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Research on optimal control method of distributed generation considering the influence of controllable load

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Abstract. On the basis of optimal allocation of distributed generation in conventional distribution network, and considering the characteristics of active distribution system and the influence of controllable loads, a two-layer optimal configuration model of distributed generation is established. The upper layer model is used to solve the optimal allocation and sizing of distributed power sources for active distribution systems and the lower layer model is used to solve the optimal strategy of controllable loads in each period. The output uncertainty of uncontrollable distributed generators, such as wind power generation and photovoltaic power generation, is characterized by box uncertain set based on robust optimization theory.With this model, the optimal configuration of distributed generation can be solved and the factors of operation and dispatch can be taken into account. To some extent, the overall planning and operation of active distribution system can be realized.Finally, the genetic algorithm is used to solve the two-layer optimization model.The rationality of the proposed model, the applicability of genetic algorithm, and the strong ability of global optimization are verified by case studies of IEEE 33-bus distribution system.

1. Introduction

Wind power and photovoltaic power generation are becoming the most promising new energy because of its rich resources, environmental protection and low carbon attributes.However, with the large-scale wind and photovoltaic power generation connected to the grid, its intermittent and stochastic characteristics make it difficult to be accurately predicted. Also, the stability control and fast regulation performance of wind and solar power is poor, which brings great challenges to the safe and stable operation of the grid[1].

Experts and scholars at home and abroad have done a lot of research, and put forward mathematical models of various objectives from different angles on the issue of optimal configuration of distributed generation.For example, in the literature [2], Nash equilibrium theory is used to construct the non-zero sum game mathematics problem with environmental protection and economic indicators as participants, and the calculation model is established; in the literature [3], according to the distribution characteristics of the node voltage and the marginal capacity of the distribution network, the optimal principle of the installation position of the distributed power supply is proposed; in the literature [4], the multi-source optimization configuration and economic dispatching problem of active distribution network are introduced.From the stochastic characteristics of intermittent DG such as wind power and photovoltaic power generation and their corresponding flexible adjustment requirements, the concept of power system flexibility is introduced; literature [5] fully considers the demand side's demand for power resources and the efficiency of use, and introduces a demand response mechanism in distribution network lines and economic benefit planning with distributed power sources. In terms of the characteristics of the distributed power supply, literature [6] proposed a two-phase solution approach to RT-OPF; literature [7] proposes a predictive update method to cope with the conflict between the rapid change of wind power generation and the slow response of optimized calculation; literature [8] developed a new look-up table based RT-AR-OPF framework; literature [9] develops a new strategy that can improve A-R-OPF by considering UWP; literature [10] uses the recently developed internal and external approximation methods to roughly solve OPF with limited opportunities.

The planning problem is a constrained decision system. Under the constraints of the feasible set, the decision maker can make the optimal decision. If planning is a system with two-tiered decisions, then the lower layers make their own decisions, and the upper managers can control and influence the underlying decisions through decision variables. At the same time, the upper layer can know the feedback of the lower layer on its own decision and further determine the overall goal. The single-layer optimization model has certain limitations in solving the power system planning problem. It requires a single objective function, and the constraints cannot be too much, and the speed is slow in the process of solving.Thus,in this paper, a two-layer optimal configuration model of distributed generation considering controllable load is established, and the operation and scheduling factors are included in the model. The upper layer model is used to solve the optimal position and capacity of distributed power supply connected with controllable loads, and the lower layer is used to solve the optimal strategy of controllable loads in each period. At the same time, due to the uncertainty of wind and solar power, the box uncertain set-based robust optimization is carried out. Genetic algorithm is used to solve the two-layer optimization problem. Finally, an example of IEEE 33-bus distribution system is analyzed.

2. Two-layer optimal configuration model

2.1. Two-layer optimization model architecture

The optimal configuration model constructed in this paper considering the influence of controllable loads is divided into upper and lower layers. The upper layer model solves the optimal position and capacity of the distributed power source connected to the controllable load. The distributed power sources involved in this paper are uncontrollable distributed power sources, including wind turbine (WT) and photovoltaic (PV) power generation. The output power is determined by natural factors such as real-time wind speed and radiation intensity, which cannot be artificially regulated. In the lower layer model, the influence of the controllable loads is considered, and the optimization variable is the real-time power of the controllable loads.The upper and lower models interact with each other, and the solution process alternates iterations. The established two-layer optimization model architecture is shown in Figure 1:

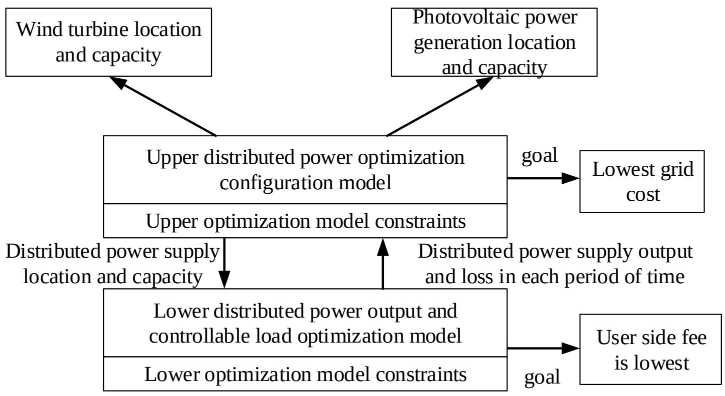

Figure 1. Two-layer optimization model architecture.

2.2. Upper distributed power optimization configuration model

2.2.1. The objective function of the upper model. The objective function of the upper model is the minimum integrated cost on the grid side. The comprehensive costs include operating and maintenance costs, distributed power investment costs, and system network loss costs.

$$f = \min(C_1 + C_2 + C_3) \tag{1}$$

(1) Distributed power operation and maintenance costs

$$C_1 = \lambda_1 W_{1i} \tag{2}$$

Among them, λ_1 is the operating and maintenance costs for distributed power supply to unit power generation, in yuan / (kW • h); W_{1i} is annual power generation.

(2) Equipment investment cost

$$C_2 = \sum_i \left[\frac{r(1+r)^{T_i}}{(1+r)^{T_i} - 1} \lambda_{2i} W_{2i} \right] \tag{3}$$

Among them, r is the annual interest rate; T_i, λ_{2i} and W_{2i} respectively are the life of the distributed power supply connected to the node i, the unit cost investment cost and the installed capacity.

(3) System network loss cost

$$C_3 = \sum_{t=1}^{T} \lambda_t P_{Loss}^t t \tag{4}$$

Where λ_t is the electricity price in the t period; P_{Loss}^t is the network loss in the annual maximum load period t, in kW, which is obtained by the lower model.

2.2.2. Upper layer model constraints. The constraints of the upper model are as follows:

(1) Distributed power capacity limit for each node access

$$0 < W_{2i} \le W_{2i}^{\max} \tag{5}$$

Where $W_{2i}^{\max}$ is the maximum capacity of the distributed power source that the node i is allowed to be connected.

(2) System distributed power penetration constraints

If the distributed power supply capacity is too large, it may cause a relatively large impact on the user during operation. For example, the sudden exit of the distributed power supply may cause a sharp drop in the node voltage. In order to make the impact of the distributed power supply on the system controllable, it is necessary to limit the distributed power penetration. This paper sets the distributed power supply installed capacity to not less than 15% of the total system load, and does not exceed 40% of the total system load[11].

$$15\% \le \sum_i W_{2i} / W_Z \le 40\% \tag{6}$$

Where $\sum_i W_{2i}$ is the sum of the distributed power supply capacity of the access; W_z is the total system load.

2.3. Lower distributed power output and controllable load optimization model

2.3.1. Objective function of the lower model. Based on the upper layer model results, the lower layer controllable distributed power output and controllable load optimization model obtains a set of optimal distributed power configuration schemes, and solves the optimal distributed power supply and controllable load in this case. The objective function of the lower optimization model is that the user side has the lowest electricity cost and can be expressed as:

$$f = \min C_P \tag{7}$$

Among them, the annual maximum load of all-day user electricity costs is:

$$C_P = \sum_{t=1}^{T}\sum_{i}^{N}\lambda_t P_{Li}^t \tag{8}$$

Where P_{Li}^t is the load active size of the t period at node i.

2.3.2. Lower layer model constraints. The constraints of the lower model are as follows:

(1) Power flow equation constraint

$$\begin{cases} P_{Gi}^t - P_{Li}^t = U_i^t \sum_{j\in\Omega_i} U_j^t (G_{ij}\cos\theta_{ij}^t + B_{ij}\sin\theta_{ij}^t) \\ Q_{Gi}^t - Q_{Li}^t = U_i^t \sum_{j\in\Omega_i} U_j^t (G_{ij}\sin\theta_{ij}^t - B_{ij}\cos\theta_{ij}^t) \end{cases} \tag{9}$$

Where P_{Gi}^t and Q_{Gi}^t are the active power and reactive power injected by the power supply at node i during the t period, respectively; P_{Li}^t and Q_{Li}^t are the active power and reactive power consumed by the load at node i during the t period, respectively; U_i^t and U_j^t are the amplitudes of the nodes i and j at t period, respectively; Ω_i represents all nodes directly connected to node i, including node i itself ; G_{ij} and B_{ij} are the real and imaginary parts of the corresponding elements in the node admittance matrix, respectively.

(2) Distributed power active and reactive power constraints

$$P_{Gi}^t = \begin{cases} P_{WTi}^t \\ P_{PVi}^t \end{cases} \tag{10}$$

$$Q_{Gi}^t = \begin{cases} Q_{WTi}^t = P_{WTi}^t \tan\delta_{WT} \\ Q_{PVi}^t = P_{PVi}^t \tan\delta_{PV} \end{cases} \tag{11}$$

Among them, P_{WTi}^t and P_{PVi}^t are the active output of the WTs and PVsat t period connected by node i, respectively, which are random and uncontrollable; δ_{WT} and δ_{PV} are the power factor angles of WTs and PVs, respectively.

Due to the uncertainty of P_{WTi}^t and P_{PVi}^t, the box uncertain set-based robust optimization method is adopted, which makes the constraint satisfy all the possible values in the set of uncertain variables. Equation (9)-(15) constitutes a complete robust optimization model:

$$\begin{cases} \left(\gamma_i^t\right)'' \overline{\eta_i} - \left(\delta_i^t\right)'' \underline{\eta_i} \le \sum_{j\in\Omega_i} P_{ij}^{\max} - \overline{P_{PVi}^t} + P_{Li}^t + \left(U_i^t\right)^2 \sum_{j\in\Omega_i} G_{ij} \\ \left(\delta_i^t\right)''' \underline{\eta_i} - \left(\gamma_i^t\right)''' \overline{\eta_i} \le -\sum_{j\in\Omega_i} P_{ij}^{\max} - \overline{P_{PVi}^t} + P_{Li}^t + \left(U_i^t\right)^2 \sum_{j\in\Omega_i} G_{ij} \\ 1-\left(\delta_i^t\right)''' + \left(\gamma_i^t\right)''' = 0, -1-\left(\delta_i^t\right)'' + \left(\gamma_i^t\right)'' = 0 \\ \left(\delta_i^t\right)'' \ge 0, \left(\gamma_i^t\right)'' \ge 0 \\ \left(\delta_i^t\right)''' \ge 0, \left(\gamma_i^t\right)''' \ge 0 \\ i \in S_3 \end{cases} \tag{12}$$

Among them, $\left(\delta_i^t\right)''$, $\left(\gamma_i^t\right)''$, $\left(\delta_i^t\right)'''$ and $\left(\gamma_i^t\right)'''$ are Lagrangian daily coefficients; $\overline{\eta_i}$ and $\underline{\eta_i}$ are fluctuations determined by factors such as meteorology.

(3) Controllable load operating constraints

$$P_{Li}^t = P_{Li}^{t(0)} + P_{Li}^{t(1)} + P_{Li}^{t(2)} \tag{13}$$

$$\sum_{t=1}^{T} (P_{Li}^{t(1)} \bullet 1) = W_{Li}^{(1)} \tag{14}$$

$$P_{Li}^{t(2)} = \begin{cases} P_{Lin}^{t(2)} & \lambda_t < \lambda_L \\ P_{Li}^{t(2)}(\lambda_t) = P_{Lin}^{t(2)} - \dfrac{P_{Lin}^{t(2)} - P_{Lir}^{t(2)}}{\lambda_H - \lambda_L}(\lambda_t - \lambda_L) & \lambda_L \le \lambda_t < \lambda_H \\ P_{Lir}^{t(2)} & \lambda_t \ge \lambda_H \end{cases} \tag{15}$$

Where $P_{Li}^{t(0)}$, $P_{Li}^{t(1)}$, and $P_{Li}^{t(2)}$ are the uncontrollable load, transferable load, and active power that can reduce the load on node i in time t; $W_{Li}^{(1)}$ is the power consumption of the transferable load connected to node i for the whole period; $P_{Lin}^{t(2)}$ is the active power connected to node i to reduce the normal operation of the load; $P_{Lir}^{t(2)}$ is the rigid active power that can be used to reduce the load on node i; λ_H and λ_L are the upper and lower critical prices of the user's sensitivity to electricity prices, respectively.

Equation (14) indicates that the total power consumption of the transferable load is constant throughout the period, but the electricity consumption period can be changed[12]; Equation (15) shows that for the load reduction, the electricity fee depends on the electricity tariff [12].

3. Using genetic algorithm to solve double-layer optimization model

Compared with traditional heuristic optimization search algorithms, the main essential features of genetic algorithms are group search strategies and simple genetic operators. Genetic operators only use adaptive value metrics as operational indicators for random operations, reducing the general heuristic algorithm in the search process. Dependence on human-computer interaction [13].

The upper and lower optimization models of this paper are all solved by genetic algorithm. The basic steps are the same. Only when solving the upper fitness, it is required to enter the lower model to solve, that is, a genetic algorithm process is nested. Specific steps are as follows:

a. Initialize the basic parameters of the upper-level genetic algorithm. Randomly select the initial population to determine X, the solution of the objective function. Using real number coding, each gene is a real number vector, and the crossover probability of the objective function solution in each generation is δ_j ; the crossover probability is chosen between 0 and 1; the mutation probability is δ_b ; the mutation probability is selected between 0 and 1; and the effective individual is randomly selected according to the number of the objective function solution to initialize the population P, and the genetic algebra calculator is initialized;

b. Taking the reciprocal of the upper objective function as the fitness function, the solution of the initialized objective function is substituted into the fitness function. The larger the fitness value is, the better the individual is, so as to determine the fitness value of each group solution;

c. The genetic selection operator is used to obtain the solution with high fitness value of K group. The old population is selected from the old group with a certain probability to form a new population to breed the next generation of individuals. The probability of the individual being selected is related to the fitness value. The fitness value The larger the probability of being selected, the higher the probability of being selected in the implementation of the present invention, the probability that the individual is selected is $P_x = (1/f_j)/\sum_{j=1}^{X}(1/f_j)$, and the w fitness values are randomly selected from the $1/f_j$ solutions of the solutions in step b for size comparison. The one with the highest fitness value is passed to the next generation, and the above process is repeated K times to obtain K individuals of the next generation population;

d.Intersection and mutation operations are performed on the solutions obtained in c; cross-operation refers to randomly selecting two individuals from the population, and inheriting the superior characteristics of the previous generation to the next generation through the exchange and combination of genes, thereby generating new excellent individuals; The main purpose of the operation is to maintain the diversity of the population.

e.Enter the lower model and solve the lower optimization according to the steps of the genetic algorithm to calculate the fitness value of the upper model;

f.If the current fitness value is better than the previous fitness value, update the new individual to the next generation of individuals;

g.Determine whether the number of iterations or the search accuracy meets the termination condition, and if yes, go to step h; otherwise, go to step c and re-optimize;

h.The global optimal solution and the optimal individual value are the outputs.

4. Case analysis

This paper takes the IEEE33 node power distribution system as an example, as shown in Figure 2. The node 33 is connected to the upper-level power grid, and the power flow is calculated as a balanced node, and the voltage after the standardization is $1\angle 0^{\circ}$. The system has a reference capacity of 10 MVA and a reference voltage of 12.66 kV.

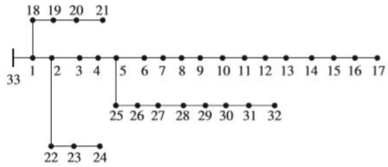

Figure 2. IEEE33 node power distribution system diagram.

Using the genetic algorithm program written by matlab, the initial parameters are set as follows: scale population pop=30, maximum iteration number gen=100, step factor α =0.25. In this example, there are 32 load nodes (excluding the power supply node). Thus, 32 nodes $X_1 \sim X_{32}$ are set to form the control variable POP_X. If X_i is 0, it means that DG is not installed at load node i.If it is non-zero constant C, it means that DG is planned to be installed at node i, and its installation capacity is $C\times 10$ kW. The maximum annual utilization hours of the $\tau_{\max}$ =8760h. The real-time electricity tariff is used. According to the different importance of the problem, the weighting coefficient is different. The weight coefficient α_1 is 0.6 and α_2 is 0.4.

4.1. *Analysis of distribution network loss and node voltage with distributed power supply*

The active network loss of the IEEE-33 node is 211.52 kW.However, the distributed power supply with the active network loss as the objective function is optimized. The minimum network loss is 110.992 kW, which is 42% lower. This shows that the distributed power optimization can effectively reduce the network losses.

Under steady state operating conditions, the voltage of each load node will gradually decrease along the direction of the feeder flow. After connecting the distributed power supply, the power distribution component is added to the distribution network, and the original network structure is changed, from a single power radiation type network to a multi-terminal active network; and when it is connected to the distribution network, the transmission on the feeder line is caused. The power is reduced, and the voltage of each node in the direction of the feeder is raised, which may cause the partial load node voltage to shift beyond the allowable range, and the voltage offset is related to the installation position and total capacity of the distributed power source. In order to verify the impact of the distributed power supply on the voltage of each node after the distribution network, Figure 3 compares the system node voltages before and after connecting the distributed power supply.

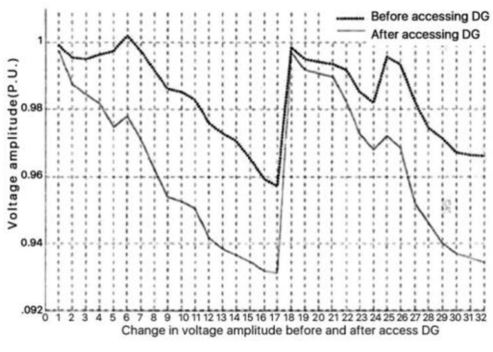

Figure 3. Comparison of system node voltage before and after connecting DG.

It can be seen from the comparison results in Figure 3 that after the distributed power supply is connected, the voltage on the line is significantly improved, and the distributed power supply distributed in the distribution network has an obvious effect on the voltage distribution of the feeder, and the voltage of the lowest node is obvious. It has increased from 0.9323 to around 0.9581. It can be seen that installing a small-capacity distributed power supply can better increase the voltage of the node. Table 1 shows the results of the distributed power optimization of the active network loss as the objective function.

Table 1. Analysis of optimization results.

	DG installation location and capacity(kW)	Network loss(kW)	Minimum voltage(p.u.)
No DG	0	211.52	0.9323
DG	6(2570)	110.992	0.9581

4.2. Distributed power optimization configuration and controllable load optimization control results

The candidate installation location set of the distributed power source is the node {7, 8, 9, 12, 27, 28}, and it is considered that each node location in the power distribution system has the same wind and photovoltaic resources. The ratio of the predicted value of the fan and photovoltaic power output to the rated power at each time of the maximum load day of a certain year is shown in Figure 4.

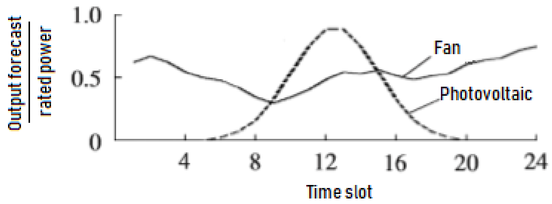

Figure 4. Uncontrollable distributed power active output curve.

The loads connected to the nodes 17, 21, 24, and 31 are transferable loads, and the loads connected to the nodes 20 and 32 are load-reducible. The active power of each time period of each controllable load before optimization is shown in Figure 5 and Figure 7.

The distributed power supply optimal configuration scheme obtained by the solution is shown in Table 2, and the distributed power optimization configuration scheme is compared as a comparison without considering the controllable load (assuming that all loads are not involved in the optimization). Table 3 lists the costs for the grid side and the user side in the two cases.

It can be seen from Table 2 and Table 3 that after considering the influence of the controllable load in the process of optimizing the distributed power distribution configuration of the active power distribution system, the integrated power grid cost and the user power consumption cost corresponding to the obtained configuration scheme are reduced. And the cost of the grid side reduction is mainly reflected in the part of the system network loss cost. It can be seen that when the distributed power supply optimization configuration of the active power distribution system is performed, the controllable load scheduling can be reasonably considered, which can effectively reduce the system network loss and the user power consumption cost, and achieve a win-win situation between the grid side and the user side.

Figure 6 and Figure 8 show the active power of each stage that can be converted and load-reduced after optimization. Compared with Figure 5 and Figure 7, it can be found that the power distribution of the transferable load becomes uniform, the daily maximum load is reduced, and part of the power is transferred from the peak period of 18-20 (high electricity price period) to the first 1-6 hours (The low power price period), while the power that can reduce the load during the 18-21 period of the high electricity price is cut, and the load value of the 22 period with the relatively low electricity price is the maximum load period of the day because it has not been cut. This shows that the controllable load scheduling model used in this paper can effectively reflect the followability of the controllable load to the electricity price, and explains why the reasonable control of the controllable load can effectively reduce the user's electricity consumption.

Table 2. Distributed power supply optimal configuration.

DG candidate installation node	Irrespective of controllable load		Consider a controllable load	
	Types	Capacity/KW	Types	Capacity /KW
7			WT	22
8	WT	19		
9	WT	64	WT	72
12	PV	270	WT	221
27	WT	185	PV	199
28	WT	67	WT	45

Table 3. Costs of grid side and user side.

Cost (ten thousand yuan)		Irrespective of controllable load	Consider a controllable load
Grid comprehensive cost	Cost of investment	20.205	18.728
	Operation and maintenance cost	1.133	0.905
	System network loss cost	22.492	17.164
	Total	43.83	36.797
Full-time user electricity costs		4.9032	4.7464

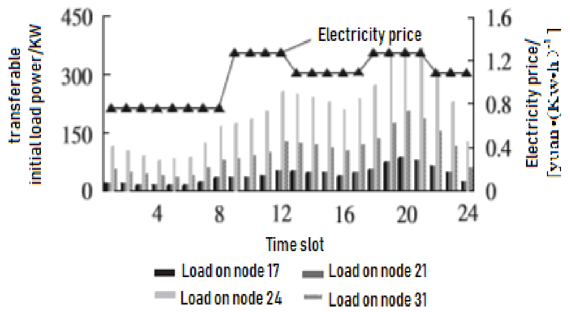

Figure 5. Transferable active power before optimization.

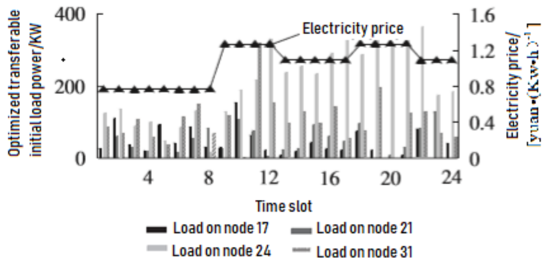

Figure 6. Optimized transferable active power.

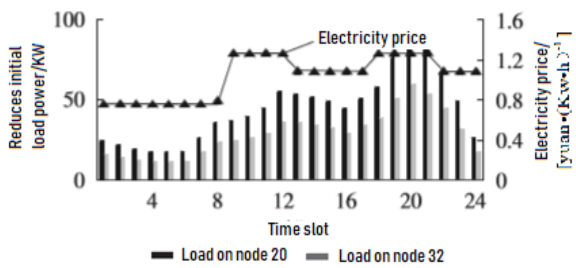

Figure 7. Reduced load active power before optimization.

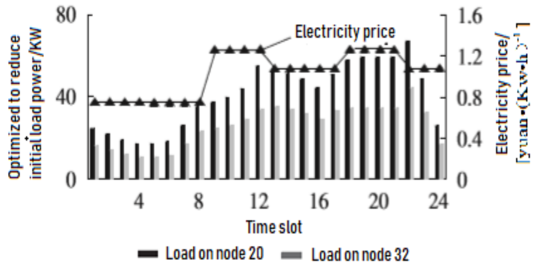

Figure 8. Optimized to reduce load active power.

5. Conclusions

In this paper, the two-layer optimal configuration model of distributed generation in active power distribution system considering the influence of controllable loads is established and the uncertainty of the uncontrollable distributed power supply such as wind power and photovoltaic is characterized by the box uncertain set. The node voltage, installed total capacity constraints, and line transmission constraints are established to obtain the optimal connecting capacity and location of the distributed generation under all constraints. The genetic algorithm is used to solve the two-layer optimization model, and the simulation results demonstrate that the rationality of the model, the applicability of the genetic algorithm, and the strong global optimization ability. Reasonable consideration of the controllable load scheduling in the active distribution network distributed power optimization configuration can effectively reduce the system network loss and user power consumption, and achieve a double-win situation between the grid side and the user side.

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