energies

MDPI

Article

Battery Swapping Station Pricing Optimization Considering Market Clearing and Electric Vehicles' Driving Demand

Xuewen Geng [1], Fengbin An [2], Chengmin Wang [2],* and Xi He [1],*

[1] China Power International Development Limited, Hong Kong 999077, China
[2] Department of Electrical Engineering, Shanghai Jiao Tong University, Shanghai 201100, China
* Correspondence: wangchengmin@sjtu.edu.cn (C.W.); hexicpi@hotmail.com (X.H.)

Abstract: With the development of the new energy vehicle market, the pricing of battery swapping stations (BSS) is becoming a concern. The pricing models of BSS usually only consider the interaction between the distribution system operator (DSO) and the BSS or between the BSS and electric vehicles (EVs). The impact of DSO and EVs on the pricing strategy of BSS has received less attention, which does not reflect the actual complex situation. Therefore, we propose a three-level BSS pricing method that includes market clearing and EV behaviors. Firstly, the distribution locational marginal price (DLMP) is modeled to determine the impact of the DSO on BSS. Secondly, the EV demand response is used to estimate the impact of EVs on BSS. Thirdly, to increase the adaptability of this model, an iteration algorithm with approximations and relaxations is used with mixed integer linear programming, effectively solving the pricing optimization. According to this optimization, it is evident that the BSS make decisions in the market environment by monitoring the quantity of batteries in various states and generate extra income by acting in response to price fluctuations in the electricity market. The model's viability and applicability are confirmed.

Keywords: battery swapping station; DLMP; driving demand; iteration method

check for updates

Citation: Geng, X.; An, F.; Wang, C.; He, X. Battery Swapping Station Pricing Optimization Considering Market Clearing and Electric Vehicles' Driving Demand. *Energies* **2023**, *16*, 3373. https://doi.org/10.3390/en16083373

Academic Editor: Anna Pinnarelli

Received: 3 March 2023
Revised: 30 March 2023
Accepted: 2 April 2023
Published: 12 April 2023

1. Introduction

More people are expected to purchase electric vehicles (EVs) because of their advantages for energy conservation and emission reductions. In the United States, 18.7 million electric vehicles are anticipated to be on the road by 2030, making up 7% of the estimated total number of vehicles [1]. The growing number of EVs will have a substantial influence on the electrical system. Through strategic charging and discharging, EVs can serve as system-wide temporary energy sources in addition to being a flexible load with controllable charging features [2,3]. Therefore, an operator such as a battery charging station (BCS) which polymerizes the charging and discharging behavior of EVs is needed. However, the charging process of electric vehicles at a BCS requires more time than refueling non-electric vehicles at a gas station, which hinders the promotion of EVs [4]. Different from BCS, battery swapping stations (BSS) have the advantages of high energy supplement efficiency, electricity savings, and prevention of excessive battery charging and discharging. By participating in the market and offering services such as demand response and energy storage, BSS aim to maximize earnings. However, the price of swapping batteries has become a concern for most people. The traditional modeling methods of BSS consider the interaction either between the distribution system operator (DSO) and BSS or between BSS and EVs. The combined interactions of DSO, BSS, and EVs have always been neglected. Thus, it is necessary to propose a model considering the three as a whole.

The development of Battery-to-Grid mode (B2G) and Grid-to-Battery mode (G2B) technology enables BSS to provide more service types [5] and also leads to greater requirements for flexibility in the power grid electricity price. Recently, a coordinated and distributed bi-level peer-to-peer transaction energy management framework has been proposed in [6] which uses distribution locational marginal price (DLMP) and allows producers and sellers to participate in the local power market through iterative distributed energy pricing. The five parts of DLMPs—marginal costs for active power, reactive power, congestion, voltage support, and loss—offer price signals to encourage market participants to help control congestion and provide voltage support [7]. In [8], the generation cost is integrated into the BSS operation optimization problem, and a BSS battery charging scheme for different power exchange scenarios is proposed. There needs to be more DSO regulation and supervision of the relatively disordered load. Reference [9] integrates the grid-connected operation of electric buses into a dynamic market framework and uses the allocation location marginal price algorithm for load congestion management. Therefore, it is necessary to introduce DLMP to calculate the DSO market clearing process and improve BSSs' charging and discharging behavior.

Although the construction of BSS is relatively slow, the research on the operation and business model of BSS has made some preliminary progress. Considering the charging and discharging state of a BSS battery, binary variables are introduced, and a BSS operation model has been developed using a large-size mixed integer nonlinear programming (MINLP) technique. In this model, the configuration of rechargeable, replaced, and standby batteries and the different battery rental costs of BSS are analyzed as a whole to meet the users' battery exchange needs and improve the profitability of BSS [10]. Considering the scheduling flow of BSS in the past and using G2B and B2G services to obtain market profits, a complete BSS operation model is established in [11]. In another model, the impacts of battery degradation, market price uncertainty, and battery demand uncertainty are analyzed to determine the economic benefits. To determine the BSS batteries' charging procedure, the number of batteries withdrawn from stock to fulfill all swap orders from incoming EVs is calculated [12]. However, the influence of EV behavior on BSS operation is not considered, and the pricing decision of BSS is not involved. Hence, in order to model the BSS pricing process and achieve more adaptable service costs, a dynamic battery replacement price calculation method should be used.

The traditional EV models consider the travel characteristics of electric vehicles, but only a Monte Carlo simulation is carried out in these existing models [13], which is quite different from the real situation. Reference [14] uses an uncertainty modeling approach with stochastic intervals for the uncertainty of PV generation and electric energy prices and iteratively solves a stochastic model for EV charging demand. Another bi-level model of BSS and EV operation optimization based on microgrids aims to minimize EV operation cost and maximize BSS profit and adopts incentive-based pricing rules. That is, the price of the power exchange service is positively related to the proportion of electric vehicle load [15]. Reference [16] considers a network flow model in a bi-level autonomous mobility-on-demand system to maximize the system's profit. In [17], a battery charging optimization model based on the Markov process is proposed to minimize PV charging station power and user cost while maximizing renewable energy consumption. As a result, it is crucial to take into account EV travel demand and travel patterns. With knowledge of potential EV travel routes, BSS can employ dynamic electricity rates to increase market revenues.

Considering the problems above, this paper proposes a three-level pricing model of BSS in the electricity market. This new model contains a mathematical formulation and a market strategy and is built on a framework including DSO, BSS, and EVs. Firstly, DLMP for BSS to trade electricity is proposed to explain the market-clearing process of DSO. Secondly, the BSS operation model is established to determine the optimal time-varying swapping price. Then, the EV driving mode is considered in EV running costs. Finally, by introducing a penalty function, an iteration method is used to solve the three-level model and calculate the optimal swapping price of BSS and the driving schedule of EVs, converting the three-level BSS business model into an iterative BSS optimization search process. The main contributions are summarized as follows:

(1) A business framework for BSS is proposed which includes bidding in the electricity market and pricing for EVs.

(2) A method for solving the Nash equilibrium solution of the three-level model is proposed.
(3) Driving demand for EVs is analyzed to fit the situation closely.

The rest of this paper is organized as follows. The details of the BSS operation mechanism are presented in Section 2. The business model of BSS is examined in Section 3. The three-level business model's reformulation and relaxation strategies are provided in Section 4. The case study is elaborated on in Section 5, and the conclusion and suggestions for future research are given in Section 6.

2. Framework of the BSS Business Model

2.1. Operation Mechanisms for the BSS

BSS is a proposed battery operation mode for supplying power to EVs. As opposed to BCS, the BSS can quickly complete the battery change and even prepare the batteries for EVs in advance. BSS charges the battery in the station by purchasing electricity from the electric network and provides EVs with a battery swapping service to obtain profits. In order to maximize the daily operation revenue, the composition of BSS revenue and cost is analyzed to determine an optimal power exchange price and charging and discharging scheme. This paper designs a business framework for BSS interacting with DSO and EV, which is shown in Figure 1. A BSS chooses the best battery charging and discharging schedules and buys and sells electricity by submitting bids and offers in the electrical market in order to optimize its own earnings. In addition, considering the influence of EV behavior, BSS determines the price of the power replacement service while meeting the EV battery demand.

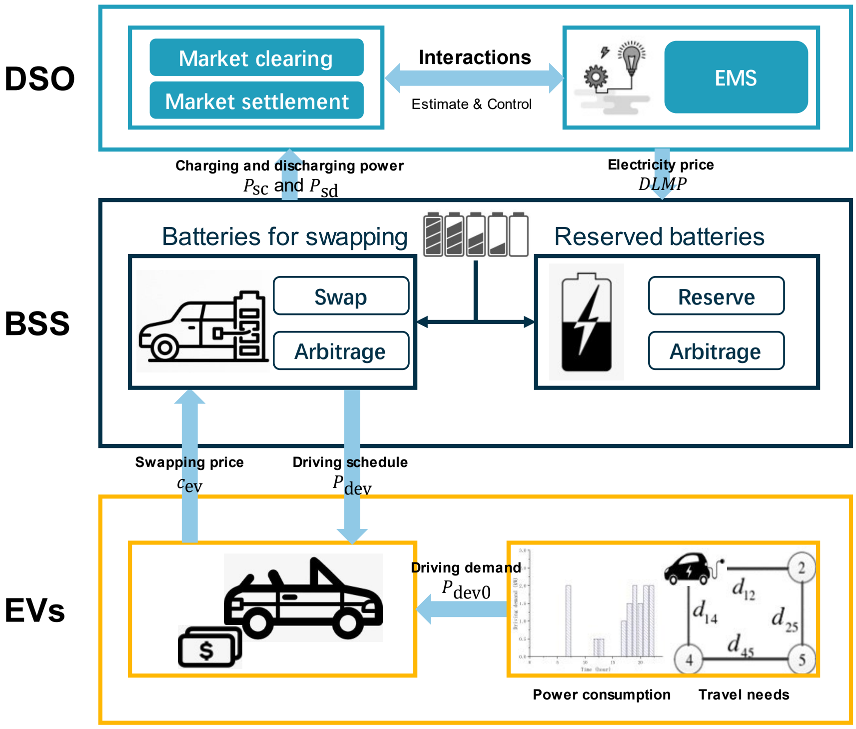


Figure 1. Operation mode of battery swapping station (BSS).

As shown in Figure 1, the transactions involved in a BSS business model include the following three types.

① Electricity transactions between DSO and BSS. Both batteries for swapping and reserved batteries are charged by purchasing electricity from the power grid, and the remaining electricity can be used to sell electricity to the power grid for arbitrage when the electricity price is high.

② Battery status exchange inside BSS. The batteries in BSS are divided into two groups: batteries for swapping and reserved batteries. For batteries used for power exchange, a certain amount of state of charge (SOC) needs to be satisfied before the time of switching. For reserved batteries, it is necessary to participate in the process of swapping batteries when the number of batteries to be swapped is insufficient or the SOC does not meet the requirements.

③ Battery swapping transactions between BSS and EVs. A BSS formulates the swap price and publishes it to EV owners. The EV owner determines the next charging and discharging plan and reports it to the BSS.

Using the time difference of the wholesale price of electricity, BSS can use the G2B mode to buy electricity in the low-price period and the B2G mode to sell electricity in the high-price period to realize more flexible arbitrage, which is similar to traditional energy storage [18].

2.2. Assumptions of the Model

Let $N_{BSS} := \{1, 2, \ldots, N\}$, which is the set of batteries in the BSS, where N is the total number of batteries in storage. Let $N_{EV} := \{1, 2, \ldots, n\}$, which is the set of EVs, where n is the total number of EVs in the system.

The management of the battery in the BSS is the foundation for the suggested BSS pricing model in this study. The operation must, however, also adhere to the market context and fundamental physical constraints. The following premises are made before the model is built:

1. Considering the impact of deep charge and discharge on battery life, the battery can only participate in one deep charge and discharge in one day, that is, one battery replacement process with an EV;
2. The batteries N in the BSS are divided into two categories, namely batteries to be replaced and backup batteries in the t period. Among them, the battery to be replaced in the t period is fully charged at the $t-1$ period. The backup battery does not participate in the electric vehicle power exchange process and remains in the BSS;
3. It is assumed that the power exchange demand of the electric vehicle in the t period is reported to the BSS at the beginning of the t period.
4. The models of BSS and EVs use the same time granularity. It is assumed that the swapping speed of the BSS is no more than five minutes [19], the time interval is 1 h for both the BSS and EVs, and the state-of-charge (SOC) of batteries to be replaced in the t period is the minimum value.

3. Mathematical Formulation of the BSS Business Model

3.1. DSO Market Schedule

In the proposed three-level pricing model, the DSO is responsible for the management of branch currents and node voltages of the entire transmission network in a centralized form. To reduce overall energy costs, DSO makes separate system-level trading plans for energy services. The market clearing model is listed in (1)–(8), where the objective function is formulated in (1), day-ahead domains are restricted by (2)–(8), and the location and time indices of variables are neglected for brevity.

DLMP depends on factors such as the load size, electrical location of nodes, line blockage, etc., so DLMP differs in time and space. In this paper, the marginal cost of electricity consumption at each node of the distribution network at different times is obtained through the second-order cone AC Optimal power flow (SOC-ACOPF) model, and a linearized power flow is established to obtain the DLMP, including the blocking cost.

Target function:

$$\min \sum_{t=1}^{T} \sum_{(i,j)\in L} r_{ij} i_{ij,t}^{2} \tag{1}$$

where r_{ij} is the resistance of branch ij; and $i_{ij,t}$ is the current of branch ij at time t.

Constraints:

(1) Power flow balance constraints:

$$P_{\mathrm{L},t} = P_{ij,t} - r_{ij} i^2_{ij,t} - \sum_{k:j\to k} P_{jk,t} : \tau^{\mathrm{p}}_{jt} \tag{2}$$

$$Q_{\mathrm{L},t} = Q_{ij,t} - x_{ij} i^2_{ij,t} - \sum_{k:j\to k} Q_{kj,t} : \tau^{\mathrm{q}}_{jt} \tag{3}$$

$$u^2_{j,t} = u^2_{i,t} - 2(r_{ij}P_{ij,t} + x_{ij}Q_{ij,t}) + (r^2_{ij} + x^2_{ij}) i^2_{ij,t} : \tau^{\mathrm{u}}_{ijt} \tag{4}$$

$$0 \le i_{ij,t} \le I_{\max} : \lambda^{\mathrm{I}}_{ijt}, \varphi^{\mathrm{I}}_{ijt} \tag{5}$$

$$U_{\min} \le u_{j,t} \le U_{\max} : \lambda^{\mathrm{U}}_{ijt}, \varphi^{\mathrm{U}}_{ijt} \tag{6}$$

(2) Node voltage constraints:

$$u_{\min,j} \le u_{j,t} \le u_{\max,j} : \lambda^{\mathrm{u}}_{jt} \ge 0, \varphi^{\mathrm{u}}_{jt} \le 0 \tag{7}$$

(3) Second-order cone constraints on the variables $U_{j,t} = u^2_{j,t}$ and $I_{ij,t} = i^2_{ij,t}$:

$$\left\| \begin{matrix} 2P_{ij,t} \\ 2Q_{ij,t} \\ I_{ij,t} - U_{j,t} \end{matrix} \right\|_2 \le I_{ij,t} + U_{j,t} : \lambda^{\mathrm{a}}_{ij,t}, \lambda^{\mathrm{b}}_{ij,t}, \lambda^{\mathrm{c}}_{ij,t}, \lambda^{\mathrm{d}}_{ij,t} \tag{8}$$

where $P_{ij,t}$ and $Q_{ij,t}$ are the active and reactive power of the first end of branch ij at time t; x_{ij} is the reactance of branch ij; $u_{\min,j}$ and $u_{\max,j}$ are the minimum and maximum value of voltage of node j at time t; and $U_{j,t}$ and $I_{ij,t}$ are the second power of node i voltage and branch ij current at time t. The variables τ, λ and φ at the end of the constraints are their Lagrange multipliers, and τ^{p}_{jt} is the DLMP of bus i at time slot t.

The constraint space corresponding to Equation (8) is a quadratic cone, and the problem is transformed into second-order cone programming (SOCP). The optimal global solution is obtained quickly by common commercial solvers such as YALMIP [20].

To write the dual-cone model, the cone constraint is transformed to obtain the dual problem.

$$\max \sum_{t=1}^{T} \sum_{j\in J} \left(-\lambda^{\mathrm{p}}_{j,t} P_{\mathrm{L},t} - \lambda^{\mathrm{q}}_{j,t} Q_{\mathrm{L},t} + \lambda^{\mathrm{U}}_{ijt} U_{\min} - \varphi^{\mathrm{U}}_{ijt} U_{\max} \right) - \sum_{t=1}^{T} \sum_{(i,j)\in L} \varphi^{\mathrm{I}}_{ijt} I_{\max} \tag{9}$$

$$-\tau^{\mathrm{p}}_{j,t} + \tau^{\mathrm{p}}_{i,t} + 2r_{ij}\tau^{\mathrm{u}}_{ijt} - 2\lambda^{\mathrm{a}}_{ij,t} = 0 \tag{10}$$

$$-\tau^{\mathrm{q}}_{j,t} + \tau^{\mathrm{q}}_{i,t} + 2x_{ij}\tau^{\mathrm{u}}_{ij,t} - 2\lambda^{\mathrm{b}}_{ij,t} = 0 \tag{11}$$

$$\tau^{\mathrm{U}}_{ij,t} - \sum_{k:j\to k} \tau^{\mathrm{U}}_{jk,t} - \lambda^{\mathrm{U}}_{ijt} + \varphi^{\mathrm{U}}_{ijt} + \sum_{k:j\to k} \lambda^{\mathrm{c}}_{jk,t} + \sum_{k:j\to k} \lambda^{\mathrm{d}}_{jk,t} = 0 \tag{12}$$

$$r_{ij} - r_{ij}\tau^{\mathrm{p}}_{j,t} - x_{ij}\tau^{\mathrm{q}}_{j,t} - \left(r^2_{ij} + x^2_{ij} \right) \tau^{\mathrm{U}}_{ij,t} - \lambda^{\mathrm{I}}_{ijt} + \varphi^{\mathrm{I}}_{ijt} - \lambda^{\mathrm{c}}_{ij,t} - \lambda^{\mathrm{d}}_{ij,t} = 0 \tag{13}$$

$$\lambda^{\mathrm{I}}_{ijt}, \varphi^{\mathrm{I}}_{ijt} \ge 0 \tag{14}$$

$$\lambda^{\mathrm{U}}_{ijt}, \varphi^{\mathrm{U}}_{ijt} \ge 0 \tag{15}$$

$$\left\| \lambda^{\mathrm{a}}_{ij,t} \quad \lambda^{\mathrm{b}}_{ij,t} \quad \lambda^{\mathrm{c}}_{ij,t} \right\|_2 \le \lambda^{\mathrm{d}}_{ij,t} \tag{16}$$

Solving the second-order cone current dual problem yields the DLMP $\tau_{j,t}^{\mathrm{p}}$ for each node j at time t.

3.2. BSS Pricing Model

The BSS buys electricity from the DSO and charge its batteries. The BSS obtains its main source of income by swapping batteries for EVs. Meanwhile, the BSS can sell excess electricity from the reserve batteries to the DSO for arbitrage. The BSS swaps EV batteries to maximize the operation's total profits. Considering the life cycle of the battery, each charging and discharging process has an impact on the battery. The battery loss is included in the BSS optimization objective function as a factor for the BSS to formulate the electricity price and charging and discharging plan [21]. The BSS operation model is listed in (17)–(26), where the objective function is formulated in (17). Numerous rounds of charging and discharging the batteries in the BSS shorten their lifespan and lower their maximum capacity. As seen in the third formula of this article, the battery properties are significantly dependent on the number of cycles. The charge/discharge constraints and battery SOC constraints are restricted by (18)–(23) and (24) and (25).

The objective of the BSS-level model is to minimize its operation cost, which depends on the number of batteries for swapping, the electricity price, and the degradation cost of charging and discharging.

Target function:

$$\max \sum_{t=1}^{T=24} [\sum_{i=1}^{n} c_t^{\mathrm{ev}} \alpha_{i,t} - \lambda_t^{\mathrm{c}} P_t^{\mathrm{sc}} + \lambda_t^{\mathrm{d}} P_t^{\mathrm{sd}} - \sum_{j=1}^{N} \tau \frac{P_{j,t}^{\mathrm{c}} + P_{j,t}^{\mathrm{d}}}{\mathrm{Q_b}}] \tag{17}$$

where c_t^{ev} is the swap price determined by BSS at time t; $\alpha_{i,t}$ is a binary variable representing whether the EV is charged at time t; λ_t^{c} and λ_t^{d} are the charge and discharge price in the electricity market at time t; P_t^{sc} and P_t^{sd} are the total charge and discharge power of BSS at time t; τ is the battery degradation coefficient; $P_{j,t}^{\mathrm{c}}$ and $P_{j,t}^{\mathrm{d}}$ are the charge and discharge power of the battery j at time t; and $\mathrm{Q_b}$ is the capacity of a single battery.

Constraints:

(1) Battery charge/discharge constraints:

$$0 \le P_{j,t}^{\mathrm{c}} \le k\overline{P_{\mathrm{c}}} \tag{18}$$

$$0 \le P_{j,t}^{\mathrm{d}} \le (1-k)\overline{P_{\mathrm{d}}} \tag{19}$$

$$\underline{SOC} \le SOC_{j,t} \le \overline{SOC} \tag{20}$$

$$SOC_{j,t+1} = SOC_{j,t} + \frac{\left(\eta_{\mathrm{c}} P_{j,t}^{\mathrm{c}} - P_{j,t}^{\mathrm{d}}/\eta_{\mathrm{d}}\right)\Delta t}{\mathrm{Q_{bat}}} \tag{21}$$

$$P_t^{\mathrm{sc}} = \sum_{j=1}^{N} P_{j,t}^{\mathrm{c}}, t = 1,2,\ldots,T \tag{22}$$

$$P_t^{\mathrm{sd}} = \sum_{j=1}^{N} P_{j,t}^{\mathrm{d}}, t = 1,2,\ldots,T \tag{23}$$

(2) Swapping battery constraints:

$$SOC_{i,\alpha_t} = \underline{SOC} \tag{24}$$

$$SOC_{i,\alpha_t-1} = \overline{SOC} \tag{25}$$

(3) Swap price constraints:

$$\underline{c_{\text{ev}}} \leq c_t^{\text{ev}} \leq \overline{c_{\text{ev}}} \tag{26}$$

where k is a binary variable to ensure that the charging process and discharge process cannot be carried out at the same time; $SOC_{j,t}$ is the SOC of battery j at time t; $\underline{SOC}$ and $\overline{SOC}$ are the minimum and maximum value of the SOC of a battery; η_{c} and η_{d} are the charging and discharge efficiency; Δt is the time interval; α_t is the time of battery i to be swapped; $\underline{c_{\text{ev}}}$ and $\overline{c_{\text{ev}}}$ are the minimum and maximum values of the swap price.

3.3. EV Behavior

From the EVs′ perspective, EV owners should not only consider the cost of battery replacement, but also the satisfaction of their own travel needs. Because the electricity price offered by the BSS varies during the day, the swapping schedule should be optimized to minimize the electricity cost over the entire swapping duration.

The objective function is set up in terms of a monetary value to find the best exchanging time and driving schedule. The cost for serving the EV swapping orders is as follows. Equation (27) is the target function minimizing the daily vehicle maintenance cost, which is composed of the swap cost and driving dissatisfaction cost. Equations (28) and (29) are EV discharge constraints, and Equations (30)–(34) are EV discharge and swap status constraints.

Target function:

$$\min \sum_{t=1}^{T} c_t^{\text{ev}} \alpha_t + \sum_{t=1}^{T} \sum_{i=1}^{n} \left| p_{i,t}^{\text{dev}} - p_{i,t}^{\text{dev0}} \right| c_{i,t}^{\text{s}} \tag{27}$$

where $p_{i,t}^{\text{dev}}$ is the discharge power of EV i at time t; $p_{i,t}^{\text{dev0}}$ is the primal driving demand of EV i at time t; $c_{i,t}^{\text{s}}$ is the expectation punishment coefficient of EV i at time t.

Constraints:

(1) EV discharging constraints:

$$\sum_{t=1}^{T} P_{i,t}^{\text{dev}} \leq \sum_{t=1}^{T} P_{i,t}^{\text{dev0}} \tag{28}$$

$$0 \leq P_{i,t}^{\text{dev}} \leq \beta_{i,t} P_{\max}^{\text{dev}} \tag{29}$$

(2) Discharge and swap status constraints:

$$\alpha_{i,t} + \beta_{i,t} \leq 1 \tag{30}$$

$$\sum_{t=1}^{T} \alpha_{i,t} = 1 \tag{31}$$

$$\alpha_{i,0} = 0 \tag{32}$$

$$\beta_{i,t_1-1} = 1, \sum_{t=t_1}^{T} \beta_{i,t} = 0 \text{ if } \alpha_{i,t_1} = 1, t_1 = 2, \ldots, T \tag{33}$$

$$\sum_{t=1}^{t_1} \beta_{i,t_1} = t_1 \text{ if } \alpha_{i,t_1} = 0, t_1 = 2, \ldots, T \tag{34}$$

where $\beta_{i,t}$ is a binary variable representing whether the EV is discharged at time t.

4. Approximations and Relaxations of the BSS Business Model

Considering the nonlinear problem caused by the absolute value in the BSS objective function, set $y_{i,t} = \left| p_{i,t}^{\mathrm{d}} - p_{i,t}^{\mathrm{d0}} \right|$, and z_1 and z_2 are binary variables.

$$-M(1-z_1) \leq y - \left(p^{\mathrm{d}} - p^{\mathrm{d0}}\right) \leq M(1-z_1) \tag{35}$$

$$p^{\mathrm{d}} - p^{\mathrm{d0}} \geq -M(1-z_1) \tag{36}$$

$$-M(1-z_2) \leq y + \left(p^{\mathrm{d}} - p^{\mathrm{d0}}\right) \leq M(1-z_2) \tag{37}$$

$$p^{\mathrm{d}} - p^{\mathrm{d0}} \geq M(1-z_2) \tag{38}$$

$$z_1 + z_2 = 1 \tag{39}$$

By introducing linear, binary, and relaxation variables, the nonlinear objective function of BSS is converted into linear form, improving the calculation speed.

Considering the relationship between layers of the three-layer model, in order to solve the optimal BSS pricing strategy, we adopt the iterative solution method to decouple the interaction between the DSO, BSS and EVs. Iteration is the most typical mathematical method for solving multi-layer models. The logic of iteration is illustrated in Algorithm 1.

Algorithm 1. DSO–BSS–EV iteration method.

```
Input:
Number of network nodes, branches, network topology, line parameters and load output.
The iteration parameters include the convergence error $\varepsilon$ and the maximum number of iterations $N_{\max}$.
Output: the optimal price of BSS and optimal driving schedule of EV.
1. Initialization: Set iteration number $l$=1. Set initial network load and charging and discharging power of BSS.
2. repeat:
3. DSO: According to the charging and discharging power of the BSS, the network load is redefined, the market is cleared and the DLMP is calculated.
4. Algorithm 2 BSS pricing iteration method: Calculate the equilibrium of BSS and EV objective functions $P^{\mathrm{sc}}$ and $P^{\mathrm{sd}}$.
5. $l \leftarrow l+1$ Calculate $\Delta_{DLMP} = \left| DLMP^{l} - DLMP^{l-1} \right|_2$.
6. if $l \geq N_{\max}$ then
7. break
8. end if
9. until $\Delta_{DLMP} \leq \varepsilon$
```

The logic of the BSS pricing iteration method is illustrated in Algorithm 2.

In order to improve the convergence speed, the iterative objective is added to the optimization objective function of BSS as a penalty term.

$$\max \sum_{t=0}^{T=24} \left[\sum_{i=1}^{n} c_t^{\mathrm{ev}} \alpha_{i,t} - \lambda_t^{\mathrm{c}} P_t^{\mathrm{sc}} + \lambda_t^{\mathrm{d}} P_t^{\mathrm{sc}} - \tau \frac{P_{i,t}^{\mathrm{c}} + P_{i,t}^{\mathrm{d}}}{\mathrm{Q_b}}\right] - \left| c_l^{\mathrm{ev}} - c_{l-1}^{\mathrm{ev}} \right|_2 \tag{40}$$

Algorithm 2. BSS pricing iteration method.

```
Input:
EV driving demand $p^{d0}$.
The iteration parameters include the convergence error and the maximum number of iterations.
Output: the optimal price of BSS
1. Initialization: Set iteration number $l$=1. Set initial EV driving schedule.
2. repeat:
3. BSS: According to the EV driving schedule, the BSS operator optimizes the swapping price $c^{ev}$ and calculates the optimal profit.
4. EV: According to the swapping price $c^{ev}$, EV owners calculate the optimal driving schedule $p^{d}$.
5. $l \leftarrow l+1$ Calculate $\Delta_{cev} = \left| c_l^{ev} - c_{l-1}^{ev} \right|_2$.
6. if $l \geq N_{\max}$ then
7. break
8. end if
```

5. Case Studies

In this section, the optimization model and algorithm are verified on a modified IEEE 33-bus distribution network [22] shown in Figure 2. The reference voltage and capacity values are 12.66 kV and 1 MW, respectively. The NREL Database is used to produce the data on solar radiation and wind speed [23]. The data for BSS and EV in Table 1 are from Reference [24]. All numerical simulations are carried out through Gurobi 9.5.1 [25] and YALMIP within MATLAB on a desktop computer with an Intel® Core™ i5 of a 1.6 GHz CPU and 16 GB of memory.

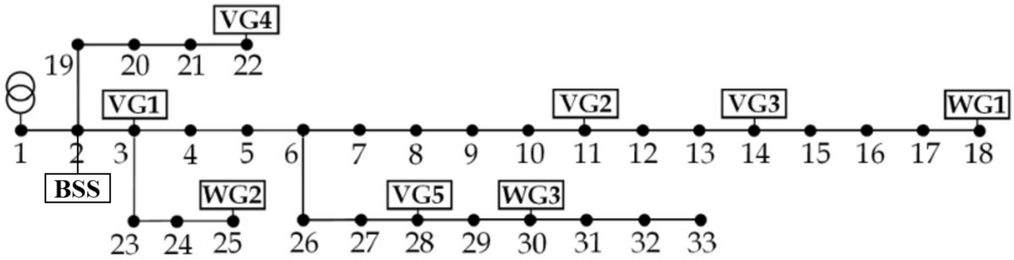


Figure 2. IEEE 33-bus distribution network diagram.

Table 1. Parameters in the case study.

Parameter	Value	Parameter	Value
N	10	τ (USD)	0.05
T	24	Q_b (kWh)	10
$\overline{P_c}$ (kW)	3	$\underline{c_{ev}}$ (USD)	1
$\overline{P_d}$ (kW)	3	$\overline{c_{ev}}$ (USD)	5
$\underline{SOC}$	0.9	n	4
$\overline{SOC}$	0.1	c^s (USD/kWh)	2
η_c (%)	0.9	$P_{\max}^{dev}$ (kW)	3
η_d (%)	0.9	M	10,000

We determined the daily time-series EV profiles for typical EV demand [26]. Combined with the BSS data of Li-ion batteries, the raw EV power of discharge shown in Figure 3 is designed to characterize the EV owners' daily activities.

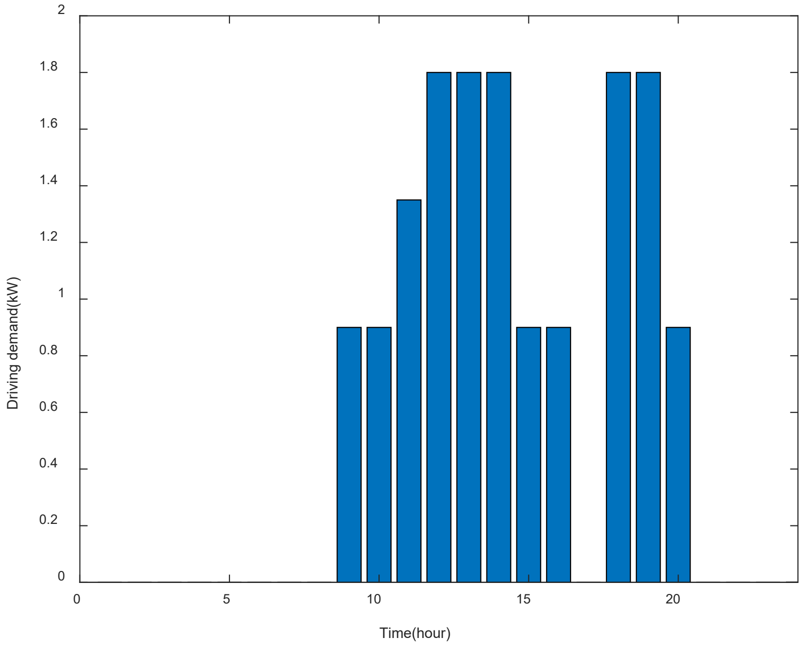


Figure 3. Initial driving demand of EV.

5.1. Designed Cases and Arrangements

The following cases investigate the benefits brought by the market clearing process and EV behavior simulation.

1. Case 1: Optimal BSS scheduling considering bidding without pricing. In this case, the BSS provides EVs with a swapping service at a fixed price.
2. Case 2: Optimal BSS scheduling considering pricing without bidding. In this case, the pricing process of the BSS ignores the market clearing process, and the time-of-use electricity price is used to represent the grid electricity price.
3. Case 3: Optimal BSS scheduling considering pricing and bidding. In this case, the BSS swapping pricing optimization model considering DSO market clearing and EV driving demand proposed in this paper is adopted.
4. Case 4: On the basis of Case 3, the data scale is increased with a primal algorithm, specifically increasing the number of BSS batteries and the number of EVs in the distribution network. In this case, the BSS swapping pricing optimization model considering DSO market clearing and EV driving demand proposed in this paper is adopted. This case requires no model reconstruction, with 100 batteries in the BSS and 60 EVs.
5. Case 5: On the basis of Case 3, the data scale is increased with reformulation of the algorithm, specifically by increasing the number of BSS batteries and the number of EVs in the distribution network. In this case, the BSS swapping pricing optimization model considering DSO market clearing and EV driving demand proposed in this paper is adopted. This case requires model reconstruction, with 100 batteries in the BSS and 60 EVs.

The case study is performed as follows. Firstly, the benefits of the dynamic pricing approach are examined, and profit fluctuations in BSS are also evaluated, using Cases 1 and 3. Secondly, the profit resulting from BSS participation in market bidding is analyzed by comparing the results obtained from Case 2 and Case 3. Thirdly, the practicability of the proposed pricing approach is verified by testing a large-scale distribution system. The computational performance and application are finally explored.

5.2. Pricing Strategy Analysis

The pricing strategy analysis is performed by comparing the traditional EV demand considered as an uncertain variable and fixed-price pricing based on the experience method (i.e., Case 1), modeling EV behavior but ignoring the market impact method (i.e., Case 2) and the proposed three-level pricing method (i.e., Case 3).

As can be seen from Table 2, Case 1 which ignores the dynamic pricing of the BSS and Case 2 which ignores the impact of the DSO results in an artificially high daily operating profit for the BSS. Neither Case 1 or Case 2 can meet the daily driving needs of EV owners to the maximum, which is not conducive to the long-term operation and development of the BSS. Only in Case 3, and with full consideration of the impact of market clearing and EV dynamics, can the optimal pricing and operation scheme of the BSS be realized.

Table 2. Influence of different factors on pricing and cost.

	System Operation Cost (USD)	Profit of BSS (USD)	Electricity Cost of EVs (USD)
Case 1	1162.74	15,804.29	37.2
Case 2	-	15,816.29	40.80
Case 3	1162.73	15,440.32	36.80

As shown in Figure 4, BSS affects the market clearing process by adjusting strategies, effectively reducing DLMP. The DLMP reduction during peak and valley periods in the figure is more prominent, corresponding to the peak charge and discharge of the BSS, which is conducive to reducing BSS electricity costs.

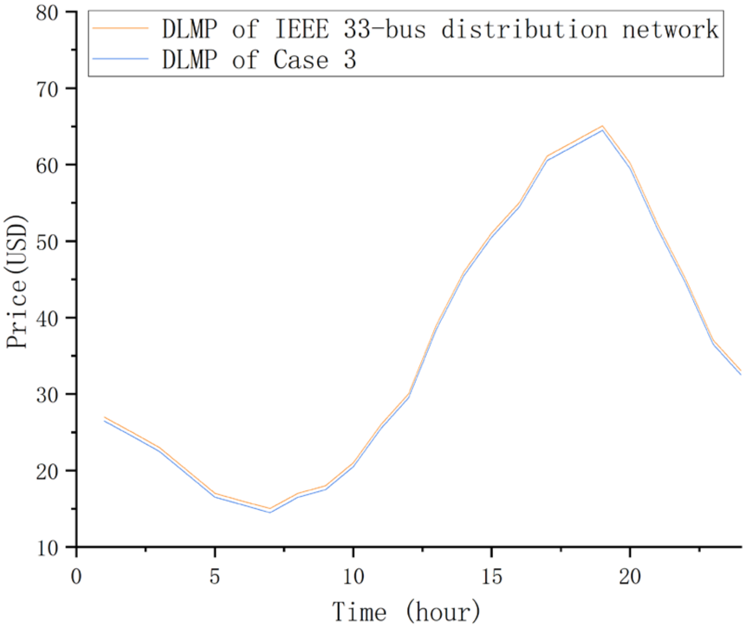
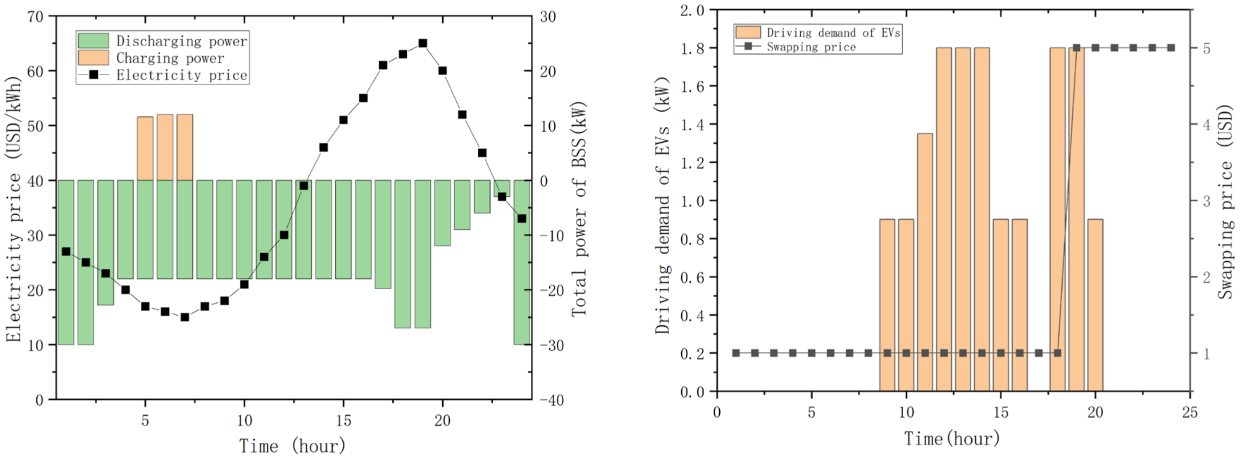


Figure 4. DLMP curve of node 2 in IEEE 33-bus distribution network and Case 3.

Figure 5a represents the time-varying electricity price and charging/discharging power of the BSS in Case 2. The electricity price is in line with the supply and demand relationship with electricity consumption and decreases with the load reduction in the morning and late at night. The BSS charges when the electricity price is low (5:00–7:00) and discharges larger amounts when the electricity price is high (17:00–19:00) to reduce the cost of electricity purchases. Due to the existence of standby batteries, BSS uses the spare batteries for low storage and high-power generation with the power grid to realize arbitrage and obtain additional income beyond the power exchange service.



(**a**) (**b**)

Figure 5. (**a**) Time-varying electricity price and charging/discharging power of BSS in Case 2; and (**b**) swapping price and driving demand of EVs in Case 2.

Figure 5b represents the swapping price and driving demand of EVs in Case 2. The power exchange price of BSS is affected by the power exchange plan of BSS and users, reaching the maximum level from 19:00 to 24:00. On the premise of meeting the driving demand, the EV adjusts its driving behavior according to the impact of the BSS electricity exchange price to reduce the cost of using the EV.

5.3. Calculation Speed and Convergence Analysis

The convergence rates of the above three cases are analyzed and listed in Table 3. Due to the consideration of market clearing and in Case 1 and Case 3, the number of iterations required for calculation increases, and the convergence speed slows down. The main reason is that the equilibrium of the BSS and EVs is easy to solve through generations. However, this iterative result is challenging to converge when iterating with the settlement of the upper-level DSO market clearing.

Table 3. Calculation speed and convergence of cases.

	Case 1	**Case 2**	**Case 3**
Speed (s)	25.900845	13.268103	30.840949

To compare the computation and convergence speed of the algorithm in a large-scale distribution network, we designed application scenarios with a BSS containing more batteries and a more significant number of EVs.

Compared with the model before modification, which is Case 4, the model of Case 5 has better convergence and faster convergence speed, which is shown in Table 4. Modifying the objective function of the BSS and introducing a convergence penalty term is beneficial when applying the model proposed in this paper in large-scale power distribution systems.

Table 4. Model convergence of cases.

	Case 4	**Case 5**
Speed (s)	-	147.421108
Convergence	No	Yes

6. Conclusions

This paper proposes a BSS swapping pricing optimization model considering DSO market clearing and EV driving demand. The establishment of the dynamic swap price affects the income of the BSS. In addition, the revenue of the BSS is under the influence of the charge/discharge electricity prices. Here, DLMP is used to express the impact of the power exchange with the DSO. The results show that the BSS pricing scheme considering the synergy of DSO and EVs, can effectively improve the operating income of the BSS, reduce the electricity cost to EV owners, and facilitate the regulation and adjustment of real-time electricity prices to market behavior.

The random variables in the model are yet to be modeled. Future studies should simulate should this uncertainty fully. In addition, the spatiotemporal coupling characteristics of EVs are well worth studying. Distinguished from EV demand, the space–time coupling problem combines the actual actions of EVs in the grid for analysis and consideration, which is more appropriate to the actual EV operation mode in practice.

Author Contributions: Conceptualization, X.G. and F.A.; methodology, X.G. and F.A.; validation, C.W. and X.H.; writing—original draft preparation, X.G.; writing—review and editing, F.A. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Shalaby, A.A.; Shaaban, M.F.; Mokhtar, M.; Zeineldin, H.H.; El-Saadany, E.F. A Dynamic Optimal Battery Swapping Mechanism for Electric Vehicles Using an LSTM-Based Rolling Horizon Approach. *IEEE Trans. Intell. Transport. Syst.* **2022**, *23*, 15218–15232. [CrossRef]
2. Yang, S.; Yao, J.; Kang, T.; Zhu, X. Dynamic Operation Model of the Battery Swapping Station for EV (Electric Vehicle) in Electricity Market. *Energy* **2014**, *65*, 544–549. [CrossRef]
3. Ke, X.; Wu, D.; Lu, N. A Real-Time Greedy-Index Dispatching Policy for Using PEVs to Provide Frequency Regulation Service. *IEEE Trans. Smart Grid* **2019**, *10*, 864–877. [CrossRef]
4. Wu, H. A Survey of Battery Swapping Stations for Electric Vehicles: Operation Modes and Decision Scenarios. *IEEE Trans. Intell. Transport. Syst.* **2022**, *23*, 10163–10185. [CrossRef]
5. Revankar, S.R.; Kalkhambkar, V.N. Grid Integration of Battery Swapping Station: A Review. *J. Energy Storage* **2021**, *41*, 102937. [CrossRef]
6. Ullah, M.H.; Park, J.-D. DLMP Integrated P2P2G Energy Trading in Distribution-Level Grid-Interactive Transactive Energy Systems. *Appl. Energy* **2022**, *312*, 118592. [CrossRef]
7. Bai, L.; Wang, J.; Wang, C.; Chen, C.; Li, F. Distribution Locational Marginal Pricing (DLMP) for Congestion Management and Voltage Support. *IEEE Trans. Power Syst.* **2018**, *33*, 4061–4073. [CrossRef]
8. Liang, Y.; Zhang, X. Battery Swap Pricing and Charging Strategy for Electric Taxis in China. *Energy* **2018**, *147*, 561–577. [CrossRef]
9. Wu, Z.; Guo, F.; Polak, J.; Strbac, G. Evaluating Grid-Interactive Electric Bus Operation and Demand Response with Load Management Tariff. *Appl. Energy* **2019**, *255*, 113798. [CrossRef]
10. Liang, Y.; Cai, H.; Zou, G. Configuration and System Operation for Battery Swapping Stations in Beijing. *Energy* **2021**, *214*, 118883. [CrossRef]
11. Sarker, M.R.; Pandzic, H.; Ortega-Vazquez, M.A. Optimal Operation and Services Scheduling for an Electric Vehicle Battery Swapping Station. *IEEE Trans. Power Syst.* **2015**, *30*, 901–910. [CrossRef]
12. Ko, H.; Pack, S.; Leung, V.C.M. An Optimal Battery Charging Algorithm in Electric Vehicle-Assisted Battery Swapping Environments. *IEEE Trans. Intell. Transport. Syst.* **2022**, *23*, 3985–3994. [CrossRef]
13. Zhang, T.; Chen, X.; Yu, Z.; Zhu, X.; Shi, D. A Monte Carlo Simulation Approach to Evaluate Service Capacities of EV Charging and Battery Swapping Stations. *IEEE Trans. Ind. Inf.* **2018**, *14*, 3914–3923. [CrossRef]
14. Tostado-Véliz, M.; Kamel, S.; Hasanien, H.M.; Arévalo, P.; Turky, R.A.; Jurado, F. A Stochastic-Interval Model for Optimal Scheduling of PV-Assisted Multi-Mode Charging Stations. *Energy* **2022**, *253*, 124219. [CrossRef]
15. Zhang, M.; Chen, J. The Energy Management and Optimized Operation of Electric Vehicles Based on Microgrid. *IEEE Trans. Power Deliv.* **2014**, *29*, 1427–1435. [CrossRef]
16. Ding, Z.; Tan, W.; Lu, W.; Lee, W.-J. Quality-of-Service Aware Battery Swapping Navigation and Pricing for Autonomous Mobility-on-Demand System. *IEEE Trans. Ind. Inf.* **2022**, *18*, 8247–8257. [CrossRef]

17. Han, X.; Wei, Z.; Hong, Z.; Zhao, S. Ordered Charge Control Considering the Uncertainty of Charging Load of Electric Vehicles Based on Markov Chain. *Renew. Energy* **2020**, *161*, 419–434. [CrossRef]
18. Pantos, M. Exploitation of Electric-Drive Vehicles in Electricity Markets. *IEEE Trans. Power Syst.* **2012**, *27*, 682–694. [CrossRef]
19. Ahmad, F.; Saad Alam, M.; Saad Alsaidan, I.; Shariff, S.M. Battery Swapping Station for Electric Vehicles: Opportunities and Challenges. *IET Smart Grid* **2020**, *3*, 280–286. [CrossRef]
20. YALMIP. Available online: https://yalmip.github.io/ (accessed on 19 February 2023).
21. Mahoor, M.; Hosseini, Z.S.; Khodaei, A. Least-Cost Operation of a Battery Swapping Station with Random Customer Requests. *Energy* **2019**, *172*, 913–921. [CrossRef]
22. Baran, M.E.; Wu, F.F. Network Reconfiguration in Distribution Systems for Loss Reduction and Load Balancing. *IEEE Trans. Power Deliv.* **1989**, *4*, 1401–1407. [CrossRef]
23. Data and Tools | NREL. Available online: https://www.nrel.gov/research/data-tools.html/ (accessed on 27 March 2023).
24. Ahmad, F.; Alam, M.S.; Shariff, S.M. A Cost-Efficient Energy Management System for Battery Swapping Station. *IEEE Syst. J.* **2019**, *13*, 4355–4364. [CrossRef]
25. The Leader in Decision Intelligence Technology-Gurobi Optimization. Available online: https://www.gurobi.com/ (accessed on 15 February 2023).
26. Quiros-Tortos, J.; Ochoa, L.F.; Lees, B. A Statistical Analysis of EV Charging Behavior in the UK. In Proceedings of the 2015 IEEE PES Innovative Smart Grid Technologies Latin America (ISGT LATAM), Montevideo, Uruguay, 5–7 October 2015; IEEE: Montevideo, Uruguay, 2015; pp. 445–449.