State Estimation of Distribution Network Based on KH-QPSO Optimization Algorithm

Fu Xiao1, 2, 3, a, Pei liang1, 2, 3, b

1Institute of Oceanographic Instrumentation, Qilu University of Technology (Shandong Academy of Sciences)
2Shandong Provincial Key Laboratory of Ocean Environmental Monitoring Technology
3National Engineering and Technological Research Center of Marine Monitoring Equipment, Qingdao China

Corresponding author e-mail: a.dawn_fu@163.com, bPeiliang2002@163.com

Abstract. Accurate state estimation is the basis to ensure the normal distribution network operation. To solve the nonlinear optimization problem of distribution state estimation, a state estimation model supply was established by taking the node load value and the output value of distributed power supply as state variables. This paper proposes that Krill herd-quantum behaved particle swarm optimization (KH-QPSO) can avoid premature convergence, and the minimum value is rapidly obtained. In particular, KH and QPSO allow all individuals to obtain truly global optimal solutions without introducing additional operators into the basic KH and QPSO algorithms. An IEEE-33 system is used as a simulation example, which has obvious advantages over other distribution network state estimation models, and the estimation results can provide valuable information for distribution network enterprises and managers.

1. Introduction

The user-oriented characteristics of the distribution network determine the safety, economy and reliability of the system, which is directly related to whether it can meet users’ requirements. Therefore, state estimation as a means of system operation monitoring becomes more and more important. Distribution state estimation [1-5] (DSE) is use the limited information distribution measurement, computer technology and mathematical methods, estimate the high precision, complete, reliable real-time state method. It usually with adding weight least square method, the solution can be regarded as the objective function of optimization problem. However, the devices in the distribution network all have nonlinear characteristics, which makes the DSE objective function and related formulas nondifferentiable and discrete, and the traditional numerical method is difficult to be applied in practice [6-10].

To solve the nonlinear problem, the intelligent algorithm is introduced into DSE. Tong linghua et al. [11] proposed a method of combining genetic algorithm and ant colony algorithm which estimate the state value by genetic algorithm, and to modify the state value by ant colony algorithm. The model can effectively integrate the state distribution network estimation results based on genetic algorithm and ant colony algorithm, accurately describe the state change characteristics, and improve the accuracy. Zuo siran et al. [12] proposed an improved state estimation method based on artificial colony algorithm, in
which the amplitude and phase of node voltage can be estimated effectively and the convergence rate is also doubled compared with the existing artificial colony algorithm, and the average absolute error is significantly reduced compared with the weighted least square method. Nikman et al. [13] also proposed a local optimization algorithm for state estimation based on Nelder-Mead. When the state variables are small, it has good convergence and fast convergence speed. The application scope of single algorithm is relatively narrow. In the face of the complex grid structure and data type in practice, it is impossible to effectively obtain the results. Literature [14-18] adopts the hybrid algorithm combining local optimization algorithm and global optimization algorithm in the optimization of power system parameters, drawing on each other's strengths and making up for each other's weaknesses.

This paper presents a new hybrid strategy KH-QPSO combined with KH and QPSO method. In KH-QPSO, the entire population is divided into two equal subpopulations. Both KH and QPSO execute their own operators to update individuals in their subpopulations separately. After that, the two subpopulations merged to form a complete population. This combination can make full use of the information of the optimal individual, keep the randomness of the solution and avoid premature convergence. Again, it is used to update personal information for the next generation to use. In this paper, the KH–QPSO algorithm is applied to the IEEE 33-node distribution system and compared with other algorithms to prove the effectiveness and superiority of the KH–QPSO algorithm.

2. Distribution network State estimation model

The power system state estimation can be mathematically regarded as an integer nonlinear optimization problem with equality and inequality constraints. The objective function is the sum of the difference between the quantity measurement and the calculated value. Different from the traditional state estimation, the state estimation model is established by taking the active power of the node load value and the output value of the distributed generation as the state variables.

2.1. Objective Function

\[
\min f(X) = \sum_{i=1}^{m} \omega_i (z_i - h_i(X))^2
\]

\[X = [P_G, P_{Load}]_{(m \times 1)}\]

\[P_G = [P_{G,1}, P_{G,2}, \ldots, P_{G,N_g}]\]

\[n = N_g + N_L\]

where \(X\) is the state variable, which is composed of the load active power and distributed generation (DG) active power output; \(z_i\) is the measurement variable; \(\omega_i\) is the weight factor of the \(i\) th measurement variable; \(h_i\) is the equation of state of the \(i\) th measurement variable; \(m\) is the number of measured variables; \(N_g\) is the quantity of DG output variables; \(N_L\) is the number of load variables; \(P_{G,i}\) is the active power output of the \(i\) th DG; \(P_{Load,i}\) is the active power of the \(i\) th load, \(i = 1,2,\ldots,N_L\); \(n\) is the number of state variables.

2.2. Inequality Constraints

The \(j\) th DG active power constraint equation is:
where \( P_{G_{-j, \text{min}}} \) and \( P_{G_{-j, \text{max}}} \) are the maximum and minimum values of the \( j \) th DG active power output, respectively.

The distributed line power constraint is:

\[ |P_{\text{Line}_{-ij}}| \leq P_{\text{Line}_{-ij, \text{max}}} \]  

where \( |P_{\text{Line}_{-ij}}| \) and \( P_{\text{Line}_{-ij, \text{max}}} \) are the absolute value of the line power flow and the maximum transmission power between node I and node j, respectively.

The bus voltage amplitude constraint is:

\[ V_{i, \text{min}} \leq V_{i} \leq V_{i, \text{max}} \quad i = 1, 2, ..., N_{b} \]  

where \( V_{i, \text{min}} \) and \( V_{i, \text{max}} \) are the minimum and maximum voltage amplitudes of node \( i \) th; \( N_{b} \) is the number of buses in the system.

The active power constraint of the load is:

\[ P_{\text{Load}_{-l, \text{min}}} \leq P_{\text{Load}_{-l}} \leq P_{\text{Load}_{-l, \text{max}}} \quad l = 1, 2, ..., N_{L} \]  

where \( P_{\text{Load}_{-l, \text{min}}} \) and \( P_{\text{Load}_{-l, \text{max}}} \) is the minimum and maximum of node \( l \) load, respectively.

The branch current constraint is:

\[ 0 \leq I_{ij} \leq I_{ij, \text{max}} \]  

where \( I_{ij} \) and \( I_{ij, \text{max}} \) are the current and maximum current of the branch between node I and node j, respectively.

3. **Hybrid algorithm based on KH-QPSO search**

3.1. **Krill herd (KH) algorithm**

KH [19] is a new type can help solve the problem of complex optimization strategy. The KH method repeats the implementation of these three actions and takes the direction of finding the best solution:

1. movement influenced by other krill;
2. foraging action;
3. physical diffusion.

KH is expressed by Lagrange model:

\[
\frac{dX_{i}}{dt} = N_{i} + F_{i} + D_{i} \tag{10}
\]

where \( N_{i} \) is the motion induced by other krill, \( F_{i} \) is the foraging motion, and \( D_{i} \) is the physical diffusion. \( i = 1, 2, ..., NP \) and \( NP \) is population size.

For the first motion, its motion direction \( \alpha_{i} \) is mainly determined by the local effect of target effect and repulsion effect. For \( i \) th krill, it can be expressed as:
where \( N_{i}^{\text{max}} \) is the maximum induced speed, \( \omega_{b} \) is the inertia weight, and \( N_{i}^{\text{old}} \) is the last motion.

The second action is mainly determined by two factors: the position of the food and its previous experience. For the \( i \) th krill, it can be defined as:

\[
F_{i} = V_{i}^{\text{best}} + \omega_{i} F_{i}^{\text{old}}
\]

(12)

\[
\beta_{i} = \beta_{i}^\text{food} + \beta_{i}^\text{best}
\]

(13)

where \( V_{i} \) is the foraging speed, \( \omega_{i} \) is the inertia weight for the second motion, and \( F_{i}^{\text{old}} \) is the last motion.

The third motion is essentially a random process and it has two parts: the maximum diffusion velocity and the random direction vector and it can be expressed as:

\[
D_{i} = D_{i}^{\text{max}} \delta
\]

(14)

where \( D_{i}^{\text{max}} \) is the maximum diffusion speed and \( \delta \) is the random vector.

Based on the three above-mentioned movements, the position of a krill from \( t \) to \( t + \Delta t \) is given as:

\[
X_{i}(t + \Delta t) = X_{i}(t) + \Delta t \frac{dX_{i}}{dt}
\]

(15)

In standard KH, foraging behavior and physical dispersal during movement influenced by other krill continue for a certain number of generations or until termination conditions are met.

3.2. The QPSO algorithm

Inspired by the group behavior of some species, PSO [20] is a classical optimization strategy. PSO realizes a population-based search to optimize all possible solutions of a function, called particles, composed of a population, which are randomly initialized according to their own and the optimal experience of the whole, by updating the speed and position:

\[
V_{i}^{t+1} = V_{i}^{t} + \alpha r (X_{i}^{t} - X_{\text{best}}^{t}) + \beta r (g^{*} - X_{i}^{t})
\]

(16)

\[
X_{i}^{t+1} = X_{i}^{t} + V_{i}^{t+1} \Delta t
\]

(17)

where \( X_{i} \) and \( V_{i} \) are the position and velocity of particle \( i \) respectively, \( g^{*} \) and \( X_{\text{best}}^{t} \) are the optimal position of particle \( i \) and the whole particles, respectively, \( \alpha \) is an inertia parameter that can control the dynamics of flight, and \( \alpha \) and \( \beta \) are often called the learning parameters. The time interval \( \Delta t \) is equal unit.

Through trajectory analysis, it is proved that if each particle can find its local optimal solution \( p_{i} = (p_{i1}, p_{i2}, \ldots, p_{in}) \), PSO may find the final optimal solution:
\[ p_i(k) = \varphi P_i(k) + (1 - \varphi) P_g(k) \] (18)

where \( \varphi \) is a random number in \((0, 1)\). Here \( p_i \) is a stochastic attractor of particle \( i \) that are related to \( P_i \) and \( P_g \). It can be seen that the velocity is no use in QPSO. The position in QPSO is a single property for an individual particle, which is updated as:

\[ X_i(k+1) = p_i(k) + \alpha |C(k) - X_i(k)| \ln(\frac{1}{u}) \] (19)

where \( \alpha \) is the contraction–expansion coefficient and \( u \) is a random number in \((0, 1)\). Mean best position \( C(k) \) can be computed by the mean value of \( P_i \):

\[ C(k) = (C_1(k), C_2(k), ..., C_n(k)) \]

\[ = \left( \frac{1}{M} \sum_{i=1}^{M} P_{i1}(k), \frac{1}{M} \sum_{i=1}^{M} P_{i2}(k), ..., \frac{1}{M} \sum_{i=1}^{M} P_{in}(k) \right) \] (20)

The QPSO update allows particles to move throughout the search space each time, whereas PSO allows particles to appear in a limited space.

3.3. KH–QPSO

When krill are drawn to the local optimal solution, in the KH standard algorithm, krill doesn't have the ability to jump out local minimum in order to overcome these shortcomings, the KH algorithm and QPSO algorithm hybrid, formed a new hybrid KH-QPSO algorithm under normal circumstances, the hybrid heuristic algorithm try to merge two or more heuristic method that can give full play to the original algorithm of useful features in the proposed hybrid KH-QPSO, in order to improve its search ability, introduces the ideas of QPSO in KH.

The detailed description of the KH-QPSO for solving the optimization problem is as follows:

Step 1: initializing population, including NP individuals, is a randomly generated set of KH and other parameters used in QPSO.

Step 2: assess according to the all individual position in the population.

Step 3: the entire population is randomly divided into two subpopulations (subpopulation 1 and subpopulation 1) on average. This partition is prepared for the next KH and QPSO processes.

Step 4: KH process for NP/2 individuals in subpopulation 1, their positions are updated by three actions in the KH method.

Step 5: corresponding to subpopulation 1, for the NP/2 individuals in subpopulation 2, the individual position is updated by the rules in the QPSO method.

Step 6: combine a population of all individuals (subpopulation 1 and subpopulation 2). When produced in this manner, the two subpopulations merge into a population.

Step 7: find the best solution calculate the fitness of all individuals and find the best solution for this generation

Step 8: if the best solution is the required solution, then KH-QPSO stops, otherwise the description of returning to Step 2 KH-QPSO can also be given in Fig. 1
4. Simulation results
In order to verify the performance of the KH-QPSO algorithm mentioned in this paper, the IEEE 33-node distribution system was used for simulation on MATLAB. The wiring of IEEE 33-node distribution system is shown in Fig. 2.

| Node | Average active power output /kw | Active deviation/% | Power factor |
|------|---------------------------------|-------------------|-------------|
| 4    | 140                             | 10                | 1           |
| 8    | 200                             | 15                | 1           |
| 12   | 250                             | 15                | 1           |
| 15   | 150                             | 10                | 1           |
| 28   | 100                             | 20                | 1           |
Table 2. Values of node loads.

| Node | Active power output /kw | Active deviation/% | Power factor |
|------|-------------------------|--------------------|-------------|
| 4    | 120                     | 10                 | 1           |
| 8    | 200                     | 15                 | 0.97        |
| 12   | 60                      | 15                 | 0.85        |
| 15   | 150                     | 10                 | 0.65        |
| 28   | 100                     | 20                 | 0.62        |

In order to investigate the estimated error processing energy of KH–QPSO hybrid algorithm, the individual maximum relative error maximum individual relative error (MIRE) and maximum individual absolute error (MIAE) maximum individual absolute error were defined:

\[
MIRE = \max\left(\frac{X_k - X_A}{X_A} \times 100\right)\% \tag{21}
\]

\[
MIAE = \max(X_k - X_A) \tag{22}
\]

Tab. 3 and Tab. 4 respectively show the estimated value of DG output power of four algorithms, namely KH–QPSO algorithm, PSO algorithm and genetic algorithm Genetic algorithm (GA), and the comparison of MIRE and MIAE of node load estimated value.

Table 3. Comparison of the estimation of DG output power between MIRE and MIAE among four algorithms.

| Algorithm | MIRE | Node position | MIAE | Node position |
|-----------|------|---------------|------|---------------|
| KH–QPSO   | 0.82 | 4             | 1.11 | 8             |
| PSO       | 3.01 | 4             | 5.15 | 4             |
| GA        | 3.92 | 4             | 5.88 | 22            |

Table 4. Comparison of the estimation of load value between MIRE and MIAE among four algorithms.

| Algorithm | MIRE | Node position | MIAE | Node position |
|-----------|------|---------------|------|---------------|
| KH–QPSO   | 1.29 | 4             | 2.11 | 4             |
| PSO       | 3.56 | 4             | 4.32 | 15            |
| GA        | 4.65 | 4             | 6.01 | 4             |

According to the comprehensive Tab. 3 and Tab. 4, compared with PSO algorithm and GA algorithm, KH–QPSO algorithm has the smallest MIRE and MIAE, the smallest estimation error and the best performance.

5. Conclusion

Aiming at the problem of power distribution state estimation, this paper proposes a mixed KH-QPSO algorithm, which randomly generated after an individual species population division. After population division, KH and QPSO processes were applied to produce new individuals. Assess individual fitness to find the best solution for this generation. All individuals in KH-QPSO exchange information indirectly through the division and combination of population. The KH-QPSO algorithm is applied to the state distribution estimation. The example shows that the algorithm overcomes the nonlinear characteristics of the distributed generation in the distribution network, which verifies the effectiveness and superiority.
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