Journal of Computers Vol. 33 No. 1, February 2022, pp. 179-188
doi: 10.53106/199115992022023301016

Research for Fault Diagnosis Method and System for Diesel Engine Based on ANFIS

Ying-Ji Liu[1,2*], Qi-Hang Wang[1,2], Hai-Ying Xia[1,2], Xin-Lei Wei[1,2], Hong Jia[1,2], Guo-Liang Dong[1,2]

[1] Key Laboratory of Operation Safety Technology on Transport Vehicles, Ministry of Transport
[2] Research Institute of Highway, Ministry of Transport
Beijing 100088, China
{yj.liu, wang.qh, hy.xia, xl.wei, h.jia, gl.dong}@rioh.cn
Received 1 December 2021; Revised 2 January 2022; Accepted 2 February 2022

Abstract. After compliance verification, operating vehicles can enter the road transportation market. Diesel engine is the main power source of these vehicles, there will be some typical faults during the use of diesel engine, which will affect the technical status of vehicles. According to the fault diagnosis problem of diesel engine, a fault diagnosis method based on Adaptive-Network-Based Fuzzy Inference System(ANFIS) was proposed, Subtractive clustering algorithm was used to confirm the original structure of fuzzy inference model, and ANFIS was used to build an original fault diagnosis model of diesel engine. Hybrid algorithm is used to train the parameter of fuzzy rule, and the final model is established. Simulation experiment results show that the modeling algorithm based on subtractive clustering-ANFIS is effective. It has been found that the average error is 7%, the recognition accuracy is 93.33%. Simulation results show that the fitting ability, convergence speed and recognition accuracy of ANFIS model are all superior to back propagation neural networks (BPNN), and much more suitable as diesel engine fault diagnosis model. Finally, an effective fault diagnosis system is developed by using the given method.

Keywords: adaptive-network-based fuzzy inference system, diesel engine, fault diagnosis, subtractive clustering, hybrid algorithm

1 Introduction

At present, in China, after the verification of the road transport vehicles if they meets the relevant national standards, these vehicles will obtain relevant qualifications for carry out road transport business. As shown in Fig. 1. In the process of road transportation, diesel engine is a power equipment widely used by a large number of road transportation vehicles. How to ensure its safe and reliable operation is directly related to the safety of equipment and personnel, as well as the economic interests of the user department. It is also an important part to ensure that the technical conditions of specific vehicles meet the requirements of road transportation. Therefore, fault diagnosis has important economic significance and social benefits for improving the use safety of diesel engine, reducing pollution, saving maintenance cost and reducing energy consumption. The intake and exhaust system of diesel engine is one of the most fault prone parts of internal combustion engine, especially the valve, which often bears the impact of high temperature and high-speed air flow, so the working condition is bad. if the main faults such as abnormal of valve clearance and air leakage cannot be identified and handled in time, it will seriously affect the working performance of diesel engine. Therefore, how to collect diesel engine operation state information, extract fault features, analyze and judge whether each component is in or about to be in what fault state, it has always been the research focus of diesel engine fault diagnosis method [1].

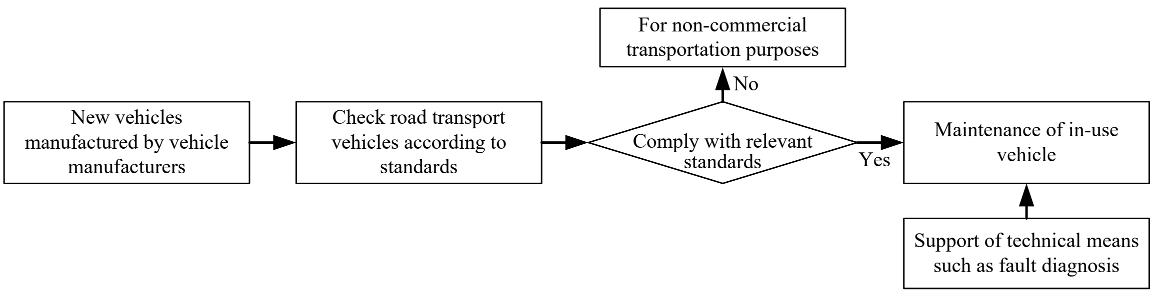


Fig. 1. Transformation process of vehicles for commercial transportation

* Corresponding Author

At present, artificial neural network and fuzzy theory have been widely used in the fields of equipment fault diagnosis and intelligent prediction and analysis [2]. Fuzzy logic system has the ability to summarize and extract prior knowledge, while neural network has good learning and induction ability for unknown characteristics. Adaptive-Network-Based Fuzzy Inference System (ANFIS) can organically combine the characteristics of the two. It has the characteristics of approaching nonlinear functions with arbitrary accuracy, fast convergence and strong generalization ability [3]. In this paper, a diesel engine fault diagnosis model is established based on ANFIS, and the subtractive clustering method is introduced to adaptively determine the initial structure and parameters of the fuzzy system to eliminate randomness and blindness; In order to improve the efficiency of parameter optimization, the hybrid learning algorithm [4-10] combining the least square method and gradient descent algorithm is used to test the recognition accuracy and other performance of the model by using the specific diesel engine fault test data, and the identification results are compared with the BP network model.

2 Fault diagnosis model

Fault diagnosis is mainly based on the prompt information generated by all kinds of equipment, the change of equipment operation state and the analysis of fault characteristics, so as to judge the possible occurrence and type of fault. Based on the existing models, this paper proposes a modeling method based on subtractive clustering and ANFIS.

Fault diagnosis can be divided into two processes. Stage I is the training and learning process: after preprocessing the collected original training samples, firstly, subtractive clustering is used to determine the number of membership functions and rules of system input and output variables, and then the established ANFIS model is further input for learning, and the results are stored in the fault history information database; Stage II is the real-time fault diagnosis process: input the operation status information collected from the equipment in real time into the model, then the fault history knowledge is used for comparison, and directly give the diagnosis results if it is the existing knowledge. Otherwise, input the ANFIS model for learning to obtain the knowledge of new fault types and store it in the knowledge base for the diagnosis of new types of faults. Finally, follow-up processing and early warning are carried out according to the fault identification results.

3 Whole cycle symptom extraction of cylinder head vibration signal based on wavelet packet decomposition

In order to diagnose the fault of intake and exhaust system of 295 diesel engine, wavelet packet decomposition is used to extract the fault symptoms of the whole cycle from the vibration signal of diesel engine cylinder head. Firstly, a discrete sampling sequence in a complete working cycle is obtained by using of the synchronous sampling method, and the sampling length is $L=2^M$. This sequence is decomposed by n-layer wavelet packet decomposition to obtain the wavelet packet decomposition coefficients of each sequence in this layer. These coefficients are arranged into a matrix of 2^N rows and 2^{M-N} columns. The elements are marked as $a_{m,n}$, and the subscript m represents the position of the wavelet packet, corresponding to a section of crankshaft angle; Subscript n represents the wavelet packet sequence number, corresponding to the linearly divided frequency band [1].

Assuming that the sampling frequency of the original signal is f_s and according to the sampling theorem, the highest analysis frequency is $f_{max}=f_s/2$, then the frequency band corresponding to the wavelet packet decomposition with sequence number n is ($nf_{max}/2^N$, $(n+1)f_{max}/2^N$), then the whole cycle diagnosis eigenvector $\{A(\theta_m)\}$ can be defined as:

$$\{A(\theta_m)\} = \sum_{n=J_1}^{J_2} a_{m,n}^2 \qquad m = 0,1,\cdots,2^{M-1}-1 \cdot \tag{1}$$

J_1 and J_2 are characteristic frequency bands. Or select elements from the matrix $\left[a_{m,n}^2\right]$ to form a characteristic matrix.

After using the above method to extract the corresponding feature vector $\{A(\theta_m)\}$, considering the cyclic fluctuation characteristics of vibration signal, the parameter average method is used to improve the accuracy of feature vector. Therefore, the average value of $\{A(\theta_m)\}$ is selected as the final eigenvector to train and test the neural network and fuzzy Inference system.

4 BP model about extracting feature vectors based on interval wavelet packet decomposition

Under the fault state of the intake and exhaust system of 295 diesel engine, the cylinder head vibration signals of 36 cycles process are obtained respectively. After wavelet noise reduction and wavelet packet decomposition, the feature vectors are extracted. Considering the cyclic fluctuation characteristics, the parameter average method is used for taking the mean value of the feature vectors of every four cycles, the feature vectors of each working condition is processed, and finally 9 groups of feature vectors are obtained under each working condition [1]. A total of 45 groups of eigenvectors under 5 working conditions are used as the training samples of neural network. The test samples are randomly selected from the 36 groups of eigenvectors before averaging, and 4 groups are averaged. Some training data and test data obtained are shown in Table 1 and Table 2.

Input test samples to verify the generalization ability of BP network, some comparison results is shown in Table 3. The meaning of each output value in the table is: 1 - normal state; 2 - the clearance is too small; 3 - the clearance is too large; 4 - air leakage of exhaust valve; 5 - air leakage of intake valve.

The simulation results show that there is misjudgment in the diagnosis results of BP network model, and the error between the output value and the expected value is large, which cannot achieve a good fault discrimination effect. Through 100 simulation tests, it is found that the output value is unstable. Through statistical calculation, the average diagnostic accuracy of the model is 73.33%.

Table 1. Training samples extraction of vibration signal with wavelet packet decomposition (part)

Operating conditions	Network input (eigenvector)								Network output
	A30	A42	A43	A44	A45	A46	A47	A11	
normal state	2.155	1.807	2.179	2.339	1.011	1.377	0.824	2.560	1 0 0 0 0
	2.025	1.464	2.275	2.445	1.069	1.395	0.927	2.546	1 0 0 0 0
the clearance is too small	2.486	1.686	2.450	1.707	1.605	1.936	1.120	3.482	0 1 0 0 0
	2.951	1.760	2.420	1.971	1.581	1.883	1.070	3.355	0 1 0 0 0
the clearance is too large	2.611	1.270	1.865	1.913	1.411	1.463	0.640	2.839	0 0 1 0 0
	2.308	0.890	1.870	1.733	1.068	1.318	0.489	2.106	0 0 1 0 0
air leakage of exhaust valve	1.655	1.106	2.089	1.596	1.246	1.389	0.728	2.594	0 0 0 1 0
	1.991	1.476	3.123	1.867	1.675	1.733	0.847	3.071	0 0 0 1 0
air leakage of intake valve	1.817	8.163	2.524	1.718	1.280	1.646	0.648	2.501	0 0 0 0 1
	2.148	1.316	2.308	2.111	2.054	2.389	0.691	3.510	0 0 0 0 1

Table 2. Training samples extraction of vibration signal with wavelet packet decomposition (part)

Sample number	Operating conditions	Network input (eigenvector)							
		A30	A42	A43	A44	A45	A46	A47	A11
1	normal state	2.092	1.439	2.330	2.626	1.016	1.440	0.902	2.512
2		2.211	1.894	2.272	2.777	1.492	1.682	1.061	2.881
3	the clearance is too small	2.760	1.805	2.203	1.813	1.664	1.798	1.023	3.265
4		2.233	1.420	1.983	1.519	1.284	1.833	1.091	3.122
5	the clearance is too large	2.707	1.172	2.080	2.013	0.994	1.259	0.559	2.255
6		2.545	1.300	2.137	2.240	1.651	1.823	0.635	2.952
7	air leakage of exhaust valve	1.784	1.299	2.193	1.613	1.305	1.540	0.731	2.636
8		2.132	1.541	3.380	2.410	1.459	1.986	0.919	3.333

9	air leakage of intake valve	1.892	0.902	2.459	1.804	1.274	1.733	0.654	2.512
10		2.247	1.732	2.576	2.345	2.430	3.024	0.703	3.787

Table 3. Fault diagnosis results of BP network (part)

Expected output	BP network model output					BP diagnostic results
	normal state	the clearance is too small	the clearance is too large	air leakage of exhaust valve	air leakage of intake valve	
1	0.4152	0.1470	0.2329	0.1894	0.1883	1
1	0.5465	0.0946	0.0889	0.0827	0.2594	1
2	0.1570	0.0700	0.0251	0.3115	0.0549	4
2	0.1167	0.0331	0.0786	0.1051	0.0865	1
3	0.1656	0.0401	0.6456	0.0889	0.1689	3
3	0.2395	0.0426	0.5097	0.0740	0.2211	3
4	0.1227	0.2265	0.0609	0.6697	0.1050	4
4	0.1232	0.1704	0.1052	0.5976	0.1090	4
5	0.2182	0.1656	0.4047	0.4758	0.0999	4
5	0.2821	0.0826	0.1852	0.1195	0.5245	5

5 Engine fault diagnosis model based on Adaptive-Network-Based Fuzzy Inference System

In this paper, ANFIS is used to establish the fault diagnosis model of diesel engine. The model uses the parameter and structure training method of neural network to realize the self-learning and self-adaptive of fuzzy system, with strong generalization ability and fast convergence speed. In order to simplify the ANFIS model and improve its learning rate and output accuracy, the subtractive clustering method is applied to the establishment process of the model.

5.1 Principle of Adaptive-Network-Based Fuzzy Inference System

ANFIS proposed by Jang is a Sugeno fuzzy system [2-3, 5-10]. For a typical Sugeno fuzzy system with multiple inputs and single outputs, the fuzzy reasoning rules are:

$$\begin{aligned} &R^i:\ IF\ x_1\ is\ A_1^i \wedge x_2\ is\ A_2^i \wedge \cdots \wedge x_m\ is\ A_m^i, \\ &THEN\ y^i = f_i(X) = b_0^i + b_1^i x_1 + \cdots + b_m^i x_m \quad . \end{aligned} \tag{2}$$

Where A_j^i is the fuzzy set, b_j^i is the true value parameter, $f_i(X)$ is the output obtained by the system according to the rules, $i=1, 2,\ldots, n$; $j=1, 2,\ldots, m$.

Sugeno model has the function of approaching linear and nonlinear function with any accuracy, and has fast convergence speed and less sample size.

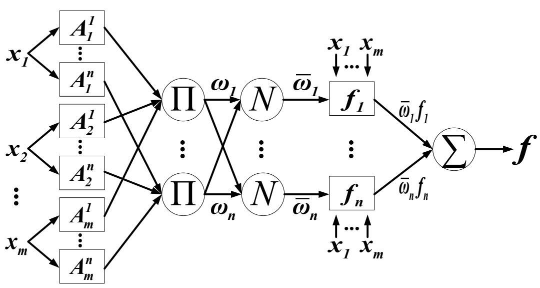


Fig. 2. Structure of ANFIS

According to equation (2), assuming that the system has m inputs x_1, x_2, ..., x_m, and the single output can be represented by a set composed of n fuzzy rules of “If-Then”, the corresponding ANFIS structure is shown in Fig. 2.

The network structure of ANFIS is divided into five layers: membership function generation layer, rule reasoning layer, fuzzification layer, defuzzification layer and output layer. The contents of each layer are as follows.

(1) The input variable is fuzzified and the membership degree of the corresponding fuzzy set is output. The transfer function of each node is expressed as:

$$O_{1,i} = \mu_{Aj}^{k}(x_j) \cdot \tag{3}$$

Among them, $j = 1, 2, \cdots, m$; $k = 1, 2, \cdots n$; $i = n \times m$, $O_{1,i}$ is the membership function of fuzzy set, and Gaussian function is selected.

$$\mu_{Aj}^{k}(x_j) = \exp[-(x_j - c_j^k)^2 / 2(\sigma_j^k)^2] \cdot \tag{4}$$

Where, μ_{Aj}^{k} is the membership function; x_j is the input of the node c_j^k , $ó_j^k$ are the center and width of the membership function respectively, which are called premise parameters. By adjusting these parameters, the shape of the membership function will change; j is the number of layers which the membership function belonged, and k is the number of nodes in the layer.

(2) the multiplicative rule is used to calculate the applicability of each rule.

$$O_{2,j} = \omega_i = \prod \mu_{Aj}^{i}(x_j) \cdot \tag{5}$$

Among them, $j = 1, 2, ..., m$; $i = 1, 2, ..., n$.

Each node in this layer is a fixed node labeled Π. The output of this layer is not necessarily in the form of product, but can also be other operators representing fuzzy and other. Through this calculation, the activation intensity of each fuzzy rule is determined.

(3) Calculate the normalized value of applicability.

$$O_{3,i} = \bar{\omega}_i = \omega_i / S, \; S = \sum \omega_i \quad i = 1, 2, \cdots, n \; . \tag{6}$$

Each node of this layer is a fixed node labeled N.

(4) Calculate the output of each rule.

$$O_{4,i} = \bar{\omega}_i f_i \quad i = 1, 2, \cdots, n \; . \tag{7}$$

The barycenter method is used for weighted summation, and b_j^i is the conclusion parameter. By self adjusting these parameters, the fuzzy rules can be changed accordingly, and each node of this layer is an adaptive node.

(5) This layer is the defuzzification layer of the diagnosis result. This layer has only one node. The circular node marked in the figure with” $\sum$ ”, and its output is the sum of all input signals, that is, the result of fuzzy reasoning. Namely

$$O_{5,i} = \sum \bar{\omega}_i f_i = \sum \omega_i f_i / S \quad i = 1, 2, \cdots, n \; . \tag{8}$$

$O_{1,i}$ represents the output of the ith node of the first layer, where f_i is the set operator of each layer of the fuzzy neural network.

From equations (2) to (8), the multi input single output model of the system can be transformed into the following functional expression:

$$\begin{aligned} y &= \left[\sum_{i=1}^{n} f_i(X) \prod_{j=1}^{m} \mu_{Aj}^{i}(x_j) \right] \Big/ \left[\sum_{i=1}^{n} \prod_{j=1}^{m} \mu_{Aj}^{i}(x_j) \right] \\ &= \left[\sum_{i=1}^{n} f_i(X) \exp\left[-\sum_{j=1}^{m} \frac{(x_j - c_j^k)^2}{2(\sigma_j^k)^2} \right] \right] \Big/ \left[\sum_{i=1}^{n} \exp\left[-\sum_{j=1}^{m} \frac{(x_j - c_j^k)^2}{2(\sigma_j^k)^2} \right] \right] . \end{aligned} \tag{9}$$

The premise parameters and conclusion parameters are unknown parameters. Using the hybrid algorithm to train ANFIS, these parameters can be obtained according to the specified training indexes, and then the fuzzy model can be established.

5.2 Principle of Adaptive-Network-Based Fuzzy Inference System

In order to improve the speed and quality of learning, the model parameters are decomposed into nonlinear premise parameters and linear conclusion parameters, and the hybrid algorithm is used for parameter optimization [3-10].

Firstly, the premise parameters are fixed, and the linear least squares estimation algorithm is used to optimize the conclusion parameters of the neural network. Make equivalent transformation to formula (9) to separate the conclusion parameters:

$$\begin{aligned} y = f(X) &= \phi_0^1(X)b_0^1 + \phi_1^1(X)b_1^1 + \cdots + \phi_m^1(X)b_m^1 \\ &+ \cdots + \phi_0^n(X)b_0^n + \phi_1^n(X)b_1^n + \cdots + \phi_m^n(X)b_m^n \end{aligned} \quad . \tag{10}$$

Where, $\phi_e^i(X) = (x_e \prod_{j=1}^{m} \mu_{Aj}^i(x_j)) \Big/ (\sum_{i=1}^{n} \prod_{j=1}^{m} \mu_{Aj}^i(x_j))$, n is the number of fuzzy rules, m is the number of input variables, x_0=1. Further, formula (10) can be simplified as:

$$y = \phi^T(X)D \quad . \tag{11}$$

Where $\phi(X)$ and D are vectors of $(n+1)m \times 1$.

When there are n sample points $(X(t), y(t))$ $(t = 1, 2, \cdots, N)$, the system output is:

$$\hat{Y} = \phi D \quad . \tag{12}$$

Where ϕ is the matrix whose size is $N \times (n+1)m$. Let the error index function be $J(D) = 1/2\|Y - \phi D\|^2$, according to the principle of least square method, to minimize $J(D)$, there must be:

$$D = \left[\phi^T \phi\right]^{-1} \phi^T Y \quad . \tag{13}$$

In the second step of parameter optimization, the conclusion parameters are fixed, and the error back propagation algorithm with gradient descent is used to train the premise parameters.

Take the error function as:

$$E = 1/2 \sum_{t=1}^{N} (y(t) - \hat{y}(t))^2 \quad . \tag{14}$$

Then the premise parameters of training are expressed as:

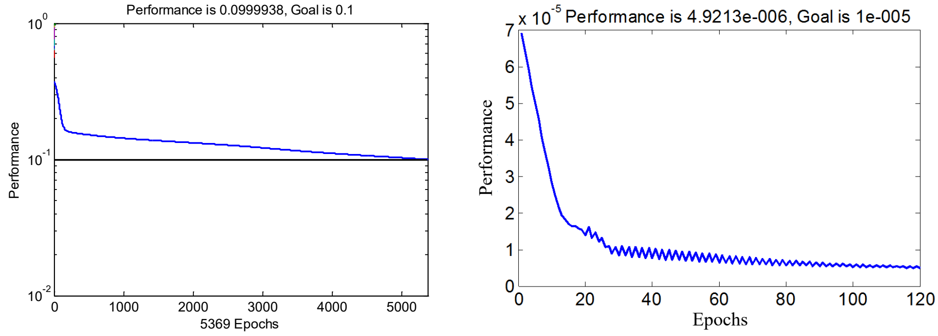
$$c_j^k(p+1) = c_j^k(p) - \beta \frac{\partial E}{\partial c_j^k} \quad . \tag{15}$$

$$\sigma_j^k(p+1) = \sigma_j^k(p) - \beta \frac{\partial E}{\partial \sigma_j^k} \quad . \tag{16}$$

Where $\beta > 0$ is the learning rate.

5.3 Examples of diesel engine fault diagnosis

Based on the complete training data and test data listed in Table 1 and Table 2, the fault diagnosis model is established by using ANFIS. The training simulation results are shown in Fig. 3(b).



（a） BPNN （b） ANFIS

Fig. 3. Simulation result of ANFIS model with wavelet packet decomposition and BPNN

It can be seen from Fig. 3 that under the approximation requirement of minimum error, BP neural network and subtraction clustering ANFIS model all tend to converge. But the BP neural network reaches the error value of 0.0999938 after 5369 training, while the subtractive clustering ANFIS model can converge the error to 8.83233×10^{-6} after the 28th training. The selection of the number of nodes in the rule layer of BP network needs experience, and once the structure is determined, it will not be adjusted, which may lead to differences between the actual structure of data and the structure selected by experience; Subtractive clustering automatically selects the appropriate number of membership functions and rules on the actual data, and uses the least square algorithm and back-propagation algorithm to train the parameters at the same time. It eliminates the adverse effects of human factors and makes full use of the characteristics of the two algorithms in parameter adjustment. Through the comparison of various indexes in Table 4, it can be seen that ANFIS model is superior to BP network model in training speed, fitting ability and convergence.

Table 4. Comparison between training results of ANFIS and BPNN

Network type	Training steps	Training time	Error accuracy	Output	Accuracy
ANFIS	120	2.4413s	4.9213×10^{-6}	stable	93.33%
BP	6747	24.8877s	9.99938×10^{-2}	unstable	73.33%

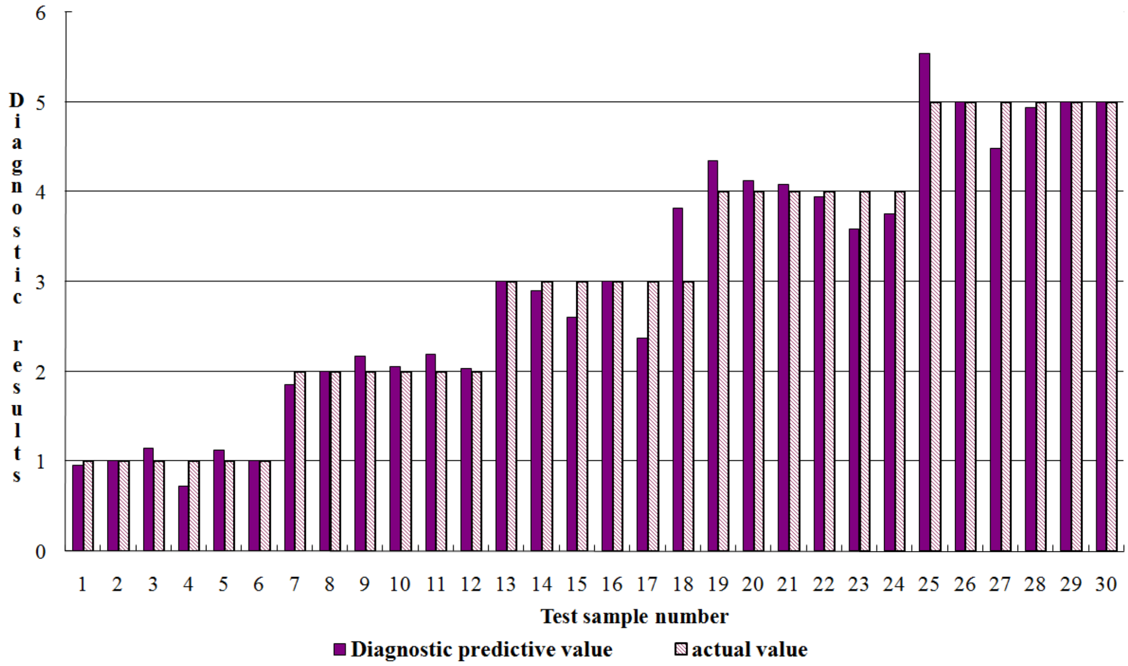


Fig. 4. Comparison of diagnosis prediction and actual fault

The comparison between the actual value and the predicted value for fault diagnosis by subtractive clustering ANFIS model is shown in Fig. 4. By calculating the predicted value of a single sample, the maximum error is 28.04%, the minimum error is 0.0005%, and the average error is 7%. The diagnostic accuracy of the model reaches 93.33%, and the output value is stable. The actual value is in good agreement with the diagnosis predicted value. It shows that taking the characteristic value of diesel engine vibration signal as the input, the established ANFIS model has better fault diagnosis ability than BP neural network model, which further proves the applicability of ANFIS in fault diagnosis.

6 Development and application of fault diagnosis system

In order to effectively use and verify the fault diagnosis method based on artificial intelligence proposed in this paper, a set of engine monitoring and fault diagnosis system software is designed and developed by using MATLAB language and its GUI development tool based on visualization technology, as shown in the Fig. 5. The fault diagnosis process becomes visual and systematic.

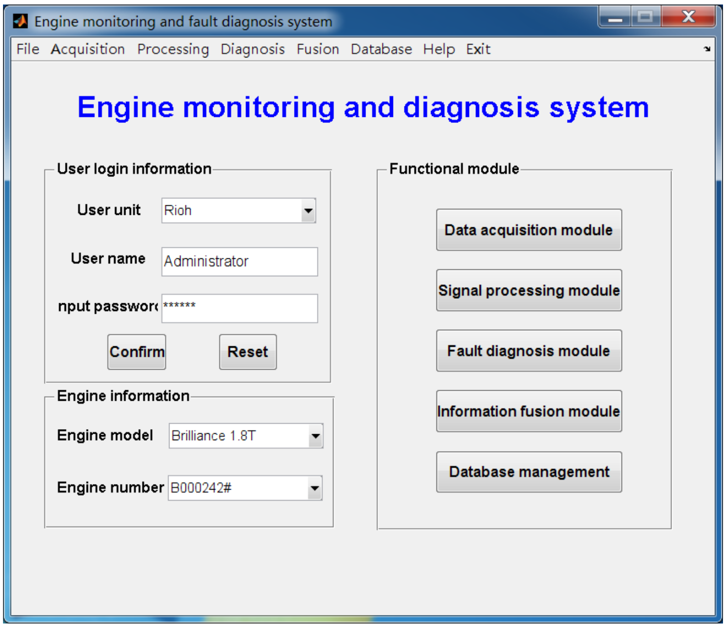


Fig. 5. Engine monitoring and fault diagnosis system software

The system includes data acquisition, signal processing, fault diagnosis, information fusion and other functional modules. The fault diagnosis module integrates diagnosis models such as BP network, RBF network and adaptive fuzzy inference system, and can realize the training of various models with feature vectors according to the set parameters. The trained model is used to diagnose the diagnostic samples, display the diagnostic results and relevant instructions, and store the diagnostic results in the database. If the system receives the standard signal of a new fault type, after signal processing, combined with the sample data extracted from the historical fault database, it enters existing diagnostic models for training. The new data can be used to train and correct the network, so that the system can form the diagnostic ability for this new fault. For example, the adaptive fuzzy inference system's diagnosis sub module and modeling subroutine are shown in Fig. 6. Meaning of fault code in the figure: such as "DC004", in which the first letter "d" indicates diagnosis; The second letter "C" indicates data acquisition based on CAN bus mode. If "V" here indicates data acquisition based on vibration signal mode; The remaining numbers "004" represent order number of the fault, and the corresponding in the text represents the cavitation fault of the water pump. At the same time, the system can give the main causes of the corresponding fault, maintenance methods and suggestions.

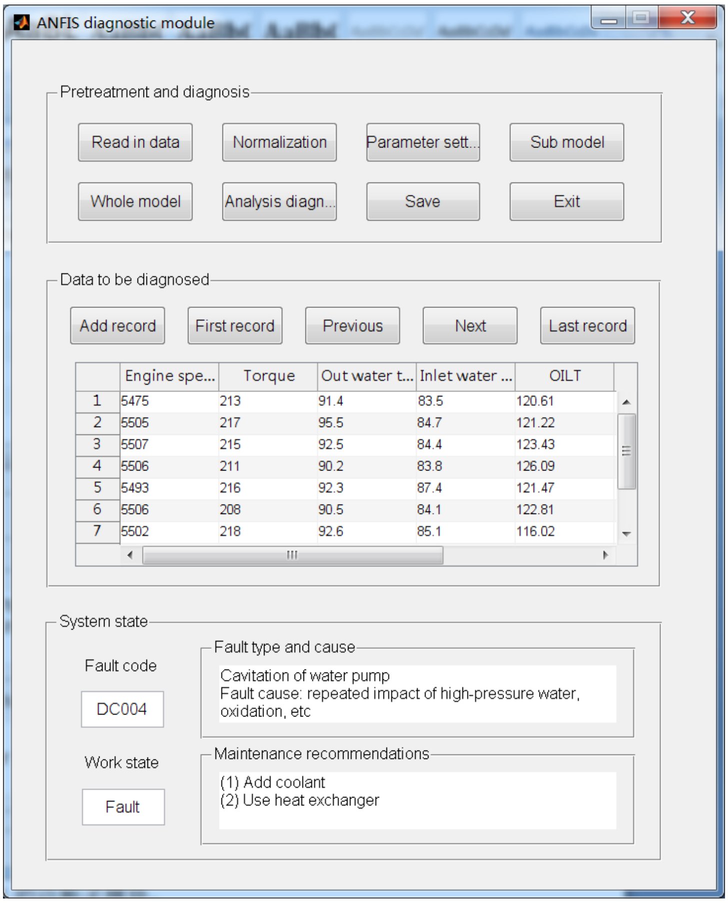


Fig. 6. Diagnostic sub module based on ANFIS

7 Conclusion

Aiming at the complex nonlinear relationship between diesel engine fault characteristic information and fault type, this paper proposes a diesel engine fault diagnosis modeling method based on subtractive clustering and ANFIS by using two abilities of Adaptive-Network-Based Fuzzy Inference System, one is to deal with deterministic and uncertain information at the same time, another is dynamic nonlinear analysis. The simulation verification by using the fault characteristic data of diesel engine intake system shows that the fault diagnosis accuracy and convergence speed of subtractive clustering ANFIS are better than BP neural network, the operation processing time of the model is short and the accuracy of diagnosis results is high, which shows that the model established in this paper is effective and feasible. Adaptive-Network-Based Fuzzy Inference System combines the advantages of fuzzy logic and neural network. It not only has a “transparent” internal structure and can determine the network structure according to the characteristics of sample data, but also has a self-learning function. It has strong practicability in diesel engine fault diagnosis. Finally, based on the research results, an effective fault diagnosis system is developed as a fault diagnosis tool.

Acknowledgements

This paper is supported by the Central Public Research Institutes Special Basic Research Foundation (2021-9065b), the special fund project for the basic research work of the central public welfare research institute (2021-9036a).

References

[1] Q. Huang, Application of neural network technology in diesel engine fault diagnosis and control, [dissertation] Wuhan:

Huazhong University of Science and Technology, 2003.
[2] J.Z. Jiang, X.R. Meng, H. Li, et al., Study on application of subtractive clustering and adaptive network-based fuzzy inference system in network fault diagnosis, Computer Engineering and Applications 47(8)(2011) 76-78.
[3] Y.T. Han, J.Z. Fei, Z.W. Wang, Multi Information Fusion Diagnosis Method for Diesel Engine Based on Optimized ANFIS, Journal of Physics: Conference Series 1828(1)(2021) 012040.
[4] G. Sujesh, S. Ramesh, Modeling and control of diesel engines: A systematic review, Alexandria Engineering Journal 57(4) (2018) 4033-4048.
[5] S. Lin, Z.Y. He, S. Chen, et al., ANFIS-based fault classification approach for UHV transmission lines, Journal of Southwest Jiaotong University 46(4)(2001) 611-619.
[6] L.F. Kong, H. Zhang, The vibration parameter fault diagnosis cloud model for auto mobile engine based on ANFIS, Manufacturing Automation 32(10)(2010) 20-24.
[7] J. Zhang, X.P. Li, Z.Y. He, Fault classification technique for power distribution network using adaptive network based fuzzy inference system, Proceedings of The Chinese Society for Electrical Engineering 30(25)(2010) 87-93.
[8] J. Zhang, Adaptive fault diagnosis method based on FNN, Journal of Networks 9(8)(2014) 2145-2152.
[9] W.D. Zhou, Y.Q. Wang, Research on fault diagnosis system of hydraulic pump based on ANFIS system, Machine Tool & Hydraulics 39(9)(2011) 155-156.
[10]W.W. Duan, Y.B. Song, A fault diagnosis method for diesel engine based on Adaptive Network-based Fuzzy Inference System, In: Proceedings of the 29th Chinese Control Conference. Beijing, China: IEEE, 2010.