2) Develops a bilevel optimization model capturing internal-external storage coordination and wind uncertainty, where the upper level maximizes profit and the lower level represents joint market clearing.

3) Analyzes the influence of deviation penalties on bidding, leasing, and profitability, revealing their interrelations and offering insights for market-based penalty mechanism design.

The rest of this paper is organized as follows. Section II develops the bi-level optimization model of the WSS incorporating both self-owned and leased storage. Section III describes the solution approach. Section IV provides case studies, and Section V concludes the paper.

II. Bilevel Optimization Model of WSS With Energy Storage Capacity Leasing

A. Upper-level model: WSS

The upper level maximizes the net profit of the WSS by considering market revenues, deviation penalties, and storage leasing costs.

$$\max_{x}\left(F_1-F_2+F_3-F_4-F_5\right) \tag{1}$$

$$F_1=\sum_{i=1}^{Ni}\sum_{t=1}^{N_t}\lambda_{i,t}^{\text{EN,DA}}P_{i,\text{hs},t}^{\text{DA}} \tag{2}$$

$$F_2=\sum_{i=1}^{N_i}\sum_{t=1}^{N_t}\left[P_{i,\text{c},t}^{\text{DA,DIS}}(H^{\text{DIS}}G+V_{\text{Cost}}^{\text{Pump}})+P_{i,\text{c},t}^{\text{DA,CHA}}V_{\text{Cost}}^{\text{Comp}}\right] \tag{3}$$

$$F_3=\sum_{i=1}^{N_i}\sum_{t=1}^{N_t}\left[\lambda_t^{\text{UP}}r_{i,\text{c},t}^{\text{DIS,UP}}+\lambda_t^{\text{DN}}\left(r_{i,\text{c},t}^{\text{CHA,DN}}+r_{i,\text{c},t}^{\text{DIS,DN}}\right)\right] \tag{4}$$

$$F_4=\sum_{i=1}^{N_i}\sum_{s=1}^{N_s}\pi_s\sum_{t=1}^{N_t}M(\sigma_{i,t,s}^{+}+\sigma_{i,t,s}^{-}) \tag{5}$$

$$F_5=\sum_{i=1}^{N_i}N*E_i \tag{6}$$

where F_1 represents the revenue of the WSS from the DA energy market; F_2 represents the operating cost of the compressed air energy storage (CAES); F_3 represents the income from reserve markets; F_4 represents the deviation penalty cost; F_5 represents the cost of leasing external storage capacity; $\lambda_{i,t}^{\text{EN,DA}}$ is the DA locational marginal price at bus i at time t; $P_{i,\text{hs},t}^{\text{DA}}$ is the active power output of the WSS at bus i at time t; $P_{i,\text{c},t}^{\text{DA,CHA}}$ and $P_{i,\text{c},t}^{\text{DA,DIS}}$ are the charging and discharging power of the storage unit at bus i at time t; H^{DIS} is the heat rate in discharging mode; G is the natural gas price; $V_{\text{Cost}}^{\text{Comp}}$ and $V_{\text{Cost}}^{\text{Pump}}$ are the operating and maintenance costs in compression and pumping modes; λ_t^{UP} and λ_t^{DN} are the clearing prices for upward and downward reserves; $r_{i,\text{c},t}^{\text{DIS,UP}}$ and $r_{i,\text{c},t}^{\text{DIS,DN}}$ are upward/downward reserve provided by storage in discharging mode; $r_{i,\text{c},t}^{\text{CHA,DN}}$ is downward reserve provided by storage in charging mode; π_s is the probability of scenario s; M is the penalty coefficient; $\sigma_{i,t,s}^{+}$ and $\sigma_{i,t,s}^{-}$ are the positive and negative deviations; N is the daily cost per unit of leased storage capacity; E_i is the leased capacity at bus i.

$$0\le\hat{P}_{i,\text{c},t}^{\text{DA,DIS}}\le P_{\max}^{\text{Pump}}U_{i,\text{c},t}^{\text{DIS}} \tag{7}$$

$$0\le\bar{P}_{i,\text{c},t}^{\text{DA,CHA}}\le P_{\max}^{\text{Comp}}U_{i,\text{c},t}^{\text{CHA}} \tag{8}$$

$$0\le\hat{P}_{i,\text{w},t}^{\text{DA}}\le P_{i,t}^{\text{WF}} \tag{9}$$

$$\hat{\lambda}_{i,t}^{\text{DA}}\ge 0 \tag{10}$$

where $\bar{P}_{i,\text{c},t}^{\text{DA,CHA}}$ and $\hat{P}_{i,\text{c},t}^{\text{DA,DIS}}$ are the discharging bids and scheduled charging of the storage in the DA market; $P_{\max}^{\text{Pump}}$ and $P_{\max}^{\text{Comp}}$ are the maximum power limits in pumping and compression modes; $U_{i,\text{c},t}^{\text{DIS}}$ and $U_{i,\text{c},t}^{\text{CHA}}$ are binary variables indicating the discharging and charging states; $\hat{P}_{i,\text{w},t}^{\text{DA}}$ is the wind power bid; $P_{i,t}^{\text{WF}}$ is the predicted wind generation; $\hat{\lambda}_{i,t}^{\text{DA}}$ is the DA bid price of the WSS.

$$0\le\hat{\boldsymbol{r}}_{i,\text{c},t}^{\textbf{DA}}\le\boldsymbol{R}_{\textbf{max}}\boldsymbol{U}_{i,\text{c},t} \tag{11}$$

$$\hat{o}_{i,\text{c},t}^{\text{CHA,DN}},\ \hat{o}_{i,\text{c},t}^{\text{DIS,UP}},\hat{o}_{i,\text{c},t}^{\text{DIS,DN}}\ge 0 \tag{12}$$

where $\hat{\boldsymbol{r}}_{i,\text{c,t}}^{\text{DA}}=[\hat{r}_{i,\text{c,t}}^{\text{DIS,UP}}、\hat{r}_{i,\text{c,t}}^{\text{CHA,DN}}、\hat{r}_{i,\text{c,t}}^{\text{DIS,DN}}]$ are the DA reserve bidding vector of the storage unit; $\boldsymbol{R}_{\textbf{max}}$ are the upper limits of reserve capacity; $\hat{o}_{i,\text{c},t}^{\text{CHA,DN}}$ 、 $\hat{o}_{i,\text{c},t}^{\text{DIS,UP}}$ and $\hat{o}_{i,\text{c},t}^{\text{DIS,DN}}$ are the corresponding bidding prices.

$$\bar{P}_{i,\text{c},t}^{\text{DA,CHA}}+\hat{r}_{i,\text{c},t}^{\text{CHA,DN}}\le U_{i,\text{c},t}^{\text{CHA}}P_{\max}^{\text{Comp}} \tag{13}$$

$$\hat{P}_{i,\text{c},t}^{\text{DA,DIS}}+\hat{r}_{i,\text{c},t}^{\text{DIS,UP}}\le U_{i,\text{c},t}^{\text{DIS}}P_{\max}^{\text{Pump}} \tag{14}$$

$$\hat{r}_{i,\text{c},t}^{\text{DIS,DN}}-\hat{P}_{i,\text{c},t}^{\text{DA,DIS}}\le 0 \tag{15}$$

Equations (13)-(15) ensure that the sum of the energy and reserve bids of the storage unit remains within its maximum charging and discharging power limits.

$$\begin{aligned}\sigma_{i,t,s}^{+}-\sigma_{i,t,s}^{-}&=P_{i,t}^{\text{WF}}+P_{i,t,s}^{\text{error}}+P_{i,\text{c},t}^{\text{DA,DIS}}\\&-\bar{P}_{i,\text{c},t}^{\text{DA,CHA}}+(P_{i,\text{z},t}^{\text{DIS}}-P_{i,\text{z},t}^{\text{CHA}})-P_{i,\text{w},t}^{\text{DA}}\end{aligned} \tag{16}$$

$$\sigma_{t,s}^{+}\ge 0;\quad \sigma_{t,s}^{-}\ge 0 \tag{17}$$

Equations (16)-(17) describe the power imbalance caused by wind forecast errors. $P_{i,t,s}^{\text{error}}$ is the forecast error of the wind turbine under scenario s; $P_{i,\text{z},t}^{\text{CHA}}$ and $P_{i,\text{z},t}^{\text{DIS}}$ are the charging and discharging power provided by the leased storage, respectively.

$$U_{i,\text{c},t}^{\text{CHA}}+U_{i,\text{c},t}^{\text{DIS}}\le 1 \tag{18}$$

$$E_{i,\text{c},t}=E_{i,\text{c},t-1}+\bar{P}_{i,\text{c},t}^{\text{DA,CHA}}\eta_{\text{c}}-P_{i,\text{c},t}^{\text{DA,DIS}}/\eta_{\text{d}} \tag{19}$$

$$E_{i,\text{c},t}+r_{i,\text{c},t}^{\text{CHA,DN}}+r_{i,\text{c},t}^{\text{DIS,DN}}\le E_{i,\text{c},\max} \tag{20}$$

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$$E_{i,\mathrm{c,min}} \le E_{i,\mathrm{c},t} - r_{i,\mathrm{c},t}^{\mathrm{DIS,UP}} \quad (21)$$

$$E_{i,\mathrm{c},t1} = E_{i,\mathrm{c},t24} \quad (22)$$

Equations (18)-(22) define the charging-discharging exclusivity and state-of-charge constraints of the self-owned storage system. η_c and η_d are the charging and discharging efficiencies. $E_{i,\mathrm{c,min}}$ and $E_{i,\mathrm{c,max}}$ are the minimum and maximum allowable energy capacities.

$$0 \le P_{i,\mathrm{z},t}^{\mathrm{DIS}} \le \frac{1}{2} E_{i,\mathrm{z,max}} U_{i,\mathrm{z},t}^{\mathrm{DIS}} \quad (23)$$

$$0 \le P_{i,\mathrm{z},t}^{\mathrm{CHA}} \le \frac{1}{2} E_{i,\mathrm{z,max}} U_{i,\mathrm{z},t}^{\mathrm{CHA}} \quad (24)$$

$$U_{i,\mathrm{z},t}^{\mathrm{CHA}} + U_{i,\mathrm{z},t}^{\mathrm{DIS}} \le 1 \quad (25)$$

$$E_{i,\mathrm{z},t} = E_{i,\mathrm{z},t-1} + P_{i,\mathrm{z},t}^{\mathrm{CHA}} \eta_\mathrm{c} - P_{i,\mathrm{z},t}^{\mathrm{DIS}} / \eta_\mathrm{d} \quad (26)$$

$$E_{i,\mathrm{z,min}} \le E_{i,\mathrm{z},t} \le E_{i,\mathrm{z,max}} \quad (27)$$

$$E_{i,\mathrm{z},t1} = E_{i,\mathrm{z},t24} \quad (28)$$

Equations (23)-(28) are similar to those of the self-owned storage. $E_{i,\mathrm{z,max}}$ is the decision variable for leased storage capacity.

B. *Lower-level model: Market Clearing*

In the lower-level model, the wholesale electricity market operator jointly clears the energy and reserve markets to maximize the social welfare.

$$\max \ -\sum_{i=1}^{N_i}\sum_{t=1}^{N_t} \hat{\lambda}_{i,t}^{\mathrm{DA}} P_{i,\mathrm{hs},t}^{\mathrm{DA}} - \sum_{g=1}^{N_g}\sum_{t=1}^{N_t}\left[O_{g,t}^{\mathrm{EN}} P_{g,t} + O_{g,t}^{\mathrm{RS}}\left(r_{g,t}^{\mathrm{UP}} + r_{g,t}^{\mathrm{DN}}\right)\right] \quad (29)$$
$$-\sum_{i=1}^{N_i}\sum_{t=1}^{N_t}\left[\hat{o}_{i,\mathrm{c},t}^{\mathrm{CHA,DN}} r_{i,\mathrm{c},t}^{\mathrm{CHA,DN}} + \hat{o}_{i,\mathrm{c},t}^{\mathrm{DIS,UP}} r_{i,\mathrm{c},t}^{\mathrm{DIS,UP}} + \hat{o}_{i,\mathrm{c},t}^{\mathrm{DIS,DN}} r_{i,\mathrm{c},t}^{\mathrm{DIS,DN}}\right]$$

The lower-level objective function consists of three components: (1) the payments from the market operator to the WSS for purchasing energy; (2) the costs of procuring energy and reserve capacity from conventional generators; and (3) the payments for reserve capacity purchased from WSS. $O_{g,t}^{\mathrm{EN}}$ and $O_{g,t}^{\mathrm{RS}}$ are the bidding prices of generator *g* for energy and reserve capacity at time *t*; $P_{g,t}$ is the cleared energy output; $r_{g,t}^{\mathrm{UP}}$ and $r_{g,t}^{\mathrm{DN}}$ are the cleared upward and downward reserves.

$$\sum_{d=1}^{N_d} P_{d,t} - \sum_{i=1}^{N_i} P_{i,\mathrm{hs},t}^{\mathrm{DA}} - \sum_{g=1}^{N_g} P_{g,t} = 0 : \lambda_t^{\mathrm{EN,DA}} \ \forall t \quad (30)$$

$$\sum_{i=1}^{N_i} r_{i,\mathrm{c},t}^{\mathrm{DIS,UP}} + \sum_{g=1}^{N_g} r_{g,t}^{\mathrm{UP}} = R_t^{\mathrm{UP}} : \lambda_t^{\mathrm{UP}} \ \forall t \quad (31)$$

$$\sum_{i=1}^{N_i} r_{i,\mathrm{c},t}^{\mathrm{CHA,DN}} + \sum_{i=1}^{N_i} r_{i,\mathrm{c},t}^{\mathrm{DIS,DN}} + \sum_{g=1}^{N_g} r_{g,t}^{\mathrm{DN}} = R_t^{\mathrm{DN}} : \lambda_t^{\mathrm{DN}} \ \forall t \quad (32)$$

Equations (30)-(32) define the system power and reserve balance constraints, where the dual variables $\lambda_t^{\mathrm{EN,DA}}$; λ_t^{UP} and λ_t^{DN} are the respective clearing prices. $P_{d,t}$ is the load demand; R_t^{UP} and R_t^{DN} are the reserve requirements at time *t*.

$$0 \le P_{g,t} \le P_{g,\max} : \ \underline{\nu}_{g,t}, \overline{\nu}_{g,t} \ \forall g \forall t \quad (33)$$

$$0 \le r_{g,t}^{\mathrm{DN}} \le R_g^{\mathrm{DN}} : \ \underline{\nu}_{g,t}^{\mathrm{DN}}, \overline{\nu}_{g,t}^{\mathrm{DN}} \ \forall g \forall t \quad (34)$$

$$0 \le r_{g,t}^{\mathrm{UP}} \le R_g^{\mathrm{UP}} : \ \underline{\nu}_{g,t}^{\mathrm{UP}}, \overline{\nu}_{g,t}^{\mathrm{UP}} \ \forall g \forall t \quad (35)$$

$$P_{g,t} + r_{g,t}^{\mathrm{UP}} \le P_{g,\max} : \ \nu_{g,t}^{\mathrm{UP}} \ \forall g \forall t \quad (36)$$

$$r_{g,t}^{\mathrm{DN}} - P_{g,t} \le 0 : \ \nu_{g,t}^{\mathrm{DN}} \ \forall g \forall t \quad (37)$$

Equations (33)-(37) are the operating limits of conventional generators. $P_{g,\max}$ is the maximum generation limit; R_g^{UP} and R_g^{DN} are he maximum upward and downward reserves.

$$P_{i,\mathrm{hs},t}^{\mathrm{DA}} = P_{i,\mathrm{w},t}^{\mathrm{DA}} + P_{i,\mathrm{c},t}^{\mathrm{DA,DIS}} : \ \nu_{i,\mathrm{hs},t}^{\mathrm{DIS}} \ \forall i \forall t \quad (38)$$

$$0 \le P_{i,\mathrm{w},t}^{\mathrm{DA}} \le \hat{P}_{i,\mathrm{w},t}^{\mathrm{DA}} : \ \underline{\nu}_{i,\mathrm{w},t}^{\mathrm{DIS}}, \overline{\nu}_{i,\mathrm{w},t}^{\mathrm{DIS}} \ \forall i \forall t \quad (39)$$

$$0 \le P_{i,\mathrm{c},t}^{\mathrm{DA,DIS}} \le \hat{P}_{i,\mathrm{c},t}^{\mathrm{DA,DIS}} : \ \underline{\nu}_{i,\mathrm{c},t}^{\mathrm{DIS}}, \overline{\nu}_{i,\mathrm{c},t}^{\mathrm{DIS}} \ \forall i \forall t \quad (40)$$

Equations (38)-(40) define the WSS dispatch constraints, where total output equals wind generation plus storage discharging power.

$$0 \le r_{i,\mathrm{c},t}^{\mathrm{DIS,UP}} \le \hat{r}_{i,\mathrm{c},t}^{\mathrm{DIS,UP}} : \ \underline{\nu}_{i,\mathrm{c},t}^{\mathrm{DIS,UP}}, \overline{\nu}_{i,\mathrm{c},t}^{\mathrm{DIS,UP}} \ \forall i \forall t \quad (41)$$

$$0 \le r_{i,\mathrm{c},t}^{\mathrm{DIS,DN}} \le \hat{r}_{i,\mathrm{c},t}^{\mathrm{DIS,DN}} : \ \underline{\nu}_{i,\mathrm{c},t}^{\mathrm{DIS,DN}}, \overline{\nu}_{i,\mathrm{c},t}^{\mathrm{DIS,DN}} \ \forall i \forall t \quad (42)$$

$$0 \le r_{i,\mathrm{c},t}^{\mathrm{CHA,DN}} \le \hat{r}_{i,\mathrm{c},t}^{\mathrm{CHA,DN}} : \ \underline{\nu}_{i,\mathrm{c},t}^{\mathrm{CHA,DN}}, \overline{\nu}_{i,\mathrm{c},t}^{\mathrm{CHA,DN}} \ \forall i \forall t \quad (43)$$

$$r_{i,\mathrm{c},t}^{\mathrm{DIS,DN}} \le P_{i,\mathrm{c},t}^{\mathrm{DA,DIS}} : \ \nu_{i,\mathrm{c},t}^{\mathrm{DIS,DN}} \ \forall i \forall t \quad (44)$$

Equations (41)-(44) are the upper and lower limits of upward and downward reserves for charging and discharging modes, respectively.

$$-\overline{F}_l \le \sum_{g=1}^{N_g} G_{l,g} P_{g,t} + \sum_{i=1}^{N_i} S_{l,i} P_{i,\mathrm{hs},t}^{\mathrm{DA}} - \sum_{d=1}^{N_d} D_{l,d} P_{d,t} \quad (45)$$
$$\le \overline{F}_l : \ \underline{\nu}_{l,t}, \overline{\nu}_{l,t} \ \forall l \forall t$$

Equation (45) represents the transmission capacity constraint of the network , where $\overline{F}_l$ is the upper limit of the transmission capacity of line *l*; $G_{l,g}$; $S_{l,i}$ and $D_{l,d}$ are the shift factor matrices associated with conventional units, WSSs and loads, respectively.

III. Solution Approach

The proposed solution approach reformulates the bilevel optimization model of the WSS into a computationally tractable single-level problem, as illustrated in Fig. 1. Given the linear and continuous characteristics of the lower-level market-clearing problem, the KKT optimality conditions are applied to transform the original bilevel structure into a single-level mathematical program with equilibrium constraints. Moreover, the strong duality theorem is employed to replace the lower-level objective function with its dual equivalent, leading to a MILP model that can be efficiently solved by commercial solvers. The detailed mathematical derivations of the non-linear constraints and objective linearization are omitted here due to space limitations.

The strong duality theorem is applied to the DA market-clearing problem to incorporate dual variables and construct a linear equivalent of the lower-level objective function. Through the combination of primal-dual formulations and linearization procedures, the upper-level objective of the WSS can be linearized accordingly.

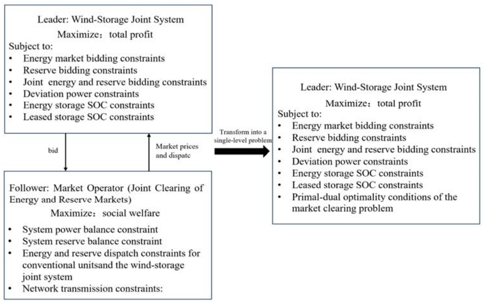

Fig. 1. Solution framework of the bilevel optimization model for WSS considering storage leasing.

IV. CASE STUDIES

The modified IEEE 39-bus system, as shown in Fig. 2, is used as the test system. Wind farms with a rated capacity of 300 MW are installed respectively at buses 3, 7, and 16, while CAES units with a rated power of 50 MW and an energy capacity of 100 MWh are configured at buses 3 and 7. Bus 3 applies the proposed strategy, bus 7 operates as a conventional WSS, and bus 16 is a wind farm leasing external storage for deviation mitigation. The DA market horizon is 24 h with a 1 h time resolution. The CAES parameters follow [10], with a charge/discharge cost of 34.8 CNY/MWh and a natural gas price of 110 CNY/GJ. The deviation penalty coefficient M is set to 600 CNY/MWh. The proposed MILP model in Section III is implemented in GAMS and solved using Gurobi.

To assess the impact of wind power forecast errors on DA market clearing, 1000 wind power output scenarios are generated via Latin hypercube sampling, decorrelated using Cholesky decomposition, and reduced by K-means clustering to eight representative scenarios per hour.

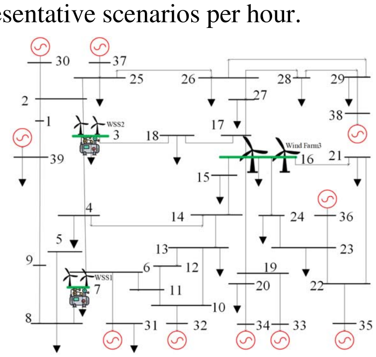

Fig. 2. 39-bus network.

A. WSS Operation Strategy under Low Penalty M

As illustrated in Figs. 3-4, both the WSS1 and the stand-alone wind farm (WF3) exhibit distinct operational behaviors under a low deviation penalty scenario. The WSS1 demonstrates a clear arbitrage-oriented strategy, characterized by charging during low-price hours and discharging when market prices rise. By absorbing excess wind generation and curtailing part of its output, the WSS effectively reduces its cleared energy quantity, thereby increasing the marginal cost of the system and driving up the market clearing price at specific hours (i.e., 1, 5, and 15). During low-price periods, WSS1 does not lease external storage, since the leasing price is economically unattractive. Instead, it relies on its self-owned capacity to optimally balance wind power uncertainty and maximize overall profit considering both market revenues and deviation costs. This behavior highlights the WSS's capability to actively influence market dynamics and enhance its total profit through coordinated energy and reserve market participation.

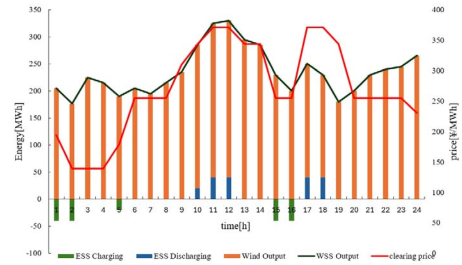

Fig. 3. WSS1 operation under low penalty.

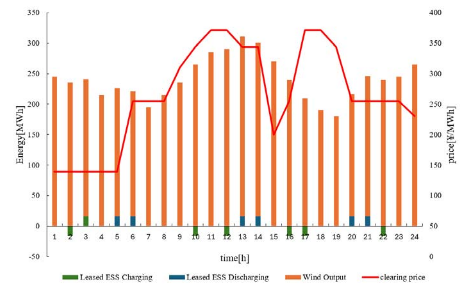

Fig. 4. WF3 operation under low penalty.

In contrast, the stand-alone wind farm (WF3) lacks the intrinsic capability of energy shifting and thus cannot exploit temporal price spreads as effectively as WSS1. Under low deviation penalties, WF3 leases 32 MW of external storage capacity to mitigate wind forecast deviations. However, given the relatively low penalty level, the optimal leased capacity remains modest lower than WSS1's self-owned storage because the combined effect of leasing costs and deviation reduction benefits limits further economic gains. As a result, even with deviation control as its main objective, WF3 still experiences slightly higher penalty costs and a lower total profit compared with WSS1, as shown in Table I.

TABLE I. TABLE REVENUES AND COSTS UNDER LOW PENALTY CASE

	Energy market revenue(CNY)	Reserve market revenue(CNY)	Penalty cost (CNY)	Leased capacity (MW)	Profit (CNY)
WSS1	1637640	46775	79284.1	0	1605130
WF3	1522990	0	88630.2	32	1408760

B. WSS Operation Strategy under High Penalty M

As shown in Table II, under high deviation penalties, WSS1 achieves the highest overall profit among the three configurations, followed by WSS2 and WF3. The superior performance of WSS1 is attributed not only to its lower penalty cost but also to its substantially higher market revenues enabled by coordinated operation with leased storage. Under high-penalty conditions, all participants adopt more conservative bidding strategies to reduce the risk of large deviations and the resulting penalties. However, the degree of conservatism differs among the configurations. For WF3, which relies entirely on external storage leasing and faces

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higher operational costs, the bidding strategy becomes even more risk-averse, leading to reduced energy commitments and a further decline in total revenue.

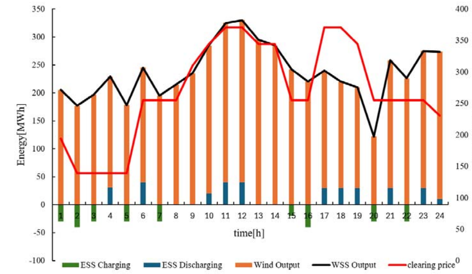

Fig. 5. WSS1 operation under high penalty.

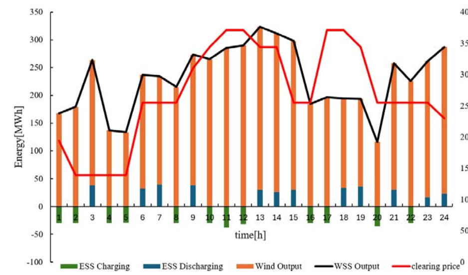

Fig. 6. WSS2 operation under high penalty.

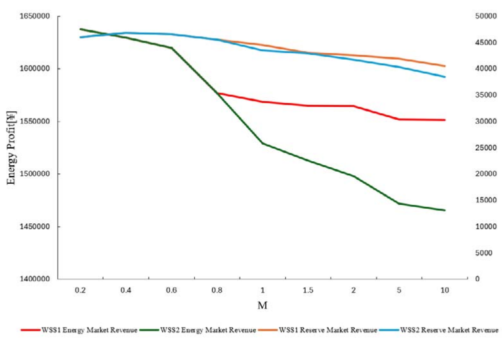

Fig. 7. Revenues of WSS1 and WSS2 under different penalty M.

TABLE II. REVENUES AND COSTS UNDER HIGH PENALTY CASE

	Energy market revenue(CNY)	**Reserve market revenue(CNY)**	**Penalty cost (CNY)**	**Leased capacity (MW)**	**Profit (CNY)**
WSS1	1575580	44494.6	247669	83.183	1305859
WSS2	151340	42341	304811	0	1254870
WF3	1449750	0	315148	97	1057002

Fig. 5. and Fig. 6. show that as the penalty coefficient increases, both WSS1 and WSS2 shift away from the profit-maximizing strategies observed under low-penalty conditions, adopting more conservative operational patterns to limit deviation risks. However, WSS1 maintains a strategy that remains closer to the optimal arbitrage pattern because the leased external storage helps buffer wind power fluctuations and share regulation tasks. This additional flexibility allows WSS1 to preserve a more balanced trade-off between deviation control and market participation, whereas WSS2, constrained by its self-owned storage, exhibits reduced adaptability and a larger deviation from its optimal operating trajectory. As observed in Fig. 7. the total profit of both systems decreases as the penalty M increases; however, the decline for WSS1 is notably slower, and its profit consistently remains higher than that of WSS2. This indicates that the operation strategy of WSS1 exhibits stronger market adaptability and resilience to increasing deviation penalties. Sensitivity analysis has been conducted to examine the impacts of parameters M and N. It is shown that parameter M determines the economic damage of inflexibility, while N determines the price of flexibility.

V. CONCLUSIONS

This paper proposes a DA optimal bidding strategy for a WSS considering both self-owned and leased storage. A bilevel MILP model is developed to jointly optimize market revenues, deviation penalties, and leasing costs. Case studies on the modified IEEE 39-bus system show that external storage leasing enhances WSS flexibility and profitability under high penalty conditions. By utilizing leased storage to buffer wind fluctuations and share regulation tasks, the WSS effectively reduces deviation penalties while maintaining high market revenues, demonstrating strong adaptability to varying penalty environments. The results also provide insights for market designers: overly low penalties encourage WSSs to focus on arbitrage rather than deviation control, whereas excessively high penalties suppress participation incentives. An appropriate penalty level is therefore essential to balance economic efficiency and operational reliability in DA markets.

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