Aggregate Static Power Load Modeling in Coalmine

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Abstract：-In order to overcome the defects of the traditional static load modeling in coalmine, a new modeling method is proposed in this paper. First, a new clustering method based on improved PSO algorithm is presented to classify the load data in order to reduce the number of load model before modeling. Second, RBF neural network based on improved PSO algorithm is put forward to establish aggregate load model. Finally, verified by an example, the method in this paper can greatly improve the accuracy of the model compared with traditional static load model.

Key-Words:-aggregate static load model; particle swarm clustering algorithm; subtractive clustering algorithm; K-means clustering algorithm; radial basis neural network; power grid in coalmine

1 Introduction

Underground power grid in coal mine is a special branch of the power system. Its operating environment is severe because it is impacted by geological conditions, gas and other factors. In the past, underground aggregate static load model is built by using statistical synthesis method based on traditional static model. In practice, there are many problems by using this approach during modeling. First, since the number of underground electrical equipment are more, their types are complex and management is scattered, these may cause statistical inconvenience and incomplete. Second, electrical equipment may often be increased or decreased with the actual condition of production. This will cause that real-time of statistic becomes bad. Third, it makes aggregate load static characteristic curve complex because the new applications of power electronic devices are used and the nonlinear loads are added. Fourth, the static characteristic coefficients of typical load often come from the relevant literature. This will cause that the results are inconsistent with the actual situation. In summary, these factors often cause that the results of underground load modeling results are not accurate.

In recent years, with the pace of information construction continues to accelerate in the coal mine, power monitoring systems are more and more introduced into production of mine. Nonlinear load modeling methods such as neural networks and support vector machines are used to build aggregate static load model. This can make real-time modeling and accurate modeling possible.

A new clustering method based on improved PSO algorithm is presented in this paper. This clustering method is used to classify the load data in order to reduce the number of load model before modeling. Then, RBF neural network based on improved PSO algorithm is proposed to establish aggregate load model. Data of a

monitoring point in a mining area is taken as the object of study in this paper. Verified by the results of simulation, compared with traditional static load model, the method proposed in this paper can greatly improve the accuracy of the model.

2 Clustering Method Based Improved PSO Algorithm

2.1 Subtractive Clustering Algorithm

Subtractive clustering algorithm [1, 2] is a simple and relatively efficient clustering algorithm. Compared with the other clustering algorithm, the number of clusters need not be pre-determined by using subtractive clustering algorithm. And cluster center is determined by the density index based on sample data mainly. The steps of algorithm are shown as follows.

1) It is supposed that $X = \{x_1\}_{l=1}^{L}$ is the sample set to be clustered. Density index at sample point x_1 is defined as follows.

$$D = \sum_{j=1}^{L} \exp(-\frac{\|x_1 - x_j\|^2}{(\gamma_a / 2)^2}) \quad (1)$$

Where, γ_a is positive. If the density of this point is bigger, there are more data around this point. Density index of each sample point $x_1 (1 = 1,\ldots,L)$ is computed. The sample point with the maximum of density index is selected as the first cluster center.

2) It is supposed that x_{c_k} is the kth selected cluster center. D_{c_k} is its density index. The density index of other sample point is modified by using the following formula.

$$D_l = D_l - D_{c_k} \sum_{j=1}^{L} \exp(-\frac{\|x_l - x_{c_k}\|^2}{(\gamma_b / 2)^2}), \quad 1 \neq c_k \quad (2)$$

The point with the maximum of density index is selected as the new cluster center $x_{c_{k+1}}$. Where γ_b is positive. It defines a neighborhood that the density index function is significantly reduced.

3) To judge the condition in following formula, whether the condition is met the following formula or not. If the condition is not met, it goes to step 2). If the condition is met, it exits the process.

$$\frac{D_{c_{k+1}}}{D_{c_k}} < \delta \quad (3)$$

Where δ need to be predetermined.

2.2 K-means clustering algorithm

K-means clustering algorithm [3, 4] is a basic division method in cluster algorithms. It can make square sum of the distance between cluster center and all the sample points in the clustering neighborhood arrive the minimum. This algorithm is simple and can cluster quickly. The steps of the algorithm are shown as follows.

1) Original cluster centers are selected at random. They are $z_1, z_2, \cdots, z_K$.

2) Each sample in sample set is distributed to cluster center $z_j (j = 1,2,\cdots,K)$ according to the principle of minimal distance individually.

3) The new cluster center $z_j' (j = 1,2,\cdots,K)$ is computed. That is $z_j' = \frac{1}{N_j} \sum_{X \in S_j} X$, where N_j is the number contained by the jth cluster field S_j.

4) If $z_j' \neq z_j (j = 1,2,\cdots,K)$, it goes to step 2). Otherwise, the algorithm is convergent and calculation ends.

2.3 Clustering Method Based on the Basic Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) algorithm [5, 6] is an effective global optimization algorithm. It is a theory of optimization algorithm based on swarm intelligence. Though group cooperation and competition among particles, the search is

guided and optimized. For the clustering problem [7, 8], it can be taken as a complex global optimization problem. An approximate optimal division of data set can be obtained by using the global optimization ability of PSO algorithm. The steps are shown as follows.

1) PSO is initialized. It is supposed that n dimensional sample data is divided into K classes. There are m particles in a group, where the K class centers are taken as a particle. The ith particle is recorded as $Z_i = (z_{i11}, z_{i12}, \cdots, z_{i1n}, z_{i21}, z_{i22}, \cdots, z_{i2n}, \cdots, z_{iK1}, z_{iK2}, \cdots, z_{iKn})$ ($i = 1,2,\cdots,m$). The centers are selected at random and the value of the centers is given to every particle. The velocity of particle is produced at random.

2) The optimal individual location $p_{ik}(t)$ and global extreme location p_{gk} are obtained according to the original particle swarm.

3) The velocity and location are updated according to the following formula.

$$v_{ik}(t+1) = w \times v_{ik}(t) + c_1 \times r_1 \times (p_{ik}(t) - z_{ik}(t)) + c_2 \times r_2 \times (p_{gk} - z_{ik}(t))$$

$$\begin{cases} v_{ik}(t+1) = v_{\max} & if\ v_{ik}(t+1) > v_{\max} \\ v_{ik}(t+1) = -v_{\max} & if\ v_{ik}(t+1) < -v_{\max} \end{cases} \quad (4)$$

$$z_{ik}(t+1) = z_{ik}(t) + v_{ik}(t+1)$$

Where $k = 1,2,\cdots,K$ and $i = 1,2,\cdots,m$. t is the number of iteration. $v_{ik}(t)$ is the velocity of the ith particle after t iterations. $z_{ik}(t) = (z_{ik1}, z_{ik2}, \cdots, z_{ikn})$ is the location of the ith particle after t iterations. $p_{ik}(t)$ is the best solution searched by the ith particle in the tth generation. p_{gk} is the best solution searched by the whole particle group. w、r_1、r_2 are random numbers in $[0,1]$. Generally, $c_1 = c_2 = 2$. $V_{max} > 0$ is the maximal velocity of particle in each dimension.

4) Each sample is coded according to the cluster center. The cluster division is determined accordance with most adjacent principle. It is shown as following formula.

$$F = \text{fitness}(C_{ij}) = \sum_i \sum_j \left\| Y_i - C_{ij} \right\| \quad (5)$$

The fitness of each particle is computed. The individual extreme value is updated.

5) The fitness of each particle is compared with the fitness p_{ik}. If the fitness is better than p_{ik}, the fitness is given to p_{ik}, that is p_{ik} is updated.

6) The fitness of each particle is compared with the fitness p_{gk}. If the fitness is better than p_{gk}, the fitness is given to p_{gk}, that is p_{gk} is updated.

7) If the end conditions are met (A good enough location is obtained or the maximal number of iteration is reached), the algorithm is terminated and global optimal solution is output. Otherwise, step 3) is carried on and continued to iterate.

2.4 Cluster Algorithm Based on Improved PSO Algorithm

First, the number of cluster groups and approximate location of cluster centers are determined by using subtractive clustering algorithm. Then, the result is taken as a particle to be added in the PSO algorithm. This will reduce the degree of the dependence on the initial location in PSO algorithm.

The idea of K-means algorithm is used to re-compute the cluster center base on completing the division in step 4) of part 2.3. If the new cluster center is worse than original cluster center, the new cluster center is abandoned. Otherwise, the current location is updated. The convergence rate of PSO algorithm is improved by K-means algorithm.

In order to make the global searched ability and local improved ability reach equilibrium, nonlinear dynamic inertia weight coefficient is used to determine the weight in step 3) of part 2.3 adaptively. Its expression is shown as follows.

$$w = \begin{cases} w_{\min} - \dfrac{(w_{\max} - w_{\min}) * (f - f_{\min})}{(f_{avg} - f_{\min})}, & f \le f_{avg} \\ w_{\max}, & f > f_{avg} \end{cases} \quad (6)$$

Where w_{max} and w_{min} are the maximum and minimum of w respectively. f is the target function value of current particle. f_{avg} and f_{min} are the average target value and minimal target value of all current particles.

When the particles tend to consistency or tend to reach the local optimum, this condition will make the inertia weight increase. But when target value of the particles are scattered, the inertia weight will decrease. At the same time, for the particles that their target function value are better than the average target particles, the corresponding inertia weight factors is smaller. The particles are protected. Whereas, for the particles that their target value are worse than the average target particles, the corresponding inertia weight factors is bigger. It makes the particles move closer to a better search area.

In addition, in the foregoing step 3) of part 2.3, the learning factor c_1 and c_2 are express into the form changed with time during the optimization process. They are shown as follows.

$$c_1 = c_{1,ini} + \frac{c_{1,fin} - c_{1,ini}}{t_{max}} * t \quad (7)$$

$$c_2 = c_{2,ini} + \frac{c_{2,fin} - c_{2,ini}}{t_{max}} * t \quad (8)$$

Where $c_{1,ini}$ and $c_{2,ini}$ are represented the initial value of c_1 and c_2. $c_{1,fin}$ and $c_{2,fin}$ are represented the final iteration value of c_1 and c_2. Value of learning factor makes the particles have the larger self-learning ability and the smaller of social learning ability at the initial stage of optimization. The global search capability is enhanced. It also makes the particles have the larger social learning ability and the smaller self-learning ability. The convergence rate can be accelerated at the late stage of optimization. It also does not fall into local optimum easily.

3 RBFNN Based on Improved PSO Algorithm

Radial basis neural network (RBFNN) [9, 10] is a forward network with the global convergence. It is composed by the input layer, hidden layer and output layer. It completes the following nonlinear mapping.

$$f_n(X) = \sum_{i=1}^{n} w_i \phi(\|X - c_i\|) \quad (9)$$

Where, $X \in R_n$ is an input vector. $\phi(\bullet)$ is a nonlinear function from R^+ to R. Generally $\phi(\bullet)$ is appointed as the Gaussian function.

$$\phi(\|X - c_i\|) = \exp(-\frac{\|X - c_i\|^2}{\sigma_i^2}) \quad (10)$$

w_i is the weight from hidden layer to output layer. c_i and σ_i are data center and width of the basic function. n is the number of the center.

There are two types in the parameters to be determined of RBF neural network. One is center c_i of the basic function, width σ_i and the number of center n. The other are connected weights between the output layer and hidden layer. The research results show that, the number of hidden units in RBF networks, the center of radial basis function in hidden units and width have a great impact on the network performance. These parameters need to be determined by learning. In this paper, RBF network is trained by hybrid learning method. Clustering method based on improved PSO algorithm as described in part 2 is used to determine the center. After the RBF center and width are determined, RBF neural network from input to output becomes a linear equation group. The weight may be determined by using basic PSO algorithm.

The coding structure of particle is shown as follows.

$$Z_{11}, Z_{12}, \cdots Z_{1k}, \sigma_1, Z_{21}, Z_{22}, \cdots, Z_{2k}, \sigma_2, \cdots, Z_{m1}, Z_{m2}, \cdots Z_{mk}, \sigma_m$$
$$V_1, V_2, \cdots, V_{m\times(k+1)}$$

Where, m is the number of particle. Z_{ij} is the

center location of RBF. σ_i is the width. $V_{i\times n}$ is the velocity of particle. ($i = 1,2,\cdots,m$, $j = 1,2,\cdots,k$, $n = 1,2,\cdots,k+1$).

4 Aggregate Static Power Load Modeling in Coalmine

Aggregate static load model [11] is defined as the law that the power absorbed from the power grid changes with voltage and frequency slowly. The general description is shown as follows.

$$\begin{cases} P = P(U,f,\alpha) \\ Q = Q(U,f,\beta) \end{cases} \quad (11)$$

Where, P and Q are active power and reactive power of aggregate static load. U is the voltage of aggregate load bus. f is the frequency of system. α and β are the parameter vector of the model. The law that power changes with voltage slowly is studied in practical load modelling because the frequency is constant under the coal mine generally.

In the past, underground aggregate static load model is built by using statistical synthesis method [12] based on traditional static model. First of all, various types of load ratio are counted. Then, the characteristics of various types of static load are determined, and they are integrated into one characteristic of the static load on the same bus. The impact of transmission components is estimated. Characteristic of aggregate static load is obtained by integrating from the low voltage level to the high voltage level. The aggregate static load model is obtained at last.

In order to accurately reflect the load characteristics, a different load model should be built for different loads at different time points. Or even when the same model class is created, the model parameters will also have large dispersion. This is the inevitable result caused by the characteristic of aggregate static load. However, considered from a practical engineering perspective, the aggregate static load model should be simple and less in the same power grid. Otherwise, we will not know what to do with when using them. This is a pair of contradictions between accurate load modeling and engineering application. To solve this problem, clustering method described in part 2 is proposed to classify the voltage data, reactive data and active data in a period of time from the underground power load monitoring points. Then, model is built according to each class data by using the improved RBF model in part 3. This can reduce the number of load model and the accuracy of the model can be guaranteed. Reasonable compromise is achieved between the accuracy of model and the practicality of model.

5 Practical Example

Two hundred and forty groups of voltage data, active power data and reactive power data in ten days about a load monitoring point in mining area are taken as the research object.

First, the sample data is changed into reference value. The sample data is classified by using improved PSO clustering method proposed in this paper. The number of population of particles is given as 20. $c_{1,ini} = 2.5$, $c_{1,fin} = 0.5$, $c_{2,ini} = 0.5$, $c_{2,fin} = 2.5$, $w_{max} = 0.9$、$w_{min} = 0.6$. The result of cluster is obtained by 20 iterations. It is shown in Fig. 1.

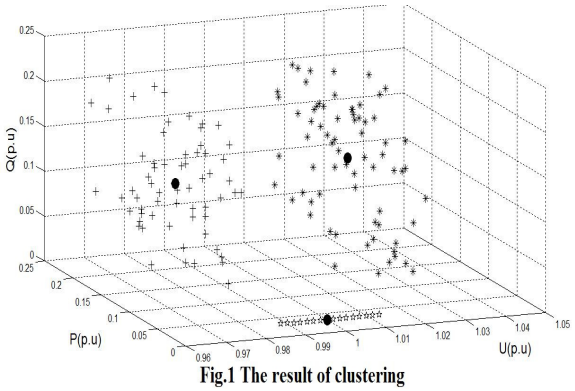

Fig.1 The result of clustering

From Fig. 1, it is shown that the sample data is classified into three classes. They are represent by symbol '+', '*' and '□' in the figure respectively. x axis, y axis and z axis represent the reference values of voltage, active power and reactive power respectively. The location of cluster center is represented by symbol '●', and their values are (0.9769, 0.1377, 0.1219), (0.9968, 0.01, 0.01) and (1.0211, 0.1454, 0.1286). The first class contains 62 groups of data. The scopes of change of voltage, active power and reactive power are [0.9672, 0.9852], [0.07, 0.23] and [0.02, 0.22]. The second class contains 106 groups of data. The scope of change of voltage is [0.9852, 1.0099], and the values of active power and reactive power are constant. The third class contains 72 groups of data. The scopes of change of voltage, active power and reactive power are [1.0099, 1.0328], [0.07, 0.23] and [0.02, 0.22].

From the results of cluster, it is shown that active power and reactive power of the second class data are not changed with the voltage. Constant power model may be built by using the second class data. But the active power and reactive power of the first and the second data are changed with the voltage that the RBF neural network based on improved PSO algorithm need to be used to build the model in this paper.

The models are built by using RBF neural network based on improved PSO algorithm for the first class data and the third class data. Parameters of algorithm are given as follows. The number of population of particles is given as 20. $c_{1,ini}=2.5$, $c_{1,fin}=0.5$, $c_{2,ini}=0.5$, $c_{2,fin}=2.5$, $w_{max}=0.9$, $w_{min}=0.6$. The number of iteration is 20. The mean square errors of model are shown into Table 1.

Table 1 Mean square errors of model built by using RBF neural network based on improved PSO algorithm

	The first class data		The second class data	
	P-U model	Q-U model	P-U model	Q-U model
Using method proposed in this paper	1.44×10^{-9}	1.96×10^{-10}	3.05×10^{-9}	2.43×10^{-8}

To compare the effectiveness of model, a polynomial model is built by using the same sample data. The model parameters and mean square errors are shown in Table 2.

Table 2 Parameters and mean square errors of polynomial model

	Parameters of model			MSE
	Quadratic coefficient	Monomial coefficient	Constant coefficient	
P-U model	159.79	-319.108	159.36	7.26×10^{-1}
Q-U model	125．27	-250.24	125.00	8.64×10^{-1}

From Table 1 and Table 2, compared with traditional static load model, it is shown that the new method in this paper can greatly improve the accuracy of the model. The level of increase can arrive at 8 magnitudes.

6 Conclusion

In order to solve the contradiction between accurate load modelling and engineering application, a new clustering method based on improved PSO algorithm is presented in this paper. This new clustering method is used to classify the load data in order to reduce the number of load model before modelling. Then, to enhance the accuracy of load model, RBF neural network based on improved PSO algorithm is proposed to establish aggregate load model. In this paper, a monitoring point in mining area is taken as research object, compared with traditional static load model, the new method in this paper can greatly improve the accuracy of the model. The effectiveness of method is verified.

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