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Stochastic Optimal Scheduling Analysis of Electric Vehicle Access to Microgrid Considering Multiple Uncertainties

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Abstract

The integration of new energy generation equipment into the microgrid can effectively reduce energy consumption and operational costs. However, due to the inherent spatial and temporal variability of sources such as wind and photovoltaic (PV) power, their integration poses challenges for grid stability. To address these issues, this paper proposes a stochastic optimal scheduling model for microgrids incorporating electric vehicle participation and multiple sources of uncertainty. Historical data on loads, wind power, and PV generation are first collected and modeled to capture their spatiotemporal uncertainties. As bidirectional energy carriers integrated into the power grid, electric vehicles (EVs) possess both charging and discharging capabilities, which can effectively alleviate the operational pressure on traditional energy storage systems. Against this backdrop, this study establishes an EV user travel model by collecting relevant data, and further regards EVs as an aggregated cluster connected to the power grid to conduct charging and discharging scheduling optimization. Since the charging and discharging processes contribute to battery degradation, participating EV users are provided with subsidies to compensate for associated costs. This mechanism reduces both the operational costs of the microgrid and the charging expenses for EV users, while enhancing power system stability and reducing carbon emissions. Simulation results demonstrate that, compared to the conventional distribution network operating independently, the proposed model significantly improves the overall benefits for both the microgrid and its users. Additionally, it achieves cost and carbon emission reductions, enhances system stability and economic performance, and offers a novel approach for optimal microgrid scheduling.

Keywords: new energy, electric vehicle, microgrid, uncertainty, battery degradation, stochastic optimization

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1. Introduction

Microgrids, as a crucial component of power systems, improve energy storage devices, thereby achieving low-carbon operation[1]. Nowadays, the proportion of renewable energy in the microgrid is gradually increasing. However, the large-scale integration of renewable energy into the power grid inevitably introduces substantial changes and operational challenges to the existing system, necessitating a range of measures to ensure its secure and stable operation[2]. Meanwhile, the market penetration of new energy vehicles in China has exhibited a sustained upward trend. This rapid expansion has not only redefined the competitive dynamics of the conventional automotive sector but has also imposed new demands and constraints on the existing power infrastructure[3-4]. Current research on low-carbon

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economic dispatch in power systems can be divided into two primary areas: source-load collaborative low-carbon operation and low-carbon dispatch of flexible load-storage resources. In terms of source-load collaborative low-carbon operation, power generation can achieve low-carbon electricity production by optimizing the combination of power plants, considering carbon emission costs[5-6]. However, as the share of renewable energy sources, such as wind and solar power, increases in the power system, the inherent uncertainty of these energy sources will significantly affect the stable operation of the system[7-8]. As the proportion of wind power in the system rises, the volatility and randomness of wind power will inevitably impact the safe and stable operation of the system, potentially leading to severe consequences. This is particularly evident during prolonged extreme weather events, where the likelihood of wind power ramping phenomena—sharp increases (ramping up) or decreases (ramping down) in wind power output—significantly increases. These phenomena not only severely affect grid stability, such as deteriorating power quality, but may also lead to system frequency instability or load shedding[9]. When the proportion of photovoltaic (PV) power generation in the system increases, it is essential to configure energy storage systems as buffers to mitigate the time-varying nature of PV power generation, ensuring the system's stable operation[10-12]. When PV generation is less than the electricity load, the energy storage system must supply power to meet demand; when PV generation exceeds the load, the energy storage system charges to store excess energy[13-15]. The uncertainty of photovoltaic power generation requires in-depth research[16-18]. Research on the uncertainty of wind and solar power has made notable progress. Some literatures combine genetic algorithms and adaptive cuckoo search algorithms to reduce the total operating cost of microgrids[19]. Some literatures employ deep learning models to quantitatively analyze uncertainty and its probability density[20]. Some literatures formulate the operational cost of the microgrid system, user load demand response compensation, and penalties for wind and solar power curtailment as objective functions in the optimization scheduling model, thereby enhancing the integration capacity of distributed energy sources[21]. Some literatures establish a robust optimization scheduling model for multi-microgrids incorporating uncertainty[22]. Some literatures integrate demand response mechanisms with PV grid connection to effectively mitigate the uncertainties associated with PV generation[23]. Some literatures address wind power prediction uncertainty by maximizing the probability of correct selection and minimizing expected opportunity costs[24]. Most of the aforementioned studies primarily integrate the uncertainty of new energy generation with existing mechanisms, such as batteries and demand response, using relatively simple methods that incur higher costs. If the charging and discharging functions of EVs are effectively integrated with renewable energy generation, a power system operation centered around EV users can be achieved, thereby reducing operational costs and improving the stability of the power system.

Currently, research has been conducted on the participation of EVs in power grid dispatching, with the majority focusing on their orderly participation. Some literatures analyze the impact of EV charging and discharging behaviours on the power supply capacity of microgrids containing EVs[25]. Some literatures investigate the optimization of interests between agents and EV owners[26]. Some literatures propose a scenario-based stochastic optimal dispatching model for microgrids with EV integration[27]. Some literatures guide EV charging behaviors by regulating time-of-use electricity prices during peak and off-peak periods[28]. Some literatures introduce a mathematical model for peer-to-peer (P2P) electricity trading among EVs, based on the Hyperledger Fabric framework, facilitating electricity sharing between vehicles[29-31]. Some literatures use the Monte Carlo Simulation (MCS) method to model the driving rules of EVs, determining the probability of daily driving distance and user travel characteristics, in order to develop models for optimal dispatching[32]. Some literatures explore the relationship between battery discharge and capacity degradation, establishing a battery cycle life loss model that incorporates discharge depth and intervals[33-36]. Some literatures examine the effects of the joint dispatching model for EVs and the agent dispatching model on day-ahead market electricity prices[37].

However, most of the existing literature focuses on relatively single models, which fail to coordinate EV dispatching with other energy sources in the grid and do not address the diverse internal infrastructure in microgrids at the current stage. Some of them does not account for the travel patterns of EVs or the timing of their grid connection. Some others optimizes only the charging scenarios of EVs without considering discharging conditions. Some others considers only the unordered charging model of EVs and neglects their discharging model. And some studies investigate the battery degradation characteristics under the scenario of orderly charging, yet they fail to incorporate the unordered charging mode of EVs into the established model.

To address the aforementioned issues, reduce carbon emissions, and enhance the economic benefits of microgrids as well as the electricity consumption experience of EV users, this paper proposes a stochastic optimization scheduling model for microgrids integrated with electric vehicles, which takes into account various uncertainties. To mitigate the impact of the uncertainty associated with new energy generation, Latin hypercube sampling (LHS) and the PAM algorithm are employed to generate new energy output scenarios, thereby capturing their inherent uncertainty. The Monte Carlo method is then used to simulate EV travel patterns, determining the time intervals for EV charging and discharging, as well as their associated electricity losses. Based on this, this paper refers to various literature to simulate the battery loss during the charging and discharging process of electric vehicles and compensates users, thereby better fitting the actual situation. Guided by constraint functions, the paper aims to minimize the total operational cost of the microgrid and the total cost of EV charging and discharging as optimization objectives. An optimal scheduling model for microgrids with EV integration is developed, and MATLAB programs along with the CPLEX solver are utilized to solve the target model. Finally, the effectiveness and feasibility of the model are verified through. case studies

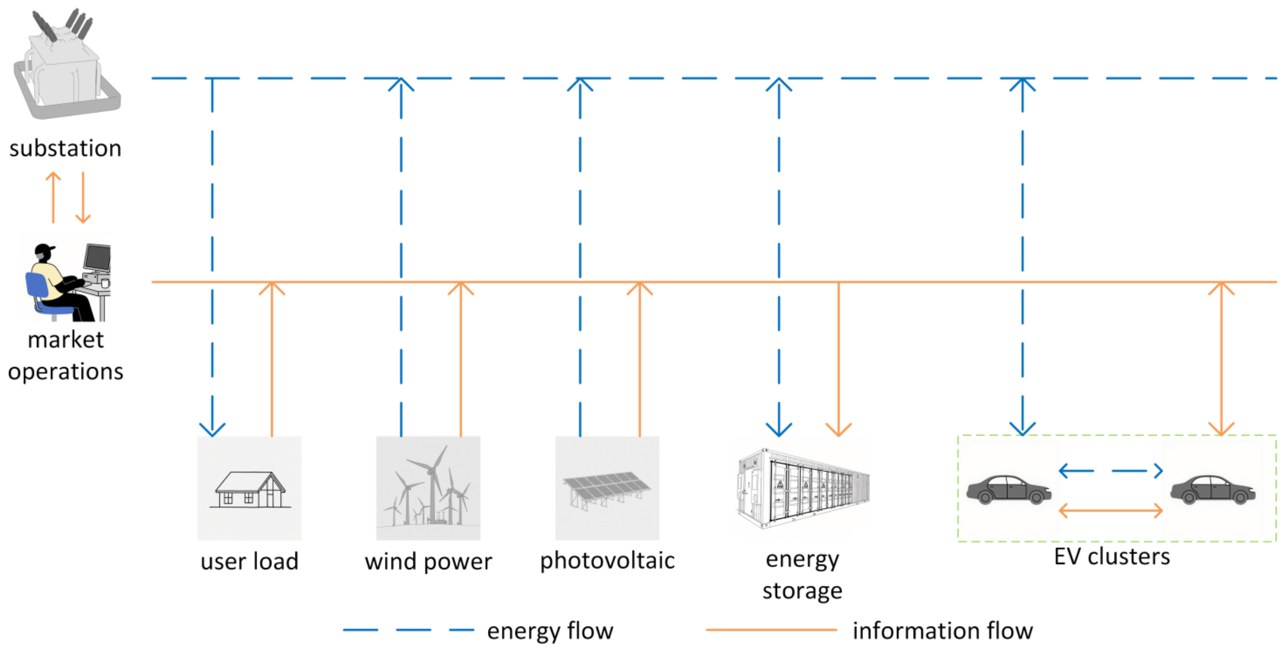

Figure 1. Microgrid Structure Diagram

2. Model Establishment

2.1. Multi-functional microgrid model structure

The system architecture is shown in Figure 1. The power generation section integrates various energy conversion devices, such as wind and PV power generation, to achieve efficient coordination and supply of solar energy, wind energy, and electrical energy. The power consumption section consists of user loads, EV clusters, and energy storage devices. Both the EV clusters and energy storage facilities can draw power from the grid and return power to the grid, thereby enabling peak shaving and valley filling, which enhances the stability and economic efficiency of grid operations. First, data from the previous day is collected, including user loads, wind and PV power generation, EV charging loads, and battery SOC, and this data is provided to the market operator. The market operator exchanges data with the substation and optimizes the scheduling strategy to create the scheduling plan for the day. Since user loads and wind and PV power generation are uncontrollable, the controllable factors include the charging and discharging of energy storage devices and the charging and discharging of EV clusters. Additionally, EVs within the cluster can engage in P2P power transmission, exchanging information and electricity with one another, which reduces energy losses caused by power exchanges between EVs and the grid.

2.2. Wind power scenario generation

Commonly used simulation models for wind speed probability distributions include the Rayleigh distribution, Weibull distribution, and log-normal distribution. This paper selects the Weibull distribution model to simulate actual wind speeds, with the probability density function given by:

$$g(v) = \left(\frac{k}{c}\right)\left(\frac{v}{c}\right)^{k-1} \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{1}$$

Where v represents the wind speed; c and k are the scale and shape parameters of the Weibull distribution, respectively. In this study, k is set to 1.5767, and c is set to 3.7985.

The cumulative distribution function of wind speed is:

$$G(v) = 1 - \exp\left[-\left(\frac{v}{c}\right)^{k}\right] \tag{2}$$

The output power of a wind turbine is related to the wind speed, and the relationship is expressed as follows:

$$P_{WT} = \begin{cases} 0 & v < v_{ci}, v > v_{co} \\ \dfrac{v^3 - v_{ci}^3}{v_r^3 - v_{ci}^3} P_r & v_{ci} \le v \le v_r \\ P_r & v_r \le v \le v_{co} \end{cases} \quad (3)$$

Where P_r and P_{WT} represent the rated and actual power of the wind turbine, respectively; v_r v_{ci} and $v_{co}$are the rated wind speed, cut-in wind speed, and cut-out wind speed of the wind turbine, respectively. In this paper, these values are set to 14 m/s, 3 m/s, and 25 m/s, respectively.

2.3. Generation and reduction of photovoltaic and load scenarios

LHS is employed to generate PV scenarios, while the PAM algorithm is used to reduce the number of scenarios.

LHS is a sampling method commonly used in statistical simulations, uncertainty analysis, and experimental design. It aims to efficiently capture the distribution characteristics of high-dimensional variable spaces. It is particularly effective for large-scale data as it can sample values in the tails with fewer samples. The specific steps are as follows: Suppose there are m random variables X_m , an d th eir di stribution functions are given by:

μ_D^{ti}o

$$Y_m = F(X_m) \quad (4)$$

Divide *Ym* into *n* equal intervals, extract a random value from each interval, and then use the inverse function to determine the corresponding variable X_{mn} as follows:

$$x_{mn} = F^{-}\left(\frac{1}{n} rand + \frac{n-1}{n}\right) \quad (5)$$

Where *rand* is a random number between 0 and 1, and the expression inside the parentheses represents the random value selected from this interval; F^- is the inverse function of the distribution function.

Using this method, a total of $m \times n$ scenarios can be generated, where *m* is the number of random variables, and each variable generates *n* scenarios. However, the number of generated scenarios is very large, resulting in complex computations. Therefore, an algorithm should be applied to reduce the scenarios, thereby minimizing the computational burden.

The PAM algorithm is a classic k-medoids algorithm used in cluster analysis. Its goal is to partition a dataset into k clusters in such a way that the total dissimilarity between each object and the medoid of its cluster is minimized, fulfilling the requirement of scenario reduction in this paper. The specific steps are as follows:

1)Randomly select k distinct points from the sample as initial medoids.

2) Calculate the Euclidean distance from each point in the sample to the selected medoids, and assign each point to the cluster with the closest medoid.

3) Calculate the average value of all points in each cluster; the point with the shortest distance to this average is selected as the new medoid.

4) Repeat steps 2) and 3) until the medoids no longer change or the preset number of iterations is reached, then output the result.

2.4. Establishment of EV Cluster Model

Surveys indicate that the use of EVs does not significantly affect users' travel behaviour. Therefore, based on the 2017 National Household Travel Survey (NHTS 2017) in the United States, the daily driving distance of EV users can be approximated by a log-normal distribution, with the probability density function given by:

$$f_D(x) = \frac{\mu_D}{x\sigma_D\sqrt{2\pi}} \frac{1}{} \exp\left[-\frac{(\ln x - \mu_D)^2}{2\sigma_D^2}\right] \quad (6)$$

In this study, μ_D=3.20, σ_D=0.88. The corresponding probability distribution is shown in Figure 2.

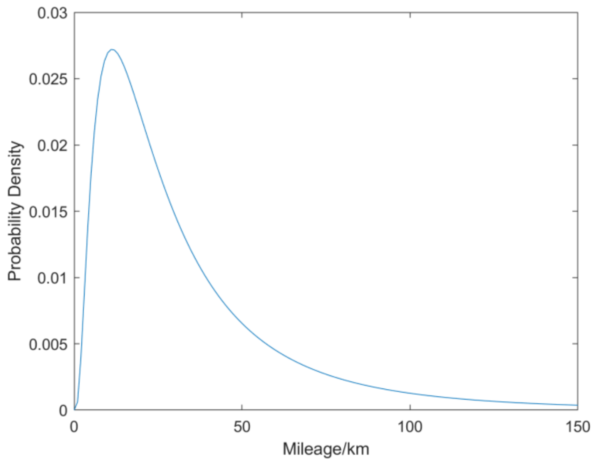

Figure 2. Probability Density of EV Miles Traveled

The arrive time Tr of EVs follows a normal distribution, with its probability density function expressed as:

$$f(T_r) = \begin{cases} \dfrac{1}{\sqrt{2\pi}\sigma_r} \exp\left[-\dfrac{(T_r - \mu_r)^2}{2\sigma_r^2}\right] & \mu_r - 12 < T_r \le 24 \\ \dfrac{1}{\sqrt{2\pi}\sigma_r} \exp\left[-\dfrac{(T_r + 24 - \mu_r)^2}{2\sigma_r^2}\right] & 0 < T_r \le \mu_r - 12 \end{cases} \quad (7)$$

In this paper, μ_r=16.63, σ_r=2.41. Similarly, the probability density function for the user's departure time T_d is given by:

$$f(T_d) = \begin{cases} \dfrac{1}{\sqrt{2\pi}\sigma_d} \exp\left[-\dfrac{(T_d - \mu_d)^2}{2\sigma_d^2}\right] & 0 < T_d \le \mu_d + 12 \\ \dfrac{1}{\sqrt{2\pi}\sigma_d} \exp\left[-\dfrac{(T_d - 24 - \mu_d)^2}{2\sigma_d^2}\right] & \mu_d + 12 < T_d \le 24 \end{cases} \quad (8)$$

Here, μ_D=7.921, σ_D=1.90. The probability distribution of users' travel characteristics is shown in Figure 3.

In general, predicting the charging behavior of a single EV is challenging. However, when the number of EVs reaches a sufficiently large scale, the charging behavior follows a certain probability distribution, making it possible to simulated. Assuming that users begin charging their EVs immediately upon returning home, the EV charging load can be simulated using the MCS method, as shown in Figure 4. The process is as follows: First, random sampling is performed through MCS to initialize the parameters, based on the statistical data presented earlier. Next, the relevant parameters are substituted into the calculation model to determine the charging power. Finally, the number of EVs in the charging state during each time period is summed, and the result is multiplied by the charging power to obtain the final EV charging load.

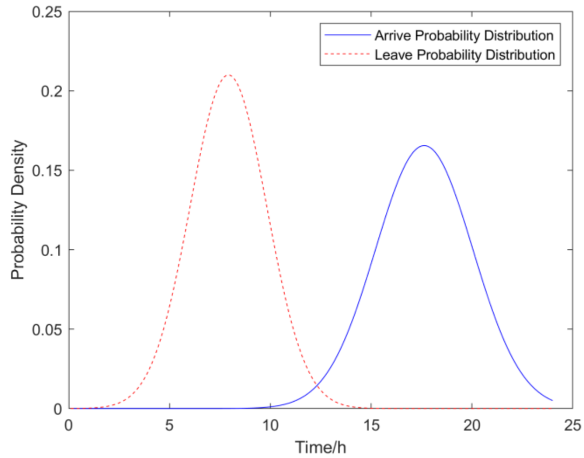

Figure 3. Probability Distribution of EV Arrival and Travel Time

The rated capacity of an EV battery refers to the total amount of electric charge that can be discharged under standard conditions. In practical applications, as the number of charging and discharging cycles increases, the battery's service life gradually decreases, leading to a progressive decline in actual capacity. The degree of capacity degradation during each cycle is influenced by factors such as depth of discharge (DOD), discharge rate (C-rate), discharge interval, and the ambient temperature during the charging and discharging process.

A study proposes a model for EV battery capacity degradation that considers both DOD and discharge interval[38].In addition, a study presented the results of capacity degradation of EV batteries under different temperatures and varying charge-discharge currents[39]. In this article, the ambient temperature is set at 25℃, and the change in ambient temperature during the charging and discharging process is ignored, assuming that the temperature acceleration factor T_{acc} remains constant. Since EVs need to maintain a slow charging state when participating in charging and discharging activities, the charging and discharging rate (C-rate) of EVs is set to 1. By deriving the formula, a battery cycle life degradation model that accounts for both DOD and discharge interval is obtained. Substituting various parameters allows for the conversion of the actual cycle count for any charging and discharging process into an equivalent number of cycles under standard conditions, as expressed by the following equation:

$$n_{\mathrm{eq}}^{\mathrm{V2G}} = 1 \times \frac{N_0}{N_{\mathrm{life}}} = 1 \times \left(\frac{\mathrm{DOD}}{\mathrm{DOD}_{\mathrm{ref}}} \right)^{\lambda_1} \mathrm{e}^{\lambda_2 \left(\mathrm{SOC}_{\mathrm{dis\_init}} - \mathrm{SOC}_{\mathrm{ref}} \right)} \tag{9}$$

Where N_0 represents the cycle life of the battery under standard test conditions; N_{life} is the capacity fade rate; DOD is the depth of discharge (ranging from 0 to 1); $\mathrm{DOD}_{\mathrm{ref}}$ is the reference depth of discharge; SOC is the state of charge (ranging from 0 to 1); $\mathrm{SOC}_{\mathrm{dis\_init}}$ is the initial state of charge; $\mathrm{SOC}_{\mathrm{dis\_ref}}$ is the standard value of the initial state of charge; λ_1 and λ_2 are fitting parameters derived from experimental data, both of which are greater than 1. The equivalent number of cycles corresponding to different charging and discharging behaviors of EVs is shown in Figure 5.

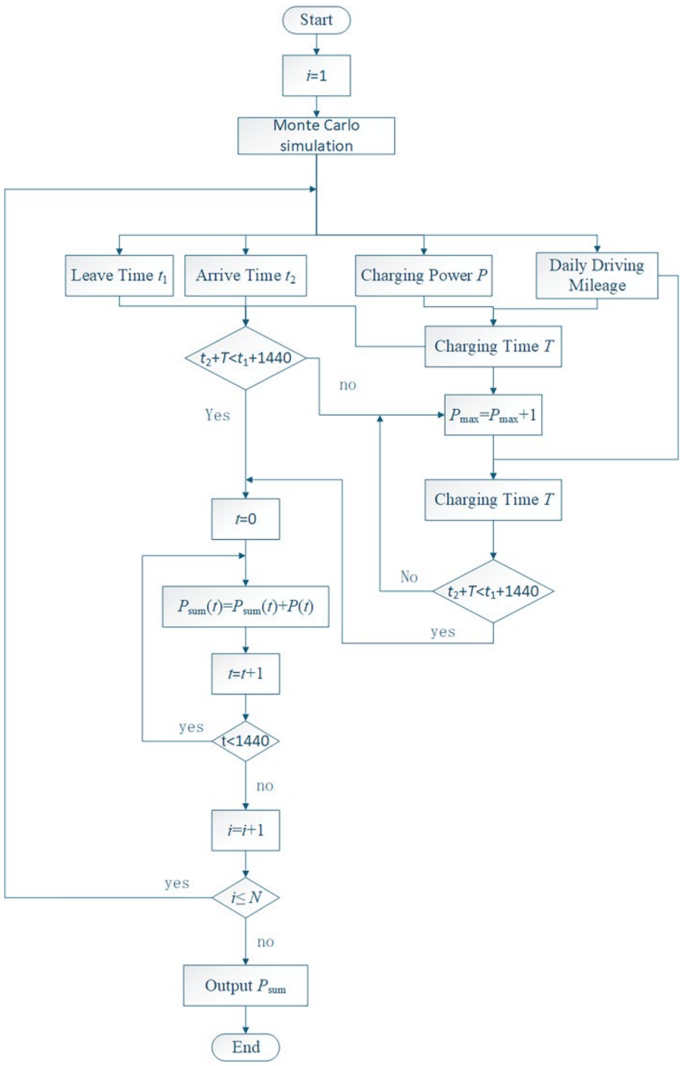

Figure 4. Monte Carlo Simulation Generation Flowchart.

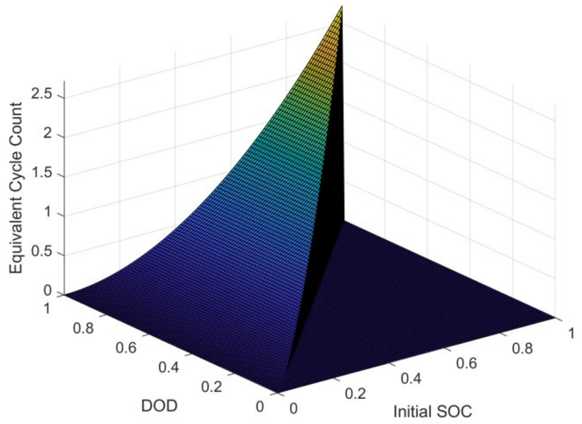

Figure 5. V2G Equivalent Times of Cycles for Different Discharge Behaviors

2.5. Carbon Accounting Model

One of the key distinctions between this microgrid and traditional microgrids lies in the fact that EV clusters are treated as chargeable and dischargeable facilities for flexible regulation, thereby facilitating better consumption of green energy within the microgrid. Consequently, the electric energy in this microgrid can be categorized into two types: green electricity and carbon electricity, based on whether it contains carbon or not. In this article, green electricity is represented by wind power, photovoltaic output, EV discharge, and carbon electricity is represented by purchasing electricity from the upper level, energy storage discharge. If we can enhance the consumption of green electricity and reduce the usage of carbon electricity, we can simultaneously increase the on-site consumption rate of renewable energy and decrease carbon emissions within the microgrid.

For the EV cluster within the microgrid, changes in its charging and discharging behavior will lead to alterations in the utilization of the aforementioned two types of electric energy. Therefore, this paper employs the consumption of green electricity within the microgrid during time period t, denoted as P_t^{WP}, P_t^{PV}, and $P_t^{EV,dis}$, as well as the utilization of carbon-based electricity within the station, denoted as P_t^{ch,CO_2} and P_t^{ES}, to represent the electric energy usage of the microgrid. Under the constraint of energy balance within the station, the sum of these variables should equal the electricity consumption in the microgrid, that is:

$$P_t^{WP} + P_t^{PV} + P_t^{EV,dis} + P_t^{ch,CO_2} + P_t^{ES} = P_t^{load} + P_t^{EV,ch} \tag{10}$$

Where the subscript t denotes the scheduling period t; P_t^{load} represents the electricity load in the microgrid during period t; $P_t^{EV,ch}$ denot es the E V ch arg ing power in th e m icro grid during period t.

3. Optimized Scheduling Strategy

3.1. Objective Function

The objective function of the microgrid optimal scheduling model aims to minimize the grid operation cost, the grid stability index, and the EV cluster charging cost, and is formulated as follows.

Microgrid Operation Cost

One key condition for the stable operation of a power grid is maintaining minimal system load fluctuations. Therefore, the objective function, representing the total operating cost of the microgrid, can be expressed as:

$$\min C_1 = \sum_{t=1}^{24} [C_{PV}(t) + C_{WP}(t) + C_{EV}(t) + C_{ES}(t) + C_{load}(t) - C_{dr}(t) + C_{CO_2}(t)] + \gamma \cdot S \tag{11}$$

Where C_1 represents the total day-ahead operating cost of the microgrid; $C_{PV}(t)$ and $C_{WP}(t)$ denote the operating costs of the PV unit and the wind turbine (WT) unit at time t, respectively, calculated based on the unit output as discussed earlier; $C_{EV}(t)$ represents the energy transmission cost associated with charging and discharging EVs at time t; $C_{ES}(t)$ is the operating cost of the energy storage system (ESS) at time t; $C_{load}(t)$ refers to the dispatching cost of demand response loads participating in the power grid; $C_{dr}(t)$ represents the revenue from reserve energy in the microgrid at time t; $C_{CO_2}(t)$ refers to the carbon emission cost incurred from purchasing electricity from the superior in time period t; γ is the microgrid stability index coefficient; S denotes the microgrid load fluctuation Index:

$$S = \sum_{t=1}^{24} \left[W(t+1) - W(t) \right]^2 \tag{12}$$

Where $W(t)$ represents the net load of the microgrid at time t.

EV Cluster Charging Cost

The total cost of personal EV charging is given by:

$$\min C_2 = \sum_{i=1}^{n} \sum_{t=1}^{24} \left[P_{t,i}^{ch} \cdot \eta - P_{t,i}^{dis} / \eta \right] \cdot price_t + C_{loss}^i \tag{13}$$

Where C_2 represents the comprehensive charging cost for EV clusters; $P_{t,i}^{ch}$ is the charging power of the i-th EV at time t; $P_{t,i}^{dis}$ is the discharging power of the i-th EV at time t; $price_t$ is the electricity price at pime t; η is the charging and discharging efficiency; C_{loss}^i is the EV battery capacity degradation cost for the i-th EV on that day.

Linear Weighting

Linear weighting is applied as follows:

$$\begin{cases} \min C = a \cdot C_1 + b \cdot C_2 \\ a + b = 1 \end{cases} \quad (14)$$

Where C is the multi-objective optimization function of the microgrid; a and b are the optimization weights corresponding to the microgrid cost C_1 and the user cost C_2, respectively.

3.2. Constraints

EV Charging and Discharging Constraints

- Charge-Discharge Power Constraint:

EVs can participate in the optimal dispatch of the power grid and also enable P2P connections between EVs at different charging stations within the same area for electricity sharing. This helps reduce power losses and optimize charging costs. Therefore, the charging and discharging of EVs can be divided into two modes: connection to the power grid and connection to other EVs. Since charge and discharge dispatching can only occur during slow charging, the maximum charging and discharging power is limited to 3.5 kW:

$$-P_{\max}^{\mathrm{EV}} \le P_t^{\mathrm{EV}} \le P_{\max}^{\mathrm{EV}} \quad (15)$$

$$P_t^{\mathrm{EV}} = P_t^{\mathrm{EV,G}} + P_t^{\mathrm{EV,P2P}} \quad (16)$$

$$P_t^{\mathrm{EV,G}} \cdot P_t^{\mathrm{EV,P2P}} = 0 \quad (17)$$

Where $P_{\max}^{\mathrm{EV}}$ represents the maximum charging power; P_t^{EV} is the current charge-discharge power of the EVs, which a positive value indicating charging and a negative value indicating discharging; $P_t^{\mathrm{EV,G}}$ is the power when the EV participates in the grid's charge and discharge processes; $P_t^{\mathrm{EV,P2P}}$ is the power when the EV establishes a P2P connection with other EVs in its area; $P_t^{\mathrm{EV,G}} \cdot P_t^{\mathrm{EV,P2P}} = 0$ indicates that an EV cannot share electrical energy with both the power grid and other EVs simultaneously. When connected to one of them for charging or discharging, the power between the EV and the other party must be zero.

- Charge-Discharge Time Period Constraint

$$T_s \le T \le T_e \quad (18)$$

Where T represents the current time, T_s denotes the start of the regulation period, and T_e represents the end of the regulation period.

- SOC Lower Limit Constraint

If the dispatch cycle is one day, the SOC at the end of charging shall not be lower than the SOC when the EV left home on the previous day.

$$E_{out} \le E_0 \le E_{\max} \quad (19)$$

Where E_{out} represents the SOC of the EV when it leaves home, E_0 denotes the SOC of the EV at the end of charging, and $E_{\max}$ stands for the maximum SOC of the EV, which is 70 kWh.

- Battery Capacity Constraint

When a battery is charging or discharging, there must be residual charge, and the SOC shall not exceed the upper limit.

$$0 \le E \le E_{\max} \quad (20)$$

Where E represents the current SOC of the EV.

Energy Storage Constraint

- Energy Storage Power Constraint

The maximum charge-discharge power of the energy storage system is 500 kW; therefore:

$$-P_{\max}^{ES} \le P^{ES} \le P_{\max}^{ES} \quad (21)$$

Where $\mathrm{P}_{\max}^{\mathrm{ES}}$ represents the maximum charging power for the energy storage system.

- Energy Storage Capacity Constraint

To prevent damage to energy storage batteries due to complete discharge, a lower limit for the energy storage system’s capacity should be set:

$$E_{\min}^{ES} \le E^{ES} \le E_{\max}^{ES} \quad (22)$$

Where E^{ES} represents the current SOC of the energy storage system, $E_{\max}^{\mathrm{ES}}$ denotes the upper limit of the energy storage system's SOC, and $E_{\min}^{\mathrm{ES}}$ stands for the lower limit of the energy storage system's SOC.

Translational Load Constraint

$$D_{\min}^{DR} \le P_t^{DR} \le D_{\max}^{DR} \quad (23)$$

Where P_t^{DR} represents the dispatched power of the transferable load at time t; $D_{\min}^{DR}$ and $D_{\max}^{DR}$ denote the lower and upper limits of the transferable load power, respectively.

Microgrid Total Power Constraint

$$-P_{m,\max} \le P_t^{PV} + P_t^{WP} - P_t^{load} - P_t^{EV} - P_t^{ES} - P_t^{DR} \le P_{m,\max} \quad (24)$$

Where $P_{m,\max}$ represents the upper limit of the interaction power between the microgrid and the upper-level grid, which is 2000kw in this paper; P_t^{PV}, P_t^{WP} and P_t^{load} represent the PV power generation data, wind power generation data, and load generation data obtained through generation and curtailment based on historical data (mentioned in the preceding text) at time t; P_t^{EV} and P_t^{ES} are denote the charge-discharge powers of the EV and the energy storage system at time t, where positive values indicate charging and negative values indicates discharging; P_t^{DR} is the transferable load obtained through optimal allocation at time t.

3.3. Model Establishment and Solution

1) Decision Variables: The decision variables considered in this paper include the charging and discharging variables of EVs, output variables of the energy storage system, transferable load variables, and others.

2) Objective Function: The objective of this paper is to minimize the grid operation cost, the grid stability index, and the charging cost of the EV cluster.

3) Constraint Conditions: The constraints include the time constraints of EVs, power constraints of EVs, energy storage power constraints, transferable load constraints, microgrid power balance constraints, and interaction constraints between the microgrid and the upper-level grid.

4) Scenario Generation: The LHS algorithm is employed to generate scenarios for PV output and load, which are then reduced using the PAM algorithm. The Weibull distribution model is used to simulate wind speed, and the MCS is applied to simulate EV travel patterns, thus generating an EV cluster model.

5) Optimization Model Formulation: The parameters generated in the previous steps are imported to establish the objective model.

6) Model Solution: The model is solved using the CPLEX solver, obtaining results and the corresponding function values.

7) Optimization and Adjustment: Finally, the model's solutions are output, and the parameters are adjusted based on practical conditions.

4. Case Studies

This paper generates data based on historical PV and load data from a microgrid system in a region of Jilin Province. A large number of scenarios are created using the LHS method, followed by scenario reduction using the PAM algorithm. The generated PV and load scenario results are shown in Figure 6. Ultimately, five sets of reduced data are obtained, each representing one of the five typical scenarios.

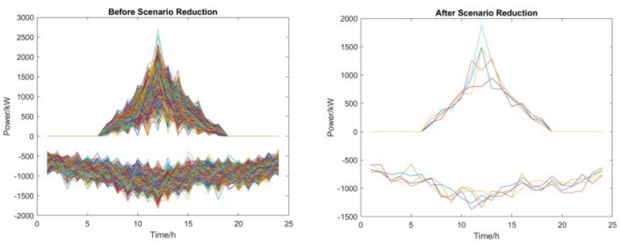

Figure 6. Schematic Diagram of PV and Load Scenario Generation and Reduction

Figure 7. illustrates the random wind speed simulated using the Weibull distribution, along with the corresponding wind power data derived from it. Local historical wind speed data are used as the original dataset.

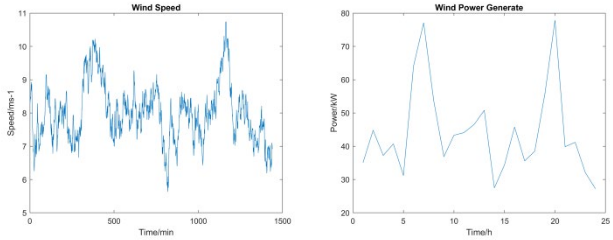

Figure 7. Schematic Diagram of Wind Speed Random Generation

The above data are imported into the model for solving. Prior to solving, parameter settings must be configured, with specific data provided in Table 1.

Table 1. Model Parameter Table

Constraint	Range
Energy Storage	$P_{s,\max}$=500,$E_{s,\max}$=1800,$E_{s,\min}$=400
Translational Load	$D_{DR,\max}$=200,$D_{DR,\min}$=50
Microgrid Interactive Power	$P_{m,\max}$=2000

In typical scenarios, with the objectives of minimizing grid operation costs, grid stability indicators, and the charging costs of EV clusters, the optimal power dispatch results of the microgrid are obtained through solving the model under constraint conditions, as shown in Figure 8. The following conclusions can be drawn from the data analysis:

In typical scenarios, with the objectives of minimizing grid operation costs, grid stability indicators, and the charging costs of EV clusters, the optimal power dispatch results of the microgrid are obtained through solving the model under constraint conditions, as shown in Figure 8. The following conclusions can be drawn from the data analysis:

(1) During the daylight hours from 8:00 AM to 6:00 PM, PV power serves as the primary power source. When PV output is insufficient to meet load demand, the microgrid purchases electricity from the upper-level grid. During other periods, due to the lack of sunlight, the PV system does not generate power, and purchasing electricity from the upper-level grid becomes the main source. Additionally, the energy storage system performs peak shaving and valley filling through charging and discharging operations. This helps mitigate the volatility and instability associated with renewable energy generation, enhances grid stability, meets the electricity demand of shiftable loads, and reduces fluctuations in grid operation.

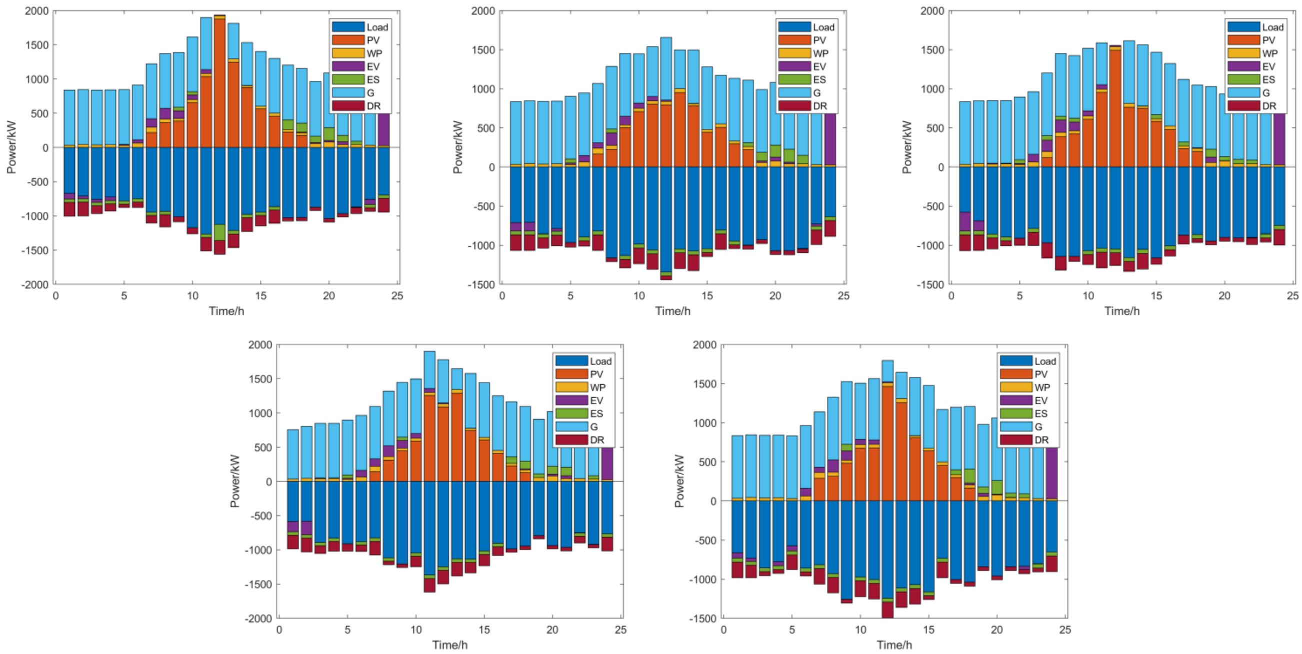

Figure 8. Optimization Result Chart for Each Scenario

(2) During peak electricity price periods, most EVs are in operation and do not charge, while the remaining EVs that are not in operation charge infrequently, with only P2P energy sharing taking place among them. At this time, the electrical energy supplied by the PV system exceeds the load demand, prompting the energy storage system to charge and store energy. At night, when electricity prices are at a trough, most EVs return to their parking state and participate in grid power regulation through charging and discharging. During this period, the system load increases, and the energy storage system discharges to balance the power supply. This enhances the economic efficiency of the grid, reduces EV charging costs, and improves energy utilization efficiency.

(3) In the early morning, most EVs are parked or returned. Since the PV output is zero at this time, and the energy storage system has already discharged from 6:00 PM to 11:00 PM to participate in dispatching, it has insufficient power and requires recharging in the early morning. Meanwhile, the microgrid load increases. Therefore, EVs with sufficient remaining power discharge to alleviate the grid load, reduce power fluctuations, and improve the stability of the system operation.

Table 2 provides a comparative analysis of the comprehensive costs prior to and subsequent to the participation of EVs in optimal dispatch. In scenarios where EVs are not involved in dispatch, the microgrid dispatch approach can be referenced from the literature [40-41]. When EVs do not engage in optimal dispatch, they only perform charging operations and are integrated into the grid as electricity-consuming devices. In this scenario, the grid consists solely of PV power generation, wind power generation, and energy storage devices, with electricity purchased from the upper-level grid when internal power supply is insufficient.

Table 2. Comprehensive Cost Comparison Before and After EV Participation in Optimized Scheduling

Cost of EV Cluster Participating in Optimal Dispatching (million yuan)	Cost of EV Cluster Not Participating in Optimal Dispatching (million yuan)
3.696473	4.859385
3.588973	4.784397
3.857164	4.995278
3.497733	4.704665
3.555619	4.741639

Based on calculations, when EVs participate in grid regulation as charge-discharge devices, the final costs for the five typical scenarios are 3.696473 million yuan, 3.588973 million yuan, 3.857164 million yuan, 3.497733 million yuan, and 3.555619 million yuan, respectively. Compared to the costs when EVs do not participate in optimal dispatch, these values represent reductions of 23.93%, 24.99%, 22.78%, 25.65%, and 25.01%, respectively.

The results show that the participation of EVs in optimal dispatch through charging and discharging can effectively reduce both grid operation costs and EV charging costs for users, thereby maximizing the benefits of the power system.

5. Conclusion

To mitigate power fluctuation issues arising from the integration of renewable energy sources and EVs into microgrids, an optimal dispatching model for microgrids with the incorporation of EV clusters is proposed. This model comprehensively incorporates multiple uncertainty factors, including the output of renewable energy sources, the travel behaviour of EV users, load variations, and battery degradation effects. Case verification and simulation analysis demonstrate that this model can effectively reduce microgrid operation and EV charging costs. Furthermore, it is capable of better handling fluctuations in EV charging demand and the inherent uncertainties of new energy sources, thus improving the economy and stability performance of the power grid and enhancing energy utilization efficiency. However, this study has certain limitations. Future work will focus on further improving the modelling of EV charging and discharging behaviours and incorporating additional factors for consideration.

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