Acta Technica 62 (2017), No. 7A, 213–224

Distribution automation cooperative detection technology in service system of specific occasion

Ming Zeng[1], Qiongxiong Zhong[1], Xu Han[1], Ran Li[1]

Abstract. To improve the accuracy of state estimation for distribution network, a kind of state estimation method for distribution network combined with simulated annealing and AFSA is proposed. First, the objective function of state estimation for distribution network is built, followed by the optimization solution for objective function with AFSA and introduction of mutation operator to maintain the diversity of artificial fish-swarm state, as well as simulated annealing operation for the optimal solution calculated by AFSA, and in the end, the performance test shall be conducted via simulation experiment, of which the results show that relative to AFSA and other comparison algorithms, this method in Paper not only accelerates the convergence speed of the algorithm to solve, but also improves the accuracy of the state estimation of the distribution network.

Key words. Distribution network, State estimation, Simulated annealing, AFSA, Mutation operator.

1. Introduction

With the rapid economic development and increasing electricity capacity, the users require higher stability and power supply quality for distribution network. As correctly mastering the operation state of network system is the basis to decide and plan the network, therefore, the state estimation for distribution network becomes an important task in researching network.

The state estimation for distribution network refers to the accurate and complete estimation for state of the distribution system according to the network history information and distribution measurement information. Aiming at state estimation of

[1]School of Economics and Management, North China Electric Power University, Changping Beijing 102206, China

network, many scholars have studied it deeply and proposed some estimation algorithms [2]. The state estimation for the most classical distribution network is deemed as the optimization of objective function, solved by weighted least square method [3], a kind of linear modeling method. However, the accurate mathematical model is difficult to be built by weighted least square method, caused by nonlinearity of objective function as the distributed power supply has obvious nonlinear characteristics and the output characteristic can be expressed as a nonlinear equation with constant impedance, constant current and constant load, with low estimation accuracy, which cannot meet the actual requirements [4]. Thereafter, the sate estimation methods for nonlinear distribution network [5-7] such as GA, PSO and neural network are provided. The neural network is capable of modeling the relation between input and output of any unknown system, a kind of adaptive modeling tools, with defects of undetermined structure and overfitting; AG, with advantages of simple programming and fast convergence speed, designs different genetic operators for different network system at each time, and the genetic operators is designed by experience without unified theoretical guidance, resulting in the instable results of state estimation for distribution network. PSO, with advantages of few parameter setting and strong parallel search capability, is easy to be caught in local optimal. Therefore, it is necessary to find a new state estimation method for distribution network to improve the accuracy and reliability of state estimation for distribution network [8].

Artificial fish swarm algorithm (AFSA), is a kind of new-type swarm intelligence optimization algorithm, with strong global optimization ability [9]. Based on optimization of simulated annealing algorithm, a kind of state estimation method for distribution network combined with simulated annealing (SA) and AFSA is provided, and its performance is tested via specific simulation experiment.

2. State estimation for distribution network

2.1. System measurement

(1) Real-time measurement

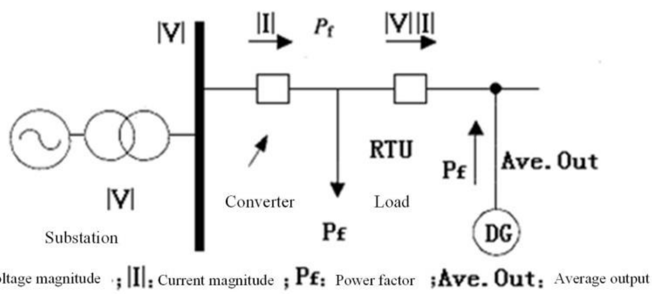

Fig. 1. Measurement data configuration

The real-time measurement of distribution network state is to collect the data in real time via measurement device installed on the feeder. In the distribution network system, the injection power of root node, branch power, voltage of root node, load power, voltage of node and amplitude of branch current can be used for real-time measurement data. The Paper researches on the measurement voltage and current amplitude of satellite substation and RCU and adopts the following assumptions. The state for distribution network can be estimated by measurement shown in Fig. 1.

(2) Pseudo measurement

Pseudo measurement is mainly sourced from historical data for each user load. As the real-time measurement redundancy of the whole system is very small, a large number of pseudo measurement information can determine the effectiveness of the distribution state estimation results [9].

2.2. Basic algorithm

The objective function of the state estimation for distribution network is:

$$\min J(x) = \sum_{i=1}^{m} w_i (z_i - h_i(x))^2 \,. \tag{1}$$

Where x represents state variable, z_i means the size of measured i, w_i refers to the weight factor of measured variable i and h_i represents the state equation of measured variable i.

Each of state variable shall be in line with the following constraint condition:

$$x_{j\,\min} \le x_j \le x_{j\,\max} \,. \tag{2}$$

Where, $x_{j\,\min}$ and $x_{j\,\max}$ represent the minimum and maximum value of the state variable, respectively.

The state estimation for distribution network is to minimize the error between the measured value and calculated value in the formula (1), actually, a process to optimize the objective function in formula (1).

As a higher estimation accuracy is difficult to be obtained for the traditional algorithm on account of nonlinear characteristic of the objective function caused by the addition of distributed power, therefore, the Paper combines SA and AFSA to complement each other to overcome their defects. The distribution network state of SA-AFSA shall be estimated by two steps:

(1) Global search. Regarding the objective function of state estimation for distribution network as the fitness function of AFSA to quickly search its optimal value and introduce the mutation operator in the process of searching optimal value, change the state of some artificial fish and maintain the diversity of artificial fish populations to speed up convergence.

(2) Local search. After the optimal value of state estimation for distribution network is obtained via Step (1), the local optimization of "fine search" shall be carried out for the optimal artificial fish individual with SA.

3. SA-FASA

3.1. Basic AFSA

AFSA, a kind of swarm intelligence algorithm, featuring fast rate of convergence, strong global optimization ability, and low requirement to initial value and objective function, is to realize the global optimization and obtain the optimal solution [10] of the problem by imitating the behaviors such as foraging, swarm and following of fishes in Mother Nature.

(1) Foraging behavior. Assuming that the current state of artificial fish is X_i, randomly select a state X_j within its field of view, if $Y_i < Y_j$, take a step in this direction, referred to formula (3) for details; if the conditions are not met, then move one step at random, referred to formula (4) for details.

$$X_i^{t+1} = X_i^t + \frac{X_j - X_i^t}{\|X_j - X_i^t\|} \cdot Step \cdot Rand() \,. \tag{3}$$

$$X_i^{t+1} = X_i^t + Step \cdot Rand() \,. \tag{4}$$

Where, Y_i represents the food concentration in X_i, *Step* refers to the shift step length, and the *Rand*() represents the random number within scope of (0,1).

(2) Swarm behavior. The current artificial fish X_i explores the number of partners *nf* within its field of view and the central position state *Xc*. If $Yc/nf > \delta Yi$, it shows that more food is gathered in the partner center, not too crowd, and then move a step toward partner center, referred to formula (5) for details; otherwise, carry out foraging behavior.

$$X_i^{t+1} = X_i^t + \frac{X_c - X_i^t}{\|X_c - X_i^t\|} \cdot Step \cdot Rand() \,. \tag{5}$$

(3) Following behavior. The current artificial fish X_i explores the partner X_j with the maximum food concentration Y_j within its field of view. If $Y_j/nf > \delta Y_i$, take a step toward to the artificial fish X_i with the maximum food concentration; otherwise, carry out foraging behavior.

(4) Random behavior. The artificial fish randomly selects a state in the field of view and then moves in that direction, which defaults to foraging behavior.

(5) Bulletin board is used for recording the optimal state of artificial fish. After each artificial fish is finished with each act, its state in that moment will be compared with the state recorded in the bulletin board, and if the optimal state is shown in the bulletin board, then update it. After the algorithm is completed, the element value in the bulletin board is the optimal value and its corresponding state is the optimal solution.

3.2. Introduction of mutation operator

In the later period of AFSA, the mutation operator shall be introduced in the AFSA on account of slow rate of convergence, and the mutation shall be operated for the artificial fish to maintain the diversity of artificial fish state and improve the search speed of the algorithm [11]. If there is no or little change in the bulletin board in multiple evolutionary processes, the mutation shall be operated for the artificial fish rather than bulletin board in artificial fish-swarm. The mutation operation is designed as follows:

(1) Generate a random number $u \in (0,1)$ in each dimension, and set the threshold u_m of variation probability for each artificial fish.

(2) If $u \leq u_m$, the dimension of the artificial fish is randomly initialized; otherwise, remain unchanged.

(3) Calculate the fitness function of newly formed artificial fish individuals and compare with that on the bulletin board, if superior, then update the bulletin board.

3.3. Introduction of annealing

As AFSA with mutation operator is difficult to obtain global optimal solution for its poor local search ability, contrary to SA, therefore, the optimal solution obtained from AFSA with mutation operator shall be remained and abandoned in accordance with Metropolis principles [12]. In the iteration of SA, if the fitness function of the optimal solution is increased, it will be accepted, otherwise, to determine whether or not to be accepted via formula (6).

$$Q(T_{i+1}) = \begin{cases} 1 & f_{i+1} < f_i \\ \min\left[1, exf(\frac{f_{i+1}-f_i}{f_{i+1}})\right] > random(0,1) & otherwise \end{cases} \tag{6}$$

where, f_i represents the fitness value of the optimal solution in the ith iteration, $Q(T_{i+1})$ eans the acceptance probability under temperature T_{i+1}, and T_{i+1} can be expressed as:

$$T_{i+1} = \alpha \times T_i\,. \tag{7}$$

Where, α refers to the coefficient of temperature cooling.

As AFSA with mutation operator is affected by random step length, range of vision and random behavior, resulting in the low accuracy of the optimal solution obtained in initializing the weight vector of the blind equalizer, therefore, after AFSA with mutation operator obtains the optimal solution, SA with strong local search ability shall be cascaded to obtain the global optimal solution with "high accuracy".

3.4. Workflow of SA-AFSA

The workflow of SA-AFSA after introducing the mutation operator and SA algorithm with strong local search capability is shown in Fig. 2.

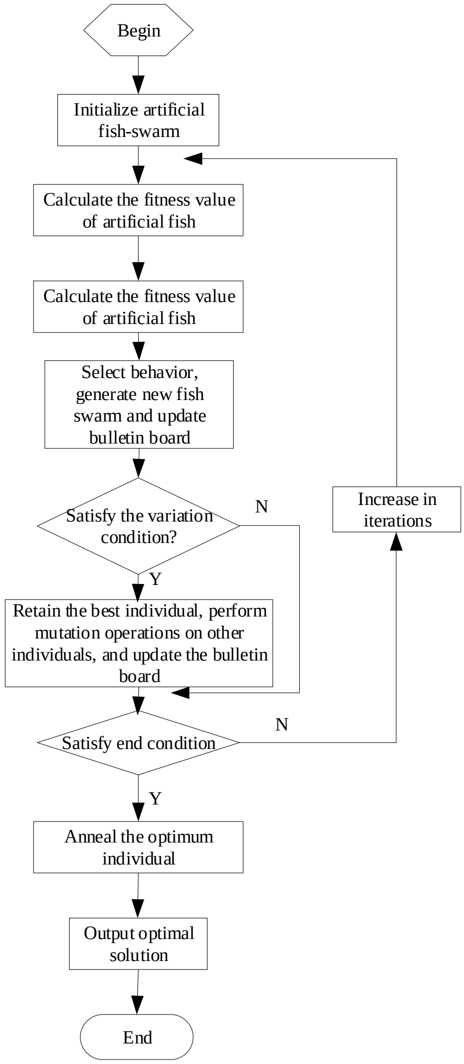

Fig. 2. Workflow of SA-AFSA

4. Steps for state estimation for distribution network of SA-AFSA

Step1: Read the output value and load value of the distribution network, and use them as the state variables to form admittance matrix.

Step2: Initialize artificial fish parameters, including location, maximum move length *Step*, radius of view *Visaul*, population size n, congestion factor δ and maximum iterations $max_$iterate, etc.

Step3: According to measurement matrix and weight coefficient matrix, construct objective function in formula (1), and the state estimation of distribution network is transformed into nonlinear and constrained optimization problem.

Step4: Randomly generate n artificial fish within the feasible domain and set initial iteration times passed_ *iterate* =0.

Step5: Calculate the fitness value $f(k)$, $k = 1, 2, \ldots, n$ of artificial fish according to formula (8), and record the state of artificial fish with the maximum fitness value in the bulletin board.

$$f(k) = \sum_{i=1}^{m} w_i(z_i - h_i(k))^2 \,. \tag{8}$$

Step6: Evaluate the results of foraging, following and swarm behavior of an artificial fish, and if the state of the artificial fish is superior to current state after performing some acts, then the artificial fish advances in this direction.

Step7: Judge the variation condition, if condition is satisfied, keep the optimal artificial fish and perform mutation operation for other artificial fish, calculate the fitness value of newly formed artificial fish individual and compare it with that on the bulletin board, if superior, then update the bulletin board.

Step8: Update bulletin board and record the best state of artificial fish.

Step9: Judge the end conditions, if not satisfied, then perform *passed_ iterate* = *passed_* iterate +1, and continue Step5; otherwise, output the artificial fish state in the bulletin board.

Step10: The output of the state estimation for the distribution network is obtained by annealing the optimal solution of the artificial fish.

5. Simulation experiment

5.1. Distribution network model

In order to verify the estimation performance of SA-AFSA distribution network, the distribution network model with distributed power is used for simulation test, referred to Fig. 3 for details. The distribution network system consists of 2 static voltage regulating transformers and 1 distributed generators with constant output function, resulting in nonlinear trend of distribution network state.

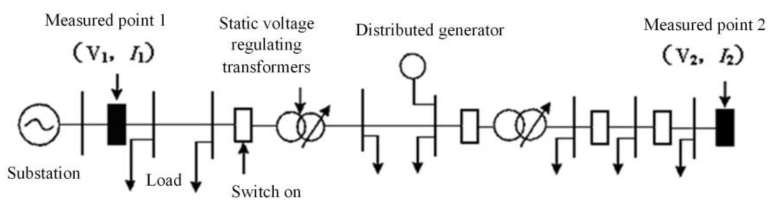

Fig. 3. Distribution network state

5.2. Contrast algorithm and parameter setting

In order to make SA-AFSA's estimation more convincing, the genetic algorithm (GA), particle swarm optimization (PSO) and the basic mermaid swarm algorithm (AFSA) are used as contrast algorithms to compare the experiments. The GA is set up with crossover probability of 0.77 and mutation probability of 0.15; PSO parameters are set with the weight factor for C1=C2=2, the maximum and minimum weights for 0.9 and 0.3 respectively; SA-AFSA parameters are set with view for 0.12 and step length for 0.03, congestion factor for 0.525, initial temperature for $T = 40$ and cooling parameters for $\alpha = 0.85$, similar to that of AFSA; The population size of all algorithms is 20, and the maximum number of iterations is 200. Relative mean error (*MAE)* and root-mean-square error ($RMSE$)), as criteria for performance evaluation of algorithms, are defined as follows:

$$MAPE = \frac{1}{N}\sum_{t=1}^{N}\frac{|\hat{y}_t - y_t|}{y_t} \times 100\,. \tag{9}$$

$$RMSE = \frac{1}{N}\sqrt{\sum_{t=1}^{N}(\hat{y}_t - y_t)^2}\,. \tag{10}$$

Where, y_t refers to actual value, $\hat{y}_t$ represents the estimated value of algorithm and N refers to the number of measured point.

5.3. Results and analysis

(1) Performance comparison of artificial fish swarm algorithm before and after improvement

The objective function change curve of SA-AFSA and AFSA for distribution network problem solving is shown in Figure 4, showing that relative to AFSA, the convergence speed of SA-AFSA is obviously accelerated, better overcoming the local extreme problem of AFSA, both of which the performance is shown in Table 1. As we can see from Table 1, the estimated value of SA-AFSA is quite close to the measured value, and the deviation between the estimated value of AFSA and the measured value is large, with low estimation accuracy. The comparison results reflect that SA-AFSA improves the local search ability of the algorithm by introducing mutation operator and simulated annealing operation, and can find better state estimation for distribution network.

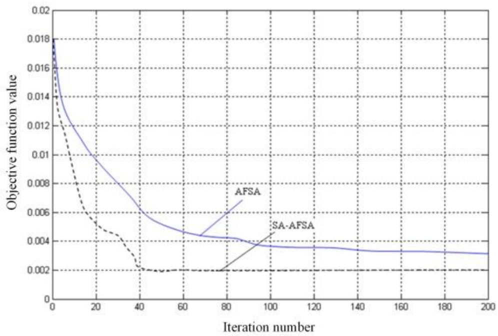

Fig. 4. Comparison of convergence curves of SA-AFSA and AFSA

Table 1. Estimation accuracy comparison of SA-AFSA and AFSA

Measured point	Measured value	AFSA	SA-AFSA
1	150	150.82	150.30
2	6500	6534	6506
3	0	0	0
MAPE		0.36%	0.38%
RMSE		19.64	18.48

(2) Performance comparison of SA-AFSA and other algorithms

SA-AFSA and GA, PSO distribution network state estimation results are shown in Table 2, showing that SA-AFSA has the highest estimation accuracy, with most reliable results in all algorithms. The comparison results reflect that by introducing mutation operators, SA-AFSA has a larger global search range and improves the local search ability accordingly by introducing the annealing operations, with relatively fast search accuracy and speed, able to well deal with the state estimation of distribution network with nonlinear characteristics.

Table 2. Performance comparison of SA-AFSA and other algorithms

Measured point	Measured value	SA-AFSA	GA	PSO
1	150	150.30	150.78	150.95
2	6500	6506	6537	6532
3	0	0	0	0
MAPE		0.10%	0.36%	0.38%
RMSE		3.47	21.37	18.48

6. Conclusion

For the nonlinear variation characteristics of state estimation for distribution network, based on the analysis on state estimation principle of distribution network and ASFA, a kind of state estimation method for distribution network with SA-

AFSA is proposed, which solves the problems by AFSA and solves the defects of AFSA by introducing the mutation operator and simulated annealing. The simulation results show that relative to AFSA and other algorithms, this algorithm, an effective method for the state estimation of distribution network, not only accelerates the convergence speed, but also improves the accuracy of the state estimation for distribution network.

Acknowledgement

This work was supported by the Fundamental Research Funds for the Central Universities (Grantno.2016XS84); Science and Technology Project of State Grid (Research on the Operation Mode of Distributed Generation and Micro Grid for Electric Power Reform).

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Received May 7, 2017