Price maker optimization strategy for microgrid alliance with shared energy storage

Di Liu
Department of Automation
Tsinghua University
Beijing, China
kfliudi@163.com

Junwei Cao
Beijing National Research Center for Information Science and Technology
Beijing, China
jcao@tsinghua.edu.cn

***Abstract*—Distributed energy storage installed on the demand side can increase the local consumption of photovoltaics (PV), thereby reducing the energy consumption cost on the demand side. However, energy storage is not always fully utilized, and the sharing of energy storage among multiple demand-side entities can further reduce energy costs. In this paper, a collaborative framework for microgrids (MGs) equipped with energy storage is proposed, in which the energy storage own by each MG is uniformly controlled by the vitural coordinator. Besides, the vitural coordinator participants the regional electricity market as an independent entity, bidding for the electricity to satisfy the load demand of MGs. Since MG alliance is big enough to affect the clearing price in the market, a soft actor critic (SAC) algorithm is applied in this paper to obtain the optimal bidding strategy as a price maker, while considering the control of energy storage. Simulation results show that the proposed collaborative framework can improve the local consumption of PV, thereby reducing the energy cost, and the required electricity can always be purchased from market with the SAC algorithm.**

Keywords—energy storage, price maker, microgrid alliance, vitural coordinator.

I. Introduction

With the development of distributed renewable energy, the flexibility of the power system decreases rapidly, and the security and stability of its operation is threatened. Energy storage can store excess renewable energy and provide reliable and flexible dispatch resources for the power system. According to the research by Bloomberg New Energy Finance (BNEF), by 2030, 58GW/178GWh of energy storage will be deployed globally every year, with a compound annual growth rate of 30% [1]. Traditionally, energy storage devices are installed and controlled by the system operator, but many incremental energy storage devices belong to different entities [2], so centralized optimal control is difficult to achieve.

In a microgrid (MG), energy storage devices are commonly deployed to mitigate the output fluctuations of distributed renewable energy sources and address price variations in the electricity market. The rational utilization of energy storage devices can reduce the energy cost of the microgrid. The optimization adjustment method based on Double-Q Learning proposed in reference [3]effectively reduces user energy costs by optimizing the adjustment of energy storage devices. Reference [4][4] focuses on the frequency issues of microgrids, achieving frequency stability through optimized adjustments of energy storage devices. Reference [5] emphasizes the intermittent nature of distributed renewable energy output and achieves minimization of demand-side electricity costs through the synergistic optimization of distributed photovoltaics and energy storage devices.

Reference [6] investigates the transaction mechanism design of a zero-net-energy community MG and achieves optimal scheduling of energy storage through transactions. Reference [7] considers the system's robustness, balancing robustness and economic efficiency through robust optimization.

Usually, the regulation capability of energy storage is not fully utilized. Therefore, sharing excess regulation capacity could theoretically enhance the utilization rate of energy storage devices and consequently improve the microgrid's overall performance. Current research on energy storage sharing includes a summary of common centralized modes in [2], a consumer-centric active distribution network energy-sharing mechanism considering household energy storage in [8], and a novel energy-sharing cloud mechanism for intelligent microgrids with renewable energy and energy storage in [9]. In [10], a game theory-based energy storage sharing mechanism is established, where each agent determines both capacity trading and energy storage charging/discharging schedules simultaneously. To reflect differences among end-users, [11] proposes a credit-based capacity sharing method, enhancing total net profit and self-sufficiency.

In addition to local renewable energy sources, MGs need to purchase electricity from external sources to meet diverse power demands. When multiple MGs form alliances, their capacity may be significant enough to influence market clearing prices. In this case, the MG alliance is referred to as a price maker. In formulating bidding strategies, the MG alliance, in addition to considering local renewable energy output and load demand, must also consider the impact of bidding on market clearing prices [12]. Related studies, such as [13] and [14], respectively, focus on the bidding strategies of price makers in day-ahead and real-time markets. Uncertainty is a crucial factor affecting bidding outcomes, and [15] introduces probability distribution functions to describe the demand-price-quota curve, while [16] uses robust optimization to handle uncertainty in the electricity market.

However, existing research only models and analyzes uncertainty in bidding, while MG alliances face various uncertainties when formulating bidding strategies, including uncertainty in local photovoltaic output, user load demand, and energy storage sharing. To address these issues, this paper proposes a soft actor-critic (SAC) optimization algorithm based on Monte Carlo sampling. By obtaining estimates of coupled uncertain states through multiple samples, the algorithm's stability is improved. Additionally, a Power Allocation Method

This work is supported by Tsinghua-Toyota Joint Research Institute Inter-disciplinary Program.

based on Offset Proportional Coefficient is designed to achieve rapid error correction in shared energy storage, further reducing the impact of uncertainty and ultimately enhancing the overall efficiency of the MG alliance.

II. PROBLEM DESCRIPTION

A. Architecture of MG Alliance

Considering an MG alliance composed of n MGs and the coordinated architecture is shown in Fig. 1. The collaboration of multiple MGs is realized through vitural coordinator (VC). Different from the central control mode, VC can not directly control each MG, but coordinate MGs through mechanism design and sag coefficient signal.

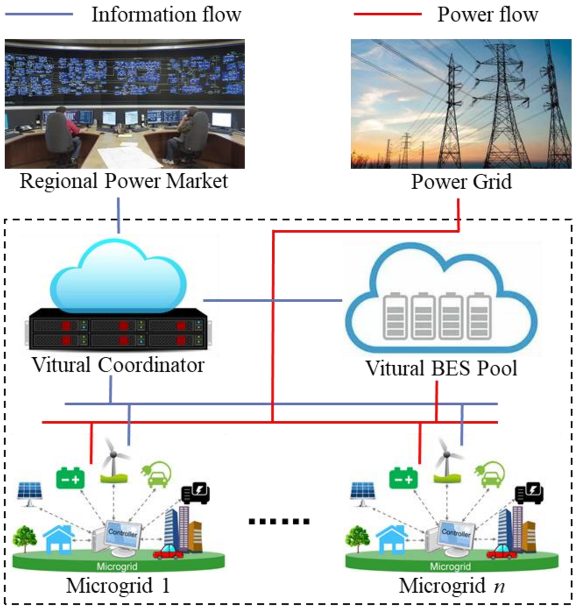


Fig. 1. Architecture of microgrid Alliance

MG alliance participates in regional power market as an independent entity through VC. In the regional power market, VC provides bidding or offering to purchase the demand power, or sell the exceeded power harvested from distributed energy resources of consumers e.g., photovoltaic (PV), wind power etc. In the MG alliance, the energy storages are aggregated by VC, and the social benefit of the MG alliance can be improved through bidding and the control of shared energy storages.

B. Regional power market

In the regional power market, the operator collects the bidding/offering curve of each participant, and clearing the market with the goal of maximize social welfare, as shown in Fig.2.For each buyer, they need to report multiple price electricity pairs in the market to represent the price they are willing to pay for each segment of electricity they purchase. Similarly, sellers also need to report a price electricity pair to represent their expected price for selling electricity. The electricity market combines the price electricity pairs reported by buyers into a decreasing step curve, while the reports of sellers are combined into an increasing step curve. All electricity quantities purchased at prices higher than the selling price can be traded.

Due to the substantial load requirements of the MG Alliance, its bidding activities in the regional electricity market have a significant impact on the market's clearance prices. When its power demand is high, the settlement prices increase; otherwise, the settlement prices decrease. For specific participants in the regional electricity market, attention is directed towards the residual demand/supply curve. The residual demand curve can be derived based on the demand of other buyers and the total supply from sellers. Taking bidding as an example, each participant engages in segmented bidding, and there are two forms of settlement prices, as illustrated in Fig. 2.

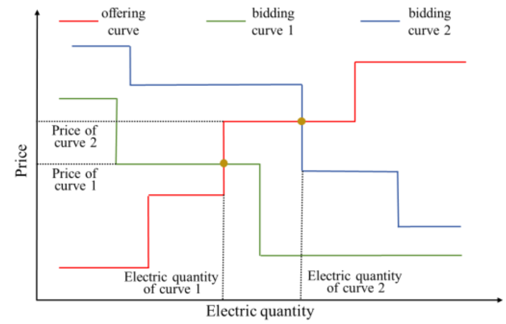


Fig. 2. Residual supply curve in power market with different bidding curve

III. MODELING

A. Shared energy storage model

In each time slot, VC can control the charging/discharging power of the shared energy storage, and the dynamic transition of energy storage is as follows [20]:

$$V_t = V_{t-1} + \eta_t^c P_t^c \Delta t - \frac{1}{\eta_t^d} P_t^d \Delta t, \quad (1)$$

$$0 \le V_t \le \sum_{i=1}^{N} V_i^{\mathrm{H}}, P_t^c \le P_t^{c,max}, P_t^d \le P_t^{d,max}, \quad (2)$$

where P_t^c and η_t^c are the charging power and efficiency of energy storage, respectively, P_t^d and η_t^d are the discharging power and efficiency of energy storage, respectively, and the stored energy in time slot t should not exceed the shared energy storage capacity $\sum_{i=1}^{N} V_i^{\mathrm{H}}$.

B. Objective function

The optimization objective of VC is to minimize the operation cost of MG alliance, which is composed of energy cost in regional power market, the incentive of energy storage sharing and the cost of cycle life loss of energy storage:

$$minC_a = \sum_{t=0}^{T} R_{sum,t} + \sum_{t=0}^{T} \lambda_{clear,t} P_{clear,t} + \sum_{t=0}^{T} C_{B,t}, \quad (3)$$

where $\lambda_{\mathrm{clear},t}$ and $P_{\mathrm{clear},t}$ are the clearing price and the clearing power in the time slot t of the regional electricity market, respectively. The loss of energy storage equipment increases with the increase of discharge depth, so the cost of using energy storage equipment can be approximated in the form of a quadratic function, as follows:

$$C_{B,t} = \tau |V_t - V_{t-1}|^2, \quad (4)$$

where τ is the loss factor, V_t is the amount of electricity stored in the energy storage.

In the optimization, the power balance constraint must be satisfied:

$$P_{clear,t} + \sum_{i=0}^{n} P_{i,t}^{MG} + P_t^c - P_t^d - \sum_{i=0}^{n} P_{t,i}^{PV} = 0. \quad (5)$$

IV. BIDDING STRATEGY BASED ON MONTE CARLO-SAC

A. MONTE CARLO based Markov process

The bidding process can be described by a 5-tuple Markov decision process, i.e., $M=(S,A,T,r,\gamma)$. Where S is the state space, including the residual supply curve, load, state of charge, and PV output. A is the action space, i.e., the bidding strategy. γ is the discount factor. r is the reward for action.

1) State: When the VC participates in the market bidding, it needs to know the load demand and PV output of the MG alliance, so as to know how much electricity it needs to buy from the market. A large number of studies are devoted to the prediction of load and PV output, so the predicted load demand $\hat{P}_t^{\mathrm{MG}}$ and PV output $\hat{P}_t^{PV}$ are used as elements state. The bidding of other participants directly determines the clearing result of the market. Therefore, the predicted bidding pair $(\hat{\boldsymbol{\lambda}}_o, \widehat{\boldsymbol{P}}_o)$ in the market is also one of the elements of the state. Although the relevant prediction work has achieved good results, there are always errors in the prediction. Multiple types of prediction errors coexist, and a single prediction error is likely to have an impact on the optimization results. In order to reduce this impact, according to the central limit theorem, multiple independent samples follow a normal distribution. Therefore, this paper designs a Monte Carlo sampling module to sample the predicted state variables multiple times and obtain their expected values as the input states of the algorithm. Finally, the maximum energy storage capacity $V_{t,max}$ electricity stored in energy storage cannot violate constraints, so state of charge (SOC) is also an element of state. In summary, the state of time slot t is as follows:

$$\hat{S}_t=\{\hat{P}_t^{\mathrm{MG}}, \hat{P}_t^{PV}, \hat{\boldsymbol{\lambda}}_o, \widehat{\boldsymbol{P}}_o, V_{t,max}\}, \tag{6}$$

$$S_t=\sum_{l=1}^{k}\hat{S}_{t,l}\Big/k. \tag{7}$$

2) Action: VC participates in market bidding and needs to submit price pairs $(\boldsymbol{\lambda}_{bid}, \boldsymbol{P}_{bid})$ to the market. In the MG alliance, VC also needs to control the charging/discharging power of energy storage. However, due to the constraints of power balance, the energy storage power is regarded as a passive variable, that is, the energy storage power is calculated by (7). Therefore, the action is $(\boldsymbol{\lambda}_{bid}, \boldsymbol{P}_{bid})$.

3) Reward: The optimization goal of the algorithm is to minimize the cost, so the cost is one of the components of the reward. Besides, since the power of BES is a passive variable, the energy storage has the risk of violating the constraints, so the penalty for exceeding the limit of the energy storage should be subtracted from the reward. Then the reward is as follows:

$$r_t=-\vartheta_1 R_{sum,t}-\vartheta_2\lambda_{clear,t}P_{clear,t}+\vartheta_3\Phi_t, \tag{8}$$

where ϑ_1, ϑ_2 and ϑ_3 are the adjustment parameters of each reward item, respectively, so that the reward obtained by the algorithm is maintained within a reasonable range, so as to promote the convergence of the algorithm. E_t is the penalty for violating the constraints. In this paper, the charge and discharge power of the SOC is constrained by the value range of the action, so the value of E_t comes from violating the capacity constraint of the SOC:

$$\Phi_t=\begin{cases}\left|V_t-\sum_{i=1}^{N}V_i^{\mathrm{H}}\right|, & V_t>\sum_{i=1}^{N}V_i^{\mathrm{H}}\\ |V_t|, & V_t\le 0.\end{cases}, \tag{9}$$

The cumulative reward is:

$$R_t=\sum_{\tau=t}^{T-1}\gamma^{\tau-t}r_t. \tag{10}$$

B. Bidding algorithm based on SAC

Since it is difficult to establish an accurate model for the bidding of other participants in the market, this paper introduces a model-free DRL algorithm to solve the optimization problem. Unlike other algorithms that aim at maximizing the expected reward value, SAC trains the network with the aim of maximizing entropy. In the bidding process, there may be a variety of actions that can achieve the optimal goal, because under the market clearing rules, as long as the segmented bidding is within a specific range, the same clearing results can be obtained. The algorithm based on SAC can avoid the bidding strategy to choose only a certain action, while ignoring other possible optimization actions. Therefore, the optimal strategy of SAC is:

$$\pi^*=\arg\max E_{(s_t,a_t)\sim\rho_\pi}\left[\sum_t R(s_t,a_t)+\alpha H\big(\pi(\cdot\,|s_t)\big)\right], \tag{11}$$

where $H\big(\pi(\cdot\,|s_t)\big)$ is the entropy and α is the weight coefficient that determines the importance of entropy.

To obtain π^*, the state value network $V_\psi(s_t)$, action value network $Q_\theta(s_t,a_t)$, and policy network $\pi_\phi(a_t|s_t)$ are set in SAC. The object function for $V_\psi(s_t)$ is:

$$J_V(\psi)=E_{s_t\sim D}\left[\frac{1}{2}\Big(V_\psi(s_t)-E_{a_t\sim\pi_\phi}\left[Q_\theta(s_t,a_t)-\log\pi_\phi(a_t|s_t)\right]\Big)^2\right], \tag{12}$$

where D is reply buffer, and the gradient of $J_V(\psi)$ can be estimated as follows:

$$\hat{\nabla}_\psi J_V(\psi)=\nabla_\psi V_\psi(s_t)\big(V_\psi(s_t)-Q_\theta(s_t,a_t)+\log\pi_\phi(a_t|s_t)\big). \tag{13}$$

The object function for $Q_\theta(s_t,a_t)$ is:

$$J_Q(\theta)=E_{(s_t,a_t)\sim D}\left[\frac{1}{2}\Big(Q_\theta(s_t,a_t)-\hat{Q}(s_t,a_t)\Big)^2\right], \tag{14}$$

where $\hat{Q}(s_t,a_t)$ is obtained using target value network $V_{\bar{\psi}}(s_{t+1})$, as follows:

$$\hat{Q}(s_t,a_t)=r(s_t,a_t)+\gamma E_{s_{t+1}\sim p}\left[V_{\bar{\psi}}(s_{t+1})\right]. \tag{15}$$

The gradient of $J_Q(\theta)$ is:

$$\hat{\nabla}_\theta J_Q(\theta)=\nabla_\theta Q_\theta(a_t,s_t)\Big(Q(s_t,a_t)-r(s_t,a_t)-\gamma V_{\bar{\psi}}(s_{t+1})\Big), \tag{16}$$

The object function for $\pi_\phi(a_t|s_t)$ is:

$$J_\pi(\phi)=E_{s_t\sim D}\left[D_{KL}\Big(\pi_\phi(\cdot\,|s_t)\Big)\Big\|\frac{\exp(Q_\theta(s_t,\cdot))}{Z_\theta(s_t)}\right], \tag{17}$$

where D_{KL} is Kullback-Leibler divergence, $Z_\theta(s_t)$ is the partition function. To minimize $J_\pi(\phi)$, the policy is reparameterized using neural networks:

$$a_t=f_\phi(\epsilon_t;s_t), \tag{18}$$

Where ϵ_t is random variable, and (17) can be rewritten as:

$$J_\pi(\phi)=E_{s_t\sim D,\epsilon_t\sim N}\left[\log\pi_\phi\big(f_\phi(\epsilon_t;s_t)|s_t\big)-Q_\theta\Big(s_t,f_\phi(\epsilon_t;s_t)\Big)\right], \tag{19}$$

the gradient of $J_\pi(\phi)$ can be written as:

$$\begin{aligned}\hat{\nabla}_\phi J_\pi(\phi)&=\nabla_\phi\log\pi_\phi(a_t|s_t)\\&+\Big(\nabla_{a_t}\log\pi_\phi(a_t|s_t)-\nabla_{a_t}Q(s_t,a_t)\Big)\nabla_\phi f_\phi(\epsilon_t;s_t)'\end{aligned} \tag{20}$$

C. Power allocation based on offset proportional coefficient

After market bidding, the virtual energy storage has obtained the adjustment target for each time period, and it is necessary to allocate the adjustment target to the physical energy storage of each MG. Due to the fact that the unit cost of energy storage increases with the amount of energy charged and discharged, in order to minimize the regulation cost of energy storage, it is necessary to comprehensively consider the current state of charge of each MG's energy storage and the target regulation amount allocated to it. Due to the fact that energy storage belongs to different MGs, fairness needs to be taken into account when formulating allocation strategies.

In summary, this paper designs a power allocation method based on offset proportional coefficient:

$$\Delta P_{i,t}^{B} = (\chi_i / \sum_{i=1}^{N} \chi_i)(P_t^c - P_t^d), \tag{21}$$

$$\chi_i = \left| \frac{V_{i,t} - 0.5V_{i,max}}{V_{i,max}} \right|. \tag{22}$$

In the above equation, χ_i is the offset coefficient, which keeps the SOC state of each energy storage at 50% as much as possible. On the one hand, it tries to reduce the adjustment cost as much as possible, and on the other hand, it leaves sufficient margin for subsequent adjustments.

V. Simulation

A. Simulation setup

Three MGs are set for simulation, and the energy storage installed by each MG is 300 kWh, 450 kWh and 150kWh respectively, and the stored power in the energy storage is 100kWh, 150kWh and 50kWh respectively. Load demand and PV output come from Pennsylvania-New Jersey-Maryland Interconnection power market [22], and the time period is from January 1, 2021 to December 31, 2021. All data from the PJM is scaled proportionally due to the smaller load demand and PV output of the MG. It should be noted that the fluctuations of the load and PV output are preserved. Residual supply curve are generated based on clearing prices from the PJM electricity market. Assume that the residual supply curve consists of 20 segments. Based on the base clearing price λ_t, randomly generate 20 prices in the range of [0, $2\lambda_t$] for each time slot, and randomly generate the electricity corresponding to each price in the range of [0, 20kW]. The charge/discharge efficiency factor η_t^c and η_t^d of energy storage are all set to be 1, the loss factor τ is set to be 0.05. All prediction errors are generated using a normal distribution with a standard deviation of 0.02.

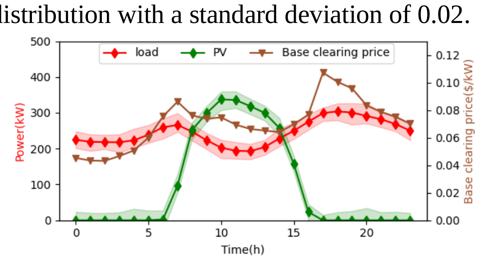


Fig. 3. Load demand and PV output of selected day

The SOC of energy storage, PV output, load demand and the residual supply curve are set as input of the algorithm, so the input dimension is set as 43. Assuming that the MG alliance uploads 3 bids in the market, the action dimension is set to 6. The value network, soft Q network and policy network are all have 3 layers, and each hidden layer has 256 nodes. Learning rate is set to be 0.00001 and the discount factor is set to be 0.99. The simulation is implemented using PyTorch in Python, on the laptop with Intel(R) Core(TM) i7-9750H processor and one single NVIDIA GeForce GTX 1660 Ti GPU. 365 days of historical data are used in the algorithm, in which the proportions of training set, validation set and test set are 80%, 10% and 10%, respectively. One day in the test set is used to demonstrate the effect of the algorithm, and its load demand, PV output and base clearing price are shown in Fig. 3.

B. Result analysis

The clearing power and the corresponding price in each time slot are shown in Fig.4. As the clearing result of the market is affected by the bidding strategy of MG alliance based on their load demand, the electricity purchased from the market in each time slot is different, and the clearing price is also fluctuating. At noon, the purchased electricity is zero due to the high output of PV. In these time slots, the PV output is surplus compared with load demand, so the MG alliance does not need any additional power. In other time slots, e.g., time slot 20, the purchased electricity is also zero without exceed PV output, because the load demand is satisfied by energy storage.

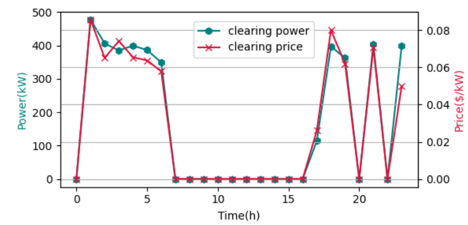
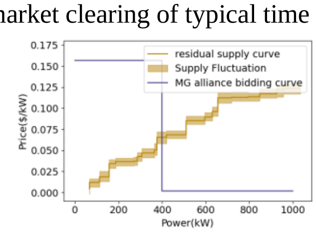


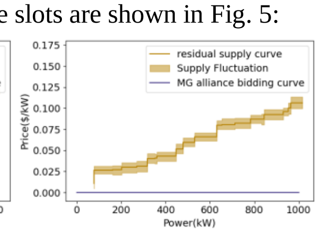
Fig. 4. Clearing result in each time slot throughout the day

Besides, as a price maker, the clearing price is positively related to the power demand of MG alliance, but it is also affected by the offering of suppliers. For example, in time slot 20, the load demand is about 260kW, and the clearing price is around 0.03$/kW. In comparation, in time slot 18, the clearing price is near 0.08 $/kW, while the load demand is about 280kW. This is because the supplier's offering during this period is relatively high.

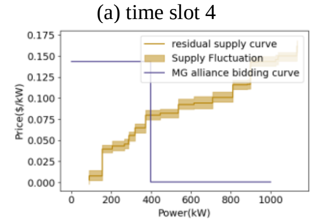
In order to ensure that MG alliance can always obtain the required electricity, the bidding strategy should be able to adapt to the changes of the residual supply curve. The bidding and market clearing of typical time slots are shown in Fig. 5:



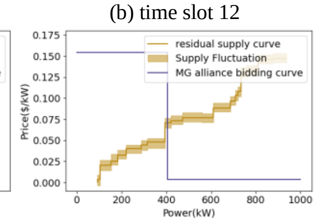
(a) time slot 4



(b) time slot 12



(c) time slot 18



(d) time slot 21

Fig. 5. Bidding curve in different time slot

In the bidding, MG alliance submits three price-power pairs in each time slot to form the bidding curve. In time slot 12, MG alliance does not need to purchase electricity from the market, so the bidding price is 0, and in other time slots, the algorithm can formulate an appropriate bidding strategy according to the offering, even if there is uncertainty (highlighted in yellow in the figure). In order to ensure that the power demand can be met, the algorithm tends to submit a high price in the first price-power pair, and the intersection of residual supply curve and bidding curve always appears in the vertical part of the bidding curve.

The utilization of energy storage can improve the local consumption of PV, the SOC of storage is shown in Fig. 6.

In Fig. 6, the green line represents the exceed PV, i.e., the remaining PV output after meeting load demand, the yellow line and purple line are the SOC with and without coordination in each time slot, respectively. It can be seen that the energy storage can store the exceed PV output at noon and satisfy the load demand in the following time slots. Due to the sharing of energy storage, PV is more fully utilized in the case of collaboration, and the local absorption rate of PV and the benefits of MGs are simultaneously improved.

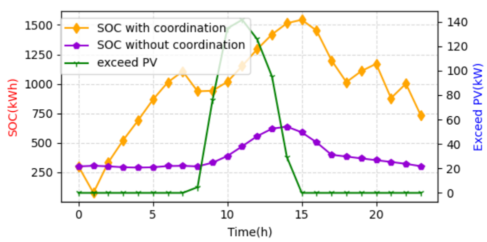


Fig. 6. SOC of energy storage in each time slot

VI. Conclusion

This paper proposes a collaborative framework for MGs equipped with energy storage. Through the sharing of the energy storage among MGs, the energy storage can be more fully utilized, and the local consumption of PV output can be improved. Then MGs participate in the regional market as an independent entity through central collaborator. Since the MG alliance is a price maker in the market, the bidding strategy affects the clearing price. Besides, the utilization of energy storage affect the load demand from the market. SAC algorithm is applied to obtain the optimal bidding strategy according to the residual supply curve. Simulation results verify the effectiveness and superiority of the proposed collaborative framework and the algorithm. In the future work, the peer-to-peer transactions among MG alliances can be studied to further improve the operation efficiency of the system.

References

[1] Bloomberg New Energy Finance, BloombergNEF predicts 30% annual g rowth for global energy storage market to 2030 [Online]. Available: https://www.energy-storage.news/bloombergnef-predicts-30-annual-growth-for-global-energy-storage-market-to-2030/

[2] R. Dai, R. Esmaeilbeigi and H. Charkhgard, "The Utilization of Shared Energy Storage in Energy Systems: A Comprehensive Review," in IEEE Transactions on Smart Grid, vol. 12, no. 4, pp. 3163-3174, July 2021, doi: 10.1109/TSG.2021.3061619.

[3] Y. Yu, Z. Cai and Y. Huang, "Energy Storage Arbitrage in Grid-Connected Micro-Grids Under Real-Time Market Price Uncertainty: A Double-Q Learning Approach," in IEEE Access, vol. 8, pp. 54456-54464, 2020, doi: 10.1109/ACCESS.2020.2981543.

[4] C. Mu, Y. Zhang, H. Jia and H. He, "Energy-Storage-Based Intelligent Frequency Control of Microgrid With Stochastic Model Uncertainties," in IEEE Transactions on Smart Grid, vol. 11, no. 2, pp. 1748-1758, March 2020, doi: 10.1109/TSG.2019.2942770.

[5] X. Li, L. Wang, N. Yan and R. Ma, "Cooperative Dispatch of Distributed Energy Storage in Distribution Network With PV Generation Systems," in IEEE Transactions on Applied Superconductivity, vol. 31, no. 8, pp. 1-4, Nov. 2021, Art no. 0604304, doi: 10.1109/TASC.2021.3117750.

[6] H. -C. Jo, G. Byeon, J. -Y. Kim and S. -K. Kim, "Optimal Scheduling for a Zero Net Energy Community Microgrid With Customer-Owned Energy Storage Systems," in IEEE Transactions on Power Systems, vol. 36, no. 3, pp. 2273-2280, May 2021, doi: 10.1109/TPWRS.2020.3036077.

[7] J. S. Giraldo, J. A. Castrillon, J. C. López, M. J. Rider and C. A. Castro, "Microgrids Energy Management Using Robust Convex Programming," in IEEE Transactions on Smart Grid, vol. 10, no. 4, pp. 4520-4530, July 2019, doi: 10.1109/TSG.2018.2863049.

[8] S. Yang et al., "A Prosumer-Based Energy Sharing Mechanism of Active Distribution Network Considering Household Energy Storage," in IEEE Access, vol. 10, pp. 113839-113849, 2022, doi: 10.1109/ACCESS.2022.3217540.

[9] S. Li, J. Zhu and H. Dong, "A Novel Energy Sharing Mechanism for Smart Microgrid," in IEEE Transactions on Smart Grid, vol. 12, no. 6, pp. 5475-5478, Nov. 2021, doi: 10.1109/TSG.2021.3094329.

[10] J. Jo and J. Park, "Demand-Side Management With Shared Energy Storage System in Smart Grid," in IEEE Transactions on Smart Grid, vol. 11, no. 5, pp. 4466-4476, Sept. 2020, doi: 10.1109/TSG.2020.2980318.

[11] S. Lai, J. Qiu and Y. Tao, "Credit-Based Pricing and Planning Strategies for Hydrogen and Electricity Energy Storage Sharing," in IEEE Transactions on Sustainable Energy, vol. 13, no. 1, pp. 67-80, Jan. 2022, doi: 10.1109/TSTE.2021.3103886.

[12] M. Song and M. Amelin, "Price-Maker Bidding in Day-Ahead Electricity Market for a Retailer With Flexible Demands," in IEEE Transactions on Power Systems, vol. 33, no. 2, pp. 1948-1958, March 2018, doi: 10.1109/TPWRS.2017.2741000.

[13] B. Hu, Y. Gong, C. Y. Chung, B. F. Noble and G. Poelzer, "Price-Maker Bidding and Offering Strategies for Networked Microgrids in Day-Ahead Electricity Markets," in IEEE Transactions on Smart Grid, vol. 12, no. 6, pp. 5201-5211, Nov. 2021, doi: 10.1109/TSG.2021.3109111.

[14] S. Wang, S. Bi and Y. -J. A. Zhang, "Demand Response Management for Profit Maximizing Energy Loads in Real-Time Electricity Market," in IEEE Transactions on Power Systems, vol. 33, no. 6, pp. 6387-6396, Nov. 2018, doi: 10.1109/TPWRS.2018.2827401.

[15] Y. Wang, D. Wang, H. Zhang and K. Zhang, "Optimal Bidding of Price-Maker Retailers With Demand Price Quota Curves Under Price Uncertainty," in IEEE Access, vol. 8, pp. 120746-120756, 2020, doi: 10.1109/ACCESS.2020.3005932.

[16] S. Shafiee, H. Zareipour and A. M. Knight, "Developing Bidding and Offering Curves of a Price-Maker Energy Storage Facility Based on Robust Optimization," in IEEE Transactions on Smart Grid, vol. 10, no. 1, pp. 650-660, Jan. 2019, doi: 10.1109/TSG.2017.2749437.

[17] B. Hu, Y. Gong, C. Y. Chung, B. F. Noble and G. Poelzer, "Price-Maker Bidding and Offering Strategies for Networked Microgrids in Day-Ahead Electricity Markets," in IEEE Transactions on Smart Grid, vol. 12, no. 6, pp. 5201-5211, Nov. 2021, doi: 10.1109/TSG.2021.3109111.

[18] A. Mu, S. Roque, F. S. Eugenio, and J. Garc, “Residual demand curves for modeling the effect of complex offering conditions on day-ahead electricity markets,” IEEE Trans. Power Syst., vol. 32, no. 1, pp. 50–61, Jan. 2017.

[19] G. Aneiros, J. M. Vilar, R. Cao, and A. M. San Roque, “Functional prediction for the residual demand in electricity spot markets,” IEEE Trans. Power Syst., vol. 28, no. 4, pp. 4201–4208, Nov. 2013.

[20] Hua, H.; Qin, Y.; Hao, C.; Cao, J. Optimal energy management strategies for energy Internet via deep reinforcement learning approach. Appl. Energy 2019, 239, 598–609.

[21] Haochen Hua, Yuchao Qin, Zicheng He, Liuying Li, and Junwei Cao, “Energy sharing and frequency regulation in energy Internet via mixed H_2/H_∞ control with Markovian jump,” CSEE Journal of Power and Energy Systems, vol. 7, no. 6, pp. 1302-1311, Nov. 2021.

[22] PJM, Data directory [Online]. Available: https://www.pjm.com/markets-and-operations/data-dictionary.