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ITJ

ISSN 1812-5638

# INFORMATION TECHNOLOGY JOURNAL

ANSInet
Asian Network for Scientific Information
308 Lasani Town, Sargodha Road, Faisalabad - Pakistan

Information Technology Journal 12 (23): 7076-7082, 2013
ISSN 1812-5638 / DOI: 10.3923/itj.2013.7076.7082


# Aluminum Electrolysis Fault Diagnosis Research Based on Principal Component Analysis

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**Abstract:** According to the characteristics of the aluminum electrolysis fault, the principal component analysis and improved BP network are used for extracting fault feature, the improved BP neural network can extract the fault feature and can also be used as preliminary diagnosis of the fault, thereby electrolytic method for multiple faults diagnosis of three neural networks aluminum is taken use, this method analyzes the deficiency of single neural network and two stage neural network fault diagnosis and in order to form the decision fusion network, the wavelet analysis and neural network are combined orgamically. The simulation results show that: the aluminum electrolysis fault diagnosis resrarch based on principal component analysis has the characteristic of large amount of ault forecast.

**Key words:** Fault diagnosis, principal component analysis, improved BP network

## INTRODUTION

The structure of equipment in aluminium electrolytic process is complex, The fault is varied and occurs frequently, sometimes kinds of faults occur at the same time, effective fault diagnosis is the key to ensure safety and stable production. In the single neural network for aluminum electrolysis for multiple fault diagnosis, if all the fault samples are training in the same network, with the increase of fault types and network unitsthe number of accidents are increasing, the possibility of fault has increased and the network generalization, association ability will be greatly reduced, especially for the multiple fault recognition ability will bevery weak. In order to overcome the defects of single network, using the combined method of sub network, namely each fault corresponds to a neural network, each network output layer with only one node, the number of nodes in input layer can be different, depending on the fault type, the output is the input of decision-making neural network and it gives the final diagnosis results (Bae, 2010). Since, the output in the diagnosis of many sub network contribution to the diagnosis results are not large, the decisive factor is often only two or three sub networks. That is to say, a lot of sub network are useless sub network more, the waste greater. So this study adopt three neural networks, the first level neural network made a tentative diagnosis of fault, to determine which sub network began to work in second level network, second level network result is input to the third network, third network output the final diagnosis results.

## NETWORK MODEL

**Structure of fault diagnosis model:** In order to realize single fault and multi fault diagnosis in the process of aluminum electrolysis fat the same time, established the fault diagnosis model of three stages of, first level mainly includes principal component analysis and preliminary diagnosis network, second level includes anode effect sub network, heat sink sub networks, cold trough sub network and rolling aluminum sub network, third level is the decision fusion network (Barakat *et al.* , 2011). The structure of fault diagnosis model as shown in Fig. 1.

The process in this model is that the output of improved BP network in first network excitate each sub network in second level, the third network gives diagnostic results. The diagnosis rules are as follows:

- If the value of output of the node in the first network is greater than 0. 1, then the node corresponding to the sub network in second level work
- If the value of output of the node in the first level is less than 0. 1, it may be considered that the detected fault samples without failure or it is a new fault model
- if the value of output of each sub network in the second level is more than 0. 5, it can be considered that the corresponding fault exists and the output value represents the fault severity
- Outputs of the second level network is the inputs of the third level network, the third network gives diagnostic results

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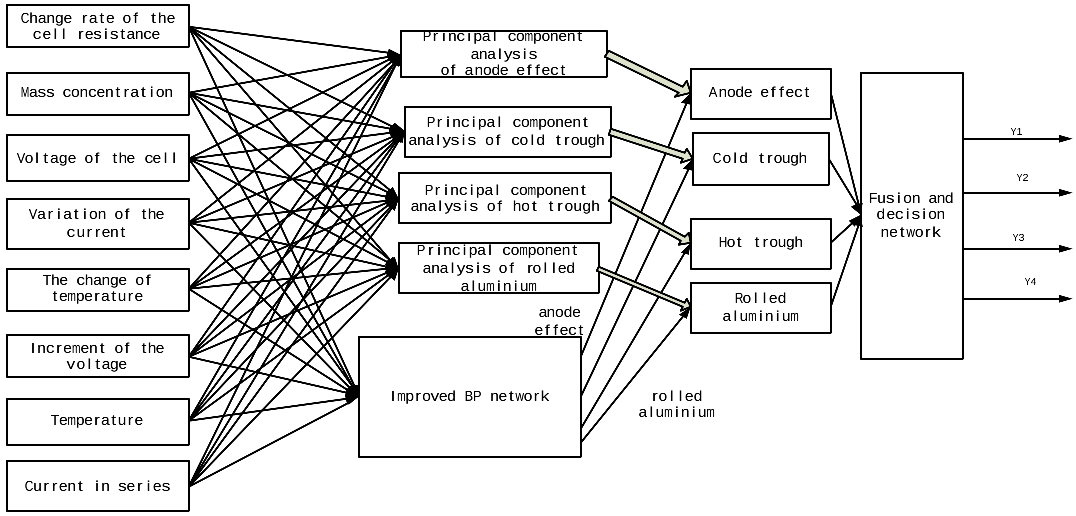


Fig. 1: Sructure of fault diagnosis model

## ESTABLISH THE MODEL OF THE SUB FAULT DIAGNOSIS

**Principal component analysis:** By using characteristic analysis and fault diagnosis model based on improved BP neural network principal component extraction in this study, the principal components analysis method is to remove the not important parameters, using the new variable less instead of more variables, fault related information in the new variables as much as possible to retain the original more variables reflect thus, reduce the dimension of input, decoupling, the variables are simplified. The basic idea is: in the study between the various variables based on the relationship of the original, multiple variables are combined properly, combined into some comprehensive index, comprehensive index of this from a combination of variables is called principal components (Lu and Zhang, 2012). The anode effect as an example, the anode effect nonlinear principal component transform as shown in Fig. 2.

The specific steps are as follows.

With the input data samplesh (p = 1, 2..., P), Each sample was i(i = 1, 2...I), There are I = 8 variables $\delta_1$, $\delta_2$, $\delta_3$,..., $\delta_i$ in this study:

- To transform the original variables $\delta_1$, $\delta_2$, $\delta_3$,..., $\delta_i$, get:

$$\zeta_{pi} = \ln \delta_{pi} - \frac{1}{I}\sum_{i=1}^{I} \delta_{pi} \tag{1}$$

- Standard processes:

$$\zeta_{pi} = \frac{\zeta_{pi}^0 - \bar{\zeta}_p}{\sigma_p}, p = 1, 2, \cdots, P, i = 1, 2, \cdots, I \tag{2}$$

Among them $\zeta^0_{pi}$, $\zeta_{pi}$ are the P component of the original vector $\zeta^0_{pi}$ and normalized vector $\zeta_{pi}$:

$$\bar{\zeta}_p = \frac{1}{I}\sum_{i=1}^{I} \zeta_{pi}^0 \tag{3}$$

$$\sigma_p^2 = \frac{1}{I-1}\sum_{i=1}^{I} \left(\zeta_{pi}^0 - \bar{\zeta}_p\right)^2 \tag{4}$$

Calculated the logarithm center sample covariance matrix of the matrix Composition by $\zeta_{pi}$:

$$S_x = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1p} \\ r_{21} & r_{22} & \cdots & r_{2p} \\ \vdots & \vdots & & \vdots \\ r_{p1} & r_{p2} & \cdots & r_{pp} \end{bmatrix} \tag{5}$$

$$r_{ij} = \frac{\sum_{k=1}^{p} (\zeta_{ki} - \bar{\zeta}_i)(\zeta_{ki} - \bar{\zeta}_j)}{\sqrt{\sum_{k=1}^{p} (\zeta_{ki} - \bar{\zeta}_i)^2 \sum_{k=1}^{p} (\zeta_{ki} - \bar{\zeta}_j)^2}} \tag{6}$$

Use $\Sigma_X$ figure outthe nonlinear principal component of the sample data. With the first principal component $F_1 = a_{11}X_1+a_{21}X_2+\dots a_{p1}X_p = a^TX$, The variance is:

$$V(F_1) = a_1^T \Sigma a_1 = a_1^T U \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_p \end{bmatrix} U^T a_1$$

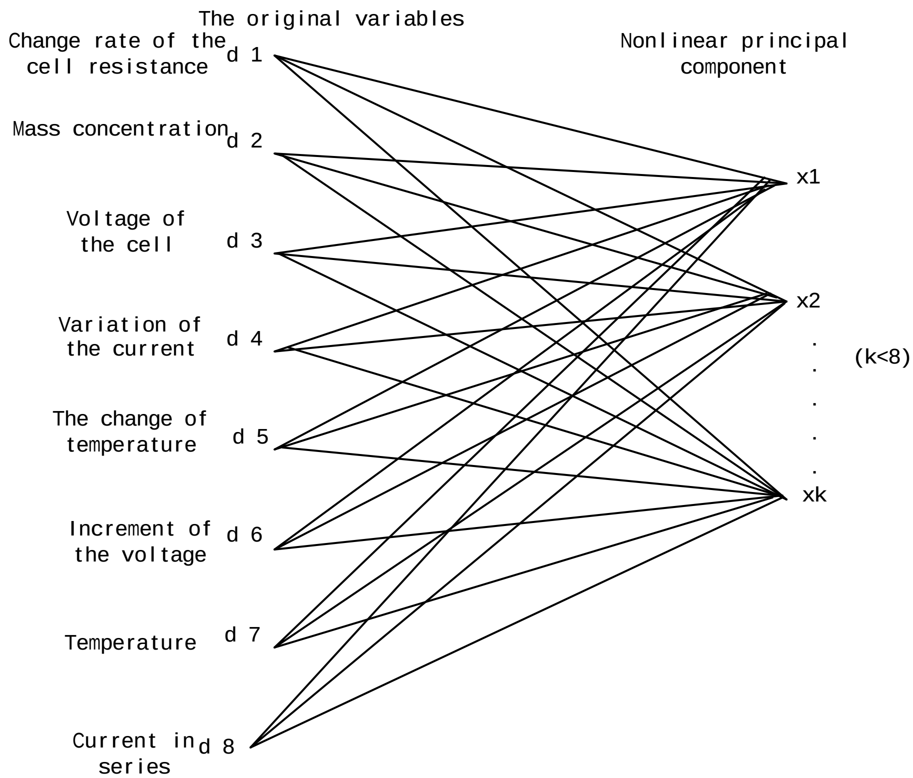


Fig. 2: Nonlinear principal

$$= a_1^T \left[u_1, u_2, \cdots, u_p\right] \begin{bmatrix} \lambda_1 & & & \\ & \lambda_2 & & \\ & & \ddots & \\ & & & \lambda_p \end{bmatrix} \left[u_1, u_2, \cdots, u_p\right]^T a_1$$

$$\begin{aligned} &= \sum_{i=1}^{p} \lambda_i a_i^T u_i u_i^T a_1 = \sum_{i=1}^{p} \lambda_i (a_i^T u_i)^2 \\ &\le \lambda_1 \sum_{i=1}^{p} (a_i^T u_i)^2 = \lambda_1 \sum_{i=1}^{p} a_i^T u_i u_i^T a_1 = \lambda_i \end{aligned} \tag{7}$$

Suppose the Characteristic value $\lambda_1 \ge \lambda_2 \ge \cdots \ge \lambda_i$ of $\Sigma_X$, the standard unit of the corresponding feature vector $a_1$, $a_2$, ..., $a_p$. The accumulated variance contribution rate is:

$$\frac{\sum_{p=1}^{n} \lambda_p}{\sum_{p=1}^{I} \lambda_p}, (n \le I) \tag{8}$$

Determine the number of principal components in nonlinear cumulative contribution rate of 85% principle, nonlinear principal components identified as:

$$X = \zeta \times a \tag{9}$$

Here, is the 8 parameters can reflect the characteristics of the anode effect of nonlinear principal component. It eliminates the correlation between the input variables, in order to meet the information loss, reduce the input dimension, decrease the complexity of network structure, according to the principal component features the new input vector component corresponding to the value, can determine the number of input variables of neural networks, reduce the uncertainty of the network.

**Improved BP neural network:** In this study, BP neural network is adopted to extract fault feature and diagnosis preliminary.

When improved BP network applicated in the aluminum electrolysis fault diagnosis, each node of the input represents a symptom, each node of the output represents a failure, the relationship between faults and symptoms through the weights of input layer to the hidden layer as well as the weights of hidden layer to the output layer to reflect and there is no direct link between node and node failure. Thus, in the process of the input layer to the hidden layer and to the output layer in multi fault diagnosis, some information between faults and symptoms, m ay be lost, resulting in the use of trained in

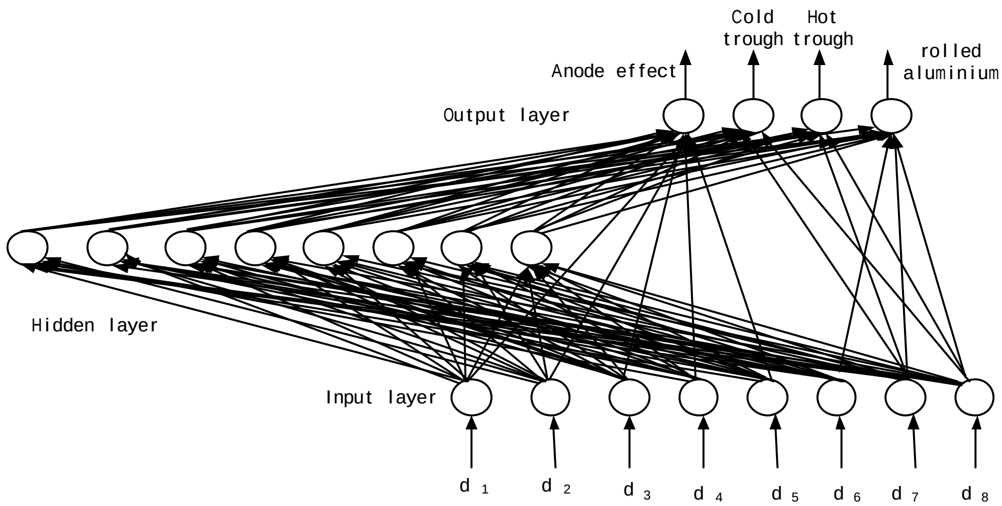


Fig. 3: Improved BP neural network

the single fault networks to identify multiple fault occur error or omission. We can according to the experience summarize the relations between fault and symptom of aluminum electrolysis. Therefore, according to the relationships between faults and symptoms to determine how to improved the BP neural network, for any fault nodes increases the direct connection between it and the symptom of fault node (Wu *et al.* , 2012). Four kinds of common fault in the process of aluminum electrolysis are used for analysis:Anode effect Y1, heat sink Y2, cold sinkY3, rolled aluminum Y4. Features are cell resistance change rate $\delta_1$, aluminum electrolytic concentration$\delta_2$, slot voltage $\delta_3$, current variation$\delta_4$, temperature change$\delta_5$, slot voltage increment$\delta_6$, temperature$\delta_7$, current in the series $\delta_8$. The improved model as shown in Fig. 3.

The network is still using feedforward calculation equation, output of the node in the hidden layer:

$$O_j = f(\sum_i W_{ij} O_i + \theta_j) \tag{10}$$

Theoutput of the node in the output layer:

$$O_k = f(\sum_j W_{kj} O_j + \theta_k + \sum_1 u_{li}\delta_i) \tag{11}$$

where, $u_{li}$ is the direct connection coefficients of the input and output layers. For there is no connected nodes, $u_{li}$ is taken as 0. Network learning is still using the BP algorithm, where $W_{ij}$, $W_{kj}$ and the calculation equation and general BP algorithm, calculation equation for $u_{li}$:

$$u_{ij}^N = u_{ij}^O - \alpha\delta_j y_j (1-y_j)\delta_i + \eta\Delta u_{ij} \tag{12}$$

$\Delta u_{ij}$ modify the weight $U_{li}$ in the process of two iterations represents.

**Model of second level neural network:** Second level neural network is sub network, use the, Elman neural network is composed of input layer, hidden layer and output layer, structure layer. The model structure as shown in Fig. 4 (Amadou *et al.*, 2009):

- **Input layer:** The input layer is the role of the input signal distribution system. According to the aluminum electrolysis fault generated to determine the mechanism of its quantity
- **Output layer:** The output layer is the output of network fault diagnosis probability
- **Structure layer:** Recursive computation structure layer, hidden layer unit is output to the memory of time value, corresponding to the hidden layer neurons number, according to the number of neurons in hidden layer make the decision
- **Hidden layer:** These neurons to extract useful information from the input mode, approximating a function, make the network learning complex tasks better

$$x_c(k) = \alpha x_c(k-1) + x(k-1) \tag{13}$$

$$x(k) = \varphi\left[\sum_{j=1}^{n} \omega_{ki}\psi_i\left(\frac{u_i \bullet x(k) - b_i(k)}{a_i(k)}\right)\right] k = 1,\ 2...n;\ i = 1,\ 2,...\ m \tag{14}$$

$$y(k) = g(w^{13}(k)x(k)) \tag{15}$$

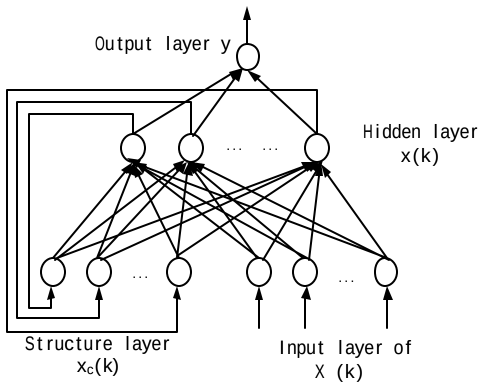


Fig. 4: Elman neural network

$$h(k) = w^{I1}(k)x_c(k) + w^{I2}(k)u(k) \tag{16}$$

Among them α the feedback gain factor;$W_{I1}$ is the connection weight matrix between contact unit and hidden unit;$W_{I2}$ is the connection weight matrix between input unit and hidden unit; $W_{I3}$ is the connection weight matrix between hidden layer unit and the output unit;g(•) is the output layer transfer function, in this study is a linear function, i.e.:

$$y(k) = w^{I3}(k)x(k) \tag{17}$$

Here, $\omega^{Ii}$ is the output of the neural network.

**Model of the third level neural network:** Third neural network is the fusion and decision network, Third neural network is the wavelet neural network, the output of the pre sub network as the input of the network (Kai and Ming, 2011). There are 5 fault diagnosis network, so the number of node in the input layer in decision fusion network is 5. In this study, use the wavelet neural network in the aluminum electrolysis fault fusion, sample data for training and testing all captured in the field data. The fault diagnosis of aluminum electrolysis are anode effect, cold trough, heat trough, rolling aluminum and composite fault. The number of the decision network output is 8. Fault categories corresponding to the various output is given in Table 1.

Fusion and decision network using wavelet neural network structure, its structure as shown in Fig. 5, is composed of input layer, hidden layer and output layer. The principle is as follows: first, the choice of wavelet functions, then the wavelet functions instead of Sigmoid in the hidden layer of BP network, then still using

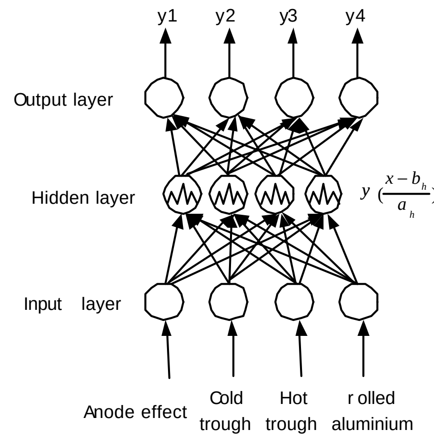


Fig. 5: Wavelet neural network

Table 1: Output value and the corresponding fault

| | Outout | | | |
|---|---|---|---|---|
| Classification of fault | $Y_4$ | $Y_3$ | $Y_2$ | $Y_1$ |
| Normal system | 0 | 0 | 0 | 0 |
| Anode effect | 1 | 0 | 0 | 0 |
| Cold trough | 0 | 1 | 0 | 0 |
| Hot trough | 0 | 0 | 1 | 0 |
| Rolling aluminum | 0 | 0 | 0 | 1 |
| Hot trough and Rolling aluminum | 0 | 0 | 1 | 1 |
| Anode effect and hot trough | 1 | 0 | 1 | 0 |
| Anode effect and cold trough | 1 | 1 | 0 | 0 |
| Anode effect and rolling aluminum | 1 | 0 | 0 | 1 |

correlation algorithm in BP network, linear superposition by wavelet basis function will be selected, thereby establishing a wavelet neural network.

## EXPERIMENTAL RESULTS AND NANALYSIS

Anode effect prediction simulation results as shown in Fig. 6.

Figure 6 for the fault diagnosis simulation curve of anode effect, electrolytic tank during normal operation, the cell voltage is about 4.2 V, we can know from the simulation curve, before18 min, didn't change obviously, electrolytic cell in normal working condition, at 18th min, slot voltage suddenly increased to 30 V, namely there are anode effect, at twentieth the cell voltage, return to normal working state, namely the anode effect fault release. The fault diagnosis model parameters, at about 15 min before the value of cell voltage, fault diagnosis model output Y1, Y2 and Y3 were compared in 0.0~0.2 change, stable, electrolytic cell in normal working condition; in 15-16 min Y1 output value increases, but not to fault prediction limit

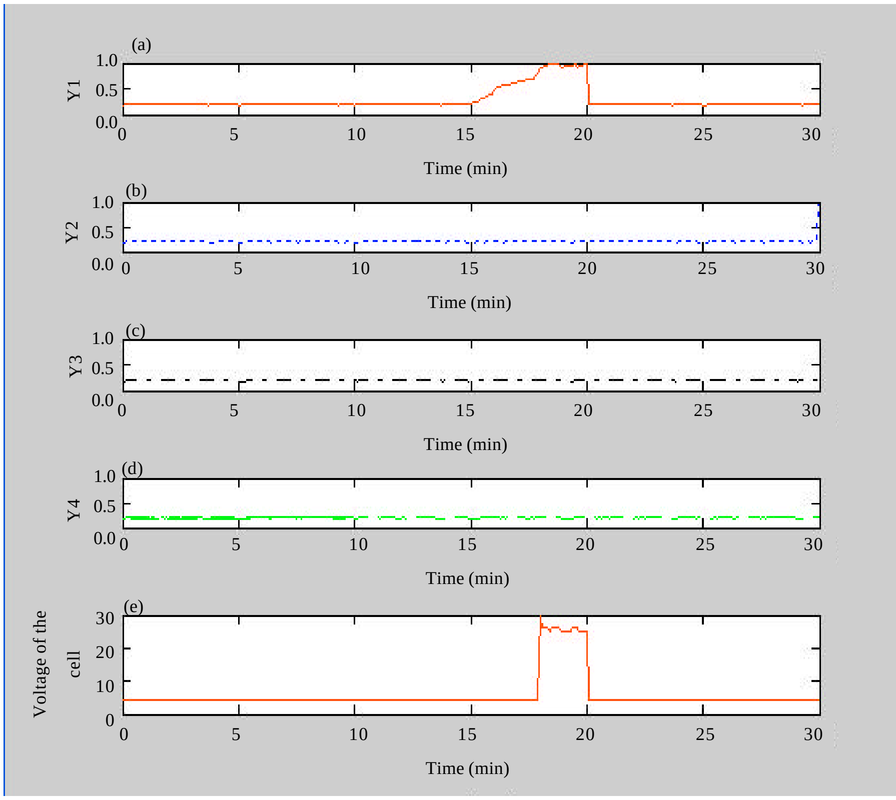


Fig. 6(a-e): Fault diagnosis simulation curve of anode effect

value, after 16th min the output value of the fault diagnosis model of Y1 is greater than 0.5, indicated that the effect of impending electrolyzer, can be used for the prediction of anode effect;at 18th min, the values of fault diagnosis model output Y1 above 0.9, close to 1, can be seen that the electrolytic cell has an anode effect, forecast ahead for about 2 min.

## CONCLUSION

This study using the principal component analysis, build thethree level network fault diagnosis network platform of the preliminary diagnosis network, sub network fault diagnosis nework, fusion and decision diagnosis network. Fusion the principal component analysis and neural network, wavelet and neural, sub network and decision information, Through the effective combination Realizate the aluminum electrolysis fault diagnosis, useing the ability of reduce the dimension of input, decoupling and nonlinear mapping of neural networks and the ability of learning and associative memory ability, make the fault diagnosis network has better fault-tolerant ability, logical reasoning ability and adaptive ability. The simulation results show that: the aluminum electrolysis fault diagnosis resrarch based on principal component analysis has the characteristic of large amount of ault forecast, verification the validity of the fault diagnosis method.

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