Generalized Energy Storage Allocation Strategies for Load Aggregator in Hierarchical Electricity Markets

Weiqing Sun, Wei Liu, Wei Xiang, and Jie Zhang

***Abstract*—The uncertainty of user-side resource response will affect the response quality and economic benefit of load aggregator (LA). Therefore, this paper regards the flexible user-side resources as a virtual energy storage (VES), and uses the traditional narrow sense energy storage (NSES) to alleviate the uncertainty of VES. In order to further enhance the competitive advantage of LA in electricity market transactions, the operation mechanism of LA in day-ahead and real-time market is analyzed, respectively. Besides, truncated normal distribution is used to simulate the response accuracy of VES, and the response model of NSES is constructed at the same time. Then, the hierarchical market access index (HMAI) is introduced to quantify the risk of LA being eliminated in the market competition. Finally, combined with the priority response strategy of VES and HMAI, the capacity allocation model of NSES is established. As the capacity model is nonlinear, Monte Carlo simulation and adaptive particle swarm optimization algorithm are used to solve it. In order to verify the effectiveness of the model, the data from PJM market in the United States is used for testing. Simulation results show that the model established can provide the effective NSES capacity allocation strategy for LA to compensate the uncertainty of VES response, and the economic benefit of LA can be increased by 52.2% at its maximum. Through the reasonable NSES capacity allocation, LA is encouraged to improve its own resource level, thus forming a virtuous circle of market competition.**

***Index Terms*—Load aggregator, generalized energy storage, narrow sense energy storage, capacity allocation strategy, ancillary service market.**

I. INTRODUCTION

WITH the increase of renewable energy penetration, the instantaneous dynamic balance of "production-transmission-consumption" of traditional "rigid" power system is becoming more and more difficult [1]. Future power systems have to be "flexible" enough to accommodate the new normal of high-penetration renewable energy [2]. At the same time, with the maturity of electricity market, the economic operation of power system is no longer only a problem to be considered at generation side. User-side resources that under the access conditions can also participate in electricity market transactions [3]. With coordinated dispatching between user side and generation side, source-load interaction can be achieved, and a "win-win" situation for the economic operation of power system can be achieved. To realize successful transformation of future power system and steady progress of the electricity market reform, it is obvious that the demand for user-side flexibility will further increase sharply.

Since user-side resources such as industrial, commercial, residential and other resources are mostly scattered and the controllable capacity of a single resource is uncertain, it will inevitably be difficult for grid managers to directly incorporate these resources into dispatch. In order to fully collect and utilize these scattered small- and medium-sized resources, a specialized demand response (DR) provider has emerged in developed countries, i.e., load aggregator (LA). As a new type of commercial organization, LA integrates user-side resources through technical and economic strategies and introduces them into the electricity market. In this way, small- and medium-sized resources can participate in DR projects or bid in the electricity market, which stabilizes the operation of the system and makes the market mechanism more mature. According to different types of resources, LA can be further divided into distributed power generation aggregator, electric vehicle (EV) aggregator, DR resource aggregator, intelligent housing aggregator, etc. The LA participates in electricity market transactions by integrating and controlling EVs, temperature control loads, and other flexible user-side resources.

In this context, as an emerging electricity seller that aggregates a large number of flexible user-side resources, LA has been developing rapidly [4]. The practical applications in Australia and Europe show that LA plays a crucial role in easing the peak power demand of power grid, slowing down the expansion of transmission and distribution capacity, and tapping the flexibility of user-side resources [5], [6]. However, user-side resources are characterized by various types, scattered layouts, different sizes, and uncertainty, which con-

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strain LA's participation in commercial application of electricity ancillary service market [7], [8]. Therefore, in the process of market improvement, how to efficiently manage and control the user-side resources and rationally configure the electric energy storage to deal with the uncertainty of LA response has become a research hotspot in recent years.

Current researches on LA mostly focus on operational control and market competition strategies. Reference [9] proposed the implementation approaches to promote the commercialization model of LA from the perspective of integrating user-side resources. The influence of the uncertainty of the user-side resources on the bidding decision of LA was studied in [10]. Reference [11] proposed an information gap decision theory-based approach to avoid the charging and discharging risk of EVs in default, which can provide pre-determined profit protection for aggregators. In [12], three types of DR were considered to optimize the power and heat consumption scheduling of customers, from which the cost was reduced by 8.5%, the pollution emission was reduced by 47.4%, and the customer satisfaction was raised to 79.3%. Through demand side management (DSM), [13] optimized the energy scheduling problem of residential intelligent distribution network, from which the operation cost can be reduced by 30.15%, and the expected load loss can be reduced by 64.25%. Reference [14] improved the economic and technical indicators of smart independent microgrid operation through demand transfer and demand reduction. In [15], a new DSM strategy was proposed. By introducing user incentives into the smart microgrid, this strategy can reduce operation costs by 21.22%, and increase users satisfaction and wind power penetration by 1.6% and 12.64%, respectively. Through the evaluation of the various strategies of EV aggregators, the optimal strategy formulated in [16] can reduce the total cost by 10.26%. Reference [17] established the Cournot model to reasonably price the DR. In practice, due to the aggregation of a large-scale small- and medium-sized user-side resources to participate in the electricity market, the controllability and response accuracy of LA were poor [18], [19], resulting in that the economic benefits were not obvious. In this paper, user-side flexible loads with certain power regulation capabilities were collectively referred to as virtual energy storage (VES). LA conducted unified management and control of VES with the trading energy structure. The process of LA stimulating users to adjust their own power is called VES response.

In addition, traditional energy storage system such as battery energy storage, flywheel energy storage, etc., is called narrow sense energy storage (NSES). Because of its advantages in separating the generation and consumption of electric energy from time and space dimensions, it has gradually become one of the key supporting technologies for future power systems. In recent years, scholars world-wide have carried out relevant research on energy storage allocation of grid side, new energy side, and user side. Reference [20] allocated grid-side NSES from the perspective of installation subject. The goal of decision-making was to ensure the maximum economic and environmental benefits. NSES on the new energy side aimed to stabilize the randomness of renewable energy and improve the schedulability on hourly time scale [21], [22]. Starting from the user side, [23] summarized the commercialization mode of NSES applied to DR, and provided new opportunities for the development of user-side NSES. Although NSES had gradually become a new way to ensure the participation of small- and medium-sized users in electricity markets with its flexibility and strong controllability [24], previous researches show that in current situations, due to the high investment and construction costs, the static investment payback period (SIPP) of the user-side NSES participating in DR can reach up to 10-20 years [25]. Therefore, this paper does not take NSES as the main means of DR, but as a method to reduce the uncertainty of VES response. NSES was allocated on the user side and combined with VES to form complementary advantages, so as to improve the response quality and benefits of LA. When the VES response is insufficient, LA will dispatch NSES for discharging. When the VES response overflows, LA schedules the NSES for charging.

To sum up, this paper proposes a generalized energy storage (GES) concept that combines VES and NSES from the perspective of power system "load-storage". As stated in [26] and [27], GES can be defined as "all devices and measures that can change the temporal and spatial characteristics of electrical energy". Specifically, it can act as a buffer between power supply and demand, e.g., NSES, EV charging and discharging management, multi-energy interconnection system. In order to improve the response accuracy of GES, a GES response strategy based on VES priority response is proposed. On this basis, an optimal allocation model of NESE based on hierarchical market access index (HMAI) is established to maximize the economic benefits. Finally, the income of LA with different compensation schemes is analyzed, which provides a reference for compensation prices to guide more LAs to participate in the electricity market. For the sake of clarity, Table SI in Supplementary Material shows the differences between this paper and the above-mentioned research works.

The main contributions of this paper are as follows.

1) This paper analyzes the operating mechanism of LA in both day-ahead and real-time markets. In day-ahead market, according to the probability distribution of GES response, the service contract is signed with independent system operator (ISO). In real-time market, the response gap caused by the uncertainty of VES response is compensated by NSES.

2) According to the response characteristics, truncated normal distribution is used to simulate the response accuracy of VES. And the response models of VES and NSES are established, respectively. On this basis, according to the strategy of VES priority response, the operation strategy of LA is analyzed.

3) The HMAI is designed to measure the risk of LA being eliminated when participating in market competition. In order to improve the market competitiveness of LA, an optimal capacity allocation model of NSES considering the HMAI is established. Through the rational allocation of NSES, both the income and response quality of LA can be significantly improved.

The rest of this paper is organized as follows. Section II is the market analysis of LA considering GES. Section III presents the model of VES and NSES response. In Section IV, the analysis of LA scheduling strategy considering VES response uncertainty is given. In Section V, an optimal capacity allocation model of NSES for LA based on HMAI is constructed. In Section VI, the numerical results based on PJM market and the corresponding explanations are given. Finally, Section VII gives the conclusions of this paper.

II. Market Analysis of LA Considering GES

A. Analysis of LA Based on Real-time Power Balancing

Based on the principle of real-time power balance [28], the power system needs to maintain energy balance at each time-space intersection, i. e., the state of each grid node in each time period. This energy balance state can be divided into instantaneous balance, short-term balance, and time balance on long-term scale. Due to the storage characteristics of energy storage, electrical energy can be transferred in different time periods. Coupled with the rise of mobile energy storage such as EVs, electric energy can also be transmitted at different nodes. In short, GES realizes the wide-area sharing of electric energy in both time and space dimensions. And the intervention of GES transforms the real-time balance of electric energy in the power system from the original point balance to the plane balance [29]. The point balance here means that electric energy can neither be transmitted in neither the time dimension nor the spatial dimension. The blue shaded area (S*) in Fig. 1 shows the wide-area shared power of GES in both time and spatial dimensions. In addition, GES spreads the cost of maintaining point balance to the plane, greatly reducing the cost of power balance and increasing the market revenue of LA.

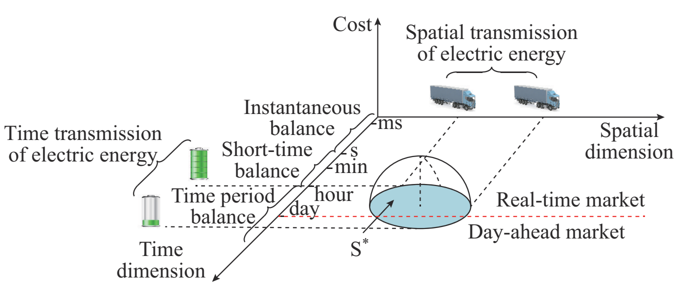

Fig. 1. Analysis of LA with GES based on real-time power balancing.

B. Operation Mechanism of LA in Electricity Market

Dispatching GES through technical and economic means, LA participates in transactions as the power supply, and signs DR contracts with ISO. The main income of LA participating in services comes from policy subsidies for electricity cost savings and DR, and NSES's profit through peak-to-valley arbitrage. With reference to the transaction process of the PJM electricity market in the United States [30], the process of LA participating in the electricity market transactions can be divided into two stages. As shown by the red dashed line in Fig. 1, the electricity market can be divided into day-ahead and real-time markets with "day" as the demarcation.

1) In the day-ahead market, LA forecasts the probability distribution of "virtual electricity" that can be provided by VES resources in the next day according to the historical data. Combined with the response power provided by the NSES, the final response power of LA is reported to ISO. ISO selects one or more qualified aggregators from several LAs to sign the DR service contracts. The unified contract price mode is adopted to clear the day-ahead market.

2) In the real-time market, LA dispatches GES to complete the DR contract signed in the day-ahead market, and uses the contract price for clearing. If the actual response power of LA reaches the contractual commitment level, LA will be rewarded, including contract compensation and real-time response compensation. Otherwise, if the actual response power of LA does not reach the committed level, the real-time marginal price will be taken as the unit power penalty. The penalty price is a single form, i. e., the penalty price for over-response and under-response is the same.

The above trading processes are shown in Fig. S1 in Supplementary Material. Since electricity consumption behaviours of the users are simultaneously affected by multiple factors such as subjective factors and real-time electricity prices, the VES response is often uncertain and time-varying. Therefore, for different response requirements at different time, the probability distribution of the actual response of LA is different. In order to best satisfy the response demands at all time, the market should try to avoid using a uniform incentive price for LA. Therefore, this paper divides different response levels according to the stability of LA response, and formulates hierarchical electricity markets for different response levels. Different hierarchical electricity markets have different incentive prices. The hierarchical electricity market can stimulate the competition among LAs, thereby obtaining better response services for the power system.

III. Model of VES and NSES Response

A. Model of VES Response

The aggregation of VES resources of different scales by LA is a complex behavior with many influencing factors, so the response of VES has greater uncertainty [31]. In order to facilitate the solution, the sequential operation theory is applied to the uncertainty analysis of the VES response [32], [33]. This paper assumes that different types of VES responses are independent each other. And the set of discretized probability sequences of different types of VES responses in the same time period is $\{A_1^t(i), A_2^t(i), \ldots, A_k^t(i)\}$, $i=1,2,\ldots,n_k$, where $A_k^t(i)$ is the sequence of the k^{th} VES response during the t^{th} period, and n_k is the length of the probability sequence of the k^{th} VES response. Then, the probability distribution $O^t(j)$ of the VES response during the t^{th} period is the volume sum of the discretized probability sequence of the various VES resources during the period, which is calculated as:

$$O^t(j) = A_1^t(i) \oplus A_2^t(i) \oplus \ldots \oplus A_k^t(i) \quad i=1,2,\ldots,n_k,\ j=\sum_{k=1}^{K} n_k \tag{1}$$

where $\oplus$ is the volume sum in the theory of sequence operations; and K is the number of types of VES responses.

Through the analysis of historical data, the uncertainty of VES response follows normal distribution [34]. Since the VES response has power, time, and continuity constraints [27], truncated normal distribution is used to simulate the response accuracy of VES in this paper. The absolute value of the actual response power of VES is distributed in the non-negative interval $[0, Q_{\text{VES}}^{\max}]$.

In order to further quantitatively describe the realized VES response in LA dispatching process, the VES response ratio δ_t is defined as the ratio between VES realized response $Q_{\text{VES},t}^{\text{real}}$ and scheduled response $Q_{\text{VES},t}^{\text{C}}$ during the t^{th} period.

$$\delta_t = \frac{Q_{\text{VES},t}^{\text{real}}}{Q_{\text{VES},t}^{\text{C}}} \tag{2}$$

where $Q_{\text{VES},t}^{\text{C}} > 0$ denotes the increase of load; and $Q_{\text{VES},t}^{\text{C}} < 0$ denotes the reduction of load.

Since the response accuracy of VES follows the truncated normal distribution, δ_t should also follow a truncated normal distribution $\delta_t \sim N(\mu_t, \sigma_t^2, \delta_t^{\min}, \delta_t^{\max})$, whose probability density function is (3):

$$f(\delta_t; \mu_t, \sigma_t, \delta_t^{\min}, \delta_t^{\max}) = \begin{cases} \dfrac{\varphi\left(\dfrac{\delta_t - \mu_t}{\sigma_t}\right)}{\sigma_t\left(\Phi\left(\dfrac{\delta_t^{\max} - \mu_t}{\sigma_t}\right) - \Phi\left(\dfrac{\delta_t^{\min} - \mu_t}{\sigma_t}\right)\right)} & \delta_t^{\min} \le \delta_t \le \delta_t^{\max} \\ 0 & \text{others} \end{cases} \tag{3}$$

where $\varphi(\cdot)$ and $\Phi(\cdot)$ are the probability density function and cumulative distribution function of the standard normal distribution, respectively; μ_t is the expection of VES response ratio during the t^{th} period; σ_t is the standard deviation of VES response riatio during the t^{th} period; and $\delta_t^{\max}$ and $\delta_t^{\min}$ are the maximum and minimum VES response ratios of during the t^{th} period, respectively. The lower limit of the probability distribution ($\delta_t^{\min}$) is 0, which means that the VES will not respond.

When dispatched by LA, the random distribution of VES response depends on its resource conditions [34]. For this reason, characteristic coefficients α and β are introduced to reflect the performance difference of VES with different scheduling requirements. The expectation of random distribution is $\mu_t = \mu(\alpha, Q_{\text{VES},t}^{\text{C}})$, standard deviation is $\sigma_t = \sigma(\alpha, Q_{\text{VES},t}^{\text{C}})$, and the maximum response ratio is $\delta_t^{\max} = \beta\mu(\alpha, Q_{\text{VES},t}^{\text{C}})$. According to the expectation expression of truncated normal distribution in [35], the expected response ratio $E[\delta_t]$ of VES can be obtained.

$$E[\delta_t] = \mu(\alpha, \delta_t) + \sigma(\alpha, \delta_t)\frac{\varphi\left(\dfrac{-\mu_t}{\sigma_t}\right) - \varphi\left(\dfrac{\delta_t^{\max} - \mu_t}{\sigma_t}\right)}{\Phi\left(\dfrac{\delta_t^{\max} - \mu_t}{\sigma_t}\right) - \Phi\left(\dfrac{-\mu_t}{\sigma_t}\right)} \tag{4}$$

With time scale τ, the expected value of VES response can be obtained as:

$$Q_{\text{VES},\tau}^{\text{E}} = \int_0^{\tau} E[\delta_t] P_{\text{VES},t}^{\text{C}} \text{d}t = \sum_{t=1}^{\tau/t} E[\delta_t] Q_{\text{VES},t}^{\text{C}} \tag{5}$$

where $P_{\text{VES},t}^{\text{C}}$ is the VES scheduled power.

B. Model of NSES Response

Various types of traditional energy storage systems constitute NSES resources that can participate in LA scheduling. The NSES is regarded as a measure to deal with the uncertainty of the VES response, so the uncertainty that may exist in the NSES response is not considered. Since NSES has multi-time scales and state dependence, the response provided by NSES is related to its state of charge (SOC) and charging and discharging power. With a certain time scale τ, the response provided by the k^{th} NSES is:

$$q_k^+\left(\tau; P_{k,t}^{\text{st},+}; E_k^{\text{st}}(t)\right) = \min\left(\int_0^{\tau} P_{k,t}^{\text{st},+} \text{d}t;\, E_k^{\max} - E_k^{\text{st}}(t)\right) \tag{6}$$

$$q_k^-\left(\tau; P_{k,t}^{\text{st},-}; E_k^{\text{st}}(t)\right) = \min\left(\int_0^{\tau} P_{k,t}^{\text{st},-} \text{d}t;\, E_k^{\text{st}}(t) - E_k^{\min}\right) \tag{7}$$

where $k \in A_{\text{NSES}}$, and A_{NSES} is the set of NSES; $q_k^+(\tau;\cdot)$ and $q_k^-(\tau;\cdot)$ are the quantities of charging and discharging responses for the k^{th} NSES, respectively; $P_{k,t}^{\text{st},+}$ and $P_{k,t}^{\text{st},-}$ are the variables representing charging and discharging power of the k^{th} NSES during the t^{th} period, respectively; $E_k^{\text{st}}(t)$ is a variable representing the quantity of energy stored in the k^{th} NSES during the t^{th} period; and $E_k^{\max}$ and $E_k^{\min}$ are the upper and lower limits of power, respectively.

Taking the charging response of NSES as an example, the visualization result of (6) is shown in Fig. 2. As shown in Fig. 2(a), if the accumulated electric quantity of NSES does not exceed the upper limit, the response quantity of the k^{th} NSES is equal to its charging electric quantity $\int_0^{\tau} P_{k,t}^{\text{st},+} \text{d}t$. When the SOC of the k^{th} NSES reaches the upper limit, the response quantity is $E_k^{\max} - E_k^{\text{st}}(t)$, as shown in Fig. 2(b).

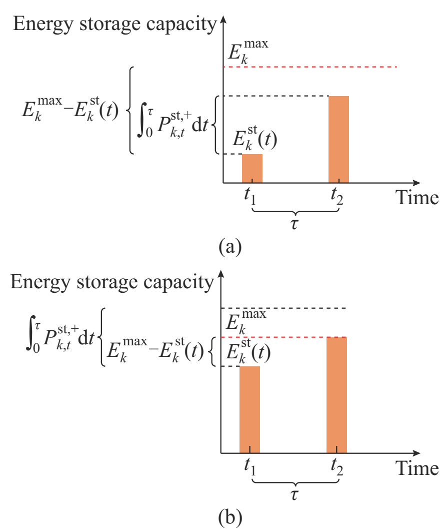

Fig. 2. Response quantity of the k^{th} NSES in charging state. (a) Not reaching upper limit of NSES capacity. (b) Reaching upper limit of NSES capacity.

Then, in the case of a certain time scale τ, the quantity of response that all NSESs in the region $Q_{\text{st}}^{\pm}$ can provide is:

$$Q_{\text{st}}^{\pm} = \sum_{k \in A_{\text{NSES}}} q_k^{\pm}\left(\tau; P_{k,t}^{\text{st},\pm}; E_k^{\text{st}}(t)\right) \tag{8}$$

IV. LA Scheduling Strategy Considering VES Response Uncertainty

In order to give full play to the dominant role of VES when participating in DR, LA can firstly schedule VES. In the case of VES priority response, NSES is used to compensate for the deviation caused by VES response and to improve the response level. To quantitatively evaluate the response level of GES, the response confidence level (RCL) is introduced in this paper. RCL is the probability value of actual response in the specified response deviation range, as shown in Fig. 3.

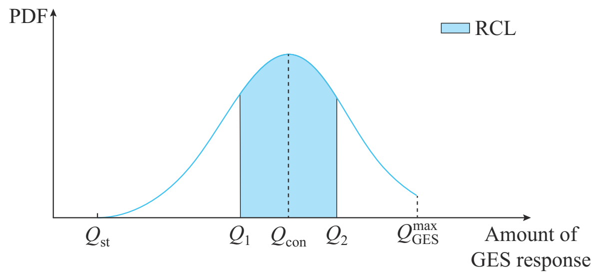

Fig. 3. RCL of GES.

The RCL of GES is calculated as:

$$RCL = F(Q_2) - F(Q_1) = \int_{Q_1}^{Q_2} f(Q_{GES}; Q_{con}, \sigma(Q_{st}, Q_{VES}), Q_{st}, Q_{GES}^{max}(Q_{st}, Q_{VES}))\, \mathrm{d}Q_{GES} \tag{9}$$

where $[Q_1, Q_2]$ is the response deviation interval; $F(\cdot)$ is the cumulative distribution function of GES response; Q_{GES} is the actual response of GES; Q_{con} is the scheduled response of GES; Q_{st} is the dispatched response of NSES, and also the lower limit of Q_{GES} when VES response is 0; and Q_{GES}^{max} is the maximum response quantity of GES response.

Assume that the deviation of VES response is ΔQ_{VES}. With this strategy, the deviation of GES response is:

$$\Delta Q_{GES} = \Delta Q_{VES} - Q_{st} \tag{10}$$

The VES probability density curves before and after NSES response are presented in Fig. 4, where $f_1(Q_{GES})$ is the probability density function (PDF) of GES response when the NSES response is 0, and the standard deviation is $\sigma = \sigma(\alpha, Q_{con})$; $f_2(Q_{GES})$ is the PDF when NESE response is Q_{st}; and the standard deviation is $\sigma = \sigma(\alpha, Q_{con} - Q_{st})$. When the NESE response is Q_{st}, the RCL in the response deviation interval $[Q_{con} - \Delta Q_{GES}, Q_{con} + \Delta Q_{GES}]$ is equal to that in the interval $[Q_{con} - \Delta Q_{VES}, Q_{con} + \Delta Q_{VES}]$ of no NESE response, i.e., the area of shadow S_1 is equal to the area of shadow S_2.

$$RCL_{f_2} = RCL_{f_1} \Rightarrow F_2(\Delta Q_{GES} + Q_{con}) - F_2(Q_{con} - \Delta Q_{GES}) = F_1(\Delta Q_{VES} + Q_{con}) - F_1(Q_{con} - \Delta Q_{VES}) \tag{11}$$

where $F_1(\cdot)$ is the cumulative distribution function of GES response when NESE response is 0; and $F_2(\cdot)$ is the cumulative distribution function when NESE response is Q_{st}.

It can be seen from Fig. 4 that the narrower the deviation range of the GES response is (reduced from $[Q_{con} - \Delta Q_{VES}, Q_{con} + \Delta Q_{VES}]$ to $[Q_{con} - \Delta Q_{GES}, Q_{con} + \Delta Q_{GES}]$), the more accurate the response is. Moreover, the larger Q_{st} is, the narrower the deviation range is. In other words, the larger Q_{st} is, the smaller the standard deviation of PDF of GES is. And the standard deviation σ^G is a single-valued function:

$$\sigma^G = g(Q_{con}; Q_{st}) \tag{12}$$

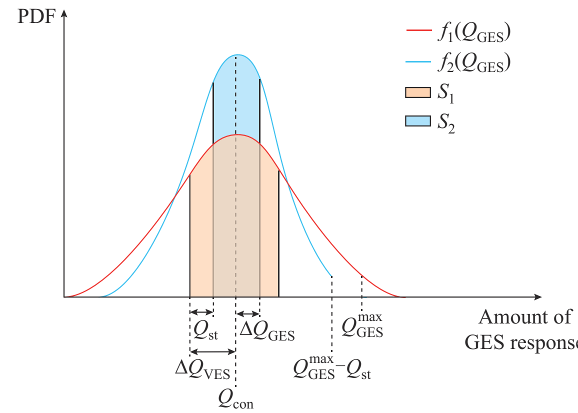

Fig. 4. VES probability density curve before and after NSES response.

If the above relation is converted to the response ratio of GES, (11) can be rewritten as:

$$\int_{1-\Delta Q_{GES}/Q_{con}}^{1+\Delta Q_{GES}/Q_{con}} f_2^*(\delta^G; \mu, \sigma^G, 0, \delta_{max}^G)\mathrm{d}\delta^G = \int_{1-\Delta Q_{VES}/Q_{con}}^{1+\Delta Q_{VES}/Q_{con}} f_1^*(\delta^G; \mu, \sigma^N, 0, \delta_{max}^N)\mathrm{d}\delta^G \tag{13}$$

where δ_{max}^N and δ_{max}^G are the upper limits of the GES response ratio before and after NSES response, respectively; $f_1^*(\cdot)$ is the probability density function of GES response ratio when the NSES response is 0; and $f_2^*(\cdot)$ is the probability density function when the NSES response is Q_{st}.

The expected value of GES response ratio is:

$$E[\delta^G] = \int \delta^G f_2^*(\delta; \mu, \sigma^G, 0, \delta_{max}^G)\mathrm{d}\delta^G \tag{14}$$

V. Optimal Capacity Allocation Model of NSES for LA Based on HMAI

A. Hierarchical Electricity Market Evaluation Criteria

Affected by the bonus calculation rules, this paper defines HMAI. This index is used to measure the risk of LA being eliminated when participating in market competition. According to the response fluctuation of LA, the response quality is divided into three levels. The corresponding HMAI reward rules are formulated, in order to support and cultivate high-quality LA.

$$M = \left|1 - E[\delta^G]\right| \tag{15}$$

where M is a variable representing the HMAI of LA. Set ω_q and ω_g as a threshold of qualified response and a threshold of high-quality response, respectively. The response levels of LA are divided as follows: ① the first level is high-quality response (HQR), $M \le \omega_g$; ② the second level is qualified response (QR), $\omega_g < M \le \omega_q$; ③ the third level is low-quality response (LQR), $M > \omega_q$.

If the value of HMAI is in the LQR, the risk of LA being eliminated in the market competition is greater under such response conditions. Therefore, LA needs to choose the appropriate GES scheduling scheme and NSES allocation strategy to avoid losing market competitiveness due to the excessive HMAI value.

B. Optimal Capacity Allocation Model of NSES for LA

LA can install a certain quantity of NSES to suppress the uncertainty of VES response. The established optimal capacity allocation model of NSES for LA is shown as below.

1) Objective function

Dividing one day into n time intervals by time interval Δt, ISO usually issues multiple intermittent peak and valley continuous response periods. For example, assume that the "charging" response period and "discharging" response period of GES are (01:00-05:00) and (11:00-13:00; 19:00-21: 00), respectively. That is, there are three continuous response periods, and there is usually a long-time interval between them. During the interval of no response demand (00:00-01:00; 05:00-11:00; 13:00-19:00; 21:00-24:00), the NSES resources in GES can be charged or idle. In view of the complex response characteristics and coupling relationship of resources in GES, it is assumed that various response resources in GES are independent each other.

As shown in Section II-B, the income of LA mainly consists of two parts: market compensation rewards including I_{V}, I_G, and I_{e} and sales profit I_{NSES} when NSES releases the electricity.

According to the realized VES response, the compensation revenue of LA can be expressed as:

$$I_{\mathrm{V}}=\left(E[\delta_t^{\mathrm{G}}]\left|Q_{\mathrm{VES},t}^{\mathrm{C}}\right|\pi_{\mathrm{inc},t}\right) \tag{16}$$

where t is the t^{th} response period, $t\in[1,2,\dots,n]$; and $\pi_{\mathrm{inc},t}$ is the unit compensation price during the t^{th} response period.

Considering response mechanism and HMAI, the market penalties that LA can circumvent after installing NSES are:

$$I_{\mathrm{G}}=\sum_{t=1}^{n}(1-E[\delta_t])\left|Q_{\mathrm{VES},t}^{\mathrm{C}}\right|\pi_{\mathrm{pun}}-\sum_{t=1}^{n}(1-E[\delta_t^{\mathrm{G}}])\left|Q_{\mathrm{VES},t}^{\mathrm{C}}\right|\pi_{\mathrm{pun}}=\sum_{t=1}^{n}(E[\delta_t^{\mathrm{G}}]-E[\delta_t])\left|Q_{\mathrm{VES},t}^{\mathrm{C}}\right|\pi_{\mathrm{pun}} \tag{17}$$

where $E[\delta_t]$ and $E[\delta_t^{\mathrm{G}}]$ are the expected response ratios before and after the addition of NSES during the t^{th} period, respectively; and π_{pun} is the unit price for penalty.

If the NSES installation reaches a certain capacity, the response level of the LA can be improved, and an additional compensation income can be obtained:

$$I_{\mathrm{e}}=\sum_{t=1}^{n}(\lambda'-\lambda)E[\delta_t^{\mathrm{G}}]\left|Q_{\mathrm{VES},t}^{\mathrm{C}}\right|\pi_{\mathrm{inc},t} \tag{18}$$

where λ and λ' are the reward multiples before and after the addition of NSES, respectively.

In addition, the sales profit (discharging) and purchasing cost (charging) of LA dispatching NSES are:

$$I_{\mathrm{NSES}}=\sum_{t=1}^{n}\left[\sum_{k\in A_{\mathrm{NSES}}}\left(\int_0^{\Delta k_t}-H_{k,t}^{\mathrm{st},+}P_{k,t}^{\mathrm{st},+}\mathrm{d}t+\int_0^{\Delta k_t}H_{k,t}^{\mathrm{st},-}P_{k,t}^{\mathrm{st},-}\mathrm{d}t\right)\right]\pi_t^{\mathrm{rr}} \tag{19}$$

where Δk_t is the duration of the t^{th} response period; if $P_{k,t}^{\mathrm{st},+}>0$, then $H_{k,t}^{\mathrm{st},+}=1$; if $P_{k,t}^{\mathrm{st},-}>0$, then $H_{k,t}^{\mathrm{st},-}=1$; and π_t^{rr} is the retail price during the t^{th} response period. To maximize the revenue of LA, NSES is controlled to charge during the valley load period.

The life cycle cost (LCC) of an NSES usually consists of the initial investment cost C_k^{in} and the operation and maintenance cost C_k^{op}. The initial investment cost C_k^{in} is directly related to the rated capacity and rated power of NSES. Moreover, for convenience, C_k^{op} in this paper is estimated as a percentage of C_k^{in}.

$$C_k^{\mathrm{in}}=(m_k^{\mathrm{e}}E_k+m_k^{\mathrm{p}}P_k^{\max})\frac{(1+r)^{T_k}r}{(1+r)^{T_k}-1} \tag{20}$$

$$C_k^{\mathrm{op}}=(a_k m_k^{\mathrm{e}}E_k+b_k m_k^{\mathrm{p}}P_k^{\max})\frac{(1+r)^{T_k}r}{(1+r)^{T_k}-1} \tag{21}$$

where a_k is the percentage of operation and maintenance cost of the k^{th} NSES in rated capacity cost; b_k is the percentage of operation and maintenance cost of k^{th} NSES in rated power cost; m_k^{e} is the unit capacity cost of the k^{th} NSES; m_k^{p} is the unit power cost of the k^{th} NSES; r is the discount ratio; T_k is the life cycle of the k^{th} NSES; and E_k and $P_k^{\max}$ are the variables representing the rated capacity and the maximum power of the k^{th} NSES, respectively.

The objective function of the optimal capacity allocation model is to maximize the annual revenue of LA scheduling GES to participate in DR. With one year as the calculation period, the net revenue of LA can be calculated as:

$$\max R=\rho(I_{\mathrm{NSES}}+I_{\mathrm{V}}+I_{\mathrm{e}}+I_{\mathrm{G}})-\sum_{k\in A_{\mathrm{NSES}}}(C_k^{\mathrm{in}}+C_k^{\mathrm{op}}) \tag{22}$$

where ρ is the number of days in a year for LA participating in DR.

2) Constraints

The constraints are:

$$M\le\omega^{\mathrm{THR}} \tag{23}$$

$$P_{k,t}^{\mathrm{st},+}\le\min\left\{\frac{\left|(\delta_t-E[\delta_t])Q_{\mathrm{VES},t}^{\mathrm{C}}\right|}{\Delta\tau_t},P_k^{\max},\frac{(SOC_k^{\max}-SOC_k^{\mathrm{st}}(\tau))E_k}{\Delta\tau_t\cdot\eta_k^{\mathrm{ch}}}\right\} \tag{24}$$

$$P_{k,t}^{\mathrm{st},-}\le\min\left\{\frac{\left|(\delta_t-E[\delta_t])Q_{\mathrm{VES},t}^{\mathrm{C}}\right|}{\Delta\tau_t},P_k^{\max},\frac{(SOC_k^{\mathrm{st}}(\tau)-SOC_k^{\min})E_k\eta_k^{\mathrm{dch}}}{\Delta\tau_t}\right\} \tag{25}$$

$$SOC_k(\tau_t)=SOC_k(\tau_t-1)+\frac{\left(H_{k,t}^{\mathrm{st},+}P_{k,t}^{\mathrm{st},+}\eta_k^{\mathrm{ch}}-\dfrac{H_{k,t}^{\mathrm{st},-}P_{k,t}^{\mathrm{st},-}}{\eta_k^{\mathrm{dch}}}\right)\Delta\tau_t}{E_k} \tag{26}$$

$$\sum_{t=1}^{n}\int_0^{\Delta\tau_t}\eta_k^{\mathrm{ch}}P_{k,t}^{\mathrm{st},+}\mathrm{d}\tau_t=\sum_{t=1}^{n}\int_0^{\Delta\tau_t}\frac{P_{k,t}^{\mathrm{st},-}}{\eta_k^{\mathrm{dch}}}\mathrm{d}\tau_t \tag{27}$$

$$H_{k,t}^{\mathrm{st},-}+H_{k,t}^{\mathrm{st},+}\le 1 \tag{28}$$

where ω^{THR} is the HMAI threshold; $\Delta\tau_t$ is the duration of the response period; $H_{k,t}^{\mathrm{st},+}$and $H_{k,t}^{\mathrm{st},-}$ are the boolean variables representing the charging and discharging flag bits of the k^{th} NS-

ES during the t^{th} response period, respectively; and $SOC_k(\tau_t)$ is the SOC of NSES at the end of the t^{th} response period and $SOC_k^{\max}$ and $SOC_k^{\min}$ are the maximum and minimum SOCs of the k^{th} NSES, respectively. Inequality (23) is the LA response level constraint. The target of different response levels can be achieved by setting the value of the constraint upper limit ω^{THR}. Constraints (24) and (25) can be derived from (6) and (7). They represent the charging and discharging power limits of NESE, respectively. Taking (24) as an example, the first item is the expected value of charging power obtained from the expected value of response ratio; the second item is the maximum charging and discharging power of the k^{th} NSES; and the third item is the charging power evaluated by the current charging state of NSES. The final charging power is based on the minimum of these three terms. Constraint (26) is the constraint of the SOC. Constraint (27) requires that the charging capacity of the NSES is equal to the discharging capacity. Constraint (28) limits that the NSES cannot charge and discharge at the same time.

C. Solution Process

After the establishment of the proposed model, in the MATLAB software environment, this paper firstly simulates the expected response ratio of GES by Monte Carlo method. Then the adaptive particle swarm optimization algorithm is used to solve the above optimization problem, and the capacity allocation strategy of the LA installed NSES is obtained [38]. It should be noted that in the first iteration, the expected response ratio of GES is equal to that of VES because NSES has not been configured. The termination condition of the optimization process is set as whether the maximum number of iterations is satisfied. The detailed solution process is shown in Fig. S2 in Supplementary Material.

VI. Case Study

A. Case Study Conditions

Based on the data from PJM market in the United States [36], it is assumed that the 8 response time periods by ISO are 01:00-05:00, 11:00-13:00, and 19:00-21:00, respectively. The response demand capacity in the corresponding period is 3.5 , 3, 3, 3.2, −3.5, −3, −3.7, and −3.7 MWh, respectively. The time-of-use (TOU) electricity prices of PJM are shown in Table I [37]. Through the analysis of historical data of an LA [37], in the first iteration, the parameters of VES response ratio are $\mu=\mu(\alpha, Q_{\text{VES}}^{\text{C}})=1$ and $\sigma=\sigma(\alpha, Q_{\text{VES}}^{\text{C}})=0.2$. The characteristic coefficients are $\alpha=0.05$ and $\beta=1.5$. The upper and lower limits of GES response ratio are 1.5 and 0, respectively.

TABLE I
TOU Electricity Prices for Consumers

Time interval	Price (\$/MWh)
00:00-08:00, 21:00-24:00 (valley)	52.10
11:00-17:00 (flat)	103.20
08:00-11:00, 17:00-21:00 (peak)	162.26

Due to the various NSES resources on the user side, a unified scheduling reward and punishment system has not yet been formed. Therefore, this paper assumes that the NSES installed in LA only includes lithium batteries for large-scale applications. And during the response process, the charging and discharging power of the NSES and VES are constant. The capacity cost and power cost parameters of NSES are $m_1^{\text{e}}=224$ \$/kWh and $m_1^{\text{p}}=90$ \$/ kW, respectively. Its capacity and the maximum charging and discharging power meet a certain proportion, i.e., $E_1=2P_1^{\max}$. Life cycle of NSES is $T_1=10$ days. The charging and discharging efficiencies of the battery are $\eta_k^{\text{ch}}=\eta_k^{\text{dch}}=90\%$. The annual operation and maintenance cost ratios are $a=b=2\%$. The discount ratio is $r=10\%$.

Finally, the parameters of the algorithm are set as follows. The individual learning factor and population learning factor of adaptive particle swarm optimization are 2 and 1.5, respectively, and the population size is 50. The value of inertia weight ranges from 0.5 to 0.9, and its evolution coefficient is 1.12. The maximum number of iterations is 200. The number of Monte Carlo simulation is 5000, i.e., 5000 sampling points. The above optimization model is implemented on a computer with an Intel i7-10710U processor and 16 GB RAM.

B. Iterative Solution Process

For reasonably setting the standard deviations, the δ with different standard deviations is observed for 5000 times. δ of truncated normal distribution with different standard deviations is shown in Fig. 5.

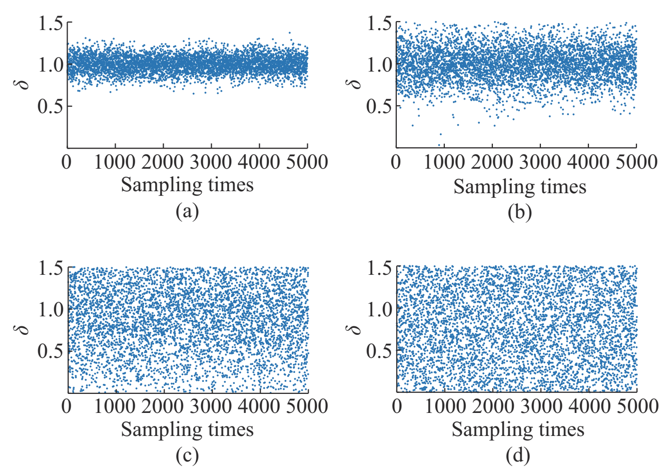

Fig. 5. δ of truncated normal distribution with different standard deviations. (a) $\mu=1, \sigma=0.1$. (b) $\mu=1, \sigma=0.2$. (c) $\mu=1, \sigma=0.5$. (d) $\mu=1, \sigma=1$.

The simulation results show that when the standard deviation is less than 0.1, the VES response ratio is concentrated in a small range. In this case, there is basically no possibility of user default, which is not in line with realistic logic. That is, this scenario does not reflect the advantages of configuring NSES. When the standard deviation of normal distribution exceeds 0.5, the distribution of sampling points is almost uniform. In this situation, the probability of user default is too high. That is, the resource response level of LA is so low that it cannot compete in the market. When the standard deviation of truncated normal distribution is 0.2, the distribution of sampling points not only reflects the response positivity of users, but also reflects the uncertainty of the VES response. Therefore, the standard deviation of the truncated normal distribution obeyed by δ is set to be 0.2.

Taking the promotion of LA response level to QR in Section VI-C as an example, Fig. 6 shows the convergence process. The results show that the model is optimal at about the 30$^{\text{th}}$ iteration, and the total calculation time is about 7500 s, which is acceptable for day-ahead calculation.

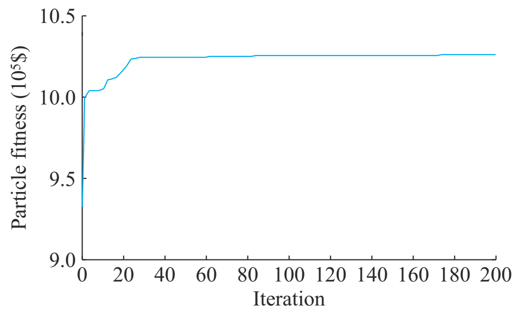

Fig. 6. Calculation convergence process.

C. Analysis on Influence of Different HMAIs

Firstly, this paper analyzes the impact of HMAI classification standard on upgrading the resource quality of LA. Assume that the market is divided into the following three specific categories of response quality: HQR, whose HMAI is less than 10%; QR, whose HMAI is between 10% and 20%; and LQR, whose HMAI is greater than 20%. The thresholds of the above conditions are $\omega_g = 10\%$ and $\omega_q = 20\%$.

The HMAI of LA without participation of NSES can be observed in Table II, all of which are greater than 20%. In order to guarantee the LA response quality and improve the market competitiveness of LA, NSES allocations with different market access index thresholds are calculated. The results are shown in Table II.

TABLE II
HMAI of LA at Different Levels

Period	HMAI without NSES (%)	HMAI of QR (%)	HMAI of HQR (%)
1	22.5	17.80	7.30
2	22.9	14.60	4.20
3	23.0	14.70	4.20
4	23.2	16.30	5.70
5	23.0	14.67	4.21
6	23.5	17.90	7.40
7	23.7	19.20	9.90
8	23.7	19.20	9.90

1) The HMAI threshold ω^{THR} is set to be 20%, i.e., the LA response quality is upgraded to QR after the allocation of NSES. The NSES capacity to be installed at this time is 2.66 MW/5.32 MWh. And the cost of avoiding punishment for LA is \$$5.5\times10^5$.

2) ω^{THR} is set to be 10%, i.e., the LA response quality is upgraded to HQR after the allocation of NSES. The NSES capacity to be installed at this time is 3.23 MW/6.46 MWh. Due to the level promotion, the cost of avoiding punishment for LA is \$$14.7\times10^5$.

From Table II, it can be found that the optimized allocation of NSES capacity can effectively reduce the HMAI value and improve the LA response quality. The revenue of LA under different targets of response level is shown in Fig. 7.

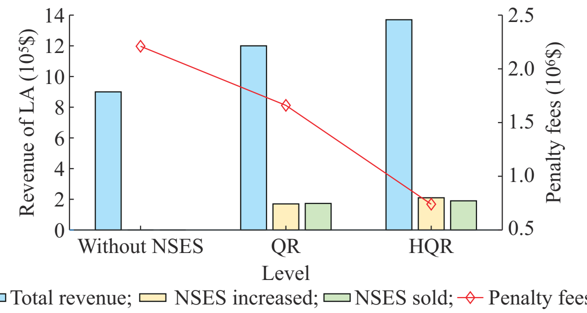

Fig. 7. Revenue of LA and penalty under different targets of response level.

As can be seen from Fig. 7, the total revenue of LA increases steadily with the improvement of response quality (from the original total revenue of \$$9.0\times10^5$ to the total revenue of QR of \$$1.2\times10^6$, and then to the total revenue of HQR of \$$1.37\times10^6$). Among them, the total income at the QR level increases by 33.3%, and the total income at the HQR level increases by 52.2%. In addition, with the increase of the allocation capacity of NSES, the discharging income of NSES (NSES sold) and the economic compensation for improving the response level (NSES increased) increase by 9.8% and 23.5%, respectively (NSES sold: \$$1.73\times10^5$ to \$$1.9\times10^5$; NSES increased: \$$1.7\times10^5$ to \$$2.1\times10^5$). At the same time, the penalty cost of LA has gradually decreased from \$$2.21\times10^6$ to \$$1.66\times10^6$ and then to \$$7.4\times10^5$. Among them, the penalty cost at the QR level decreases by 24.9%, and the penalty cost at the HQR level decreases by 66.5%. In other words, the penalty cost of LA evasion gradually increases. To sum up, the model proposed in this paper can meet the optimal capacity allocation of NSES under different HMAIs. The capacity allocation of NSES not only helps LA avoid huge penalty, but also plays a significant role in improving the economic benefits of LA.

D. Analysis on Influence of Compensation Rules

Limited by the technology, the investment and construction costs of lithium battery energy storage and other battery energy storage are still high. Therefore, LA should be guided to actively improve its own response quality level by formulating reasonable compensation rules. Three different scenarios of compensation rules are set to analyze the net income of LA and the SIPP of NSES in each scenario.

Scenario 1: the compensation price of QR and that of HQR are both equal to spot market prices.

Scenario 2: the compensation price of QR is equal to the spot market price, and the compensation price of HQR is 0.5% higher than the spot market price.

Scenario 3: the compensation price of QR is 0.5% higher than the spot market price, and the compensation price of HQR is 1.0% higher than the spot market price.

The comparison of net revenue and SIPP of LA in different market scenarios is shown in Fig. 8. In scenario 1, the net revenue of LA is $1.04×10^6$ and the SIPP of NSES is 7.9 years at QR level, while the net revenue of LA decreases by 7.7% ($9.6×10^5$) and the SIPP of NSES is 8 years at the HQR level. Obviously, as the compensation price among different response levels is the same, it is not economical for LA to upgrade its response level to the highest level. In this case, LA will choose to upgrade to the QR level as the target. However, a large number of LAs make this upgrade choice, which will lead to the lack of HQR resources in the market.

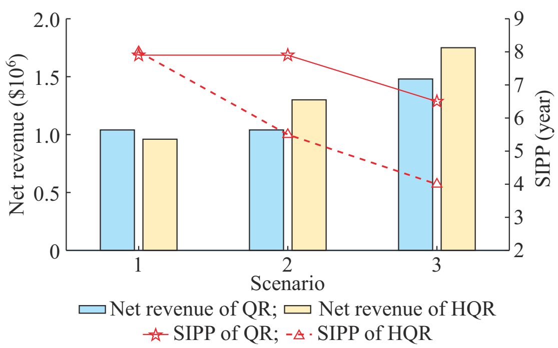

Fig. 8. Comparison of net revenue and SIPP of LA in different market scenarios.

For the sake of reliable and stable operation of electricity market, ISO will encourage LA to improve its response quality. Therefore, it is necessary to provide additional economic compensation for LA at the HQR level. Under the incentive effect of additional compensation, i.e., scenario 2 and scenario 3, the net revenue of LA at the HQR level increases by 35.4% and 82.3% compared with scenario 1, i.e., $1.3×10^6$ and $1.75×10^6$, respectively. Those are higher than the LA net revenue of QR level ($1.04×10^6$ and $1.48×10^6$). Driven by the profit, the response quality of LA will be closer to the expected goal of ISO, which is more conductive to the stable operation of the market. In order to sign a contract with ISO, each LA will improve its response quality level as much as possible to reflect its own competitive advantage, so as to realize a virtuous circle of the market.

The SIPPs of NSES in the three scenarios are shown by the red line in Fig. 8. SIPP is equal to the ratio of LCC of NSES to annual net revenue. Obviously, the increase of compensation price can significantly shorten the SIPP of NSES. Since the compensation price at the QR level in scenario 1 and scenario 2 remains unchanged, the SIPPs of NSES are both 7.9 years. At the HQR level, the SIPP of NSES decreases from 8 years to 5.5 years. In scenario 3, the compensation price at the QR level and HQR level increases, thus the SIPP of NSES reaches the minimum value of 6.5 years and 4 years respectively. To sum up, reasonable compensation rules can make the investment return of NSES at the QR and HQR levels faster, thus LA will more actively allocate the NSES.

E. Analysis on Influence of Market Rules

Sections VI-C and VI-D discuss the impact of HMAI classification standard and compensation rules on the investment of LA in NSES, respectively. Since different types of markets have different requirements for the response quality of LA, there are also differences in the design of the above two in the market rules.

Through the adjustment of HMAI classification standard and compensation rules, this paper analyzes the change of SIPP when LA reaches HQR level. The HQR thresholds ω_g are set to be 10%, 5%, and 1%, respectively. Compensation coefficients, i. e., the ratios of compensation price to spot market price, are set to be 1.00, 1.01, 1.05, and 1.10, respectively. The SIPP values of NSES in different permutations are observed, as shown in Table III.

TABLE III
SIPP VALUES OF NSES IN DIFFERENT PERMUTATIONS

ω_g (%)	Compensation coefficient	SIPP (year)
10	1.00	8.0
	1.01	5.5
	1.05	4.0
	1.10	3.8
5	1.00	17.0
	1.01	12.7
	1.05	9.3
	1.10	7.1
1	1.00	26.0
	1.01	19.1
	1.05	14.3
	1.10	10.6

The numerical results show that the stricter the HQR threshold is set, the more NSES the LA needs to allocate. As a result, the SIPP of NSES becomes larger. When the HQR threshold is set to be 1%, even if the compensation coefficient is as high as 1.1, i. e., the compensation price is 10% higher than the spot market price, the SIPP of NSES still has 10.6 years. At present, the life of lithium battery is mostly 10 years, so it can be roughly judged that the threshold setting is not economical. In addition, a reasonable compensation price is also crucial. According to the results in Table III, with the increase of compensation price, the SIPP of NSES decreases. However, it should be noted that the trend of SIPP reduction of NSES is gradually weakening. Taking the HQR threshold of 10% as an example, when the compensation coefficient increases by 1%, i.e., the compensation coefficient increases from 1.00 to 1.01, SIPP is shortened by 2.5 years. When the compensation coefficient increases from 1.01 to 1.05, SIPP is shortened by only 1.5 years. Therefore, it is uneconomic for ISO to set too high compensation price. To sum up, ISO needs to formulate reasonable classification standards and the corresponding compensation rules according to the actual situation.

F. Analysis on Influence of NSES Allocation Capacity

Finally, it analyzes the influence of the NSES allocation capacity on the economic benefits of LA. The threshold value of QR and HQR levels adopts the parameters of Section VI-C, and the compensation price adopts the parameters in scenario 3 of Section VI-D. Table IV shows the economic parameters of different NSES allocation strategies.

TABLE IV
NET INCOME PER NSES AND SIPP OF LA UNDER DIFFERENT NSES ALLOCATION STRATEGIES

Configuration power of NSES (MWh)	Configuration capacity of NSES (MWh)	Net income per NSES ($/MWh)	SIPP (year)
1.924	3.848	199109.5	7.44
2.448	4.896	214272.4	7.06
3.172	6.344	233291.3	6.50
3.496	6.992	236598.1	5.63
3.611	7.222	242315.1	4.00
3.844	7.688	237950.5	5.44
4.468	8.936	229823.9	6.36
5.392	10.784	201828.7	7.02
5.916	11.832	147252.7	7.14
6.240	12.480	132277.0	7.73
7.164	14.328	120894.9	8.27

The market profit of LA can be significantly improved by scheduling NSES to suppress the response uncertainty of VES. However, as the installed capacity of NSES increases, there will be a redundancy in capacity. And the redundant capacity cannot further improve the economic benefits of LA. In addition, the high cost of NSES makes the net income of unit energy storage increase first and then decrease. The results show that the net income per NSES increases to a maximum of 242315.1 $/MWh when the installed capacity is 3.611 MW/7.222 MWh. At this time, the SIPP of NSES is 4 years. To sum up, LA can obtain better investment return and shorter SIPP by reasonably allocating the capacity of NSES.

VII. CONCLUSION

When LA participates in electricity market transactions to obtain profits, it will face the problem of default due to the influence of VES response uncertainty. In order to ensure the stability of LA participating in the market, this paper takes the NSES as a means to reduce default risk. Based on this, a capacity allocation model of NSES with HMAI is established. Finally, in order to verify the effectiveness of the model, four examples are analyzed from HMAI classification standard, compensation rules, market rules (combining the above two), and NSES allocation capacity. The main conclusions are as follows.

1) By limiting different HMAI, LA will allocate NSES to improve its response level, so as to improve its own economic benefits. In the given case study, when the response level reaches HQR, the total revenue of LA increases from $\$9\times10^5$ to $\$1.37\times10^6$, which is an increase of 52.2%. The avoidable penalty cost is $\$1.47\times10^5$.

2) By setting reasonable compensation rules, LA can allocate NSES more actively and improve its response quality level. In the given case study, the net income of LA at the HQR level will increase from $\$9.6\times10^5$ to $\$1.75\times10^6$, which is an increase of 82.3%. The SIPP of allocated NSES will also be shortened from 8 years to 4 years.

3) By establishing reasonable market rules, it can not only promote the upgrading of LA to HQR level, but also ensure the reliability of electricity market operation. In the case study, the SIPP of NSES can be reduced to 3.8 years at most.

4) By allocating appropriate NSES allocation capacity on the user side, the redundancy of energy storage capacity and waste of resources can be avoided. And LA can obtain better return to investment and shorten the SIPP. In the case study, the optimal installed capacity of NSES is 3.611 MW/7.222 MWh, and the SIPP of NSES is 4 years.

This paper aims to provide a model for emerging electricity sellers to avoid default response, without consideration of the benefits of other electricity sellers. Therefore, it is worth further study on the profit of other market players and their competitive game with other players in the market.

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