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Recharging and transportation scheduling for electric vehicle battery under the swapping mode

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A B S T R A C T

Electric vehicle battery recharging on the swapping mode has grown up as an important option other than the plug-in recharging mode in China, given that several auto giants have been dedicated in constructing their battery swapping systems. However, the lack of effective operational methods on battery recharging and transportation scheduling has aroused a big challenge on the practical application of the swapping mode, which enables the necessity of our work. This study proposes a joint optimization model of recharging and scheduling of electric vehicle batteries with a dynamic electricity price system which is able to identify the optimal charging arrangement (the recharging time and the quantity of recharging batteries) as well as the optimal transportation arrangement (the transportation time and the quantity of transporting batteries). For the validation purpose, a numerical study is implemented based on dynamic electricity prices in Beijing. A sensitivity analysis of parameters is carried out to increase the robustness and provide more managerial insights of the model.

A R T I C L E   I N F O

Keywords:
Electric vehicle;
Battery recharging;
Battery swapping;
Battery logistics;
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1. Introduction

Carbon emission reduction is becoming a privilege for an increasing number of countries across the world to counter global warming effects. At the Climate Ambition Summit in December 2020, the leaders of the 27 EU member states stated that by 2030 their net greenhouse gas emissions would be reduced to no more than 45 % of 1990. China has also made a commitment to peak carbon dioxide emissions before 2030 and achieve carbon neutrality before 2060. Given that automobile exhaust is one of the major sources of carbon emissions while electric vehicles (EVs) are clean, the use of EVs has considerable potential in reducing vehicle emissions [1-5]. Therefore, the extensive application of EVs is an important available measure to help the countries fulfill their commitments. Furthermore, for a country, some pillar industries like manufacturing could enjoy extra emission credits saved by the transportation sector using EVs, and thus have more development vigor.

However, the range anxiety of consumers has severely limited the popularity of EVs. It usually takes hours for EVs to recharge an EV, which is a matter of great concern for consumers, in addition to the imperfect recharging infrastructure [6, 7]. According to the Development Strategy Report of the Ministry of Industry and Information Technology, the number of EVs in China will reach 60 million by 2030. If a large scale of EVs is charged in a disordered way (randomly connected to the power grid for charging), it will bring damages to the power grid [8]. Different from in the plug-in recharging mode, the depleted battery of an EV in the swapping mode is replaced with a full one, then the EV could continue to run and the depleted battery is left to be recharged. The swapping mode separates the recharging process from the battery swapping, which enables three advantages: (1) the whole operation takes less than 10 minutes, which is much faster than plug-in recharging; (2) the charging time and the quantity of charging batteries can be scheduled reasonably so as to reduce the impacts on the safety and quality of power grid [9-10]; (3) the depleted batteries can be charged during off-peak hours of a discounted electricity price and consequently reduce the charging cost. Actually, the swapping mode has been booming in China, e.g., NIO, a Chinese giant EV-maker, has set up 139 swapping stations, BAIC Group made a plan to construct 100 swapping stations capable to serve no less than 10,000 EVs, Changan Auto set up a battery swapping alliance to promote the swapping business, etc.

Although the key challenges for operating battery swapping mode is to optimize both the charging time of depleted batteries and the battery transportation scheduling between battery swapping station (BSS) and battery charging station (BCS) [11], current studies on the battery swapping mode rarely address the joint optimization of the above two problems, not to mention the joint problem with the dynamics of electricity price. To bridge this gap, we study a joint optimization problem of charging time and transportation scheduling based on a battery swapping and charging system (BSCS). Although the BSCS hereby has a simple structure to comprise one BSS and one BCS, it is able to unveil the nature of the swapping and charging systems and could be easily extended to complex ones. This study aims to answer the following two questions: (1) how to determine the optimal charging time and quantity of the charging batteries; (2) how to optimize the transportation scheduling of batteries between BCS and BSS. All abbreviations are detailed in Table 7 in Appendix.

The uniqueness of this work is multifold. First, the proposed model takes into account the dynamic electricity prices, which not only maintains the security of the grid but also reduces charging costs. Secondly, this work is the first to address the joint optimization problem of the centralized charging and the transportation scheduling of batteries with consideration of the dynamic electricity price, which could identify the optimal charging time of the depleted batteries, as well as the optimal time and quantity of the battery transportation between BSS and BCS. Finally, we highlight the managerial implication by carrying out a sensitivity analysis.

The remainder of this paper is organized as follows. Section 2 reviews the latest studies on the battery swapping mode. Section 3 elaborates the problem and the mathematical model. Section 4 shows the details of a numerical study and a sensitivity analysis, based on which, Section 5 provides managerial insights. Section 6 concludes this study and discusses some potential future directions.

2. Literature review

Substantial studies have been made on the charging strategies of EVs [12-15], however, there are also many insurmountable challenges on the charging strategies, such as long charging time, charging inconvenience, etc. In recent years, with the invention of battery swapping station, the battery-swapping mode has been obtaining increasingly more attention from industries and the academia [16].

Most of the studies on the battery swapping strategy focus on the optimal charging time of batteries. Kang *et al.* [17] proposed a novel centralized charging strategy of EVs under the battery swapping scenario based on spot electric price and design a population-based heuristic approach to minimize total charging cost while reducing power loss and voltage deviation of power networks. Zheng *et al.* [18] focused on EV battery swapping station coordinated charging dispatch method based on CS algorithm to achieve the optimization of daily charging plan of battery swapping station (BSS). Yang *et al.* [19] propose a dynamic operation model of BSS in electricity market based on the short-term battery management, and acquires additional revenue by responding actively to the price fluctuation in electricity market. Song *et al.* [20] designed a typical connection mode of electric vehicle charging and battery exchange infrastructure, which can provide guidance for the planning of electric vehicle charging and battery exchange infrastructure interconnected with the grid. Zhang *et al.* [21] proposed an optimized charging mode (OCM) to determine the impact of drivers' switching behavior on power grid and power generation cost. Wang *et al.* [22] proposed a comprehensive optimal allocation method for EV switching stations based on orderly charging strategy. Infante *et al.* [23] considered the demand of EV users and the load of power grid, and proposed a strategy model of EV switching station to optimize the benefits. Sarker *et al.* [24] proposed the optimization framework of the battery switching station operation model. Wang *et al.* [25] proposed an integrated optimization model with EV charging station, battery-swap station and energy storage system, which aims to find a balance status between the power grid and the EV users during the power flow exchange in the background of internet energy.

To the best of our knowledge, most of the existing studies focus on the charging process of the battery exchange system, while ignoring the transportation scheduling between BCSs and BSSs. Given that the operation of BSCS needs to coordinate the two perspectives, it is necessary to propose a joint optimization model to identify the optimal charging time and the optimal quantity of the charging battery, as well as the optimal battery transportation schedule (transportation time and transportation quantity) between BCS and BSS.

3. Model definition

3.1 Problem formulation

We study the battery charging process of the battery charging station (BCS) and the swapping process of the battery swapping station (BSS) in the battery swapping and charging system (BSCS). There are three subsystems in BSCSs: the battery swapping station (BSSs), the battery charging station (BCSs) and the logistics system between them. In this system, users send the depleted batteries (DBs) back to BSSs and remove the fully charged batteries (FBs). After a while, BSSs will ship the accumulated depleted batteries back to BCSs. The depleted batteries (DBs) will be charged centrally by BCSs within a reasonable time and then shipped back to BSSs for further use by future customers. Based on the above process, we propose a mathematical model of battery centralized charging and transportation scheduling. Furthermore, we assume that the service time of logistics system will not be discussed in our model.

We introduce a mathematical formulation of this problem. First, the model discretizes the continuous time according to a certain time granularity. According to the time-of-use electricity price mechanism and the uncertainty of demand, managers need to make decisions at the endpoints of each time grain. For BSS, the managers need to make decisions about when to transport how many batteries from BCS to meet the customer's demand for electricity conversion. For BCS, the decision is when to charge the depleted batteries, so as to meet the demand of BSS while minimizing the charging cost. Certain transportation costs will be incurred in the process of transportation. For the whole system, in order to minimize the total cost, on the basis of meeting the demand, when to transport and how many batteries to transport are also the contents to be decided.

The model makes the following assumptions:

1. On the BSCS side, we assume that there is only one BCS, which is responsible for charging the battery. There is only one BSS, which is responsible for battery replacement for users. The logistics process between BCS and BSS does not consider the transport time and route temporarily, we only study the number and quantity of transport.
2. In terms of electricity price, this section assumes that electricity price only change at the time granularity endpoint. According to the State Grid, electricity price is divided into three levels, peak, normal and trough, and only change at the hourly point of each day. The

electricity price fluctuates periodically in a stepped manner. Therefore, this setting is also realistic.

3. In terms of battery charging process, we assume that each battery will charge for the same time. In fact, the residual power of the battery is random and the time required for full charge should also be random. But EV users who generally go to BSS for energy renewal have a relatively low battery surplus. We generally set the initial SOC of depleted batteries as 0.2, and the SOC at full charge is between 0.9-1. Consider that the batteries currently used by car manufacturers are mostly made by BYD (mainly for BYD's own use) and Ning-de Times. So even if the car brand is different, the battery specifications are similar, which makes the time required for different batteries to be fully charged is basically the same, so this assumption will not lead to a greater deviation from reality.

3.2 Model specification

Without loss of generality, we characterize the scenario of our model as follows:

1. The battery belongs to BSS in BSCS;
2. There is only one BCS;
3. BSS cannot charge DBs;
4. The battery type is the same. DBs all have the same SOC, so does WBs, so they are charged at the starting point of time granularity, and all batteries have the same charging time;
5. The battery delivery time between BCS and BSS is not considered;
6. The total operating period is divided into discrete time periods. Let g represent the time granularity;
7. Electricity prices change over time and only at the end points of time granularity.
8. To extend battery life, the battery does not stop charging until it is fully charged.

It is notable that although the BSCS hereby comprise one BSS and one BCS, it is sufficient to reflect the nature of the swapping and charging systems and could be easily extended to complex ones. The natation of variables and parameters are shown in Table 1.

Table 1 Variables and parameters of the model

Variable	Meaning
t	t time granularity;
TP	Single vehicle single transport cost
P_t	Electricity price at the t time granularity
W_t	The number of full batteries in the BSS at the beginning of the t period
D_t	Power exchange demand at the beginning of t
Q_t^*	BCS full battery number at the beginning of t
Q_t	Number of batteries charged at the beginning of t
Q_t^+	Number of batteries charged in t period
TQ_t^{out}	Number of batteries shipped from BSS to BCS at the beginning of t
TQ_t^{in}	Number of batteries shipped from BCS to BSS at the beginning of t
T_t^{out}	Number of vehicles transporting batteries from BSS to BCS at the beginning of t
T_t^{in}	Number of vehicles transporting batteries from BCS to BSS at the beginning of t
Q_c	The maximum transport capacity of a single vehicle
N_{occup}	The ratio of full batteries to the capacity of the swapping station at initial time
N_c	The proportion of charging piles that are not occupied in the initial BCS
M	Number of time particles required for a single battery to be fully charged
C_{aps}	The maximum number of cells a BCS can hold
C_{apc}	The maximum number of cells a BCS can hold
PoC	Charging power
T	The total time window length of this study

The model:

$$Min\ S = \sum_{t=1}^{T}\left(g \cdot PoC \cdot Q_t \cdot \sum_{i=t}^{t+M-1} P_i\right) + TP\sum_{t=1}^{T}\left(T_i^{in} + T_t^{out}\right) \tag{1}$$

Subject to

$$W_1 = C_{aps} \times N_{occup} \tag{2}$$

$$W_t = W_{t-1} - D_{t-1} + TQ_{t-1}^{in} \tag{3}$$

$$W_t \geq D_t \tag{4}$$

$$Q_1^* = (1 - N_c) \times C_{apc} - TQ_1^{in} \tag{5}$$

$$Q_t^* = Q_{t-1}^* + Q_{t-1}^+ - TQ_t^{in} \tag{6}$$

$$TQ_t^{in} \leq Q_t^* \tag{7}$$

$$Q_t^+ \begin{cases} Q_{t-M+1}, t \geq M \\ 0, t \leq M \end{cases} \tag{8}$$

$$\sum_{i=1}^{t} Q_i \leq \sum_{i=1}^{t} TQ_i^{out} \tag{9}$$

$$\sum_{i=1}^{t} TQ_i^{out} \leq \sum_{i=1}^{t} D_i \tag{10}$$

$$\sum_{i=1}^{t} TQ_i^{in} - \sum_{i=1}^{t} TQ_i^{out} \leq C_{aps}\left(1 - N_{occup}\right) \tag{11}$$

$$\sum_{i=1}^{t} TQ_i^{out} - \sum_{i=1}^{t} TQ_i^{in} \leq N_c \cdot C_{apc} \tag{12}$$

$$\frac{TQ_t^{out}}{Q_c} \leq T_t^{out} \leq \frac{TQ_t^{out}}{Q_c} + 1 \tag{13}$$

$$\frac{TQ_t^{in}}{Q_c} \leq T_t^{in} \leq \frac{TQ_t^{in}}{Q_c} + 1 \tag{14}$$

$$t, P_t, W_t, Q_t^*, Q_t, Q_t^+, TQ_t^{in}, TQ_t^{out}, T_t^{in}, T_t^{out} \geq 0 \tag{15}$$

Objective function Eq. 1 is the minimum sum of battery charging cost and transportation cost. Specifically, the total cost of BSCS consists of two parts: (1) The electricity cost for battery charging under the time-of-use tariff mechanism; (2) The transportation cost of batteries dispatched between BCS and BSSs.

The constraints can be divided into 4 categories, including:

Constraints on the number of fully charged batteries in BSS

Constraint Eq. 2 indicates that the number of full batteries in the initial BSS is equal to the number of available batteries placed in the initial BSS.

Constraint Eq. 3 indicates that the number of full batteries in BSS in period t is equal to the sum of the number of full batteries in BSS in period $t-1$ and the number of batteries shipped into BSS, minus the number of batteries required in period $t-1$.

Constraint Eq. 4 indicates that the electrical changing demands that can be met in each phase should not exceed the total amount of fully charged batteries available in the current phase of the electrical changing station.

Constraint Eq. 11 is the inventory capacity constraint in BSS, indicating that the difference between the number of batteries shipped in and out of BSS in period t should not exceed the inventory capacity in BSS in period $t-1$.

Constraints on the number of fully charged batteries in BCS

Constraint Eq. 5 The number of fully charged cells in the initial BCS is equal to the number of available cells placed in the initial BCS minus the number of fully charged cells shipped out of the first BCS.

Constraint Eq. 6 indicates that the number of fully charged cells in BCS at period t is equal to the sum of the number of fully charged cells in BCS at the beginning of period $t-1$ and the number of fully charged cells at the beginning of period $t-1$ minus the number of cells shipped out of BCS at the beginning of period t.

Constraint Eq. 7 indicates that the number of batteries shipped out of BCS in each period should not exceed the total amount of fully charged batteries available in the charging station in the current period.

Constraint Eq. 12 is the constraint of BCS internal free charging capacity, indicating that the difference between the number of batteries transported in and out of BCS in period t should not exceed the spare charging capacity in BCS in period $t-1$.

Battery charge time constraint

Constraint Eq. 8 indicates that when the charging time of the battery is greater than or equal to the time particle size of M, the battery is fully charged.

Battery transport constraints in logistics system

Constraint Eq. 9 indicates that the number of batteries charged from the initial period to the current period should not exceed the total number of empty batteries in each BCS period.

Constraint Eq. 10 indicates that the number of batteries shipped out of BSS from the initial period to the current period should not exceed the demand for changing electricity.

Constraints Eq. 13 and Eq. 14 are vehicle constraints for transport.

Constraint Eq. 15 indicates that all variables are integers not less than 0.

This is a typical nonlinear mixed integer programming problem that can be solved by mathematical softwares such as MATLAB, CPLEX, and LINGO.

4. Numerical study and sensitivity analysis

To illustrate the effectiveness of the model, this section is based on the time-of-use electricity price mechanism of the power grid, and parameters are set according to the actual situation. We solve the problem by using LINGO mixed integer programming solver. In order to show the quantitative relationship among demand distribution, initial battery storage ratio and optimal charging time, we study the influence of demand distribution and initial battery storage ratio on the centralized charging strategy.

4.1 Parameter settings

- g = 0.5: The time particle size is 0.5, indicating that a decision should be made every 0.5 hour in the charging station, including whether to start charging a new batch of empty batteries and whether to transport the fully charged batteries to the changing station;
- M = 10: Suppose it takes 5 hours to fully charge a battery. That is 10 time granularities;
- C_{aps} = C_{apc} = 400: BSS and BCS can hold up to 400 batteries;
- N_{occup} = 0.8: Initially, 20% of the inventory capacity of BSS is idle, which means 80% of the existing inventory is occupied by full batteries;
- N_c = 1: There is no battery in the initial state of BCS;
- Q_c = 50: The maximum transport capacity of a single vehicle is 50 batteries;
- TP = 200: A transportation cost is 200 yuan;
- PoC = 3: The charging power is 3 kWh;
- $D \sim Passion(15)$: Referring to the average visit times of gas stations in real life, the demand is set to follow the Poisson distribution with an average of 15;

- P: According to the peak hours and corresponding electricity prices published by China Power Grid. The specific setting of electricity price is shown in Table 2:
- T: The research time is set as the time for all the initial fully charged batteries in BSS to be swapped out plus an integer multiple of M, combined with the above parameters, $a\ research\ cycle\ =\ 21 + 3 \cdot M$, considering the continuity of the model for the study cycle and repeatability, will postpone back 10 research cycle time granularity, namely the total time of this study window set to $21 + 3 \cdot M + 10$, the start time of study based on real life set to 7:00 in the morning.

Table 2 Electricity price distribution in different periods

Electricity Intensity	Period of time	Electricity price (yuan/kWh)
Peak	7:00-11:00	1.234
Normal	11:00-19:00	0.856
Peak	19:00-23:00	1.234
Trough	23:00-7:00（Next day）	0.376

4.2 Model solving

This part assumes that the electrical changing demand D follows the Poisson distribution with an average value of 15, and a group of samples with a capacity of 61 are randomly sampled. According to the electrical changing demand represented by this group of samples, the optimal charging time and quantity distribution as well as the battery transportation time and quantity distribution between the electrical changing station and the charging station are solved.

Fig. 1 shows the quantity distribution of electrical changing demands represented by this group of samples.

According to the determination principle of total time window length, the study cycle is 61 time granularity. The optimal solution under this sample electrical changing demand is shown in Fig. 2.

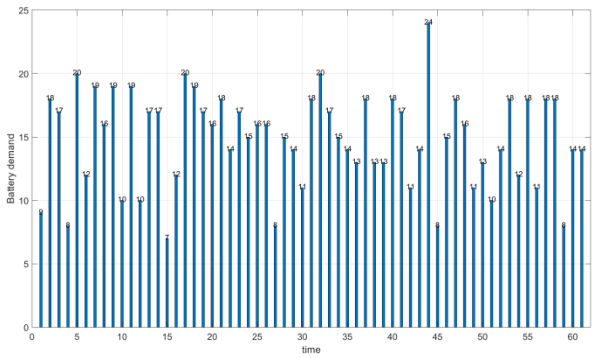

Fig. 1 Electrical changing requirements for each time granularity during the study period

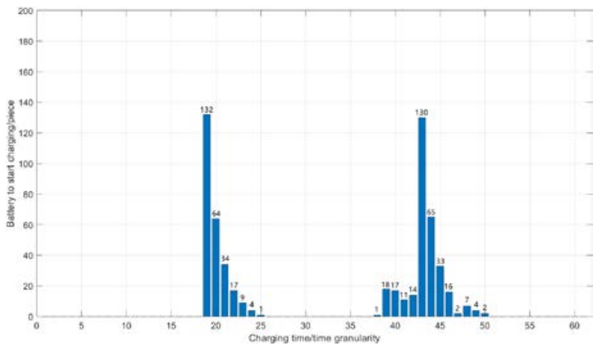

Fig. 2 Optimal charging time and quantity distribution of BCS

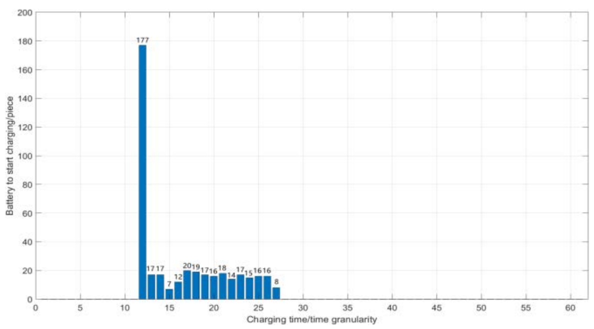

Fig. 3 Optimal time and quantity distribution of batteries from BSS to BCS

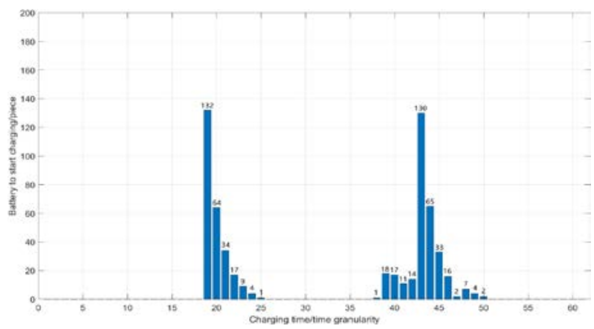

Fig. 4 Optimal time and quantity distribution of the battery from BCS to BSS

In the scenario of EV energy update set in this article, the following conclusions can be drawn:

- The optimal charging time and quantity distribution are shown in Table 3. Obviously, most batteries avoid the peak electricity consumption period and choose to start charging when the electricity price is normal or low.
- Table 4 shows the distribution of transportation time and quantity of batteries between BCS and BSS. We can found that the battery transportation time is relatively concentrated. As shown in Tables 4, the battery transportation presents asymmetry. The amount of transportation from BSS to BCS is greater than that in the opposite direction. The reason is that batteries are transported between BCS and BSS, and some batteries are still placed in BSS when the research time is cut off. Therefore, although there are inconsistencies in battery transportation in this experiment, it does not violate business logic and actual operation. The continuous operation of charging and changing station can be regarded as the periodic repetition of the time period studied in this paper. Therefore, we can use the same method to make optimization decisions regularly, so as to ensure the minimum charging and transportation costs under the premise of meeting the electrical changing needs in each cycle.
- As shown in Figs. 3 and 4, in the optimal time and quantity distribution of battery transportation between BSS and BCS, the number of batteries to be transported in the decision of the individual time granularity is very small. The research results show that the number of transport batteries is less than 10 in some cases, especially when the batteries are transported from BCS to BSS, the minimum number of transport is even one or two. In fact, the transportation cost is generally determined by the number of trips the vehicle takes, regardless of whether the vehicle is fully loaded. Therefore, it is necessary to increase the vehicle carrying rate to reduce transportation times and reduce the transportation cost when time permits. The reason why this situation still occurs is to meet urgent needs. Although the charging cost is high during the peak period, the prerequisite for reducing the cost requires priority to meet the demand for power exchange. Therefore, such a low single shipment would not be desirable from a cost standpoint, but such an arrangement is necessary from a demand standpoint.

Table 3 Optimal charging time and quantity distribution

Period of time	Electricity intensity	Electricity price	Number of batteries to start charging
7:00-11:00	Peak	1.234	0
11:00-19:00	Normal	0.856	267
19:00-23:00	Peak	1.234	74
23:00-7:00 (Next day)	Trough	0.376	247

Table 4 Optimal transportation time and quantity distribution of batteries

Period of time	Electricity intensity	Number of batteries shipped (BSS to BCS)	Number of batteries shipped (BCS to BSS)
7:00-11:00	Peak	0	0
11:00-19:00	Normal	366	260
19:00-23:00	Peak	40	1
23:00-7:00 (Next day)	Trough	0	314
7:00-11:00 (Next day)	Peak	0	6
11:00-13:30 (Next day)	Normal	0	0

4.3 Sensitivity analysis

The influence of demand distribution D on charging strategy

We did 100 rounds of sampling, and the sample size of each round was 61 to form 100 groups of samples. Fig. 5 and Fig. 6 show the distribution characteristics of 100 sets of samples.

We substituted 100 groups of random demand samples into the model to solve the optimal charging time and quantity distribution of batteries, as well as the transportation time and quantity distribution of batteries between BSS and BCS. The results show that the optimal charging time is basically concentrated in the 9th, 28th to 32nd and 33rd time particle size, and the number of batteries starting charging at the 9th and 33rd time particle size is the largest, with the number not less than 200. The number of batteries that started charging at time 28 to 32 was approximately 65. It can be seen that the uncertainty of demand has little influence on the final optimization result.

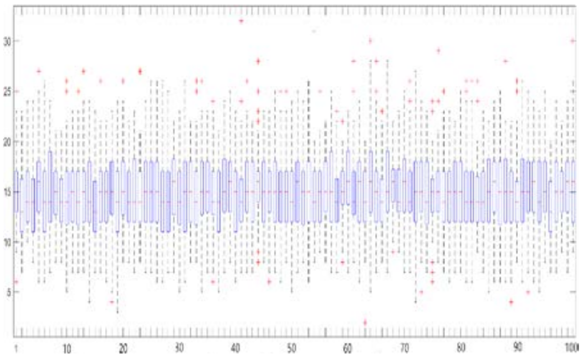

Fig. 5 100 sets of sample boxplot of electrical changing requirements

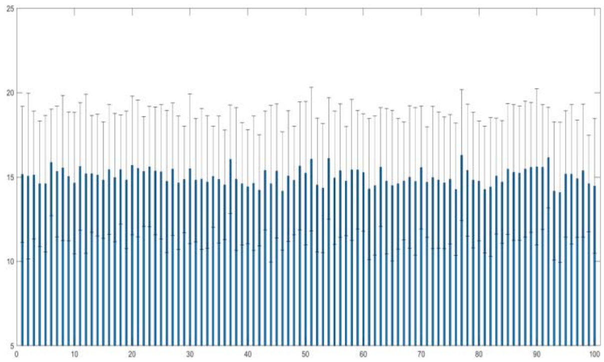

Fig. 6 100 sample mean and standard deviation distribution of electrical demand

The influence of initial battery storage ratio on charging strategy

The parameter represents the ratio of the available battery storage capacity in the BSS at the initial time. When the capacity of the BSS is determined, the value of represents the number of full batteries available in the initial BSS. It takes M (M = 10) time granularity for a depleted battery to be fully charged, which means that the system's electrical changing demands need to be met by artificially placed full batteries in the BSS during the initial 10 time granularity. Therefore, the value of has a very important impact on the operation of the system.

Fig. 7 and 8 show the value of $Q_{(t)}$ at each time granularity when N_{occup} takes values 0.5, 0.6, 0.7, 0.8, 0.9 and 1, respectively. When N_{occup} changes between 0.5 and 1, the model can concentrate most of the batteries on normal and low electricity prices. As the number of full batteries placed in the initial BSS increases, the number of batteries charged in the peak period decreases. This is because the system will give priority to meet the demand for electricity exchange. When the initial full battery quantity is low, the number of rechargeable batteries will increase at the peak.

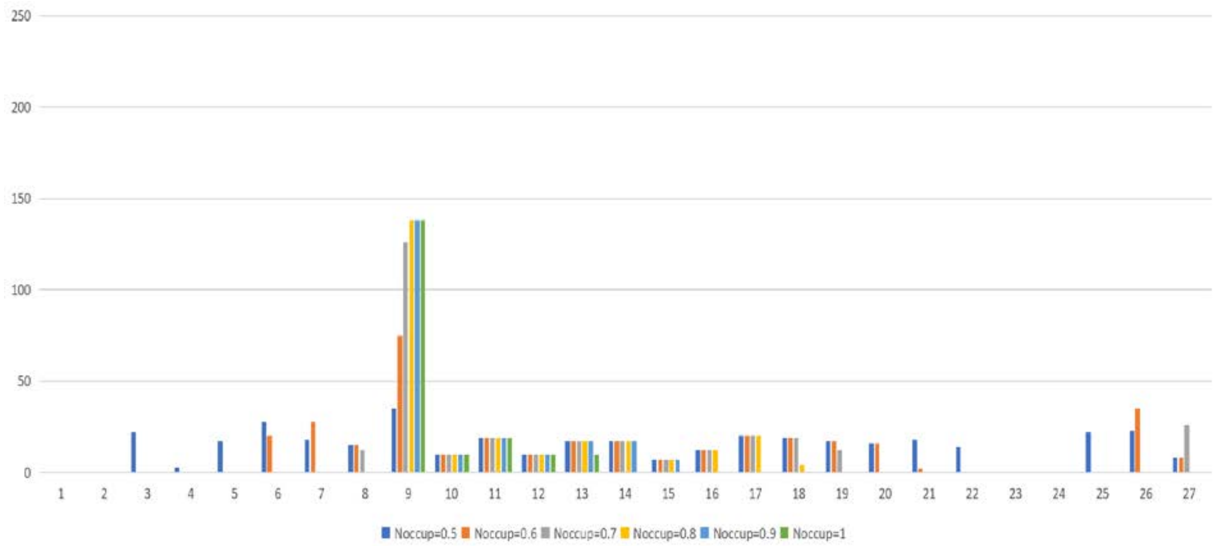

Fig. 7 The sensitivity change of *N_occup* to the optimal charging time (time: 1-27)

Fig. 9 is obtained by summing up $Q_{(t)}$ when N_{occup} takes different values according to the power consumption intensity.

Obviously, as the value of N_{occup} continues to increase, the total number of batteries charged during the research period decreases, and the number of batteries charged during peak periods also decreases.

As the value of the parameter N_{occup} continues to increase, the minimum cost value continues to decrease. This is because if the demand remains unchanged, the more fully charged batteries are artificially put into the system at the beginning, the fewer batteries need to be charged and transported in the later period of the system, thus reducing the cost. But in practice, the more batteries you put in, the more upfront costs you have. Table 6 shows that when N_{occup} takes 0.8, 0.9 and 1, the number of batteries charged in the peak period is not much different. Taking into account the trade-offs between the front and later costs, we recommend that the value of N_{occup} is 0.8.

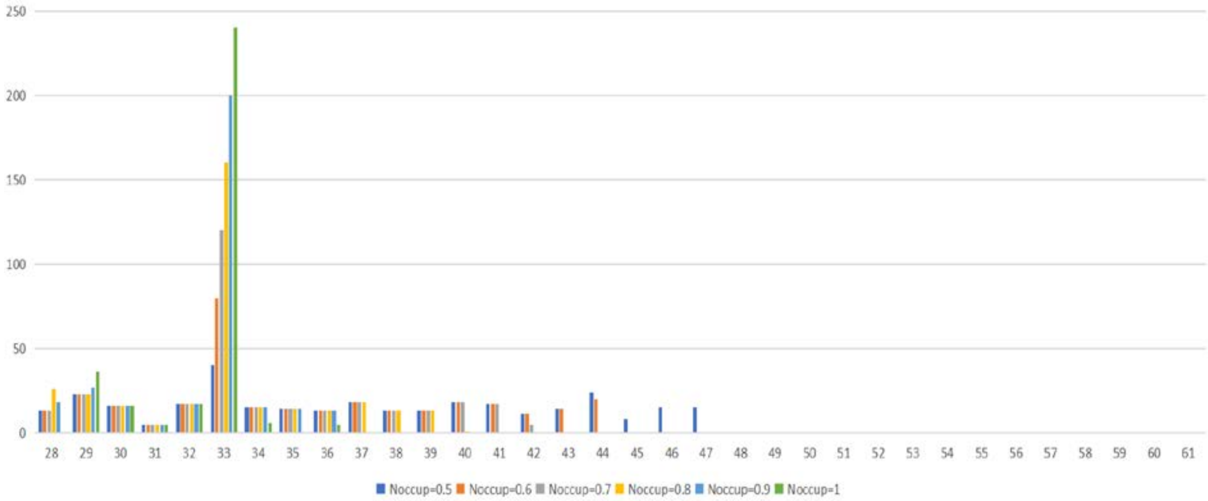

Fig. 8 The sensitivity change of *N_occup* to the optimal charging time (time: 28-61)

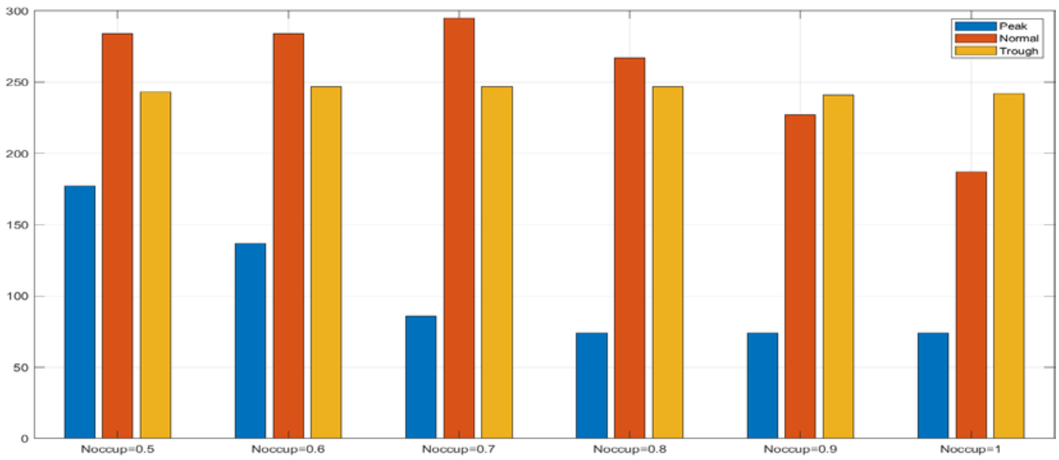

Fig. 9 Sensitivity analysis of N_{occup} to optimal charging time

Table 6 Distribution of optimal charging time and cost when takes different values

	Peak	Normal	Trough
N_{occup} = 0.5	177	284	243
N_{occup} = 0.6	137	284	247
N_{occup} = 0.7	86	295	247
N_{occup} = 0.8	74	267	247
N_{occup} = 0.9	74	227	241
N_{occup} = 1.0	74	187	242

5. Managerial implication

Based on the battery swapping mode, this study aims to introduce the joint optimization of battery charging and transportation and enrich the application of EVs in practice. Some constraints on the centralized battery charging and scheduling model are given special consideration. Although algorithm parameters and computational instances affect the calculation results, some specific conclusions are generalized as follows:

First, the model results are robust and easy to support the actual decision. In the example, the optimal solutions of 100 groups of random samples generated according to Poisson(15) are roughly the same, indicating that the random fluctuation of demand does not have a great impact on the final optimization results. This means that in the actual decision, even if there is some deviation in the estimation of future requirements, the optimization results still have high availability. What needs to be pointed out is that the above results are obtained on the premise that the electricity changing demands are subject to the Poisson(15) distribution. If the electricity changing demands are subject to the Poisson distribution with greater fluctuations or other random distributions, further tests are needed.

Second, the enterprises should focus on the time of centralized charging batteries to save charging costs and reduce power grid losses. From Table 3, nearly 90 % of the batteries can be charged in the off-peak period to avoid the peak period, so as to enjoy a discounted charging price. Furthermore, considering that the higher the power grid load is, the shorter the service life will be, our optimized charging scheme is helpful to reduce the peak load of the power grid and reduce the power grid loss, thus extending the power grid life. An interesting phenomenon is that about 10 % of the batteries are charged in the peak period, mainly because BSS must meet the demand of electrical changing in each period, but charging takes a certain time, so in some cases it must be charged in time regardless of the cost.

In order to save the charging cost in BSCS and improve the life of the power grid, when enterprises need to charge the depleted batteries, the optimization model should be adopted to centralized charge the rechargeable batteries in the period of low power consumption. Different enterprises have different requirements on service quality and response speed, so managers should choose a reasonable balance of charging time points according to their business status and demand network characteristics.

Third, the enterprises need to evaluate the tradeoffs between reducing charging costs and purchase cost of batteries at the initial time of BSS. From Table 9, if enterprises did not put enough full batteries in BSS at initial time, then in the later stage of BSCS operation, some batteries will be charged in the peak period in order to give priority to customer needs, which will increase the cost of battery charging. However, if enterprises placed more full batteries in the initial BSS, although in the later operation process there will be less batteries need to be charged and the charging cost will also be reduced, they need to pay more for the initial battery purchase cost. Considering that different enterprises have different service scope and volume, the configuration of parameter especially the purchase cost of EV batteries at initial time and battery charging costs should be well-balanced according to their business condition and demand network characteristics.

This paper makes full use of the dynamics of electricity prices to reduce the operating costs of enterprises and improve the security of the power grid. Nowadays, multiple major countries, like China, America, Germany and Japan, see expanding applications of battery swapping. For the swapping business operators in the above countries, this study provides a sharp tool and managerial insights in terms of battery recharging and battery transport scheduling. This work contributes to the realization of the standardization of the electric vehicle battery industry and the optimal allocation of resources, and can also improve the satisfaction rate of demand, reduce charging costs, and accelerate the popularization and promotion of battery swapping mode.

6. Conclusion and the future work

In this study, the electrical changing behavior of EVs is decoupled into two processes of battery charging and battery exchange, and the problem is modeled as a mathematical model of transportation and charging cost minimization in the BSCS closed-loop supply chain to achieve reasonable battery scheduling. The validity of the model is proved by solving an example with LINGO. Finally, the results of the example are explained and analyzed, and the managerial implications of the centralized charging strategy and the optimal scheduling method of EV under the mode of electrical changing is emphasized.

The future work should further consider the benefit distribution among the three entities in BSCS under the cost optimization scheme. Transportation times between BSSs and BCS should also be further studied in the future. In addition, this study does not discuss the initial SOC of the battery in the battery swapping mode. In fact, the battery capacity for the battery exchange has a certain randomness. Future research can divide the battery initial SOC into segments to further refine the battery charging time.

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Appendix

Table 7 Abbreviations of variables

Abbreviations	Meaning
EV	Electric vehicle
BCS	Battery charging station
BSS	Battery swapping station
BSCS	Battery swapping and charging system
SOC	SOC is the state of charge, which is used to reflect the remaining capacity of the battery
DB	The depleted battery
FB	The fully charged battery