Research on aircraft burst fault diagnosis based on T-S fuzzy neural network

Hui Yang, Lijing Wang*, Zheng Deng

College of Computer Science and Technology, Civil Aviation University of China, No. 2898 JINBEI Road, Dongli District, Tianjin, China

Received 1 October, www.cmnt.lv

Abstract

Aircraft burst fault is uncertainty and ambiguity. Considering QAR data as the research object, the fault diagnosis system based on the T-S fuzzy neural network combined with aircraft maintenance processes is built. First, the system designs the network performance oversight function to improve genetic neural network program. Then the fuzzy logic is used to deal with fuzzy rules, which can determine the location and severity of fault. And the result proves that the system has strong ability to deal with the questions.

Keywords: aircraft burst fault, QAR data, fuzzy rules, genetic neural network algorithm, T-S fuzzy neural network

1 Introduction

QAR is used for recording flight parameters and working conditions of the various components of airborne equipment [1]. It is streaming data acquired from the sensor, and its sampling frequency is once every second. QAR record details of the true state about aircraft in flight, and the data provide a strong basis to the real-time status monitoring and fault diagnosis of the aircraft.

U.S. National Aeronautics and Space Administration (NASA) have developed APMS (Aviation Performance Measuring System) software to build a model to identify abnormal QAR data, which can found the problems in the mass flight data [2]. UK CAA research centre devote to the Insight FDM system for airlines flight data analysis [3]. However, QAR data are only invoked when the faults happen and need to be removed, resulting in the gradual deterioration of some minor malfunction and causing serious consequences.

This paper uses T-S fuzzy neural network for fault diagnosis, then processes the QAR data modularly according to the structure characteristics of T-S fuzzy neural network system. Firstly, the BP neural network is improved to solve its existing problems for processing data, then making use of the expert experience and knowledge to turn the expert's experience into fuzzy logic rules, and adding fuzzy logic system to the improved BP neural network. Due to the excessive number of the input fuzzy rules, which caused by the size of input attribute values, the parallel network structure is raised in the fault diagnosis of T-S fuzzy neural network. Thus, faults could be detected and repaired according to the discrimination of fault types and assessment of failure severity detected by the output data.

2 The structure of fault diagnosis system

2.1 RELATED PROPERTIES

QAR data has the following characteristics: the sampling frequency is once per second, and the amount of data is very large; meanwhile, the QAR data is strictly in accordance with time, so the relationship between data is strong; besides, the QAR data has many uncertain factors such as some interference. QAR records lots of attribute values, but only parts have close relationship when particular fault occurs.

Related properties of air turbulence and air parking are analysed according to attribute reduction method based on rough set [4] and the maintenance experience provided by airlines, and eight related attributes are statistical: EPR (engine pressure ratio), ALV (vertical acceleration), N1 (low pressure rotor speed), N2 (high pressure rotor speed), EGT (exhaust gas temperature), TAT (total temperature probe signal), V1 (N1 vibration) and V2 (N2 vibration).

2.2 SYSTEM STRUCTURE

Neural network has the advantages of parallel computing, the ability of self-learning and nonlinear mapping ability. The complex relationship between a given input to the desired output can be realized through the network. It has been widely used in processing time series data such as fund price predicting [5], stock trend prediction [6] and so on. But the neural network is not suitable to process expert knowledge based on rules, while ignoring the system of expert experience knowledge often have a lot of defects in engineering; and fuzzy logic is suitable for processing some fuzzy or uncertain knowledge, but it does not have the ability of adaptive learning [7].

***Corresponding author** e-mail: wljroom@163.com

Aircraft quick access recorder (QAR) stores complex and a large number of data. Simply using the BP neural network to detect the abnormal data presents some problems, such as network convergence instability, slow and low accuracy. Therefore, on the basis of BP neural network, we propose an improved genetic neural network. Because of the defect of improved neural network model in lacking of using the expertise knowledge to handle aircraft emergencies troubleshooting process, we introduce the T-S fuzzy neural network exploration to research aircraft fault diagnosis. Figure 1 shows the whole procedures.

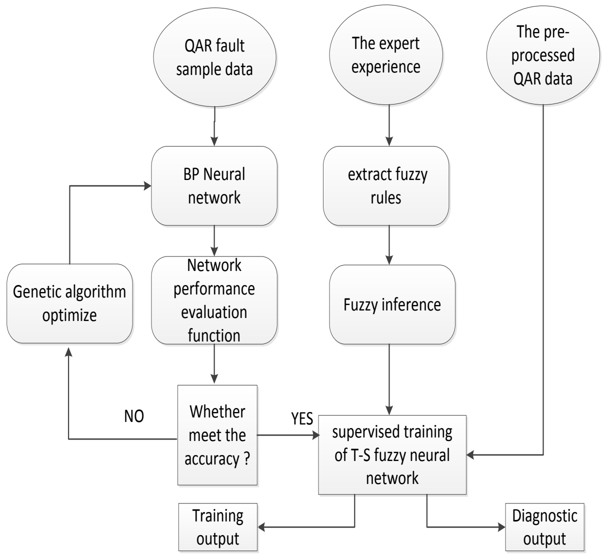

FIGURE 1 Fault diagnosis flow chart of T-S fuzzy neural network

3 Improved BP neural network algorithm

Back Propagation neural network is nonlinear mapping, parallel computing and self-learning [8]. However, simply using BP neural network to process fault QAR data has many problems such as the poor stability of convergence and low speed. As global search optimization algorithms, Genetic Algorithms is always used to improve BP neural network [9]. According to the characteristics of QAR data, we design a function to evaluate network convergence performance.

The network training times are divided into some parts with the same number, then calculating and recording the average error of each section, comparing the current average error with the last average error and the error setting before. If the current is greater than the set and less than the last, it shows that the internet has not yet reached saturation, continue training; if the current is greater than the set and equal to the last, it indicates that the network has been plunged into saturation, and genetic algorithms should be introduced. Terminate network training, extract weights and thresholds in BP neural network and encode as chromosome, which is used to form population with randomly generated chromosomes for genetic operation. The improved genetic neural network flow chart is shown in Figure 2.

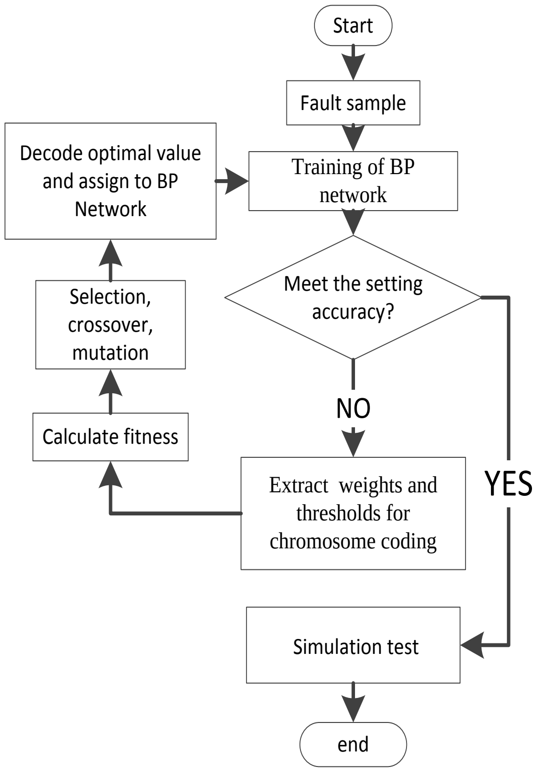

FIGURE 2 The process of improved genetic neural network

Based on the flow chart of improved genetic neural network, the steps of the algorithm can be designed for the diagnosis of QAR abnormal data.

1) Enter the eight values of air turbulence and air parking $X = \{x_1, x_2, \cdots x_8\}$, named EPR, ALV, N1, N2, TAT, EGT, V1 and V2, and the two kinds of output fault types are air turbulence and air parking. The appropriate number of neurons in the hidden layer based on empirical values and experiment is eight.

2) The input feature value is passed to the hidden layer neurons through the input layer neurons, and the transfer function is S-shaped function:

$$f(x) = 1/1 + e^{-ax}, \tag{1}$$

where a is the slope factor of S-function which can be adjusted freely. After calculation of hidden layer neurons function, we can get the output:

$$H_j = f\left(\sum_{i=1}^{8}\sum_{j=1}^{8} w_{ji} * X + \theta_j\right), \tag{2}$$

where w_{ji} is random initialization weights matrix between input layer and hidden layer; θ_j is random initialization threshold matrix of hidden layer neurons function, and the linear transfer function of output layer is:

$$\phi(x) = ax + b. \tag{3}$$

And the final output is:

$$O_k = \phi\left(\sum_{j=1}^{8}\sum_{k=1}^{2} \upsilon_{kj} * H_j + \theta_k\right), \tag{4}$$

where υ_{kj} is the random initialization weights matrix between hidden layer and output layer; θ_k is random initialization threshold matrix of output layer, and the total error is:

$$E = \frac{1}{2}\sum_{s=1}^{S}\left(O_s - T_s\right)^2, \tag{5}$$

where E is the sum of squared errors between the supervise values and the actual output value after sample data is trained, S is total number of the sample data, and the error back propagation algorithm named train is used.

3) Determine whether to use genetic algorithm to optimize BP neural network by the network performance evaluation function. Set the training times to n, $[1,n]$ represents the interval of training times, the value of n is set based on the sample size combined with the experiment, while the principle is to make the network speed as fast as possible. Training times will be divided as the same interval, and the quantity is $k = L/n$. $\bar{E}$ is the mean square error for each interval training of network, so

$$\bar{E} = E_1 + E_2 + \cdots + E_n / n. \tag{6}$$

Within such a range of k, we can obtain a row vector of error: $\left[\bar{E}_1 \quad \bar{E}_2 \quad \cdots \quad \bar{E}_k\right]$, for any two elements of the vector $\bar{E}_i$ and $\bar{E}_{i+1}$ $(i \in 1,2,\cdots,k)$, set $E_{trainerror}$ as error precision of network, if BP neural network training error satisfies the following Equation:

$$\begin{cases} \bar{E}_{i+1} > E_{trainerror} \\ \bar{E}_i > \bar{E}_{i+1} \end{cases}. \tag{7}$$

It means the BP neural network has not reached saturation point, continue training; if BP neural network training process error satisfies the following Equation:

$$\begin{cases} \bar{E}_{i+1} > E_{trainerror} \\ \bar{E}_i = \bar{E}_{i+1} \end{cases}. \tag{8}$$

It means the network reaches saturation and the error does not converge to the range of setting accuracy, then turn into the genetic algorithm optimization.

4) Terminate the train of BP neural network and extract the neural network weights and thresholds matrix when the neural network reached saturation. Do real number code according to the order of weight matrix of input layer to the hidden layer, the threshold matrix of hidden layer, weight matrix of hidden layer to the output layer and the threshold matrix of output layer, and the code can be expressed as

$$chrom = (w_{ji}\ \ \theta_j\ \ v_{kj}\ \ \theta_k). \tag{9}$$

Randomly generate the rest of the chromosomes to form the initial population.

5) Each chromosome is decoded as the BP neural network weights and thresholds, and the actual output of the network can be drawn from the sample data entered. The corresponding chromosome fitness is the reciprocal value of the sum of squares of the error between the actual output and the supervising:

$$f(i) = 1\Big/\frac{1}{2}\sum_{s=1}^{S}\left(O_s - T_s\right)^2, \tag{10}$$

where s is the number of samples. Crossover and mutate on population until genetic algorithm optimization process achieve the iteration times. Find out the chromosome with maximum fitness value, and decode the optimal chromosome as weights and thresholds matrix according to the inverse operation of encoding, then assigned the values to BP neural network, turn to steps 2 to continue training;

6) If the network converges, finishing the training, and the network can be used to QAR data detection; if not, turn to step 4).

4 Fuzzy neural network model

T-S model uses the consequent of fuzzy rules as function of the input linguistic variables [10]. In the fuzzy reasoning part of T-S network, fuzzy rules will exponentially grow with the input fuzzy partition number increasing. If fuzzy partition number is too many, it will result in the dimensionality curse of rules [5]. In order to reduce the difficulties, we set two T-S fuzzy neural networks apart for fault types. And the network framework is as follows:

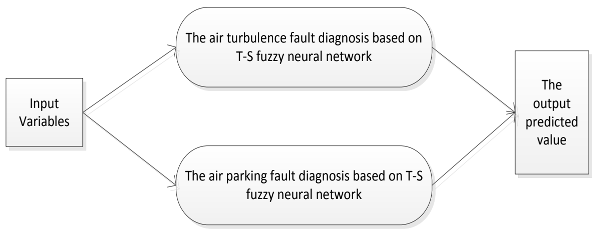

FIGURE 3 The overall design of the T-S network diagnosis system

We set air turbulence T-S fuzzy neural network as example to build network structure. The network structure is shown in Figure 4. Air parking T-S fuzzy neural network can be structured with the same approach of air turbulence, and then constitute a parallel network.

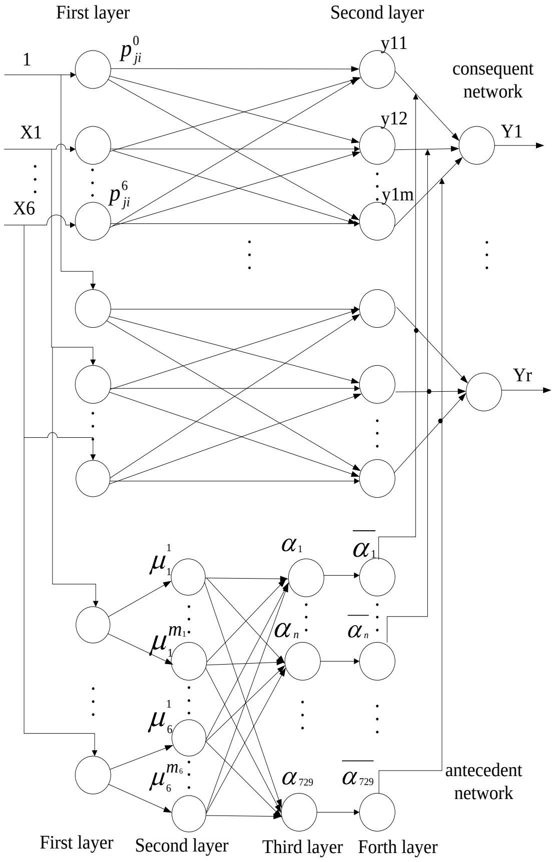

FIGURE 4 T-S network diagnosis structures

4.1 ANTECEDENT NETWORK

Antecedent network consists of four layers. The first layer is the input layer, and the input values $x=[x_1, x_2 ... \; x_6]^T$ represent 6 attribute values associated with air turbulence. The number of nodes in first layer is $N_1 = n$. At the second layer, each node represents a linguistic variable values, such as positive, zero, negative. Its role is to calculate the membership degree of the input component part $\mu_i^{S_i}$, where $\mu_i^{S_i} = \mu_{A_i^{S_i}}(x_i) \quad (i=1,2,\cdots,6; S_i = 1,2,3)$. Input dimension number is 6, and fuzzy division number of x_i is 3. Membership function is Bell-shaped represented by Gaussian functions.

$$\mu_i^{S_i} = \exp - \left\{ \frac{\left(x_i - c_{is_i}\right)^2}{\sigma_{is_i}^2} \right\}, \tag{11}$$

where C_{iS_i} and σ_{iS_i} denote the centre and the width of the membership function. The number of nodes in second layer is $N_2 = \sum_{i=1}^{n} m_i = 6 \times 3 = 18$. Each node of the third layer represents a fuzzy rule, and its role is to match the antecedent of the fuzzy rules and calculate the applicable of each rules. The value of a_j is

$$a_j = \min\left\{\mu_1^{S_{1j}}, \mu_2^{S_{2j}}, ..., \mu_n^{S_{nj}}\right\} \tag{12}$$

and the necessary value to calculate a_j is

$$\begin{cases} S_{1j} \in \{1,2,...,m_1\} \\ S_{2j} \in \{1,2,...,m_2\} \\ ... \\ S_{nj} \in \{1,2,...,m_n\} \\ j = 1,2,\cdots,m \\ m = \prod_{i=1}^{n} m_i = 3^6 = 729 \end{cases}. \tag{13}$$

The number of nodes in third layer is $N_3 = m = 729$. For the given input, only linguistic variables near it could have greater membership grade, and those far away from it have smaller values. Therefore only some nodes have greater output, which is equal to a local approximation network. The fourth layer has the same number of nodes as the third layer, $N_4 = N_3 = m = 729$. It mainly do normalized operation

$$\overline{\alpha}_j = \alpha_j \Big/ \sum_{i=1}^{m} \alpha, \; j = 1,2,\cdots,729. \tag{14}$$

4.2 CONSEQUENT NETWORK

This part is composed of parallel sub-networks, and the output is calculated through the network.

The first layer of sub-network is the input layer; it transfers the input variables to the second layer. The node No.0 has value $x_0 = 1$, and its role is to provide the constant term for consequent fuzzy rules. The nodes in the second layer represent fuzzy rules, and its role is to calculate consequents for each rule. The Equation is as follows:

$$y_{kj} = p_j^{k_0} + p_j^{k_1} x_1 + \cdots + p_j^{k_n} x_n = \sum_{l=0}^{n} p_j^{k_l} x_l, \tag{15}$$

where $k = 1,2,\cdots,r$; $j = 1,2,\cdots,m$; $x_0 = 1$.The third layer of sub-network is to compute system's overall output:

$$y_k = \sum_{j=1}^{m} \overline{\alpha}_j y_{kj}, \; (k = 1,2,\cdots r), \tag{16}$$

where y_k is the weighted sum of consequent rules, and the weighting coefficients is the connection weights of third layers of the antecedent network.

4.3 ALGORITHMS OF T-S NETWORK

Weights of the consequent network $p_{ji}^k \left(j=1,2,\cdots,729; \; i=1,2,\cdots,6; \; k=1,2,3\right)$, central value of membership function c_{ij} and width σ_{ij} $\left(i=1,2,\cdots,729; \; j=1,2,3\right)$ should be installed if the T-S fuzzy neural network is used, which could make the linear mapping from input to output complicated. Set the error cost function as follows:

$$E=\frac{1}{2}\sum_{k=1}^{3}\left(y_{dk}-y_{k}\right)^{2}, \tag{17}$$

y_{dk} and y_k are expected output value and actual output value. Learning algorithm of p_{ji}^{k}, c_{ij} and σ_{ij} is as follows:

1) Set weights between nodes in the network p_{ji}^{k}, central value of membership function c_{ij} and width σ_{ij} randomly.

2) Input the sample data of air turbulence, then train the network according to the following formulas:

$$\frac{\partial E}{\partial p_{jl}^{k}}=\frac{\partial E}{\partial y_{k}}\frac{\partial y_{k}}{\partial y_{kj}}\frac{\partial y_{kj}}{\partial p_{jl}^{k}}=-\left(y_{dk}-y_{k}\right)\overline{\alpha_{j}}x_{l}. \tag{18}$$

$$p_{jl}^{k}(t+1)=p_{jl}^{k}(t)-\beta\frac{\partial E}{\partial p_{jl}^{k}}=p_{jl}^{k}(t)+\beta\left(y_{dk}-y_{k}\right)\overline{\alpha_{j}}x_{l}. \tag{19}$$

$j=1,2,\cdots,m;\quad l=0,1,\cdots,n;\quad k=1,2,\cdots,r.$

$$c_{is_i}(k+1)=c_{is_k}(k)-\beta\frac{\partial E}{\partial c_{is_i}}, \tag{20}$$

$$\sigma_{is_i}(k+1)=\sigma_{is_i}(k)-\beta\frac{\partial E}{\partial\sigma_{is_i}}, \tag{21}$$

$i=1,2,\cdots,n;\quad s_i=1,2,\cdots,m^{i}\ ;\beta>0,$

and β is learning rate. Regulate the values of p_{ji}^{k}, c_{ij} and σ_{ij} with the formulas above. And set up a network error oversight function (Specific constructor of the function is described in Section 2.2.1). Monitor the error of output value.

3) If the error is reduced continuously in the setting times of training, then go on using the Equations in step 2 to calculate the error convergence. If the error keeps constant or has minor change in the setting times of training, suspend the network training process temporarily and introduce genetic algorithm to find the optimal values of p_{ji}^{k}, c_{ij} and σ_{ij}, then assign the values to the network node. Turn to step 2 and continue to train. If the error can reach to the setting precision, it means the network has finished training, stop the training process; if not, go to step 2 and continue training.

5 Experiments and analysis

According to maintenance experience and analysis of failure data, we sort out the six properties and the severity of fault associated with the air turbulence in Table 1. The severity of fault can be inferred through the level of air turbulence fault.

This experiment is designed with the MATLAB R2009a system. 800 groups of sample data collected from the B737-800 aircraft are used, while 750 groups are randomly selected as the training samples and the remaining 50 groups are testing samples. The training times is =1000. According to the repeated experiment, when the learning rate is 0.006, the network has the best effect, and the error precision of training is 0.01. Considering the influence of the uncontrollable factors, the simulation output values representing fault classification should be allowed to exist reasonable error, and the error range in this article is as shown in the Table 2.

TABLE 1 Division of property values and fault level

	Normal	Relatively normal	Slight	Relatively heavy	Heavy
Engine pressure ratio	1.45	1.3	1.2	1.1	1
Vertical acceleration (m/s2)	0.95	0.8	0.7	0.6	<0.5
VIB Vibration ()	0.5	0.4	0.3	0.2	<0.1
Low pressure rotor speed (r/s)	120	110	95	80	<65
High pressure rotor speed (r/min)	90	80	65	45	<25
Exhaust temperature (℃)	650	550	450	400	<400
Output value	1	2	3	4	5

TABLE2 The error range of simulation output

	Normal	Relatively normal	Slight	Relatively heavy	Heavy
Simulation output value (x)	0.5<x<1.5	1.5<x<2.5	2.5<x<3.5	3.5<x<4.5	4.5<x<5.5

Air turbulence fault experiment is done according to the given data and T-S fuzzy neural network system. After experiments, we find that when the training times is 33~56, the error can reach the setting precision. Select the data which could reach the precision within 40 times, and draw an error graph as shown below:

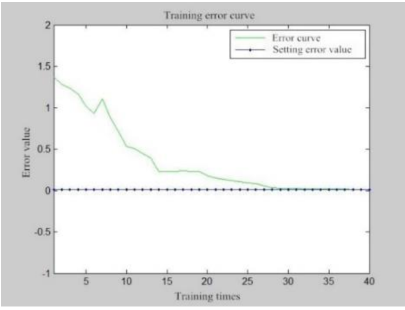

FIGURE 5 Training error curve

The picture is taken from an intermediate value after many training times. As shown in the figure, there is a smooth curve at 15-20 times in the process of training, and the network turns into the genetic algorithm optimization process through the network supervision function, then continue to train after the parameters are optimized until reach the setting error precision value. In order to test the rationality and validity of fault diagnosis system, 50 groups of sample data are used, and the results are as shown below:

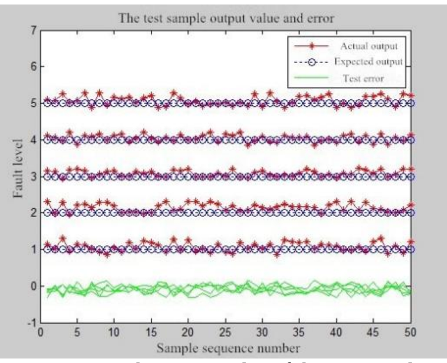

FIGURE 6 The output value of the test sample

As we can see, the result is in the permitted error, and the system can predict fault severity well, which can provide decision support and guidance for the repair. It also reaches our expectation.

6 Conclusions

In this paper, the aircraft faults warning system based on QAR data is realized. The system includes two fault diagnosis subsystems, air turbulence and air parking. Fault models based on QAR data and QAR outlier detection algorithm has been researched and realized. The parallel double network thought has been referred to separate the experimental data and import them to different fault diagnosis sub-system, which greatly simplifies the increasing quantity of fuzzy rules with the input. At the same time, the network training algorithm based on improved genetic algorithm is introduced into the antecedent and consequent parameters in the network training adjustment. The experimental results show that the algorithm has a good effect on sudden fault. It can diagnose the fault type and severity of aircraft effectively.

Because of the complexity of QAR data and information, only two fault types are built, and the fault models combine technical data with expert experience provided from airlines. Whether we need to build more models should be further studied.

Acknowledgments

The research work was supported by The National Natural Science Foundation of China and Chinese aviation jointly funded project No. 61179063.

References

[1] Lin C 2011 QAR principle analysis and application in aircraft maintenance *Jiangsu Aviation* **1** 36-7 (*in Chinese*)

[2] McCown G D, Patricia M, Conway, T J, Jessen K M 1991 *Methods and Apparatus for Monitoring System Performance* USA 5067099

[3] Knotts R M H, Exeter M A 1999 Civil aircraft maintenance and support Fault diagnosis from a business perspective *Journal of Quality in Maintenance Engineering* **5**(4) 335-48

[4] Li Y, Zhu S, Chen X, Zhang D, Han Z 1999 Data mining model based on rough set theory *Tsinghua Univ (Sci &Tech)* **39**(1) 110-3 (*in Chinese*)

[5] Xiao G 2011 Application Research of Fund Net Value Prediction Based on BP Neural Network *Computer simulation* **28**(3) 373-6

[6] Wang W, Chen L 2012 Modeling and Simulation of Stock Price Prediction *Computer simulation* **29**(1) 344-7

[7] Wang L, Guo Y 2010 T-S Fuzzy Neural Network Based Control of Accelerating Process of Turbo-fan Engine *Computer simulation* **27**(2) 26-9

[8] Zhang P, Wang Y, Fan S 2009 Civil Aviation Aircraft Fault Diagnosis Research Based GA and BP Net *Microcomputer Information* **25**(7) 110-2

[9] Li S, Liu L, Xie Y 2011 Chaotic prediction for short-term traffic flow of optimized BP neural network based on genetic algorithm *Control and Decision* **26**(10) 1581-5

[10] Ke Y, Xie B, Wu Qing 2012 The Vehicle Fault Diagnosis Research Based on T-S Model Fuzzy Neural Network *Journal of Hangzhou Dianzi University* **32**(2) 41-4 (*in Chinese*)

Authors

Hui Yang, born in 1957, Tianjin, China

Current position: professor.
Research direction: artificial intelligence, data mining and fault diagnosis.
Publications: many articles and a book.

Lijing Wang, born in 1990, Hebei, China

Current position: graduate student in the Civil Aviation University of China.
University studies: artificial intelligence, data mining and fault diagnosis.
Scientific interest: fault diagnosis.
Publications: 1 paper.

Zheng Deng, born in 1987, Henan, China

Current position: graduate student.
University studies: artificial intelligence, data mining and fault diagnosis.
Scientific interest: fault diagnosis.
Publications: 1 paper.