Reactive power optimization method of power distribution networks based on OCSFLA

Z R Wu¹ᵃ, X Z Dong¹ᵇ, L M Chen¹ᶜ, Z W Liu¹ᵈ and X L Xu²ᵉ∗
¹Electric Power Research Institute of China Southern Power Grid, Guangzhou, Guangdong, 510080, China
²Nanjing NARI-Relays Electric Co., Ltd, Nanjing, Jiangsu, 211102, China

ᵃwuzr@csg.cn,ᵇdongxz@csg.cn,ᶜchenlm2@csg.cn,ᵈliuzw2@csg.cn,
ᵉ1296685433@qq.com

Abstract: A power grid reactive power optimization algorithm was proposed in this paper to ensure that distribution network systems run efficiently, which is called the opposition-based chaos shuffled frog leaping algorithm (OCSFLA). A mathematical model of reactive power optimization was established based on the consideration of the constraint conditions. The initial swarm of the model was optimized based on the opposition strategy. The leading role changed gradually from the shuffled frog leaping algorithm to chaotic search in the iterative process by setting the appropriate chaotic variables. Thus, the global optimal solution was searched more quickly. In the simulation tests of the IEEE30 system, the results show that a better compensation effect was obtained when the reactive power compensation was performed in nodes 12 and 24. After completing the reactive power optimization based on the improved leapfrog algorithm, the active network loss value of the system was reduced by 13.85%. The algorithm was more efficient compared with other traditional optimization algorithms because OCSFLA can avoid falling into local optimization.

1. Introduction
Grid voltage control depends largely on reactive power optimization control. The reasonable distribution of reactive power has a direct impact on the safety and stability of the power system. The reactive power optimization problem is an integral part of the optimal power flow calculation in a power system.

The reactive power optimization in a power system is a mixed nonlinear programming problem with multivariable and multi-constrained characteristics. Traditional reactive power optimization algorithms such as the interior point method[1], the genetic method[2], the peak group algorithm[3], the particle swarm algorithm[4] and so on[5] were widely used. A power grid reactive power optimization algorithm was proposed in this paper to solve the problem of slow convergence in the original algorithm and to ensure that the distribution network system runs efficiently, which is called OCSFLA. OCSFLA combines the idea of shuffling complex evolution[6] and particle swarm optimization with the evolutionary properties of cultural genetic algorithms. It is a new type of post-heuristic optimization algorithm based on collective cooperative intelligence.

2. Reactive power optimization algorithm based on OCSFLA
The parameters of the reactive power constraints, according to the mathematical model of the reactive power optimization algorithm mentioned in the previous section, such as $V_{GK}$, $T_i$, $C_j$, $V_i$ and $Q_{G_j}$, are optimized based on OCSFLA. In this section, two improved strategies were proposed.

1) **Optimizing the initial swarm.** The random initialization of the frog swarm in the shuffled frog leaping algorithm (SFLA) ensures the even distribution of the swarm to a certain extent. However, it does not guarantee the quality of the individuals. The quality of the initial swarm affects the optimization efficiency and quality of the algorithm. To this end, an improved method based on an opposite strategy was presented in this paper.

2) **Variable updating strategy.** When the worst individual in the current subgroup is iteratively updated, an appropriate chaotic variable initial value is set so the algorithm is updated mainly with the update strategy of SFLA, and the chaos search plays an auxiliary role at the beginning. As the number of local depth search iterations increases, the algorithm gradually enters the predominant chaos search to help the algorithm jump out of the local extremum.

In this paper, the parameters of the reactive power constraints in the mathematical model of reactive power optimization algorithm are simplified such that, $(V_{GK}, T_i, C_j, V_i, Q_{G_j}) = (n_1, n_2, n_3, n_4, n_5)$.

The algorithm iterative optimization steps are as follows:

1) Set the algorithm parameters, such as the total number of frog individuals in the swarm $N$, the frog individual dimension $d$, the number of individuals in each sub-swarm $m$, the number of sub-swarms $n$, the number of local iterations in sub-swarm $g$, mixing iteration number $G$, initial value of chaos variable $i(0)$, chaos factor $\lambda$, coefficient $a$, constants $a_1$ and $a_2$.

2) Generate the initial swarm using the opposition strategy, and set the swarm size as $N$ ($N = 5$ in this algorithm).

   a) Randomly initialize the frog individuals $x_i$, $(x_i \in (a_i, b_i))$, and find their opposite individuals $\hat{x}_i$, $(\hat{x}_i = a_i + b_i - x_i)$, in order to form a frog swarm of size of $2N$.

   b) Calculate the fitness values of all the individuals in the swarm and sort them from good to bad according to their values.

   c) Select the individuals of $N$ frogs randomly to form the initial swarm with a certain probability. The principle of probability selection is that individuals with better fitness values are selected into the initial swarm easily. The probability selection formula is as follows:

$$p_i = \frac{(2N - i)}{2N}, \quad i = 1, 2, \cdots, 2N \quad (1)$$

3) Divide $N$ frog individuals into subgroups, and choose $Q$ frog individuals according to the triangle selection probability of $2(m+1-i)/[m(m+1)]$.

4) Repeat the following steps $g$ times for each subgroup.

   a) Update the optimal individual position $X_b$ and the global optimal individual position $X_w$ of the current iteration subgroup according to the fitness values. Then, determine the worst individual position $X_n$ of the subgroup in the current iteration.

   b) Update $X_n$.

$$newX_w(k) = X_w(k) \cdot \exp \{[1 - \exp(-\alpha \cdot y(k))] \cdot (\mu \cdot X_w(k)) \cdot (1 - X_n(k))] + e^{-2\omega \gamma(k)} \cdot \Omega(k)$$

where $\Omega(k)$ is the frog jump step update formula, $y(k)$ is the chaos variable.

$$\Omega(k) = a_1 \cdot \text{rand}(\alpha) \cdot (X_s(k) - X_n(k)) \quad (3)$$

$$y(k) = y(k - 1) \cdot (1 + \lambda)$$

In Eq. (3) and Eq. (4), $X_s(k)$ and $X_n(k)$ denote the best and the worst individual in the $k^{th}$ iteration of the current subgroup, respectively. $\text{rand}(\alpha)$ denotes a random number uniformly distributed in $[0,1]$. $a_1$ is a constant, and $k$ is the number of iterations. $\lambda$ is a chaos factor less than $1$, and $X_n(k)$ represents the $i^{th}$ dimension of the worst individual $X_n(k)$ of the current subgroup at the $k^{th}$ iteration. $\Omega(k)$ represents the $i^{th}$ dimension of $\Omega(k)$, and $\alpha$ and $\mu$ denote positive constants.
c) If the fitness value of $newX_w$ is better than $X_w$, replace $newX_w$ with $X_w$.  
d) Update $\Omega(k)$ based on Eq. (5) and $X_w$ based on Eq. (3) and Eq. (4).  
\[
\Omega(k) = a_2 \cdot \text{rand}(\cdot) \cdot \left( X_g(k) - X_w(k) \right)
\]  
where $X_g(k)$ denotes the globally optimal individual of the current sub-swarm at the $k^{th}$ iteration. $a_2$ is a constant.  
e) If there is still no improvement, generate $newX_w$ according to Eq. (6).  
\[
newX_w(k) = O_{\text{max}} + (O_{\text{max}} - O_{\text{min}}) \cdot \text{rand}(\cdot)
\]  
where $O_{\text{max}}$ and $O_{\text{min}}$ represent the maximum and minimum of the search range of the algorithm, respectively.  

5) After all the subgroups have completed the local depth search, the evolution process is finished if the global mixing iteration number $G$ is satisfied, and the global optimal value is output. Otherwise, remix all the frog individuals and return to step 3.  

The diagram of the chaos shuffled frog leaping algorithm is shown in Figure 1.

![Diagram of the chaos shuffled frog leaping algorithm](image)

**Figure 1.** Diagram of the chaos shuffled frog leaping algorithm

### 3. Example analysis of the reactive power optimization

#### 3.1 Example setting

The control variables used in this paper are as follows:

\[
X = (V_{GK}, T_i, C_j)
\]  
The state variables are as follows:

\[
U = (V_i, Q_{Gj})
\]  

![Structure diagram of IEEE 30 nodes system](image)

**Figure 2.** Diagram of the reactive power optimization algorithm

**Figure 3.** Structure diagram of IEEE 30 nodes system
where $V_{Gk}$ is the voltage amplitude of the adjustable generator node. $T_i$ denotes the tap position of adjustable transformer. $C_i$ is the group number of capacitor switching of reactive power compensation. $V_i$ is the voltage of the $PQ$ node. $Q_{Gj}$ is the reactive power of the generator output.

The coding of all control variables can be expressed as follow, according to the above analysis:

$$X = [C, T, V] = [C_1, C_2, \ldots, C_i, T_1, T_2, \ldots, T_j, V_{G1}, V_{G2}, \ldots, V_{Gk}]$$

where $i$, $j$ and $k$ represent the nodes number of reactive power compensation, the number of adjustable transformers and the nodes number of power generations, respectively.

The example initial parameter values in this paper are set as below.

Set the total number of frog individuals in the swarm as 200, the number of individuals in each sub-swarm as 20, the number of subgroups as 10, the number of local iterations in the sub-swarm as 10, the number of global mixing iterations as 30, and the initial value of the chaotic variable $y(0)$ as $10^7$. The chaos factor $\lambda$ is 0.5, and the coefficient $a$ is 100. $a_1 = a_2 = 3$. The diagram of the reactive power optimization algorithm is shown in Figure 2.

### 3.2 Example analysis of power grid optimization

The IEEE30 node system was tested as an application example in order to verify OCSFLA. The structure diagram of IEEE 30 nodes system is shown in Figure 3. Six generator nodes ($PV$ nodes such as 1, 2, 5, 8, 11 and 13) were distributed in the system. Other nodes were $PQ$ nodes. In addition, adjustable transformers (branches 6-9, 6-10, 4-12 and 27-28) were set in the IEEE30 node system. The initial transformers ratios are listed as follows: $T_{6.9} = 1.0155$, $T_{6.10} = 0.9629$, $T_{4.12} = 1.0129$, $T_{27.28} = 0.9581$.

The IEEE30 node system was simulated by the Monte Carlo method, and the six reactive compensation points were compensated. Statistical results of the reactive power compensation are shown in Table 3 after 10000 sampling iterations. It can be seen from Table 1 that the maximum compensation probability occurs at 12 nodes and 24 nodes. In other words, voltage safety problems are most likely to occur in these two nodes. Therefore, the best compensation effect will be achieved if reactive power compensation equipment is installed at these two nodes when considering the voltage safety level and economic cost.

### Table 1. Statistical results of reactive power compensation in IEEE30

| Node number | $U_{av}$ (p.u.) | $U_{max}$ (p.u.) | $U_{min}$ (p.u.) | Compensation times | Compensation probability |
|-------------|----------------|-----------------|-----------------|--------------------|-------------------------|
| 2           | 1.0338         | 1.05            | 1.0309          | 173                | 17.3%                   |
| 4           | 1.0258         | 1.0309          | 1.0058          | 201                | 20.1%                   |
| 12          | 1.0564         | 1.0913          | 1.0883          | 618                | 61.8%                   |
| 18          | 1.0319         | 1.0459          | 1.0307          | 128                | 12.8%                   |
| 20          | 1.0354         | 1.0404          | 1.0307          | 138                | 13.8%                   |
| 24          | 1.0292         | 1.0314          | 1.0298          | 359                | 35.9%                   |

A power flow program was written based on OCSFLA to optimize the IEEE30 system. Comparison of the node voltage phase angles after 100 iterative steps of reactive power optimization are shown in Figure 4 and Figure 5. In Figure 6, changes in node network loss before and after reactive power optimization are revealed. It can be seen from Figure 6 that the voltage at each load node increases and becomes more balanced after reactive power optimization. The most voltage increase of node 7 is up to 0.02816 p.u. The loss of the IEEE30 system after reactive power optimization is reduced from 7.0901 MW to 6.1079 MW, which is a 13.85% decrease.

Figure 7 and Figure 8 show the cumulative area distributions of active power $PL$, reactive power $QL$ and generator output residual power $PR$ before and after reactive power optimization, respectively. It can be seen from the figures that the reactive power loss $QL$ at nodes 12 and 24 is significantly reduced after reactive power optimization except for the active power loss. The total output power generator of the IEEE30 system decreased from 10.2474 MW to 8.9099 MW, a decline of 13.05%.
Leveraging the mutual complementarity will improve the overall optimization.

Therefore, reactive power optimization can balance the voltage of each node within the allowable range of voltage and reduce system losses through the traditional means of reactive voltage regulator, resulting in good economic benefits.

Due to the different performance results of the different algorithms in different stages of the evolutionary process, realizing the mutual complementarity will improve the overall optimization efficiency [7]. The traditional Particle Swarm Optimization (PSO), SFLA and OCSFLA were...
compared in this paper to validate the superiority of OCSFLA. These algorithms were used for simulations in the IEEE30 system. As shown in Figure 9, SFLA, which has not been improved, falls into a local optimum when it is updated several times with a minimum loss of 6.5549 MW. The convergence of PSO is very poor, having not completely converged after 100 iterations. When OCSFLA gets into the local optimum, weight variation occurs, helping the system to develop in a better direction. The minimum loss is 6.1079 MW. Thus, the OCSFLA proposed in this paper has some feasibility to improve the operational efficiency and reduce the network loss.

4. Conclusion
Reactive power optimization calculation is an important technique to improve power system analyses and operation. A power grid reactive power optimization algorithm was proposed in this paper to ensure that a distribution network system runs efficiently, which is called OCSFLA. It overcomes the shortcomings of the traditional SFLA in global search ability when solving the nonlinear optimization problem with complex constraints. The conclusions are as follows in the IEEE30 system optimization simulation:

Reactive compensation at nodes 12 and 24 will achieve better compensation in the IEEE30 system. The voltage of the IEEE 30 system increases and is more balanced after the reactive optimization of OCSFLA. The voltage increase of node 7 is up to 0.02816 p.u. The loss of the IEEE30 system after reactive power optimization is reduced from 7.0901 MW to 6.1079 MW, which is a 13.85% decrease. The load reactive power $Q_L$ at nodes 12 and 24 is significantly reduced after the reactive optimization of OCSFLA. The total output power of the system generator decreased from 10.2474 MW to 8.9099 MW, a decrease of 13.85%. OCSFLA is more efficient compared with the PSO algorithm and SFLA; OCSFLA can avoid falling into local optimization, and it is feasible for use to optimize the power grid. The reactive power optimization of a power system covers a wide range of technology, and a number of areas are worth further study, including expanding the search range of OCSFLA and choosing parameters to achieve the optimal search performance that greatly influence the performance and efficiency of the system for problems of different scales and different characteristics.

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