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Reliability and Optimization of Electric Vehicle Photovoltaic Charging Scheduling Based on Stochastic Production Simulation

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Abstract

To solve the problems of low resource utilization and poor grid stability in current photovoltaic electric vehicle charging, this study uses the K-means clustering algorithm to cluster data in a Monte Carlo random production simulation. This reduces subsequent solving time and allows for the construction of an optimization scheduling model for photovoltaic electric vehicle charging. Afterwards, the particle swarm optimization algorithm with strong global search ability and fast convergence speed is used to solve the model and obtain the optimal scheduling strategy. The study analyzed the random simulation method and found that the simulation accuracy was higher than 96% in different scenarios. When the particle swarm algorithm was used to solve the optimization scheduling model, its solving time during peak hours, daytime dispersion time, and nighttime trough time was 2.4 s, 1.9 s, and 1.4 s, respectively. The calculation time was less than 2.5 s, and the calculation errors in the three scenarios were 2.3%, 1.4%, and 1.2%, respectively, indicating a relatively low calculation error. After optimizing the scheduling strategy, the resource utilization rates of electric vehicle photovoltaic charging in three scenarios were 98.6%, 97.4%, and 97.3%, respectively, which can improve the power supply reliability and equipment reliability of the photovoltaic system during electric vehicle charging. From the above results, it can be concluded that the proposed photovoltaic charging optimization scheduling model for electric vehicles based on stochastic production simulation can improve the resource utilization efficiency and charging reliability during charging.

Keywords

stochastic production simulation, electric vehicles, photovoltaic charging, Monte Carlo, K-means clustering, particle swarm algorithm

1 Introduction

With the development of society, the global energy structure is transitioning from fossil fuels to renewable energy (RE) sources such as wind and solar power (Taghavi et al., 2024). Although the use of electric vehicles (EVs) is expanding, charging large numbers of them will have adverse effects on grid load, power quality, and energy supply stability (Taghavi and Lee, 2025). As a representative of distributed RE, photovoltaic (PV) power generation (PG) has the advantage of being highly flexible and can alleviate pressure on the power grid. (Taghavi and Lee, 2024). Furthermore, PV PG relies on solar energy. It can directly convert light energy into electrical energy through the PV effect of semiconductor interfaces. It can directly generate electricity using clean energy and reduce energy consumption (Soonmin and Taghavi, 2022). PV charging can serve as a clean energy source for EV charging, reducing its energy consumption (Ebrahimi et al., 2022). Moreover, research on the reliability and optimization scheduling methods of EV charging can optimize the charging efficiency of EVs, improve the utilization efficiency of RE, enhance the stability and reliability of the power grid, and reduce environmental pollution (Jian et al., 2024). Many scholars have conducted research on optimizing and scheduling EV charging. Qian et al. (2023) designed a joint model based on a nonlinear battery charging curve and minimum charging power to schedule EV charging. The results showed that the model could improve grid stability by 12.4% (Qian et al., 2023). A charging scheduling method for EVs based on evolutionary computation was designed by the Ahmed et al. (2023) to improve the scheduling level of EVs. The results showed that the method could increase resource utilization by 23.5% (Ahmed

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et al., 2023). In addition, in order to reduce the waiting time in EV charging scheduling methods, that is, the time EVs wait for charging at charging stations, Tan et al. (2023) designed an EV charging scheduling optimization method based on fairness index and online scheduling algorithm, and compared the waiting time before and after using this method. The results showed that this method can reduce waiting time by 43.7% (Tan et al., 2023). Aiming at the poor effect of fast charging plan scheduling method for EVs, Saner et al. (2023) designed a charging scheduling framework based on EV charging profile and battery management system. The framework was used in real situations for testing. The results indicated that the method was able to improve the scheduling efficiency by 31.8% (Saner et al., 2023). However, after the above methods for OS of EVs charging, PV charging still still exists with low resource utilization and high grid load. The current grid scheduling methods need to be optimized.

Stochastic production simulation (SPS) can consider various stochastic factors such as load fluctuation and resource fluctuation in the grid. These stochastic factors can make the production simulation closer to the actual situation, provide the optimal operation of different systems, optimize the system scheduling and enhance the reliability of the system. Monte Carlo (MC) performs SPS due to its ability to simulate the stochastic behavior of the system through its stochastic sampling (Kagganty et al., 2024). A number of people have studied the method. For example, Gao and Yin (2024) proposed an MC-based SPS method in order to perform SPS on the decision-making process of spare parts assembly in an electronics company. Moreover, the practical effect of the method was analyzed. The results showed that its simulation accuracy reached 98.3% (Gao and Yin, 2024). Wang et al. (2023) designed a MC-based machine random generation simulation method for parameter identification in response to the low parameter identification during remote maintenance of heavy manipulator operation. The method was tested in real situations. The results revealed that the parameter identification accuracy of the method could reach 93.5% (Wang et al., 2023). K-means clustering algorithm (K-means) is able to classify and analyze the data in the stochastic production process, thus providing support for stochastic generation simulation (Wibowo and Wihayati, 2023). Particle swarm optimization (PSO) is able to solve various models by virtue of its strong search capability and fast convergence. The above two algorithms are often studied by various scholars. For example, Singh et al. (2023) proposed a K-means clustering based SPS method for power load fluctuation in order to improve the stability of power system. Moreover, the method was tested. The results indicated that the accuracy of the method could reach 92.6% (Singh et al., 2023). Masoud (2023) designed an electronic oscilloscope downtime detection model for the problem of long downtime of electronic oscilloscopes. Moreover, the PSO algorithm was used to solve the model. The results showed that the PSO algorithm could reach 97.3% of the solution accuracy (Masoud, 2023).

In summary, although the current optimization scheduling methods for EVs can to some extent optimize scheduling, there are still various problems such as low resource utilization and weak grid load stability. To solve the problems of low resource utilization and weak grid load stability in EV charging, this study uses the results of random production simulation to construct a PV charging optimization scheduling model for EVs. The model is solved using PSO to obtain the optimal scheduling (OS) method for EVs. This study innovates by using MC and K-means to conduct random production simulations for the scheduling optimization of PV charging for EVs in order to obtain an optimization scheduling model. Then, the PSO algorithm solves the constructed optimization scheduling model based on random production simulations to obtain an OS method and improve the reliability of PV charging for EVs. The research contribution lies in the optimized scheduling scheme, which more reasonably arranges EV charging times and power. This reduces waiting time for users, enables them to charge more quickly and stably, and improves charging efficiency. Additionally, it effectively mitigates the impact of large-scale EV charging on grid load and enhances grid operation reliability and stability. The random production simulation, MC, K-means clustering, and PSO algorithms used in the study provide new ideas and methods for technological innovation in EV charging optimization scheduling. This helps promote technological progress and development in the entire industry.

2 Methods and materials

2.1 MC-K-means based method for stochastic production simulation

When scheduling PV charging reliability and optimization for EVs, accurate modeling of the charging demand (CD) and driving model of EVs is a critical step in scheduling (Chen et al., 2024). SPS is a core tool in power system and energy planning, as well as reliability analysis. It can provide a scientific basis for system planning, operation, and decision-making by quantifying uncertainty (Jomah et al., 2024). MC is a numerical computation method based on probability and statistical theory, which can simulate the random behavior in PV charging of EVs through random sampling, so as to perform SPS of PV charging of EVs (Ji et al., 2025). The main idea behind MC is to simulate a large number of random samples in order to estimate the solution of a difficult issue. The basic flow of MC is shown in Fig. 1.

In Fig. 1, MC consists of problem modeling, stochastic sampling, simulation computation and statistical analysis. In problem modeling, the problem to be solved is transformed into a probabilistic model or a stochastic process, and the target quantity of the problem is determined. Meanwhile, in stochastic sampling, a large number of random samples are generated based on the probabilistic model of the problem. These samples are all random numbers, random variables or random samples. The simulation is then computed for each random sample to obtain the corresponding result. Finally, the computational results of all samples are statistically analyzed. Based on these results, the solution to the problem or the value of the target quantity is estimated. The steps of SPS for PV charging of EVs using MC are shown in Fig. 2.

In Fig. 2, SPS is performed by first determining the input parameters, i.e., EVs battery capacity, initial state of charge of the battery, charging efficiency, and other related parameters. The above parameters can be obtained directly from actual measurements or data provided by the manufacturer. It is also necessary to determine the PV system parameters such as rated power (RP) and conversion efficiency of PV panels, user behavioral parameters

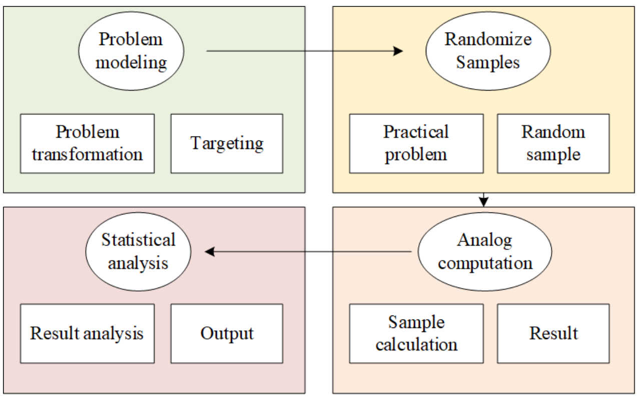

Fig. 1 Basic process of MC

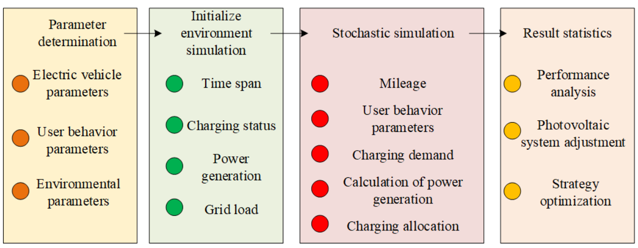

Fig. 2 Stochastic production simulation based on MC

such as user's travel habits and travel time, and environmental parameters such as sunlight intensity and temperature variation. After all the parameters are collected, the initialization environment is simulated and the appropriate time span is selected according to the research model. Moreover, the charging status of the EVs, the PG of the PV system, and the load of the grid are stored in the database. After that, the driving mileage of each EVs in each time step is randomly generated according to the user's behavioral parameters using MC method. Furthermore, based on its driving mileage and battery parameters, the CD of EVs is calculated. The calculation is shown in Eq. (1).

$$E_{ch} = \max\left(0, M \times \frac{C_{ev}}{S_0} - C_{ev}\right) \tag{1}$$

In Eq. (1), M denotes the EV driving range (unit: km). C_{ev} denotes the battery capacity (unit: kWh). S_0 is the initial battery charge (unit: %). E_{ch} is the CD (unit: kWh). The max(0,) function is designed to ensure that the CD is not negative. When the calculated result is negative, it means that the initial power is sufficient to support the driving distance M and is even greater than it, and no additional charging is required at this time. Then, the sunlight intensity dataset is established based on environmental parameters and historical meteorological data. In the actual situation, the PG of the PV system of the EVs in each time step is calculated based on the PV system parameters and sunlight intensity data set. The calculation formula is shown in Eq. (2).

$$P_g = P_p \times \eta_p \times I_s \tag{2}$$

In Eq. (2), P_g denotes the PG (unit: kWh), P_p denotes the RP of the PV panel (unit: kW), η_p is the conversion efficiency (unit: %) and I_s is the sunlight intensity (unit: W/m²). Finally, based on the CD and PG calculated in Eqs. (1) and (2), the PV electric energy is allocated to EVs for charging. Moreover, the charging status of each EVs is updated and the unsatisfied CD during the charging process is recorded. Afterwards, multiple simulations are then performed to improve the reliability of the stochastic simulation results. Each simulation uses a different random sample to generate various driving distances and CDs of EVs. Finally, PV charging performance for EVs is analyzed based on the statistical results. To increase the effectiveness of PV charging for EVs, the PV system layout and charging strategy are modified based on the analysis results. However, the amount of CD and mileage data generated by the SPS using the MC method is too large.

This data must be clustered to reduce the time required for subsequent calculations. K-means can cluster the data produced in SPS (Sun and Fan, 2023). After optimization based on K-means, the process of MC random production simulation consists of four steps: data preprocessing, data clustering, iterative optimization, and result output.

In Fig. 3, MC-K-means SPS consists of four steps: data preprocessing, data clustering, iterative optimization, and result output. In data preprocessing, the MC SPS generates the CD of EVs, and all the CDs are normalized to eliminate the differences between different features. The normalization formula is shown in Eq. (3).

$$x_n = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{3}$$

In Eq. (3), x_n denotes the normalized data, representing a series of CD related data generated in MC random production simulation. $x_{\min}$ and $x_{\max}$ are the minimum and maximum values of the data. x is the original data. Then, the data are checked for outliers and data points (DPs) that deviate from the policy range are eliminated. In data clustering, the appropriate number of clusters k is selected first. Then, k DPs are randomly selected as the initial cluster centers, and each DP is assigned to its nearest cluster according to the initial cluster center. The way of expression in assignment is shown in Eq. (4).

$$j = \arg\min d\left(x_i, c_j\right) \tag{4}$$

In Eq. (4), x_i denotes the i^{th} DP. j denotes the j^{th} cluster. c_j denotes the center of the j^{th} cluster. $d(x_i, c_j)$ is the distance from the DP to the center of the cluster. The new cluster center is then determined by averaging the values of all the DPs in each cluster. The formula is shown in Eq. (5).

$$c'_j = \frac{1}{\left|C_j\right|} \sum_{x_i \in C_j} x_i \tag{5}$$

In Eq. (5), C_j is the set of DPs in the j^{th} cluster. $\left|C_j\right|$ denotes the number of DPs in the cluster. Finally, the above steps are repeated for iterative optimization until the change in the center of the cluster is less than a predetermined threshold or the maximum iteration is reached. Finally, the clustering result is output. This clustering result is used as a basis for MC SPS.

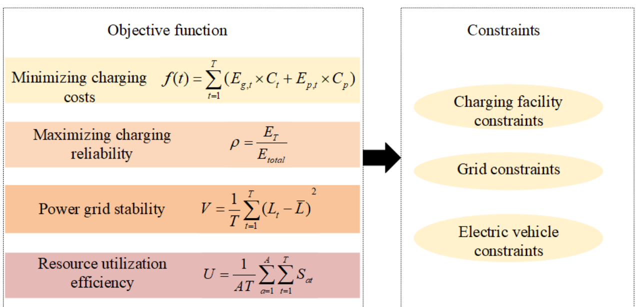

Fig. 3 Optimization scheduling model

2.2 Optimization scheduling strategy model

After MC-K-means performs SPS, a series of data about the CD of EVs and the PG of PV charging system will be obtained. These data can be used to construct an OS model for PV charging of EVs, which would enhance resource utilization, improve charging reliability, and minimize charging costs. The OS model of PV charging for EVs is shown in Fig. 3.

In Fig. 3, when constructing the OS model, the objective function (OF) of the model needs to be defined first. It includes four OFs: charging cost minimization, charging reliability maximization, grid stability and resource utilization efficiency. The goal of grid stability is to control the stability of EV charging and ensure the stability of grid load during EV charging. Resource utilization efficiency is the ability of EVs to use solar energy fully and without waste when charging on the power grid. Among them, the minimization of charging cost mainly includes the cost of purchasing electricity from the grid and the cost of using PV charging equipment. Equation (6) displays the OF of the entire cost.

$$f(t) = \sum_{t=1}^{T}\left(E_{g,t} \times C_t + E_{p,t} \times C_p\right) \tag{6}$$

In Eq. (6), C_t denotes the electricity price. t denotes the t^{th} time interval. $E_{g,t}$ is the amount of electricity purchased at the t^{th} time interval. C_p denotes the cost of using PV equipment. $E_{p,t}$ is the amount of PV charging at the t time interval. T is the total quantity of time intervals in a day. Charging reliability maximization is expressed by the completion rate of EVs. Its OF for charging reliability maximization is shown in Eq. (7).

$$\rho = \frac{E_T}{E_t} \tag{7}$$

In Eq. (7), E_T denotes the power of EVs at the end of the day. E_t is the total amount of electricity that EVs need to charge in one day. The grid stability OF is to measure the stability of the grid when the PV charging system is charging and minimize the load fluctuation of the grid. Its expression is shown in Eq. (8).

$$V = \frac{1}{T}\sum_{t=1}^{T}\left(L_t - \bar{L}\right)^2 \tag{8}$$

In Eq. (8), V denotes the load variance. $\overline{L}$ is the average load. L_t denotes the total load in time t. The expression of the resource utilization OF is shown in Eq. (9).

$$U = \frac{1}{AT}\sum_{a=1}^{A}\sum_{t=1}^{T} S_{at} \tag{9}$$

In Eq. (9), U denotes the resource utilization rate. A denotes the quantity of charging piles (CPs). a denotes the ath CP. S_{at} denotes the state of the a^{th} CP. Its charging status can be divided into idle state, charging state, fault state, and reservation state. The idle state refers to a charging station that is ready to provide charging services to vehicles at any time, but currently has no EV connection for charging operations. The charging status is when an EV is connected to a charging station for charging. A fault state occurs when a charging station is unable to provide charging services for EVs due to hardware failure, software issues, or other abnormal situations. The reservation status indicates whether the charging station has been reserved by a user in advance or is not specifically reserved for a vehicle. It also indicates how long the reserved vehicle has to charge. During this period, the charging station cannot provide services without other vehicles. The above OF constitutes the total objective of the OS model, and the OS model also needs constraints to constrain the OF. The constraints are also an important part of the model construction. In the optimization scheduling model for PV charging of EVs, the constraints include charging facility constraints, grid constraints, and EV constraints. Among them, the charging facility constraints include the charging power limit and the charging facility number limit. Its expression is shown in Eq. (10).

$$\begin{cases} P_{at} \le P_{a,\max}, \forall a, t \\ N_a \le A \end{cases} \tag{10}$$

In Eq. (10), P_{at} is the charging power of a CP in time t, $P_{a,\max}$ is the RP of the CP a and N_a is the quantity of EVs being charged. The grid constraints and EVs constraints are shown in Eq. (11).

$$\begin{cases} L_t \le L_{\max}, \forall t \\ p_{jt} \le P_{j,\max}, \forall j, t \end{cases} \tag{11}$$

In Eq. (11), L_t denotes the total load in time t, $L_{\max}$ is the transmission capacity of the grid, p_{jt} denotes the charging power of EVs j in time t and $P_{j,\max}$ is its maximum charging power. The PV charging model for EVs is constructed using the above OF and the limiting conditions of the constraints. After constructing the model, it must be solved. The PSO algorithm can find the optimal solution by simulating the collaboration and competition between particles in the population, i.e., it can obtain the OS decision.

When solving the OS model using the PSO algorithm, each possible EVs charging scheduling scheme is taken as a particle in the particle swarm. Next, each particle's fitness is determined using the OS model's constraints and OF. Equation (12) presents the fitness function.

$$F(X) = \alpha \times \frac{1}{f(t)} + \beta\rho + \lambda V + \mu U \tag{12}$$

In Eq. (12), α and β represent the weights of minimizing cost and maximizing reliability, respectively. λ and μ represent the weights of grid stability and resource utilization efficiency, respectively. Redistribution can affect the center of optimized scheduling. If the optimization scheduling focuses on cost, then α value is larger. Moreover, if the optimization scheduling focuses on grid reliability, then β value is larger. The particle's location and velocity are updated following the computation of the adaption value. The above steps are repeated until the maximum iteration is reached, and the global optimal position is finally obtained. The scheduling scheme corresponding to this global optimal position is the optimal EVs PV charging electric scheme, which can maintain the grid balance and charging reliability.

3 Results

3.1 Results of MC-K-means stochastic production simulation

To analyze the specific effects of the SPS proposed in this research, the gap between the different scenarios in the SPS and the actual scenarios will be observed. The simulated CD distribution and mileage distribution are analyzed to confirm whether they are similar to the actual observations. Table 1 displays the setup of the experiment's setting.

The Norwegian new energy vehicle real-time operation dataset from the official website of the Butler Public Science Data Center for Basic Disciplines is chosen as the experimental dataset (Deng and National Basic Discipline Public Science Data Center 2023). This dataset collects

Table 1 Experimental environment configuration

Environment	Index	Configuration
Hardware environment	CPU	Intel Core i9-12900K
	GPU	NVIDIA GeForce RTX 3090
	Windows	Windows 11
	Memory	64GB DDR4 3200MHz
Software environment	Programming environment	Python
	Data visualization	Matplotlib library

and records various operational data such as mileage, power consumption, charging method, charging time, driving speed, etc. of new energy vehicles in the actual process. Moreover, based on previous research experience, when the k value of K-means is set to 3 and the maximum number of iterations is set to 500, the performance of K-means is optimal during the experiment. The value of k can cause the data within each cluster to be highly similar while the data between clusters is obviously different. Setting the number of iterations to 500 gives the algorithm enough time to adjust the cluster center so that it can reach a stable state. This ensures that there is no significant change in the cluster center and that the algorithm fully converges. The experiment is carried out through the experimental environment configuration, experimental dataset and parameter settings as described above. First, the coverage of MC-K-means for SPS is analyzed to analyze the coverage effect under peak time period, daytime dispersed charging time period, and nighttime trough time period field. The results are shown in Fig. 4.

In Fig. 4 (a), after the SPS of EV PV charging using MC-K-means, its SPS is able to cover most of the actual values in the real-world scenario when it is simulated during peak hours. Only a few values are not included. In Fig. 4 (b) and Fig. 4 (c), when the SPS is performed during the daytime dispersed time period and the nighttime trough time period using MC-K-means, the values simulated by this method are able to cover all the actual values. Then, the gap between the scenarios simulated by the method and the real scenarios is analyzed, and the actual results are normalized with the simulated results. Fig. 5 displays the findings.

Simulation accuracy is the comparison between simulated values and actual data values. In Fig. 5 (a), the MC-K-means method is utilized for the simulation of mileage, CD, power consumption and PV PG of EVs for PV charging during peak hours. The gap between its simulated and actual values is low and the simulation accuracy is high. In Fig. 5 (b) and Fig. 5 (c), the simulation accuracy of the metrics in the daytime dispersal time period and the nighttime trough time period using MC-K-means are relatively high. The simulation accuracy of the MC-K-means method is higher than 96% when simulated in all three scenarios. In Fig. 5, the driving range, CD, power consumption, and PV PG of EVs are higher than the other two scenarios in the peak time period. This result shows that the proposed MC-K-means SPS based method can accurately simulate different scenarios of PV PG by EVs.

3.2 Analysis of model solving effect

The effects of the simulation are analyzed followed by the effects of the model solving method based on the PSO algorithm. The experimental environment configuration and dataset are the same as in the Section 3.1. The initial inertia weight of the PSO algorithm is set to 0.9, the two learning factors are set to 2.0, the maximum iteration is set to 100, and the population size is set to 50. The performance of the PSO algorithm for solving the optimized scheduling model is verified by comparing the results of solving the model based on the PSO algorithm, as well as the solving effect using genetic algorithm (GA) and convolutional neural network (CNN). First, the computational time consumption of the three algorithms in different scenarios is compared. The results are shown in Fig. 6.

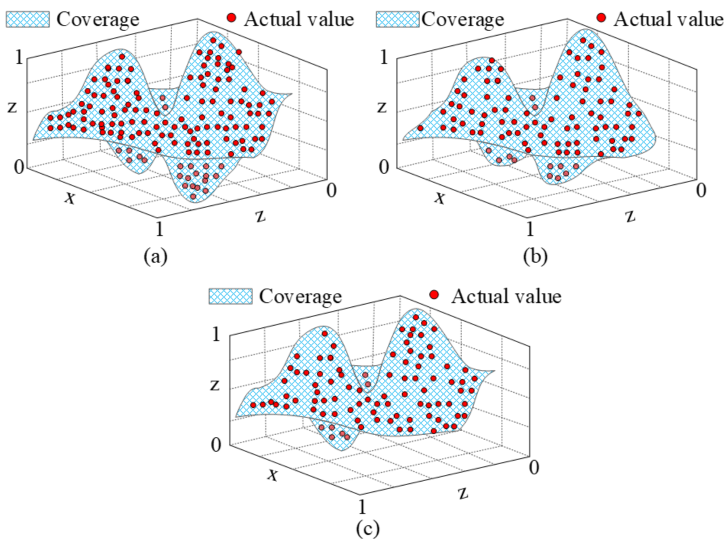

Fig. 4 Stochastic production simulation coverage analysis: (a) coverage during peak hours; (b) coverage daytime dispersed time period; (c) coverage nighttime trough period

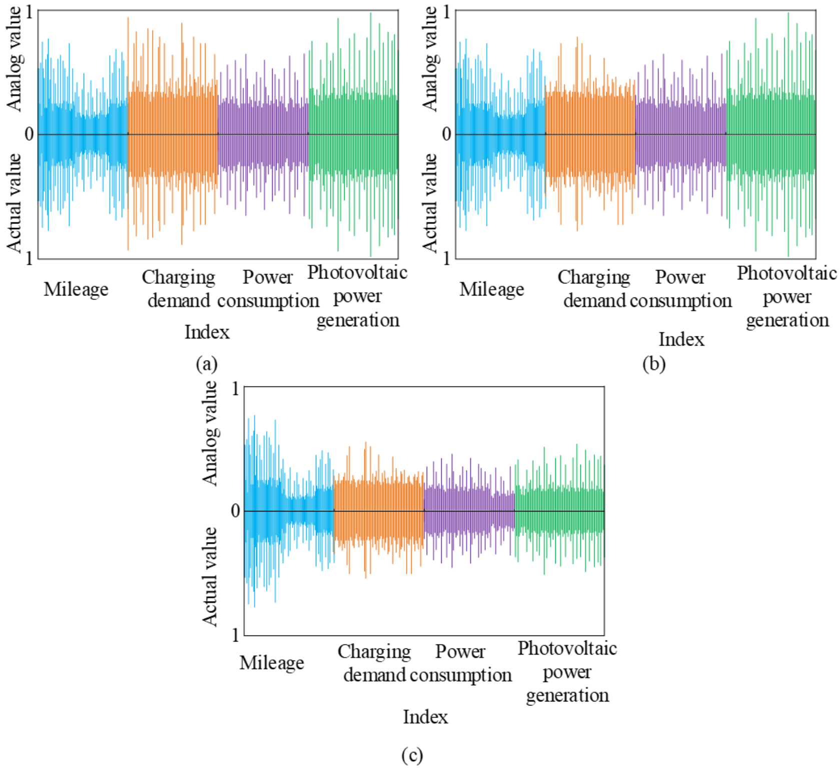

Fig. 5 Simulation accuracy analysis: (a) simulation accuracy during peak hours; (b) simulation accuracy daytime dispersed time period; (c) simulation accuracy nighttime trough period

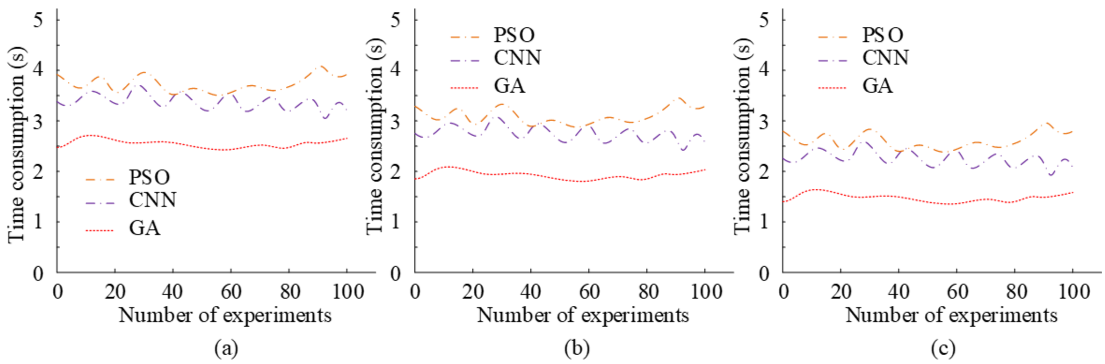

Fig. 6 Algorithm solving time: (a) slgorithm solving time simulation accuracy during peak hours; (b) slgorithm solving time simulation accuracy daytime dispersed time period; (c) algorithm solving time simulation accuracy nighttime trough period

In Fig. 6 (a), when the PSO algorithm is used to solve the OS model for EVs PV charging during peak hours, the time consumed by this algorithm to obtain the OS is only 2.4 s on average. Whereas, the CNN algorithm is used to perform the solution, which takes 3.2 s. Moreover, the GA takes a longer time, which takes 3.7 s on average. In Fig. 6 (b), when solving the OS model for PV charging of EVs using the three algorithms during the daytime dispersed time period, the PSO algorithm also has a lower time-consuming time of only 1.9 s. Whereas, the CNN algorithm and GA have higher time-consuming time of 2.9 s and 3.2 s, respectively. In Fig. 6 (c), the PSO algorithm still takes the lowest time among the three algorithms to solve the model in the nighttime trough time period, which is only 1.4 s. The computational errors of the three algorithms for the OS model in different scenarios are then analyzed. The results are shown in Fig. 7.

In Fig. 7 (a), when solving the OS model which is in the peak time period using the three algorithms, the PSO algorithm has a lower solving error, and its average value is 2.3%. Moreover, the fluctuation of its error is also low. Whereas the errors of CNN algorithm and GA are 3.2% and 4.1% respectively. Moreover, the fluctuation range of the error bands of CNN algorithm and GA is larger. In Fig. 7 (b) and Fig. 7 (c), the PSO algorithm has a relatively low solution error when solving the OS model of EVs

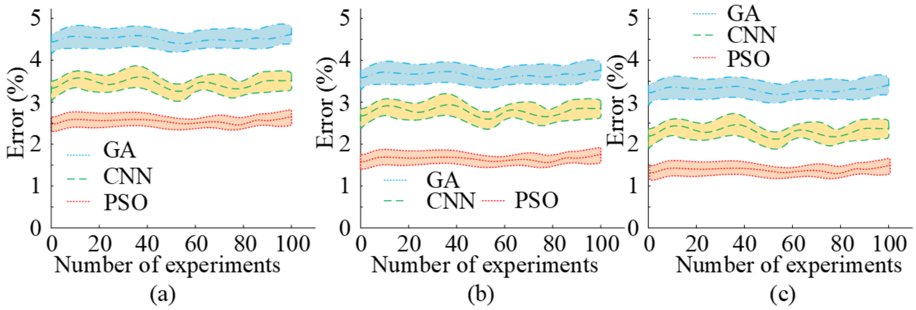

Fig. 7 Calculation error analysis: (a) calculation error simulation accuracy during peak hours; (b) calculation error simulation accuracy daytime dispersed time period; (c) calculation error simulation accuracy nighttime trough period

during the daytime dispersed time period and the nighttime trough time period using the three algorithms. The computational errors of the PSO algorithm in the two scenarios are 1.4% and 1.2%, respectively. In conclusion, PSO algorithm has the best performance in solving the OS model with low computational time and computational error.

3.3 Analysis of optimized scheduling strategy

After verifying the effectiveness of the SPS method and the OS solution algorithm, the actual results of the OS strategy obtained based on MC-K-means SPS and PSO algorithm solution are verified. The PV resource utilization and grid stability during charging of EVs are analyzed before and after comparing the optimization. The utilization rate of PV resources and grid stability are analyzed during peak hours, as well as during the daytime and nighttime off-peak periods. The peak period usually occurs in the evening when residents have a high demand for electricity and EVs are concentrated in one place for charging. The PV PG will gradually decrease due to sunset. There is sufficient sunlight during dispersed periods throughout the day, resulting in high PV PG and low, relatively dispersed electricity consumption. The nighttime trough period usually occurs from late at night to early in the morning. During this time, residents' electricity consumption is low, as is the demand for EV charging. The charging fee for EVs remains the same before and after optimization, and all vehicles are connected to the power grid. The results are shown in Fig. 8.

In Fig. 8 (a), PV resource utilization is improved in different scenarios during PV charging by EVs after optimization scheduling. The PV resource utilization is 98.6%, 97.4%, and 97.3% for EVs PV charging during peak hours, daytime dispersed hours, and nighttime trough hours, respectively. In Fig. 8 (b), the grid stability is also improving after using the optimization scheduling strategy. After the optimization strategy scheduling, the grid stability are improving when EVs PV charging. After optimization, the grid stability is higher than 95%. The reliability of EVs charging before and after optimization is compared and statistically analyzed. Table 2 displays the findings.

In Table 2, the power supply reliability, equipment reliability, and PV system reliability of EVs PV charging are improved after optimization scheduling. Among them, in power supply reliability, the adequacy of PV power increases from 73.1% to 89.7%. Moreover, the frequency of power supply interruption is reduced from 10 times/month to 1 time/month. In the equipment reliability, the failure rate of PV equipment is reduced from 5 times/thousand hours to

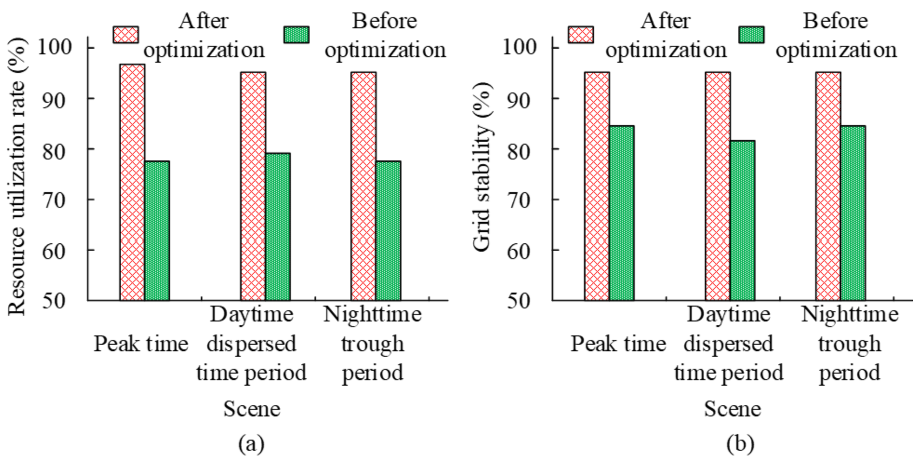

Fig. 8 Changes in PV resource utilization and grid stability: (a) utilization rate of photovoltaic resources; (b) stability

Table 2 Charging reliability analysis

Performance	Index	Before optimization	After optimization	*p*
Power supply reliability	PV power adequacy ratio	73.1%	89.7%	**
	Power interruption frequency	10 times/month	2 times/month	**
	Duration of power interruption	2 times/h	1 times/h	**
Equipment reliability	PV equipment failure rate	5 times/1000 hours	2 times/1000 hours	**
	Charging equipment failure rate	3 times/thousand hours	1 times/1000 hours	**
	Average repair time of equipment	3 h	1 h	**
System reliability	Charge efficiency	85.7%	96.8%	**
	System response time	15 s	8 s	**

Note: ** indicates $p < 0.01$

2 times/thousand hours. Moreover, the charging efficiency of the system is increased by 11.1% and the system response time is reduced by 7 s. Moreover, all the above results are statistically analyzed ($p < 0.01$). In conclusion, the proposed optimization scheduling model based on MC-K-means SPS and the optimization scheduling strategy obtained by solving the PSO algorithm can improve the efficiency of PV charging of EVs and ensure the reliability of charging.

4 Discussion and conclusion

Aiming at the current problems of low reliability of PV charging of EVs and poor utilization of PV charging resources, this study conducted SPS for optimization scheduling of PV charging of EVs using MC and K-means. Moreover, an optimization scheduling model was constructed based on this simulation method. Finally, the PSO algorithm was used to solve the model in order to obtain the optimization scheduling strategy. To verify the effectiveness of this optimization scheduling strategy, the study first analyzed the performance of the MC-K-means stochastic simulation method. The results indicated that the SPS method provided a high coverage of the PV charging of EVs in different scenarios. In addition, the modeling accuracy of this simulation method was higher than 96% for EVs mileage, CD, power consumption, and PV PG. The above results were similar to the findings of Bakhshayesh and Kebriaei (2023). However, Bakhshayesh and Kebriaei (2023) performed SPS with an average accuracy of 89.2%, which was slightly lower than the stochastic simulation production method proposed in this study (Bakhshayesh and Kebriaei, 2023). After analysis, it was hypothesized that the reason leading to the high accuracy of MC-K-means SPS could be the ability of the K-means algorithm to cluster EVs according to mileage and CD. By adopting different simulation strategies for vehicles in different clusters, the method could simulate their charging behavior more accurately. In addition, the solution effect of PSO algorithm was analyzed, and the solution effects of PSO algorithm, CNN algorithm, and GA were compared. The results showed that the PSO algorithm had the lowest solving time for the optimization scheduling model in different scenarios. During peak hours, the daytime dispersion time, and the nighttime trough time, the PSO algorithm had solving times of 2.4 s, 1.9 s, and 1.4 s, respectively, for the optimization scheduling model, indicating a lower model solving time. Moreover, when the PSO algorithm was used to calculate the optimized scheduling model, the computation times were 2.3%, 1.4%, and 1.2% in the three scenarios, respectively, with minimal calculation error. This result was approximately the same as the experimental result of Yin et al. (2023). However, in the result of Yin et al. (2023) the elapsed time was longer reaching 13.2 s. The reason for this result might be that Yin et al. (2023) used a multi-objective optimization algorithm to solve the optimization scheduling model. This algorithm had to deal with multiple conflicting OFs simultaneously. This made the search space more complex, thus prolonging the computational time consuming (Yin et al., 2023). Finally, the optimization scheduling strategy obtained after PSO solving was utilized for scheduling the PV charging of EVs. The results indicated that after optimization, its PV resource utilization in peak time period, daytime dispersed time period, and nighttime trough time period were improved to 98.6%, 97.4%, and 97.3%, respectively. Moreover, its power supply reliability, equipment reliability, and PV system reliability were improving.

In summary, the proposed optimization scheduling method for EVs PV charging based on SPS can improve the reliability of EVs charging and increase its resource utilization efficiency. However, in this study, the uncertainty of dynamic changes in the electricity market and electric market was not considered, which may reduce the optimization effect of the optimization scheduling strategy. In the future, data mining techniques can be used to analyze the market dynamic change data in depth to ensure that the study can keep up with the actual changes in the market.

Nomenclature

RE	Renewable energy
PV	Photovoltaic
OS	Optimal scheduling
MC	Monte Carlo
CD	Charging demand
DPs	Data points
CPs	Charging piles
CNN	Convolutional neural network
EVs	Electric vehicles
PG	Power generation
SPS	Stochastic production simulation
PSO	Particle swarm optimization
RP	Rated power
OF	Objective function
GA	Genetic algorithm

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