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Optimal Configuration of Distributed Generation in a Distribution Network Considering Environment Effects

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Abstract

With the development of smart distribution networks, the future distribution network becomes an important platform for distributed power system in forms of consumption, acceptance and transmission. Reasonably planning the location and capacity of a distributed power supply system can improve the stability margin of the voltage distribution system, reduce the distribution network loss and increase the load rate of a distribution system effectively. However, without a suitable optimization method to solve distributed power supply system problem, it will not only increase system operation cost, but also seriously affect the safe operation of micro grids. Therefore, the problem of optimal configuration such as sizing of distributed power system has become an important research content of distribution network planning. This paper is focus on optimizing a multi-objective programming which relates to the distributed power planning. Considering various optimization objectives such as investment efficiency, voltage stability and the reduction of network loss, this paper builds a multi-objective distributed power optimization model and proposes a configuration method for optimizing the distributed power using improved particle swarm optimization algorithm based on the pareto planning concept. Example analysis shows that the proposed distributed power optimization configuration method has improved the investment benefit of the distributed power system, meanwhile the proposed method can provide a variety of reasonable alternatives from different aspects for decision makers.

Keywords: distributed generation configuration, multi-objective programming, improved particle swarm optimization

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INTRODUCTION

As a systematic and complex capacity mode, since the concept of distributed generation (DG) supply was proposed, its optimization planning and design problems have attracted enough attention from research institutions in various countries (Yu et al. 2017). The application of DG to new micro-grid is conducive to optimizing the energy structure, achieving energy saving and consumption reduction, and rationally using clean energy (Fang et al. 2014). For the optimal configuration problem of DG, site and size are the first steps in implementing a distributed generation project. It also plays an important foundation for the research of some issues such as ‘distributed power generation system scheduling’, ‘microgrid participation in demand response’, and ‘regional energy Internet’ (Li et al. 2009).

With the deepening of the research on DG optimal configuration, the planning problem of DG is gradually developed from a single target to a multi target planning problem (Dai 2013, Haghifam et al. 2008, Javadian and Massaeli 2011, Li et al. 2013, Maciel et al. 2012). Domestic and foreign scholars have made some research on the multi-objective programming of distributed power supply and have made some related

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achievements. Although multi objective technology is considered in Maciel et al. (2012), the optimization problem is considered only from two angles, and the consideration is not comprehensive enough. Li et al. (2013) considers investment costs, network loss and voltage indicators from three perspectives, proposes a game optimization theory, and optimizes DG's site and size. Haghifam et al. (2008) proposes a multi-objective fuzzy function model, but the model does not consider the effects of distributed generation technologies and environmental factors. Javadian and Massaeli (2011) gives indicators of the environmental benefits of DG. Comparing the cost of power generation with traditional power generation costs taking into account the environmental benefits of DG. Dai (2013) uses the principal component analysis to determine the weight of the sub-objectives and establishes a multi-objective model including economic indicators, voltage stability indicators and constraints. The optimal position and capacity of the DG are obtained by using an improved particle swarm optimization (PSO). Although this document considers more comprehensively, the multi-objective problem is treated as a single-objective problem and there is a relationship between sub-goals. This approach is not appropriate. In order to better deal with the possible constraints and conflicts of each target in the multi-objective programming problem and a variety of feasible schemes are proposed to adapt to different requirements. This paper uses a multi-objective planning method based on pareto optimization and proposes an improved PSO to obtain the optimal solution.

PSO is an evolutionary algorithm with parallel processing features, good robustness, and strong implementation. It has a higher probability of finding a global optimal solution and a higher computational efficiency. And it is used to solve various complex optimization problems, especially in power systems (Abido 2002, Kennedy and Eberhart 1995). However, similar to other evolutionary algorithms, PSO is also easy to fall into local optimum, and has the disadvantages of slow convergence and poor accuracy in the late evolution. Therefore, to overcome the limitations of the PSO, Gandomkar et al. (2005) proposes a hybrid genetic algorithm and simulated annealing algorithm to solve the problem of the location of the distributed power installation in the case of optimal network loss. Wu et al. (2009) has improved the classical PSO and applied it to the weight solution of electric load forecasting model. Zhao and Cao (2004) applies an improved PSO to solve power system unit combination problems. In this paper, a number of improvements are made to the PSO and used to solve distributed power optimization problems.

Experts and scholars have conducted extensive research on DG's site selection and volume determination in distribution networks from different perspectives. In Yu et al. (2017), Wang and Nehrir (2004), Zheng et al. (2009), Liu (2008) and Pan (2016), the optimization function is set up to minimize the construction cost and operation cost of the network. The literatures Zheng et al. (2009) and Liu (2008) aims at minimizing network loss and taking into account the influence of greenhouse gases (CO_2, SO_2, etc.). In Pan (2016), it takes into account the capacity allocation problem in case of load changes. Gradually increased the capacity of the distributed power supply installed at a given location until the network loss is minimum and the installation location is determined Yue et al. (2015). Zhao et al. (2009) focuses on the location of the controllable distributed power by considering the total cost and reliability. Through the total amount of distributed power, under the condition that the location, capacity and number of distributed power sources are unknown, the genetic algorithm is used to optimize the design (Celli and Pilo 2001). But the investment cost of distributed power is not considered. In Griffin et al. (2002), under the condition that the distributed power capacity is determined, the optimal installation position of the distributed power on a single radiating line is studied by analytical method. Among them, assume that the load is evenly distributed along the feeder, but in addition to the building load in the actual distribution network, the rest of the load distribution is uncertain, assuming it is not general. Deng and Fang (2015) applies the voltage stability limit surface normal vector to DG location, but do not consider the uncertainty of DG output, load demand and conforming to the actual situation. The planning scheme is irrational. In addition, a multi-stage photovoltaic power generation-load mixture probability model is proposed for the randomness of photovoltaic output and the fluctuation of load, then establishes the location and constant volume model of photovoltaic generation (Bai et al. 2015). In Zhang et al. (2015), it considers the time-series correlation between wind speed.

The above studies have played a role in promoting the research of DG optimization configuration problems. Firstly, this paper establishes a multi-objective model of DG optimization configuration, and then constructs investment efficiency index, voltage stability index and system network loss index as the three optimization objectives of this study. Based on the idea of Pareto optimization in multi-objective programming, an improved PSO is proposed to solve the DG optimal configuration problem. The simulation results verify the feasibility of the optimization method and provide planners with diversified solutions for DG site selection and capacity configuration.

MULTI-OBJECTIVE MODELING OF DISTRIBUTED GENERATION OPTIMIZATION CONFIGURATION

Investment benefit and safety operation are the important premise to carry out the micro power grid construction of the distributed power. Therefore, optimal allocation of distributed power must consider a variety of factor about impacting the distributed power constructions popularization. For this purpose. Considering the multiple optimization indexes, mainly including the investment benefit index, the voltage stability index and the system network loss index, under satisfying the normal operation constraint conditions of grid, this paper establish the optimal configuration multi-objective mathematical model of distributed power.

Optimization Objectives

DG investment income index

From the angle of establishing economic index, the annual income of the unit distributed power investment is set up as the index of investment income of DG (Zhang et al. 2011).

$$f_1 = \frac{E_{TPF}}{E_{INV}} \tag{1}$$

In the formula, E_{TPF} is to convert investment DG into annual income, including the income of DG selling electricity and government related subsidies for new energy construction; E_{INV} is the DG annual average investment cost, including installation cost, running maintenance cost and fuel consumption. The specific mathematical models of E_{TPF} and E_{INV} are:

$$E_{TPF} = 8760\sum_{i=1}^{N_{DG}}(E_{Si} + E_{Bi})S_{DGi}\lambda_i \tag{2}$$

$$E_{INV} = \sum_{i=1}^{N_{DG}} x_{DGi}S_{DGi}E_{Ti} + 8760\sum_{i=1}^{N_{DG}} E_{Fi}S_{DGi}\lambda_i \tag{3}$$

where N_{DG} is the DG access number, E_{SI} indicates grid-connected electricity price of DG at access node *i*. E_{Bi} represents the government subsidy electricity price of DG at access node *i*. S_{DGi} is the installed capacity of DG at access point *i*. λ_i means the capacity coefficient. x_{DGI} represents the DG level years input amount discount coefficient, E_{Ti} is the unit investment amount at access point *i*, E_{Fi} indicates the DG unit power consumption required for maintenance and the fuel costs for this type of DG.

Voltage stability index

From the angle of establishing reliability index, the voltage stability index is constructed. The voltage stability index is considered in two aspects: the offset index of the node voltage L_{VN} and the stability index of the branch voltage L_{vb} (Li et al. 2014). The offset index of the node voltage is summed up by the offset between the node voltage and the reference voltage in the system. The stability index of the branch voltage is summed up by each branch voltage stability index of the system, which reflects the stability margin situation of the branch voltage. The above two indexes can objectively reflect the reliability of the system.

The formula about the offset index of the node voltage L_{VN} and the stability index of the branch voltage L_{vb} are as follows:

$$\begin{cases} L_{vn} = \sum_{i=1}^{N}\left|V_i - V_{iref}\right| \\ L_{vb} = \sum_{i=1}^{N}\sum_{j=1}^{M}\frac{4\left[\left(P_jX_{ij} - Q_jR_{ij}\right)^2 + \left(P_jXR_{ij} - Q_jX_{ij}\right)U^2\right]}{U_i^4} \end{cases} \tag{4}$$

In the formula: V_{iref} represents the reference value of the node voltage; N and M are node labels; P_j and Q_j are the active total consumption and total reactive energy consumption at node *i* respectively; R_{ij} and X_{ij} are the resistance values and reactance values for line *i-j* respectively.

The voltage stability index is combined with the weighted sum of the above two evaluation index. The smaller the value is, the better the reliability of the grid is, and the more stable the operation is:

$$f_2 = \omega_1 L_{vn} + \omega_2 L_{vb} \tag{5}$$

where ω_1 and ω_2 are the evaluation coefficients between the two evaluation indicators respectively.

System network loss index

The reasonable access of DG can improve the network loss so that can improve the economic model of distribution network operation. The network loss index established in this paper is:

$$f_3 = \sum_{i=1}^{N}\sum_{j=1}^{M}\left[V_i^2 Y_{ij}\cos\theta_{ij} - V_iV_jY_{ij}\cos\left(\delta_{ji} + \theta_{ij}\right)\right] \tag{6}$$

In the formula, Y_{ij} and V_j are the voltage values of i^{th} and j^{th} nodes respectively; Y_{ij} is the admittance parameter of line i-j; Q_{ij} and δ_{ji} are the difference between the impedance angle and the voltage phase angle of the line i-j.

Constraint Conditions

After access to DG, the voltage, power and other parameters of the micro grid will be affected to varying degrees. In order to ensure the safe and stable operation of the micro grid after access to DG and to make sure that the DG can be fully utilized. After determining the objective function, the following constraints need to be met.

Equality constraints

In order to ensure the power balance of each node of the micro grid, the following equations need to be satisfied:

$$\begin{cases} P_{DGi} - P_{Li} = V_i \sum_{j=1}^{N} V_j \left(G_{ij} \cos\delta_{ij} + B_{ij} \sin\delta_{ij} \right) \\ Q_{DGi} - Q_{Li} = V_i \sum_{j=1}^{N} V_j \left(G_{ij} \sin\delta_{ij} + B_{ij} \cos\delta_{ij} \right) \end{cases} \tag{7}$$

In (7), P_{DGi} and Q_{DGi} are the active and reactive power injection of DG connected with node i; P_{Li} and Q_{Li} are the total consumption of active and reactive power for node i; $V_i$and V_j are the voltage amplitude of node i and node j respectively; G_{ij} and B_{ij} are the conductance and susceptance in the circuit admittance matrix respectively.

Inequality constraints

The capacity of the micro grid is limited, under normal conditions, the capacity of the micro grid to accept distributed power is limited. The total amount of DG connected to micro grid should meet the following conditions:

$$\sum_{i=1}^{N_{DG}} P_{DGi} \leq P_{DGmax}, i = 1,2, \cdots N_{DG} \tag{8}$$

P_{DGi} is the active power of DG connected with the node i and P_{DGmax} is the maximum value of active power output which is allowed the power distribution system accessing to DG.

At the same time, the voltage, active and reactive power of the micro grid must be kept within the allowable range.

$$\begin{cases} V_{imin} \leq V_i \leq V_{imax} \\ 0 \leq Q_{DGi} \leq Q_{DGimax} \\ 0 \leq P_{DGi} \leq P_{DGimax} \end{cases} \tag{9}$$

V_{imin} and V_{imax} are the upper and lower limit of the voltage allowed on the node i respectively; and represent the maximum allowable value of active and reactive power for accessing DG on the node i respectively.

THE SOLUTION OF DG OPTIMIZATION CONFIGURATION PROBLEM

The optimization problem can be divided into single-objective optimization and multi-objective optimization from the perspective of the number of objective functions. The actual project planning problem are mostly multi-objective optimization problems. In the multi-objective optimization process, there are often conflicting and mutually restrictive relationships before dealing multiple functions. It usually doesn't have a solution that enable the multiple objective functions to achieve the optimal conditions at the same time. There are usually three methods to consider the planning of multi-objective optimization: Based on the weight coefficient method. By comparing the important relationships between each objective function, each objective function is set a weight coefficient to add summation and the multi-objective problem is transformed into a single target problem for optimization; Bi-level planning method. The two planning objective functions are divided into two hierarchical steps. The decision variable obtained after the previous level optimization is optimized as the known quantity of the next level, at the same time, the planning results of the next level will be fed back to the previous level of planning in order to achieve the objective of double objective function optimization; Based on Pareto optimal method. The basic idea is to characterize the mutual restriction between the objective function which can no longer continue to optimize the situation at the same time and convert the solution to the multi-objective problem into the Pareto solution set. The Pareto solution set can be regarded as a non-inferior solution set for each fitness value and treated by optimizing method. The Pareto solution can be got at last. The pareto optimal planning method will provide a variety of solutions for planners, which will be sorted by different preferences in order to get the optimal solution.

Pareto Optimal Multi-objective Planning Method

In order to provide planners with multi-directional DG configuration solutions, this paper uses Pareto optimal multi-objective planning method and some basic concepts of the Pareto optimal multi-objective planning methods are presented as follows: domination and non-inferiority. If the objective function value of at least one solution in the decision vector X_1 is superior than the decision vector X_2 and the value of the objective function of the decision vector X_1 does not have to be the difference to the decision variable X_2. It can be said that the decision variable X_1 dominates the decision variable X_2 and it can also be said that X_1 is noninferior to X_2; Pareto front. The set of objective functions corresponding to Pareto optimal solution sets. Rank. If the decision variable X_1 rank is lower than the decision variable X_2, then X_1 dominates X_2. If the two decision variables do not know each other (mutually not bad), then two decision variables are the same value. The front end of the non-inferior solution corresponding to the decision variable with the ordinal value of 1 belongs to the first front end, the front end of the non-inferior solution corresponding to the decision variable with the order value 2 belongs to the second front end, and the first front end controls the second front end and the front end can be sorted by the way. Decision variables are divided into different front ends according to the rank.

Particle Swarm Optimization Algorithm

The main idea of PSO algorithm comes from social cognition theory, which shows the characteristics of swarm intelligence and achieves the task of group optimization by evaluating, comparing and imitating these three processes. The decision space of the population is N dimension, the size of the particle swarm is M and the position of the i^{th} particle is expressed as $X_i^t = (x_{i1}^t, x_{i2}^t, \cdots, x_{in}^t)$, the velocity can be expressed as $V_i^t = (v_{i1}^t, v_{i2}^t, \cdots, v_{in}^t), i = 1, \cdots, M$.The position and velocity of the particle are updated according to the equation below:

$$v_{ij}^t = \omega^t v_{ij}^{t-1} + c_1 rand_1\left(p_{ij}^{t-1} - x_{ij}^{t-1}\right) + c_1 rand_1\left(g_j^{t-1} - x_{ij}^{t-1}\right) \quad (10)$$

$$x_{ij}^t = x_{ij}^{t-1} + v_{ij}^t \quad (11)$$

where ω^t is the inertia weight coefficient; c_1 and c_2 are the acceleration factor; $rand_1$ and $rand_2$ are the random real number between (0,1); p_{ij}^{t-1} is the j^{th} dimension of the i^{th} particle in the optimal position of the i-1 generation. $g_j^{t-1}$is the j^{th} dimension of the most position of the i-1 population (the position of the guiding particle).

Improved Multi-objective Particles Swarm Optimization Algorithm (MPSO)

The optimal direction of particles is often based on the optimal individual history and the direction of the guiding particle (that is optimal global fitness or local fitness) in the classical PSO. But the selected guiding particles should be able to dominate as many other individuals as possible and the areas where the particles are located should be as sparse as possible in MPSO. That is to say that the whole particle swarm will fly to the Pareto front and keep as uniform as possible at there.

In this paper, PSO is applied to solve the multi-objective optimization problem. The method is to combine the Pareto non-dominated sorting principle and the classical PSO and to guide the particle flight by the domination relation and update the non-inferior solution set. But there are some main problems in the MPSO: The improper update strategy of the non-inferior solution set will lead to the poor diversity of Pareto sets and it is difficult to maintain good distribution; The replacement strategy of the optimal location (that is, the position of the guiding particle.) of the population is different, and it lacks the effective guidance; There is a lack of consideration of the characteristics of the iterative particles in the selection of the linear inertia weight coefficient; The optimization of the algorithm is easy to fall into the local optimum, which leads to the loss of population diversity. An improved MPSO is proposed to solve the problems mentioned above, and the improvement of the main functions is described as follows:

The method of determining the optimal position of individual history

Generally, the method of MPSO is to use the dominance relationship to judge. If the current individual optimal position $P_i^{t-1}$is dominated by a new generation, the optimal position of individual history will be replaced. If each other is not dominated, the original position remains unchanged. This approach will cause less updates of optimal historical individual in the later period of the operation. Therefore, this article has made some appropriate improvements: When the position of a new individual dominates the optimal position of a historical individual P_i^{t-1}, the optimal position of the current individual should be replaced and updated. When X_i^t and P_i^{t-1} do not dominate each other, the number of the particles that they dominate in the current population should be compared and the location of a large number of dominant particles is taken as the new optimal position of the historical individual.

The strategy of rotation system with dynamic crowding distance

The diversity of the Pareto solution set can be guaranteed and a good uniform distribution can be maintained by using the dynamic crowding distance rotation system strategy in the process of updating the set of non-inferior solutions (Kukkonen and Deb 2005). The dynamic crowding distance is used to characterize the intensity of the other solutions around a particle and to prevent the local density of the solution. Considering each particle under the same ordinal value, first a certain objective function value of first front-end particle is to be sorted, and the location of the two nearest particles to particle X_i is X_{i-1} and X_{i+1} and the crowding distance of particle can be expressed as:

$$D(X_i) = \sum_{y=1}^{Y} \frac{\left|f_y(x_{i+1}) - f_y(x_{i-1})\right|}{f_{ymax} - f_{ymin}} \tag{12}$$

In (12), Y is the number of objective functions; $f_y(x_i)$ is the y^{th} objective function value of particle; f_{ymax} and f_{ymin} are the maximum and minimum values of the y^{th} objective function in the feasible region.

The dynamic crowded distance rotation strategy is: After finding the crowded distance of each particle in the non-inferior solution set, sort it according to the crowded distance from big to small. It is different from the conventional practice of taking the first N solutions with large crowded distances for non-inferior solution set update. Because it is very easy to make the selected non-inferior solution set less uniform in the conventional practice. The rotation strategy of dynamic crowded distance is to remove the last particle after sorting (that is, the particle with the least congestion), and then recalculate the crowded distance of the remaining non-inferior solutions. The crowded distances of the remaining non-inferior solutions will be recalculated and removed one by one after reordering. A reciprocal cycle is then performed until the update of the non-inferior solution set of the last remaining N particles is completed.

Optimal population location replacement of elite parent retention strategy

In this paper, an external archive mechanism is used to select the optimal population positio, and the non-inferior solution front end is externally stored and updated (Peng et al. 2010). The conventional approach is to randomly select the optimal population position G_{t-1} in the external archive data. In this paper, a variable-capacity external storage is set up based on the external archiving mechanism, and the elite parent retention strategy is introduced. The father and offspring are merged and unified, and the optimal position of the population is finally determined through the dynamic crowding distance rotation strategy.

The introduction of the elite parent retention strategy avoids the loss of optimal solutions. It also expands the distribution range of non-inferior solution sets in the external archiving mechanism and improves the diversity of particle populations.

Adaptive inertia weight coefficient

Adjusting the inertia weight coefficient is to balance the algorithm's global searching ability and local searching ability. In general, the transformation of inertia weight coefficients decreases linearly with the number of iterations. However, this method does not fully feedback the information of the current generation to the next generation, and it is easy to prematurely converge the particles to local optimum. Therefore, the change of is guided by the difference between the current position of the particle and the position of the guidance particle. When the gap is relatively large, the current particle should be instructed to have a strong global searching capability. At this time, a larger value should be used. When the gap is small, the current particle should be guided to stop near the current position to search, so that it will have a better local searching capability. And a smaller ω value should be used at this time. The adaptive inertia weight coefficient for characterizing population iteration particle information is established as follows:

$$L_i^t = \frac{1}{x_{max} - x_{min}} \frac{1}{N} \sum_{n=1}^{N} |g_n^t - x_{in}^t| \tag{13}$$

$$\omega_i^t = \omega_{begin} - \left(\omega_{begin} - \omega_{and}\right)(L_i^t - 1)^2 \tag{14}$$

where L_i^t is the relative distance difference between the particle i and the guide particle position in the t iterations; N is the dimension of the decision variable; ω_i^t is the inertia weight coefficient of particle i in the t^{th} iteration; ω_{begin} and ω_{and} are the start and end values respectively which are set by the inertia weight coefficient; x_{max} and x_{min} are the maximum and minimum values of the position of the decision variable, respectively.

Cross variation mechanism

The fast convergence of MPSO may lead to convergence into local optimum. To avoid the above situation, put the new genes into populations by crossover and mutation mechanism. The search for a larger solution space ensures the diversity of population solutions. The relative distance difference between the particle i and the position of the guiding particle is used as the starting basis, and the specific operation steps are as follows:

1. Set the threshold L_{min}, the mutation rate P_m, and the cross-rate P_c.

2. When the relative distance difference between the particle i and the position of the guiding particle is less than L_{min}, the optimal position of the population in the velocity is maintained. Configure a random number r_{in} between [0,1] for each dimensional velocity variable of particle i, if r_{in} is less than P_m, start the mutation mechanism to initialize the n-dimensional of particle i's velocity:

$$V_{in} = V_{min} + (V_{max} - V_{min})r \tag{15}$$

In the above formula: V_{max} and V_{min} are the maximum and minimum values of particle velocity, and r is random number between [0,1].

1. Cross-process the mutated population. If r_{in} is less than P_c, replace the n-dimensional position vector of particle i and the n-dimensional vector corresponding to the guide particle, and generate new population to continue the optimization search.

2. Asymmetric adjustment strategy for acceleration factor. The acceleration factor c_1 and c_2 reflect the communication for information between particles. If c_1 is larger, the particle will depend more on individual experience, resulting in excessive reciprocating in local area. If c_2 is larger, the population will fall into the local optimum earlier. Usually, the improved way is to use larger c_1 and smaller c_2 in the earlier iteration process. The higher the number of iterations, decrease c_1 and increase c_2 to adjust acceleration factor. The adjustment formula is as follows:

$$V_{in} = V_{min} + (V_{max} - V_{min})r \tag{16}$$

$$c_2 = \left(c_{2end} - c_{2begin}\right)\frac{t}{t_m} + c_{2begin} \tag{17}$$

where: C_{begin} and C_{end} are the starting and ending values of the acceleration factor, t is the number of iterations, and is the maximum number of iterations. The normal setting method is that linear decrease C_1 from 2.5 to 0.5, and linear increase C_2 from 0.5 to 2.5. However, this method tends to cause premature convergence in multi-peak functions. Therefore, this paper adopts the adjustment strategy of asymmetric change. Linear decrease C_1 from 2.75 to 1.25, and linear increase C_2 from 0.5 to 2.25.

THE METHOD FOR SITING DG

DG is connected with microgrid, and the traditional radial network is transformed into a new active network. It is usually installed on a nearby large electricity load. And it plays a positive role in reducing the node load, debasing the network loss of the power distribution system and increasing the voltage stability. However, the equivalent resistance between the nodes and the root nodes in the power distribution system is different. Therefore, different nodes have different effects on the active network loss of the system. The function of the load node and system network loss can be derived from (Zhuang and Wang 2012). The function of active load on different nodes and active power loss of the system can be deduced in a system with fixed network structure and determined equivalent. Therefore, the location of DG is determined from the active network impact index.

$$T_i = \left| \frac{\left(P_i^2 + Q_i^2\right)\sum R_{si}^2 + 2P_i \sum R_{si}\left(P_i \sum R_{si} + Q_i \sum X_{si}\right) -}{\left(P_i \sum R_{si} + Q_i \sum X_{si}\right)^2} \right| \tag{18}$$

where P_i and Q_i are active and reactive power consumption respectively. R_{si} and X_{si} represent the equivalent resistance and reactance of first nodes to the root node respectively.

Influence index of active network loss T_i reflects the influence of active load access to different nodes on the active loss of the system. The corresponding value T_i of the i^{th} node is small, indicating that the impact of the node on the system network loss is small. In the same way, the value of the node T_i is large, and the size of its access load with have greater impact on the system active network loss. Therefore, it is just the nodes need to be connected to DG to improve system network loss indicators. The alternative installation DG node for the site selection could be obtained by sorting the active network loss index of each node from high to low.

CASE STUDY

The optimal location and installation capacity configuration of distributed power is researched based on the PG&E 69 notes power distribution system (Aman et al. 2014). The reference voltage of the distribution system is 12.66 kV, and the topological structure is as **Fig. 1**.

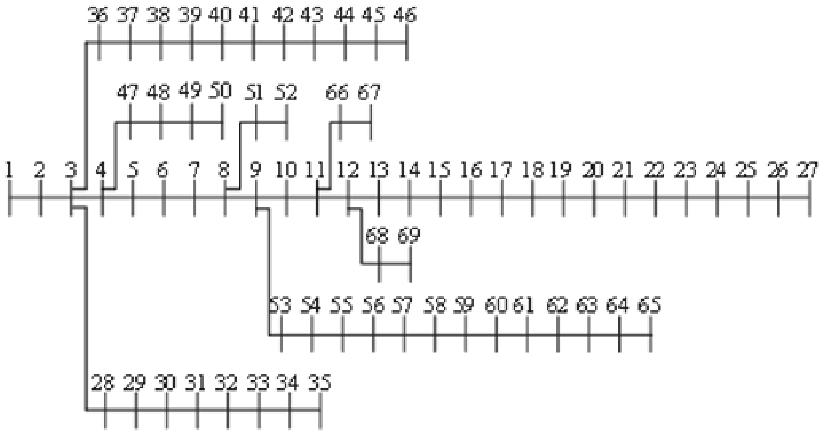

Fig. 1. The topological structure of the PG&E 69 notes power distribution system

Table 1. DG technical parameters

Type	Capacitance coefficient	Investment cost (yuan/kW)	Conversion coefficient	Maintenance cost (yuan/kW)	Electricity selling price (yuan/kW·h)	government grant (yuan/kW·h)
WT	0.40	13.0	0.1006	0.045	0.56	0.25
PV	0.29	43.5	0.0859	0.015	0.56	0.25
MT	1.00	9.5	0.1006	0.189	0.43	0
FC	1.00	18.4	0.8578	0.360	0.43	0

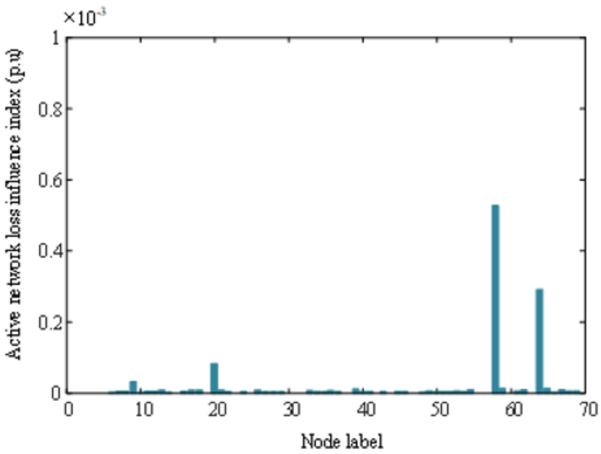

Fig. 2. Active network loss influence index of PG&E 69 nodes power distribution system

The parameters of the planning model are set as follows: The types of DG to be selected are wind turbine generator (WT), photovoltaic (PV), micro turbine generator (MT) and fuel cell generator (FC). Investment and operation parameters of DG are as **Table 1**. The parameters of MPSO are set as: The number of particles is 100. The maximum number of iterations is 100. The change interval of ω is 0.5-0.8. Asymmetric acceleration factor c_1 decreases from 2.75 to 1,25 in uniform steps, and C_2 increases from 0.5 to 2.25 in uniform steps. L_{min} is 0.1, P_m is 0.05, and P_c is 0.2. The maximum total capacity of distributed power access is less than 40% of the total active load of the distribution system.

Table 2. Active network loss influence indexes and DG types of installation nodes

Node label	Active network loss influence index (10^{-3} p.u.)	DG type
58	0.5325	WT
63	0.2890	PV
20	0.0747	MT
9	0.0389	FC

RESULTS AND DISCUSSION

Analysis of Simulation Results under the Same Load Condition

According to the location method proposed in the Section 4, the value of T_i of each node can be calculated. The values are as **Fig. 2**, which shows that there are obvious differences in the inductive degree of each node to the system active network loss in the distribution system, which suggests that a reasonable selection of nodes to be selected can improve the network loss index of the system. The influence index of the active network loss T_i of each node is sorted from large to small, and nodes numbered 58, 63, 20 and 9 are selected to install DG. The influence indexes of the active network loss of these nodes and the types of DG are as **Table 2**.

After determining the optimal installation location scheme of DG, MPSO is used to optimize the installation capacity of DG. The optimal Pareto front solution aggregate is as **Fig. 3**.

Table 3. Typical schemes and parameters of DG optimal configuration

Typical scheme	DG capacity (Installation position)				Network loss index (kW)	Voltage stability index (p.u)	Investment benefit index (p.u)
	WT(kW)	PV(kW)	MT(kW)	FC(kW)			
S1	360(58)	400(63)	360(20)	390(9)	48.3846	0.4173	0.4981
S2	370(58)	390(63)	380(20)	370(9)	44.3746	0.3657	0.4635
S3	390(58)	400(63)	320(20)	360(9)	43.6547	0.3728	0.4823
S4	400(58)	230(63)	150(20)	390(9)	72.2737	0.5654	0.7342
S5	370(58)	400(63)	390(20)	300(9)	47.2748	0.3978	0.4287

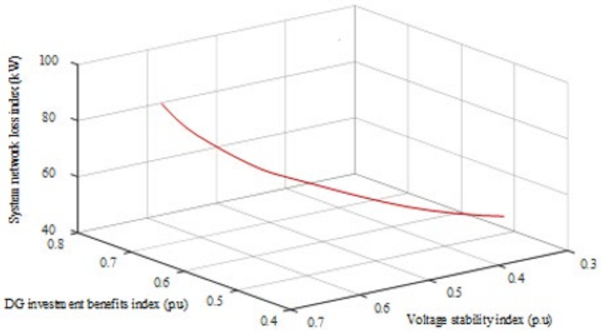

Fig. 3. Pareto front solution of multi-objective optimization configuration

As can be seen in **Fig. 3**, the optimal Pareto front solution aggregate has good distribution. According the trend of the curve, the increase of investment benefit index will cause the increase of system network loss index and voltage stability index, which suggests that economy and stability are a set of relative conflicting objective functions. In response to this situation, the optimal Pareto front solution aggregate can provide a variety of schemes based on different angles.

Several representative schemes in the optimal Pareto front solution aggregate are selected for discussion. The data of the schemes are as **Table 3**.

Table 3 shows that the technical indexes are closely related to the installation location and capacity of the DG. In S3, the system network loss is the minimum, but the voltage stability and investment benefit are not the best. According to the comparison between S2 and S3, the system voltage stability margin of S2 is relatively better. This is because the total DG installed capacity is larger. However, the system network loss index is lower, and this is because the installed capacity of nodes numbered 58 and 63 is larger. According to **Fig. 2**, the active network loss influence indexes of nodes numbered 58 and 63 are relatively high, so the active power of the access is more effective to reduce the active power loss. Even if the capacity of DG in node 21 of S2 is larger than that of S3, the network loss index of S3 is still better. This comparison suggests that a reasonable configuration for DG is very important to reduce the active network loss.

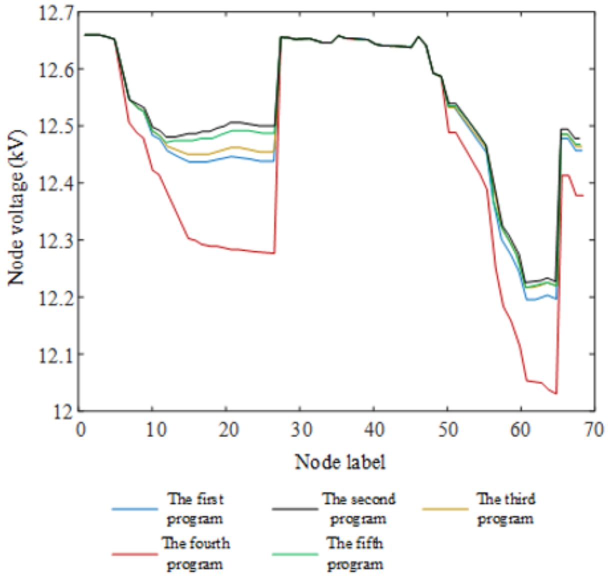

Fig. 4. Node voltage data of different typical schemes

According to the comparison between S1 and S4, the system network loss and the voltage stability index of S1 are lower, but the investment benefit is no better than S4. In the five schemes, the investment benefit of S4 is the best, but it does not perform well on the other two indexes. Analogously, the voltage stability index of S5 is better than S1, but the other two indexes are worse. These two comparisons suggest that there are conflicts and contradictions between technical indicators. Therefore, in the selection of the schemes, the balance between the economy and the stability needs the planners to stand in different angles. Multi objective programming balances all kinds of relative contradictory objective functions and establishes a set of optimal plans with different angles. It provides diverse choices for the planners in the formulation of plans. Node voltage in different planning schemes are as **Fig. 4**, which that different schemes will produce different effects on node voltage quality improvement. Meanwhile, a scheme has different improvement effects on different nodes.

Analysis of Simulation Results under Different Load Conditions

Considering that the growth of the economy increases the level of node load, this growth will have a

Table 4. Optimization schemes and parameters for different load conditions

Typical scheme	DG capacity (Installation position)				Network loss index (kW)	Voltage stability index (p.u)	Investment benefit index (p.u)
	WT(kW)	PV(kW)	MT(kW)	FC(kW)			
S1	360(58)	400(63)	360(20)	390(9)	48.3846	0.4173	0.4981
S2	370(58)	390(63)	380(20)	370(9)	44.3746	0.3657	0.4635
S3	390(58)	400(63)	320(20)	360(9)	43.6547	0.3728	0.4823
S4	400(58)	230(63)	150(20)	390(9)	72.2737	0.5654	0.7342
S5	370(58)	400(63)	390(20)	300(9)	47.2748	0.3978	0.4287

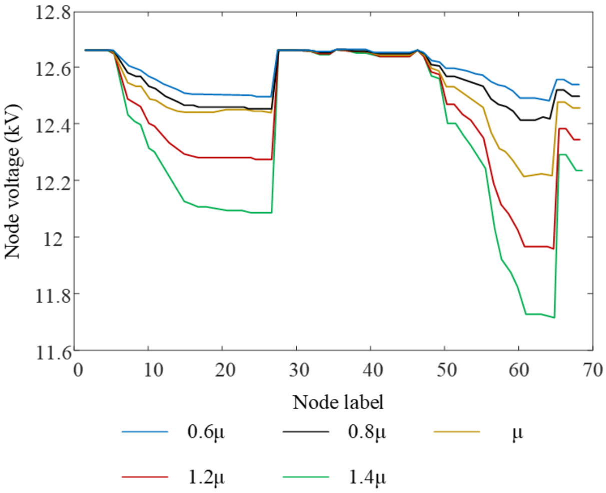

Fig. 5. Node voltage data of different schemes

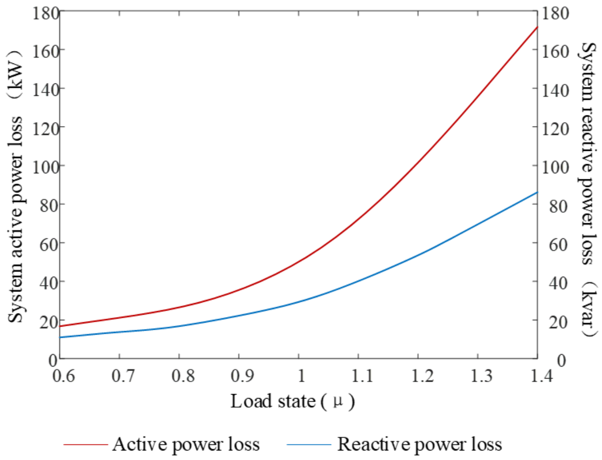

Fig. 6. Active and reactive network loss of different load conditions

corresponding impact on the optimal configuration of DG. The optimal configuration of DG under different load conditions is discussed in this paper. Five load conditions are selected, which are 0.6D (D is the original conforming condition), 0.8D, D, 1.2D, 1.4D. DG configuration results are as **Table 4**. Node voltage, active power loss and reactive power loss are summarized in **Figs. 5-6**.

It can be seen in **Fig. 5** that under different load conditions, the reliability of system voltage is decreasing with the increase of load access. At the same time, due to the different configuration of DG, the voltage level of each node is different under all load conditions. **Fig. 6** shows that the active power loss and reactive power network loss increase with the increase of load access. Therefore, it is necessary to take account of the growth of load and plan a reasonable expansion plan for DG installation.

CONCLUSIONS

This paper analyzes the multi-objective programming method of DG optimal configuration problem. System network loss index, voltage stability index and investment benefit index are constructed for multi-objective programming. Based on pareto programming method, MPSO is proposed. For Select the appropriate installation position, the DG optimization location method based on active network loss impact index is proposed. According to the results and analysis, it is shown that using different schemes, the DG access to microgrid has different effects on the node voltage, and the improvement effect for the microgrid loss is also different. At the same time, when the load condition changes, the optimal scheme will also change. Therefore, it is needed to take the changes in load into consideration in DG planning and prepare the expansion plan for the nodes with increasing load. The DG configuration scheme proposed in this paper can help to improve investment efficiency and technical indicators. Meanwhile, the multi-objective optimization method can provide planner with various reasonable alternatives based on different angles.

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