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Research paper

Dispatchable capacity optimization strategy for battery swapping and charging station aggregators to participate in grid operations

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ABSTRACT

Taking the aggregator as a unit, battery swapping and charging stations (BSCSs) for electric vehicles (EVs) can be aggregated and dispatched by grid operators, to realize the demand-side resource regulation. Considering the characteristics of an aggregator's multilateral services, in this study, BSCSs need to ensure the quality of swapping service for EV users and participate in the demand-side regulation response. Firstly, we analyze the operation mechanism of a BSCS in the aggregation mode and propose a state transition model for EV batteries. On this basis, the EV demand uncertainty is incorporated by a distributed robust optimization (DRO) approach for multi-timescale inventories, and an optimization model to maximize the BSCSs' income is established, which obtains the optimal load planning and dispatchable capacity scheduling for a BSCS aggregator. Extensive simulations and numerical results show that the BSCS aggregator with demand-side regulation capacity can increase its income by 59.05% and 36.78% on working and non-working days, respectively. Also, the aggregator does not worsen the original power load while meeting the EV swapping demand and can decrease the daily load fluctuations by 0.65% and 12.89%, reduce the peak–valley difference by 5.81% and 7.80%, and increase the load rate by 3.67% and 4.08% in working and non-working day situations through providing the dynamic dispatchable capacity for the grid.

1. Introduction

With the popularity of EVs, the number of BSCSs has been increasing gradually, to realize effective EV charging through swapping batteries (Ding et al., 2022; Sui et al., 2022). In addition to meeting the EV swapping demand, a BSCS can also be used as an energy storage resource to make its redundant charging and discharging power capacities available for grid regulations. However, the power capacity of a single BSCS is relatively small compared to a large-scale power grid, and EV charging demand is stochastic (Zhang et al., 2021). It is not possible for a BSCS to directly participate in the operation and dispatch of the power system.

Multiple BSCSs with similar operational characteristics can be lumped together through an aggregator to participate in power grid regulations (Bruninx et al., 2020). An aggregator integrates the dispatchable charging and discharging power capacities of BSCSs using an optimization algorithm and reports them to grid operators. Then the aggregated BSCSs can participate in grid operation services through bidding and negotiation in the electricity market. During power system operations, grid operators can issue power dispatch instructions based on the regulation capacity BSCS aggregator can provide, and then the aggregator executes the instructions to support the active power balance of the power system (Chen et al., 2023; Diaz-Londono et al., 2022).

In the aggregation mode, a BSCS aggregator needs to consider interfacing with EV users to meet their swapping demands and also the power grid to serve BSCSs' surplus capacity for system operations. Thus, this involves the interaction and coordination of multiple units. To enable BSCSs' participation in power grid dispatch, a BSCS aggregator needs to provide two pieces of information for grid operators in the day-ahead stage: BSCSs' own load plan and the dispatchable capacity schedule that can be dispatched by grid operators. BSCSs need to provide battery swapping services for EVs as their primal task (Tao et al., 2022), but the practical EV demands in every time step are different and uncertain. This makes the dispatchable capacity of BSCSs different in every time step, which is difficult to accurately determine. This poses great challenges for BSCS aggregators to make optimal operational decisions.

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The essence of BSCSs' strategy is a reasonable balance between their charging plan and dispatchable capacity. Regarding the charging plan of EV batteries (EVBs), most studies propose the EVBs' orderly charging strategy through establishing some mathematical models from the perspective of economic indicators (Mahoor et al., 2019; Zhang et al., 2023; Ren et al., 2021) or power distribution network operation characteristics (Ding et al., 2022; Tian et al., 2022; Chowdhury et al., 2023). For example, authors in Mahoor et al. (2019) built the BSCS optimal dispatch issue considering EV demand uncertainties as a main sub-problem. They realized the iteration between the state of batteries and the minimal operation cost by Benders decomposition technique, to develop the BSCS optimal operation strategy. Based on this, the research in Zhang et al. (2023) and Ren et al. (2021) considers serving the power grid. Researchers in Zhang et al. (2023) proposed a charging cost model considering EVs to absorb surplus energy under the vehicle-to-grid mode, optimizing EVs' orderly charging and discharging schedule according to their flexibility requirements. Authors in Ren et al. (2021) further investigated EVs' aggregation and established an integer programming model to maximize the economic benefits of aggregators. This problem is developed under the minimum satisfaction of EV users and the minimum load transfer capacity of the power distribution network, thereby formulating the real-time optimal dispatch strategy for aggregators. Considering the power grid operation indicators, authors in Tian et al. (2022) used Monte-Carlo method to predict EV charging behavior and proposed an optimal charging plan for EVs to minimize the total regional load variance. Authors in Chowdhury et al. (2023) considered the unified configuration of EV charging stations and distributed generation units in the distribution network, to minimize the line loss of the grid, and achieve EV charging state calculation. In Ding et al. (2022), the economy and load characteristics indicators are considered in the optimization objective, and a multi-objective optimization model is established to simultaneously maximize the BSCS income and minimize the root mean square and the peak–valley difference of the load. Poisson distribution is used to describe the arrival characteristics of EVs and formulate the optimal charging strategy of a BSCS.

To determine the dispatchable capacity of energy storage aggregators, current studies mainly focus on the aggregation of load-side distributed battery energy storage stations (BESSs) to respond demand-side incentive mechanism and participate in regulation services of power systems. For example, authors in Oshnoei et al. (2020) used a model predictive control method to process the power system frequency signals and developed a robust control scheme for distributed BESSs aggregation for load frequency regulation. Authors in Zhou et al. (2021) proposed an optimal operation strategy for BESS clusters in commercial buildings to minimize the peak demand for regional substations. Researchers in Wang et al. (2019) focused on the control algorithm of distributed small-scale ESS aggregators and analyzed the charging state balance mechanism of each ESS serving the secondary frequency regulation of the power grid. Authors in Khojasteh et al. (2022) aggregated BESSs with wind farms and proposed the day-ahead and real-time optimal dispatch strategies for their joint participation in the energy and reserve markets. Authors in Lu et al. (2020) discussed the business mode and the important role of aggregators in demand response, and Biggins et al. (2022) explored the potential value of energy storage aggregators participating in energy arbitrage and power balance markets in power systems. The purpose of building energy storage aggregators is to participate in grid operation control, so the rated power capacity of several ESSs managed by the aggregator can be directly superimposed as the dispatchable capacity. In contrast, a BSCS aggregator needs to first ensure the swapping demands of EV users and then reports its regulation capacity.

In summary, there are only a few studies on BSCS optimal operation strategies in the aggregation mode, and research on operational mechanism of a BSCS aggregator is also limited. There is a lack of research on the development of the coordinated scheme between the optimal charging strategy and the dynamic dispatchable capacity of BSCSs. This study aims to address the issue that a BSCS aggregator needs to determine the dispatchable capacity of BSCSs in each time step while meeting the EV stochastic swapping demands. To do so, we propose a dynamic dispatchable capacity determination scheme considering EV swapping uncertainties in a BSCS aggregator. The main contribution of this study is two-fold:

- An operation mechanism of a BSCS and a state transition mathematical model of EVBs are proposed within a BSCS in the aggregator mode, to characterize the interaction and coordination of BSCSs, power grids, and EV users.
- With grid incentives and swapping incomes, an optimal dispatchable capacity model is established to maximize the income of an BSCS aggregator, to achieve the optimal load plan and the dynamic dispatchable capacity for BSCSs.

The rest of the paper is organized as follows. Section 2 describes the operational characteristics of a BSCS. Section 3 establishes the optimization model for determining the dispatchable capacity of a BSCS aggregator. Section 4 presents case studies and numerical results. Section 5 concludes this study.

2. Operation model of a BSCS

The dispatchable capacity is a BSCS aggregator's maximum charging and discharging power that can be dispatched by power system operators to participate in active power operations at each time step. The dispatchable capacity after aggregating BSCSs depends on their operation strategies. In this section, the working principle of a BSCS in the aggregation mode will be presented with the characteristics of state transition analyzed. This provides the foundation for an aggregator to make decisions.

2.1. Operation mechanism of a BSCS

A number of M BSCSs are aggregated and managed by an aggregator. In this paper, the BSCSs are aggregated with the same EV swapping demand characteristics. The schematic of the system operation mode is shown in Fig. 1. This paper adopts the BSCS operation structure proposed in Zhang et al. (2021), a BSCS contains two main parts: the retired battery energy storage system (RBESS) and the EVBs. Both of them can interact with power grids. In addition, the RBESS can charge EVBs inside the BSCS through discharging, to form a self-sufficient resource mode. When controlling the energy storage system from the perspective of the dispatch center, the equivalent state-of-charge (SoC) of the storage system is considered to be regulated. The imbalance of SoC among the individual components of the energy storage system does not affect the charging and discharging performance of the system. In this study, the effects of temperature constraints and converter limitations on the charging and discharging performances of BSCSs are ignored.

The dispatchable charging capacity of a BSCS is the superposition of the capacity of EVBs in the BSCS that can be charged under the grid arrangement and the charging scheduling of the RBESS. The dispatchable discharging capacity is the superposition of the full-electricity EVBs in a BSCS that can participate in grid regulations and the discharging scheduling of the RBESS. In the aggregation mode, the discharging of EVBs and charging of the RBESS are determined by the grid operator. The charging of EVBs

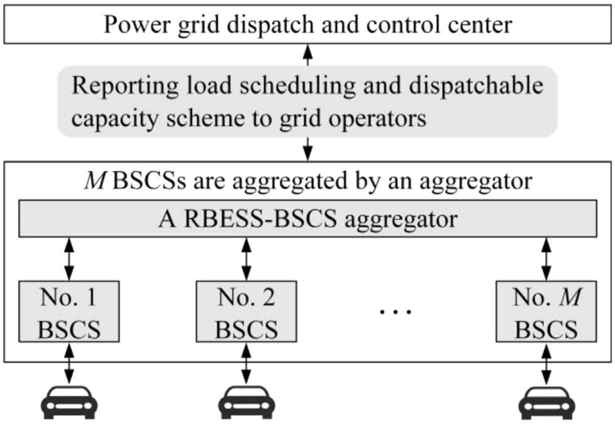


Fig. 1. Schematic diagram of the system operation mode.

is to meet the swapping demand and the grid dispatch requirements, as in (1a), where the charging energy used to meet the swapping demand can be obtained from grids and the RBESS, as in (1c). In addition to charging the EVBs, the RBESS can export electricity to the power grid under the dispatch arrangement, as in (1g). Define $P^{\mathrm{ch}}_{\mathrm{EVB},t}$ and $P^{\mathrm{dis}}_{\mathrm{EVB},t}$ as the charging and discharging power of EVBs dispatched by the grid operator at time step t, $P^{\mathrm{ch}}_{\mathrm{R},t}$ as the charging power of RBESS dispatched by the grid operator at step t, $P^{\mathrm{ch}}_{\mathrm{need},t}$ as the charging power of EVBs at step t to meet EV demands, $P_{\mathrm{G2P},t}$ as the charging power of EVBs from power grids at step t to meet EV demands, $P_{\mathrm{R2P},t}$ as the discharging power of RBESS to charge EVBs in a BSCS at step t, and $P_{\mathrm{R2G},t}$ as the discharging power of RBESS to feed to the power grid at step t. Equations (1a)–(1g) depict the operation model of a RBESS-BSCS.

$$P_{\mathrm{CB}}N_{\mathrm{Cing},t} = P^{\mathrm{ch}}_{\mathrm{need},t} + P^{\mathrm{ch}}_{\mathrm{EVB},t} \tag{1a}$$

$$P^{\mathrm{ch}}_{\mathrm{need},t} = P_{\mathrm{CB}}N^{\mathrm{need}}_{\mathrm{Cing},t} \tag{1b}$$

$$P^{\mathrm{ch}}_{\mathrm{need},t} = P_{\mathrm{G2P},t} + P_{\mathrm{R2P},t} \tag{1c}$$

$$P^{\mathrm{ch}}_{\mathrm{EVB},t} = P_{\mathrm{CB}}N^{\mathrm{dac}}_{\mathrm{Cing},t} \tag{1d}$$

$$P^{\mathrm{dis}}_{\mathrm{EVB},t} = P_{\mathrm{CB}}N_{\mathrm{Ding},t} \tag{1e}$$

$$N_{\mathrm{Cing},t} + N_{\mathrm{Ding},t} \le N_{\mathrm{CB}} \tag{1f}$$

$$P^{\mathrm{dis}}_{\mathrm{R},t} = P_{\mathrm{R2P},t} + P_{\mathrm{R2G},t} \tag{1g}$$

where P_{CB} is the charging and discharging power for a standard pile in a BSCS. Terms $N_{\mathrm{Cing},t}$ and $N_{\mathrm{Ding},t}$ represent the numbers of EVBs being charged and discharged in a BSCS at time step t, and $N^{\mathrm{need}}_{\mathrm{Cing},t}$ and $N^{\mathrm{dac}}_{\mathrm{Cing},t}$ represent the charging numbers of EVBs at step t to meet EV demands and be dispatched by the grid operator. Term N_{CB} in (1f) is the number of piles in a BSCS.

According to the above analysis, the dispatchable charging and discharging capacities $P^{\mathrm{ch,DS}}_{\mathrm{BSCS},t}$ and $P^{\mathrm{dis,DS}}_{\mathrm{BSCS},t}$ of a BSCS can be written as

$$P^{\mathrm{ch,DS}}_{\mathrm{BSCS},t} = P^{\mathrm{ch}}_{\mathrm{EVB},t} + P^{\mathrm{ch}}_{\mathrm{R},t} \tag{2a}$$

$$P^{\mathrm{dis,DS}}_{\mathrm{BSCS},t} = P^{\mathrm{dis}}_{\mathrm{EVB},t} + P_{\mathrm{R2G},t} \tag{2b}$$

2.2. EVB state transition characteristics

There are four states of EVBs in a BSCS: charging state (i.e., C state), discharging state (i.e., D state), waiting state (i.e., W state), and fully charged state (i.e., F state). In addition, EVBs that are about to be swapped from EVs are in "need" state. The state transition diagram of EVBs in the aggregation mode is shown in Fig. 2, where the solid blue lines represent the transition controlled by a BSCS itself, and the dotted red lines show the transition dispatched by grid operators.

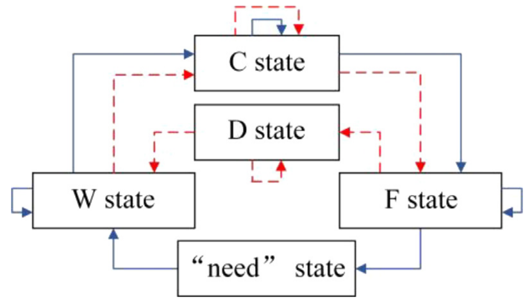


Fig. 2. Schematic diagram of the EVBs state-transition. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this paper.).

Define $N_{\mathrm{C},t}$, $N_{\mathrm{F},t}$, $N_{\mathrm{D},t}$, and $N_{\mathrm{W},t}$ as the numbers of EVBs in the C, F, D, and W states in a BSCS at step t, respectively. Terms $N^{\mathrm{need}}_{\mathrm{C},t}$ and $N^{\mathrm{dac}}_{\mathrm{C},t}$ indicate the numbers of EVBs at the charging state at step t to meet EV demands and are dispatched by the grid operator. $N^{\mathrm{b,need}}_{\mathrm{C},t}$ and $N^{\mathrm{f,need}}_{\mathrm{C},t}$ are the numbers of EVBs that begin and finish charging at step t to meet EV demands, $N^{\mathrm{b,dac}}_{\mathrm{C},t}$ and $N^{\mathrm{f,dac}}_{\mathrm{C},t}$ are the numbers of charging EVBs to be dispatched by grid at step t, and $N^{\mathrm{b}}_{\mathrm{D},t}$ and $N^{\mathrm{f}}_{\mathrm{D},t}$ are the numbers of EVBs that start and finish discharging at step t. Term T_{ful} is the time required for an EVB to complete charging or discharging, and E_{B} is the rated electricity capacity of an EVB. Define SoC_{end} and SoC_{ini} as the SoC of EVBs in the F and W states. We assume that EVBs exit operations only after fully charged or discharged. EVBs in various states are transferred to each other, and their transfer relationships are described as in (3a)–(3n).

$$N_{\mathrm{C},t} = N^{\mathrm{need}}_{\mathrm{C},t} + N^{\mathrm{dac}}_{\mathrm{C},t} \tag{3a}$$

$$N^{\mathrm{need}}_{\mathrm{C},t+1} = N^{\mathrm{need}}_{\mathrm{C},t} + N^{\mathrm{b,need}}_{\mathrm{C},t} - N^{\mathrm{f,need}}_{\mathrm{C},t} \tag{3b}$$

$$N^{\mathrm{dac}}_{\mathrm{C},t+1} = N^{\mathrm{dac}}_{\mathrm{C},t} + N^{\mathrm{b,dac}}_{\mathrm{C},t} - N^{\mathrm{f,dac}}_{\mathrm{C},t} \tag{3c}$$

$$N_{\mathrm{F},t+1} = N_{\mathrm{F},t} + N^{\mathrm{f,need}}_{\mathrm{C},t} + N^{\mathrm{f,dac}}_{\mathrm{C},t} - N^{\mathrm{b}}_{\mathrm{D},t} - N^{\mathrm{rea}}_{\mathrm{need},t} \tag{3d}$$

$$N_{\mathrm{D},t+1} = N_{\mathrm{D},t} + N^{\mathrm{b}}_{\mathrm{D},t} - N^{\mathrm{f}}_{\mathrm{D},t} \tag{3e}$$

$$N_{\mathrm{W},t+1} = N_{\mathrm{W},t} + N^{\mathrm{rea}}_{\mathrm{need},t} + N^{\mathrm{f}}_{\mathrm{D},t} - N^{\mathrm{b,need}}_{\mathrm{C},t} - N^{\mathrm{b,dac}}_{\mathrm{C},t} \tag{3f}$$

$$N^{\mathrm{b,need}}_{\mathrm{C},t} = N^{\mathrm{f,need}}_{\mathrm{C},t+T_{ful}-1} \tag{3g}$$

$$N^{\mathrm{b,dac}}_{\mathrm{C},t} = N^{\mathrm{f,dac}}_{\mathrm{C},t+T_{ful}-1} \tag{3h}$$

$$N^{\mathrm{b}}_{\mathrm{D},t} = N^{\mathrm{f}}_{\mathrm{D},t+T_{ful}-1} \tag{3i}$$

$$T_{ful} = \lceil E_{\mathrm{B}}(SoC_{end} - SoC_{ini})/P_{\mathrm{CB}} \rceil \tag{3j}$$

$$N_{\mathrm{Cing},t} = N^{\mathrm{need}}_{\mathrm{Cing},t} + N^{\mathrm{dac}}_{\mathrm{Cing},t} \tag{3k}$$

$$N^{\mathrm{need}}_{\mathrm{Cing},t} = N^{\mathrm{need}}_{\mathrm{C},t} + N^{\mathrm{b,need}}_{\mathrm{C},t} \tag{3l}$$

$$N^{\mathrm{dac}}_{\mathrm{Cing},t} = N^{\mathrm{dac}}_{\mathrm{C},t} + N^{\mathrm{b,dac}}_{\mathrm{C},t} \tag{3m}$$

$$N_{\mathrm{Ding},t} = N_{\mathrm{D},t} + N^{\mathrm{b}}_{\mathrm{D},t} \tag{3n}$$

Term $N^{\mathrm{rea}}_{\mathrm{need},t}$ is the actual number of EV swapping demands met by a BSCS in step t, and its value is decided by the number of EVBs that can provide the swapping service and the number of EV demands $N_{\mathrm{need},t}$ in step t. Its expression is as follows,

$$N^{\mathrm{rea}}_{\mathrm{need},t} = \min\left\{N_{\mathrm{F},t} + N^{\mathrm{f,need}}_{\mathrm{C},t} + N^{\mathrm{f,dac}}_{\mathrm{C},t} - N^{\mathrm{b}}_{\mathrm{D},t},\ N_{\mathrm{need},t}\right\} \tag{4}$$

3. Dispatchable capacity optimization model for a BSCS aggregator

3.1. Idea of dispatchable capacity determination

From Fig. 1, a BSCS aggregator aggregates the number of M of individual BSCSs to participate in grid operations, and the integrated dispatchable capacity after aggregation is the sum of the dispatchable capacity of total BSCSs. The dispatchable capacity of each BSCS is the remaining capacity of the station under the condition that it can meet the EV swapping demands, which depends on the charging scheduling of EVBs and the swapping scheduling of full-electricity EVBs in a BSCS to achieve swapping services.

The operation strategies of BSCSs include the charging scheduling of EVBs to meet EV demands, the charging and discharging EVBs that can be dispatched by grid operators, the power scheduling of the RBESS charging for EVBs, and the charging and discharging abilities of the RBESS that can be dispatched in each period of daily operation. Therefore, based on the statistical characteristics of EV swapping demands and considering their uncertainties, through the coordination with EV users and participating in the grid electricity's pricing mechanism and incentive response, a BSCS aggregator can formulate optimization operation strategies and then obtain the optimal dispatchable capacity.

In summary, if the operation strategy of a BSCS aggregator is well formulated, there should be sufficient dispatchable capacity, so that BSCSs have greater capacities to participate in grid operations to obtain more benefits, and the regulation ability of the demand-side resources is reinforced, to avoid waste.

The operation states of EVBs within a BSCS are transferred to each other in each time step, and the SoC of the RBESS has sequential characteristics, which make the operation strategies of BSCSs couple in different periods, instead of being independent of each other. In addition, there is a mutual capacity constraint for satisfying EV charging demands and providing regulation for the grid. Therefore, it is necessary to uniformly coordinate and balance various operation strategies and propose optimal sequential decisions to achieve global optimization for a BSCS aggregator.

3.2. Objective of the proposed model

Define E_{sw} as the swapping income of a BSCS in daily operations, E_{grid} as the income from providing dispatchable capacity by a BSCS, and E_{ele} as the cost of a BSCS to charge the EVBs. Since the charging behavior is not a part of participating in the grid regulation, E_{ele} is calculated through the time-of-use price mechanism. The optimization objective of a BSCS aggregator of proposing load and dispatchable capacity schedule is to maximize the income I_{A} of the BSCSs, i.e.,

$$\text{maximize } I_{\mathrm{A}} = M\left(E_{sw} + E_{grid} - E_{ele}\right) \tag{5}$$

where

$$E_{sw} = \sum_{t=1}^{\Gamma} e_{sw} N_{\mathrm{need},t}^{\mathrm{rea}} \tag{6a}$$

$$E_{grid} = \sum_{t=1}^{\Gamma} c_{\mathrm{A},op}\left(g_t P_{\mathrm{BSCS},t}^{\mathrm{ch,DS}} + f_t P_{\mathrm{BSCS},t}^{\mathrm{dis,DS}}\right)\Delta t \tag{6b}$$

$$E_{ele} = \sum_{t=1}^{\Gamma} e_{\omega,t} P_{\mathrm{G2P},t}\Delta t \tag{6c}$$

where Γ is the total number of operation periods in an operation day. Term e_{sw} is the income of a BSCS generated by meeting the EV battery swapping demand, and $c_{\mathrm{A},op}$ is the unit income of providing dispatchable capacity for a BSCS aggregator. Terms g_t and f_t are the binary (i.e., 0 or 1) variables representing the peak and valley states of grid load. Term g_t is set to 0 in the peak to ensure that a BSCS does not charge during peak hours or discharge during valley periods. Similarly, f_t is set to 0 in valley-load periods. Term Δt is a unit time step, which is 1 hour. Term $e_{\omega,t}$ is the grid electricity price at step t.

3.3. Constraints of the proposed optimization model

1) Operation constraints of a RBESS-BSCS: Further to the operation characteristics described in equation set (1), a BSCS must meet the following constraints:

$$QoS = \sum_{t=1}^{\Gamma} N_{\mathrm{need},t}^{\mathrm{rea}} \Big/ \sum_{t=1}^{\Gamma} N_{\mathrm{need},t} \geq QoS_{\min} \tag{7a}$$

$$\mathbf{1}\left\{N_{Cing,t} = 0\right\} \parallel \mathbf{1}\left\{N_{\mathrm{Ding},t} = 0\right\} = 1 \tag{7b}$$

$$\mathbf{1}\left\{P_{\mathrm{EVB},t}^{\mathrm{ch}} = 0\right\} \parallel \mathbf{1}\left\{P_{\mathrm{R2G},t} = 0\right\} = 1 \tag{7c}$$

$$\mathbf{1}\left\{P_{\mathrm{EVB},t}^{\mathrm{dis}} = 0\right\} \parallel \mathbf{1}\left\{P_{\mathrm{R},t}^{\mathrm{ch}} = 0\right\} = 1 \tag{7d}$$

Constraint (7a) is enforced to ensure the quality of service (QoS) of a BSCS to EV users, where $QoS_{\min}$ is the minimum QoS of a BSCS needed to satisfy in the daily operation. Constraints (7b)–(7d) represent mutual exclusion during the BSCS operation. The three logic relations indicate that the charging and discharging of EVBs must not happen at a given time step, the charging of EVBs and discharging of the RBESS are not dispatched by grid operators at the same time, and the discharging of EVBs and charging of the RBESS are not arranged simultaneously. $\mathbf{1}\{\cdot\}$ is an indicating function, which value is 1 if the event occurs, and 0 otherwise.

2) Constraints of the RBESS: The operations of the RBESS need to consider the following constraints. In (8a), $P_{\mathrm{R},t}$ is the power of the RBESS, and we set the discharging power as positive in this paper. Term $P_{\mathrm{R},t}^{\mathrm{dis}}$ represents the discharging power of the RBESS in a BSCS at step t, and it is used to describe the charging EVBs and participation in demand-side ancillary services, as in (8b). Constraints (8c) and (8d) are the charging and discharging power limitations of the RBESS, where $P_{\mathrm{R}}^{\max}$ is the rated power of the RBESS in a BSCS. Term r_t is a Binary variable: "1" if RBESS is discharging in step t, and "0" otherwise. Constraint (8e) is the relation between power and energy, where $\Delta E_{\mathrm{R},t}$ is the energy consumption of the RBESS in a BSCS at step t, and η_C and η_D are the charging and discharging efficiency of the RBESS. The energy time-coupling constraint of the RBESS is enforced in (8f), where $E_{\mathrm{R},t}$ is the energy of the RBESS in a BSCS at step t. To ensure safe operations, over-charging and over-discharging of the RBESS must be prevented (Zhang et al., 2020), and thus $SoC_{\max}$ and $SoC_{\min}$ in (8g) are introduced to set the maximum and minimum values of the SoC. Term E_{rate} is the rated capacity of the RBESS in a BSCS, and $SoC_{\mathrm{R}}^{\mathrm{ini}}$ is the initial SoC of the RBESS in a day. The constraint in a daily operation cycle is expressed as (8h).

$$P_{\mathrm{R},t} = P_{\mathrm{R},t}^{\mathrm{dis}} - P_{\mathrm{R},t}^{\mathrm{ch}} \tag{8a}$$

$$P_{\mathrm{R},t}^{\mathrm{dis}} = P_{\mathrm{R2P},t} + P_{\mathrm{R2G},t} \tag{8b}$$

$$0 \leq P_{\mathrm{R},t}^{\mathrm{dis}} \leq P_{\mathrm{R}}^{\max} r_t \tag{8c}$$

$$0 \leq P_{\mathrm{R},t}^{\mathrm{ch}} \leq P_{\mathrm{R}}^{\max}\left(1 - r_t\right) \tag{8d}$$

$$\Delta E_{\mathrm{R},t} = P_{\mathrm{R},t}^{\mathrm{dis}}/\eta_D \Delta t - P_{\mathrm{R},t}^{\mathrm{ch}} \eta_C \Delta t \tag{8e}$$

$$E_{\mathrm{R},t+1} = E_{\mathrm{R},t} - \Delta E_{\mathrm{R},t} \tag{8f}$$

$$E_{rate} SoC_{\min} \leq E_{\mathrm{R},t} \leq E_{rate} SoC_{\max} \tag{8g}$$

$$E_{\mathrm{R},1} = E_{\mathrm{R},25} = E_{rate} SoC_{\mathrm{R}}^{\mathrm{ini}} \tag{8h}$$

3) Constraints of EVBs: In addition to the state relationships (as in (3a)–(3n)), the quantity conservation and operation cycle constraints are considered during the EVB operations, i.e.,

$$N_S = N_{F,t} + N_{C,t} + N_{D,t} + N_{W,t} \tag{9a}$$

$$\sum_{t=1}^{\Gamma} P_{EVB,t}^{ch} \Delta t = \sum_{t=1}^{\Gamma} P_{EVB,t}^{dis} \Delta t \tag{9b}$$

where N_S is the total number of EVBs in a BSCS.

3.4. Uncertainty treatment and optimization model transformation

In practice, EV swapping demand at a time step is unknown or uncertain. Generally, to deal with uncertain factors in optimization problems, a few methods can be adopted, such as stochastic programming (SP) (Lin et al., 2023; Noorollahi et al., 2022), chance constrained programming (Hong et al., 2022; Fallahi et al., 2022), robust optimization (RO) (Lu et al., 2023; Qiu et al., 2022), deep learning (Wang et al., 2022).

Although the actual operation statistics of uncertainty are not fully available, some probability information or approximate distribution can be obtained. Therefore, the DRO method that combines the advantages of RO and SP can be employed to meticulously describe various discrete scenarios in the EV swapping demand space at each time step (Bertsimas and Thiele, 2006; Wei et al., 2011; Song and Jing, 2023).

Denote the EV swapping demand space in step t as $Z_t = \{N_{need,t}^1, N_{need,t}^2, \dots, N_{need,t}^{N_t}\}$, wherein the number of scenarios is N_t. The amount of actual EV demand in step t satisfies $N_{need,t}^{n_t} \in Z_t$, where $n_t \in \{1, \dots, N_t\}$. Therefore, Eq. (4) can be further described as,

$$N_{need,t}^{rea,n_t} = \min\left\{N_{F,t} + N_{C,t}^{f,need} + N_{C,t}^{f,dac} - N_{D,t}^{b},\ N_{need,t}^{n_t}\right\} \tag{10}$$

The DRO method simultaneously considers the distribution characteristic and robustness characteristic of uncertainty. The distribution characteristic refers to the occurrence probability of each EV demand scenario, which is considered based on the interval value of uncertain parameters. The probability of each scenario can be described as the sum of its expected probability and the probability deviation. We set $\boldsymbol{P}_t$ as the column vector composed of the occurrence probabilities of scenarios in Z_t. Define $\widetilde{\boldsymbol{P}}_t$ as the column vector of the occurrence probability of each scenario under the probability distribution to which uncertainties are most likely to obey. Let $\boldsymbol{\Theta}_t$ denote the probability deviation vector, which belongs to the convex set $\left[\underline{\boldsymbol{\Theta}}_t,\ \overline{\boldsymbol{\Theta}}_t\right]$. Therefore, we have

$$\boldsymbol{P}_t = \widetilde{\boldsymbol{P}}_t + \boldsymbol{\Theta}_t \tag{11}$$

Therefore, the distribution characteristics of uncertainties are mainly reflected in the deviation between the actual and expected probabilities of scenarios.

From the above analyses, we can know that the swapping income $E_{sw,t}$ of a BSCS in step t is satisfied as,

$$E_{sw,t} = \boldsymbol{E}_{sw,t}^{T} \boldsymbol{P}_t = \boldsymbol{E}_{sw,t}^{T}\left(\widetilde{\boldsymbol{P}}_t + \boldsymbol{\Theta}_t\right) \tag{12}$$

where $\boldsymbol{E}_{sw,t}$ is a column vector consisting of N_t elements, $\boldsymbol{E}_{sw,t} = (E_{sw,t}^1, E_{sw,t}^2, \dots, E_{sw,t}^{N_t})^T$, where term $E_{sw,t}^{n_t}$ is the swapping income when the EV demand in step t is $N_{need,t}^{n_t}$.

The robustness characteristic refers to the ability that the operators obtain the optimal operation strategies under the worst-case scenario. This can ensure the robust performance of decisions. In this paper, the worst-case scenario refers to the probability deviations of demand scenarios that make a BSCS aggregator have the minimum swapping income in a day. The optimal operation strategy is the aggregator's decision when the total income of BSCSs is maximized of the aggregator. Therefore, the objective function of the DRO model is a double-layer nested problem in the form of "max-inf", and the inner-layer problem shown in (6a) can be further described as,

$$\begin{aligned} \inf E_{sw} &= \sum_{t=1}^{\Gamma} \boldsymbol{E}_{sw,t}^{T} \widetilde{\boldsymbol{P}}_t + \inf \sum_{t=1}^{\Gamma} \boldsymbol{E}_{sw,t}^{T} \boldsymbol{\Theta}_t \\ \text{s.t.} &\begin{cases} \boldsymbol{\varepsilon}_t^{T} \boldsymbol{\Theta}_t = 0 \\ \boldsymbol{\Theta}_t \in \left[\underline{\boldsymbol{\Theta}}_t,\ \overline{\boldsymbol{\Theta}}_t\right] \\ \overline{\boldsymbol{\Theta}}_t \geq \boldsymbol{0},\ \underline{\boldsymbol{\Theta}}_t \leq \boldsymbol{0} \end{cases} \end{aligned} \tag{13}$$

To achieve the optimal solution, the "inf" problem of the second term on the right side of (13) can be equivalently transformed into a "sup" problem through the duality theory (Bertsekas et al., 2003), and then, we have

$$\begin{aligned} \sup\ & \overline{\boldsymbol{\Theta}}_t^{T} \boldsymbol{\lambda}_t^{(2)} + \underline{\boldsymbol{\Theta}}_t^{T} \boldsymbol{\lambda}_t^{(3)} \\ \text{s.t.}\ & \begin{cases} \boldsymbol{\varepsilon}_t \lambda_t^{(1)} + \boldsymbol{\lambda}_t^{(2)} + \boldsymbol{\lambda}_t^{(3)} = \boldsymbol{E}_{sw,t} \\ \boldsymbol{\lambda}_t^{(2)} \leq \boldsymbol{0},\ \boldsymbol{\lambda}_t^{(3)} \geq \boldsymbol{0} \end{cases} \end{aligned} \tag{14}$$

where term $\boldsymbol{\varepsilon}_t$ represents a column vector of length N_t with all elements of 1, i.e., $\boldsymbol{\varepsilon}_t = (1,\ 1,\ \dots,\ 1)^T$. Terms $\lambda_t^{(1)}$, $\boldsymbol{\lambda}_t^{(2)}$, and $\boldsymbol{\lambda}_t^{(3)}$ are the free variable and variable vectors introduced when solving the dual problem, respectively.

After the transformation, the objective function of the proposed optimization problem is as follows,

$$\text{maximize}\ I_A = M\left(E_{grid} - E_{ele} + \left(\sum_{t=1}^{\Gamma}\left(\boldsymbol{E}_{sw,t}^{T}\widetilde{\boldsymbol{P}}_t + \overline{\boldsymbol{\Theta}}_t^{T}\boldsymbol{\lambda}_t^{(2)} + \underline{\boldsymbol{\Theta}}_t^{T}\boldsymbol{\lambda}_t^{(3)}\right)\right)\right) \tag{15}$$

By solving the above model, the optimal charging and dispatchable capacity scheduling after BSCSs aggregation in each time step of the daily operation can be obtained.

3.5. Solution method of optimization model

The flowchart of the proposed optimization model is shown in Fig. 3.

The model established in this paper belongs to the mixed integer linear programming problem, and its solution can be obtained from CPLEX.

4. Case studies

A BSCS aggregator needs to make sequential decisions on the numbers of charging and discharging of EVBs and the operation power of the RBESS that can be dispatched by grid operators in each time step, as well as the discharging power of the RBESS for the self-sufficiency resource in BSCSs. Since EV demands have different statistical characteristics in working day and non-working day typical situations, and the BSCS operation strategies are different in different situations, which makes the dispatchable capacity different. In this section, the optimization results are analyzed to verify the effectiveness of the proposed scheme through numerical simulations.

4.1. Simulation data

A BSCS aggregator is set to aggregate ten BSCSs, and a BSCS can provide service for 200 EVs. The EV demand parameters are shown in Fig. 4 (Zhang et al., 2021). The scenarios of the EV demand space in each time step are assumed to obey Gaussian distribution (Said et al., 2017). We set $\overline{\boldsymbol{\Theta}}_t = -\underline{\boldsymbol{\Theta}}_t$, and the maximum probability deviation is ±5%. Time-of-use electricity prices are shown in Table 1, which are obtained according to

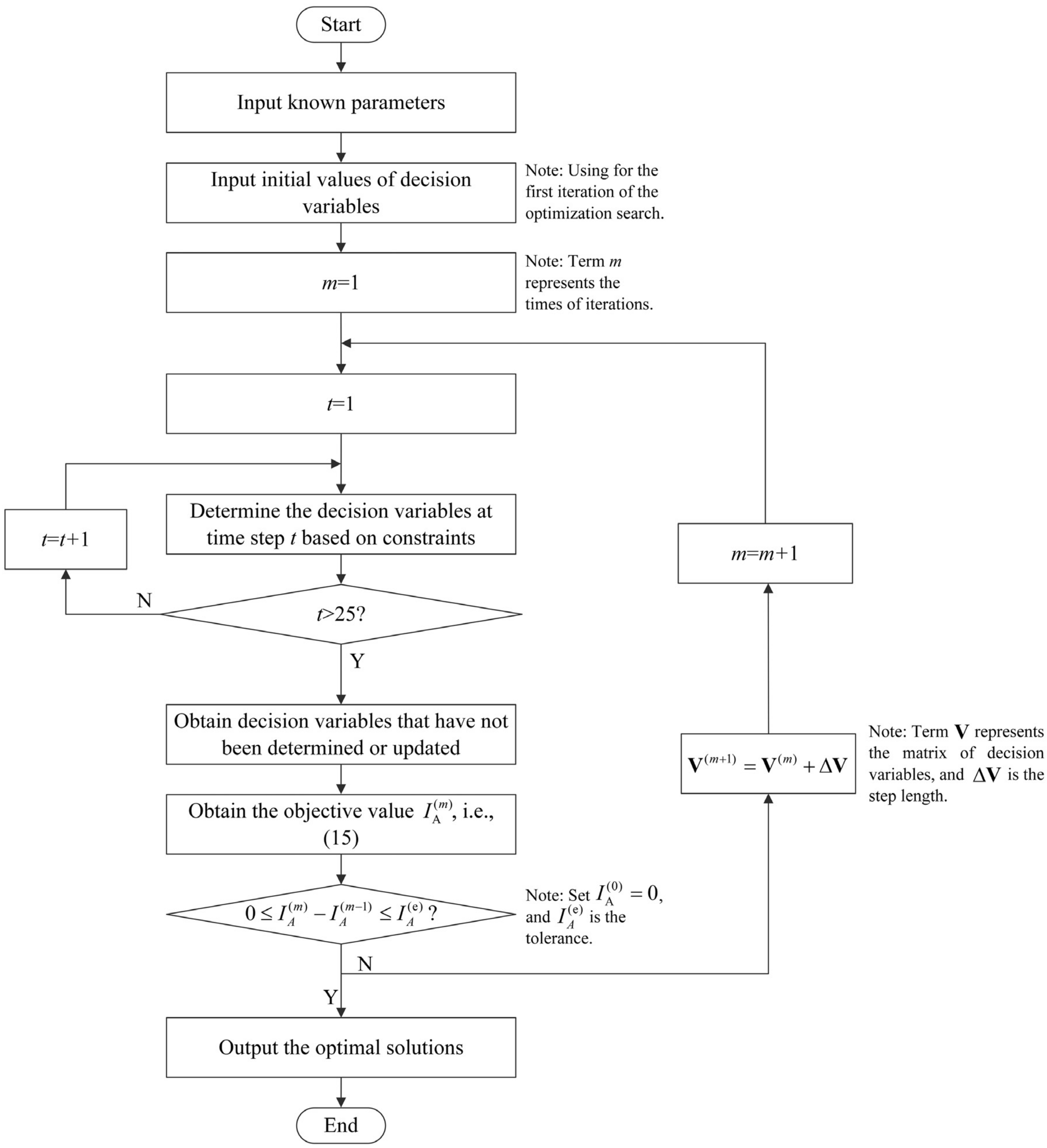


Fig. 3. Calculation flowchart of the proposed optimization problem.

Table 1
Time-of-use price (\$/kWh).

Situations/Periods	1–7	8–11	12–16	17–20	21–24
Working day	0.050	0.113	0.085	0.127	0.085
Non-working day	0.050	0.050	0.050	0.127	0.050

Table 2
Relevant parameters in optimization model.

Parameters	Values	Parameters	Values	Parameters	Values
P_{CB}	0.04 MW	N_{CB}	25	N_S	60
E_B	0.06 MWh	SoC_{end}	100%	SoC_{ini}	33.33%
$QoS_{\min}$	98%	$P_R^{\max}$	1 MW	η_C, η_D	95%
E_{rate}	4.9 MWh	$SoC_{\min}$	10%	$c_{A,op}$	30 \$/MWh
$SoC_{\max}$	90%	SoC_R^{ini}	50%	e_{sw}	\$14.16

time-of-use electricity price policy in China. Other parameters in the optimization model are shown in Table 2 (Zhang et al., 2021). The relative gap tolerance of the CPLEX solver is set at 0.01%. The simulations in this paper are conducted on the 4-core AMD Ryzen 3 3200G with Radeon Vega Graphics@3.60 GHz processor.

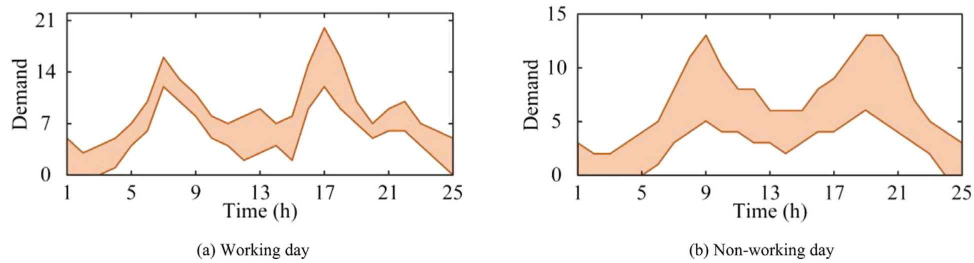


Fig. 4. EV swapping demands for a BSCS in working day and non-working day situations.

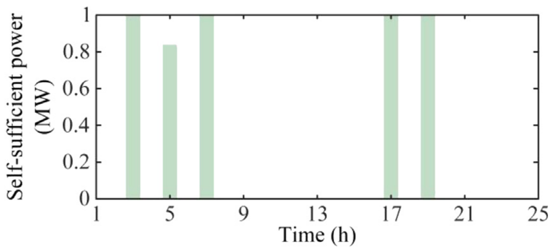


Fig. 5. Self-sufficient power in a RBESS-BSCS in a working day.

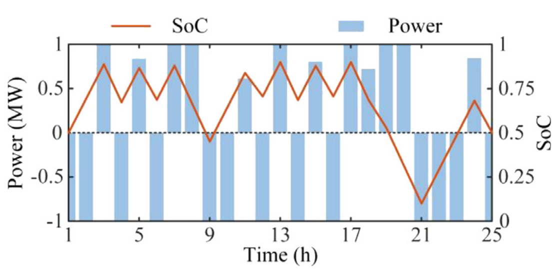


Fig. 6. Power and SoC of RBESS in the BSCS in a working day.

4.2. Operation strategies in a working day

The solution time of the proposed case is 17 seconds and 21 seconds for working and non-working days, respectively, which can meet the time requirement for a BSCS aggregator to bid for day-ahead regulation planning.

The total income of a BSCS aggregator in a working day is \$32.60K. The load scheduling of BSCSs in each period is 0. That is, EVBs' charging power used to meet the EV swapping demands is from the RBESS in BSCSs, which greatly saves the cost. The discharging curve of the RBESS to charge EVBs in a BSCS is shown in Fig. 5, and Fig. 6 depicts the power and SoC of the RBESS of the BSCS. The number of dispatchable EVBs is shown in Fig. 7.

From the above optimization results, we can see that the BSCSs can be compensated when they are dispatched for charging in valley-load periods, so RBESSs are charged to participate in the incentive mechanism in these periods, and the charged energy will be used to provide EVBs that need to meet the EV demands. These arrangements can respond to grid operations and improve the economic benefits of BSCSs. The discharged energy from RBESSs during valley periods is used for self-sufficiency resources in BSCSs. There are few EVBs dispatched to participate in the charging response in valley periods, and the charging of EVBs in these periods are mainly used to meet EV demands to ensure the QoS of BSCSs.

During the normal-load periods, a large number of idle EVBs in W and F states in BSCSs can be dispatched through the integrator management, and RBESSs also respond to the incentive mechanism through their charging and discharging. While meeting EV demands, the dispatchable capacities of EVBs are determined by the number of piles available in each BSCS, and also the number of EVBs that do not provide swapping services in the waiting EVB inventory and fully charged EVB inventory. The 17–20 periods are the peak of load and late-peak of EV demands. RBESSs discharge to grids and EVBs in these periods, and the SoC of RBESSs drops to the minimum safety threshold after the peak period. The EVBs in F state in these periods can also provide grids with dispatchable discharging capacities under the condition that they can meet the swapping demands.

The dispatchable capacities provided by a BSCS aggregator to the grid are shown in Fig. 8. The aggregator can help the power regulations for the grid with dispatchable charging/discharging power of no less than 10 MW. It is in line with the provisions in the "Operation rules of northeast electric power ancillary service market" (Anon, 2020), i.e., the minimum power capacity of the energy storage facility that can be directly dispatched by the provincial power dispatch center is 10 MW. Therefore, with the proposed optimization model, BSCSs can participate in demand-side ancillary services as a directly dispatchable unit after their aggregation, to support grid operations.

4.3. Operation strategies in non-working day situation

The total income of a BSCS aggregator in non-working day is \$20.85K. The load schedule of BSCSs at each time step is 0 in this situation, and the power and SoC of the RBESS are presented in Fig. 9.

Different from the working-day situation, most hours of the non-working day belong to the valley periods, and the main functions of the RBESS charging in these periods are as follows: 1) It can provide the dispatchable charging capacity. 2) The unit income of the RBESS participating in the grid response is less than the electricity price, so the RBESS is charged to save energy in these periods, to discharge for EVBs with swapping tasks. To enable the RBESS to feed all discharged energy into power grids in the peak-load period, the aggregator fully charges the EVBs used for EV demands before the peak-load period. The self-sufficiency resource in a BSCS is shown in Fig. 10. 3) Discharging capability is available during peak-load periods. As can be seen from Fig. 9, the SoC of a RBESS drops from the maximum to minimum safety thresholds after the peak period. The idle EVBs in W and F states that are not used to meet EV swapping demands can be charged in valley-load periods and be discharged in peak-load periods, respectively. The number of EVBs that can be dispatched by the grid operator in each period is shown in Fig. 11.

The dispatchable capacities reported by a BSCS aggregator to grid operators are shown in Fig. 12. The dispatchable capacity of BSCSs after aggregation in non-working day situation is less than that in working day situation, but it can still respond to the demand-side incentive mechanism and help to grid operations.

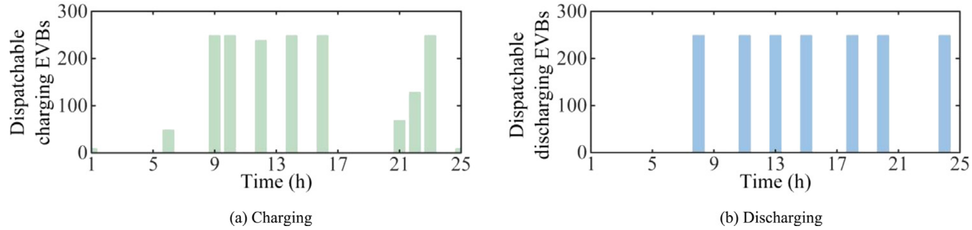


Fig. 7. Dispatchable numbers of EVBs for a BSCS aggregator in working day situation.

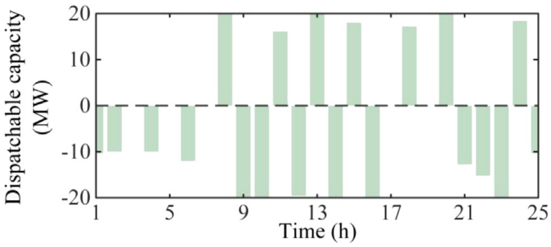


Fig. 8. Dispatchable capacity schedule of a BSCS aggregator in working day situation.

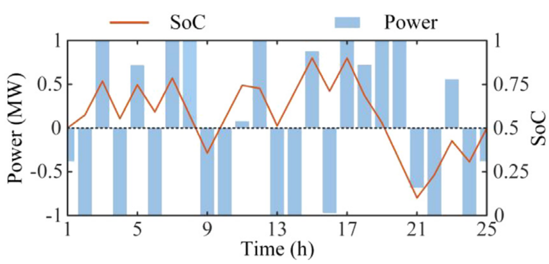


Fig. 9. Charging/discharging power and SoC of the RBESS in a BSCS in non-working day situation.

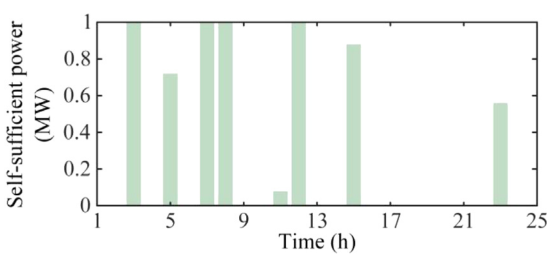


Fig. 10. Self-sufficient power in a RBESS-BSCS in non-working day.

4.4. Comparison of operation strategies

To further illustrate the superiority of the proposed scheme, our strategies are compared with the scheme that a BSCS aggregator does not provide the dispatchable capacity to grids (i.e., the non-dispatchable mode). BSCSs in the non-dispatchable mode only meet EV demands, and do not interact with grids. The RBESS is charged when the electricity price is low to have the ability to discharge to EVBs in peak periods and discharging of a RBESS is entirely used for self-sufficiency resources in a BSCS.

For the economy, the benefits of BSCS aggregation in the non-dispatchable mode are decreased by 37.13% and 26.89% compared to our proposed scheme on typical working and non-working days, respectively. The aggregation of BSCSs can significantly enhance their economic benefits by using the dispatchable capacity power grid operations.

For the power system operation, daily load fluctuations (i.e., Eq. (16a), where term $P_{\mathrm{D},t}$ is power load in step t, and $\overline{P}_{\mathrm{D}}$ is the average load value in a whole day), peak–valley load difference (i.e., Eq. (16b)), and load rate (i.e., the ratio of the average load to the maximum load in a day, as in (16c)) are selected as the load characteristic indexes. We can quantitatively analyze whether a BSCS aggregator can provide dispatchable capacity for grid operators on working and non-working days. The original grid loads in working day and non-working days can be found in Zhang et al. (2021), and the obtained relevant indexes are shown in Table 3.

$$\sum_{t=1}^{\Gamma} \left(P_{\mathrm{D},t} - \overline{P}_{\mathrm{D}}\right)^2 \tag{16a}$$

$$\max\left\{P_{\mathrm{D},t}\right\} - \min\left\{P_{\mathrm{D},t}\right\} \tag{16b}$$

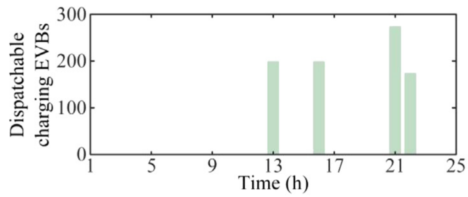
$$\overline{P}_{\mathrm{D}} / \max\left\{P_{\mathrm{D},t}\right\} \times 100\% \tag{16c}$$

From Table 3, in a working day the load fluctuations and peak–valley differences can be reduced by the dispatchable BSCSs. This is due to the significant load variations among peak, normal, and valley periods in this situation, which can stimulate the coordinated operation flexibility among BSCSs and multiple units. The load fluctuation value in our scheme is higher than that in the non-dispatchable mode, because BSCSs alternately provide the charging and discharging capacities to increase the dispatchable capacity in normal-load periods. However, the peak–valley difference and load rate performances are optimal in our scheme. Under the non-dispatchable mode in non-working day situation, since most hours in this situation are the valley-load periods, the charging energy of EVBs directly comes from grids, which increases load demands in the grid. But the load of BSCSs in our scheme is 0, and the load curve can be smoothed by providing regulation services, which reduces the load by 12.89% compared to the original load. The peak and valley loads are not changed in the non-dispatchable mode, and the load rate enhances due to the increased average load. The peak–valley load difference can be reduced, and the load rate is improved significantly with the proposed method.

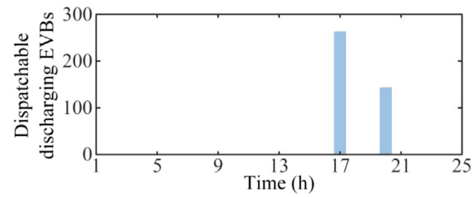
5. Conclusions

To achieve the optimal coordination operations among BSCSs, EV users, and power grids, in this paper, we propose a BSCSs load scheduling scheme and dispatchable capacity from the perspective of a BSCS aggregator with the objective of maximizing the income of BSCSs. Theoretical analyses and numerical results have led to the following conclusions,

- The proposed operation strategy can be used to arrange the aggregated BSCSs as demand-side resources and report their surplus charging and discharging capacities to power grid operators, on the premise of ensuring the QoS of BSCSs for EV users. The income of a BSCS aggregator generated from providing the dispatchable capacity accounts for 29.44% of



(a) Charging



(b) Discharging

Fig. 11. Dispatchable numbers of EVBs for a BSCS aggregator in non-working day situation.

Table 3
Load characteristic indexes.

Situations/Indexes		Daily load fluctuations	Peak–valley load differences	Load rates
Working day	Original load	770.61 MW^2	19.80 MW	73.54%
	Non-dispatchable mode	741.41 MW^2	18.90 MW	74.11%
	Our scheme	765.57 MW^2	18.65 MW	76.24%
Non-working day	Original load	550.10 MW^2	17.70 MW	73.81%
	Non-dispatchable mode	562.87 MW^2	17.70 MW	74.13%
	Our scheme	479.19 MW^2	16.32 MW	76.82%

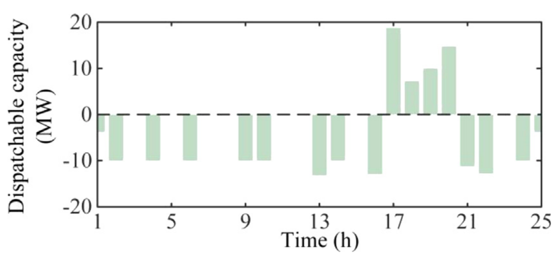


Fig. 12. Dispatchable capacity schedule of a BSCS aggregator in non-working day situation.

its income in typical working day situations and 25.16% for non-working day situations.
- The proposed strategy eliminates the power drawn from the grid for the BSCSs in each time step in both working and non-working day situations. The charging energy of EVBs used for EV swapping services is entirely from the RBESS in the BSCS, which fully utilizes advantages of the internal resources in BSCSs and saves the electricity cost of BSCSs.
- Compared to the non-dispatchable mode, the income of BSCSs with the proposed method under working and non-working days has increased by 59.05% and 36.78%, respectively. Moreover, the proposed strategy does not increase the grid load and further reduces the peak–valley load difference and enhances the load rate, thus better contributing to power system operations.

The provision of dynamic dispatchable capacity involved in this paper does not consider different types of BSCSs participating in active power regulations of grids. The proposed strategy has not incorporated the aggregation effect of BSCSs with different spatial and temporal distribution characteristics. These factors will be our research focus in future work.

CRediT authorship contribution statement

Mingze Zhang: Conceptualization, Methodology, Data curation, Writing – original draft. **Samson S. Yu:** Supervision, Visualization, Writing – review & editing. **Hanlin Yu:** Conceptualization, Software, Validation. **Ping Li:** Resources, Writing – review & editing. **Weidong Li:** Supervision, Project administration. **S.M. Muyeen:** Investigation, Formal analysis.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors are unable or have chosen not to specify which data has been used.

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