

# Optimal Dispatching Strategy of Battery Swapping Station Based on User Adaptive Response

Jie Yang, Zhengxu Zhang, Kai Ma, Yong Yang, Anhu Zhu, and Zhiyuan Yue

**Abstract**—With the popularity of electric vehicles (EVs), the impact of disorderly charging on power grid stability cannot be ignored. As one of the energy supply methods of electric vehicles, the optimal scheduling of battery swap station (BSS) can not only reduce the cost of BSS, but also ensure the stable operation of the power system. Therefore, this paper designs a BSS electricity price mechanism based on load demand forecasting and a user adaptive response mechanism based on battery health status and user satisfaction. On this basis, an optimal scheduling model of BSS system aiming at maximizing the revenue of BSS system is established. The simulation results show that the pricing strategy proposed in this paper can reduce the fluctuation of battery demand at each time and increase the revenue of BSS by 8.76%. In addition, the BSS optimal scheduling model proposed in this paper reduces the peak-to-average ratio of charging load from 2.52 to 2.10, realizing peak shaving and valley filling in the power system.

**Index Terms**—Battery swapping station, pricing mechanism, electric vehicle, load shifting, state of health

## I. INTRODUCTION

WITH the development of society and economy, the problems of environmental pollution and resource shortage are becoming more and more serious. The United Nations has nominated the realization of carbon neutrality by 2050 as the most urgent task in the world [1]. The transportation industry has become a key research object for achieving carbon neutrality because its fuel consumption accounts for 62.30% of the world's total consumption and

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produces about a quarter of the world's greenhouse gases [2]. Therefore, electric vehicles (EVs) with the characteristics of environmental protection and energy saving have been widely promoted around the world [3, 4]. However, the problems of long charging time, short cruising range, and imperfect charging equipment of EV have seriously affected its popularity [5]. In addition, the disorderly charging of a large number of EVs may increase the peak-valley difference of the power system and affect the stable operation of the power system [6, 7]. The emergence of battery swap station (BSS) perfectly solves the above problems. BSS can not only fully charge EV in just a few minutes [8], but also make full use of its energy storage flexibility to respond to grid electricity prices, thereby reducing BSS charging costs [9], reducing peak-to-valley difference of the grid, and realizing EV and BSS collaborative optimization.

With the promotion of EV, the charging demand of its battery has become an important load of the grid [10]. Therefore, it is necessary to study the charging demand and energy demand characteristics of EVs and formulate charging scheduling strategies for EVs to reduce the impact on the power system [11]. Guo et al. [12] proposed a new method to decouple the impact of charging load characteristics on the power grid, and analyzed the impact of different vehicle sizes on the stability of the power grid from the perspectives of load curves, power fluctuations, and frequency shifts. To reduce the impact of random charging by EV users on the power grid, Zhang et al. [13] proposed a two-stage optimization strategy for EV charging considering elastic demand response to reduce the charging cost of EVs and the peak-to-valley difference of grid load by responding to grid electricity price. In addition, the large-scale integration of new energy into the grid will bring strong random fluctuations to the power grid [14]. Regarding this, researchers established a dispatching model of two-way energy supply between EV and power grid, through which EV bought electricity at a low price and fed at a high price, reducing the peak-valley difference of power grid and improving the consumption of renewable energy [15–17]. However, the above literature ignores battery damage caused by vehicle-to-grid (V2G), and lacks research on the impact of price mechanism and battery loss on user decisions.

Aiming at the charging and swapping price mechanism of EVs, some researchers have studied the optimal operation mode of BSS system from different aspects such as battery swapping price (BSP), battery charging scheduling, and charging and swapping cost analysis [18–21]. In order to

optimize the total revenue of BSS and the interests of EV owners, Wang and Yang [22] proposed a joint optimization method based on reward and penalty tiered pricing mechanism. Electric vehicle owners are urged to respond to grid electricity prices and replace batteries with the best charging state according to grid load states, reducing the charging and swapping costs of BSS and electric vehicle owners. Ma et al. [23] and Aujla et al. [24] considered the impact of charging price and regional hotspot information on the charging choice of EVs, and established a multi-leader-multi-follower Stackelberg model of EVs and charging stations, which reduced the charging cost of EVs and the charging waiting time. In Ref. [25], considering the uncertainty of market prices, an optimal scheduling model for BSS systems based on multi-band robust optimization was established. The profit of BSS is maximized by the demand response to the market price. However, the above works ignore that different users have different sensitivities to the price mechanism, and there are uncertainties in user decisions, which will affect the optimization effect of the model.

Aiming at the problem that frequent charging and discharging affects the service life of batteries, Yang et al. [26] proposed the concept of shared battery stations and used the partition control method of batteries to reasonably solve the large-scale battery charging scheduling problem. Connor et al. [27] studied the impact of communication on energy saving and battery loss reduction in electric buses. The simulation shows that vehicles involved in networked communication can save 27.00% of the total cost. In Ref. [28], BSS made decisions by tracking the number of batteries in different states, and actively responded to price fluctuations in the electricity market, increasing the revenue of the BSS system while ensuring the service life of the battery. Ko et al. [29] proposed an optimal battery charging algorithm. The evaluation results show that compared with the random charging scheme, the optimal battery charging algorithm can increase the net profit of BSS by 43.00%, avoid excessive charging and discharging of batteries, and reduce battery loss. However, the above work ignores the battery status of health (SOH), which is an important battery parameter. With the increase in the number of battery charging and discharging cycles, battery loss will also increase, which will shorten battery life. Therefore, SOH is introduced to measure battery life.

Aiming at the above problems, this paper designs a power pricing mechanism based on load forecasting in BSS system to reduce the peak-to-valley difference of battery load. Considering the difference of battery health status and the uncertainty of user demand response, an adaptive response model for electric vehicles based on battery health status and user satisfaction is proposed. On this basis, the charging optimal dispatching model of BSS system is established, which improves the income of BSS by responding to the grid price and realizes peak shaving and valley filling of grid load. The main contributions are as follows:

(1) The pricing mechanism of BSS power exchange based on battery demand power is designed, which encourages EVs to adjust the power exchange plan and realizes peak shaving and valley filling of power exchange load.

(2) A user adaptive response model based on SOH and user satisfaction is established, and an elastic matrix is introduced to adjust the power demand of users with different sensitivities, so that the response model is more realistic.

(3) The optimal dispatching model of BSS system with the greatest benefit of BSS system is established, which improves the benefit of BSS system on the basis of ensuring battery supply and contributes to the stable operation of power grid.

The rest of this paper is organized as follows. The system model and problem formulation, including the BSS system model, pricing mechanism, user adaptive response model, and load shifting model, are proposed in Section II. In Section III, BSS system optimization and scheduling models are established. A series of simulation results are shown in Section IV to verify the proposed models and strategy. Conclusions are summarized in Section V.

## II. SYSTEM MODEL AND PROBLEM FORMULATION

This section includes BSS system model, pricing mechanism, load shifting model, and user adaptive response model. First, the system model mainly describes the operation mode of BSS system. Second, the price mechanism provides a guarantee for the exchange behavior of users. Finally, the user adaptive response is considered in the optimization operation of the BSS system to achieve the load shifting of the power system.

### A. BSS System Model

EV users do not need to wait for the charging process and they can directly swap their empty battery with a full battery at any BSS system [30]. The battery swap system model containing  $n$  EVs is shown in Fig. 1. To reduce the mileage anxiety of users, when the energy of EV is consumed to a certain level, the user enters the BSS system to swap batteries. The user makes a decision by considering the state of charge (SOC) and SOH information, and chooses whether to swap battery through adaptive response. When users do not participate in the optimization operation, they will leave the BSS system and choose another BSS system to swap the battery. The empty battery allocates charging start time through optimization operation. The full batteries are used as the standby batteries in the BSS system. In addition, the price mechanism can guide users to achieve load shifting. Therefore, BSS system is not only conducive to optimal scheduling of batteries, but also can effectively reduce load fluctuation of system. It is worth mentioning that the BSS system provides battery charging services, namely, centralized

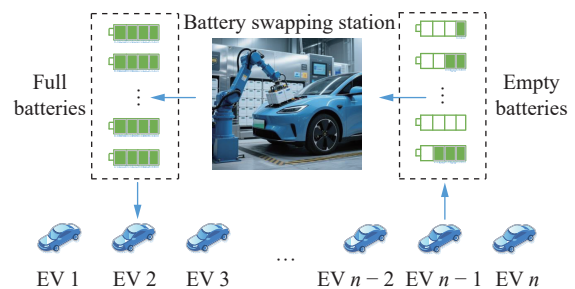


Figure 1 System model of BSS.

management of empty batteries to optimize charging, which makes the system more economical and efficient. Due to the fact that discharge shortens the lifespan of batteries and increases their potential costs, BSS systems do not seek to profit from selling electricity to the power system.

### B. Pricing Mechanism

As the provider of EVs battery-swapping service, the BSS system has right to charge the service fee according to BSP, which is directly paid by EV users to BSS. However, EV load has the characteristic of temporal and spatial randomness. Without a reasonable BSP to guide it, large-scale EV charging load aggregation could occur, increasing the peak-to-valley difference. Therefore, the BSP can not only achieve the purpose of load transfer by guiding EVs to orderly swap batteries, but also contribute to the safe operation of power system. The following pricing mechanism of BSS system is designed by considering the total charging power  $P_{BSS,i}$  in time slot  $i$  and average charging power  $P_{av}$  to ensure the profitability of the BSS system.

$$pr_i = \begin{cases} \left\lfloor \frac{P_{BSS,i} - P_{av}}{\text{step}_p} \right\rfloor \cdot \text{step}_{pr} + pr_{i-1}, \\ P'_{BSS,i} > 0, P_{BSS,i} - P_{av} > \text{step}_p; \\ pr_{i-1} - \left\lfloor \frac{P_{BSS,i} - P_{av}}{\text{step}_p} \right\rfloor \cdot \text{step}_{pr}, \\ P'_{BSS,i} < 0, P_{BSS,i} - P_{av} > \text{step}_p; \\ pr_{i-1}, \text{ else} \end{cases} \quad (1)$$

$$P_{BSS,i} = \eta \cdot P_i \cdot D'_i \quad (2)$$

$$P_{av} = \frac{1}{T} \cdot \eta \cdot \sum_{i=1}^T P_i \cdot D'_i \quad (3)$$

where  $pr_i$  is the BSP,  $i$  is the time slot,  $\text{step}_p$  is the power step,  $\text{step}_{pr}$  is the price step,  $P'_{BSS,i}$  is the slope of the total charging power curve of the BSS system,  $P_i$  is the charging power,  $D'_i$  is the adaptive response battery demand of EV users,  $\eta$  is the charging efficiency, and  $T$  is the total time period, respectively. The product of the downward round value of  $(P_{BSS,i} - P_{av})/\text{step}_p$  and  $\text{step}_{pr}$  is the BSP adjustment value.

The price mechanism is shown in Eq. (1). When the total charging power of the BSS system in time slot  $i$  increases and the difference between the total charging power and the average charging power increases by one power step, the BSP will increase a price step on the original basis. Conversely, when the total charging power of the BSS system in time slot  $i$  decreases by one power step and the power is greater than the average charging power, the BSP will decrease by one price step.

The constraints of the BSP model are

$$pr_{\min} \leq pr_i \leq pr_{\max} \quad (4)$$

$$P_{BSS,\min} \leq P_{BSS,i} \leq P_{BSS,\max} \quad (5)$$

$$D'_{\min} \leq D'_i \leq D'_{\max} \quad (6)$$

where  $pr_{\min}$  and  $pr_{\max}$  are the minimum and maximum values

of BSP, respectively.  $P_{BSS,\min}$  and  $P_{BSS,\max}$  are the minimum and maximum charging powers of the BSS system, respectively.  $D'_{\max}$  and  $D'_{\min}$  are the upper and lower limits of the number of batteries that can be provided to EVs in time slot  $i$ , respectively.

The real need for batteries is unknown. Based on the daily battery demand curve, it can be estimated. Suppose that actual battery demand fluctuates frequently around the predicted battery demand [31, 32], it is proved that the SOC and demand of the batteries swapped follow the Gaussian distribution approximately [33, 34]. Thus, the predicted model can be denoted as

$$SOC_f \sim \frac{1}{\sigma_1 \sqrt{2\pi}} e^{-\frac{(SOC_i - u_1)^2}{2\sigma_1^2}} \quad (7)$$

$$G_f \sim \begin{cases} \frac{1}{\sigma_s \sqrt{2\pi}} e^{-\frac{(G_i - u_{s,1})^2}{2\sigma_s^2}}, & 0 < i \leq 7; \\ \frac{1}{\sigma_s \sqrt{2\pi}} e^{-\frac{(G_i - u_{s,2})^2}{2\sigma_s^2}}, & 7 < i \leq 24 \end{cases} \quad (8)$$

where  $SOC_f$  and  $G_f$  are probability density functions (PDFs) of SOC and battery demand, respectively.  $SOC_i$  and  $G_i$  are SOC and battery demand at time slot  $i$ , respectively.  $u_1$  is the mean value of SOC.  $u_{s,1}$  and  $u_{s,2}$  are mean values of battery demand in each period, respectively.  $\sigma_1^2$  and  $\sigma_s^2$  are variances of SOC and battery demand, respectively. In the optimization process, the SOC and battery demand can be calculated according to Eqs. (7) and (8), respectively. The BSS system updates the battery demand and SOC at the beginning of time slot  $i$ .

### C. User Adaptive Response Model

EV users change their swap behavior to reduce costs by responding to BSP signals. The EVs with low SOC are sensitive to price due to the constraint of the remaining driving distance. Thus, they will choose to swap battery in the previous time slot or the adjacent time slot. But the EVs with high SOC have no restriction of driving distance and are not sensitive to price. They will search the whole time period to choose a time slot that is more beneficial to themselves to swap batteries. Since different EV users have different sensitivities to price, they are divided into three groups according to SOC.

$$SOC = \begin{cases} [0\%, 30\%], & \text{group 1 user;} \\ (30\%, 60\%], & \text{group 2 user;} \\ (60\%, 100\%], & \text{group 3 user} \end{cases} \quad (9)$$

EV batteries are constantly recycled between the BSS and the users. With the continuous charging and discharging process, the available capacity of the battery decreases gradually. The SOH is used to indicate the health of the battery. The SOH is one of the most important monitoring parameters in battery management system. If the battery SOH is lower than 80%, the battery in the BSS system will not be swapped to EV users and needs to be maintained or disposed. During the first 500 cycles or so, the battery capacity

gradually decreases. As the battery life approaches, the capacity degradation becomes more severe [35].

$$\text{SOH}_{n,k} = \frac{B_{n,k}}{\text{Cap}} \times 100\% \quad (10)$$

$$\text{SOH} = \begin{cases} [0\%, 80\%], & \text{maintenance or disposal;} \\ (80\%, 100\%], & \text{battery swapping} \end{cases} \quad (11)$$

where  $\text{SOH}_{n,k}$  is the battery SOH of the  $n$ -th EV user of group  $k$ ,  $\text{Cap}$  is the rated capacity of the battery, and  $B_{n,k}$  is the available capacity of the battery, respectively.

An adaptive response model is established by considering the SOH and satisfaction cost. The satisfaction cost is the satisfaction of the user with the battery-swapping cost. The users choose the SOH and satisfaction cost weights during the adaptive response process. This signifies that they take part in the response process when the response willingness value is higher than or equal to the response threshold. Users have cognitive bias and preference in the response process because of the uncertainty of the external environment (such as unexpected events) and the differences in their abilities to recognize and process information. While some EV consumers favor satisfaction cost, others prefer battery SOH.

$$r_{n,k} = w_1 \cdot \text{SOH}_{n,k} + w_2 \cdot \theta_{n,k} \quad (12)$$

$$w_1 + w_2 = 1 \quad (13)$$

$$\theta_{n,k} = \frac{C_{i,0} - C_i}{C_{i,0}} \quad (14)$$

$$C_{i,0} = \text{pr}_{i,0} \cdot (1 - \text{SOC}_i) \cdot \text{Cap} \quad (15)$$

$$C_i = \text{pr}_i \cdot (1 - \text{SOC}_{n,k}) \cdot \text{SOH}_{n,k} \cdot \text{Cap} \quad (16)$$

where  $r_{n,k}$  is the response willingness value of the  $n$ -th EV user of group  $k$ ,  $w_1$  and  $w_2$  are weight factors,  $\theta_{n,k}$  is the satisfaction cost of the  $n$ -th EV user of group  $k$ ,  $C_{i,0}$  is the battery-swapping cost before optimization,  $C_i$  is the battery-swapping cost after optimization,  $\text{pr}_{i,0}$  is the battery-swapping price in the disordered charging mode, and  $\text{SOC}_{n,k}$  is the SOC of the  $n$ -th EV user of group  $k$ , respectively.

EV users should decide whether to respond to load shifting based on their experience. First, the user needs to select the weight factor. If the user selects a battery with a higher SOH, then  $w_1$  is larger than  $w_2$ . Otherwise,  $w_1$  is less than  $w_2$ . It is chosen by the users independently, which guarantees the user satisfaction for the battery-swapping service.

A 0-1 binary variable is introduced to represent the response and non-response states of EV users. The state variable is established as

$$x_{n,k} = \begin{cases} 1, & r_{n,k} > \delta; \\ 0, & \text{else} \end{cases} \quad (17)$$

$$D'_{i,k} = \sum_{n=1}^{S_{i,k}} x_{n,k} \quad (18)$$

where  $x_{n,k}$  is the adaptive response state,  $\delta$  is the response threshold of EV users,  $D'_{i,k}$  is the number of battery demands of group  $k$  users in response to load shifting, and  $S_{i,k}$  is the number of EV users in group  $k$  at time slot  $i$ , respectively.

The response degree of user is indicated by user responsiveness. The user responsiveness  $d_i$  is

$$d_i = \frac{D'_i}{G_i} \cdot 100\% \quad (19)$$

$$D'_i = \sum_{k=1}^K D'_{i,k} \quad (20)$$

$$G_i = \sum_{k=1}^K G_{i,k} \quad (21)$$

where  $K$  is the number of EV groups and  $G_{i,k}$  is the battery demand of group  $k$  at time slot  $i$ .

#### D. Load Shifting Model

EV users have different sensitivities to BSP. In general, once the BSP increases, the battery demand decreases correspondingly. EV users prefer to swap the battery when the BSP is low to save cost and achieve load shifting. The elasticity coefficient is the percentage of change in demand and price. At the same time, it is a sensitive index reflecting the response of demand to price changes.

The elastic matrix can be referenced to represent the effect of prices on user behavior in each time slot. The time slots are divided into three periods: peak, mid peak, and valley. Different EV users have different sensitivities to BSP. Therefore, the distribution of non-zero elements in the existence of elastic matrices is different. The elastic matrices of the three groups of users can be shown as

$$E_1 = \begin{bmatrix} \varepsilon_{1,1} & 0 & 0 \\ 0 & \varepsilon_{2,2} & 0 \\ 0 & 0 & \varepsilon_{3,3} \end{bmatrix} \quad (22)$$

$$E_2 = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & 0 \\ \varepsilon_{2,1} & \varepsilon_{2,2} & \varepsilon_{2,3} \\ 0 & \varepsilon_{3,2} & \varepsilon_{3,3} \end{bmatrix} \quad (23)$$

$$E_3 = \begin{bmatrix} \varepsilon_{1,1} & \varepsilon_{1,2} & \varepsilon_{1,3} \\ \varepsilon_{2,1} & \varepsilon_{2,2} & \varepsilon_{2,3} \\ \varepsilon_{3,1} & \varepsilon_{3,2} & \varepsilon_{3,3} \end{bmatrix} \quad (24)$$

where  $E_1$ ,  $E_2$ , and  $E_3$  represent the price elasticity matrices of group 1, group 2, and group 3, respectively.

The total electricity demand in time slot  $i$  caused by price change in time slot  $i$  can be shown as

$$Q_{i,i} = Q_{i,0}^k \left( 1 + \varepsilon_{i,i} \frac{\text{pr}_i - \text{pr}_{i,0}}{\text{pr}_{i,0}} \right) \quad (25)$$

and the total electricity demand in time slot  $i$  caused by price change in time slot  $j$  can be shown as

$$Q_{i,j} = Q_{i,0}^k \left( 1 + \varepsilon_{i,j} \frac{\text{pr}_j - \text{pr}_{j,0}}{\text{pr}_{j,0}} \right) \quad (26)$$

where  $Q_{i,0}^k$  is the demand quantity of the group  $k$  users before the price change in time slot  $i$ ,  $\varepsilon_{i,i}$  is the coefficient of self-elasticity, and  $\varepsilon_{i,j}$  is the coefficient of mutual elasticity.

Therefore, the total demand electricity in period  $i$  is superimposed by the demand electricity in time slot  $i$  caused by the change of price in time slot  $i$  and the demand electricity in time slot  $i$  caused by the change of price in time slot  $j$ . The

total demand electricity caused by price change in time slot  $i$  can be shown as

$$Q_i^k = Q_{i,i} + Q_{i,j} = Q_{i,0}^k \left( 2 + \varepsilon_{i,i} \frac{pr_i - pr_{i,0}}{pr_{i,0}} + \varepsilon_{i,j} \frac{pr_j - pr_{j,0}}{pr_{j,0}} \right) \quad (27)$$

where  $Q_i^k$  is the total electric quantity demanded by the group  $k$  users in time slot  $i$ .

The total electric quantity demand is converted into the battery swapping demand. The swapping demand is redistributed through the elastic matrix under the BSP. The swapping demand in each time slot can be shown as

$$D_{i,k} = \left[ \frac{Q_i^k}{\sum_{n=1}^{S_{i,k}} \text{Cap}(1 - \text{SOC}_{n,k})} \right] \quad (28)$$

$$D_i = \sum_{k=1}^K D_{i,k} \quad (29)$$

where  $D_{i,k}$  represents the battery-swapping demand of the group  $k$  users after the load shifting in time slot  $i$  and  $D_i$  is the total battery demand.

EV users select the most favorable time slot for them by considering the price factors in the current time slot and other time slots. The load shifting rate  $F_i$  is defined to indicate the degree of load shifting from the current time slot to other time slots.

$$F_i = \frac{|D_i - D'_i|}{D'_i} \cdot 100\% \quad (30)$$

### III. BSS OPTIMIZATION AND SCHEDULING

#### A. Optimization Problem

As the energy supply station of EVs, BSS system collects service fees for battery-swapping on one hand. On the other hand, it pays to the power system. The time-of-use price determined according to the characteristics of the power load curve is shown in Table 1. In order to maximize the revenue of BSS system, an objective function is established. It consists of three parts: battery swapping revenue  $I_R$ , penalty revenue  $I_P$ , and battery charging cost  $C$ . The objective function is shown as

$$\begin{aligned} \max U = I_R + I_P - C = & \sum_{i=1}^T \sum_{n=1}^{D_{i,k}} \sum_{k=1}^K pr_i \cdot (1 - \text{SOC}_{n,k}) \cdot \text{SOH}_{n,k} \cdot \text{Cap} + \\ & \sum_{i=1}^T \sum_{n=1}^{D_{i,k}} \sum_{k=1}^K M_{i,n} \cdot R \cdot (\text{SOH}_0 - \text{SOH}_{n,k}) - \\ & \sum_{i=1}^T \sum_{n=1}^N X_{i,n} \cdot g_i \cdot P \cdot \Delta t \end{aligned} \quad (31)$$

where  $U$  is the net income of the BSS system,  $N$  is the total number of batteries in the BSS system,  $M_{i,n}$  represents the punishment state of EV users,  $R$  is the penalty price,  $\text{SOH}_0$  is

the battery health threshold (EV users whose battery SOH is lower than this threshold will be punished),  $P$  is the charging power,  $X_{i,n}$  represents the battery charging state,  $g_i$  is the time-of-use price, and  $\Delta t$  is the unit charging time, respectively.

**Table 1** Time-of-use price.

State	Time	Price (\$/kWh)
On peak	10:00–15:00 and 18:00–21:00	1.2682
Mid peak	07:00–10:00, 15:00–18:00, and 21:00–23:00	0.8745
Off peak	06:00–07:00 and 23:00–24:00	0.3798

To indicate how the batteries in the BSS system are charged, a 0-1 binary variable is introduced as

$$X_{i,n} = \begin{cases} 1, & \text{charging;} \\ 0, & \text{else} \end{cases} \quad (32)$$

The following introduces a 0-1 binary variable, which stands for the penalty state of EV users

$$M_{i,n} = \begin{cases} 1, & \text{SOH} \in [0\%, 80\%), \text{ punishment;} \\ 0, & \text{else, no punishment} \end{cases} \quad (33)$$

The constraint conditions are shown as follows.

The battery SOH and SOC meet the constraints in Eqs. (34) and (35), respectively.

$$0 \leq \text{SOH} \leq 100\% \quad (34)$$

$$0 \leq \text{SOC} \leq 100\% \quad (35)$$

The battery swapping demand is less than the constraint of the maximum supply demand of the BSS system.

$$D_{i,k} \leq D_{i,\max} \quad (36)$$

where  $D_{i,\max}$  provides the maximum value of swapping battery for the BSS system. The number of charging batteries is less than the number of charging piles CH in the BSS system.

$$\sum_{n=1}^N X_{i,n} \leq \text{CH} \quad (37)$$

The number of full batteries in the current time slot is larger than the battery swapping demand in the next period.

$$N + \sum_{n=1}^N X_{i,n} \geq D_{i+1} \quad (38)$$

#### B. Allocation Strategy

In order to improve the service satisfaction of users and ensure the rational use of batteries, the battery allocation strategy designed in this paper is as follows. As shown in Fig. 2, firstly, the user determines that the battery is swapped in the BSS system through adaptive response. And user with battery SOH below 80% should be punished. The purpose is to limit the user from discharging the battery excessively. Secondly, the unloaded batteries are transferred to BSS system, and the batteries with SOH less than 80% should be

maintained or disposed. For batteries with SOH greater than 80%, the start charging time of each battery is determined by optimized charging. Finally, at the beginning of each time slot, the fully charged batteries in BSS system are sorted from large to small according to the battery SOH. The BSS system distributes the SOH of battery from large to small according to the time sequence of EV users arriving at the BSS system.

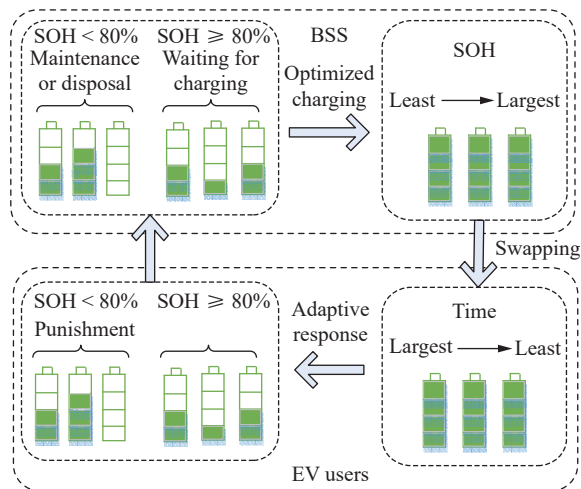


Figure 2 Battery allocation strategy.

#### IV. SIMULATION RESULT

Based on the proposed model, we simulate the battery swapping and charging operation of BSS system. Moreover, we analyze the operation state of BSS system under four scenarios with different response thresholds, as shown in Table 2. The particle swarm optimization (PSO) algorithm is used for solving the optimization problem.

Table 2 Four scenarios.

Scenario	Adaptive response (Y/N)	Price mechanism (Y/N)
S1	Y ( $\delta_1 = 0.6$ )	Y
S2	Y ( $\delta_2 = 0.7$ )	Y
S3	Y ( $\delta_2 = 0.7$ )	N
S4	N	Y

Note: Y indicates that adaptive response or price mechanism is considered in this scenario. N indicates that adaptive response or price mechanism is not considered in this scenario.  $\delta_1$  and  $\delta_2$  are response thresholds of different values.

In this section, we use simulation based on an area load curve to test the optimization model. Our scheduling time is one day, each hour for a period of time. The simulation uses a probability distribution of an area to determine the daily battery consumption curve [29]. A battery sample is used, which follows the Gaussian distribution of SOC. Other parameters are given in Table 3 [15]. Considering the size of the customer, 90 batteries are installed in the BSS system. In addition, there are 300 EV users. The BSS system is operated under the guidance of both traditional and optimal strategies. The traditional charging method is to charge the battery immediately after swapping it until it is fully charged.

Among the monitoring parameters of battery management system, SOC is one of the most intuitive ones. Users can observe the battery level and then decide whether to swap battery. The SOC of the swapping battery is shown in Fig. 3. Most users swap the battery between 30% and 60% of the SOC, and more than 60% of users swap the battery when the SOC is more than 40%. According to the day-ahead battery demand forecast, the battery demand is shown in Fig. 4. Obviously, the battery demand shows a downward trend in 00:00–05:00 and 19:00–24:00, and an upward trend in 06:00–15:00. The battery demand reaches its maximum value in 16:00–18:00. At the same time, the peak demand of battery and the peak load of power system are overlapped, resulting in the increase of peak-valley difference, which is not conducive to the safe operation of power system. In addition, since different EV users have different sensitivities to price, users are divided into three groups according to batteries SOC, as shown in Fig. 5. Since the number of batteries with SOC in the range of 30% to 60% is the highest, the demand for batteries in group 2 is the highest, followed by group 1, and the lowest demand for batteries in group 3.

Table 3 Parameter of EV and BSS system.

Parameter	Meaning	Value	Unit
Cap	Capacity of battery	45	kWh
$P_i$	Charging power	9	kW
$pr_{\min}$	Minimum BSP	0.7	\$/kWh
$pr_{\max}$	Maximum BSP	1.2	\$/kWh
$pr_{i,0}$	Original BSP	1.0	\$/kWh
$P_{BSS,\max}$	Maximum power of the BSS system	400	kW
$step_p$	Power step	7	kW
$step_{pr}$	Price step	0.015	\$
CH	Number of charging piles	35	—
$N$	Total number of BSS system batteries	90	—
$\delta_1$	Response threshold	0.6	—
$\delta_2$	Response threshold	0.7	—

The BSS system charges users for the swapping service based on the BSP. In order to smooth load fluctuations and achieve load shifting, the established price mechanism is that when the load increases, the battery BSP increases, and when the load decreases, the battery BSP decreases. In addition, users are encouraged to swap when BSP is low. Considering the total charging power and average charging power of BSS system, the BSP model is established and shown in Table 4. The BSP reaches a minimum value of 0.70 \$/kWh in 18:00–19:00, and reaches a maximum value of 1.20 \$/kWh in 15:00–16:00.

EV users adaptively respond to make the most appropriate decision for themselves by considering the weight between battery SOH and satisfaction cost. As shown in Fig. 6, in S1 and S2 scenarios, the main body of EV response is the group 2 users. On one hand, due to the limited remaining mileage,

users may choose to replace the battery in advance to drive longer distances. On the other hand, the group 2 customer is also the main body of BSS system consumption, who can avoid the battery damage caused by excessive discharging of the battery.

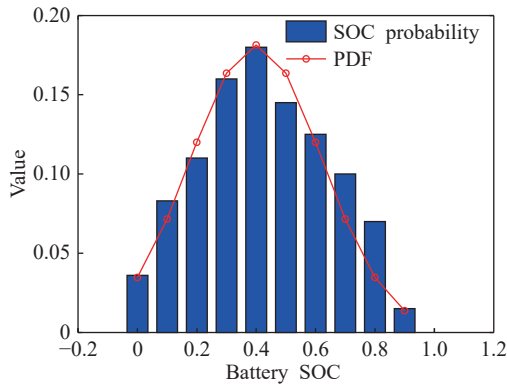


Figure 3 Probability distribution of battery SOC.

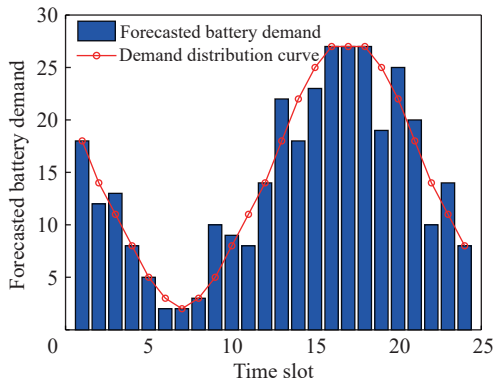


Figure 4 Battery demand in a day.

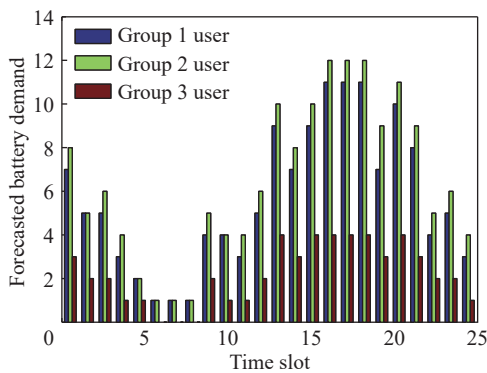


Figure 5 Battery demand for each group of user in a day.

After considering the BSP excitation, the battery demand of EVs under two response thresholds is shown in Fig. 7. Compared with the battery demand situation in Fig. 4, when BSP excitation is not considered, the fluctuation of battery demand response in Fig. 4 is significantly reduced. The charging peak from 14:00 to 20:00 in Fig. 4 is dispersed to other moments, avoiding the situation of centralized charging of EVs. Based on the BSP price in Table 4, it can be found that at the low electricity price moment from 18:00 to 19:00,

the battery demand in both S1 and S2 scenarios reaches the maximum value. At the high electricity price moment from 14:00 to 17:00, compared with Fig. 3, the battery demand in both S1 and S2 scenarios is significantly reduced. At this high electricity price moment, as shown in Fig. 7, the battery demand in S1 scenario is less than that in S2 scenario, because the response threshold in S1 is less than the threshold in S2. This also means that EVs in S1 scenario are more price sensitive and will make greater demand adjustments. To sum up, the BSP model in this paper can encourage EVs to adjust the charging demand, reduce the fluctuation of battery demand at each time, and avoid the situation of insufficient BSS battery reserve caused by centralized charging of EVs.

Table 4 Battery swapping price.

Number	Time	BSP (\$/kWh)
1	18:00–19:00	0.70
2	02:00–12:00, 17:00–18:00, and 20:00–24:00	0.80
3	00:00–02:00, 13:00–14:00, and 19:00–20:00	0.90
4	12:00–13:00	0.95
5	14:00–15:00 and 16:00–17:00	1.00
6	15:00–16:00	1.20

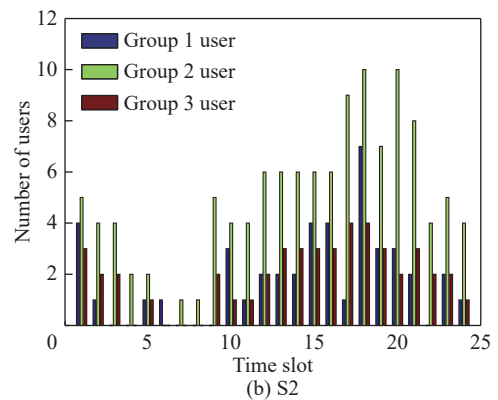
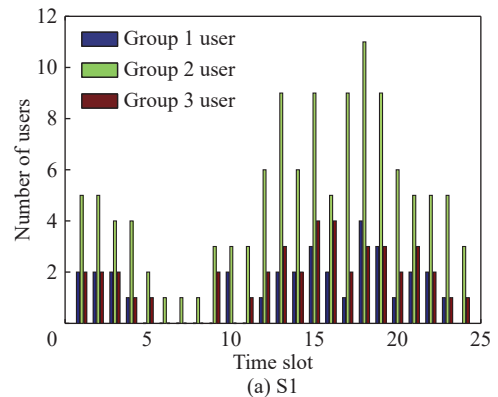


Figure 6 Number of users adaptive response.

In order to analyze the influence of BSP model on BSS income, this paper solves the income under S2 and S3 scenarios 10 times, and further calculates their average values. The single convergence result is shown in Fig. 8. The average

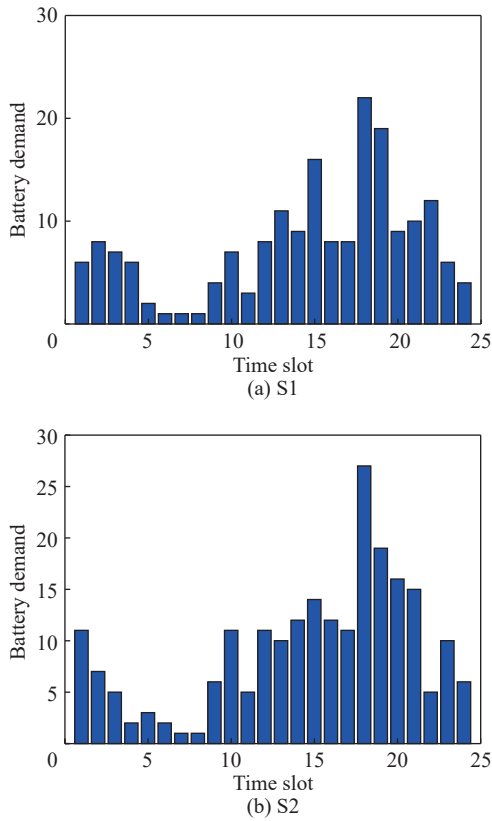


Figure 7 Redistribution of battery demand.

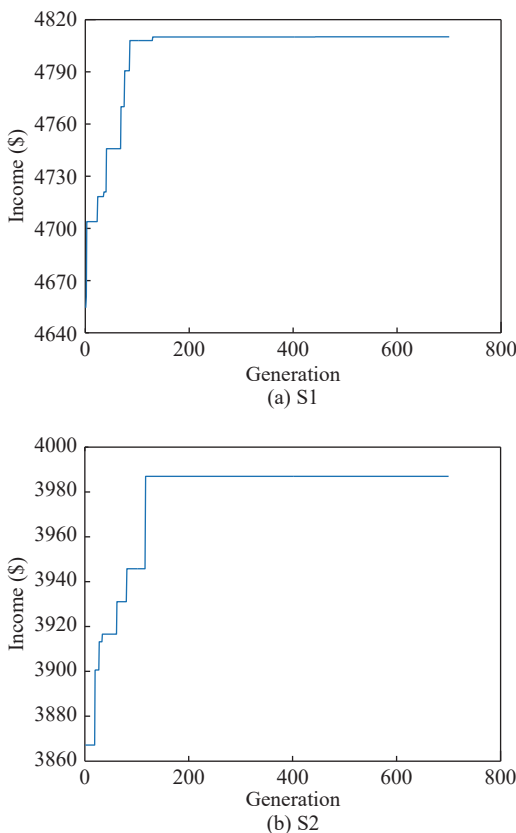


Figure 8 Optimization result of income of BSS system.

incomes in S2 and S3 scenarios are \$4516 and \$4120, respectively. Under S2 scenario, revenue grows 8.76% on average. This is because that the BSP incentive is not considered in S3 scenario, the EVs are concentrated on charging from 14:00 to 20:00, and the battery demand during this period is greater than the total battery reserve of BSS. This means that BSS needs to charge the battery at the high electricity price time from 14:00 to 15:00 and the intermediate electricity price time from 15:00 to 18:00, resulting in an increase in BSS charging costs and a decrease in revenue. Therefore, the introduction of the BSP model helps to reduce the charging cost of the BSS, thus increasing the benefits of the BSS.

In order to verify the effectiveness of the BSS optimal scheduling model proposed in this paper, we compare the charging costs of the BSS system under the traditional strategy and the optimized strategy in S1 scenario. The results show that the charging cost of BSS under the traditional strategy is \$4474, while the cost of BSS under the optimized strategy is \$3679, which is reduced by 17.78%. In addition, this paper also analyzes the impact of battery capacity and number of EVs on BSS revenue, and the results are shown in Fig. 9. In S1 scenario, as the battery capacity increases, the revenue of BSS increases. However, when the battery capacity increases to a certain value, the benefit of BSS no longer

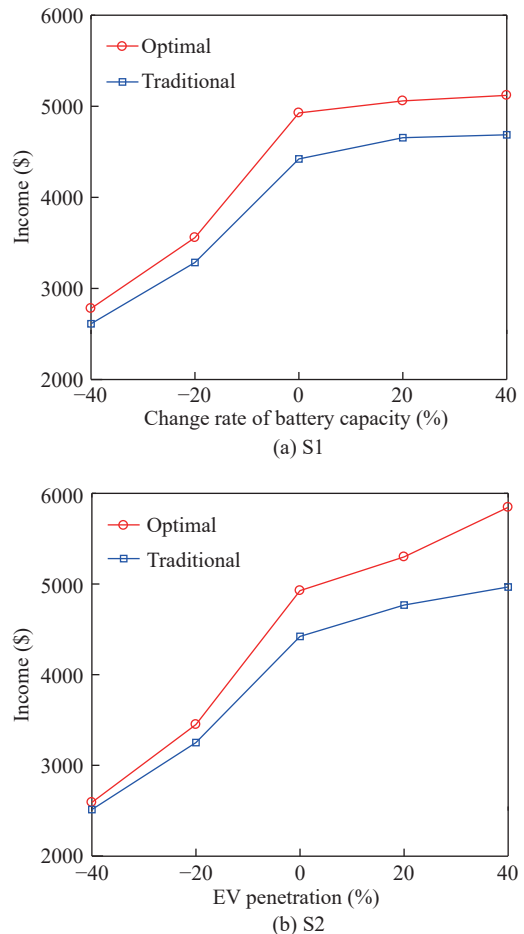


Figure 9 Sensitivity analysis.

increases with the increase of battery capacity. This is because when the capacity increases to a certain value, the charging time of the battery also becomes longer, resulting in a decrease in the flexibility of BSS charging scheduling and an increase in BSS charging costs. In S2 scenario, the revenue of BSS increases with the increase of the number of EVs, and will not stop increasing after reaching a certain number. To sum up, the BSS optimization model proposed in this paper helps to reduce the charging cost of BSS and improve the revenue of BSS. The load curves obtained by optimizing the charging state of the battery in the station are shown in Fig. 10. It can be observed that most batteries are charged when electricity prices are at their lowest value. Before optimization, the charging peak-to-average ratio (PAR) of BSS is 2.52. After optimizing the charging strategy, the PAR decreases to 2.10 in S1 scenario and 2.15 in S2 scenario. They decrease by 0.42 and 0.37, respectively. Therefore, the BSS optimal scheduling model proposed in this paper can realize coincidence transfer, thereby reducing load fluctuation and load peak-valley difference.

In the user adaptive response model and load shifting model, responsiveness and load shifting rate are introduced to represent the degree of response. The responsiveness and load shifting rate of each time slot are shown in Fig. 11. Since the battery demand and user preference are different in each time slot, the responsiveness and load shifting rate are different in each time slot.

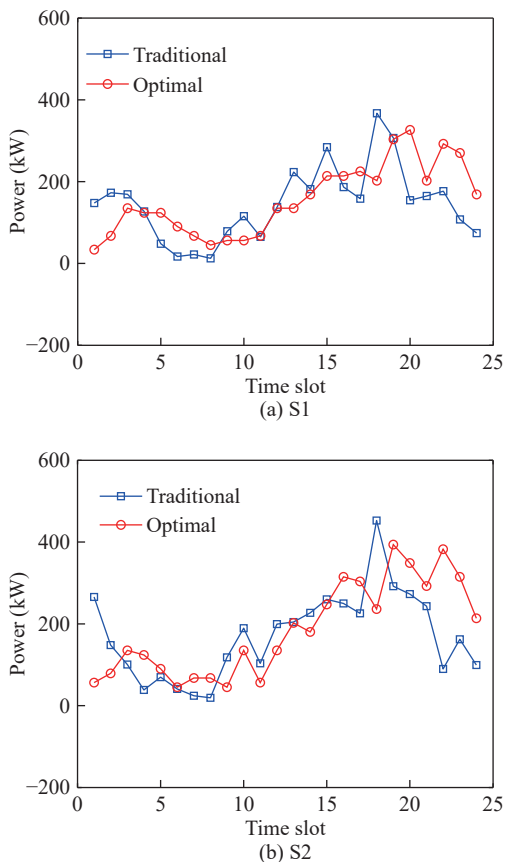


Figure 10 Optimization result of BSS system load.

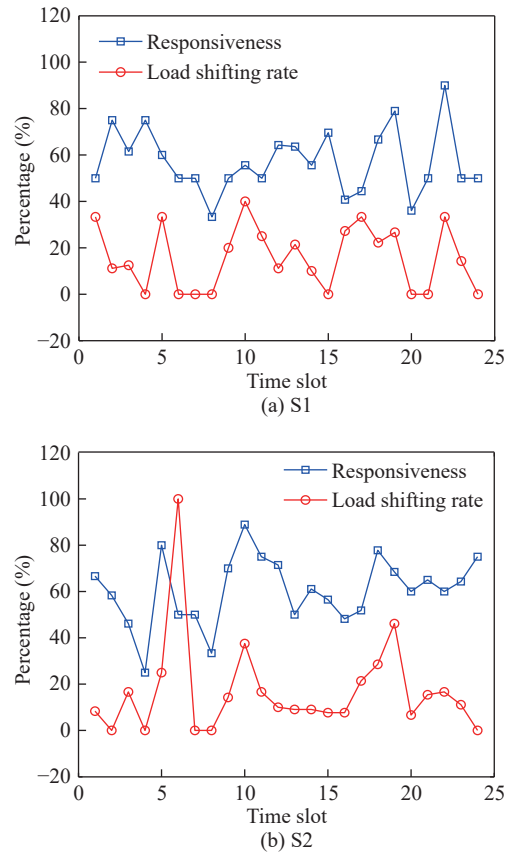


Figure 11 Responsiveness and load shifting rate.

## V. CONCLUSION

This paper mainly studies the optimal scheduling strategy of BSS system based on user adaptive response. First, a pricing mechanism based on battery demand power is designed to provide reference for power exchange behavior of EVs. Second, a user adaptive response model based on SOH and user satisfaction is established. Aiming at the problem that users have different sensitivities to electricity price, an elastic matrix of user response is established to adjust electricity demand. Finally, the charging optimization model of BSS system is established to maximize the revenue of BSS system, and the PSO algorithm is used to solve the model. Simulation results show that the model can improve the revenue of BSS system, reduce the peak-valley difference of power grid load, and is beneficial to the stable operation of power system. In this paper, the discharging of BSS system to power system is not considered. In the future, we will further consider BSS system which provides auxiliary services to power system through V2G technology, and further enhance its flexibility.

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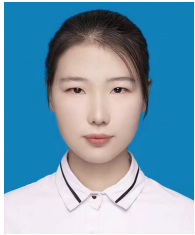
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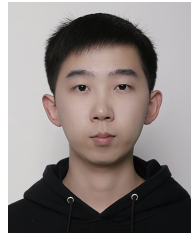


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