Implement an Advanced Soft Measurement Method of Mine Dust Concentration Based on K-RBF Neural Network

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Abstract — In view of the coal dust concentration measurement elements, the measurement pollution environment will reduce the measurement accuracy. The paper proposes a soft measurement method of mine dust concentration based on the K-RBF neural network theory. It takes the electrostatic signal as the measurement signal and extracts the short-term energy, RMS and rectification value of the electrostatic signal as the characteristic quantities of signal. And then a measurement method model has been created due to the dust concentration network study. The method shows the high speediness, little measurement error and high precision characteristic after it compared with the simulation modeling and performance evaluation of BP soft measurement method as well as the traditional optical measurement method. The method can be used to coal mine to realize real-time rapid detection of dust concentration.

Keyword — Mine dust concentration, The electrostatic signal, K-RBF neural network, Soft measurement

I. INTRODUCTION

The coal dust is one of the major dangers of coal mining, causing the pneumoconiosis disease and coal-dust explosions when the dust concentration is too high [1]. Therefore, dust concentration must be accurately and rapidly tested in order to ensure the safety of the coal miners and also to facilitate production. In present, dust measurement instruments and dust concentration sensors are mainly used in coal mines to detect dust concentration [2]. Samples are primarily collected by a specific drying and weighing operations. They are depended on optical mechanisms and optical measurement elements which are vulnerable to environmental pollution reduced accuracy. In order to overcome the limitations and indirection of the previous test measurements, the paper sets up a dust concentration soft measurement model based on the dust-charged characteristic and RBF neural network to reduce the error in the measurement principle.

II. ESTABLISHING THE DUST CONCENTRATION SOFT MEASUREMENT MODEL

The soft measurement method is a new process inspection and has been developed since 1970 [3, 4, 5, 6, 7]. Its essence is to use measurable secondary variables (input control variables or process state variables) to evaluate which cannot be measured directly through a mathematical method. Recently, the modeling method is mainly based on mechanism analysis, experimentation, pattern identification and etc [8,9,10,11,12]. All of these methods are depend on the different situations and need know the different measurement conditions. In order to obtain the mathematical function relationship between the estimated variables and secondary variables, the mechanism modeling method has to be known. The method is difficult to be implied due to the relatively complex environment. The pattern identification method processes the data and extracts the system features according to the input and output and then models it directly.

In this paper, the measurement of dust electrostatic signals with nonlinear characteristics is a random signal as Fig.1 shows.

Some information such as the dust concentration is contained in the signal and the prior knowledge of dust concentration is unknown. A soft measurement model is established due to a pattern identification method in this paper.

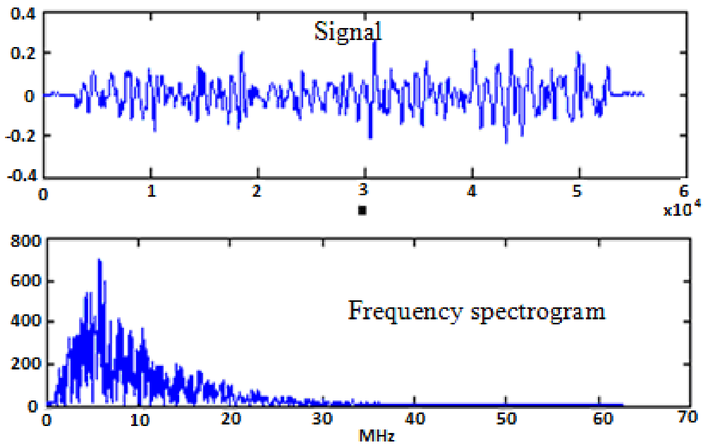

Fig.1 The chart of the signal after filtering

Fig.2 shows the soft measurement model. Once the noises process has been applied to the dust electrostatic signal, some features are then extracted. The features are taken as the input of the soft measurement model and through training and learning, the output is dust concentration.

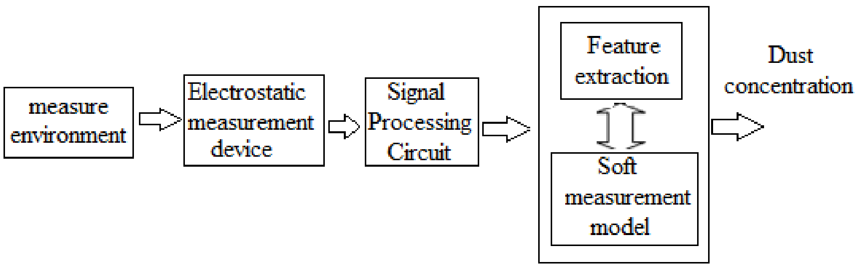

Fig.2 The dust concentration soft measurement system frame

III. EXTRACTING THE FEATURES

99 group electrostatic signals corresponding to dust density have been detected in the experiment. The sampling time of each electrostatic signal group is 6 s at a sampling frequency 6000 Hz. Each electrostatic signal group contains 36000 points. The mean value, short-term energy, RMS and rectification value are recorded for each signal. Since the mean values of magnitude are the fourth order and smaller than the other values. The short-term energy, RMS and rectification value are used as the neural network's inputs. Each group sample data contains three input values and an expected output value. The calculation formulas of the short-term energy, RMS and rectification value are shown as Eq.1, Eq.2 and Eq.3.

$$E_0 = \sum_{i=0}^{N-1} x_i^{\ 2} \tag{1}$$

$$RMS = \sqrt{\frac{1}{N-1}\sum_{i=1}^{N} x_i^{\ 2}} \tag{2}$$

$$\left|\bar{x}\right| = \frac{1}{N-1}\sum_{i=1}^{N} \left|x_i\right| \tag{3}$$

where E_0 is short-term energy, x_i is discrete data points, N is the number of data collection point, RMS is virtual value and $\phi_1\phi_{m-1}\phi_m w_1 w_{m-1} w_m \ \bar{y} \ \left|\bar{x}\right|$ is rectification value.

IV. ESTABLISH THE RBF NEURAL NETWORK SOFT MEASUREMENT MODEL

RBF neural network is a forward network with good performance and can approximate the given nonlinear mapping with arbitrary precision [13,14,15]. It is suitable to the influence of many factors of parameters testing. It avoids long-winded calculations and local minimum trap problems and its learning is faster than BP algorithm. It is the fastest and best effect neural network used in function fitting at present.

4.1 RBF network structure

The structure of network is shown in Fig.3 and is comprised of the input layer, hidden layer and output layer. The number of neurons of the input layer and output layer are depending on the actual requirement. The number of neurons in the hidden layer is according to the experience and experimental output and input mapping. The number of neurons in hidden layer is supposed to hit the limitation requirements. In order to keep the level of complexity low and allow the network structure to learn slowly.

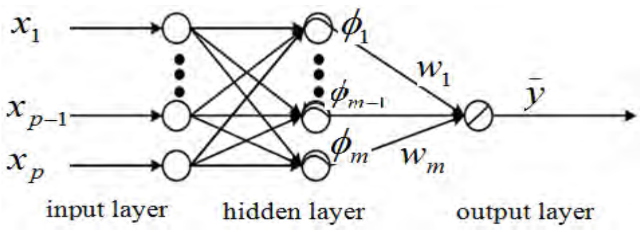

Fig. 3 RBF neural network

The weight coefficient between input layer and neuron is 1 and the weight coefficient w_k between neuron and output layer is adjustable. x is the input variable of the input layer and y is the output variable. $\phi_k(\bullet)$ is radial basis function and $\|\bullet\|_2$ is bound norm. N is the number of neurons in hidden layer and $C_k \in R^n$ is the input vector space of the radial basis function (RBF) center. For each neuron in the hidden layer, its center value and the Euclidean distance of network input must be calculated. The output of the hidden neurons is a nonlinear function of Euclidean distance and the output of the neural network is calculated by the total weighted value of output of the hidden layer.

$$y = f(x) = \sum_{k=1}^{N} w_k \phi_k(x, c_k) = \sum_{k=1}^{N} w_k \phi_k(\|x - c_k\|_2) \tag{4}$$

Gaussian function chosen by this paper is shown.

$$\phi(u) = \exp(-\frac{\|x - c_k\|_2}{2\delta_k^{\ 2}}) \tag{5}$$

δ is the width parameter and it controls the radial range of the function. If

H=($\phi_1(\| x - c_1 \|_2)$, $\phi_2(\| x - c_2 \|_2)$, ... $\phi_N(\| x - c_N \|_2)$), W=(w_1 , w_2 , ……, w_k)

So, y can be expressed as:

$$y = HW \tag{6}$$

4.2 Algorithm realization

Unsupervised learning is performed by clustering the input samples using the K–mean algorithm and ensuring the number of hidden nodes data center N and extension of constant are according to the distance among the data center. Supervised learning is then performed by determining the hidden output layer metric by the least square method.

RBF network data center c_k and the expansion of constant of the procedure δ_k obtained by K-means clustering algorithm are as follows:

(1) Algorithm initialization: Select different N numbers from input samples randomly as initial clustering center and make $m = 1$.

(2) Calculate distance between all input samples and clustering center: $\| x_i - c_k(m) \|$, $k = 1$, 2, ..., N , $i = 1$, 2, ..., M 。 M is the sample size of u .

(3) Classify the input samples according to the principle of minimum distance when $k(u_i) = \min_k \| x_i - c_k(m) \|$,

u_i belongs to class k, $x_i \in w_k(m)$.

(4) Adjust the center

$$c_k(m+1) = \frac{1}{N_k} \sum_{u \in w_k(m)} x \tag{7}$$

k=1, 2, ...N, N_k is the sample number in class k .

(5) The stop condition is $\sum_{k=1}^{N} \|x(k) - c_i(k)\|^2 \le \varepsilon$ otherwise, repeat step (2), (3), (4).

(6) Ensure the number of the hidden nodes extension of constant according to the distance among the data center. Expand constant is $\delta_k = \beta d_k$. d_k is the shortest distance between the K data center and other recent data. β is overlap coefficient.

(7) Calculate the right W by the least square method:

$$W = H^{+}Y \qquad (8)$$

H^{+} can be calculated by H in Eq.2

$$H^{+} = (H^{T}H)^{-1}H^{T}, \quad Y = (y(1), y(2),..., y(N))^{T} \qquad (9)$$

V. EXPERIMENTAL RESULTS AND ERROR ANALYSIS

5.1 BP experimental results and the error analysis

5.1.1 Data Training

90 groups have been selected from 99 groups of the pre-calculated samples as the training samples. As these are used for the training of the network, the remaining 9 groups are used as the testing samples for the trained network testing. In order to avoid excessive training network (over-fitting), network training level supervision is required. At same time, 9 sample groups have been selected randomly from 90 participated sample groups in network training samples as the fitting samples. After testing the trained network by the samples, there are 9 errors between dust concentration and expected output values of the trained network are fitting errors. The relative error between network dust concentration and expected output value is defined as the predication error. When BP neural network with the 3-6-1 structure is selected to analyze the data, the transfer function of the hidden layer and the output layer transfer function as the linear function have been created. The training network uses the L-M algorithm and the training target error is set to 0.0001. Meanwhile, the condition of the training stop is set up when the expected error is less than the setting.

5.1.2 Experimental results and the error analysis

TABLE I shows the relative error calculated by the 9 group samples with the dust concentration among 5-200mg/m^3.

TABLE I shows the relative error that the test samples trained by the network.

Energy (J)	**RMS(V)**	**Rectification value(V)**	**Expected output** (mg/m^3)	**Network output** (mg/m^3)	**Relative error**
22.5813	0.0251	0.0179	10.4	11.2665	0.0046
4.0522	0.0107	0.0076	20.8	20.765	0.0002
1.2791	0.006	0.0043	35.00	36.5791	0.0084
0.1974	0.0023	0.0017	52.0	49.815	0.0117
221.6983	0.0786	0.0613	63.4	113.6142	0.2682
135.9965	0.0615	0.0415	88.6	82.5863	0.0321
142.1067	0.0628	0.0385	104.0	105.0078	0.0054
184.5197	0.0716	0.055	142.6	120.8428	0.1162
233.8172	0.0806	0.064	187.2	167.968	0.1027

TABLE II Training sample, network output and relative error in calculation

Energy (J)	RMS(V)	Rectification value(V)	Expected output (mg/m^3)	Network output (mg/m^3)	Relative error
221.6747	0.0785	0.0517	226.4	244.7837	0.0812
226.7852	0.0794	0.0556	59.4	65.0846	0.0957
243.6842	0.0823	0.0611	299.2	363.3784	0.2145
207.0469	0.0759	0.0581	320.4	356.3809	0.1123
65.6908	0.0428	0.0277	336.6	358.5127	0.0651
173.4412	0.0701	0.0537	353.6	362.935	0.0264
156.5434	0.066	0.0521	381	443.9412	0.1652
192.657	0.0723	0.0572	389.2	439.7182	0.1298
199.2868	0.0744	0.0564	397.6	472.9452	0.1895

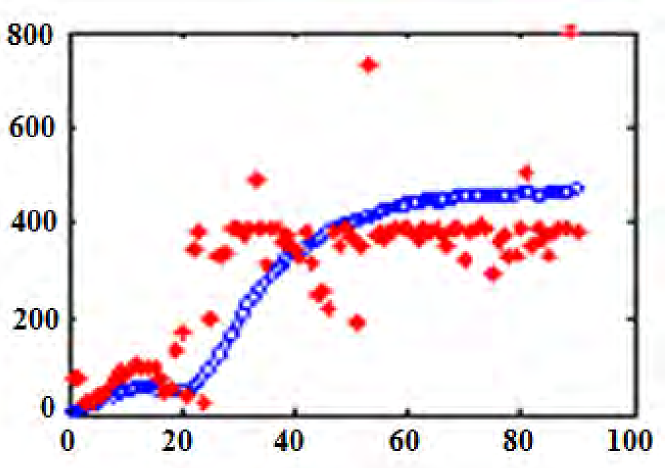

Fig.4 shows BP network output and the expected output (Expected output: “○”, Network output: “ * ”)

5.2 BP experimental results and the error analysis

5.2.1 Data training

The supposed error of RBF neural network is 0.0001. The hidden layers maximum is 100 and the radial basis expansion constant is 0.1. When the error is less than the defined error or when the hidden neurons reach the maximum number, the stop condition is set. The 99 groups of samples are used in the training and validating RBF network.

5.2.2 Experimental results and the error analysis

Table 3 shows the relative error calculated by the 9 group samples with the dust concentration among 5-200mg/m^3.

TABLE III shows the relative error that the testing samples trained by the network.

Energy (J)	RMS(V)	Rectification value(V)	Expected output (mg/m^3)	Network output (mg/m^3)	Relative error
22.5813	0.0251	0.0179	10.4	10.4	6.6369
4.0522	0.0107	0.0076	20.8	20.8	4.1702
1.2791	0.006	0.0043	35.00	35.00	2.2475
0.1974	0.0023	0.0017	52.0	52.0	5.1974
221.6983	0.0786	0.0613	63.4	63.4	1.5180
135.9965	0.0615	0.0415	88.6	88.6	8.3271
142.1067	0.0628	0.0385	104.0	104.0	2.5676
184.5197	0.0716	0.055	142.6	142.6	2.4698
233.8172	0.0806	0.064	187.2	187.2	1.0645

TABLE IV Training sample, network output and relative error in calculation

Energy (J)	RMS(V)	Rectification value(V)	Expected output (mg/m^3)	Network output (mg/m^3)	Relative error
221.6747	0.0785	0.0517	226.4	241.4103	0.0663
226.7852	0.0794	0.0556	059.4	61.9186	0.0424
243.6842	0.0823	0.0611	299.2	315.3269	0.0539
207.0469	0.0759	0.0581	320.4	332.3830	0.0374
65.6908	0.0428	0.0277	336.6	361.2055	0.0731
173.4412	0.0701	0.0537	353.6	363.3947	0.0277
156.5434	0.066	0.0521	381	394.3731	0.0351
192.657	0.0723	0.0572	389.2	395.6218	0.0165
199.2868	0.0744	0.0564	397.6	438.1552	0.1020

TABLE IV shows the training sample, network output and relative errors in implementation. The data will be used to the evaluation algorithm.

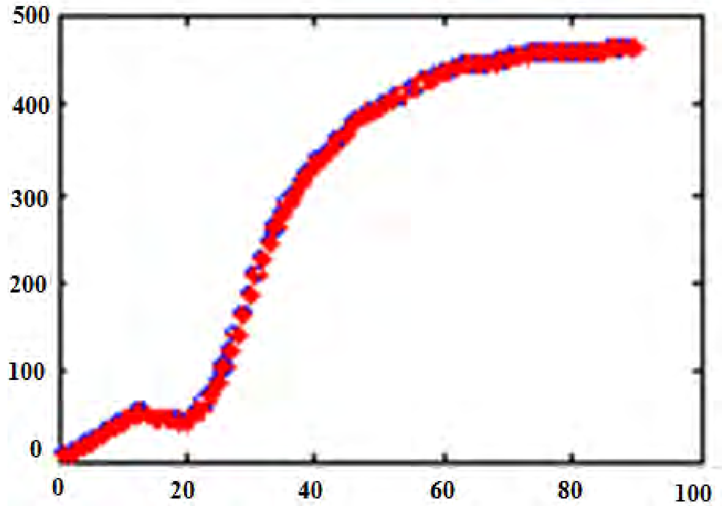

Fig.5 Shows RBF network output and the expected output (Expected output: “○”, Network output: “ * ”)

From the TABLEIII, TABLE VI and Fig.5, we can see that the relative error of RBF network is small. Network fitting degree is very good and the network prediction error range is small.

VI. ERROR COMPARISON

TABLE V shows the standard concentration data and the data obtained by AKFC-92 dust measuring instrument and we can see that the error of AKFC-92 is among 10.84%-19.42%

TABLE V standard value, AKFC-92 sampler data and relative error

Standard value	AKFC-92	Relative error	Standard value	AKFC-92	Relative error
10.4	11.5778	0.1084	353.6	422.2709	0.1942
20.8	23.4205	0.126	389.8	441.8649	0.1353
35.00	41.6873	0.1911	404.4	452.1207	0.1169
44.60	50.2366	0.1264	425.6	491.4407	0.1547
52.20	58.1303	0.1136	443.2	508.7801	0.1745
51.20	59.2881	0.158	455.0	517.5725	0.1626
48.40	53.9416	0.1145	458.2	521.3679	0.1379
45.80	53.229	0.1622	458.4	544.3932	0.1876
44.80	50.8523	0.1351	463.2	519.1426	0.1208
54.60	60.4748	0.1076	468.2	554.5505	0.1844
88.60	99.0894	0.1184	469.8	525.93	0.1195
164.40	195.6807	0.1903	471.2	528.9654	0.1226
207.80	238.7802	0.1491	474.6	530.1618	0.1171
243.40	275.9601	0.1338	475.6	533.9877	0.1228
259.40	308.6874	0.19	476.0	544.3393	0.1436
287.80	319.7804	0.1111	475.4	537.7298	0.1311
299.20	352.4651	0.178	476.2	567.7913	0.1923
320.40	360.1838	0.1242	476.2	544.3065	0.143

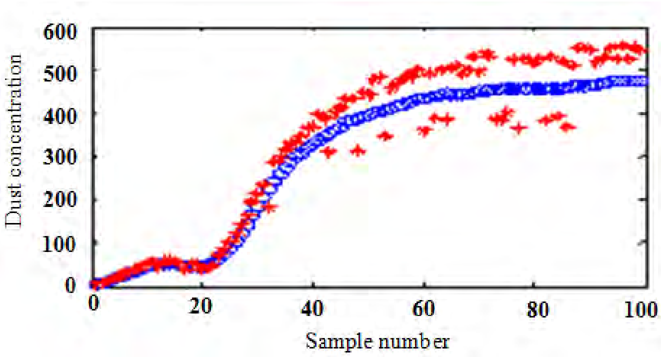

Fig.6 Shows the AKFC-92 sampler data and standard value. (Expected output: “○”, Network output: “ * ”)

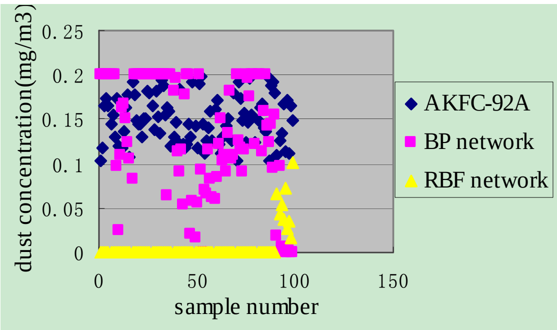

Fig.7 Relative error of three methods

Fig.7 shows the Relative error of three methods: AKFC-92A, BP network and RBF network. From the performance evaluations and the relative error analysis, they have been shown:

a) Table 1 and Table 3: the RBF network is noticeably better than BP network in network fitting.

b) Table 2 and Table 4: the forecasting error ranges of the RBF network are less than the relative errors of the BP network. The comprehensive analysis shows the RBF network is better than BP network in forecasting.

c) From Fig.4 ~ Fig.7, the error of light scattering method is smaller than BP network. It means that light scattering method is better than BP neural network. After compared BP network with light scattering method by the evaluation results, it's almost same as RBF network. The comprehensive analysis also shows that RBF neural network soft measurement method to calculate the dust concentration is more accurate. Similar past experiments have been completed numerous times in labs resulting in the same conclusion.

VII. CONCLUSION

This paper illustrates the dust concentration soft measuring system based on the soft measurement method. The system makes BP network and RBF network as the soft measurement model and makes short-term energy, RMS and rectification value as model's input and the dust concentration as the output. The corresponding relation of electrostatic signal and dust concentration by the training of BP and RBF network has been evaluated. The performance and simulation results show that the RBF network is superior to the BP neural network in both network fitting and network forecast. In addition, the measurement error of dust concentration testing of the RBF neural network is smaller and more precise. At same time, the RBF network relative error performing the measurement of dust concentration is most accuracy. The method provides a new realistic significance meaning in measuring and controlling dust scientifically.

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REFERENCES

[1] Cheng Xuezhen, Liu Mei etc. Testing and Control Technologies of Coal Dust in Coal Mine [J].Mining Research and Development, 2007,27(06):78-85.

[2] Cheng Xuezhen. Mine Dust Concentration Sensor Research Based on Microcharge Induction Principle[D]. Shandong University of Science and Technology ,2011,1-18.

[3] QI Liang,JIN Baoduo, et al. Soft sensor model for controlling methanol concentrations in direct methanol fuel cell systems[J]. J Tsinghua Univ (Sci &Tech),2008,48(12):2111-2114.

[4] Takagi T,Sugeno M..Fuzzy identification of system and its application on modeling and control[J].IEEE Trans Systems,Man,Cybernetics,1985,15(1):116-132.

[5] Dong D,Mcavoy T J.Nonlinear principal component analysis based on nonlinear principal componentanalysis ccurves and neural networks[J].Computers Chemical Engineering,1996,20(65):245-257.

[6] Li Wei,Su Hongye,Liu Ruilian.Parameter estimation of catalytic cracking model using PSO algorithm[J].CIESC Journal,2010,61(8):1927-1932.

[7] Liu Jialin.On-line soft sensor for polyethylene process with multiple production grades[J]Control Engineering Practice,2007,15:769-778.

[8] Guan Renchu,Shi Xiaohu,Marchese M,et al.Text clustering with seeds affinity propagation[J]. IEEE Transactions on Knowledge and Data Engi neering,2011,23(4):627-637.

[9] QIAO Guo-Lin,TONG Chao-Nan,SUN Yi-Kang. Study on Mould Level and Casting Speed Coordination Control Based on ADRC with DRNN Optimization[J]. ACTA AUTOMATICA SINICA,2007,33(06):641-648.

[10] Narendra K S.Identification and control of dynamical system using neural networks[J].IEEE transactions on Neural Networks,1990,1(1):4-27.

[11] SHI Xiaohu, LIANG Yanchun, XU Xu. An improved Elman model and recurrent back-propagation control neural networks[J]. Journal of Software, 2003,14(6):1110-1119.

[12] FU Hua, QIAO Dehao，Chi Jihui. CIPSO-ENN Coupling Algorithm for Nonlinear Dynamic System Parameter Identification[J]. JOURNAL OF XI'AN JIAOTONG UNIVERSITY,2011,45(2):y1-y6.

[13] Chu Yuezhong,Xu Bo. RBF neural network classifier based on manifold analysis and AP algorithm[J]. J . Huazhong Univ . of Sci . & Tech .(Natural Science Edition),2012,40(8):93-97.

[14] XIA Chang-liang,WANG Ming-chao. SINGLE NEURON PID CONTROL FOR SWITCHED RELUCTANCE MOTORS BASED ON RBF NEURAL NETWORK[J]. Proceedings of the CSEE,2005,25(15):161-165.

[15] Chang-Chun Hua,Qing-Guo Wang,and Xin-Ping Guan.Adaptive fuzzy output-feedback controller design for nonlinear time-delay systems with unknown control direction[J].IEEE Transactions on Systems,Man,and Cybernetics-Part B:Cybernetics,2009,39(2):363-374.

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