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Optimal Dispatch Strategy for a Distribution Network Containing High-Density Photovoltaic Power Generation and Energy Storage under Multiple Scenarios

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Abstract: To better consume high-density photovoltaics, in this article, the application of energy storage devices in the distribution network not only realizes the peak shaving and valley filling of the electricity load but also relieves the pressure on the grid voltage generated by the distributed photovoltaic access. At the same time, photovoltaic power generation and energy storage cooperate and have an impact on the tidal distribution of the distribution network. Since photovoltaic output has uncertainty, the maximum photovoltaic output in each scenario is determined by the clustering algorithm, while the storage scheduling strategy is reasonably selected so the distribution network operates efficiently and stably. The tidal optimization of the distribution network is carried out with the objectives of minimizing network losses and voltage deviations, two objectives that are assigned comprehensive weights, and the optimization model is constructed by using a particle swarm algorithm to derive the optimal dispatching strategy of the distribution network with the cooperation of photovoltaic and energy storage. Finally, a model with 30 buses is simulated and the system is optimally dispatched under multiple scenarios to demonstrate the necessity of conducting coordinated optimal dispatch of photovoltaics and energy storage.

Keywords: distribution network optimization; high-density photovoltaic; energy storage; multi-target; multi-scenario; improved particle swarm algorithm

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1. Introduction

The rapid development of photovoltaic (PV) power generation provides a clean and efficient solution for the use of energy, and its use as a renewable energy source has great significance for the sustainable development of the energy industry. In terms of environmental pollution, the use of photovoltaic resources can reduce the burning of fossil fuels and alleviate some of the pollution caused by fossil fuel power generation. To build a better photovoltaic power grid system, the use of distributed PV consumption is an effective way to utilize high-density PVs. However, as the number of distributed power sources increases, the control scheme needs to change significantly, and more complex coordination and interaction between controllers is required. Recently, new challenges and opportunities for voltage control in transmission and distribution grids were reviewed, and layered voltage control was performed for high-penetration distributed power sources [1]. The PV consumption problem was solved in [2], in which the authors constructed a grid-connected PV storage system and proposed a coordinated control strategy. Now that the use of renewable energy is becoming more and more popular, in research on energy use in transportation and electricity, the proportion of new energy used in various energy use situations and the efficiency of energy use have become key research focuses [3–6].

For a grid operation strategy containing PVs and energy storage, it is necessary to determine the output characteristics of PVs and the charging/discharging characteristics of energy storage. By modeling the distribution network structure and circuit configuration, and controlling and managing the power side, the grid can avoid large transient voltage fluctuations and load collapse. At the same time, this approach maximizes the use of PV power generation in the grid-connected state, coordinates the source storage in the system, and realizes the distributed integrated control of PVs and energy storage systems under the microgrid [7]. Energy storage in solar-containing distribution grids has also demonstrated a unique economic value, while research has progressed further in both siting and sizing and dispatch optimization [8–10]. This paper differs from these studies by focusing more on mobilizing the grid as a whole, providing good conditions for the use of distributed power sources and energy storage, and realizing the reactive power optimization of the system according to the change in power output on the power side and the adjustment of the transformer.

Based on the demand for active power control in grid operation, a decentralized active power control system containing distributed energy storage and distributed PVs with hierarchical control is proposed [11]. The system decentralizes the regulation of power and performance among components to keep the total system frequency as a continuous and smooth signal, which avoids a sudden change in grid frequency caused by the access to renewable energy sources. A grid with access to a large number of renewable energy sources can also be operated alone during peak hours and blackout periods, and the PV arrays are controlled hierarchically to provide power, which sets the grid supply power constraints and improves the penetration of PVs into the grid [12]. By using the alternating direction method of multipliers (ADMM) within a model predictive control (MPC) framework, a shift from centralized to decentralized control is achieved [13].

For the wide application of distributed power within the distribution network, it is necessary to solve the problems of supply demand balance and peak loads therein, as well as to optimize the distribution of tidal currents within the distribution network, and to form a corresponding demand response scheme. Considering both unbalanced network constraints and reactive power limitations, an optimal tidal optimization of distribution networks with reactive power control is proposed [14]. Then, from the perspective of a hybrid distribution transformer, the remote coordinated control of PV arrays is carried out through reactive power optimization to ensure voltage regulation and network loss reduction [15]. Research on optimization of inverter-based PV integration has also attracted a lot of attention, and topology optimization through the PV location capacity and the design of the inverter also helps to improve the reliability and stability of the system [16–18]. The application of energy storage systems can alleviate some of the scheduling challenges brought about by renewable energy access and contribute to improving the power quality of the distribution network, among others. In some studies, the advantages of energy storage systems in the optimized scheduling of distribution grid operation and the corresponding scheduling methods have been investigated [19–22]. There has also been a significant breakthrough in the progress of research on the application methods of energy storage technology in the power grid, which presents the characteristics of large-scale integration and multi-objective co-regulation [23–26]. Although a lot of research work has been conducted on energy storage technology and power system trend optimization, there is still a lot of in-depth research that needs to be carried out to coordinate and control the active output of each distributed power source and reduce the energy loss under the premise of guaranteeing the quality of power system operation.

Due to the volatility and uncertainty of renewable energy output, the output characteristics of renewable energy cannot be accurately reflected in the practical application of optimal scheduling methods, and typical scenarios need to be divided to determine its maximum output. Coordinated optimal scheduling of energy systems under PV uncertainty can improve the economy and security of grid operation and realize real-time energy utilization [27]. A large number of studies have optimized the PV output scheduling of systems with uncertainty by dividing different scenarios to achieve the coordination of multiple distributed power sources, which makes the energy supply model more efficient and improves the economy and stability of the system [28–30]. The method of PV clustering is also reflected in many studies, and an equivalent computational model can be obtained by analyzing the clustering of high-density distributed PVs connected to the distribution grid [31]. Studies have also presented the clustering method in detail and have demonstrated how it works in simulation models [32–36]. According to different control strategies, different system models have been developed for full utilization of energy in different scenarios [37]. The scenario division in this paper, on the other hand, is based on the local climate and environment, and the light radiation intensity is clustered to reflect the characteristics of PV output under different light conditions.

This paper starts from the status quo of accessing high-density distributed photovoltaics in the power grid, seeking to solve the related problems created by PV uncertainty, dividing different light radiation intensity scenarios, accessing suitable-capacity energy storage devices in the system, and inducing charging and discharging of energy storage devices according to the fluctuation in electricity prices. Then, we establish an objective function of network loss and voltage deviation, and we carry out rational scheduling for the photovoltaic storage system in the distribution grid under different scenarios, so that each bus accesses distributed photovoltaics as much as possible under the premise of stabilizing the voltage, as well as reduces the network loss.

The results of this study show that the optimally dispatched system containing a high density of PV power generation and energy storage devices can effectively reduce energy losses, and we demonstrate that the system maintains good power quality even after a large amount of PV power is connected. Section 1 of the manuscript describes the need to develop a new type of power system with multiple distributed power sources, and Section 2 presents a model for connecting PV power generation and energy storage devices to the grid, as well as a methodology for clustering and optimizing their data. Section 3 presents the results obtained for the optimization of the system under the two optimization objectives of network losses and voltage deviation values, and finally, Section 4 describes the main conclusions and future work for this research.

2. Materials and Methods

Enabling high-density distributed PV access to the distribution network requires considering not only the PV consumption brought about by the voltage limit but also considering its coordination with the distributed power supply scheduling, to reduce the network losses during system operation. At the same time, the high proportion of distributed PV power output is characterized by strong randomness and fluctuation, which challenge the safety of grid operation, and the coordinated and optimal scheduling of PVs and energy storage in the distribution grid needs to be achieved in different scenarios. Distributed photovoltaic access to the grid requires a series of conversion processes. Photovoltaic power-generation devices need to convert sunlight into electrical energy, which is controlled by the inverter to form the power that can be used for the network, with the ability to output external voltage power. An energy storage device also has the characteristics of charging and discharging and is connected to the distribution network as a distributed power source together with PV power generation. In this way, a distribution grid power system with high-density photovoltaics and energy storage devices is formed (Figure 1).

To solve the optimization problem of a distribution network with high-density photovoltaics and energy storage, the following methods are applied in this paper, among which the application of a clustering algorithm solves the problem of inaccurate operational data and improves the solving efficiency and data accuracy of the algorithm; the application of a comprehensive evaluation method solves the assignment problem in the multi-objective decision process and makes a scientific selection and reasonable decision in the face of multiple conflicting objectives; and the improved particle swarm optimization algorithm searches for optimization according to the optimization objectives, while having a faster convergence speed and avoiding falling into the local optimal solution too early.

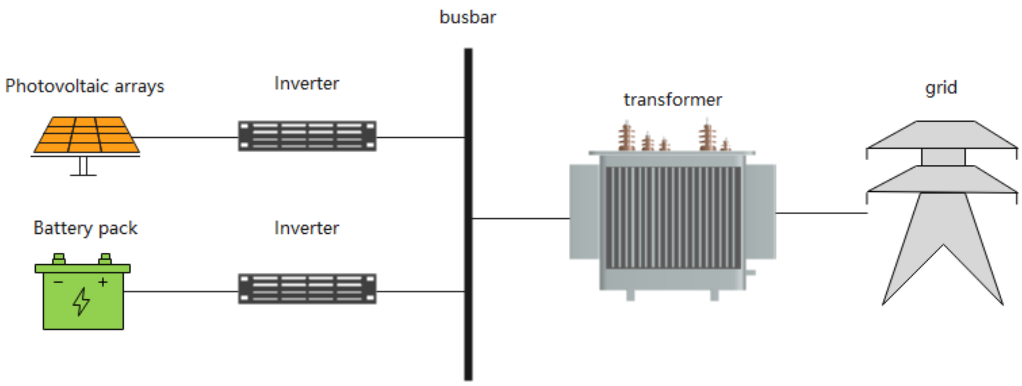

Figure 1. Distribution grid power supply model with high-density photovoltaic and energy storage batteries.

2.1. PV Output Modeling

High-density photovoltaic access to the distribution network requires the solution of two problems in terms of utilization, namely how to convert a large amount of solar energy into electrical energy and how to make this converted electrical energy available to the distribution network. For photovoltaic power generation, the photovoltaic model used to generate electricity is generally in the form of photovoltaic cells. When sunlight hits the surface of the cells, the carriers are subjected to the action of the P-N junction in the interior, and a closed circuit is formed in the exterior to generate a current. When the relevant parameters and inputs of the PV cell are given, the output characteristics of the PV cell can be obtained. However, this output method is not sufficient for the grid. When several PV cells are connected in series and parallel to form a PV array, they can output voltage and power. This electrical energy online needs to be controlled by an inverter, which can effectively control the transient current in the process of grid connection and regulate the voltage and current to guarantee the stability of the system operation.

After coordinated control of all aspects, PV power generation is equivalent to a distributed power supply for the load, while the structure of the distribution network is a radial power supply. The power supply mode is changed from the original single power supply to multiple distributed power supplies, which increases the reliability (Figure 2).

2.2. Energy Storage Modeling

The ESS energy storage system has both charging and discharging characteristics, charging when the electricity supply is sufficient and discharging when the electricity supply is insufficient and the price is high, to realize the peak regulation of the power grid.

It takes 24 h a day as an operation cycle to ensure that the energy storage battery is in the lowest charge state at the initial moment and can recover this state after one operation cycle. The 0/1 constraint is added to the control charging and discharging strategy to ensure that the charging and discharging of the energy storage battery will not be carried out simultaneously. Meanwhile, the self-discharge rate of ESS represents the coefficient of ESS power loss after a period of time. After each period of charging and discharging the battery, the power of ESS changes accordingly, which is expressed as SOC_{ESS}, and the battery state is expressed in periods as

$$SOC_{ESS,t} = (1 - \sigma_{ESS,t-1}) + (P_{ESS,t}^{charge} \eta_{ESS}^{charge} \Delta t - P_{ESS,t}^{discharge} \eta_{ESS}^{discharge} \Delta t) / C_{ESS} \tag{1}$$

where $P_{ESS,t}^{charge}$ and $P_{ESS,t}^{discharge}$ are the charging and discharging power of ESS at time t, η_{ESS}^{charge} and $\eta_{ESS}^{discharge}$ are the charging and discharging efficiency of ESS, and C_{ESS} is the battery capacity of the energy storage system.

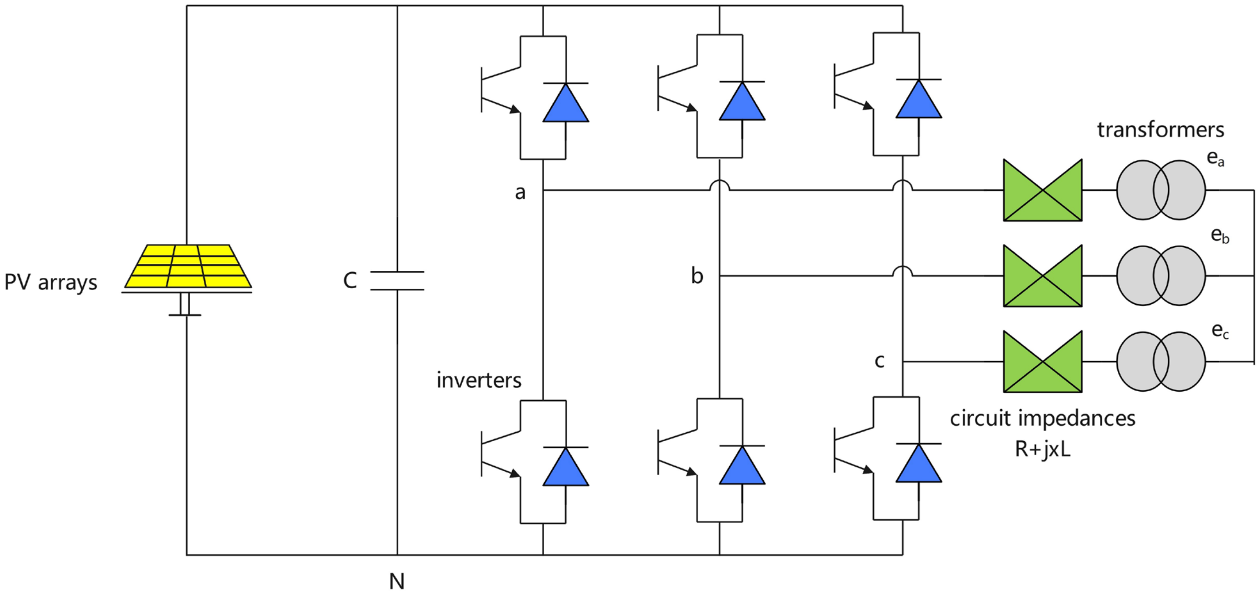

Figure 2. Distributed PV array on-grid control model.

2.3. Distributed PVs and Energy Storage Connected to the Distribution Network Modeling

An example analysis was carried out using the IEEE 30-bus test distribution system, which has a base capacity of SB = 100 MVA and a base voltage of VB = 135 KV. In the IEEE 30-bus distribution grid, distributed PVs are accessed at buses 2, 5, 8, 11, and 13, and energy storage ESS devices are accessed at buses 22 and 27. The bus types can be categorized into three: PQ buses, PV buses, and balanced buses. The voltage of balanced buses is 1.0 pu. The buses are analyzed where the buses accessing distributed PVs with energy storage devices can be classified as PQ buses. Bus 1, which is the balancing bus, is selected as the reference bus for trend calculation. There is one and only one balancing bus in the system, and in this system, bus 1 is connected to the higher grid for interaction. The rest of the buses are set as PQ buses and PV buses depending on the conditions under which the data measurements are obtained. The bus network of the 30-bus system is shown (Figure 3).

The distributed PV access to the distribution network for trend calculation, for the distribution network over a day of PVs and energy storage system coordination and optimization, can allow the PV output and storage charging and discharging to adapt to the time-sharing tariff step change, thus supporting different operating strategies. Influenced by the peak and valley periods of electricity prices, the energy storage system starts charging to accumulate power in a valley, and then it discharges to release power at a peak. At the same time, the application of high-density photovoltaics eases the problem of tight power supply during peak hours, and the application of multiple distributed power sources makes the supply of electric loads more secure.

In this system, transformer control is also an important factor in achieving reactive power optimization and voltage regulation. By controlling the gear changes of the tap's five gears, the system can be made to absorb energy, to avoid over-voltage during peak PV output, and to output energy, to avoid under-voltage at night. Therefore, when coordinating the power output of each distributed power source of the system, the action of the transformer taps should also be within the range of optimized dispatch, to achieve voltage regulation. The action of transformer taps in the system is determined according to the distribution of power tides, and when the load and distributed power generation change, guided by the optimization goal, the transformer taps will choose the appropriate gear to coordinate the control of photovoltaic power generation and energy storage charging and discharging.

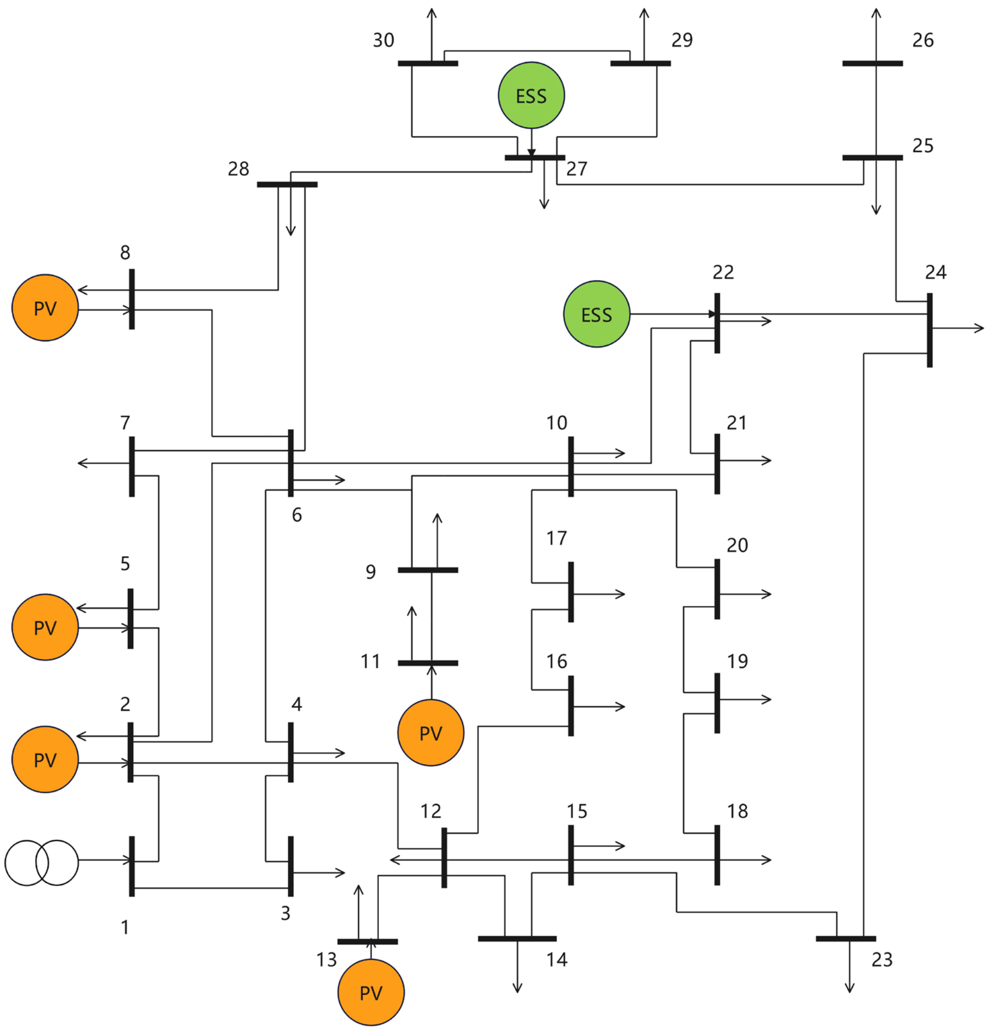

Figure 3. Arithmetic simulation for 30 buses.

2.4. Clustering Algorithm

The difficulty of PV output prediction lies in the uncertainty and uncontrollability of the power it emits. By organizing the historical data, using the clustering algorithm to filter more reliable data can provide help for system scheduling and real-time operation, and it can reduce the impact of distributed PV access on the grid. Therefore, the K-means clustering algorithm is used to categorize the historical data and gather them into K clusters according to their similarity. The process of using the K-means clustering algorithm to process the data is as follows:

Step 1: Select appropriate sample eigenvalues and normalize five statistical indicators, namely standard deviation, skewness coefficient, coefficient of variation, peaking coefficient, and total power, as the eigenvalues of the system. The formulas for the five indicators are as follows:

$$\sigma = \sqrt{\frac{\sum_{i=1}^{N} \left(P_i - P_{avg}\right)^2}{\mathrm{N}}} \tag{2}$$

$$s = \frac{\mathrm{N}\sum_{\mathrm{i}=1}^{\mathrm{N}} (P_i - P_{avg})^2}{\sigma(\mathrm{N}-1)(\mathrm{N}-2)} \tag{3}$$

$$c = \frac{\sigma}{P_{avg}} \tag{4}$$

$$k_u = \frac{\sum_{i=1}^{N} (P_i - P_{avg})^4}{\sigma(\mathrm{N}-1)} \tag{5}$$

$$P_{sum} = \sum_{\mathrm{i}=1}^{\mathrm{N}} P_i \tag{6}$$

where N is the number of sampling points, P_{avg} is the unit average PV power, and P_{sum} is the instantaneous power.

Step 2: Normalization of the indicators is calculated as

$$x_1 = \frac{x - x_{\min}}{x_{\max} - x_{\min}} \tag{7}$$

Step 3: A sample is chosen at random as the first center of mass, denoted C_1.
Step 4: The shortest distance *D(x)* between each sample and the center of mass C1 is computed, and the next center of mass is selected based on the result obtained from the probability *p(x)* that each sample is selected as the center of mass. The probability of being selected as a center of mass is calculated as

$$p(x) = \frac{D^2(x)}{\sum_{x \in X} D^2(x)} \tag{8}$$

Step 5: Repeat the previous step until K clustering centers are selected.
Step 6: Based on the distance of each sample from each center of mass, assign each sample to its nearest center of mass to form the corresponding cluster.
Step 7: Update the center of gravity of each cluster.

$$C_i = \frac{\sum_{x \in C_i} x}{|C_i|} \tag{9}$$

Step 8: Repeatedly update each cluster with the center of mass until no change occurs.

Figure 4 shows the flow of the K-means clustering-based optimal scheduling method for high-density PV resources studied in this paper.

Take the data of light radiation intensity in Beijing, for example. Through K-means clustering, all the data are categorized into five typical scenarios. The final clustering center is determined through continuous iteration, and the distribution of light radiation intensity is obtained under different scenarios. We followed these steps, and the results are shown (Figure 5). All areas of similar climate can be included.

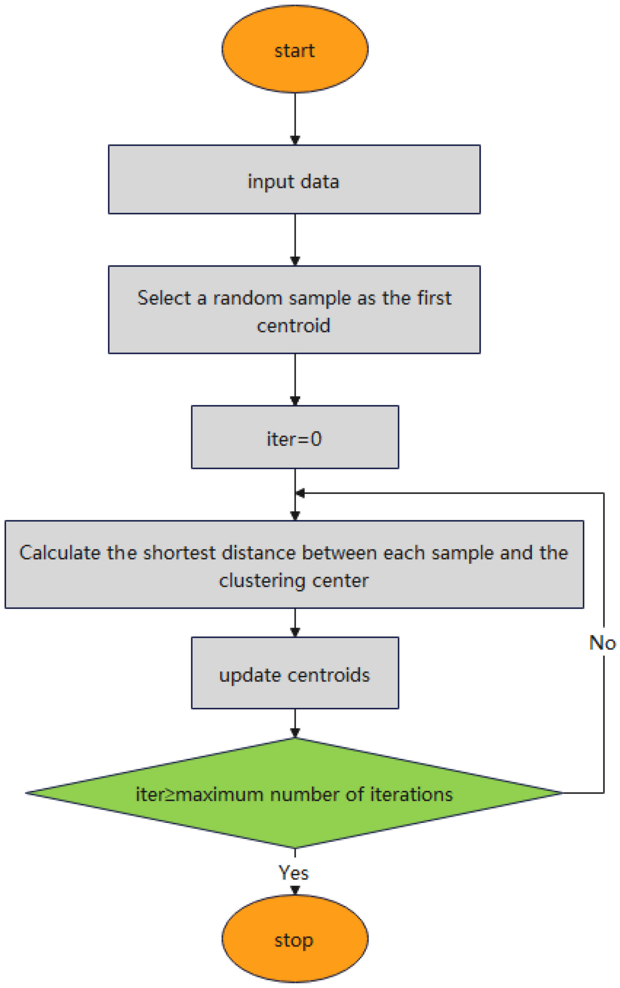

Figure 4. Flowchart of the K-means clustering.

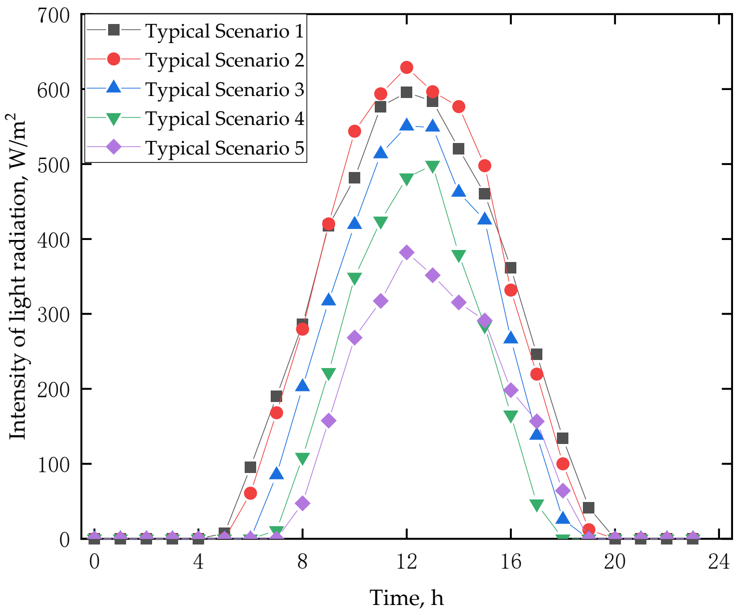

Figure 5. Typical scenario of light radiation intensity in a region.

2.5. Comprehensive Evaluation Methodology

To better evaluate the indicators of the distribution network, the hierarchical analysis method–entropy weight method is invoked to assign weights to the indicators, and the distributed power output situation is reasonably dispatched through the weight indicators. The comprehensive evaluation system of the distribution network is established with system network loss and voltage deviation as the optimization target and optimal scheduling of multiple objects in the system.

2.5.1. Hierarchical Analysis Method

When applying the hierarchical analysis method to the comprehensive evaluation system of distribution network optimization and dispatching, the optimization objectives are empowered by combining qualitative and quantitative methods, so that the optimization problem of the system has a hierarchy. The basic calculation steps are as follows:

Step 1: Establish the hierarchical structure of the system

The optimization problem is organized into a hierarchical architecture, and its elements are divided into the highest, middle, and lowest levels according to the goal, criterion, and object of decision-making. The highest level is the problem solved by the decision, the middle level comprises the criteria to be considered, and the lowest level covers the alternatives to achieve the goal.

Step 2: Construction of judgment matrix

According to the hierarchical structure, the factors are compared with each other two by two, and the relative importance of each indicator is compared using the 1–9 scale. Then, the comparison results are used as the elements of the judgment matrix in order to obtain the judgment matrix A.

$$A = (a_{ij})_{\mathrm{m}\times\mathrm{n}} \tag{10}$$

where a_{ij} is the expert's empirical weighting, m denotes the number of matrix rows, and n denotes the number of matrix columns.

Step 3: Consistency test

First, the consistency index CI is defined, and the size of the CI is calibrated by using the corresponding random consistency index RI. Then, the consistency ratio CR is calculated with the formula:

$$\mathrm{CI} = \frac{\lambda_{\max} - n}{n - 1} \tag{11}$$

$$\mathrm{CR} = \frac{\mathrm{CI}}{\mathrm{RI}} \tag{12}$$

where $\lambda_{\max}$ is the maximum eigenvalue of the judgment matrix. When $\mathrm{CR} \leq 0.1$, the matrix satisfies the consistency test. Otherwise, the judgment matrix needs to be adjusted so that it meets the condition of the consistency test.

Step 4: Determine the integrated weights

Find the maximum eigenvector of the judgment matrix, which is used as the objective weight of the index.

2.5.2. Entropy Weight Method

The entropy weight method determines the weights of the indicators according to the magnitudes of their variability, obtains the respective entropy weights through the information entropies of the indicators, and utilizes the entropy weights to correct the magnitudes of the respective weights.

According to the proposed program data, establish the original information matrix X.

$$\mathbf{X} = (x_{ij})_{m\times n} \tag{13}$$

Indicators are normalized to obtain a normalization matrix E_{ij}.

$$E_{ij} = \frac{x_{ij}}{\sum\limits_{j=1}^{m} x_{ij}} \tag{14}$$

When E_{ij} = 0, let $E_{ij} \ln E_{ij}$ = 0.
Calculate the information entropy of the indicator E_j.

$$E_j = -\frac{1}{\ln m} \sum_{i=1}^{m} E_{ij} \ln E_{ij} \tag{15}$$

Calculate the weight ω_j.

$$\omega_j = \frac{1 - e_j}{n - \sum\limits_{j=1}^{n} e_j} \tag{16}$$

2.5.3. Comprehensive Weight Calculation

According to the hierarchical analysis method and entropy weight method (used to obtain the weight matrices for $\lambda = [\lambda_1, \lambda_2, \cdots, \lambda_m]^T$ and $\omega = [\omega_1, \omega_2, \cdots, \omega_m]^T$, respectively, in order to form the substrate $[\lambda, \omega]$), the two methods' combined weight W is

$$W = \frac{\lambda \times \omega}{\sum\limits_{j=1}^{m} \lambda \times \omega} \tag{17}$$

2.6. Improved Particle Swarm Optimization Algorithm

The particle swarm optimization algorithm is an evolutionary computing technique that seeks the optimal solution of an objective through the iteration of a group of particles. However, the traditional particle swarm algorithm relies on inertia weights and learning factors, which make it easy to fall into the situation of local optimization. A single traditional intelligent algorithm may not be able to solve some problems effectively, while the use of intelligent algorithm fusion can improve traditional algorithms and obtain a better performance [38,39]. Accordingly, research in this area has been widely used in the field of power systems, seeking the optimal solution based on reactive power optimization [40,41].

Similarly, this paper improves the traditional particle swarm algorithm by searching for the optimum in an improved initialized population and adopting a chaotic search to improve the convergence and convergence speed of the algorithm (Figure 6).

The improved particle swarm algorithm containing power system tidal current calculation needs to constantly seek the optimal solution value of the objective, i.e., it constantly seeks the optimal value for the system network loss. The flow is shown in Figure 7.

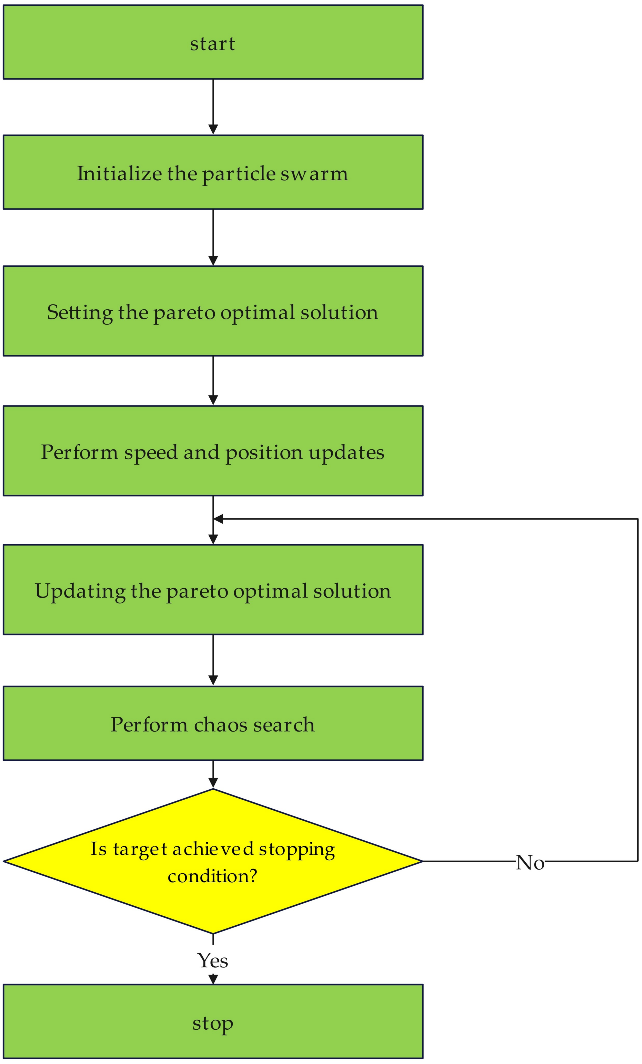

Figure 6. Improved particle swarm algorithm calculation process.

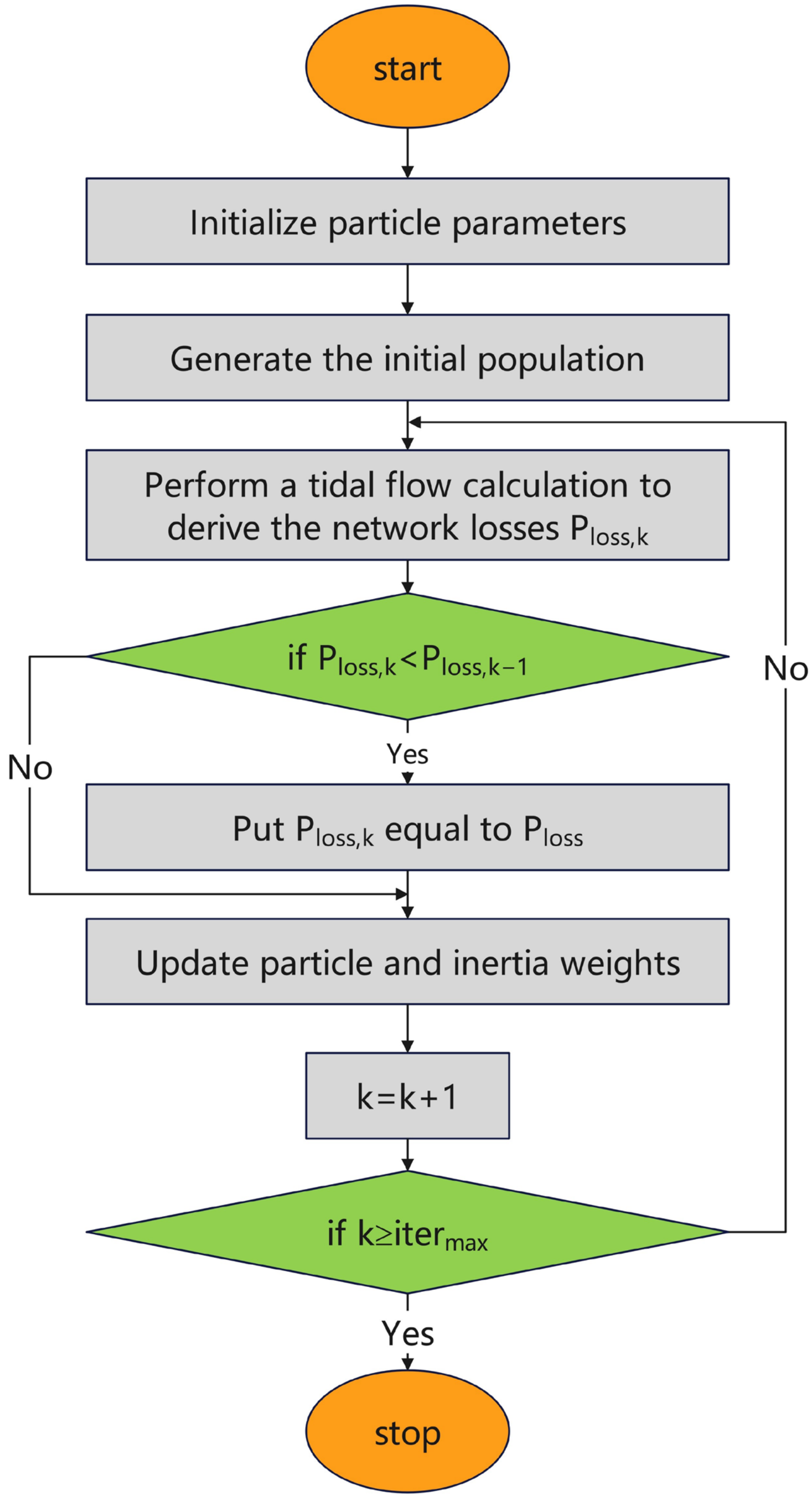

Figure 7. Flowchart of the particle swarm optimization algorithm involving power system current calculation.

3. Results

3.1. Integrated Evaluation Decision-Making for Distribution Network Optimization

The optimization objective of the distribution network includes both network loss and voltage offset. First, the active network loss of the system is used as the optimization objective, which is achieved by rationally allocating the size of the PV output. The active network loss objective function is defined as

$$\min P_{loss} = \sum \frac{P_i^2 + Q_i^2}{U_i^2} R_i \tag{18}$$

where P_i and Q_i denote the active and reactive power at bus i, respectively, U_i denotes the voltage at bus i, and R_i denotes the resistance at bus i.

Second, access to distributed energy sources will lead to changes in the voltage level; to ensure the stability of the voltage, it is necessary to set the voltage stability level as an objective function as well and adjust the voltage magnitude of each bus by adjusting the output of the distributed power supply in the system and the taps of the transformer. The voltage stability objective function is defined as

$$\min \delta U = \sum \frac{U_{\mathrm{i}} - U_N}{U_N} \tag{19}$$

where U_i is the actual voltage at bus i and U_N is the rated voltage at bus i.

Setting the objective function in these two aspects at the same time is equivalent to making requirements for the economy and security of the system, respectively, and optimizing the distribution network dispatch for economical and safe operation.

The two optimization objectives of minimal network loss and voltage deviation are assigned, and the objective function expression is as follows:

$$\min F = \beta_1 \sum \frac{P_i^2 + Q_i^2}{U_i^2} R_i + \beta_2 \sum \frac{U_{\mathrm{i}} - U_N}{U_N} \tag{20}$$

where the values of β_1 and β_2 can be calculated from the weights above.

The following constraints are also required for this distribution system, where the capacity constraints are as follows:

$$0 \leq P_i \leq P_{PV} \tag{21}$$

$$S_i \leq S_{i\max} \tag{22}$$

where P_{PV} and $S_{i\max}$ denote the maximum PV output and the maximum capacity of branch transmission, respectively.

Set the voltage constraints as follows:

$$U_{i\min} \leq U_i \leq U_{i\max} \tag{23}$$

where $U_{i\min}$ and $U_{i\max}$ are the minimum and maximum values of voltage at bus i. The lower and upper limit values are set at 0.95 pu and 1.05 pu, respectively.

The current distribution constraints of the system itself are

$$P_i + P_{Gi} = P_{Li} + U_{Li} \sum_{i=1}^{N} U_i Y \tag{24}$$

$$Q_i + Q_{Gi} = Q_{Li} + U_{Li} \sum_{i=1}^{N} U_i Y \tag{25}$$

where P_i and Q_i are the active and reactive power at bus i; P_{Gi} and Q_{Gi} are the active and reactive power injected at the bus; P_{Li} and Q_{Li} are the active and reactive power of the load; U_i is the voltage at bus i; and Y is the branch conductance.

Set the energy storage charge/discharge constraint as follows:

$$0 \leq P_{ESS,t}^{charge} \leq P_{ESS,\max}^{charge} \tag{26}$$

$$0 \leq P_{ESS,t}^{discharge} \leq P_{ESS,\max}^{discharge} \tag{27}$$

$$SOC_{ESS,\min} \leq SOC_{ESS,t} \leq SOC_{ESS,\max} \tag{28}$$

where $P_{ESS,\max}^{charge}$ and $P_{ESS,\max}^{discharge}$ are the maximum charging and discharging power of the storage battery, and $SOC_{ESS,\min}$ and $SOC_{ESS,\max}$ are the minimum and maximum power of the storage battery, respectively.

Apply the improved particle swarm algorithm to the IEEE 30-bus system for multi-objective optimization in terms of network loss and voltage deviation, where the calculation steps are as follows:

Step 1: Determine the initial data matrix according to the relevant operation data of the distribution network;
Step 2: Initialize the particle swarm, and set the number of particles and the maximum number of iterations;
Step 3: Use the forward and backward generation method to calculate the current, and analyze the particle adaptation value to select the optimal solution;
Step 4: Update the individual optimal value and the group optimal value;
Step 5: Update the particle velocity and position, and iteratively carry out the last two calculations until the iteration stop condition is satisfied.

3.2. Application Example Optimization Results

The charging and discharging strategy of energy storage in the scheduling process of the distribution grid containing PVs and energy storage should ensure the consumption of PVs as much as possible and alleviate the pressure brought to the grid by high-density PV access. For the cooperative control of PVs and storage in different scenarios, the scheduling strategy is the same. Time-of-day regulation in the system can fully utilize the role of energy storage in distribution grid scheduling, where the charging and discharging of energy storage and the output of PVs are divided into 24 time periods of the day for coordinated control. According to the optimization objectives and constraints related to storage charging and discharging and PV output, the integration of distributed power sources can be obtained for storage charging and discharging and PV output under different periods on a given day under a large power grid (Figure 8).

Figure 9 shows the magnitudes of network losses in the five cases for the power system without storage compared to that with storage and with dispatch optimization. If reactive power compensation devices can also be added at each bus, the system network loss is further optimized. For the five scenarios of distributed PV access in this system, the network loss of the system after reasonable deployment is smaller than that of the original system, which proves that distributed power can reduce the network loss of the system. Meanwhile, according to the structure of the distribution network, the optimization of the capacity and location of distributed PVs can also reduce the network loss of the system and improve the power quality of the system operation.

After optimizing the distribution system containing high-density distributed photovoltaics and energy storage in five typical scenarios, the system still maintains a stable voltage level and ensures good power quality, which proves that the optimized grid structure tends to be reasonable and the power supply modes are more diverse (Figure 10).

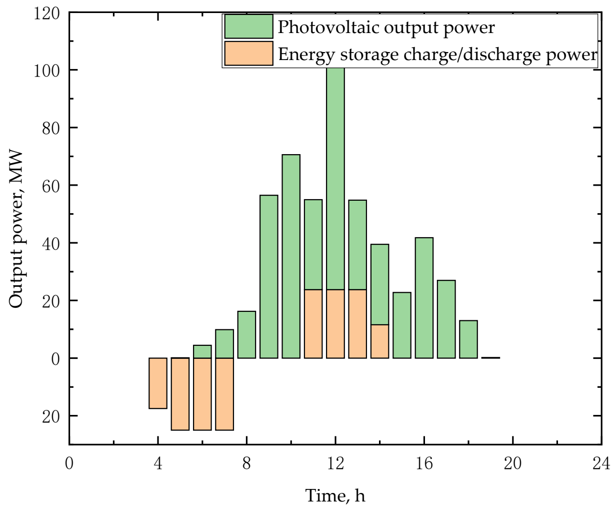

Figure 8. Photovoltaic output power and storage charging/discharging power over time.

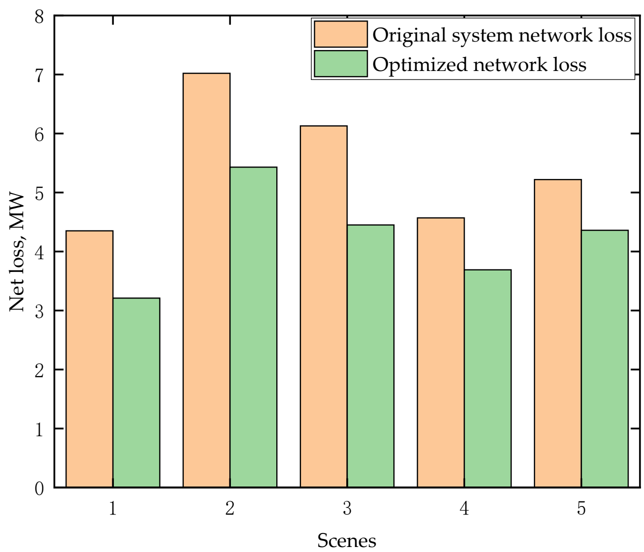

Figure 9. Comparison of network loss before and after optimization in different scenarios.

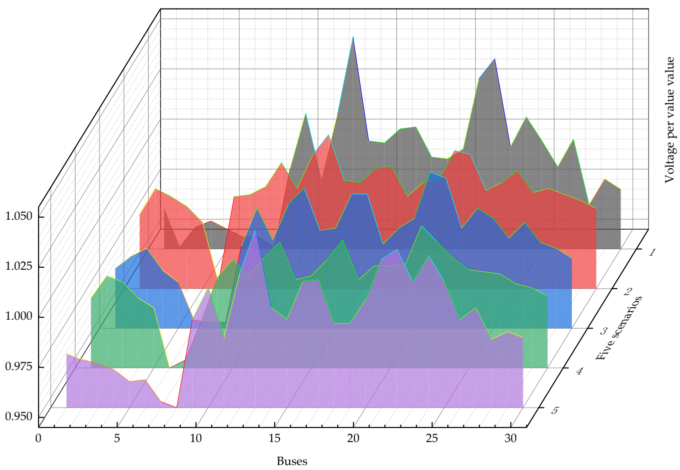

Figure 10. Bus voltage distribution under different scenario-optimized operation strategies.

The operation of the system was observed over a long period, under the control of five different operation strategies. The voltage level of each bus of the system could still be maintained at a relatively stable level, and the scheduling of the control strategies under each scenario was effective (Figure 11).

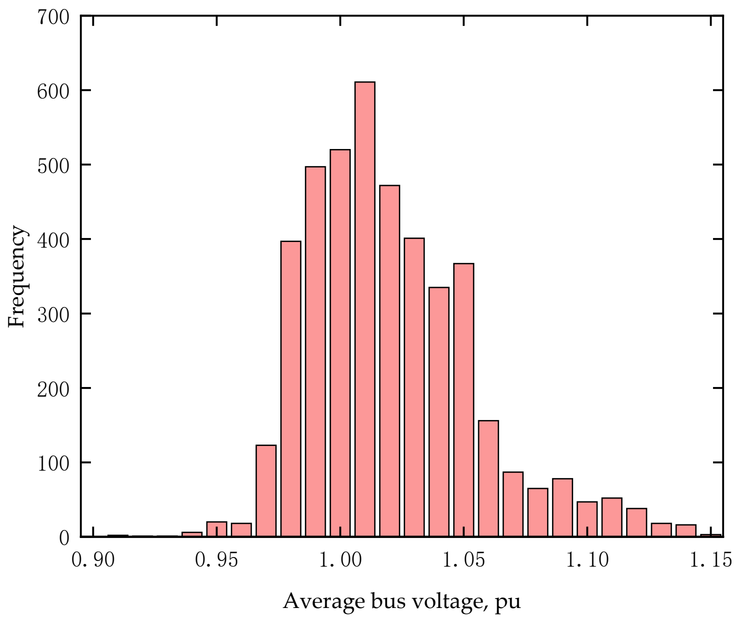

Figure 11. Bus voltage frequency distribution.

4. Conclusions

In this paper, based on the increasing high-density photovoltaic access to the distribution network and the rapid development of energy storage, the problems and solutions that may arise from the coordinated control of high PV access to the distribution network and energy storage were discussed, and different typical scenarios were delineated for the uncertainty of distributed PV generation. We tested out the coordinated scheduling of a distribution network that contained high-density PVs and energy storage, and multi-objective optimization was carried out, based on which the following can be concluded:

1. The original distribution network with high-density PVs, energy storage, and other distributed power supply modes was changed, and the coordinated optimization of PVs and energy storage could reduce the uncertainty brought about by distributed PV access. Through the protection of bus voltage stability at the same time, and distribution network loss optimization for multi-bus access to distributed PVs, energy use was more reasonable.
2. Due to the uncertainty of PV output, grid scheduling is difficult, but different typical scenarios can be divided and then optimized, which is close to the actual operation. The division of scenarios has guiding significance for the subsequent optimization, and the use of big data generation and analysis can improve the accuracy of the calculations continuously.
3. The IEEE 30-bus model simulation was carried out after considering the cooperative optimal scheduling of photovoltaic storage. We found that the deviations of each bus's voltage and the system's network loss were within a reasonable range, which proves the reasonableness of the algorithm's calculations. At the same time, this system can be further studied for optimization in dynamic operating situations.
4. Distributed photovoltaic access to the distribution network will have different impacts. The variety of distributed power supply modes will make the power supply more secure, but at the same time, the uncertainty of PV output will negatively impact on the grid scheduling and power quality. Reasonable use of an energy storage system to

configure the corresponding PV output can cut down the adverse effects, while the application of an energy storage system realizes the peak shaving and valley filling of the electricity load, and the coupling of multiple distributed power sources can also allow those play to each other's advantage.

This study examined the problems of and solutions to grid scheduling arising from high-density photovoltaic access to the grid. The maximum PV power is obtained by clustering the light intensity in the region, which, in turn, leads to the rational use of energy storage devices and reactive power optimization of the system for optimal scheduling of distributed power sources. The network losses and voltage offsets are optimized using an improved particle swarm algorithm for the actual model, and the optimization objective can be derived from the trend calculation. Since the network losses in the model are significantly reduced and the power quality is still maintained at a high level, it can be concluded that the proposed algorithm can be practically applied to compute the operating conditions of a power system with a high density of photovoltaics and energy storage devices. The model takes less account of aspects such as reverse power flow and load variations, and it is planned to complete the research by studying those aspects in the future. Future-focused modeling methodologies and theoretical studies of energy storage and distribution-grid-optimization models will also be taken into account [42–45].

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