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CVaR-constrained Stochastic Bidding Strategy for a Virtual Power Plant with Mobile Energy Storages

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***Abstract*—This paper proposes a stochastic optimization-based energy and reserve bidding strategy for a virtual power plant (VPP) with mobile energy storages, renewable energy resources (RESs) and load demands at multiple buses. In the proposed bidding strategy, the energy markets include the day-ahead and real-time energy markets, and the reserve markets include operating, regulation up and regulation down reserve markets. In view of the differences of energy and reserve prices, renewable generations and load demands between buses on the next day, the mobile energy storages can be delivered to different buses for maximizing the VPP's total expected profit considering its risk preference. In the stochastic optimization model for generating the bidding strategies, the uncertain market prices, renewable power productions and load demands are represented via scenarios, and the conditional value at risk (CVaR) is used as the risk measure to manage the VPP's risks in the worst case scenarios related to a confidence level. Since the VPP may need to manage the risks related to multiple confidence levels, the proposed model maximizes multiple CVaRs with different confidence levels. Finally, case studies are carried out to verify the effectiveness of proposed bidding strategy with mobile energy storages and multiple CVaRs.**

Keywords*— *bidding strategies, energy markets, mobile energy resources, reserve markets, virtual power plant

I. INTRODUCTION

The deregulated electricity markets in North America are operated by independent system operators or regional transmission organizations for providing reliable electricity to the consumers and maximizing the total social welfare of all the market participants [1]. The energy markets consist of day-ahead (DA) and real-time (RT) markets, which are the trading floors where the participants can buy or sell power strategically. The reserve markets, which mainly includes operating, non-operating and regulation reserve markets, are used to ensure the reliability of the power system operation, and all of these reserve markets have different clearing prices [2]. Therefore, it is a complicated portfolio optimization problem for market participants to maximize their total expected profits in multiple energy and reserve markets, where both the uncertain market prices and the properties of their physical assets should be considered. Moreover, in the last two decades, large scale intermittent renewable energy resources (RESs) have been integrated in the power grid, and these renewable power producers not only need to face the volatile energy and reserve prices, but also need to handle their uncertain renewable power productions [1]. To increase the economic benefits of multiple RESs, a framework of virtual power plant (VPP) has been proposed to manage the aggregated renewable energy and demand sources as a single participant in the electricity markets [4].

There is abundant literature on developing the optimal bidding strategies used by the VPPs in the electricity markets, where different types of market frameworks and physical assets are taken into account [3]-[8]. In [3], a nonlinear mixed-integer programming problem was established to generate a VPP's bidding strategies in energy and operating reserve markets, which was solved by using genetic algorithm. The authors of [4] studied the VPP participating in the DA and RT energy markets, where the distributed energy resources and consumers with inelastic demands were considered. In [5] and [6], energy storages were utilized in the VPP's optimal bidding strategies, where stochastic optimization and robust optimization were used to handle the uncertainties faced by the VPP, respectively. Additionally, in the bidding strategies proposed by the authors of [7] and [8], different types of demand response programs were developed based on the flexibility of the VPP's load demands. In the existing literature, energy storages were used to handle the uncertain renewable energy productions and market prices. Energy storages can help the VPP arbitrage the price differences in different time periods, because the renewable power can be stored by the storages during the time periods when the market prices are low, and then be sold by the VPP during other time periods with higher prices. Considering its response speeds are usually fast enough for providing different types of reserve services, the VPP can also pursue higher profits by participating in multiple reserve markets.

In the existing literature, the energy storages were located at fixed locations. However, the VPP may consists of multiple RESs and load demands at different buses, where the renewable power productions, load demands and market prices may be different, so the energy storages located at fixed buses may not sufficiently maximize of the VPP's total expected profit in the multiple energy and reserve markets. In recent years, large scale mobile energy storages have been used for the distribution systems and microgrids [9] and [10]. In [9], a bi-objective optimization based method was proposed for a distribution system with RESs to utilize mobile battery energy storages, which was shown to be helpful for improving the system's reliability. In [10], for the microgrids, the physical assets were modeled as shiftable loads and mobile energy storages, and a multi-objective optimization model was proposed to design the configuration of the microgrid. However, in the existing literature, the mobile energy storage has not been utilized or studied in the VPP's optimal bidding strategies in the electricity market.

To consider the uncertainty arising from market prices, renewable power productions and load demands of the VPP, stochastic optimization models are widely used to generate the bidding strategy in the market [5]. To manage the risks in the worst case scenarios, the conditional value-at-risk (CVaR) can also be used in the stochastic bidding strategies, whose value depends on the confidence level specified by the VPP. In the existing bidding strategies in the electricity market, only a single CVaR is used by the market participant, which means

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only the risk related to one confidence level is considered. However, in practice, the risks related to multiple confidence levels may need to be considered when determining the VPP's optimal bidding strategy with uncertainties. On the one hand, a VPP owner may be interested in controlling the risks related to multiple confidence levels. On the other hand, a VPP may be owned or managed by multiple decision makers, and they may care about the risks related to different confidence levels. Therefore, this paper proposes a stochastic optimization based energy and reserve bidding strategy for a VPP with mobile energy storages, in which multiple CVaRs with different confidence levels are used to measure and minimize the risks related to multiple confidence levels, and renewable energy resources (RESs) and load demands at multiple buses are considered.

The contributions of this paper are as follows: 1) Mobile energy storages are utilized in a VPP's optimal bidding strategies in multiple energy and reserve markets for the first time. 2) Multiple CVaRs with different confidence levels are optimized simultaneously in the proposed stochastic optimization model to minimize the risks related to multiple confidence levels. 3) The proposed model is formulated as a mixed integer linear programming (MILP) problem, which can be solved by using most of the existing solvers directly. 4) Comparative studies are carried out to verify the potential benefits of using mobile energy storages and multiple CVaRs for the proposed energy and reserve bidding strategy of the VPP.

II. MARKET FRAMEWORK AND RISK MANGEMENT FOR THE VPP

The VPP has both power generation and demand resources, it may either buy or sell power in the energy market, which depends on its real-time power generation and demand levels. Additionally, it can provide ancillary services in the reserve market, as long as its bidding capacities and response speed satisfy the reserve market requirements. The VPP can provide three types of reserves to the reserve market, including operating reserve, non-operating reserve, and regulation reserve. The operating and regulation reserve resources should be online and able to adjust power output within the required time frames, but the regulation reserves need to respond to power imbalances within a very short time period, which could be just several seconds. In contrast, the non-operating reserves could be offline and their response time is much longer than those of the operating and regulation reserves.

In this paper, the VPP with mobile energy storages is assumed to participate in multiple energy and reserve markets. Considered that the non-operating reserve prices are usually lower than those of the operating and regulation reserves, the non-operating reserve market is not considered for the VPP in the proposed bidding strategy Therefore, the energy, operating reserve and regulation reserve markets are assumed to be the VPP's trading floors, and the VPP is assumed to be a price-taker due to its small generation and demand capacities, which indicates the energy and reserve prices are not affected by the VPP's bidding strategies.

There are two trading floors available for the VPP, which includes the DA and RT markets. In the DA market, the energy and reserve bids are submitted by the VPP one day before the operating day, and those bids are cleared at the DA energy and reserve prices. In the RT market, the RT power deviations, the deployed operating reserves and the deployed regulation reserves are all settled at RT electricity prices on the operating day. To maximize the total profits of the VPP, the mobile energy storages can be delivered to other buses during the first several hours of the operating day. In this circumstance, the operating and regulation reserve bids are limited by both the energy levels and delivery schedules of the VPP's mobile energy storages.

When generating bidding strategies in the markets, the VPP faces multiple uncertainties, including uncertain DA energy price, uncertain RT energy price, uncertain operating reserve price, uncertain regulation up/down reserve prices, uncertain renewable energy production, and uncertain load demand. All these uncertainties can be represented using a set of typical scenarios. To manage the risks introduced by those uncertainties, the VPP may take either a risk-neutral strategy, a risk-averse strategy, or a risk-seeking strategy to determine its stochastic bidding strategy. The risk-neutral strategy is seeking the maximization of expected profit over all the scenarios. In contract, the risk-aversion strategy might be willing to scarify the expected profits but avoid potential loss or low profits in some low profitable scenarios, and the risk-seeking strategy might be willing to scarify the expected profits but avoid losing potential high profits for some high profitable scenarios. This paper only focuses on the risk-aversion strategy.

To quantity the bidding risks faced by a VPP, the CVaR can be used to measure the risks in the worst case scenarios. Each CVaR corresponds to a confidence level α_s $(0 < \alpha_s < 1)$ that specified by the decision maker. The CVaR with confidence level α_s can be denoted as $CVaR_{\alpha_s}$, whose value is equal to the expected profit of the $(1-\alpha_s) \times 100\%$ least profitable scenarios. Considered that the decision maker might need examining risks at different confident levels, multiple CVaRs are used in this paper corresponding to different confidence levels. The risk-aversion VPP can determine its bidding strategy by maximizing a weighted sum of expected profit over all uncertain scenarios and multiple CVaRs corresponding to different sets of least profitable scenarios. The weight assigned to each $CVaR_{\alpha_s}$ measures the risk aversion degree of the VPP. A larger risk aversion degree for $CVaR_{\alpha_s}$ indicates the VPP is more risk averse, who is willing to decrease the total expected profit of all the scenarios to improve the expected profit of the $(1 - \alpha_s) \times 100\%$ worst scenarios. By doing so, the total expected profit and multiple CVaRs can be maximized simultaneously by using the proposed stochastic optimization model as described in next section.

III. PROPOSED STOCHASTIC OPTIMIZATION MODEL

A stochastic optimization model is proposed for generating the bidding strategies for the VPP on the next day. The objective function of proposed model is to maximize the weighted sum of the total expected profit and the CVaRs with different confidence levels, π_{total} as described in (1):

$$\max_{\Xi} \pi_{total} = \beta_0 \sum_{w\in W} pr_w\left(\pi_w^{EM} + \pi_w^{OR} + \pi_w^{reg} - C_w^{MES} - C^{deli} - C^{inst}\right) + \sum_{s\in S} \beta_s CVaR_{\alpha_s} \quad (1)$$

where Ξ is the set of decision variables. W and S are the sets of uncertain scenarios and CVaR scenarios, respectively. β_0 is the weight assigned to the expected profit, and β_s is the weight, i.e. risk aversion degree assigned to CVaR scenario s with confidence level α_s. All weights in the objective function should satisfy $(\beta_0 + \sum_{s\in S} \beta_s) = 1$. pr_w is the probability of uncertain scenario w. π_w^{EM}, π_w^{OR} and π_w^{reg} are total revenues obtained from the DA and RT energy markets, the operating reserve market, and regulation reserve markets for scenario w, respectively. C_w^{MES}, C^{deli} and C^{inst} are the total expected costs of energy storage operation, energy storage delivery, and energy storage installation for scenario w, respectively.

The expected profit for scenario w is equal to the total expected revenue minus the total expected cost. The total expected revenue for scenario w is the sum of the revenue in the energy market π_w^{EM}, the revenue in operating reserve market π_w^{OR}, and the revenue in regulation reserve market π_w^{reg}, which are calculated using (2)-(4):

$$\pi_w^{EM} = \sum_{t\in T}\sum_{n\in N}(\lambda_{ntw}^{DA}P_{nt}^{DA} + \lambda_{ntw}^{RT}P_{ntw}^{RT+} - \lambda_{ntw}^{RT}P_{ntw}^{RT-}) \quad (2)$$

$$\pi_w^{OR} = \sum_{t\in T}\sum_{n\in N}(\lambda_{ntw}^{OR}P_{nt}^{OR} + \eta_{nt}^{OR}\lambda_{ntw}^{RT}P_{nt}^{OR}) \quad (3)$$

$$\pi_w^{reg} = \sum_{t\in T}\sum_{n\in N}\left[\lambda_{ntw}^{reg,up}P_{nt}^{reg,up} + \lambda_{ntw}^{reg,down}P_{nt}^{reg,down} + \lambda_{ntw}^{RT}\left(\eta_{nt}^{reg,up}P_{nt}^{reg,up} + \eta_{nt}^{reg,down}P_{nt}^{reg,down}\right)\right] \quad (4)$$

where, T is the set of time periods for the next day, N is the set of buses associated with VPP's resources and loads, λ_{ntw}^{DA}, λ_{ntw}^{RT}, λ_{ntw}^{OR}, $\lambda_{ntw}^{reg,up}$ and $\lambda_{ntw}^{reg,down}$ are DA energy price, RT energy price, operating reserve price, regulation up reserve price, and regulation down reserve price at bus n and time period t for scenario w. P_{nt}^{DA}, P_{nt}^{OR}, $P_{nt}^{reg,up}$ and $P_{nt}^{reg,down}$ are the power bid in DA energy market, the operating reserve bid, and the regulation up and down reserve bids at bus n and time period t. P_{ntw}^{RT+} and P_{ntw}^{RT-} are the positive and negative RT deviations at bus n and time period t. η_{tn}^{OR}, $\eta_{tn}^{reg,up}$ and $\eta_{tn}^{reg,down}$ are the percentages of the deployed operating, regulation-up, and regulation-down reserves at bus n and time period t.

The total expected cost for scenario w is the sum of the energy storage operation cost C_w^{MES}, energy storage delivery cost C^{deli} and energy storage installation cost C^{inst}, which are calculated using (5)-(7):

$$C_w^{MES} = \sum_{t\in T}\sum_{n\in N}\sum_{k\in K} OC_k\left(P_{kntw}^{dis,RT} + P_{kntw}^{ch,RT}\right) \quad (5)$$

$$C^{deli} = \sum_{n\in N}\sum_{m\in N}\sum_{k\in K} DC_k\, d_{mn} b_{km}^{ES,0} b_{kn}^{ES} \quad (6)$$

$$C^{inst} = \sum_{n\in N}\sum_{m\in N, m\neq n}\sum_{k\in K} IC_k\, b_{km}^{ES,0} b_{kn}^{ES} \quad (7)$$

where, K is the set of mobile energy storages for the VPP, $P_{kntw}^{ch,RT}$ and $P_{kntw}^{dis,RT}$ are the RT charge and discharge power of energy storage k at bus n and time period t. OC_k, DC_k and IC_k are the operation cost of per unit power, the delivery cost (i.e. fuel and labor) of per unit distance, and the installation cost (i.e. labor) per times for energy storage k. b_{kn}^{ES} is a binary variable, which is equal to 1 if the energy storage k is delivered to bus n, otherwise 0. $b_{km}^{ES,0}$ is the initial status of b_{km}^{ES} at the beginning period. d_{mn} is the delivery distance between bus m and n.

In (6), the energy storage delivery cost is proportional to the delivery distance d_{mn} if it is delivered from bus m to bus n. In (7), the installation cost is zero, if the energy storage does not reallocate to a different bus on the next day.

The $CVaR_{\alpha_s}$ is equal to the expected profit of the $(1-\alpha_s)\times 100\%$ least profitable scenarios, and calculated as:

$$CVaR_{\alpha_s} = \zeta_s - \frac{1}{1-\alpha_s}\sum_{w\in W} pr_w \eta_{ws} \quad (8)$$

where, ζ_s and η_w^s are the ancillary variables used for calculating $CVaR_{\alpha_s}$, which are subject to the constraints of (9) and (10):

$$\eta_{ws} \geq 0 \quad (9)$$

$$\zeta_s - \eta_{ws} \leq \pi_w^{EM} + \pi_w^{OR} + \pi_w^{reg} - C_w^{MES} - C^{deli} - C^{inst} \quad (10)$$

The detailed explanations for the formulation of calculating $CVaR_{\alpha_s}$ are provided in [11]. (8)-(10) can also be used to model the risk-seeking strategy with slight modifications.

The stochastic optimization model is further subject to a set of constraints (11)-(28) regarding real-time power and energy balance, bidding capacities, mobile energy storage delivery schedule and capacity limits.

Constraint (11) ensures the RT power balance of the VPP at each bus, where the total power sold to the energy and reserve markets should be equal to the RT renewable power productions and the discharged power of the energy storages minus the load demand consumption and the charged power of the energy storages:

$$P_{nt}^{DA} + \eta_{nt}^{OR}P_{ntw}^{OR} + \eta_{nt}^{reg,up}P_{nt}^{reg,up} - \eta_{nt}^{reg,down}P_{nt}^{reg,down} + P_{ntw}^{RT+} - P_{ntw}^{RT-} = \sum_{i\in\Psi_n^I} P_{itw}^{RES} + \sum_{k\in K}\left(P_{nktw}^{dis,RT}\eta_k^{dis,ES} - P_{nktw}^{ch,RT}/\eta_k^{ch,ES}\right) - \sum_{j\in\Psi_n^J} P_{jtw}^{LD} \quad (11)$$

where, Ψ_n^I and Ψ_n^J are the sets of the RESs and demands located at bus n. P_{itw}^{RES} and P_{jtw}^{LD} are the generation output of renewable resource i, and the power consumption of load demand j at time period t for scenario w, respectively. $\eta_k^{ch,ES}$ and $\eta_k^{dis,ES}$ are the charging, and discharging efficiencies of energy storage k, respectively.

Constraints (12)-(17) ensures the lower and upper bounds of the bidding capacities in the DA energy market, RT energy market, operating reserve market, regulation up reserve market and regulation down reserve market:

$$P^{DA,min} \leq P_{nt}^{DA} \leq P^{DA,max} \quad (12)$$

$$0 \leq P_{ntw}^{RT+} \leq M b_{ntw}^{RT} \quad (13)$$

$$0 \leq P_{ntw}^{RT-} \leq M(1 - b_{ntw}^{RT}) \quad (14)$$

$$0 \leq P_{nt}^{OR}, P_{nt}^{reg,up} \quad (15)$$

$$P_{nt}^{OR} + P_{nt}^{reg,up} \leq \sum_{k\in K}\eta_k^{dis,ES}P_{kntw}^{dis,RT} \quad (16)$$

$$0 \leq P_{nt}^{reg,down} \leq \sum_{k\in K} P_{kntw}^{ch,RT}/\eta_k^{ch,ES} \quad (17)$$

where, $P^{DA,max}$ and $P^{DA,min}$ are the upper and lower bounds of the bidding capacity in the DA energy market for the VPP. M is a large enough constant. b_{ntw}^{RT} is a binary variable, which is equal to 1 if the RT power deviation of the VPP is positive at bus n in time t for scenario w otherwise 0.

In (12), the lower and upper bounds of the DA bidding capacities are limited by the VPP's credits and the total generation and demand capacities. (13) and (14) ensure either the positive or the negative RT power deviation of the VPP is zero. (16) and (17) limit the reserve bidding capacities based on the charging and discharging power capacities of the energy storages, because it is assumed only the energy storages satisfy the requirements of providing the reserve services.

Constraint (18) ensures that each energy storage can be located at only one of the VPP's buses:

$$\sum_{n\in N} b_{kn}^{ES} = 1 \quad (18)$$

Constraints (19)-(21) limit the energy level of the energy storages in each time period t considering their initial locations:

$$E_{kntw} = b_{kn}^{ES}E_k^{K,0} + (P_{kntw}^{ch,RT} - P_{kntw}^{dis,RT})\Delta t \;\; if\; t = 1 \quad (19)$$

$$E_{kn(t+1)w} = E_{kntw} + (P_{kntw}^{ch,RT} - P_{kntw}^{dis,RT})\Delta t \;\; \forall t > 1 \quad (20)$$

$$0 \leq E_{kntw} \leq E_k^{K,max} b_{kn}^{ES} \quad (21)$$

where, Δt is the duration of time period, E_{kntw} is the RT energy level of storages k in time t in scenario w, and $E_k^{K,0}$ and $E_k^{K,max}$ are the initial and maximum energy capacities for energy storage k.

Constraints (22)-(26) limit the power charging and discharging capacities considering the energy storage delivery status in the first several hours on the next day:

$$P_{kntw}^{dis,RT} + P_{kntw}^{ch,RT} \leq P_k^{K,max} b_{kn}^{ES} \quad (22)$$

$$\sum_{k\in K} P_{kntw}^{dis,RT} \leq M(1 - b_{ntw}^{ch}) \quad (23)$$

$$\sum_{k\in K} P_{kntw}^{ch,RT} \leq M b_{ntw}^{ch} \quad (24)$$

$$0 \leq P_{kntw}^{ch,RT} \leq M \sum_{m\in N} b_{km}^{ES,0} f_{mnt} \quad (25)$$

$$0 \leq P_{kntw}^{dis,RT} \leq M \sum_{m\in N} b_{km}^{ES,0} f_{mnt} \quad (26)$$

where, b_{ntw}^{ch} is a binary variable, which is equal to 1 if the energy storages at bus n are charging at time period n for scenario w, and 0 if discharging. f_{mnt} is a binary parameter, which is equal to 0 if the energy storage is on the way of being delivered from bus m to bus n otherwise 1.

Specifically, (25) and (26) indicate that the energy storage cannot charge or discharge power during the delivery process, where the parameter f_{mnt} (if $m \neq n$) is calculated using (27):

$$f_{mnt} = \begin{cases} 0, & t \leq D_{mn}/v \\ 1, & t > D_{mn}/v \end{cases} \qquad \forall m, n, t \qquad (27)$$

where f_{mnt} is equal to 0 if the time t is less than the time of delivering the energy storage from bus m to n, and the energy storage cannot be charged or discharged in time period t. v is the driving speed of the carrier of the energy storages. The efficiency of the bidding strategy can be improved by increasing the carrier delivery and installation speed.

Constraint (28) address the binary variables used in the optimization model:

$$b_{kn}^{ES}, b_{ntw}^{RT}, b_{ntw}^{ch} \in \{0,1\} \qquad \forall k, n, t, w \qquad (28)$$

Therefore, after calculated the modeling parameters base on (27), the optimization model (1)-(28) can be solved as a mixed integer linear programming (MILP) problem. By doing so, the optimal energy and reserve bidding strategies for the VPP and the delivery schedules for the mobile energy storages can be generated simultaneously considering the VPP's risk preference.

IV. Case Studies

A. Simulation Setup

To verify the proposed energy and reserve bidding strategy, case studies are carried out for a VPP with load demands and RESs located at three buses, and the distances between any two buses are 30 km. The VPP participates in the Southwest Power Pool's energy and reserve markets. It has two identical mobile energy storages (e.g. batteries), and each with 8 MWh maximum energy capacity and 4 MW maximum power capacity. The charging and discharging efficiencies of energy storages are 0.9 respectively. The energy storage operation cost is \$4/MW, delivery cost for the carrier is \$2/km, and installation cost of the energy storage is \$8. The speed of the energy storage carrier is initially set to be 20 km/h. The historical energy and reserve prices are obtained from the Southwest Power Pool (SPP) Market [12]. The historical wind power data are obtained from the National Renewable Energy Lab (NREL) [13] website, and the historical demand data are the residential demand data of a utility company [14]. The percentages of the reserves deployed in the RT market are all set to be 0.9. In the studied cases, 40 scenarios of the uncertain parameters are generated by using the latest historical data of 40 days directly. The proposed MILP problem is solved by using Yalmip toolbox [15] and Gurobi 7.0 in MATLAB [16].

B. Results of the Proposed Bidding Strategy with Mobile Energy Storages

The stochastic optimization based bidding strategy is first generated for the VPP with mobile energy storages initially located at Bus 3. The VPP has considered CVaRs with confidence levels 0.8 and 0.95 as its risk measures, and assigned 0.9, 0.05 and 0.05 as the weights to the total expected profit, $CVaR_{0.8}$ and $CVaR_{0.95}$, respectively.

Fig. 1 gives the expected values of the renewable power productions and load demands of the VPP. As shown in Fig. 1, the renewable power productions at Bus 1 are higher than those at the other two buses on the next day, and renewable power productions at these three buses are more stochastic than the load demands.

Fig. 2 gives the expected values of the energy and reserve prices. As shown in Fig. 2, the RT energy prices are more volatile than the DA energy prices, because the price spikes are more likely to occur in the RT markets due to some unexpected events in the power systems, such as the power outages caused by extreme weather events.

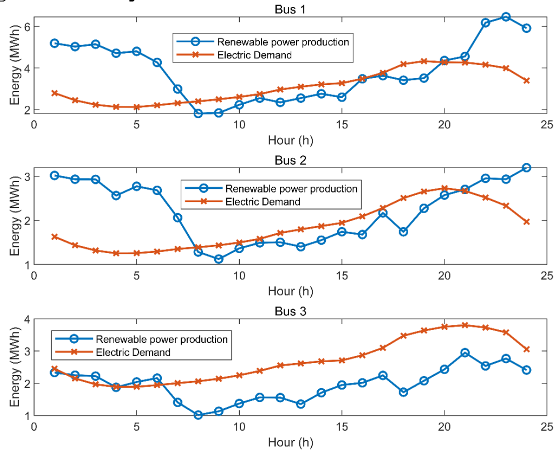

Fig. 1. The expected renewable productions and demands at three buses

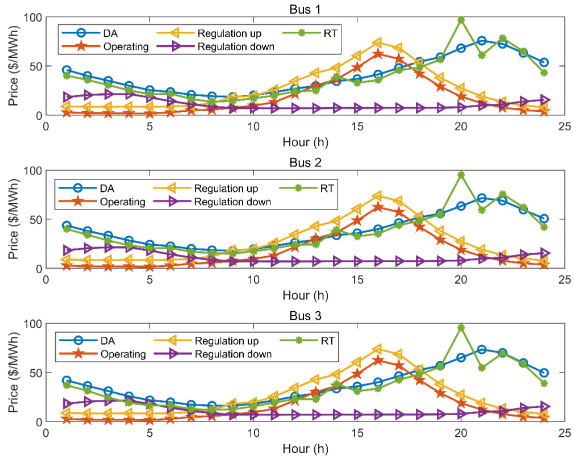

Fig. 2. The expected energy and reserve prices at three buses

By solving the model (1)-(28) for the studied case, the results of the stochastic bidding strategies for one day are obtained. Fig. 3 and 4 have provided the expected values of the bidding capacities and energy levels of the storages, respectively. It is shown that even though the energy storages are initially located at Bus 3, the reserve bids are submitted at both Bus 1 and Bus 3, and the energy level of the storages at Bus 1 is positive. These results indicate one of the VPP's energy storages is moved from Bus 3 to Bus 1, where renewable power productions are higher than those at Bus 2 and 3.

To further analyze the advantages of using mobile energy storages for the VPP, the stochastic optimization bidding strategy is also generated for the same VPP but with non-mobile energy storages, where the storage locations are fixed at the initial buses by setting the delivery speed to be zero. Table I gives the comparisons of the total expected profit and CVaRs of the VPP obtained by using different bidding strategies, where v=0 means the energy storages are located at the initial buses and cannot be moved on the next day.

Table I shows that the total expected profit, $CVaR_{0.8}$ and $CVaR_{0.95}$ in Case 2 are \$10, \$500 and \$849 higher than those in Case 1, respectively, which indicates the mobile energy storages can not only increase the expected profit, but also decrease the risk in the worst scenarios for the VPP. Additionally, to study the impacts of the VPP's risk preference on the bidding strategy, Case 3 is designed by setting β_0, β_1 and β_2 to be 0.95, 0.025 and 0.025, respectively. Compared to Case 1, the improvements of total expected profit, $CVaR_{0.8}$ and $CVaR_{0.95}$ in Case 4 are \$18, \$430 and \$732, respectively, which indicates when the VPP is less risk averse, the CVaR improvements obtained by using the mobile energy storages are decreased.

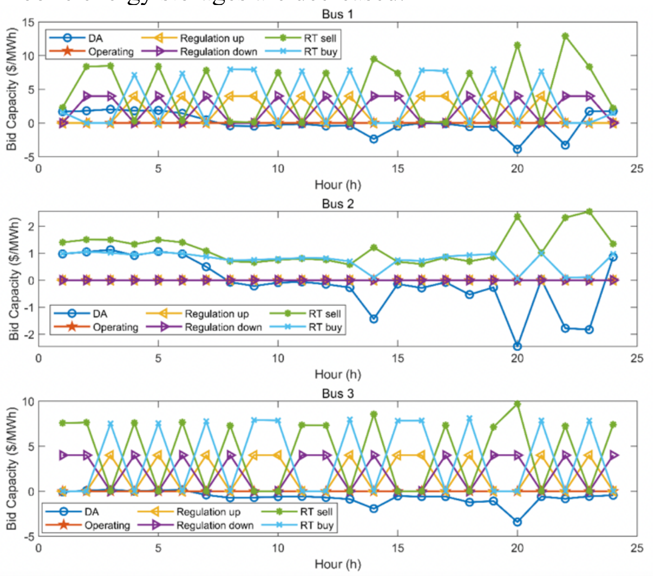

Fig. 3. The expected energy and reserve bidding capacities of the VPP

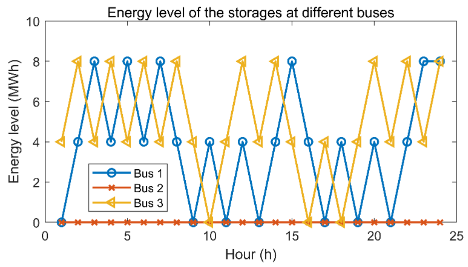

Fig. 4. The expected energy levels of the energy storages at three buses

TABLE I. THE TOTAL EXPECTED PROFIT AND CVARS OF THE VPP FOR CASES 1-3

Case No.	β_0	β_1	β_2	v (km /h)	Total expected profit(\$)	$CVaR_{0.8}$ (\$)	$CVaR_{0.95}$ (\$)
1	0.9	0.05	0.05	0	12204	4870	3457
2	0.9	0.05	0.05	20	12214	5370	4351
3	0.95	0.025	0.025	20	12222	5300	4189

C. Compare the Bidding Strategies with Single and Multiple CVaRs

To verify the effectiveness of using multiple CVaRs in the proposed bidding strategy, Case 4 and 5 are designed by setting β_1 or β_2 to be zero, respectively. Table II gives the comparisons of the simulations results of Case 2, 4 and 5.

TABLE II. THE TOTAL EXPECTED PROFIT AND CVARS OF THE VPP FOR CASES 2,4-5

Case No.	β_0	β_1	β_2	v (km /h)	Total expected profit (\$)	$CVaR_{0.8}$ (\$)	$CVaR_{0.95}$ (\$)
2	0.9	0.05	0.05	20	12214	5370	4351
4	0.9	0.1	0	20	12222	5300	4189
5	0.9	0	0.1	20	12209	5269	4416

In Case 4, since β_2 is set to be zero and $CVaR_{0.95}$ is not optimized in the stochastic optimization model, the $CVaR_{0.95}$ is \$162 lower than that in Case 2. In Case 5, since β_1 is set to be zero and $CVaR_{0.8}$ is not optimized in the stochastic optimization model, the $CVaR_{0.8}$ is \$101 lower than that in Case 2. Therefore, the simulation results in Table 2 show that the multiple risks related to different confidence levels can be optimized simultaneously by using the proposed bidding strategy. Additionally, the expected profit in Case 4 is the higher than that in Case 5, and it shows that maximizing the $CVaR_{0.8}$ does not decrease the total expected profit as much as maximizing the $CVaR_{0.95}$, because $CVaR_{0.8}$ is closer to the expected profit of all the scenarios than $CVaR_{0.95}$.

V. CONCLUSIONS

This paper proposed a stochastic energy and reserve bidding strategy for a VPP with mobile energy storages, which has RESs and load demands at multiple buses. In the proposed stochastic optimization model, the uncertainties faced by the VPP were represented via scenarios, and multiple CVaRs with different confidence levels were maximized simultaneously considering the VPP's risk preference.

Case studies have been carried out for a VPP participating in the Southwest Power Pool's energy and reserve markets, and the effectiveness of proposed bidding strategy using mobile energy storages and multiple CVaRs were verified via case studies. The simulation results showed that the total expected profit was increased and the risks were decreased for the VPP by using the mobile energy storages instead of the stationary ones. Moreover, by using the proposed bidding strategy, multiple CVaRs can be maximized simultaneously in the model considering the VPP's risk preferences in the energy and reserve markets.

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