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Multi-objective Comprehensive Optimization of Distribution Network considering the randomness of DG

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Abstract. In recent years, distributed generation technology develops rapidly due to its' flexible and environment-friendly nature. In order to better analyze the impact of DG on the economics and safety of distribution networks, a probability model for random load, micro gas turbines and photovoltaic power generation system is formulated. With the objective of minimizing the network loss, lowest static insecurity probability, and the lowest cost of purchasing electricity, the optimization of distribution network with distributed generation is carried out by adjusting the distribution network topology and the output of controllable DG. The stochastic power flow is combined with the particle swarm optimization algorithm to obtain the Pareto non-inferior solution set, and then the subject is selected to obtain the optimal solution. Finally, simulations are carried out on the IEEE 33-bus test system and it is shown that the optimized network can effectively reduce the network loss and static insecurity probability on the basis of low cost of purchasing electricity.

1. Introduction

Distribution network reconfiguration (DNR) [1-2] is to optimize the distribution network operation by combining the state of the distribution switch according to the load of the distribution network and the output power of the distributed power supply. The advantages of distributed power supply, such as flexibility, economy and environment-friendliness, make it widely used in distribution network to reduce distribution network loss and improve node voltage.

The output of distributed power supply is generally regarded as a fixed value in the research of distribution network reconfiguration [3-4]. In order to make the research of distribution network more practical, it is more and more important to deal with the uncertain factors reasonably [5-10]. In [8], scene partition method based on wasserstein distance index is used to solve the DNR problem. This method is one-sided in the consideration of uncertainty, and the result is limited, and the probability distribution of the output of state variables cannot be obtained. In [9], distribution network reconfiguration is studied considering the randomness of load and wind power generation, and two-point estimation method [10] is used to calculate stochastic power flow. When applied to the reconstruction problem, the calculation times are too many, the operation time is long. The practicability of this method is poor for the large-scale distribution system.

Considering the deficiency of the above two methods, this paper calculates stochastic power flow based on the method of reference [11]. In the case of establishing probability models with different

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injection power, the algorithm of semi-invariant method combined with Gram-Charlier series expansion is used to calculate the stochastic power flow with DG. The semi-invariant operation is used instead of convolution operation, which effectively reduces the computational complexity. This method can not only get the probability distribution of state variables, but also accelerate the calculation speed, so it is suitable to solve the problem of distribution network reconstruction.

There are two main methods to solve multi-objective optimization problems: one is the traditional algorithm, the other is the heuristic intelligent algorithm. Traditional algorithm is difficult to balance the weights between the indicators. Compared with the traditional algorithm, heuristic intelligent algorithm can effectively compromise conflicting objective function, and not only provides the decision-maker with the extreme solution of each objective function, but also can provide optimal and diverse solutions to compromise the interests of all parties. In this paper, the heuristic intelligent algorithm Pareto multi-objective optimization method is adopted.

Considering the potential of controllable DG in optimizing distribution performance operation index, the output of controllable DG is optimized as an independent variable for comprehensive optimization on the basis of reconfiguration [12-15]. Taking network loss, static unsafe probability and power purchase cost as objective functions [16-17], the optimal solution set is obtained by changing the network structure and controllable DG output, and Pareto criterion [18] is used to deal with multi-objectives. The purpose of improving the static security and economy of distribution system is achieved.

2. Multi-objective comprehensive optimization model

2.1. Objective function

(1) System static security

In this paper, the probability of voltage violation is taken as the static security index of the system. The probability λ_i that the node i voltage exceeds the limit can be expressed as:

$$\lambda_i = \Pr\{U_i > U_{i\max}\} + \Pr\{U_i < U_{i\min}\} \tag{1}$$

Where, U_i denotes the voltage of node i, U_{imax} and U_{imin} are the upper and lower limits of the node voltage, and Pr $\{\cdot\}$ denotes the probability of the inequality.

The probability of voltage not exceeding the limit is 1-λ_i, and the probability of voltage exceeding the limit of the whole system is as follows:

$$\lambda = 1 - \prod_{i=1}^{n}(1-\lambda_i) \tag{2}$$

n is the number of nodes in the system.

(2) Economy of system operation

The network active power loss and the power purchase cost per unit time (1 h) are taken as the evaluation indexes of the operation economy of the system.

The optimization objective of active power loss are expressed as follows:

$$\min f_1 = \sum_{i \in T} r_i \frac{P_i^2 + Q_i^2}{U_i^2} \tag{3}$$

In this formula, f_1 is the active power loss of the distribution network, r_i is the resistance of the line i, P_i and Q_i are the active and reactive power flowing through the end terminal of line i, U_i is the voltage amplitude of the end terminal of line i, and T is the branch set of the distribution network.

The price of purchasing electricity from gas turbine is s_1 \$/kWh, from photovoltaic power generation system, and the price of purchasing electricity from photovoltaic power generation system is s_2 \$/kWh. If the purchase price of the main network is s_3 \$/kWh, the optimization target of the purchase cost can be expressed as follows:

$$\min f_2 = \sum_{a \in C_1} s_1 \times P_a + \sum_{b \in C_2} s_2 \times P_b + s_3 \times P_c \tag{4}$$

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Where C_1 represents the node set of gas turbine output, C_2 represents the node set with PV generation output, P_a and P_b represent the active power output of gas turbine and photovoltaic power system respectively, and P_c represents the active power output of the main grid system to the system.

2.2. *Constraints*

Comprehensive optimization of distribution network needs to meet the following constraints

(1) The distribution network is radial and there are no isolated nodes in it, which means there is no loop and no islands.

$$g_k \in G_k \tag{5}$$

Where g_k represents the current network topology and G_k represents the set of network topology that satisfies connectivity and radiality.

(2) Voltage constraint

$$U_{i\min} \le U_i \le U_{i\max} \tag{6}$$

(3) Branch capacity constraint

$$\sqrt{P_i^2 + Q_i^2} \le S_{i,\max} \tag{7}$$

Where $S_{i,max}$ is the maximum power limit of branch i.

(4) Constraint of DG output

$$\begin{cases} P_{G,k} \le P_{G,k,\max} \\ Q_{G,k} \le Q_{G,k,\max} \end{cases} \tag{8}$$

Where, the control variables $P_{G,k}$ and $Q_{G,k}$, respectively represent the active power and reactive power output of the controllable DG k; $P_{G,k,max}$ and $Q_{G,k,max}$ respectively represent the maximum active power and reactive power that controllable DG k can output.

2.3. *Probability model of DG and load*

(1) Model of photovoltaic power generation

The power generated by the photovoltaic array is:

$$P_M = rA\eta \tag{9}$$

where A represents the total area of the battery panel, and η represents the photoelectric conversion efficiency.

When the illumination intensity satisfies the Beta distribution, the power generated by the photovoltaic array also satisfies the Beta distribution:

$$f(P_M) = \frac{\Gamma(\alpha+\beta)}{\Gamma(\alpha)\Gamma(\beta)} \left(\frac{P_M}{R_M}\right)^{\alpha-1} \left(1 - \frac{P_M}{R_M}\right)^{\beta-1} \tag{10}$$

Where $R_M = r_{max}A\eta$ represents the maximum output power of the photovoltaic array, α and β are two parameters of the Beta distribution.

(2) Model of micro-gas turbine

In the iterative process of power flow calculation, micro-gas turbine can be converted into PQ nodes for processing. Two states probabilistic models are used to represent the operating state of the gas turbine:

$$P(W = w_i) = \begin{cases} p & w = C \\ 1-p & w = 0 \end{cases} \tag{11}$$

where p represents the normal operating probability of the gas turbine; c represents the rated power of the gas turbine; w represents the actual power generation of the gas turbine. This paper assumes that the gas turbine input power meets the binomial distribution. It is assumed that the input power of gas turbine satisfies the binomial distribution in this paper.

(3) Load model

Operational practices have shown that the uncertainty of distribution load can be approximately reflected by a normal distribution. Thus, the probability distribution of active and reactive loads can be expressed as:

$$f(P) = \frac{1}{\sqrt{2\pi}\sigma_P} \exp\left(-\frac{(P-\mu_P)^2}{2\sigma_P^2}\right) \tag{12}$$

$$f(Q) = \frac{1}{\sqrt{2\pi}\sigma_Q} \exp\left(-\frac{(Q-\mu_Q)^2}{2\sigma_Q^2}\right) \tag{13}$$

Where μ_P and σ_P respectively represent the expected and variance of the active load. μ_Q and σ_Q respectively represent the expected and variance of the reactive load.

3. Probabilistic power flow

The existing probabilistic power flow algorithms can be roughly divided into three categories: analytical method, simulation method and approximation method. In this paper, the analytic method is used to calculate the probabilistic power flow. Based on the DC power flow equation and the linearized AC power flow equation, it is considered that there is no correlation between the random distribution of injection power. The probability distribution function of injection power is obtained according to convolution calculation, and then the probability distribution of node voltage is calculated according to the linearized power flow equation.

3.1. Power flow equation linearization

In power flow calculation, the node power equation can be represented by $S=f(X)$, random variables can be expressed by their expected values and random perturbation values obeying a certain distribution.

$$S = S_0 + \Delta S \qquad X = X_0 + \Delta X \tag{14}$$

The Taylor series expansion of (17) is:

$$S_0 + \Delta S = f(X_0 + \Delta X) = f(X_0) + J_0 \Delta X + \ldots \tag{15}$$

where $S_0=f(X_0)$.If ignoring the high order derivatives, we get:

$$\Delta X = J_0^{-1} \Delta S \tag{16}$$

By convolution calculation, the probability distribution of output random variable ΔX can be obtained from the distribution of injected power ΔS.

The semi-invariant method used in this paper replaces the complex convolution operation with simple addition-subtraction operation, which greatly reduces the computational burden.

3.2. Process of probabilistic power flow

The proposed probabilistic power flow algorithm consists of seven major steps which are described as follows:

Step1. Enter the original data.

Step2. Obtaining the initial value of output of photovoltaic power generation system.

Step3.The deterministic power flow calculation is carried out, and the sensitivity matrix S_0 is obtained.

Step4. The semi-invariant of each random variable is obtained according to the relation between moment and semi-invariant.

Step5. The calculated semi-invariants are added according to their properties, from which the semi-invariants of injection power for each node are obtained.

Step6. According to equation (16), the semi-invariants $\Delta S^{(k)}$of the injection power of each node obtained from the previous step are calculated to obtain the semi-invariants $\Delta X^{(k)}$ of each order of the state variable.

Step7. The cumulative distribution and probability density function of the state variable ΔX are obtained by using the formula of the expansion of the Gram-Charlier series [17]. The expression is as follows:

$$f(x)=\varphi(\bar{x})[1+\frac{g_3}{3!}H_3(\bar{x})+\frac{g_4}{4!}H_4(\bar{x})+\frac{g_5}{5!}H_5(\bar{x})+\frac{g_6+10g_3^2}{6!}H_6(\bar{x})+\frac{g_7+35g_3g_4}{7!}H_7(\bar{x})+\frac{g_8+56g_3g_5+35g_4^2}{8!}H_8(\bar{x})+\cdots] \quad (17)$$

$$F(x)=\phi(\bar{x})+\varphi(\bar{x})[\frac{g_3}{3!}H_2(\bar{x})+\frac{g_4}{4!}H_3(\bar{x})+\frac{g_5}{5!}H_4(\bar{x})+\frac{g_6+10g_3^2}{6!}H_5(\bar{x})+\frac{g_7+35g_3g_4}{7!}H_6(\bar{x})+\frac{g_8+56g_3g_5+35g_4^2}{8!}H_7(\bar{x})+\cdots] \quad (18)$$

Where g_υ denotes the normalized value of the semi-invariant υ-order, $\bar{x}$ is the normalized randomly variables. $\varphi(\bar{x})$ and $\phi(\bar{x})$ are the probability density function and cumulative distribution function of standard normal distribution, respectively. $H_\gamma(x)$ is Hermitian polynomial, which is the coefficient after finding the derivative of order γ for$\phi(\bar{x})$.

Step8. The state variables and the confidence interval of branch power flow can be calculated by using the obtained cumulative distribution function. Calculating of voltage out-of-limit probability of the entire distribution system according to formula (2).

4. Implementation of optimization algorithm

4.1. Particle swarm optimization

Particle swarm optimization (PSO) is a parallel evolutionary algorithm which finding the optimal solution through iteration calculation, and judges the merits and demerits of the solution by using the fitness value as the criterion.

In order to enhance the optimization ability, the PSO iterative process is dynamically optimized [19]. The particle velocity and position are calculated as follows:

$$v_{id}=\omega * v_{id}+c_1r_1(p_{id}-x_{id})+c_2r_2(p_{gd}-x_{id}) \qquad x_{id}=x_{id}+v_{id} \quad (19)$$

$$\omega=\omega_{\min}+((\omega_{\max}-\omega_{\min})\times(t_{\max}-t))/t_{\max} \quad (20)$$

$$c_1=c_{1a}+\frac{c_{1b}-c_{1a}}{t_{\max}}\times t \qquad c_2=c_{2a}+\frac{c_{2b}-c_{2a}}{t_{\max}}\times t \quad (21)$$

Where p_{id} and p_{gd} respectively represent the individual and global optimal particle positions. t and $t_{\max}$ represent the current iteration number and the maximum number of iterations respectively. v_{id} and x_{id} are particle velocity and position. r_1 and r_1 are random uniform numbers in the interval.

In addition to optimizing the iteration speed, the updated speed is optimized. Because x_{id} must be an integer. When v_i is in the interval [-0.5, 0.5], it is rounded to zero, and the iteration has no meaning. Therefore, after the speed is iterated once, it is judged whether the value of each dimension speed is zero. When the speeds of all the dimensions are zero, the random value is given to the current speed again, and then the position update. This is called speed zero elimination.

After optimization, it not only improves the iteration speed, but also maintains the diversity and directionality of the particles.

4.2. Multi-objective optimization

The mathematical model of the Pareto multi-objective optimization method can be expressed as:

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$$\begin{cases} \min F(x) = [f_1(x), f_2(x), \cdots, f_D(x)] \\ s.t \qquad g(x) = 0, h(x) \le 0 \end{cases} \tag{22}$$

Where D is the number of objective functions. $g(x)$ and $h(x)$ represent equality and inequality constraints, respectively.

The optimal solution can be obtained from the dominating relationship of the solution. The optimal solution is often a solution set composed of multiple solutions. The decision maker can choose the appropriate solution from the optimal solution set according to his own bias. In this paper, the selection strategy in [16] is used for individual selection. a、b、c are called decision factors, and their size can be determined by the decision makers, reflecting the proportion of each objective function in the evaluation value.

$$F(k) = a \times \frac{f_1(k) - f_{1\min}}{f_{1\max} - f_{1\min}} + b \times \frac{f_2(k) - f_{2\min}}{f_{2\max} - f_{2\min}} + c \times \frac{f_3(k) - f_{3\min}}{f_{3\max} - f_{3\min}}, \qquad \text{s.t} \quad a+b+c=1 \tag{23}$$

4.3. Algorithm flowchart

A flow chart of the comprehensive optimization algorithm based on stochastic power flow is shown in Fig 1.

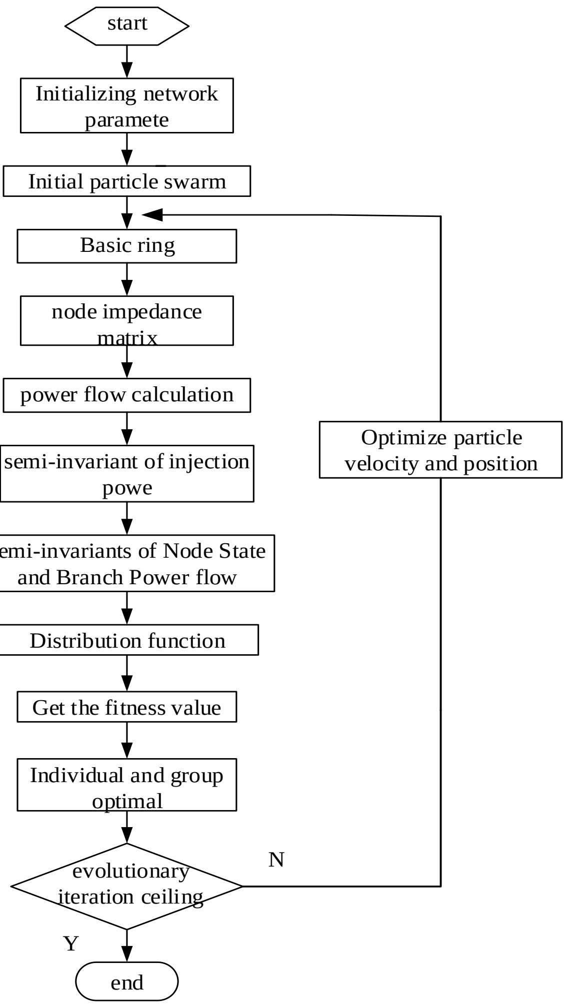

Figure 1. Flow chart of the Comprehensive optimization

5. Case study

To verify the effectiveness of the proposed algorithm, a distribution system of IEEE33 bus system shown in Fig 2. is tested. The system consists of 33 nodes,32 normally closed switches and 5 normally open switches. Set the benchmark parameter as U_b= 12.66kv and S_b =1MVA.

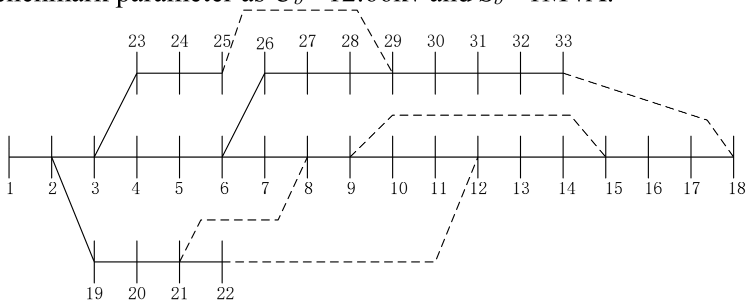

Figure 2. IEEE33 bus system

The photovoltaic power generation system was added at node 33, and the light intensity data was obtained by simulating the monthly average of the Guangzhou area (23.08°N, 113.19°E) in China using the HOMER software. A micro gas turbine (controllable DG) was added at the 18 and 29 nodes with an active output upper limit of 600 kW, a power factor of 0.9, and a usable rate of 0.9. The original load data is used as its expected value, and the standard deviation is 30% of the expected value.

Among them, the PV generation can be regarded as uncontrollable DG. It can be seen from Table 1 that in the original network structure (Case 1), the access of the PV system can reduce the network loss and the probability of static insecurity to a certain extent. When the network structure is adjusted to minimize the static insecurity probability of the system (case 2), the static insecurity probability will be increased with the addition of PV power system. The loss decreases with the increase of DG output, while the cost of purchasing electricity is the opposite. In this paper, the 100kW photovoltaic system with small rated capacity is selected in the reconfiguration optimization.

Table 1. PV impact on the distribution network

case	outage line	energy from PV/kW	network loss/kW	static insecurity probability	purchase cost /$
case 1	33 34 35 36 37	0	189.339	0.9995	182.955
		100	185.414	0.9985	183.994
		200	181.618	0.9962	184.885
		300	177.951	0.9920	185.925
case 2	6 14 9 32 28	0	139.107	1.48e-05	180.579
		100	136.170	2.527e-05	181.618
		200	133.417	0.0016	182.658
		300	130.845	0.0049	183.697

The particle swarm optimization (PSO) algorithm based on stochastic power flow is used to calculate the "non-dominant" solution set of Pareto as shown in Figure 3. The optimization results are shown in Table 2.

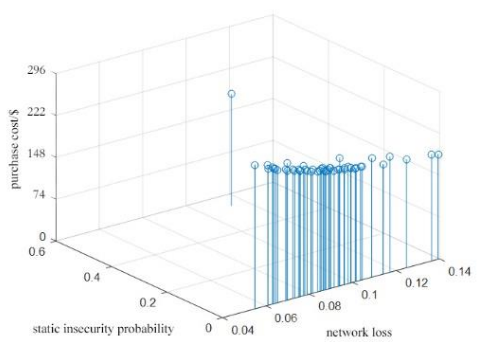

Figure 3. Distribution of Pareto solution set

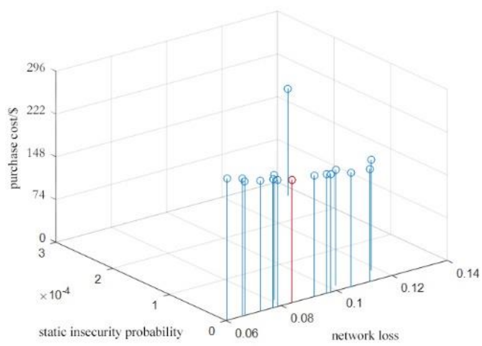

Figure 4. Distribution of optimal solution set

The final solution is selected from the Pareto solution set. Because of the restriction between the objective functions, when the purchase cost is low, the static insecurity probability often does not meet the static security requirements of the system. Therefore, the solution whose static insecurity probability is less than 0.001 is firstly eliminated. For the remaining solution, as the static insecurity probability has been satisfied with the static security requirement of the system, it is only necessary to judge the "dominance" relation between the power loss and the purchase cost. The distribution of selected optimal solution set is shown in Fig 4.

Since the static insecurity probability has met the requirement and its proportion is small, the power loss and the power purchase cost are both the indexes to evaluate the economic efficiency of the system, the proportion is the same, so the coefficients of the selection model in (29) are a =0. 4, b=0. 2, c=0. 4, then the optimal solution is obtained. The output expectation of photovoltaic system is constant, DG1 represents 18-node distributed power output, and DG2 indicates 29-node distributed power output, which is added to the distribution network. The partial results of the optimal solution set are compared with the original solution. As shown in Table 2, the lower bound of the confidence interval of the voltage is the lowest value of the voltage obtained in the voltage interval with a probability of 2.5% - 97.5%.

It can be found from Table 2 that although the cost of purchasing electricity in the original network is low, the static insecurity probability is obviously not satisfied, and the power quality is poor. After network reconfiguration and optimization, the network not only reduces the network loss, but also increases the minimum value of the confidence interval of the voltage, which greatly reduces the static insecurity probability. On the basis of satisfying the static unsafe probability, the optimal solution is balanced by the mutual restriction between the power loss and the purchase cost. The optimal solution obtained by the developed selection strategy can reduce the power loss to a greater extent. The minimum voltage of the confidence interval is improved and the static unsafe probability is kept small.

The reconstruction solution in Table 2 is a reconfiguration scheme when the output of DG1 and DG2 is set to a definite value (200kW and 150kW, respectively). At this point, the optimal output of the algorithm depends on the output of DG1 and DG2, and only represents a solution in the set of comprehensive optimization. Compared with the final solution of the optimization, although the cost of purchasing power is higher, the network loss is reduced. It can improve the probability of static insecurity and so on.

Table 2. Results comparison of partial optimal solution set

scheme	outage line	energy from DG1/ kW	energy from DG2 /kW	network loss /kW	static insecurity probability	purchase cost/ $	Lower voltage confidence interval /p.u.
Original network	33 34 35 36 37	0	0	185.414	0.9985	183.9350	0.9364
optimal solution 1	7,34,11,32,37	100	250	99.532	5.0972e-07	203.2997	0.9681
optimal solution 2	33,14,10,31,28	250	150	98.047	2.5539e-08	206.5668	0.9728
optimal solution 3	6,14,9,17,37	250	200	93.053	1.5545e-09	209.6705	0.9760
optimal solution 4	6,34,11,32,37	50	150	114.156	4.0913e-06	193.9589	0.9659
optimal solution 5	7,34,10,31,37	450	250	73.652	3.8876e-09	225.4711	0.9811
final solution	7,14,9,31,37	300	200	85.258	4.5958e-08	212.6554	0.9750
reconstruction solution	7,14,10,32,37	200	150	100.217	1.3049e-05	203.3294	0.9641

6. Conclusion

In this paper, on the basis of considering the randomness of distributed power supply and load, the influence of DG output on distribution network is considered. Through system simulation, it is found that the integration of DG can effectively reduce network loss and greatly reduce the static insecurity probability. Pareto multi-objective optimization can be selected by multiple optimization agents at one time. At the same time, this method, which combines the randomness of distributed generation, DG output and contact switch combination, has potential application value to ensure the static security and economy of distribution system.

References

[1] Wang, C.S., Sun, C.B., Li, P. (2015) Review and Perspective on the Optimization of Active Distribution Network. Electric Power Construction, 36(1): 8-15.
[2] Huang, S., Wu, Q., Cheng, L., et al. (2016) Optimal reconfiguration-based dynamic tariff for congestion management and line loss reduction in distribution networks. IEEE Transactions on Smart Grid, 7(3): 1295-1303.
[3] Yin, H., Li, D.Q., Ge, J.F., et al. (2016) Distribution Network Reconfiguration with Distributed Generation Based on CPSO Algorithm. Electric Power Construction, 37(4): 104-109.
[4] Ji, X.Q., Liu, Q., Yu, Y.J., et al. (2018) Distribution network reconfiguration based on vector shift operation, IET Generation, Transmission & Distribution, 12(13):3339-3345
[5] Dong, S.N., Liu, N., Zhao, T.Y., et al. (2014) Reconfiguration of Multi-objective Distribution Network with Distributed Generation by Considering Stochastic Loads. Proceedings of the CSU-EPSA, 26(11).
[6] Cong, W.P., Tang, W., Zhang, L., et al. (2013) Chance-Constrained Programming Based Distribution Network Reconfiguration Considering Multi-States of Distributed Generation and Load. Power System Technology, 37(09): 2573-2579.
[7] Wang, X.P., Wei, Z.N., Sun, G.Q., et al. (2016) Multi-objective distribution network reconfiguration considering uncertainties of distributed generation and load. Electric Power Automation Equipment, 36(6): 116-121.
[8] Chu, Z., Dou, X.X., Yu, Q.Y. (2017) Multi scene distribution network reconfiguration considering the randomness of wind power. Power System Protection and Control, 45(1): 132-138.
[9] Li, C.J., Liu, Q.J. (2010) Distribution Network Reconfiguration Considering Randomness of Wind Power Generation. Automation of Electric Power Systems, 34(20): 34-39.
[10] Su, C.L., (2005) Probabilistic load-flow computation using point estimate method. IEEE Transactions on Power Systems, 20(4): 1843-1851.
[11] Wang, C.S., Deng, H.F., Xie, H.Y., et al. (2005) Probabilistic Power Flow Containing Distributed Generation in Distribution System. Automation of Electric Power Systems, 29(24): 39-44.
[12] Behdad, A., Hooshmand, R.A., Gholipour, E. (2014) Decreasing activity cost of a distribution system company by reconfiguration and power generation control of DGs based on shuffled frog leaping algorithm[J]. Electric Power Systems Research, 61(10): 48-55.
[13] Bian, D., Wei, Z.N., Huang, X.Q., et al. (2013) Integrated optimization of Distributed Network Reconfiguration Considering Distributed Generation. East China Electric Power, 41(1): 127-130.
[14] Liu, C., Huang, M.X. (2013) Distribution network reconfiguration with a variety of DGs. Power System Protection and Control, 41(06): 13-18.
[15] Mao, W.J., Li, H.W., Li, C. (2017) A distribution system reconfiguration method considering the optimal active power dispatching of DGs. Power System Protection and Control, 45(13): 57-63.
[16] Eldurssi, A.M., O'Connell, R.M. (2015) A fast non-dominated sorting guided genetic algorithm for multi-objective power distribution system reconfiguration problem[J]. IEEE Transactions on Power Systems, 30(2): 593-601.
[17] Andervazh, M.R., Olamaei, J., Haghifam, M.R. (2013) Adaptive multi-objective distribution network reconfiguration using multi-objective discrete particles swarm optimization algorithm and graph theory. IET Generation, Transmission and Distribution, 7 (12): 1367-1382.
[18] Lu, Y., Wu, J.Y., Hao, L.L. (2016) Multi-objective distribution network reconfiguration with distributed generations based on improved MOBPSO algorithm. Power System Protection and Control, 44(7): 62-68.
[19] Chen, P., Mao, Y., Tong, W., et al. (2016) Multi-objective Distribution Network Reconfiguration Based on Multi-objective Particle Swarm Optimization. Proceedings of the CSU-EPSA, 28(07): 68-72.

[20] Goswami, S.K., Basu, S.K. (1992) A new algorithm for the reconfiguration of distribution feeders for loss minimization. IEEE Transactions on Power Delivery, 7(3): 1484-1491.