Reliability Analysis and Optimization of Distribution Network with Distributed Generation

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Abstract

With the access of distributed generation, the distribution network is facing the problem of voltage quality degradation and cost increase. In this paper, Markov Monte Carlo simulation method (MCMC) is used to verify the influence of distributed generation access on distribution network. Secondly, the model based on particle swarm optimization (PSO) and K-means clustering algorithm is used to minimize the cost. Finally, the improved IEEE-33 node system is used to verify the example.

Keywords: Reliability, Distribution network optimization, Energy management, PSO

1. Background

Due to the increasing scarcity of energy and the increasing demand for electricity, the penetration rate of distributed energy in the distribution network has increased significantly, reducing the dependence on fossil fuels and environmental pollution. However, this trend also brings challenges such as unstable voltage quality and rising costs. As an important part of the power system, the stability and economy of the distribution network directly affect the reliability of the power supply. Therefore, the research on the influence and planning of distributed generation on distribution network has become an important topic in power system research.

In this paper, the MCMC method was used to simulate the normal operation and fault state of the distribution network to verify the influence of the distributed power supply on the distribution network. Secondly, combined with PSO and the K-means clustering algorithm, an operation-planning joint two-layer configuration model was established: the upper layer was the location and capacity model of photovoltaic and energy storage, and the lower layer considered the optimal scheduling of abandoned light and energy storage output. Taking the IEEE33 node as an example, the particle swarm optimization algorithm was used to solve the multi-objective model of the operating cost and voltage offset of the lower layer, and the Pareto front solution set was obtained by the multi-objective particle swarm optimization algorithm. The best result was brought into the upper model to realize the solution and iterative optimization of the upper and lower models. The model not only considered the impact of distributed generation (DG) on the distribution network but also improved the economy by optimizing the allocation of resources, provided a scientific basis for power system decision-making, and promoted the efficient use of renewable energy. In summary, this paper aimed to provide theoretical support and practical guidance for the access of distributed generation through the analysis of the distribution network.

The rest of this article was organized as follows. The second section introduced the photovoltaic power generation system and energy storage system. In the third part, the algorithm principles of Markov Monte Carlo, K-means, and PSO were discussed. In the fourth section, two models were constructed. The fifth section provided two simulation examples to verify the availability of the designed model. The sixth part summarized the main content of this paper.

2. Systematic Introduction

2.1. Photovoltaic power generation system

Photovoltaic power generation uses photovoltaic effect. Semiconductor materials excite photons to generate holes under light, and convert solar radiation energy into low-voltage direct current. Subsequently, through the converter and DC/AC inverter, the low-voltage DC is converted into AC power suitable for load use, or transmitted to the appropriate voltage level of the power grid or equipment. The power conversion process of the grid-connected photovoltaic power generation system is shown in Fig.1.

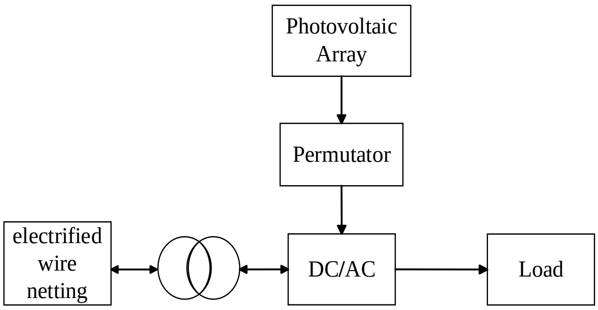

Fig.1 Grid-connected pv system

Multiple photovoltaic modules are usually combined to form a complete distributed photovoltaic power supply. In order to improve the output power of the system, multiple photovoltaic cell units can be combined into larger photovoltaic modules in series or in parallel through inverters. The schematic diagram of the structure is shown in Fig.2.In this system, the power generation performance and equivalent circuit model of photovoltaic cells can be expressed as Eq.(1).

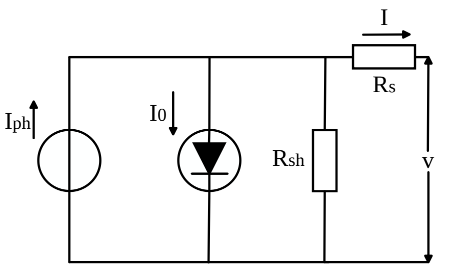

Fig.2 Solar photovoltaic cell equivalent circuit

$$I = I_{ph} - I_0 \left\{ \exp\left[\frac{q}{BKT}(V + IR_s) \right] - 1 \right\} - \frac{V + IR_s}{R_{sh}} \quad (1)$$

Where V is the output current and output voltage;I_{ph} and I_0 are the photogenerated current and reverse saturation current; q is the charge constant; K is the Pultzman constant; T is the absolute temperature; B is the diode factor; R_s and R_{sh} are the series and parallel equivalent resistances.

2.2. Distributed energy storage system

The capacity of distributed energy storage system usually does not exceed 10 MWh, and the output power is between several kilowatts and several megawatts, which is mainly used in the position near the load end. The energy storage system stores excess power when the distributed generation exceeds the load and releases it at high load. At the same time, the energy storage system can quickly respond to power fluctuations, accurately adjust current and voltage, effectively suppress load fluctuations, and solve the problem of peak load and power fluctuations in the power grid[1].

The state of charge (SOC) of the energy storage battery, as a key indicator to measure the energy utilization efficiency of the energy storage system, can directly reflect the current remaining energy of the battery. That is, in the case of following specific charging and discharging rules, the ratio between the actual stored energy inside the battery and its rated capacity after charging and discharging cycles is shown as Eq. (2).

$$SOC = \frac{E(t)}{E_r} \quad (2)$$

The SOC is the value of [0,1], E(t) is the remaining capacity of the energy storage system at time t, and Er is the rated capacity of the energy storage[2].

3. Algorithm Principle

3.1. Markov monte carlo simulation (MCMC)

MCMC can effectively capture the complex randomness and uncertainty in the system. By comparing the performance of the power system before and after the access to the distributed power supply, the specific impact of the distributed power supply on the operation of the distribution network is revealed. MCMC obtains samples from complex probability distributions by constructing a Markov chain and using random sampling, and then performs statistical inference. The detailed steps of the simulation loop are as follows :

- Initialize and read data : set basic parameters, read line and load data.
- Random fault simulation:Randomly select a component in the power grid to fail. According to the characteristics of the line and the set distribution, time to failure(TTF) and time to repair(TTR) are generated. Two sets of Gamma distribution parameters are used to determine the service time or fault repair time.

Among them, the TTF adopts a mixed distribution model, including Pareto distribution and exponential distribution are expressed as Eq.(3).

$$TTF = \begin{cases} gprnd(k,\sigma,0), rand < pf \\ -\frac{1}{\Lambda|i|}\log(rand), others \end{cases} \quad (3)$$

Where gprnd is the fault time to generate Pareto distribution, k is the shape parameter, σ is the scale parameter, Λ is the failure rate and i is the failure rate determined by the line length and failure rate.

TTR was calculated by exponential distribution model,expressed as Eq. (4).

$$TTR = -\Gamma \log(rand) \tag{4}$$

Γ depends on the repair time parameter of the line.

- Update Fidelity Time:Update the total simulation time to include the time of fault occurrence and repair. Record fault events and evaluate the load affected by the fault.
- Network reconstruction:According to the fault location and DG location, the network configuration and load power supply status are updated. When the DG is set to island mode, the system implements a reconfiguration strategy by calling the reconfigure _ network function to optimize load distribution and restore power supply. The function removes the fault line and uses the remaining DG to find the optimal path for power supply. Subsequently, the update _ network _ load _ status function is used to update the power supply status of each load, reflecting the impact of the new grid structure on the load power supply, and confirming whether each load point is covered by DG and getting power supply. During fault recovery, according to the real-time power and position generated by DG, the load point that DG can restore power supply is calculated, and the shortest path algorithm is used to check the influence of fault on the load point covered by DG.
- Calculation of reliability index:Calculate the reliability index of each power system, and analyze the specific impact of faults on network performance, such as power outage frequency and duration.

3.2. Particle swarm optimization(PSO)

The particle swarm optimization algorithm simulates the behavior of birds flying for food, and achieves the optimal purpose through the collective cooperation between birds. In the PSO system, each alternative solution is called a particle, and multiple particles coexist and cooperate to optimize. Each particle flies to a better position in the problem space according to its own experience and the best experience of the particle swarm to search for the optimal solution. The PSO algorithm is mathematically expressed as follows: Let the search space be D-dimensional, and the total number of particles is n. The vector $X_i=(x_{i1},x_{i2},\ldots,x_{iD})$ is the position of the i th particle ; $P_i=(P_{i1}, P_{i2},\ldots, P_{iD})$ is the optimal position in the flight history of the i th particle (that is, the position corresponds to the optimal solution), where the historical optimal position P_g of the g th particle is the optimal position in all $P_i(i=1,\ldots,n)$; the vector $V_i=(V_{i1},V_{i2},\ldots,V_{iD})$ is the position change rate of the i th particle.

The particle velocity update formula is expressed as Eq.(5).The particle position update formula is expressed as Eq.(6).

$$V_{i+1} = w \times v_i + c_1 \times r_1 \times \left[P_{best} - x_i\right] + c_2 \times r_2 \times \left[g_{best} - x_i\right] \tag{5}$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1) \tag{6}$$

Where c_1,c_2 are two learning factors, r_1,r_2 are random numbers, w is an inertial factor. Larger w is suitable for large-scale exploration, and smaller w is suitable for small-scale excavation. x_i is the current particle position, v_i is the current particle velocity, x_{i+1} is the updated particle position, v_{i+1} is the updated particle velocity.The initial position and velocity of the particle swarm are randomly generated. In each iteration, the particle updates the speed and position by tracking two extreme values:the individual extreme value (Pbest) is the optimal solution of the particle itself, and the global extreme value (gbest) is the optimal solution of the group[3].

3.3. K-means

The K-means algorithm divides the data into K different clusters by iteration, and minimizes the sum of the distances between each data point and the centroid of its cluster. The execution process of the K-means algorithm usually includes the following steps : First, randomly select K data points as the initial cluster centroid ; secondly, according to the distance between each data point and the centroid of each cluster, it is assigned to the nearest cluster. Then, the centroid of each cluster is recalculated, that is, the average value of all data points in the cluster is taken as the new centroid ; finally, repeat the above allocation and update steps until a certain termination condition is met.

4. Model Construction

4.1. Establishment of optimal model

The improved particle swarm optimization algorithm to solve the bi-level optimization model is shown in Fig.3.

- Input the distribution network parameters, and used K-means to process the annual historical data of photovoltaic.
- Initialize the particle position and velocity, the location and capacity of the planning layer flexibility resources, as the input of the running layer.

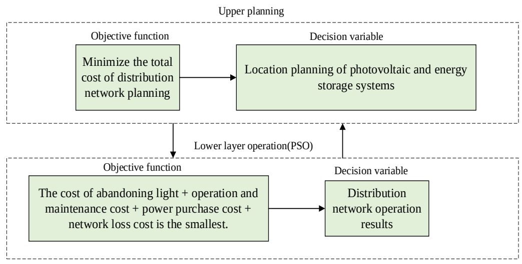

Fig.3 The upper and lower relationship of the joint model

This paper taked the system to reduce the investment cost as the optimization goal, considered the cost, benefit, environmental impact and related operating indicators.

The loan annuity factor u,investment costs,discarding penalty cost,Photovoltaic power generation,energy storage costs and total cost are as Eq.(7),Eq.(8),Eq.(9)，Eq.(10) , Eq.(11) and Eq.(12).

$$u = \frac{r(1+r)^{year}}{(1+r)^{year}-1} \quad (7)$$

$$C_{investment} = u \times (c_{pv} \times cap_{pv1} \times s_{pv} + c_{ess} \times cap_{cn} \times s_{cn}) \quad (8)$$

$$C_{loss} = c_{loss} \times \text{sum of power losses} \quad (9)$$

$$C_{pv} = cpv \times cap_{pv1} \quad (10)$$

$$C_{ess} = cess \times cap_{cn} \quad (11)$$

$$C_{total} = C_{investment} + C_{loss} + C_{pv} + C_{ess} \quad (12)$$

Where r is the discount rate, year is the service life of the equipment, c_{pv} is the investment cost of unit capacity photovoltaic, cap_{pv1} is the photovoltaic capacity, s_{pv} is the single photovoltaic capacity, c_{ess} is the investment cost of unit capacity energy storage, cap_{cn} is the energy storage capacity, s_{cn} is the rated capacity of a single group of energy storage, c_{loss} is the network loss price, and sum of power losses is the total power loss.

4.2. Constraint conditions

Abandoning light punishment, energy storage charge and discharge cost,power grid purchase cost,grid loss cost,and voltage deviation cost are as Eq.(13),Eq.(14)，Eq.(15),Eq.(16) and Eq.(17).

$$C_q = c_{qpv} \sum (gailv(i) \times (cap_{pv1} \times center(i,:) - pv1_s(i))) \quad (13)$$

$$C_y = cpvy \times \sum (gailv \times \sum (pv1_s)) + cessy \times \sum (|cn|) \quad (14)$$

$$C_{gc} = \sum (C_{buy} \times P_{gen}) \quad (15)$$

$$C_{loss} = c_{loss} \times \sum (branch\_losses) \quad (16)$$

$$V_{pc} = \sum (|V_{bus} - V_{mean}|) \quad (17)$$

Where C_{qpv} is the penalty cost of discarding light, and gailv(i) is the scene probability. Cap_{pv1} is the photovoltaic capacity,center(i,:)is the scene center, $pv1_{s(i)}$ is the photovoltaic power output, cpvy is the unit capacity photovoltaic operation cost, gailv is the scene probability, cessy is the unit capacity energy storage operation cost, cn is the energy storage charge and discharge volume, C_{buy} is the main network purchase price, P_{gen} is the power generation.

5. Example Analysis

5.1. The impact of distributed power access to the distribution network is verified.

In this section, the IEEE Bus6 F4 test system is used as the system architecture diagram of the example, and on this basis, the improvement is made. The distributed power supply is set at 13 and 25 nodes. The power generation type is photovoltaic power generation, and the power generation power is 10 MW. The operation mode is island operation. The MCMC algorithm is used to analyze it. The simulation period is 20 years. The influence of DG and no DG on the distribution network is compared.

Through simulation, the system average interruption frequency index(SAIFI) and the system average interruption duration index (SAIDI) of the system with and without DG, the customer average interruption duration index (CAIDI) of the load, and the expected energy not served (EENS) are as Eq.(18),Eq.(19)，Eq.(20)，Eq.(21).The comparison results are shown in Fig.4.

$$SAIFI = \frac{\sum (load\_fault \times load\_users)}{\sum load\_users} \quad (18)$$

$$SAIDI = \frac{\sum (load\_fault\_time \times load\_users)}{\sum load\_users} \quad (19)$$

$$CAIDI = \frac{SAIDI}{SAIFI} \quad (20)$$

$$EENS = \frac{\sum (load\_power \times load\_users)}{\sum load\_user \times N} \quad (21)$$

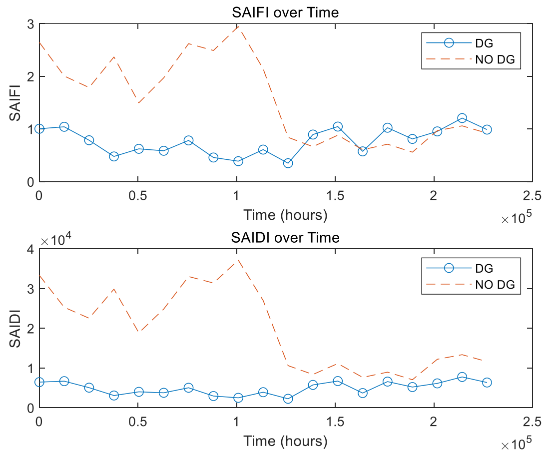

Fig.4 SAIFI and SAIDI with and without DG

It can be seen from the figure that although there are fluctuations at some time points, the average number of power outages and fault time of the system with DG are smaller than those without DG as a whole. The reliability indexes are obtained by comprehensive calculation,which is shown in Table 1.

Table 1 Reliability index of DG and no DG

Reliability index	DG	No DG
SAIFI	0.031693 times/ (year·household)	0.031741times/ (year·household)
SAIDI	1.0455hours/ (year·household)	1.5225hours/ (year·household)
CAIDI	38.807hours/ (year·household)	41.0893hours/ (year·household)
EENS	1.4106MW (year·household)	1.5166MW (year·household)
ASAI	99.9881%	99.9826%

Through simulation calculation, it is concluded that distributed generation has a positive impact on the reliability index of distribution network, which is manifested in the reduction of fault frequency, the shortening of fault recovery time, the reduction of power loss and the improvement of system availability. These results show that distributed generation plays an important role in improving the overall reliability of the distribution network.

5.2. Research on double-layer optimal configuration of photovoltaic and energy storage access to distribution network

This section used the IEEE-33 node distribution network model as a case to explore the optimal configuration strategy for photovoltaic power and energy storage. The topology of the system is shown in Fig.5. The voltage level is 10kV. The photovoltaic nodes that were selected were 2, 3, 4, 6, 8, 10, 12, 15, 18, 20, 26, 27, 29, 30, 31, and 32. The energy storage nodes that were selected were 3, 6, 9, 14, 18, 20, 28, 29, 31, and 33. The single photovoltaic capacity was 50 kW, the maximum number of photovoltaics was 15, and the minimum number of photovoltaics was 4. The rated capacity of a single group of energy storage was 10 kW, the maximum number of energy storage groups was 20, and the minimum number of energy storage groups was 8. The main network purchase price was 0.6 RMB, the network loss price was 0.4 RMB, the penalty cost of abandoning light was 0.6 RMB, the discount rate was 0.08, the service life of photovoltaic and energy storage equipment was 10 years, the investment cost of unit capacity energy storage was 8000 RMB, the operation cost of unit capacity energy storage was 0.05 RMB, the investment cost of unit capacity photovoltaic was 5000 RMB, and the operation cost of unit capacity photovoltaic was 0.1 RMB. The charging and discharging efficiency of energy storage was 90%, the minimum state of charge of energy storage equipment was 10%, and the maximum state of charge of energy storage equipment was 90%. When using the particle swarm optimization algorithm, the maximum number of iterations was 50 times, and the population size was 150.

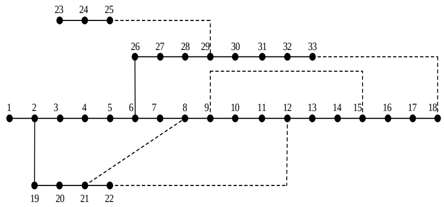

Fig.5 IEEE-33

Firstly, K-means clustering analysis is used to process the photovoltaic data, and the power generation characteristics of different time periods in a day can be classified into four scenarios, as shown in Fig.6.

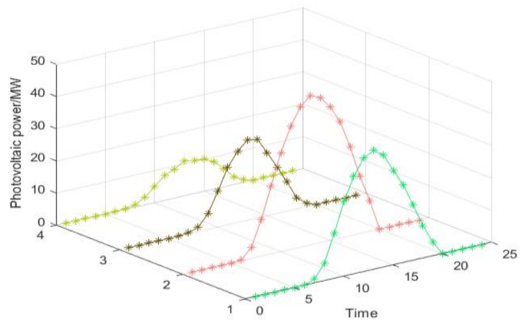

Fig.6 Photovoltaic cluster analysis results

The photovoltaic and energy storage location and capacity model is the upper model of the program, and its main goal is to realize the optimal configuration of photovoltaic and energy storage systems. Particle swarm optimization algorithm is used as the solution method. The optimal location and capacity configuration scheme of photovoltaic and energy storage system is obtained. Through the particle swarm optimization algorithm, we can get multiple pareto frontier solution sets, select the best results, and bring them into the lower model.

The optimal scheduling of light curtailment and energy storage output is the lower model of the program, which mainly considers the operating cost and voltage offset of photovoltaic and energy storage systems. In the model design, the multi-objective particle swarm optimization algorithm is used to solve the problem. The multi-objective particle swarm optimization algorithm can consider multiple optimization objectives at the same time, so as to obtain more feasible solutions, and can obtain the pareto frontier solution set by adjusting the weight. Through the multi-objective particle swarm optimization algorithm, the scheduling scheme of photovoltaic and energy storage systems is obtained, and compared with the best results in the upper model, so as to realize the iterative optimization of the whole model. The fitness curve of the algorithm,as shown in Fig.7.

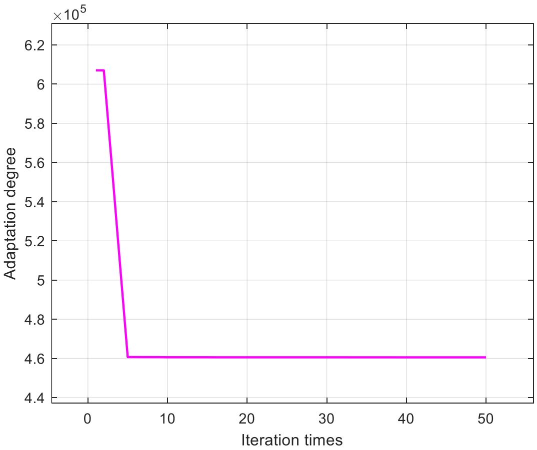

Fig.7 Algorithm fitness curve

This method not only considered the location and capacity configuration of photovoltaic and energy storage systems but also considered the optimal scheduling of light curtailment and energy storage output. Through the joint solution and iterative optimization of the upper and lower models, the optimal configuration scheme of the photovoltaic energy storage system was finally obtained, thereby realizing the flexible resource allocation and operation of the distribution network.

The load power supply is shown in Fig.8,It could be seen from the figure that the power had obvious fluctuations in different time periods, especially during the day and night. The power of photovoltaic power generation was higher during the day, while the power supply mainly depended on the power grid at night. The histogram of charging and discharging showed the operation of the energy storage system. Charging was usually carried out when the power demand was low, while discharging provided additional power support during peak demand. The power output of photovoltaic power generation during the day was significantly higher than that at night, reflecting the characteristics of solar power generation. With the change of sunshine intensity, the power of photovoltaic power generation also changed. The changes in the original load lines showed the system's demand for electricity, which usually peaked during the day and evening and was relatively low at night.

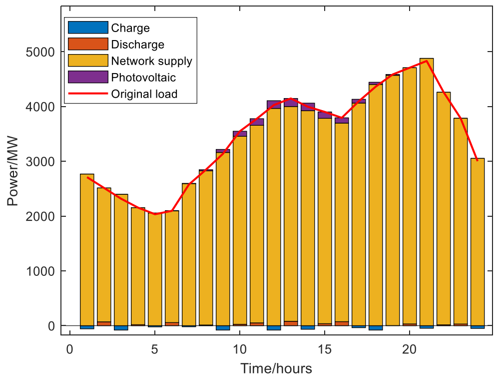

Fig.8 Load power supply situation

The results of equipment location planning are shown in Fig.9. The results show that the highest cost is 607039.544 RMB. After multiple iterations of the particle swarm optimization algorithm, the final cost of energy storage and photovoltaic is the lowest at 18 and 9 nodes, respectively. The cost is 460564.2716RMB, which is reduced by 24.16 %.

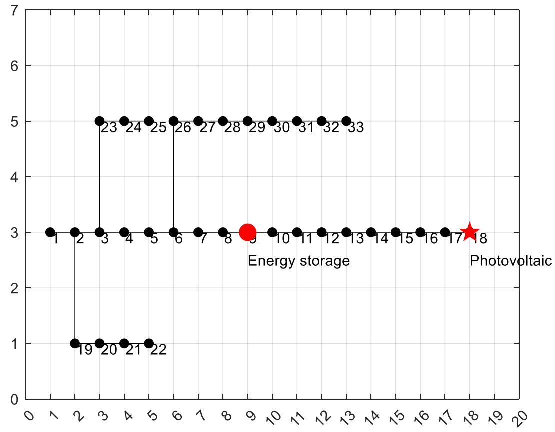

Fig.9 Equipment location planning results

6. Conclusion

This paper first used MCMC to verify the impact of distributed power access on the distribution network. The importance of optimization simulation in the power system to improve the efficiency and reliability of the power grid was expounded. The PSO and K-means clustering algorithms and their specific applications in research were introduced. Secondly, the optimization model was established with the minimum cost as the optimization objective. Finally, the test system (33-node system) was used for simulation analysis to obtain the optimal location of the photovoltaic distributed power supply and energy storage system.

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