Minimum reactive power loss optimization of power grid systems based on improved differential evolution algorithm

Yejun Xie¹, Zhendong Liu¹, Yongchao Pan¹, Fei Li¹, Taiming Jiao¹ and Xiaojuan Li³

¹State Grid Benxi Electric Power Supply Company, Liaoning, China; ³Northeastern University, Shenyang, China

³Email: 1392687126@qq.com

Abstract. With the expansion of power system scale, the operation of the power grid system has been greatly challenged. Reactive power optimization can make the power system operate safely and economically. In this paper, an improved differential evolutionary algorithm is applied to reactive power optimization of power system. We take the minimum power system loss as the objective function, the power balance condition as the equality constraint, the control variables and state variables as the inequality constraint conditions to establish the system model. Finally, IEEE30 bus and IEEE33 bus power system are selected to verify the effectiveness of the proposed algorithm.

1. Introduction
With the rapid growth of electricity demand in the areas of people livelihood, transportation and industry, the scale of power grids continues to expand and the structure becomes increasingly complex. As a result, this puts forward higher requirements for the safety, stability and economic operation of the power grid [1]. The main research goal of power system reactive power optimization is to reduce system network losses[2], ameliorate voltage quality and reduce operating risks through reasonable reactive power distribution[3]. Voltage stability is a problem that needs to be considered during the operation of the power system[4]. Voltage fluctuations and limit violations will bring great risks to operation of the power system[5].

Reactive power optimization of power system is a set of multi-objective mixed nonlinear problems [6]. For reactive power optimization, experts put forward many algorithms, which can be roughly divided into classical reactive power optimization algorithm and artificial intelligence optimization algorithm. Classical optimization algorithms mainly include linear programming[7], nonlinear programming [8], mixed integer programming[9] and dynamic programming[10]. Although the traditional optimization algorithm has certain applicability and advantages, it still has some disadvantages that cannot be ignored. Generally, limited by the size of the system, the dimension disaster will generally occur with the increase of the number of state variables.

Artificial intelligence algorithms such as genetic algorithm(GA), particle swarm optimization(PSO), simulated annealing algorithm(SA) and differential evolution algorithm (DE) are used for reactive power optimization. By using GA, the research on the reactive power optimization problem of DG entering the network can be successfully realized[11]. Although the genetic algorithm can accurately process variables and solve the local optimal problem, classical GA algorithm have a lot of shortcomings such as slow convergence speed in the later stage, poor local search ability, premature
phenomenon and long calculation time[12]. The author in [13] proposes a POS algorithm for the distribution network with distributed generators, the advantages of this algorithm are simple structure and few parameters need to be adjusted, correspondingly, its main disadvantage is that the local convergence performance is not high enough. Improved SA algorithm is applied for reactive power optimization. SA algorithm has good global convergence, but it takes a long time[14].

DE algorithm is more suitable for continuous domain problems with non-convex, uncertain and global optimization[15]. It has been widely used in reactive power optimization of power systems. But traditional differential evolution algorithms tend to mature prematurely and fall into local optimum. At present, there are three main improvement strategies for DE algorithms: changing control parameters, modifying algorithm structure and combining with other algorithms. In this paper, an adaptive mutation factor is designed for the traditional DE algorithm[16].

In this article, we first take the static reactive power operation optimization problem of the power system as the object, with the ultimate goal of minimizing active power loss, and establish a mathematical model of reactive power optimization according to the safety constraints during system operation. Then the basic principle and implementation steps of DE are introduced. According to the existing problems in the standard DE, the variation mode of the standard DE is improved to provide technical support for reactive power optimization of power grid system. Finally, the IEEE30 bus and IEEE33 bus power grid system are used for simulation verification. The results show that our improved DE algorithm has excellent convergence and stability, and can effectively solve the reactive power optimization problem.

2. System model

The reactive power optimization problem of power system is a very complex nonlinear programming problem, which involves the control of multiple variables and contains multiple constraint conditions. The reactive power compensation measures of the power system mainly include the adjust of the terminal voltage of the generator, the transformer tap and reactive power compensation devices. If the voltage variation in the power system is relatively large, it is uneconomical to only adjust the terminal voltage for reactive power optimization. Adjusting the transformer tap change can only meet the requirements of the working conditions at the node, and cannot actually reduce the loss of the system. These two methods have limitations in reactive power compensation and cannot achieve the expected reactive power optimization effect, so reactive power compensation equipment should be added.

2.1. Objective function

The objective function of reactive power optimization of power systems will change with different optimization purposes. In general, the target function can be chosen from the perspective of security and economy. In this paper, the required capacity of reactive power compensation, generator terminal voltage and transformer ratio are selected as the control variables. The state variable are the node voltage in the grid and reactive power output of the generator. Taking the minimum active power loss as the objective function. In order to deal with the state variables in the model, the node voltage over-bounds penalty and the generators reactive power out penalty are introduced. So the mathematical model of the final objective function is as follows:

$$\begin{align}
\min F &= P_{\text{loss}} + z_1 \sum_{i=1}^{n} \left( \frac{\Delta U_i}{U_{i\text{max}} - U_{i\text{min}}} \right)^2 + z_2 \sum_{i=1}^{n} \left( \frac{\Delta Q_{G_i}}{Q_{G_i\text{max}} - Q_{G_i\text{min}}} \right)^2
\end{align}$$

(1)

where $P_{\text{loss}}$ is the network loss, $z_1$ and $z_2$ respectively represent the penalty factors for node voltage and reactive power crossing the boundary, $\Delta U$ is the variation of node voltage, $U_{i\text{max}}$ and $U_{i\text{min}}$ are the upper and lower limits of node voltage, respectively, and $Q_{G_i}$ is the reactive power of generator.

$$\begin{align}
P_{\text{loss}} &= \sum_{i=1}^{n} U_i \sum_{j \in i} U_j \left( G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij} \right)
\end{align}$$

(2)
where, $G_{ij}$ is the conductance between node $i$ and $j$, $B_{ij}$ is the susceptance between node $i$ and $j$, and $\delta_{ij}$ is the voltage phase difference between node $i$ and node $j$.

The node voltage over-bounds penalty function and the generators reactive power out penalty function are denoted as follows:

$$\Delta U_i = \begin{cases} U_i - U_{i_{\text{max}}}, & U_i > U_{i_{\text{max}}} \\ 0, & U_{i_{\text{min}}} < U_i < U_{i_{\text{max}}} \\ U_{i_{\text{max}}} - U_i, & U_{i_{\text{max}}} < U_i \end{cases}$$ \quad (3)

$$\Delta Q_{Gi} = \begin{cases} Q_{Gi} - Q_{Gi_{\text{min}}}, & Q_{Gi} > Q_{Gi_{\text{min}}} \\ 0, & Q_{Gi_{\text{min}}} < Q_{Gi} < Q_{Gi_{\text{max}}} \\ Q_{Gi_{\text{max}}} - Q_{Gi}, & Q_{Gi_{\text{max}}} < Q_{Gi} \end{cases}$$ \quad (4)

2.2. Constraints

The equation constraint is the power flow equation of the power grid:

$$P_i = U_i \sum_{j=i} U_j (G_{ij} \cos \delta_{ij} + B_{ij} \sin \delta_{ij})$$

$$Q_i = U_i \sum_{j=i} U_j (G_{ij} \sin \delta_{ij} - B_{ij} \cos \delta_{ij})$$ \quad (5)

where $P_i$ is the injected reactive power of node $i$ and $Q_i$ is the injected reactive power of node $i$.

Power flow calculation variables of reactive power optimization include control variables and state variables. In addition to power constraints, control variables and state variables are also constrained. In essence, they are constraints on operating conditions and operating equipment:

$$V_{gi_{\text{min}}} \leq V_{gi} \leq V_{gi_{\text{max}}} \quad i \in N_g$$

$$T_{i_{\text{min}}} \leq T_i \leq T_{i_{\text{max}}} \quad i \in N_t$$

$$Q_{c_{\text{min}}} \leq Q_c \leq Q_{c_{\text{max}}} \quad i \in N_c$$

$$U_{i_{\text{min}}} \leq U_i \leq U_{i_{\text{max}}} \quad i \in N_b$$

$$Q_{gi_{\text{min}}} \leq Q_{gi} \leq Q_{gi_{\text{max}}} \quad i \in N_g$$ \quad (6)

where $V_g$, $T$, $Q_c$, $U$ and $Q_g$ are the generator terminal voltage, transformer ratio, capacity of reactive power compensation, node voltage and reactive power output of the generator, respectively; $N_g$, $N_t$, $N_c$ and $N_b$ are the number of adjustable generators, variable ratio adjustable transformers, reactive power compensation nodes and all nodes in the system.

3. Improved differential evolution algorithm

3.1. Differential evolution algorithm

The main idea of the DE algorithm is different from the traditional evolutionary algorithm. The traditional method uses a predetermined probability distribution function to obtain the vector perturbation. But the DE algorithm uses two different random vectors of the population to interfere with an existing vector, which is a self-organizing evolution. And all individual vectors in the population must perform interference operations. If the value of the objective function corresponding to the new vector is better than the value of the objective function corresponding to their predecessors, they will replace their predecessors into the next evolution. The three basic operations of differential evolution algorithm are mutation, crossover and selection[17]. The basic process is as follows:
(1) Mutation.
The mutation operation is to generate a new parameter vector by adding the weighted difference vector between two random members of the population to the third member. Each individual $x'_i$ of the population produces three different integers $r_1, r_2, r_3$, where $r_1, r_2, r_3$ and $i$ are not equal. The mutated individual can be obtained according to the following formula:

$$v^{t+1}_i = x'_i + F(x'_{r_1} - x'_{r_2})$$

(7)

where $F \in [0,2]$ is the variation factor, $i = 1,2,\ldots, N$, $t = 1,2,\ldots, T$, $N$ is the population size, and $T$ is the maximum number of iterations.

The search range for the variable is $[x_{\text{min}}, x_{\text{max}}]$, when the mutant individual exceeds the search space, then the mutated individual is as follows:

$$v^{t+1}_i = x_{\text{min}} + \text{rand}(1)(x_{\text{max}} - x_{\text{min}})$$

(8)

(2) Crossover.
In order to ensure the evolution of individuals in the population, through random selection, at least one of the experimental population $u^{t+1}_i$ is provided by the mutant population $v^{t+1}_i$. The other positions of $u^{t+1}_i$ can be obtained by the following selection strategy:

$$u^{t+1}_{ij} = \begin{cases} v^{t+1}_{ij} & \text{rand}(j) \leq CR \text{ or } j = \text{rand}(i) \\ x'_{ij} & \text{rand}(j) > CR \text{ or } j \neq \text{rand}(i) \end{cases}$$

(9)

where $CR \in [0,1]$ is the crossover probability factor, $\text{rand}(j)$ is to generate a random real number, and the variable $\text{rand}(i)$ produces the dimension index number.

(3) Selection.
Choose a greedy strategy, compare the fitness of the original individual $x'_i$ with that of the experimental individual $u^{t+1}_i$, and select individuals with better fitness values to keep in the next-generation population. The selection operation is as follows:

$$x^{t+1}_i = \begin{cases} u^{t+1}_i, f(u'_i) < f(x'_i) \\ x'_i, f(u'_i) \geq f(x'_i) \end{cases}$$

(10)

where $f$ is a fitness function, the selection operation is to take the better quality from $x'_i$ and $u^{t+1}_i$ as the $t+1$ generation, and increase the number of iterations by one.

3.2. Improved differential evolution algorithm
The parameters of the difference algorithm are population size $N$, variation factor $F$, cross factor $CR$, maximum iteration times $T$ and termination conditions. The rationality of parameter selection determines the performance of differential evolution algorithm. In the standard DE algorithm, $F$ is taken as a constant, however, if $F$ is too large, the convergence speed will slow down and the accuracy will decrease; if $F$ is too small, the diversity of population will be reduced, which will lead to premature. Therefore, in this paper, an adaptive variation parameter is designed, and the value of variation factor $F$ changes with the change of iteration times. The adaptive operator is calculated as follows:

$$\lambda = e^{\frac{T}{1+T^2}}$$

(11)

where $T$ is the maximum number of iterations, and $t$ is the current number of iterations.

The variation factor is expressed as:

$$F = F_0 * 2^t$$

(12)
$F_0$ is the initial variation factor.

The value of $F$ is relatively large in the initial stage of iteration, so the diversity of the population can be maintained. As the number of iterations increases, the value of $F$ gradually decreases, which can preserve good population information and avoid destroying the optimal solution. The process of differential evolution algorithm is shown in Figure 1.

4. Simulation analysis

This article selects the IEEE30-bus and IEEE33-bus power system for verification[18]. IEEE33-bus power grid system parameter settings are as follows: the range of node voltage is [1.0,1.06]. On-load transformer tap have 9 gears, their upper limit of the transformation ratio is set to 1.10, lower limit is set to 0.9, and adjustment step is set to 1.25%. A group of continuous reactive power compensation devices is set at 18th node, and their adjustment range is [-0.5Mvar,0.5Mvar]. The range of terminal voltage is [0.93,1.07]. The parameters of the differential evolution algorithm are set as: $N = 40$, $T = 60$, $CR = 0.9$, $F_0 = 0.5$, $z_1 = 40$, and $z_2 = 50$.

| Optimization algorithm | $P_{loss}$ (MW) | Number of iteration | Simulations time(s) |
|------------------------|-----------------|---------------------|---------------------|
| Power system 30-Bus    | 0.0104          | 32                  | 87                  |
| 33-Bus                | 0.0170          | 40                  | 106                 |
| GA                    | 0.1000          | 25                  | 24                  |
| The standard DE       | 0.0124          | 28                  | 66                  |
| The improved DE       | 0.0094          | 12                  | 22                  |
|                       | 0.0120          |                     | 50                  |
By analyzing and comparing the optimization results obtained by GA algorithm, the standard DE algorithm and the modified DE algorithm, the effectiveness of the modified DE algorithm is verified. The optimal value of the convergence results is shown in Table 1. For the IEEE33-bus power system, according to the power flow calculation, the initial network loss of the system is 0.0351. The network loss of the system obtained by the GA algorithm is 0.005MW higher than that of the improved differential evolution algorithm, and the optimal value can be obtained after 40 iterations. It should be that some local solutions have caused the convergence speed to be slow. As for the DE algorithm, the optimal solution was found only 28 times. This may be due to the fact that the fixed real number value of $F$ in the DE algorithm, it is difficult to ensure the balance between population diversity and convergence speed. It is obvious that the modified differential evolution algorithm has smaller network loss and only need 12 iterations to converge. And the simulation time required by the improved differential evolution algorithm is the least.

The initial network loss of the IEEE30 bus power system is 0.0119MW. The system network loss obtained by the improved DE algorithm is 0.0094MW. It also proves that the improved DE algorithm proposed in this paper can get a better optimal value, and requires less iterations and simulation time.

Figure 2 and Figure 3 is the comparison of node voltage before optimization and after optimization by improved DE algorithm. From the figure can see that the node voltage amplitude after optimization is higher, so the voltage quality of the system can be improved. Moreover, the amplitude change of node voltage after optimization is relatively small, which makes the system run more stably.

5. Conclusions
In this paper, an improved DE algorithm is proposed to solve the problem of reactive power optimization of distribution network. Compared with the standard DE algorithm and GA, an adaptive mutation operator is designed to make the convergence speed faster and the search space larger, and it can avoid the local extreme points to find the global optimal solution. Through the simulation test of the IEEE30-bus and IEEE33-bus power grid, the algorithm proposed in this paper can effectively reduce the loss of active power of the system and increase the node voltage, so that the system can operate more safely and reliably.

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