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# An Electric Power System Fault Diagnosis Method Based on PSO and FCM

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**Keywords:** Fault Diagnosis, PSO, FCM, Electric Power System.

**Abstract.** For effectively analyzing electric power faults, exactly identifying failure type, and highly providing disposal measure, depending on PSO (particle swarm optimization) algorithm, a PSO-FCM (particle swarm optimization-fuzzy c-means) algorithm was constructed by the FCM improvement of fuzzy clustering to avoid get in local optimal state. On this basis, an electric power system fault diagnosis method was established by means of PSO and FCM. Finally, this method was validated by an example. Consequently, this method can intellectively diagnose and identify the fault of electric power system, and can provide a new approach to stably operation in electric power system.

## Introduction

Power transformers, as expensive items, need to be carefully monitored throughout their operation. Fault diagnosis of it is important for safety of the device and relevant power system. Study in the past decades has proved that the dissolved gases in oil are related closely to internal faults. Dissolved gas analysis (DGA) has gained worldwide acceptance as a diagnostic method for the detection of transformer's internal faults[1,2]. Fault gases are produced by degradation of the transformer oil and solid insulating materials, such as paper, pressboard and transformer board, which are all made of cellulose.

At present, these electric power fault diagnosis methods mainly include logic operation method, expert system, enumeration method, neural network, optimal technique method, and so on. The optimal technique method highly includes inherit algorithm, chaos algorithm, simulation anneal method, PSO, and so on. There is a difficulty in gaining the integrality of sample set in complex system, so that neural network method also can not abroad apply in electric power system. Consequently, more and more researchers have focus on optimal technique method.

There were some researches of electric power system fault diagnosis aspects, such as L.V.Ganyun, et al. [3], S. Fei, et al. [4], J. Sun, et al. [5], Y. Zhang, et al. [6], R. Ghimire, et al. [7], W. An, et al. [8], Z. Jun, et al. [9], G. Rigatos, et al. [10], and so on. However, few studies have been devoted to electric power system fault diagnosis by means of fuzzy c-means. Furthermore, few researches have investigated the problem by PSO-FCM and fuzzy clustering.

For effectively analyzing electric power faults, exactly identifying failure type, and highly providing disposal measure, depending on PSO algorithm, a PSO-FCM is constructed by the FCM improvement of fuzzy clustering to avoid get in local optimal state. On this basis, an electric power system fault diagnosis method was established by means of PSO and FCM. Finally, this method was validated by an example. Consequently, this method can intellectively diagnose and identify the fault of electric power system, and provide a new support for stably operation in electric power system.

## Fuzzy Clustering Diagnosis Method Based on PSO-FCM

**Particle Swarm Optimization.** The particle swarm optimization (PSO) algorithm is a recent addition to the list of global search methods. This derivative-free method is particularly suited to continuous variable problems and has received increasing attention in the optimization community. It has been successfully applied to large-scale problems in several engineering disciplines and, being a population-based approach, is readily parallelizable. It has few algorithm parameters, and generic settings for these parameters work well on most problems [11-13].

Supposing there is N dimension object search space, and a community including m particles, the *i*th particle's position in *d* N dimension object search space is as following:

$$X_i = (x_{i1}, ... x_{id})^T \quad i = 1, 2, ... m \qquad V_i = (v_{i1}, ... v_{id})^T \quad i = 1, 2, ... m \tag{1}$$

The fitness function can be described as:

$$fitness_i = f(X_i) \tag{2}$$

The quantity of *d*th dimension weight will be changed by some formulas, and the formulas are as following:

$$\begin{aligned} &V_{id}^{t+1} = w^t V_{id}^t + c_1 r_1 (pbest_{id}^t - X_{id}^t) + c_2 r_2 (gbest_{id}^t - X_{id}^t) \qquad X_{id}^{t+1} = X_{id}^t + V_{id}^t \\ &w^t = w_{\max} - (w_{\max} - w_{\min}) t / t_{\max} \qquad e_{id}^t = pbest_{id}^t - X_{id}^t, E_{id}^t = gbest_{id}^t - X_{id}^t \\ &V_{id}^{t+1} = w^t V_{id}^t + c_1 r_1 e_{id}^t \qquad X_{id}^{t+1} = X_{id}^t + V_{id}^{t+1} \end{aligned} \tag{3}$$

Where, $V_{id}^t$ is the quantity of *d*th dimension weight of *i*th particle's flight velocity vector in the *t*th iterative process; $X_{id}^t$ is quantity of *d*th dimension weight of ith particle's position vector in the *t*th iterative process; $pbest_{id}^t$ is the quantity of *d*th dimension weight optimal position of *i*th particle's position vector in the *t*th iterative process; $gbest_{id}^t$ is the optimal position in solving space in the *t*th iterative process; $r_1, r_2$ are random number in [0,1]; $c_1, c_2$ are the acceleration coefficient; $w^t$ is the inertia weight; $c_1 r_1 (pbest_{id}^t - X_{id}^t)$ is the eognitiveterm, and is the beforetime velocity of particle. Eognitiveterm depends on its cognitive experience. $c_2 r_2 (gbest_{id}^t - X_{id}^t)$ is the socialterm, and it represents the information communion and cooperation degree among particles.

**Fuzzy c-Means.** Fuzzy c-means is a big class algorithm in fuzzy clustering algorithm [14-15]. The function of fuzzy c-means is defined as:

$$J(Z, U, V) = \sum_{i=1}^{c} \sum_{k=1}^{N} (u_{ik})^m \left\| z_k - v_i \right\|_A^2 \tag{4}$$

Where, $U = (u_{ik}) \in M_{fc}$ is fuzzy partition matrix, and $V = (v_1, v_2, ... v_c)$ $v_i \in \mathbb{R}$ is clustering centre vector of family needing ascertain.

$$D_{ikA}^2 = \left\| z_k - v_i \right\|_A^2 = (z_k - v_i)^T A (z_k - v_i) \tag{5}$$

This norm of $(z_k - v_i)$ vector comes form the reasoning of matrix *A*, and describes the distance between $z_k$ and $v_i$ . $m \in [1, \infty)$ is fuzzy index, and it decides the fuzzy degree index of clustering family. The value of cost function measures the whole covariance between $z_k$ and $v_i$ .The constricts are used in *J* by means of Lagrange Multiplicator method, and the differential coefficient is equal to 0 when $\bar{J}$ is relative to U， V， λ .

**Fuzzy Clustering Diagnosis Based on PSO-FCM.** Fuzzy clustering diagnosis method based on PSO-FCM use true coding type, the position of particle represents the centre of family in fuzzy clustering. The structure of true number is shown in Fig. 1. Where *c* is the number of family, and *n* is the dimension of data.

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $v_{11}$ | ··· | $v_{1i}$ | ··· | $v_{1n}$ | ··· | $v_{j1}$ | ··· | $v_{ji}$ | ··· | $v_{jn}$ | ··· | $v_{c1}$ | ··· | $v_{ci}$ | ··· | $v_{cn}$ |

Fig. 1. The structure of true number in fuzzy clustering diagnosis based on PSO-FCM

This algorithm easily can be got in local optimizing state. At the same time, PSO has an advantage in whole search ability, but calculation work is greatness and velocity is slow. Considering the advantages and disadvantages of two algorithms, a PSO-FCM fuzzy clustering arithmetic is proposed by the integration of two algorithms. In this new arithmetic, when one iterance in PSO, there are *m* iterance of family centre represented by each particle, so that each particle can fully deal with local optimizing. PSO comprises inertia weight $\omega$. The topology structure of PSO is Gbest structure of static topology structure.

The flow chart of fuzzy clustering diagnosis based on PSO-FCM is as following:

*Step 1*: The initialization parameters are set. The initialization parameters include maximum iterance number *IterCount*，*PsoCount*，*FcmCount*are, group scale $P_{size}$, inertia weight $\omega$, and accelerating coefficient $\phi_1$ *and* $\phi_2$.

*Step 2*: The particle of swarm are randomly initialized.

*Step 3*: The iterance counter $Gen_1$ is set as 0.

*Step 4*: The iterance counter $Gen_2$ and $Gen_3$ is set as 0.

*Step 5:* PSO algorithm is iterated.

*Step 5.1*: The position and velocity of particle swarm are updated.

*Step 5.2*: $Gen_2 = Gen_3+1$. If there is $Gen_2 < PsoCount$, the flow switch to Step 5.1.

*Step 6:* FCM algorithm is iterated. The particle is operated as following:

*Step 6.1:* The current position of particle is set as the centre of family.

*Step 6.2*: Each centre of family is renew calculated.

*Step 6.3*: $Gen_3 = Gen_3+1$. If there is $Gen_3 < FcmCount$, the flow switch to Step 6.2.

*Step 7:* $Gen_1 = Gen_1 +1$. If there is $Gen_1 < IterCount$, the flow switch to Step 4. Otherwise the flow is end.

**Electric Power System Fault Diagnosis Based on PSO and FCM**

As the automation development of electric power system, many faults can be diagnosed by electric power system fault diagnosis method based on PSO and FCM. By means of these faults analysis and operation, the resource of faults can be identified. Consequently, this method's application provides a new approach for solve the fault diagnosis problem in electric power system. Electric power system fault diagnosis procedure based on PSO and FCM is described in Fig. 2.

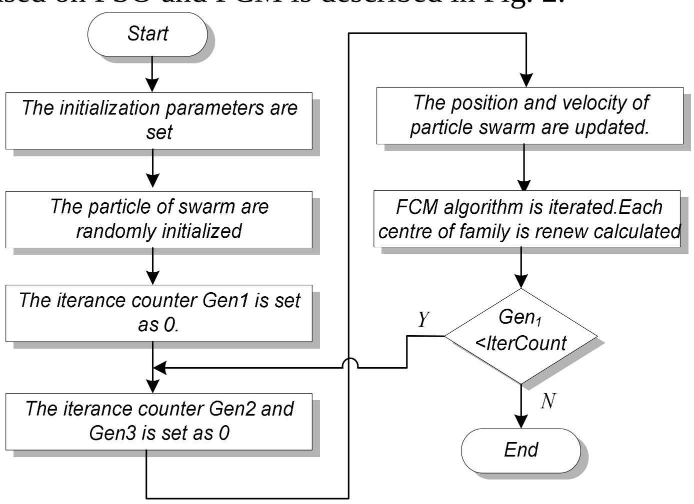


Fig. 2. Electric power system fault diagnosis procedure based on PSO and FCM

**Simulation**

An electric power system includes 28 components, 40 switchs, and 84 safeguards. The 28 components' ordinal number is $S_1 \sim S_{28}$, 40 switchs' ordinal number is $C_1 \sim C_{40}$, and 84 safeguards' ordinal number is $r_1 \sim r_{84}$. Warning signal includes *Blm*, *LZRs*, *L4Rs*, switchs *QF4, QFS, QF7, QFg, QF12*, and *QF27* tripping. This electric power system structure can be shown in Figure 3.

This electric power system structure's fault is diagnosed by PSO and FCM. There are 4 dimensions, 20 populations and maximum iterance number is 30 in PSO and FCM. This is *u*=30 for ensuring *f(s)* is plus. This fault diagnosis is the searching process of maximum *S* in *f(s)*. By MATLAB software, the simulation result is described in Fig. 4.

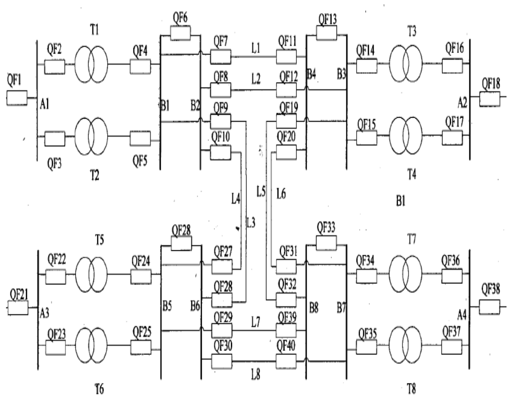

Fig. 3. An electric power system structure

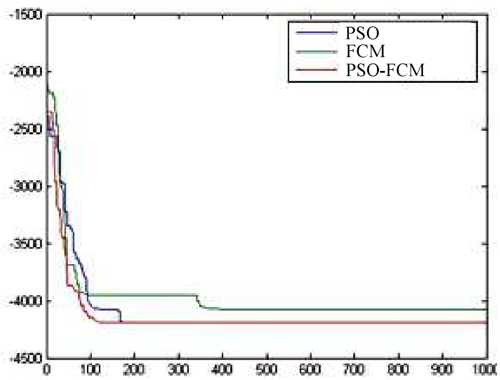


Fig.4. The simulation result of electric power system fault diagnosis

According to Fig. 4, comparing to traditional optimizing algorithm, PSO and FCM algorithm can gain optimal solving when in first iterance number. The mean of population is go stable state before eighth iterance number. Finally, *gbest*=1000, and the maximum value of *f(s)* is 26. The fifty-first component appear fault, in other words, the mother *B1* appear abnormity. Therefore, this electric power system's faults can be effectively and exactly diagnosed to assure stable operation.

## Conclusions

Depending on PSO algorithm, a PSO-FCM was constructed in this paper by the FCM improvement of fuzzy clustering to avoid get in local optimal state. On this basis, an electric power system fault diagnosis method was established by means of PSO and FCM. Finally, this method was validated by an example. Consequently, this method can intellectively diagnose and identify the fault of electric power system, and can provide a new support for effectively and exactly analyzing electric power faults, and can identify failure equipment, failure type, failure position in electric power system.

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