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Two-Stage Optimal Scheduling of Distribution Network Considering Low-Carbon Demand Response and Battery Life in Electric Vehicle Battery Swap Stations

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ABSTRACT: With the rapid growth of the electric vehicle (EV) population and the development of active distribution networks (DN), the optimal scheduling of power systems that incorporate EVs has become increasingly important. electric vehicle battery swap stations (EVBSS), leveraging their substantial battery resources and suitability for centralized scheduling, offer a new approach for enhancing DN flexibility. Accordingly, this paper proposes a two-stage optimal scheduling method for DN that considers low-carbon demand response and the battery life of EVBSS. The method employs dynamic carbon emission factors as penalty components in time-of-use electricity pricing, thereby transmitting carbon signals from the generation side to the load side and encouraging low-carbon state transitions on the user side. The carbon substitution effect generated by electric vehicles through battery swapping is incorporated into the carbon quota allocation system, constructing a reward and punishment ladder-type carbon trading mechanism. Considering the impact of battery lifespan in electric vehicle battery swap stations on scheduling, the depth of discharge is converted into equivalent cycle counts by tracking the charging and discharging processes. The planned service life of the batteries is then incorporated as a hard constraint into the optimization model, making the scheduling results more practical. Case studies verify that the proposed method can effectively curb carbon emissions of DN and mitigate load fluctuations.

KEYWORDS: Distribution network; electric vehicle battery swap stations; battery life; low-carbon demand response

1 Introduction

Driven by the replacement of conventional units with renewable energy and the proliferation of interactive devices such as distributed energy resources and electric vehicles (EVs) into distribution networks (DN), EV load has become a significant component of the grid's total load [1]. Electric Vehicle Battery Swapping Stations (EVBSS) can centrally manage the charging and discharging of EV batteries. This achieves a temporal decoupling of the batteries from the vehicles, thereby making the charging and discharging decisions of the power batteries independent of the subjective choices of EV owners [2]. While providing battery swap services, EVBSS can also utilize the redundant batteries within the station as regulating resources to support DN development [3]. Consequently, as the battery swap model gains momentum in industry, it has concurrently garnered significant interest within academia.



From the perspective of demand-side participation in DN scheduling, users can adjust their loads through demand response (DR), enabling the supply side to arrange power generation reasonably [4]. Reference [5] proposes a data-driven day-ahead scheduling model for microgrids, which incorporates multiple types of demand response to reduce intra-day scheduling pressure. Reference [6] treats flexible loads and air-conditioning clusters as DR resources, proposing a multi-objective economic operation technology for microgrids that considers DR. This approach establishes a dynamic electricity price mechanism to accurately reflect the actual system operation status. Reference [7] proposes an adjustable robust optimization method to address the uncertainty of DR. While implementing DR can effectively reduce the total system cost, coping with its uncertainty requires sacrificing some economic benefits of the system. Reference [8] introduces a novel load transfer-based DR model for scheduling residential appliances, aiming to minimize peak demand for utilities. Reference [9] proposes an IES model based on a demand response mechanism, incorporating replacement and horizontal time-shifting demand response strategies at different scheduling stages to enhance the flexible scheduling capability of the IES and suppress supply-demand imbalances caused by uncertainties in renewable energy and load. Reference [10] presents a load management strategy under dynamic pricing aimed at cost reduction and peak demand mitigation, thereby increasing or decreasing consumer energy demand. The research mentioned above on DR modes is primarily conducted from an “electrical” perspective, making it difficult to respond to actual changes in carbon emissions. Reference [11] introduces a novel demand response framework employing generalized nodal carbon emission flow theory, which targets carbon mitigation. It establishes an optimal load adjustment model to help users achieve carbon reduction targets and proposes an evaluation method for assessing carbon reduction benefits. Reference [12] uses nodal carbon intensity as a guiding signal and carbon reduction willingness or carbon market prices as incentive signals to encourage users to reduce carbon emissions. However, methods utilizing nodal carbon potential require customized DR for scenarios with numerous users, making unified operation challenging. The carbon reduction potential of DR has not been fully exploited, leaving room for further emission reductions in the system.

In response to the low-carbon development concept, the ladder-type carbon trading mechanism has emerged, which further constrains carbon emissions by setting different carbon trading prices at various tiers [13]. Reference [14] confirms the efficacy of ladder-type carbon trading in achieving low-carbon economic dispatch for hydrogen-blended integrated energy systems under several typical operating conditions. By integrating generalized energy storage with a tiered carbon trading model, the study in Reference [15] achieves a reduction in carbon emissions. Most carbon trading mechanisms discussed in the aforementioned literature are based on a single fixed-price model. To fully exploit the emission reduction potential of the system, Reference [16] presents the development of a segmented carbon trading cost model, which incorporates a reward-punishment ladder structure. To achieve low-carbon economic dispatch in agricultural integrated energy systems, Reference [17] constructs a model that incorporates a reward-punishment ladder-type carbon trading (RPLCT) mechanism and the influence of carbon capture equipment. A limitation of the aforementioned studies is that their carbon trading mechanisms do not account for electric vehicles within swap stations.

Currently, research on the participation of EV battery swap mode in system scheduling primarily focuses on operational mechanism optimization and charging/discharging strategies [18]. Reference [19] proposes an integrated electric vehicle station capable of serving all types of electric vehicles in its vicinity, demonstrating the role of battery swap stations in enhancing system flexibility. Reference [20] discusses the layout and scheduling models for EVBSS and super battery swap stations under centralized charging and unified scheduling, investigating flexible charging strategies for super stations. Reference [21] proposes an aggregation strategy for the scheduling of electric vehicles at battery swap stations, which takes into account

the integration of renewable energy and grid peak shaving. This approach effectively enables orderly charging of electric vehicles, unleashes peak shaving potential, and addresses the challenges associated with renewable energy absorption. Reference [22] proposes a battery aggregation model based on State of Charge (SOC) intervals, considering charging and discharging priorities to reduce the complexity of individual battery modeling. Reference [23] utilizes the idle battery capacity of 5G base stations and battery swap stations to respond to time-of-use electricity prices and demand response signals, thereby mitigating their impact on the peak-to-valley difference. This approach ensures both the quality of communication services and the fulfillment of battery swap demands. Reference [24] strategically charges batteries based on dynamic energy prices to maximize the profit of the EVBSS. Reference [25] considers the differentiated demands of EVs to recommend appropriate BSSs for users, aiming to minimize the total cost for each vehicle. However, the aforementioned studies fail to consider the impact of battery life on the willingness of swap stations to participate in scheduling, resulting in overly idealized scheduling outcomes.

To address the aforementioned limitations, this paper proposes a two-stage optimal scheduling method for DN that considers low-carbon demand response and the battery life of EVBSS. The specific contributions are as follows:

- (1) A novel mechanism for low-carbon demand response (LCDR), centered on dynamic carbon emission factors, is developed in this paper. By incorporating a carbon signal, it more effectively guides the demand side towards a low-carbon response.
- (2) A novel RPLCT mechanism is proposed, which incorporates battery-swap electric vehicles into the carbon trading system, leading to a more complete carbon trading mechanism for the DN.
- (3) A new EVBSS model has been established, which takes into account the impact of battery life. By tracking variations in the charging and discharging processes to calculate the depth of discharge, the model enables more reasonable scheduling outcomes.

2 Low-Carbon Demand Response Model

Traditional DR mainly focuses on enhancing system economy and security, but it can sometimes adversely affect carbon emissions, contradicting the philosophy of low-carbon scheduling. LCDR builds upon traditional DR theory. By issuing carbon emission signals, it makes users aware of the carbon impact differences of their energy usage behaviors, thereby guiding them to adjust these behaviors. The response of users to electricity prices can be described using the demand-price elasticity coefficient [26]:

$$\varepsilon = \frac{\Delta P_h}{P_h^0} \frac{D_t^0}{\Delta D_t} \quad (1)$$

where P_h^0 and D_t^0 represent the amount of electricity (MW·h) and its price before the implementation of traditional DR, respectively (¥/MW·h); ΔP_h and ΔD_t depict the variations in electricity quantity and price after the implementation of traditional DR, respectively (MW·h); ε is the demand-price elasticity coefficient.

The post-DR load for each time period is determined by the electricity price elasticity matrix [27]:

$$\begin{bmatrix} P_p^1 \\ P_s^1 \\ P_v^1 \end{bmatrix} = \begin{bmatrix} P_p^0 & 0 & 0 \\ 0 & P_s^0 & 0 \\ 0 & 0 & P_v^0 \end{bmatrix} E \begin{bmatrix} \frac{\Delta D_p}{D_p^0} \\ \frac{\Delta D_s}{D_s^0} \\ \frac{\Delta D_v}{D_v^0} \end{bmatrix} + \begin{bmatrix} P_p^0 \\ P_s^0 \\ P_v^0 \end{bmatrix} \quad (2)$$

$$E = \begin{bmatrix} \varepsilon_{ff} & \varepsilon_{fp} & \varepsilon_{fg} \\ \varepsilon_{pf} & \varepsilon_{pp} & \varepsilon_{pg} \\ \varepsilon_{gf} & \varepsilon_{gp} & \varepsilon_{gg} \end{bmatrix} \quad (3)$$

where: P_p^0, P_s^0, P_v^0 and P_p^1, P_s^1, P_v^1 represent the loads at each time period before and after traditional DR, respectively (MW·h); D_p^0, D_s^0, D_v^0 and $\Delta D_p, \Delta D_s, \Delta D_v$ represent the electricity prices and their changes at each time period before and after DR, respectively; E is the demand-price elasticity matrix.

The carbon emission factor is a key indicator in LCDR. It not only reflects the direct carbon emissions from generation-side equipment but also characterizes the indirect carbon emissions resulting from differences in energy usage behavior, serving as a critical link between the source side and the load side. This process is illustrated in Fig. 1. This paper calculates the dynamic average carbon emission factor based on the share of non-clean energy supply in the distribution network, using it as a penalty factor in electricity pricing. The specific calculation is as follows:

$$\alpha_t^{\text{CO}_2} = \frac{P_t^{\text{buy}}}{P_t^{\text{load}}} \alpha_1 \frac{P_t^{\text{buy}}}{P_t^{\text{buy}} + P_t^{\text{GT}}} + \frac{P_t^{\text{GT}}}{P_t^{\text{load}}} \alpha_2 \frac{P_t^{\text{GT}}}{P_t^{\text{buy}} + P_t^{\text{GT}}} \quad (4)$$

$$\hat{\alpha}_t^{\text{CO}_2} = \frac{\alpha_t^{\text{CO}_2} - \alpha_{t,\min}^{\text{CO}_2}}{\alpha_{t,\max}^{\text{CO}_2} - \alpha_{t,\min}^{\text{CO}_2}} \quad (5)$$

where: α_1 and α_2 represent the carbon emission factors of purchased electricity and gas turbine (GT) generation, respectively (t/MW·h); P_t^{buy} denotes the electricity purchased by DN (MW·h); P_t^{load} represents the load of DN (MW·h).

A penalty electricity price is applied only when carbon emissions exceed the set threshold, thereby driving the system toward low-carbon operation.

$$E_t^{\text{CO}_2} \geq E_{\text{threshold}}^{\text{CO}_2} \quad (6)$$

$$\hat{\alpha}_t^{\text{CO}_2} = \frac{\alpha_t^{\text{CO}_2} - \alpha_{t,\min}^{\text{CO}_2}}{\alpha_{t,\max}^{\text{CO}_2} - \alpha_{t,\min}^{\text{CO}_2}} \quad (7)$$

where: $E_t^{\text{CO}_2}$ represents the net carbon emissions of the DN (t); $E_{\text{threshold}}^{\text{CO}_2}$ denotes the set carbon emission threshold (t); $P_{\text{price},t}^{\text{LCDR}}$ is the electricity price after implementing LCDR (¥/MW·h); $P_{\text{price},t}^{\text{PBDR}}$ is the electricity price after traditional DR (¥/MW·h); κ_t is a binary state variable for price adjustment, which equals 1 when carbon emissions exceed the threshold, and 0 otherwise.

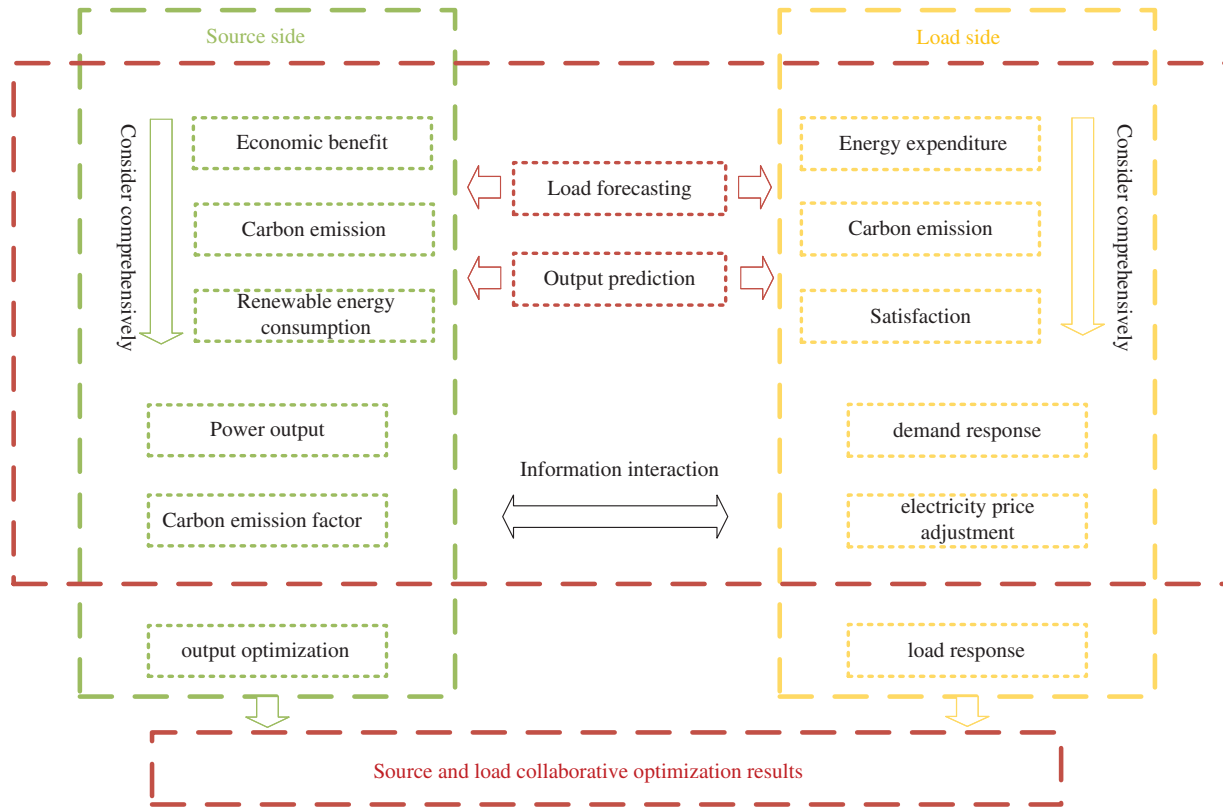


Figure 1: Schematic diagram of source load interaction

3 Reward and Punishment Ladder-Type Carbon Trading Model

The carbon trading mechanism functions as a market-based instrument for controlling carbon emissions by capping the total allowance and facilitating their trade among producers [28]. Regulatory authorities first allocate carbon emission allowances to each emission source, and producers plan their production and emissions based on their allocated quotas. This paper allocates the initial carbon allowance based on the power generation capacity of the carbon emission source, as shown in the following formula [29]:

$$\begin{cases} E_t^{q,DN} = E_t^{q,buy} + E_t^{q,GT} + E_t^{q,EV} \\ E_t^{q,buy} = \chi_e P_t^{buy} \\ E_t^{q,GT} = \chi_g P_t^{GT} \\ E_t^{q,EV} = P_t^{EV} \Delta t L_{ev} E_{gas} - \frac{P_t^{buy} P_t^{EV} E_{th} \Delta t}{P_t^{load}} \end{cases} \quad (8)$$

where: $E_t^{q,DN}$ represents the total carbon allowance (t); $E_t^{q,buy}$, $E_t^{q,GT}$, $E_t^{q,EV}$ denote the carbon allowances for purchased electricity, GT and EVs, respectively (t); χ_e and χ_g are the carbon allowance coefficients for purchased electricity and GT (t/MW·h); P_t^{buy} and P_t^{GT} represent the output of purchased electricity and GT (MW·h); L_{ev} denotes the travel distance per unit of electricity (km/MW·h); P_t^{EV} is the battery swap load (MW·h); E_{gas} represents the carbon emissions per kilometer traveled by a fuel vehicle (t/km).

The actual carbon emissions of the DN are calculated as follows:

$$\begin{cases} E_t^{a,DN} = E_t^{a,buy} + E_t^{a,GT} \\ E_t^{a,buy} = \alpha_1 P_t^{buy} \\ E_t^{a,GT} = \alpha_2 P_t^{GT} \\ E_t^{DN} = E_t^{a,DN} - E_t^{q,DN} \end{cases} \quad (9)$$

where: $E_t^{a,DN}$ denotes the actual carbon emissions of the DN (t); $E_t^{a,buy}$ and $E_t^{a,GT}$ represent the actual carbon emissions from purchased electricity and GT, respectively (t); α is the carbon emission coefficients (t/MW·h); E_t^{DN} represents the carbon emission trading volume (t).

Carbon emissions are divided into multiple intervals based on different levels, with corresponding carbon trading prices set for each interval. In the ladder-type carbon trading model, as the carbon emissions increase, the unit price for participating in carbon trading rises step by step. A positive carbon trading volume implies an excess of the load's actual carbon emissions over its allocated allowance. In this case, it is necessary to purchase additional carbon allowances from the carbon trading market. The more carbon allowances purchased, the higher the transaction price in the corresponding interval, thereby more effectively reducing the system's carbon emissions [30].

$$C_t^{CO_2} = \begin{cases} -c(2+3\zeta)h + c(1+3\zeta)(E_t^{DN} + 2h), E_t^{DN} \leq -2h \\ -c(1+\zeta)h + c(1+2\zeta)(E_t^{DN} + h), -2h \leq E_t^{DN} \leq -h \\ c(1+\zeta)E_t^{DN}, -h \leq E_t^{DN} \leq 0 \\ c(1+\gamma)E_t^{DN}, 0 \leq E_t^{DN} \leq h \\ c(1+\gamma)h + c(1+2\gamma)(E_t^{DN} - h), h \leq E_t^{DN} \leq 2h \\ c(2+3\gamma)h + c(1+3\gamma)(E_t^{DN} - 2h), E_t^{DN} \geq 2h \end{cases} \quad (10)$$

where: $C_t^{CO_2}$ denotes carbon trading cost (¥); c is the base carbon trading price (¥/t); ζ and γ are the reward and punishment coefficients, respectively; h is the length of the carbon emission interval (t).

4 Electric Vehicle Battery Swap Stations Modeling

Currently, under the EV charging mode, the grid-connection time of EVs and their participation in grid dispatch are constrained by user travel patterns and willingness, making it difficult for dispatch operators to utilize their regulation capabilities directly. Unlike charging stations, EVBSS can decouple battery clusters from EV clusters through rapid energy replenishment, enabling swap station operators to implement orderly charging scheduling for battery clusters. This allows them to benefit from renewable energy integration, electricity price arbitrage, and DR. The scheduling of battery packs within the station includes three stages: battery deposit, charging/discharging scheduling, and battery retrieval. After batteries are swapped and returned to the station, the EVBSS gains control over their charging and discharging management. While meeting swap demand, it can participate in DN dispatch by adjusting the charging and discharging power of the station's battery packs. Leveraging its unique advantages, the optimized scheduling of swap stations offers a highly promising technical pathway for the large-scale application of vehicle-grid interaction.

4.1 Electric Vehicle Battery Swap Stations Battery Life

The cycle life of an energy storage battery can be determined by power function fitting. The total number of cycles and the number of cycles within the scheduling period directly determine its cycle life expectancy. The equivalent number of cycles at 100% depth of discharge can be converted from the number of cycles

corresponding to the actual DOD of the EV battery. The specific calculation is as follows:

$$n_{eq}^{t,num} = (D_{cyc}^{t,num})^{\omega} \quad (11)$$

where: ω is the life index coefficient.

The daily equivalent full cycle count of the battery can be expressed as:

$$N_{eq}^{num} = \sum_{t=1}^T n_{eq}^{t,num} \Delta t \quad (12)$$

where: T is the scheduling period (h).

The cycle life of the battery can be calculated from the daily equivalent cycle count as follows [31]:

$$T_{cyc}^{num} = \frac{N_0}{365 N_{eq}^{num}} \quad (13)$$

where: T_{cyc}^{num} is the cycle life of the battery; N_0 is the number of cycles at 100% depth of discharge.

The actual service life of the battery can be determined based on its cycle life and float life as follows:

$$T_{life}^{num} = \min \{ T_{float}^{num}, T_{cyc}^{num} \} \quad (14)$$

where: T_{float}^{num} is the float life of the battery (year).

A complete charge-discharge cycle is defined as the process when the battery transitions from a discharging state to a charging state. The depth of discharge of the previous discharging phase is taken as the cycle depth for the current cycle:

$$D_{cyc}^{t,num} = (1 - S_{t-1}^{num}) x_{t,num}^{cyc} \quad (15)$$

where: $x_{t,num}^{cyc}$ is a binary cycle state variable, which equals 1 when a complete cycle is finished; S_{t-1}^{num} is the battery state of charge (SOC) variable.

The battery cannot be simultaneously in both charging and discharging states:

$$y_{cyc,d}^{t,num} + y_{cyc,c}^{t,num} = 1 \quad (16)$$

where: $y_{cyc,c}^{t,num}$ is a binary state variable for the charging process, which equals 1 when the battery is charging; $y_{cyc,d}^{t,num}$ is a binary state variable for the discharging process, which equals 1 when the battery is discharging.

The charging and discharging processes of the battery in the current time period are related to the charging/discharging processes of the previous time period and the charging/discharging state of the current time period:

$$\begin{cases} y_{cyc,d}^{t,num} \geq B_{b,dis}^{t,num} \\ y_{cyc,c}^{t,num} \geq B_{b,ch}^{t,num} \\ y_{cyc,d}^{t,num} \geq y_{cyc,d}^{t-1,num} - B_{b,dis}^{t,num} - B_{b,ch}^{t,num} \\ y_{cyc,c}^{t,num} \geq y_{cyc,c}^{t-1,num} - B_{b,dis}^{t,num} - B_{b,ch}^{t,num} \end{cases} \quad (17)$$

where: $B_{b,ch}^{t,num}$ and $B_{b,dis}^{t,num}$ are the charging/discharging indicator variables; $B_{b,ch}^{t,num}$ equals 1 indicates the battery is in a charging state; $B_{b,dis}^{t,num}$ equals 1 indicates the battery is in a discharging state.

A complete charge-discharge cycle is determined when the battery transitions from a discharging process to a charging process:

$$x_{t,num}^{cyc} = \max \{y_{cyc,c}^{t,num} - y_{cyc,c}^{t-1,num}, 0\} \quad (18)$$

Battery operation incurs life degradation, which can be managed by constraining the daily cycle count to regulate the battery's cycle life.

$$T_{life}^{num} \geq T_{plan}^{num} \quad (19)$$

where: T_{plan}^{num} represents the planned service life of the battery (year).

4.2 EVBSS Operational Constraints

The charge and discharge power of the EVBSS batteries is bounded by the following constraints [32]:

$$\begin{cases} 0 \leq P_{b,ch}^{t,num} \leq P_{b,ch}^{max,num} B_{b,ch}^{t,num} \\ 0 \leq P_{b,dis}^{t,num} \leq P_{b,dis}^{max,num} B_{b,dis}^{t,num} \end{cases} \quad (20)$$

where: $P_{b,ch}^{t,num}$ and $P_{b,dis}^{t,num}$ represent the active charging and discharging power of the battery, respectively (MW·h); $P_{b,ch}^{max,num}$ and $P_{b,dis}^{max,num}$ denote the maximum allowable active charging and discharging power, respectively (MW·h).

The same battery cannot be charged and discharged simultaneously, thus the following charging/discharging state constraints are defined [33]:

$$B_{b,ch}^{t,num} + B_{b,dis}^{t,num} \leq 1 \quad (21)$$

Furthermore, the total number of EV batteries being charged and discharged simultaneously must not exceed the number of charging machines available in the EVBSS.

$$\sum_{num}^{N_{battery}} (B_{b,ch}^{t,num} + B_{b,dis}^{t,num}) \leq N_{charging} \quad (22)$$

where: $N_{battery}$ is the number of batteries in the EVBSS; $N_{charging}$ is the number of charging machines in the EVBSS.

The battery swapping operation in the EVBSS is modeled through a swapping variable as follows:

$$S_{t+1}^{num} = S_t^{num} + \frac{P_{b,ch}^{t,num} \eta_{ch}^{num} \Delta t}{E_{cap}^{num}} - \frac{P_{b,dis}^{t,num} \Delta t}{E_{cap}^{num} \eta_{dis}^{num}} - H_t^{num} \left(1 - \frac{S_{ncar,t}^{EV}}{E_{cap}^{num}} \right) \quad (23)$$

$$S_{min}^{num} \leq S_t^{num} \leq S_{max}^{num} \quad (24)$$

where: η_{ch}^{num} and η_{dis}^{num} are the charging and discharging efficiencies of the charger, respectively(%); H_t^{num} is the battery swapping state variable; $S_{ncar,t}^{EV}$ is the remaining energy of EV before battery swapping.

To ensure sufficient battery charge during swapping, the battery status is constrained such that only fully charged batteries can be swapped out:

$$S_{max}^{num} M_t^{num} \leq S_t^{num} \leq S_{max}^{num} (M_t^{num} + 1) \quad (25)$$

$$H_t^{num} \leq M_t^{num} \quad (26)$$

where: M_t^{num} is the full-charge state variable.

To meet user battery swap demand, the number of fully charged batteries in each period must be greater than or equal to the swap demand:

$$\sum_{num=1}^{N_{battery}} M_t^{num} \geq N_t^{need} \quad (27)$$

where: N_t^{need} is the battery swap demand during time period t .

To ensure operational sustainability, the total energy stored and the number of fully charged batteries in the EVBSS at the end of the scheduling period must equal the respective values at the beginning of the period:

$$\begin{cases} \sum_{num=1}^{N_{battery}} S_0^{num} = \sum_{num=1}^{N_{battery}} S_T^{num} \\ \sum_{num=1}^{N_{battery}} M_0^{num} = \sum_{num=1}^{N_{battery}} M_T^{num} \end{cases} \quad (28)$$

where: S_0^{num} is the initial energy of the battery; S_T^{num} is the battery energy at the end of the scheduling period; M_0^{num} is the initial full-charge state of the battery; M_T^{num} is the full-charge state of the battery at the end of the scheduling period.

5 Two-Stage Scheduling Model for Distribution Networks

5.1 First Stage

To enhance the economic efficiency and operational reliability of distribution networks, this paper proposes an optimization model for DNs with high penetration of renewable energy, integrating LCDR and battery life degradation of. The model incorporates control variables such as on-load tap changer (OLTC) tap positions, distributed generator (DG) output, EVBSS charging/discharging, capacitor bank (CB) switching, and static var compensator (SVC) output. With the objective of minimizing total costs, the model is formulated as follows:

$$Z = \min \sum_{t=1}^T \left(C_t^{\text{grid}} + C_t^{\text{gt}} + C_t^{\text{wt}} + C_t^{\text{pv}} + C_t^{\text{CO}_2} \right) \quad (29)$$

where: C_t^{grid} is the cost of interaction with the main grid (¥); C_t^{gt} , C_t^{wt} and C_t^{pv} denote the maintenance costs of the gas turbine, wind power, and photovoltaic generation, respectively (¥).

The main constraints in the model are as follows:

(1) Power Flow Constraints [34]

$$P_{i,t} = G_{ii} U_{i,t}^2 + \sum_{j \in \Omega} U_{i,t} U_{j,t} (G_{ij} \cos \theta_{ij,t} + B_{ij} \sin \theta_{ij,t}) = P_{i,t}^{\text{grid}} + P_{i,t}^{\text{GT}} + P_{i,t}^{\text{DG}} + P_{i,t}^{\text{BSS}} - P_{i,t}^{\text{load}} \quad (30)$$

$$Q_{i,t} = -B_{ii} U_{i,t}^2 - \sum_{j \in \Omega} U_{i,t} U_{j,t} (B_{ij} \cos \theta_{ij,t} - G_{ij} \sin \theta_{ij,t}) = Q_{i,t}^{\text{grid}} + Q_{i,t}^{\text{CB}} + Q_{i,t}^{\text{SVG}} - Q_{i,t}^{\text{load}} \quad (31)$$

$$U_{i,t}^2 - U_{j,t}^2 + (r_{ij}^2 + x_{ij}^2) I_{ij,t}^2 + 2(r_{ij} P_{ij,t} + x_{ij} Q_{ij,t}) = 0 \quad (32)$$

where: $P_{i,t}$ and $Q_{i,t}$ represent the active and reactive power at node i at time t , respectively; G_{ii} and G_{ij} are the real parts of the self-admittance at node i and the mutual admittance between nodes i and j , respectively; $\theta_{ij,t}$ denotes the voltage phase angle difference between nodes i and j ; $P_{i,t}^{\text{load}}$ and $Q_{i,t}^{\text{load}}$ are the active and reactive loads at node i , respectively; $P_{i,t}^{\text{grid}}$ and $Q_{i,t}^{\text{grid}}$ represent the active and reactive power injected into node i at time t , respectively; $P_{i,t}^{\text{DG}}$ and $P_{i,t}^{\text{GT}}$ denote the active power outputs of the DG and GT, respectively; B_{ii} and B_{ij} are the imaginary parts of the self-admittance at node i and the mutual admittance between nodes i and j , respectively; $Q_{i,t}^{\text{CB}}$ is the reactive power output of CB; $P_{i,t}^{\text{bss}}$ represents the charging/discharging power of the EVBSS.

(2) Node Voltage Constraint [35]

$$U_i^{\min} \leq U_{i,t} \leq U_i^{\max} \quad (33)$$

where: $U_i^{\max}$ and $U_i^{\min}$ represent the maximum and minimum operating voltage limits at node i , respectively.

$$I_{ij,t}^2 = (G_{ij}^2 + B_{ij}^2) (U_{i,t}^2 + U_{j,t}^2 - 2U_{i,t}U_{j,t} \cos \theta_{ij,t}) \quad (34)$$

$$I_{ij,t}^2 \leq I_{ij,\max}^2 \quad (35)$$

where: $I_{ij,\max}$ represents the maximum allowable current on the line between node i and node j .

(3) CB Constraints [36]

$$Q_{i,t}^{\text{CB}} = \sigma_{i,t}^{\text{CB}} \cdot Q_{i,\text{step}}^{\text{CB}} \quad (36)$$

where: $\sigma_{i,t}^{\text{CB}}$ represents the number of CB switched in/out at time t ; $Q_{i,\text{step}}^{\text{CB}}$ is the reactive power change per unit of CB (MVA).

Typically, the adjustment range and the number of adjustments for CB units in the distribution network are also subject to certain constraints:

$$\begin{cases} \delta_{\text{CBIN},i,t} + \delta_{\text{CBDE},i,t} \leq 1 \\ \sum_{t=1}^T (\delta_{\text{CBIN},i,t} + \delta_{\text{CBDE},i,t}) \leq N_{\text{CBmax},i} \\ \sigma_{\text{CB},i,t} - \sigma_{\text{CB},i,t-1} \leq \delta_{\text{CBIN},i,t} S_{\text{RCB},i} - \delta_{\text{CBDE},i,t} \\ \sigma_{\text{CB},i,t} - \sigma_{\text{CB},i,t-1} \geq \delta_{\text{CBIN},i,t} - \delta_{\text{CBDE},i,t} S_{\text{RCB},i} \end{cases} \quad (37)$$

where: $\delta_{\text{CBIN},i,t}$, $\delta_{\text{CBDE},i,t}$ are binary indicators for CB switching operations; $N_{\text{CBmax},i}$ is the maximum number of switching operations allowed; $S_{\text{RCB},i}$ is the maximum number of CB units that can be switched per operation.

(4) SVC Constraints

The capability of the SVC to provide continuous reactive power compensation is subject to the following constraints:

$$Q_{i,\min}^{\text{SVC}} \leq Q_{i,t}^{\text{SVC}} \leq Q_{i,\max}^{\text{SVC}} \quad (38)$$

where: $Q_{i,\min}^{\text{SVC}}$ and $Q_{i,\max}^{\text{SVC}}$ represent the operating limits for the reactive power generated by the SVC, respectively (MVA).

(5) OLTC Constraints [37]

The voltage at the substation bus nodes in the distribution network can be effectively regulated by OLTC, thereby improving the voltage profile of the distribution network. This can be described as:

$$\begin{cases} U_{i,t}^2 = U_{0,f}^2 \cdot K_t^{\text{OLTC}} \\ K_{\min}^{\text{OLTC}} \leq K_t^{\text{OLTC}} \leq K_{\max}^{\text{OLTC}} \\ K_t^{\text{OLTC}} = K_{\min}^{\text{OLTC}} + \sum_s \gamma_s^{\text{OLTC}} \cdot \sigma_{s,t}^{\text{OLTC}} \end{cases} \quad (39)$$

$$\delta_N^{\text{OLTC}} + \delta_D^{\text{OLTC}} \leq 1 \quad (40)$$

$$\sum_s \sigma_{s,t}^{\text{OLTC}} - \sum_s \sigma_{s,t-1}^{\text{OLTC}} \geq \delta_N^{\text{OLTC}} - \delta_D^{\text{OLTC}} S_{\text{ROLTC}} \quad (41)$$

$$\sum_s \sigma_{s,t}^{\text{OLTC}} - \sum_{s, t-1}^{\text{OLTC}} \leq \delta_N^{\text{OLTC}} S_{\text{ROLTC}} - \delta_D^{\text{OLTC}} \quad (42)$$

$$\sum_{\tau=1}^t (\delta_{N,\tau}^{\text{OLTC}} + \delta_{D,\tau}^{\text{OLTC}}) \leq N_{\max}^{\text{OLTC}} \quad (43)$$

where: $U_{0,f}^2$ represents the square of the reference voltage; K_t^{OLTC} denotes the square of the tap ratio of OLTC; $K_{\min}^{\text{OLTC}}$ and $K_{\max}^{\text{OLTC}}$ are the minimum and maximum values of the squared tap ratio, respectively; γ_s^{OLTC} is the adjustment state variable of the tap ratio; $\sigma_{s,t}^{\text{OLTC}}$ is a binary variable indicating whether the tap ratio is adjusted; $\delta_{N,\tau}^{\text{OLTC}}$ represents the step size of the tap adjustment; $N_{\max}^{\text{OLTC}}$ is the maximum allowable number of tap adjustments within the scheduling period.

(6) Constraints on Power Exchange with Main Grid

$$P_{i,\min}^{\text{grid}} \leq P_{i,t}^{\text{grid}} \leq P_{i,\max}^{\text{grid}} \quad (44)$$

$$\Delta P_{i,\min}^{\text{grid}} \leq P_{i,t+1}^{\text{grid}} - P_{i,t}^{\text{grid}} \leq \Delta P_{i,\max}^{\text{grid}} \quad (45)$$

where: $P_{i,\max}^{\text{grid}}$ and $P_{i,\min}^{\text{grid}}$ represent the maximum and minimum values of the power exchange between the DN and the main grid, respectively (MW·h); $\Delta P_{i,\max}^{\text{grid}}$ and $\Delta P_{i,\min}^{\text{grid}}$ denote the maximum and minimum ramping power limits for the power exchange between the DN and the main grid, respectively (MW·h).

(7) Power Balance Constraints

$$P_t^{\text{grid}} + P_t^{\text{GT}} + P_t^{\text{DG}} + P_{\text{dis},t}^{\text{BSS}} = P_t^{\text{load}} + P_t^{\text{loss}} + P_{\text{ch},t}^{\text{BSS}} \quad (46)$$

where: P_t^{loss} represents the power loss of the DN (MW·h).

(8) Output Constraints

$$\begin{cases} P_{\min}^{\text{GT}} \leq P_t^{\text{GT}} \leq P_{\max}^{\text{GT}} \\ P_{\min}^{\text{DG}} \leq P_t^{\text{DG}} \leq P_{\max}^{\text{DG}} \end{cases} \quad (47)$$

where: $P_{\min}^{\text{GT}}$ and $P_{\max}^{\text{GT}}$ are the lower and upper output limits of GT, respectively (MW·h); $P_{\min}^{\text{DG}}$ and $P_{\max}^{\text{DG}}$ are the lower and upper output limits of the DG, respectively (MW·h).

5.2 Second Stage

In the second stage, the LCDR aims to maximize consumer surplus, which is achieved by minimizing the electricity purchase cost and maximizing the electricity consumption utility [38]. This results in an optimized load curve. The electricity price used in the second stage is derived from the dynamic carbon emission factor

obtained in the first stage, calculated through the LCDR model. The objective function is formulated as follows:

$$\begin{cases} \max f_{\text{LCDR}} = I(P_{\text{Load},t}^{\text{LCDR}}) - P_{\text{Load},t}^{\text{LCDR}} P_{\text{price},t}^{\text{LCDR}} \\ I(P_{\text{Load},t}^{\text{LCDR}}) = a_1 P_{\text{Load},t}^{\text{LCDR}} - \frac{a_2}{2} (P_{\text{Load},t}^{\text{LCDR}})^2 \end{cases} \quad (48)$$

where: f_{LCDR} represents the total consumer surplus; $P_{\text{Load},t}^{\text{LCDR}}$ is the load after implementing LCDR; $I(P_{\text{Load},t}^{\text{LCDR}})$ is the electricity utility function; a denotes the consumer electricity preference coefficient.

The constraints primarily include load transfer constraints, as detailed below:

$$\begin{cases} \sum_{t=1}^T P_{\text{Load},t}^{\text{PBDR}} = \sum_{t=1}^T P_{\text{Load},t}^{\text{LCDR}} \\ -b P_{\text{Load},t}^{\text{PBDR}} \leq P_{\text{Load},t}^{\text{PBDR}} - P_{\text{Load},t}^{\text{LCDR}} \leq b P_{\text{Load},t}^{\text{PBDR}} \end{cases} \quad (49)$$

where: b represents the load transfer limit under LCDR.

In the second stage, after obtaining the optimized load curve, the objective function and constraints remain identical to those in the first stage and are therefore not reiterated. The solution process is illustrated in Fig. 2.

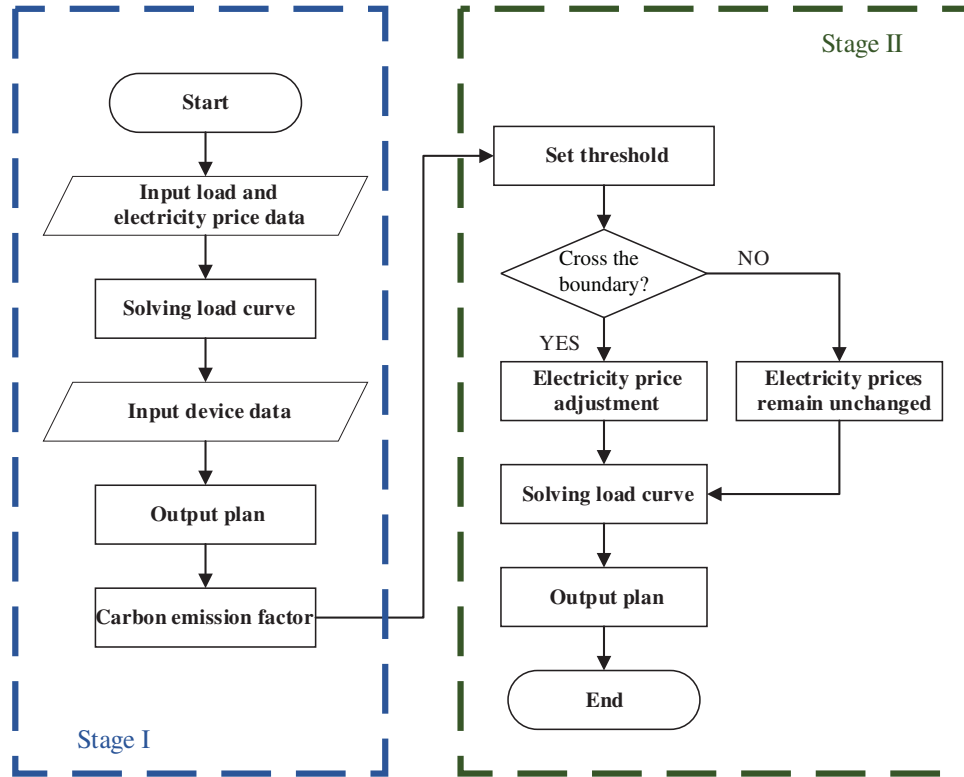


Figure 2: Solution flowchart

6 Case Study

6.1 Case Introduction

This paper employs an improved IEEE-33 bus DN for case analysis, with the system structure diagram shown in Fig. 3. The established model is implemented on the MATLAB platform using the YALMIP

toolbox and solved with GUROBI. The total scheduling period is 24 h with a unit scheduling interval of 1 h. The forecasted source and load power values are presented in Fig. 4, while the scenario information is summarized in Table 1.

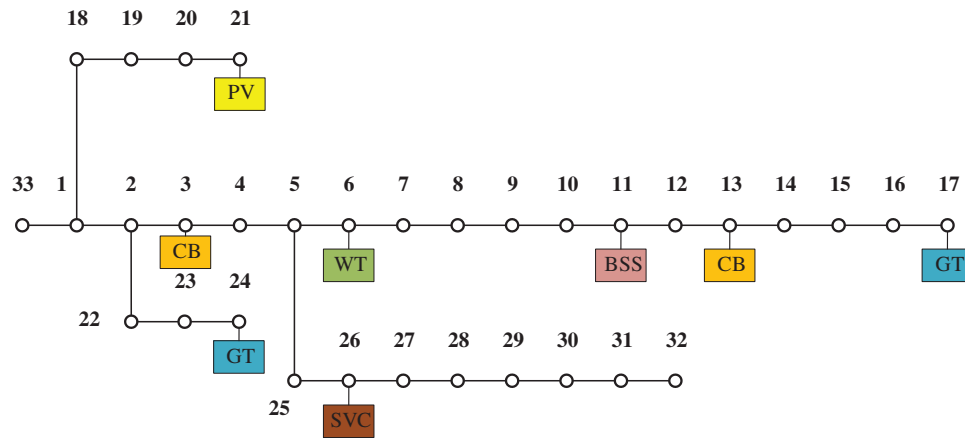


Figure 3: Distribution network topology

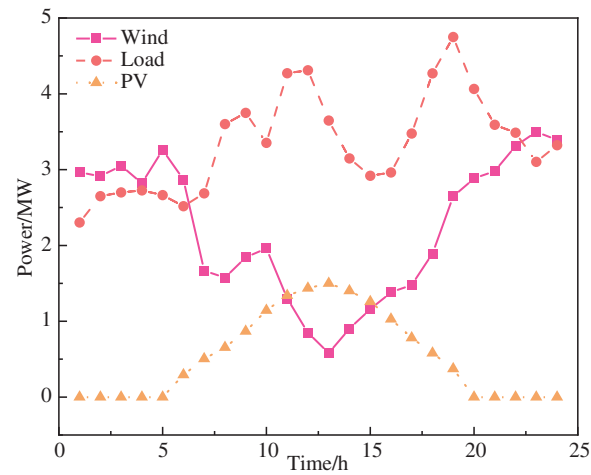


Figure 4: PV, WT and load prediction curve

Table 1: Scenario classification

Scenario	Battery life	RPLCT	PBDR	LCDR
1	×	×	×	×
2	✓	×	×	×
3	✓	✓	×	×
4	✓	✓	✓	×
5	✓	✓	✓	✓

6.2 Load Curve Optimization Analysis

Fig. 5 illustrates the load curves for Scenario 3–5. As observed, Scenario 4 considers DR, where partial load is curtailed during peak hours and shifted to off-peak periods. The peak-to-valley load difference before DR implementation was 2.45 MW·h, which reduced to 2 MW·h after DR implementation, indicating an improvement in load leveling. However, load during low-demand periods (periods 1–7) was partially shifted outward, further deepening the load valley and adversely affecting wind power integration. In contrast, LCDR shifts load from high-carbon periods to low-carbon periods, further enhancing peak shaving and valley filling, and ultimately contributing to reduced system carbon emissions.

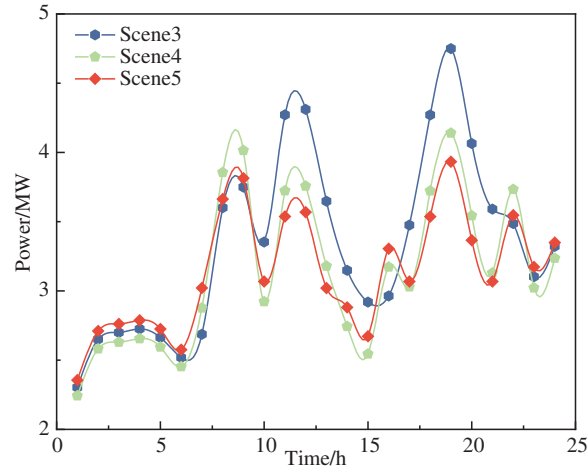


Figure 5: Load curve

6.3 Parameter Sensitivity Analysis

Fluctuations in international energy prices can impact the supply-demand balance in the energy market, which in turn affects carbon emission demands and ultimately leads to volatility in carbon trading prices. In Scenario 3, an analysis was conducted on the impacts of different carbon trading prices, carbon emission interval lengths, and carbon emission thresholds, with the results shown in Figs. 6–8.

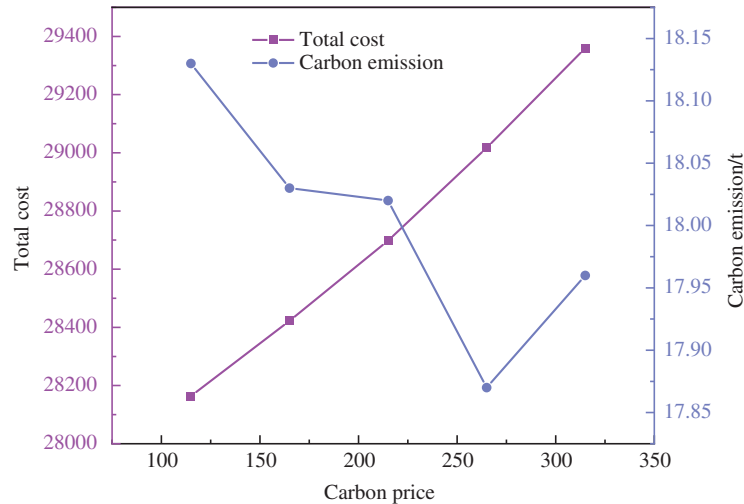


Figure 6: Impact of carbon emission price

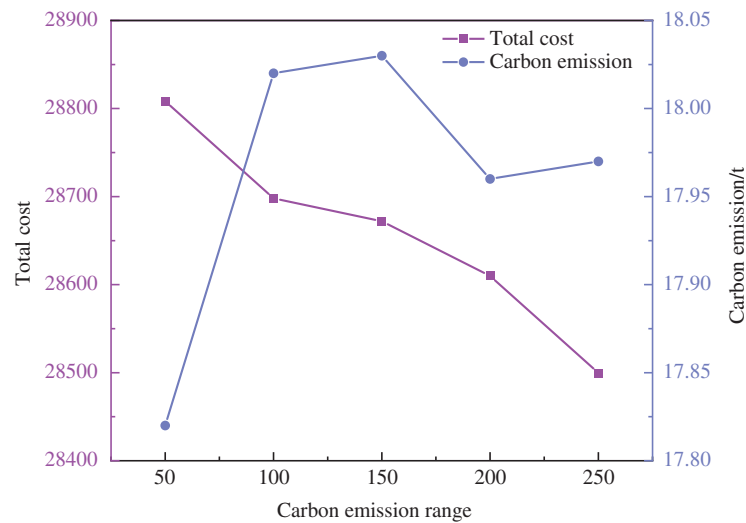


Figure 7: Impact of carbon emission interval

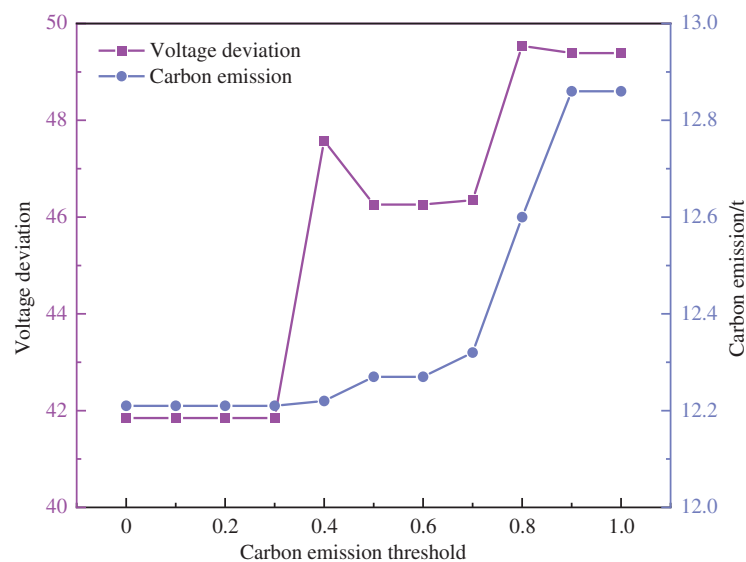


Figure 8: Impact of carbon emission threshold

It is evident that as carbon trading price increases, carbon emission level initially decreases at a relatively rapid rate. After reaching a low point, it begins to rise again. This indicates that when the carbon price exceeds a certain level, it loses its regulatory function for carbon reduction. Beyond this point, further price increases no longer lead to continued reduction in carbon emissions from the distribution network but only raise the total operating cost. As the interval length increases, the quantity of carbon allowances that need to be purchased at higher-tier prices decreases, resulting in a lower total cost. With the gradual decrease in carbon emission costs, the system's carbon emissions gradually increase. As the carbon emission threshold increases, both voltage deviation and carbon emissions rise. After exceeding 0.4 t, the voltage deviation increases significantly, which is detrimental to the stable operation of the distribution network. The best carbon reduction effect is achieved within the range of 0–0.3 t. However, an excessively low threshold would

impose penalties even during low-carbon periods, undermining the intended function of LCDR. Therefore, a value of 0.3 t is selected for the simulations in this paper.

6.4 Analysis of Scheduling Results

The scheduling schemes for each scenario are shown in Fig. 9, with results summarized in Table 2, while Fig. 10 illustrates the scheduling scheme within the EVBSS. From Fig. 9a, it can be observed that the EVBSS charges during nighttime periods of high wind power generation and discharges during the midday peak load periods, thereby promoting the integration of renewable energy. In Fig. 9b, after considering battery life constraints, discharging ceases during period 18, resulting in reduced discharge from the EVBSS. Combined with Fig. 10a, compared to other scenarios, the SOC in Scenario 2 remains at a relatively high level, which weakens the regulating capability of the EVBSS, but extends the battery life from 9.63 to 10 years. A small amount of electricity purchase occurs during periods 2–4, and data in Table 2 indicate that this increase in purchased electricity leads to higher carbon emissions.

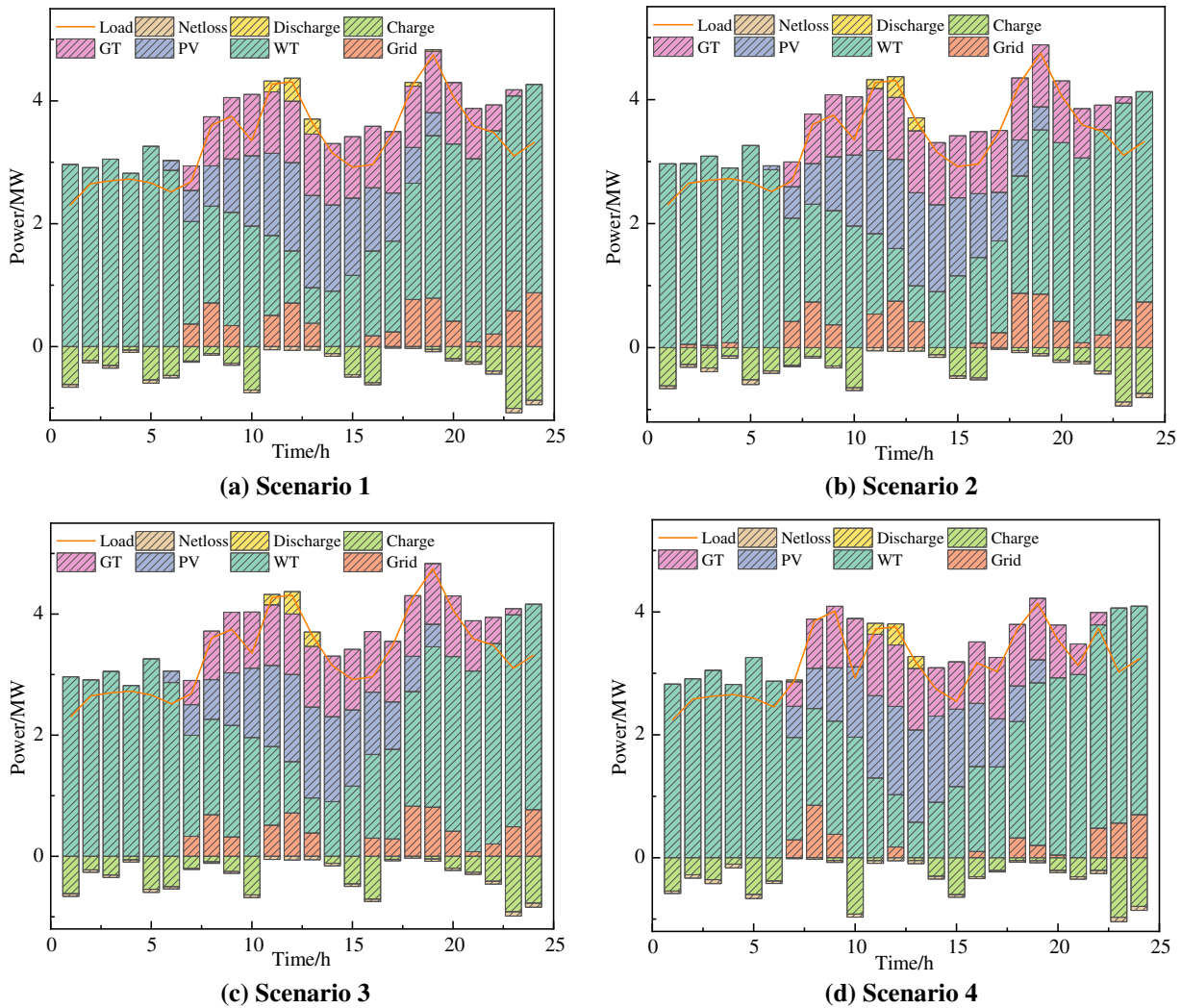
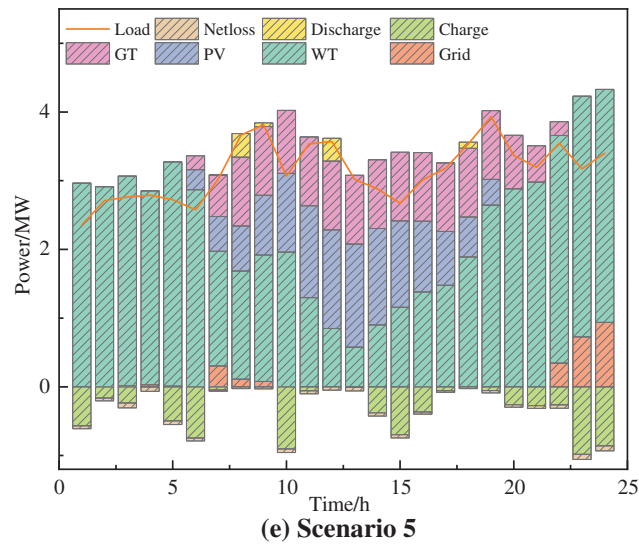
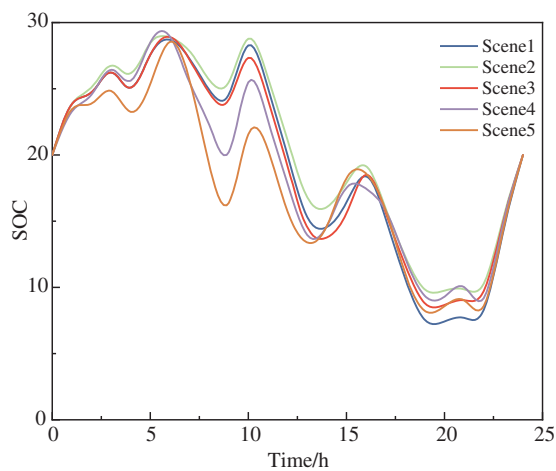
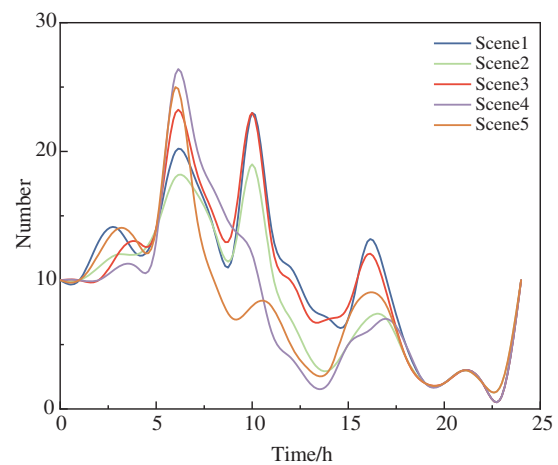


Figure 9: (Continued)

**Figure 9:** Scheduling schemes under different scenarios**Table 2:** Scheduling results under different scenarios

Scenario	1	2	3	4	5
Total cost/¥	27,355.15	27,476.28	28,755.48	25,005.9	24,596.01
Electricity purchase cost/¥	4812.37	5021.93	4883.02	2351.19	1275.25
Carbon trading cost/¥	–	–	1347.75	979.2	912.38
Carbon emissions/t	17.89	18.03	17.85	13.62	12.74
Wind curtailment/MWH	0	0	0	0.14	0
Solar curtailment/MWH	0.13	0.23	0.1	0.29	0
Average battery life/year	9.63	10	10	10	10

**(a) EVBSS SOC profile****(b) Number of fully charged batteries****Figure 10:** EVBSS scheduling scheme

In Fig. 9c, the introduction of RPLCT suppresses the output of high-carbon emission sources, eliminating electricity purchases during periods 2–4. Simultaneously, solar curtailment is reduced by 0.13 MWh, leading to a decrease in total system carbon emissions by 0.18 t. However, the distribution network remains a net emitter overall, and the incurred carbon trading cost contributes to an increase in the total cost. In Fig. 9d, load optimization significantly reduces the amount of electricity purchased, decreasing the total cost by 13.04%. However, wind and solar curtailment increase by 0.14 and 0.19 MWh, respectively, which is unfavorable for renewable energy integration.

In Scenario 5, the application of LCDR shifts loads to low-carbon periods. Compared to Scenario 4, the electricity purchase is further reduced, occurring only during 8 periods, which lowers the total cost. Combined with Fig. 10, the EVBSS charges primarily during periods of high wind and solar power generation, achieving full utilization of both wind and solar energy and reducing carbon emissions by 1.22 t.

6.5 Analysis of Carbon Reduction Effect

The carbon emission trading volumes are shown in Fig. 11. During the initial phase of the optimization cycle, the carbon emission allowances for both scenarios are extremely low negative values or zero. At this stage, when the system begins operation, carbon trading costs are not yet a dominant factor. Starting from period 7, the distribution network enters its peak energy consumption period, and the carbon emission allowance rises sharply, turning positive. This is also the phase where the strategies of the two scenarios differ most significantly. In Scenario 4, the carbon emission allowance peaks in period 8. Under demand response that considers only economic factors, the system may allow higher-carbon units to generate more power during peak periods to reduce total costs, leading to a sharp increase in carbon allowance consumption. In contrast, the peak value in Scenario 5 is significantly lower than in Scenario 4, and the carbon emission allowance throughout the peak period is generally more stable and lower. This fully demonstrates the core advantage of LCDR: by internalizing carbon costs, the system's optimal scheduling actively suppresses the output of high-carbon units and guides load shifting to cleaner energy sources or time periods, thereby effectively reducing the carbon intensity during peak hours. During periods 20–24, the carbon emission trading volume in Scenario 5 remains at a relatively low level of 0.10–0.16 t, while the values in Scenario 4 during the same period are more volatile and generally higher. After the peak period, the carbon emission allowances in both scenarios decrease, but Scenario 5 still outperforms Scenario 4 overall.

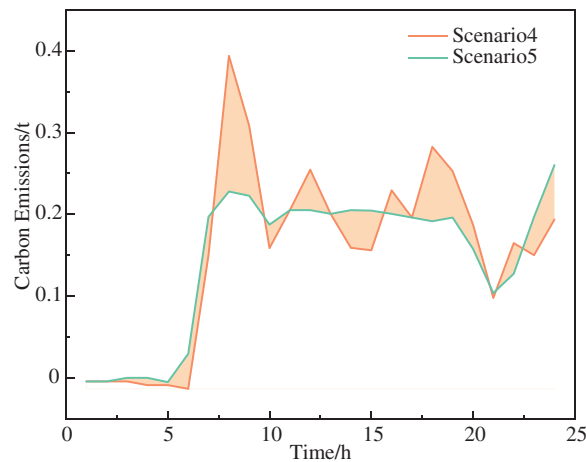


Figure 11: Distribution of carbon trading volume

LCDR significantly suppresses carbon emissions during the system's peak energy consumption periods and maintains a lower, more stable distribution of carbon emissions throughout the day. The efficacy of the proposed LCDR model is demonstrated by its successful guidance of energy consumption behavior, which promotes the power system's low-carbon operation.

6.6 Impact of Battery Swap Demand

In Scenario 5, an analysis was conducted on the impact of different battery swap demands on scheduling, with the results shown in Table 3. It is apparent from the data that the total system cost, electricity purchase cost, and carbon trading cost all exhibit a significant increasing trend as the battery swap demand rises. This is because meeting the higher load requires the system to purchase more electricity from the external grid, leading to a substantial increase in the power purchase cost.

Table 3: Scheduling results under different battery swap demands

Number	36	60	84	104
Total cost/¥	23,273.09	24,596.01	26,553.69	28,779.53
Electricity purchase cost/¥	1244.53	1275.25	2610.8	3761.35
Carbon trading cost/¥	804.84	912.38	1071.55	1221.82
Carbon emissions/t	11.19	12.74	15.15	17.26
Wind curtailment rate/%	0.13	0	0	0
Solar curtailment rate/%	2.15	0	0	0

The impact of battery swap demand on renewable energy integration exhibits a “threshold effect”. At low demand levels, the system experiences certain wind and solar curtailment rates. However, when the battery swap demand increases to 60 or more instances, both the wind and solar curtailment rates drop to zero. This indicates that a moderate battery swap demand effectively enhances the system's ability to integrate intermittent renewable energy sources. Yet, when the demand further increases to 84 and 104 instances, local renewable energy may have already reached its maximum output capacity. The additional power demand must then be met by increasing external electricity purchases. After achieving full renewable integration, both the electricity purchase cost and carbon emissions continue to accelerate their rise. Battery swap demand is a core variable affecting the scheduling strategy of EVBSS. Its growth initially helps promote renewable energy integration, but beyond a certain point, it primarily leads to a significant increase in both economic and environmental costs.

7 Conclusion

Based on a DN incorporating EVBSS, this paper constructs a two-stage optimal scheduling model that considers LCDR and the battery life of EVBSS. By introducing RPLCT on the source side and considering LCDR on the load side, the model facilitates coordination between source and load, balancing the low-carbon and economic objectives of the DN. The inclusion of battery life constraints effectively addresses the over-idealization in traditional scheduling results, providing a reference for DN scheduling involving EVBSS. The conclusions from the case study are as follows:

- (1) LCDR exploits the carbon reduction potential of the DN, reducing carbon emissions by 8.92% compared to traditional DR and achieving full accommodation of renewable energy.
- (2) RPLCT more effectively guides carbon emission reduction, demonstrating that appropriate carbon trading parameters can steer the system's carbon emissions.

- (3) Considering battery life helps develop rational scheduling strategies, avoids over-optimistic results, reduces battery degradation in EVBSS, enhances their willingness to participate in scheduling, and ensures outcome reliability and system economic optimization.

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Availability of Data and Materials: Due to the nature of this research, participants of this study did not agree for their data to be shared publicly, so supporting data is not available.

Ethics Approval: Not applicable.

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