Improved SFLA Algorithm with Hybrid SA Strategy for Multi-Objective Reactive Power Planning Optimization of Distribution Network

Meilun Zhang¹, * , Jin Zhang², Maoda Xu² and Wenbo Hao¹

¹State Grid Heilongjiang Electric Power Company Limited, Electric Power Research Institute, Harbin, China
²State Grid Heilongjiang Electric Power Company Limited, Harbin, China

*Corresponding author: zhangml@hepri.hl.sgcc.com.cn

Abstract. Aiming at the characteristics of high target dimensionality, strong nonlinearity and complex constraints of distribution network reactive power optimization problems, this paper proposes an improved shuffled frog leaping algorithm based on SA strategy (ISFLASAS) to solve the problem. Firstly, the algorithm uses the global optimization capability of SFLA to detect the optimal solution, and improves the standard SFLA. Incorporating a reciprocal strategy during population initialization to improve the uniform distribution ability of the initial solution and speed up the search for the optimal solution. Secondly, using the local escape ability of the SA strategy, in the later stage of the SFLA calculation, the SA strategy is assisted to jump out of the local optimum with a certain probability to improve the global detection ability. Finally, the IEEE 33-node system is used to simulate and analyze the proposed model algorithm to verify the proposed control strategy.

Keywords: ISFLASAS algorithm, reactive power planning optimization, distribution network.

1. Introduction

With the rapid development of renewable clean energy, the random power fluctuation characteristics of wind power and other clean energy cannot be ignored [1]. The uncertainty of wind power brings many problems to reactive power optimization. At present, the algorithm used for reactive power optimization of distribution network is relatively single, and there are still problems of poor convergence and difficulty in finding the global optimal solution [2]. This paper considers the characteristics of different algorithms, tries to complement the advantages of different algorithms, and proposes an improved shuffled frog leaping algorithm based on SA strategy which could improve the global optimal solution detection ability. The IEEE 33-node system is used to simulate and analyze the proposed model algorithm, which verifies the effectiveness of the proposed control strategy.
2. Multi-Objective Model of Distribution Network Based on Wind Farm Access

2.1. Scenario analysis of reactive power planning in distribution network considering generators

Usually double fed induction generator (DFIG) is used for analysis in the model, and the active power output of the wind turbine is closely related to the wind speed, which satisfies the Weibull distribution.

\[
F(v) = 1 - \exp[-\left(\frac{v}{c}\right)^k]
\]  
(1)

The relationship between active power of DFIG output and wind speed is defined as

\[
P_w = \begin{cases} 
0 & v \leq v_{ci}, v \geq v_{co} \\
 k_1 v + k_2 & v_{ci} < v \leq v_r \\
 k_1 v & v_r < v < v_{co}
\end{cases}
\]  
(2)

Where: \( P_w \) is the rated active output, \( v_{ci}, v_r, v_{co} \) are cut-in wind speed, rated wind speed and cut-out wind speed.

According to different wind speeds, this article divides the active power output of DFIG into three situations for discussion. The probability formula is defined as

\[
p_1 = 1 - (F(v_{co}) - F(v_{ci})) \\
p_2 = F(v_r) - F(v_{ci}) \\
p_3 = F(v_{co}) - F(v_{ci})
\]  
(3)

Where: \( p_1 \) is the corresponding scenario probability of no output, \( p_2 \) is the corresponding scenario probability of insufficient rated output, \( p_3 \) is the corresponding scenario probability of rated power output.

The typical scenario output power of DFIG is defined as

\[
P_{sw1} = 0 \\
P_{sw2} = \int_0^{P_w} \frac{k_1 P_w}{k_1 + k_2} \cdot \exp(-\frac{(P_w - k_1 c)^k}{k_1 c}) dP_w \\
P_{sw3} = P_r
\]  
(4)

At this time, the nonlinear relationship between active and reactive power is defined as

\[
\left(\frac{P_w}{1-s}\right)^2 + Q_w^2 = (3U_s I_s)^2 \\
\left(\frac{P_w}{1-s}\right)^2 + (Q_w + \frac{3U_s^2}{X_s})^2 = (3\frac{X_w}{X_s} U_s I_s)^2
\]  
(5)

Where: \( U_s \) is stator side voltage, \( s \) is slip ratio, \( X_s \) and \( X_m \) are stator leakage reactance and excitation reactance, \( I_s \) and \( I_r \) are stator winding current and rotor-side converter current.
2.2. Multi-objective reactive power planning optimization model

2.2.1. Optimization model

\[
\begin{align*}
\text{max } f &= \lambda_1 F + \lambda_2 V \\
F &= \text{profit}(x) - \text{cost}(x) \\
V &= \frac{1}{\sum_{k=1}^{N} p_k L_k}
\end{align*}
\]

\[
P_{\text{loss}} = \sum_{(i,j) \in N_c} g_{ij}(U_i^2 + U_j^2 - 2U_i U_j \cos \theta_{ij})
\]

\[
F = \sum_{k=1}^{k-n_t} \frac{K_C T_{\text{max}}(P_{\text{loss,k}} - P'_{\text{loss,k}})}{K_C Q_C + C}
\]

Where: \(\text{cost}(x)\) is the cost of reactive power compensation equipment, \(\text{profit}(x)\) is the network loss revenue after optimization, \(F\) is the planned net income function, \(V\) is the voltage stability function, \(\lambda_1\) and \(\lambda_2\) are weight coefficients, \(p_k\) is the probability of scenario \(k\), \(Q_C\) is the total capacity of the capacitor bank, \(K_C\) is the price per unit capacitor bank capacity, \(P_{\text{loss,k}}\) and \(P'_{\text{loss,k}}\) are the network loss before and after reactive power compensation in scenario \(k\), \(K_e\) is the system electricity price, \(T_{\text{max}}\) is the maximum load utilization hours, \(L_k\) is the voltage stability index in scenario \(k\), \(U_i\) is the voltage at node \(i\), \(U_j\) is the voltage at node \(j\).

2.2.2. Power flow equation constraint

\[
f(P_{\text{sw}}, Q_{\text{sw}}, P_L, Q_L, Q_C) = 0
\]

Where: \(P_{\text{sw}}\) and \(Q_{\text{sw}}\) are active and reactive output, \(P_L\) and \(Q_L\) are active and reactive load, \(Q_C\) is the reactive power compensation value of node.

2.2.3. Variable constraint

\[
\begin{align*}
T_{i,\text{min}} &\leq T_i \leq T_{i,\text{max}} \\
Q_{C_i,\text{min}} &\leq Q_{C_i} \leq Q_{C_i,\text{max}} \\
Q_{W_i,\text{min}} &\leq Q_{W_i} \leq Q_{W_i,\text{max}}
\end{align*}
\]

Where: \(T_{i,\text{max}}\) and \(T_{i,\text{min}}\) are upper and lower limits of transformer ratio of node \(i\), \(Q_{C_i,\text{max}}\) and \(Q_{C_i,\text{min}}\) are upper and lower limits of compensation capacity of node \(i\), \(Q_{W_i,\text{max}}\) and \(Q_{W_i,\text{min}}\) are upper and lower limits of wind power reactive of node \(i\). The inequality constraint is defined as

\[
U_{i,\text{min}} \leq U_i \leq U_{i,\text{max}}
\]

Where: \(U_{i,\text{max}}\) and \(U_{i,\text{min}}\) are upper and lower limits of voltage of node \(i\).

3. An Improved Shuffled Frog Leaping Algorithm based on SA Strategy

SFLA is a global search algorithm, however, it is easy to make the search of the optimal solution fall into the local optimum [3]. Therefore, this paper adopts two strategies to strengthen the global search ability and the ability to jump out of the local optimal solution of the algorithm.
3.1. SFLA algorithm

SFLA is a brand-new global optimization algorithm proposed in recent years, and has been applied to global optimization problems in various scenarios [4]. The main idea of SFLA is to find the global optimal solution by constantly updating the position and step length of the leapfrog. The specific steps of the algorithm are as follows.

1) Initialize the frog population
   Set the frog individuals as \( x_i \), the number of the population is \( N \), and randomly initialize each frog individual. The initialized individual is within the bound variable range, \( x_i \in (a_i, b_i) \).

2) Update the position of frog individuals
   According to the fitness of frog individuals in the current population, find the position of optimal frog individuals \( X_{wt} \), the worst position of frog individuals \( X_{xt} \) in the subgroup, and the position of global optimal frog individual. The update strategy is as follows

\[
newX_w(k) = X_w(k) \cdot \exp\left\{\left(1 - \exp(-\alpha)\right) \cdot \left(\mu \cdot X_w(k) \cdot (1 - X_w(k))\right)\right\} + e^{-2\alpha \cdot y(k)} \cdot \Omega(k)
\]

\( \Omega(k) \) is the step size of frog individuals update, it is defined as

\[
\Omega(k) = a \cdot \text{rand}() \cdot \left(X_s(k) - X_w(k)\right)
\]

Where: \( X_w(k) \) and \( X_s(k) \) are the best and worst individuals in the kth iteration of the subgroup, \( \text{rand}() \) is an uniformly distributed random number between 0 and 1, \( a \) is a constant, \( k \) means the kth iteration, \( X_s(k) \) represents the i-th dimension of the worst individual \( X_w(k) \) of the current subgroup at the kth iteration, \( \Omega(k) \) is the i-th dimension of \( \Omega(k) \), \( \alpha \) and \( \mu \) are constants.

3) Select new individuals
   If the fitness of \( newX_w \) is better than \( X_w \), replace it with \( newX_w \). Update the individual using the formula

\[
newX_w(k) = O_{\text{max}} + (O_{\text{max}} - O_{\text{min}}) \cdot \text{rand}()
\]

Where: \( O_{\text{max}} \) and \( O_{\text{min}} \) are the maximum and minimum values in the range of feasible solutions.

3.2. Population initialization based on reciprocity strategy

Although the population initialization in SFLA adopts a random method, which makes the initial solution have a certain probability of uniform distribution to a certain extent, there is no guarantee that the initialized solution can be evenly distributed in the solution space to the greatest extent. If the initial solution cannot be well and uniformly distributed in the solution space, it will greatly reduce the efficiency of the global optimal solution search [5,6]. Therefore, this paper proposes an initial solution generation method based on a reciprocity strategy. The specific methods are as follows.

1) Use the reciprocity strategy to generate the initial population, and the number of individuals in the population is \( N \) (\( N=6 \)).

2) Initialize the individuals of \( N \) populations, \( x_i \in (a_i, b_i) \), and find the reciprocal individuals for each individual, the expression is

\[
\bar{x}_i = a_i + b_i - x_i
\]

3) At this time, the total individuals in the population are \( 2N \), and the fitness results of the individuals are used to rank all individuals in ascending order.
4) Finally, select \( N \) individuals from \( 2N \) individuals with a certain probability as the initial population, and the expression of probability selection is shown as

\[
p_i = \frac{2N - i}{2N}
\]

(16)

3.3. Improved algorithm based on SA strategy

SFLA often makes the algorithm fall into the local extreme point in the optimization process, and it is difficult to jump out of the local optimum. Therefore, when the algorithm falls into the local extreme point, it needs to provide a kind of motivation to make it jump out of the local search. The SA algorithm can simulate the annealing operation in the industry, accept the poorly adapted solution with a certain probability in the evolution process, and jump out of the local optimum. This method can better increase the diversity of the population. In the later stage of the evolution of SFLA, considering that the evolution will tend to be stable, the algorithm is very easy to fall into the local optimum. Therefore, the introduction of SA in the later stage of the SFLA evolution will improve the ability to jump out of the local optimum to a certain extent of the algorithm, and will not destroy the local optimization ability in the early stage of the algorithm. The flowchart is shown as

![Flowchart](image)

Figure 1. The diagram of ISFLASAS.

4. Example Analysis

The example uses the IEEE 33-node system, two DFIGs are selected for wind power, the rated power is 1.5MW, the reference voltage is 12.66kV, the reference power is 10MW, and Table 1 shows the parameter settings.

| Gear adjustment      | \( K_e/(\text{Yuan/kW-h}) \) | \( K_c/(\text{Yuan/kvar}) \) | \( T_{\text{max}}/\text{h} \) |
|----------------------|-------------------------------|-------------------------------|-------------------------------|
| 1±4×1.25%            | 0.45                          | 50                            | 5000                          |

Table 1. Parameter settings.

The operation and maintenance cost of the compensation equipment is calculated at 5% of its cost, and the compensation equipment is grouped (single group capacity is 100kvar). In order to facilitate the solution, we transformed the multi-objective problem into a single-objective problem, and used the analytic hierarchy process to process the weight coefficients between different objectives, and finally obtained the final weight coefficients through the normalization method: \( \lambda_1 = 0.22 \), \( \lambda_2 = 0.78 \). Table 2 shows the probability values of wind farms in three different scenarios.
In order to further analyze the impact of wind power regulation capability on system voltage, cost and revenue under the different scenarios, three different scenarios are selected for simulation. The simulation results are shown in Table 3.

### Table 3. Analysis of optimization results in different scenarios.

| Scenario | P/Yuan | C/Yuan | L  | UP      |
|----------|--------|--------|----|---------|
| NDFIG-1  | 128360 | 72870  | 0.0788 | 0.9426 |
| DFIG-1   | 132970 | 67850  | 0.0797 | 0.9443 |
| NDFIG-2  | 141470 | 72880  | 0.0794 | 1.0084 |
| DFIG-2   | 149830 | 67760  | 0.0796 | 0.9986 |
| NDFIG-3  | 116530 | 72950  | 0.0758 | 1.0784 |
| DFIG-3   | 129310 | 67870  | 0.0774 | 1.0544 |

Where: C is the cost function, P is the profit function, NDFIG is the scenario that the reactive power adjustment capability of DFIG is not considered, DFIG is the scenario that the reactive power adjustment capability of DFIG is considered, L is the voltage stability value, UP is the grid-connected voltage of wind power.

It can be seen from the results in Table 4 that after adding DFIG reactive power adjustment in different scenarios, the system voltage, voltage stability, and revenue have all been significantly improved.

Through the comparative analysis of three different algorithms, the results are shown in Figure 2. ISFLA, the improved SFLA algorithm with reciprocal strategy is added, convergence speed is better than SFLA. It shows that the introduction of reciprocal strategy makes the distribution of initial solutions more uniform, can quickly find a better solution. Secondly, after introducing the SA strategy on the basis of ISFLA, the ISFLASAS algorithm achieved the best optimized solution. It can be seen from the figure that due to the introduction of the SA strategy; the algorithm has a large change in the integrated target value in the later stage of evolution. This also shows that the SA algorithm can jump out of the local optimum in the later stage of evolution, which increases the probability of the algorithm obtaining the global optimum solution in the evolution process.

![Figure 2](image-url). Comparison of convergence characteristics in algorithms.
5. Conclusions
The introduction of uncertain power source wind power makes the multi-objective distribution network reactive power planning and optimization problem more complicated. This paper proposes an ISFLASAS algorithm to solve the multi-objective distribution network reactive power planning problem including wind power. Firstly, the scenario method is used to turn the randomness of wind power into a deterministic scenario probability problem. Secondly, the standard SFLA is improved by adding reciprocal operators and SA strategies to improve the ability to find the global optimal solution of algorithm. The simulation results of the example show that the algorithm proposed in this paper has obvious optimization effect and convergence speed. Compared with SFLA and ISFLA, it has a significant effect improvement, and it has a significant effect on solving the reactive power optimization problem of the distribution network.

Acknowledgments
This work was financially supported by State Grid Heilongjiang Electric Power Company Limited.

References
[1] DING T, LI C, YANG Y, et al. Second-order cone programming relaxation-based optimal power flow with hybrid VSC-HVDC transmission and active distribution networks [J]. IET Generation, Transmission & Distribution, 2017, 11(15): 3665-3674.
[2] SHAO Y, ZHAO J, FANG J, et al. Multi-objective reactive power optimization of distribution network with wind turbines based on correlated scenario at operation level [J]. Power System Technology, 2018, 42(8): 2528-2535.
[3] WANG S, CHEN S, XIE S. Security constrained coordinated economic dispatch of energy storage systems and converter stations for AC/DC distribution networks [J]. Automation of Electric Power Systems, 2017, 41(11): 85-91.
[4] Li X, Gao J. Improved particle swarm optimization algorithm for multi-objective reactive power optimization of distribution network [J]. Electric Power Automation Equipment, 2019, 39(1): 106-111.
[5] ZHANG G, ZHAO L, BIAN X, et al. Framework planning of active distribution network considering supply and demand interaction and DC operation characteristics [J]. Smart Power, 2018, 46(6): 87-93.
[6] Cai B, Huang S. Multi-objective reactive power optimization based on the multi-objective particle swarm optimization algorithm [J]. Power System Protection and Control, 2017, 45(15): 77-84.