

Using Sensors Data and Emissions Information to Diagnose Engine's Faults

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Abstract

This paper proposes using engine's sensors data flow and exhaust emissions information to diagnose engine's faults, enhancing the accuracy of fault diagnosis. Engine fault diagnosis model is built using both this information and the mature BP neural network and genetic algorithms. In order to verify the method, we build a test platform, which includes South Korea Hyundai fault test vehicle and X-431 diagnosis instrument and AUTO5-1 exhaust gas analyzer and computer. The diagnostic accuracy rate can reach 98.33%, which is higher than using sensors data flow or the exhaust emissions information alone.

Keywords: Fault diagnosis; Neural network; Sensors data flow; Emissions information; Engine

1. Introduction

The engine is the main source of power and an important component of the automobile. Its performance directly affects vehicle's safety and reliability. Due to their complex structure and heavy working conditions, the engine fault generally constitutes around 40% of the failures of the entire vehicle¹. Hence, it is of a great importance to developing new approaches for quick and accurate condition monitoring and fault diagnosis of the engines.



In the past few decades, research on the engine fault diagnosis (EFD) technology has become an active area in the field of vehicle engineering²⁻⁴. Kowalski⁵ presented the concept of a multi-dimensional marine engine diagnostic tool. The dimensions of the tool were diagnostic signals, which form a vector in affine space. The distance of the resulting vector from reference vectors for considered technical states of the engine was the result of the diagnosis. Moreover, diagnostic signals, derived from the composition of the exhaust gas, were also considered. Kowalski also chose the nitric oxide, carbon oxide, carbon dioxide and oxygen contents in the

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exhaust gas and the temperatures behind all engine cylinders of the marine engine as diagnostic signals. Wu et al.⁶ described an internal combustion engine fault diagnosis system using the manifold pressure of the intake system. To verify the effect of their proposed system for identification, both the radial basis function network (RBFN) and generalized regression neural network (GRNN) were used and compared in their study. The experimental results indicated the proposed system using manifold pressure signal as data input was effective for engine fault diagnosis in the experimental engine platform. In addition, Chen and Randall⁷ used two methods to diagnose misfire fault. The first method was based on the torsional vibration signals of the crankshaft, while the second method was based on the angular acceleration signals (rotational motion) of the engine block. Following the signal processing of the experimental and simulation signals, the best features were selected as the inputs of ANN networks. The ANN systems were trained using only the simulated data and tested using real experimental cases, indicating that the simulation model can be used for a wider range of faults for which it can be considered valid. The final results have shown that the diagnostic system based on simulation can efficiently diagnose misfire, including location and severity.

In general, currently available methods for engine fault diagnosis are mainly classified into model-based, knowledge-based and data-driven^{8,9} according to Prof. PM Frank from Germany who is an international fault diagnosis authority.²⁸ Model-based diagnostics threshold are very accurate, but it is very time-consuming and labour-demanding to identify the appropriate values of the model parameters. Thus, a model-based method is too expensive to comprehensively apply in practice. Moreover, due to the different natures of faults and the modelling uncertainty, no single model-based approach can diagnose all the faults. On the other hand, knowledge-based methods have the capability of handling the qualitative symptom descriptions^{9,10}. Lastly, the data-driven methods were widely used for engine fault diagnosis. The main advantage of such methods is that they do not require much (or none at all) expertise of the operator/designer since they are mainly based on the data collected from the process, which can be historical (off-line) or real-time (on-line). This is a very important feature since data-driven methods can cope with the problem of data drift and other unpredicted disturbances.¹¹

Based on these methods' merits and demerits, we propose in this paper using both sensors data flow and emissions information to diagnose the engine faults, which can give the comprehensive running information of engine and improve diagnostic accuracy. In this research, BP neural network and GABP tools are used

to verify the method. Tests are done using Roll Brake Test Systems to realize fault diagnosis on-line during vehicle running at a different speed. In addition, the structure and work principle of the electronic control system is clearly presented. Engine fault diagnosis model is described. Experiments have been tested, which include the data sampling procedure and the application of the proposed model. The training process of the model and the results of diagnostic tests online are also analyzed.

The paper is organized as follows. Section 2 provides the research background, which includes electronic control system of the engine, BP neural network, Genetic Algorithms and GABP model. Section 3 presents the tests and experiments including experimental instruments and data acquisition. In Section 4, the algorithm model is trained using Matlab. Section 5 describes the test result of a simulation experiment. Finally, Section 6 presents the concluding remarks for this paper.

2. Background

2.1. Electronic Control System of Engine

The electronic control system of the engine is composed of sensors, actuators and engine control unit (ECU). The basic control loop is shown in Figure 1, which is Sensors detect the status and condition of the engine and send the parameters to the ECU. ECU is electronic control unit which controls a series of actuators of the internal combustion engine to ensure engine's optimal performance. It does this by reading values from a multitude of sensors within the engine bay, then interpreting the data using multidimensional performance maps (called lookup tables), and adjusting the engine actuators according to the information. Before ECUs, air-fuel mixture, ignition timing, and idle speed were mechanically set and dynamically controlled by mechanical and pneumatic means¹². The components of sensors and actuators and basic function of ECU are shown in Figure2.

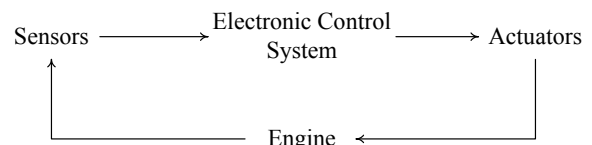


Fig. 1. The basic control loop of engine.

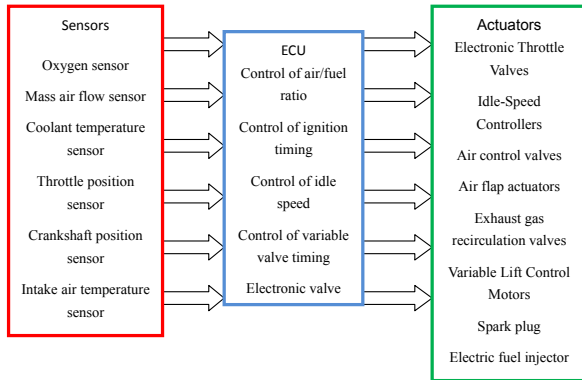


Fig. 2. Components of sensors and actuators and basic function of ECU.

2.2. BP neural network

Back propagation (BP) neural network algorithm is a multi-layer feed forward network trained based on an error back propagation algorithm and is one of the most widely applied neural network models. The BP network is used to learn and store a great deal of mapping relations of input-output model. In this network, there is no need to disclose in advance the mathematical equation that describes these mapping relations. Its learning rule is to adopt the steepest descent method in which the back propagation is used to regulate the weight value and threshold value of the network to achieve the minimum error sum of square¹³. The BP neural network toolbox in Matlab is chosen to get the ideal fault diagnosis results in this study. In order to obtain the best BP neural network structure, a large number of simulation experiments were conducted. Considering the mean squared error and percent error, hidden layer neurons of BP model are confirmed using minimum error and fast calculation speed, so hidden layer neurons are 17. Hidden and output layer incentive functions are purelin and tansig respectively to adjust weight values. The Figure3 shows the two functions.

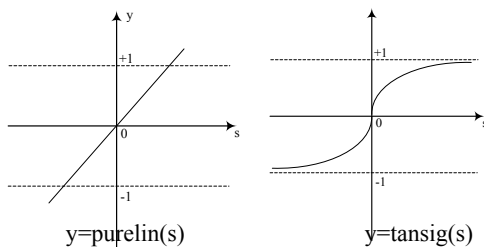


Fig. 3. Purelin and tansig function.

The input layer neurons represent input parameters of engine, while the output layer neurons represent faults,

so nodes of input and output are confirmed. Table 1 lists the BP neural network model parameters.

Table 1. BP neural network model parameters.

Item name	Content in detail	Parameters
Neurons node number	Input layer	10
	Hidden Layer	17
	Output layer	6
Network structure function	Input—Hidden layer transfer function	Purelin
	Hidden—Output layer transfer function	Tansig
	Training function	Trainlm
	Training times	1000
Training parameters	Display Interval	10
	Training goal	0.001
	Study rate	0.01

2.3. Genetic Algorithms(GA)

Genetic Algorithms (GA) are probabilistic search algorithms that emulate the biological evolution of a population, by applying genetic operators that allow the recombination of the individuals, in order to strengthen their performance with regard to a quality function¹⁵. The selection of fitness function directly influences the convergence speed of genetic algorithm and whether it can find the optimal solution. Individual fitness (F) is calculated by Equation 1.

$$F_i = k \sum_{i=1}^n |y_i - O_i| \quad (1)$$

Where y_i is expectation output of node i , and o_i is forecast output. k is coefficient, which is a uniform random number rand between 0 and 1. n is an individual number.

2.4. GABP model

Although the BP algorithm is successful, it has some disadvantages. Because the BP neural network has adopted the gradient method, the problems include a slow learning convergent velocity and easy convergence to local minima, which cannot be avoided¹⁴. GA has been proven to effectively function with ANNs in determining the most compact architecture improving the estimation performance in a variety of problems¹⁶. This paper chose GA to optimize BP neural network to avoid BP algorithm convergence to local minima. The weights and thresholds of BP neural network are optimized using GA in training process, so called this

algorithm is genetic algorithm BP neural network(GABP). First, we should confirm the original parameters of GA. The population size is set to 10, and the evolution number is 50 times, crossover probability is 0.4, mutation probability is 0.2. Second, confirm fitness function using Equation 1.

In fitness proportionate individuals are selected with a probability that is directly proportional to their fitness values²⁶. Evaluate the probability, P_i of selecting each individual in the population:

$$P_i = F_i / \sum_{i=1}^N F_i \quad (2)$$

Where N is population size.

Genetic operators are used to evolving the next generation of individuals from the current population²⁶. Here we choose crossover and mutation. So, next step is crossover and mutation using the equation3 and 4¹⁷. According to the probability P_i , randomly select two antibodies a and a_1 from the population, then the crossover operation of two antibodies in j-bit can be described as follows:

$$\begin{aligned} a_{kj} &= a_{kj}(1-b) + a_{lj}b \\ a_{lj} &= a_{lj}(1-b) + a_{kj}b \end{aligned} \quad (3)$$

Where b is a variable randomly distributed from 0 to 1.

For the selected antibody a_i , the mutation of j-gene can be calculated as follows:

$$a_{ij} = \begin{cases} a_{ij} + (a_{ij} - a_{\max}) * f(g) & r > 0.5 \\ a_{ij} + (a_{\min} - a_{ij}) * f(g) & r \leq 0.5 \end{cases} \quad (4)$$

Where a_{\max} and a_{\min} are the low and upper bounds of the gene value respectively. r is a variable randomly distributed from 0 to 1. Mutation probability is basically a measure of the likeness that random elements of your chromosome will be flipped into something else. For example, if your chromosome is encoded as a binary string of length 100 if you have 1% mutation probability it means that 1 out of your 100 bits (on average) picked at random will be flipped. So $f(g)$ is the mutation probability defined as follows:

$$f(g) = r_2 (1 - g/G_{\max})^2 \quad (5)$$

Where g is the current iterative number, G_{\max} is the maximal iterative number, r_2 is a variable randomly distributed from 0 to 1.

3. Tests and Experiments

The detection of faults in their early stages is beneficial for the avoidance of larger and more severe faults. Fault

detection and diagnosis (FDD) methods are used to monitor the system and identify faults occurring and type and location. If a fault is correctly detected and diagnosed, corrective measures can be applied to repair the fault and reduce any further damage to the system. Many researchers carried out intensive research on FDD¹⁸⁻²¹. Authors²² used the energy balance equations which balance the relation among pressure, mass flow rate and power at various locations to diagnose the faults of the space shuttle main engine. Authors²³ used vibration signals to diagnose the faults of diesel internal combustion engine's valve trains. Meanwhile, changes of exhaust emissions content reflect engine performance²⁴. Exhaust emissions compositions of engine mainly include HC, NO_x, CO, CO₂, O₂, water vapour etc. They must change in some range due to the change of operating status at different conditions, various mechanical and electronic faults²⁵. So exhaust emissions can reflect engine faults. On the other hand, engine's sensors data can also reflect engine's condition and faults. In order to get the comprehensive information of engine to help us diagnose the faults accurately, sensors data²⁷ and emissions information are all used to diagnose the faults of the engine, which are shown in Table2. Table 2 presents data about the engine, which are called faults feature factors as inputs of the BP neural network and faults type, which are the output of the BP neural network.

Table 2. Faults feature factors and faults type.

Input item	Feature factors(unit)	Output item	Faults type
x_1	CO(10^{-2} cc)	y_1	No fault
x_2	CO ₂ (10^{-2} cc)	y_2	fuel injector fault
x_3	O ₂ (10^{-2} cc)	y_3	Ignition coil fault
x_4	HC(10^{-6} cc)	y_4	Throttle position sensor fault
x_5	NO _x (10^{-6} cc)	y_5	air flow sensor fault
x_6	Crankshaft rolling speed(r/min)	y_6	Oxygen sensor fault
x_7	Throttle position(mv)		
x_8	air flow sensor (Hz)		
x_9	Oxygen sensor(mv)		
x_{10}	Intake air temperature sensor(°C)		

3.1. Experimental instruments

A test platform is built to verify the proposed method. The platform includes South Korea Hyundai fault test vehicle, X-431 diagnosis instrument and AUTO5-1 exhaust gas analyzer as well as a computer. Figure 4 shows the diagnosis test vehicle, which has eight faults setting control modules. Their names are engine(ECU) faults, ABS(antilock brake system) faults, TCS(Traction Control System), FATC(Full Automatic Air Conditioning), TCU(Transmission Control Unit), ECS(Engine Control System), ETACS(Electronic Time Alarm Control System), Air bag. In this paper, the focus will only be on the engine faults setting module because it has a more direct connection with emissions and system can get the sensors data easily. The engine can be inserted into different sensors faults and actuators faults, then diagnose the inserted faults using the proposed method and get the diagnosis results. Comparing diagnosis results with the inserted faults, which can test the diagnostic system.

The X-431 diagnosis instrument is shown in Figure 5, which can get sensors data flow. Figure 6 shows the AUTO5-1 exhausts gas analyzer, which can get exhaust information of engine. The vehicle only runs at the idle condition, because we need to connect the experiment instruments with the vehicle and get the information. In order to simulate real road conditions, we use Burke Porter's 3600 roll brake test system. Figure 7 shows the vehicle running on the platform. We can get the vehicle's information on different speed and diagnose the faults real-time (on-line).



Fig. 4. Diagnosis test vehicle.



Fig. 5. The main body appearance of X-431.



Fig. 6. AUTO5-1 exhausts gas analyzer.



Fig. 7. Vehicle running on the 3600 roll brake test systems.

3.2. Experiment data acquisition

It should be noted that the use of artificial neural networks requires the collection of large amounts of data sets. They require obtaining more than one hundred sets of data for each operating condition, which are used to teach the network. We use the diagnostic port MITSUBISHI/HYUNDAI-12+16. The 16 frame port is standard RS232. Sensors data flow can be got using X-431 PCLINK data communication soft, which can realize the following functions shown in table3. Figure 8 represents the software main interface.

Table 3. PCLINK data communication soft functions.

Functions	Explanation
Monitor and alarm	monitor the engine and give the alarm if the engine has abnormal.
Diagnose	diagnose the faults of the engine.
Restore and check	restore and check data of engine such as speed, coolant temperature and so on.
Reset system	reset system such as deleting fault code, recovering system etc.

The test vehicle and all the instruments can work normally before doing experiments in order to get the right information about the engine. Faults' code must be cleared on the X-431 diagnostic instrument and the AUTO5-1 exhaust gas analyzer must be reset. All of the fault set modules of test vehicle must keep normal. We must keep the X-431 and the AUTO5-1 to work

together, which can ensure we get the information on same time. Firstly, the vehicle runs at idle speed, and then it keeps running at this condition and gets the normal data. Parts of normal and different faults data engine at idle speed are shown in Table 4. Secondly, vehicle will accelerate until 1800r/min, and then the vehicle keeps running at this speed and gets the normal data. Parts of normal data and different faults data engine at 1800r/min are shown in table 5. We performed these steps 20 times and got 120 groups data.

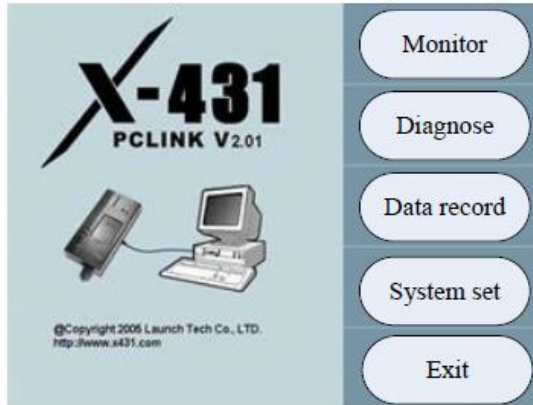


Fig. 8. Main interface of PCLINK diagnosis software.

Table 4. Training data engine at idle speed.

Fault type	x ₁	x ₂	x ₃	x ₄	x ₅
y ₁	0.01	9.1	4.43	1	431
y ₁	0.01	12.7	3.38	1	664
y ₂	0.07	7.8	10.82	1532	91
y ₂	0.08	7.8	10.81	1534	95
y ₃	0.01	10	9.32	1	984
y ₃	0.02	9.3	9.7	1	1008
y ₄	0.17	8.9	8.7	1344	38
y ₄	0.16	9.2	8.57	1344	44
y ₅	0.11	10.3	4.98	1543	89
y ₅	0.12	10.4	4.93	1543	92
y ₆	0.06	8.7	8.76	883	30
y ₆	0.07	9.1	8.52	915	31
Fault type	x ₆	x ₇	x ₈	x ₉	x ₁₀
y ₁	718.8	507.8	23.1	39.1	17
y ₁	687.5	507.8	23.1	39.1	17
y ₂	718.8	507.8	31.2	58.6	16
y ₂	687.5	507.8	31.2	58.6	16
y ₃	718.8	507.8	43.8	39.1	17
y ₃	687.5	507.8	43.8	39.1	17

Table 4, continued:

y ₄	718.8	19.5	37.5	58.6	19
y ₄	687.5	19.5	31.2	58.6	19
y ₅	718.8	507.8	0	273.4	17
y ₅	687.5	507.8	0	293	17
y ₆	718.8	507.8	37.5	19.5	16
y ₆	687.5	507.8	37.5	19.5	16

Note: x₁-CO, x₂- CO₂ x₃- O₂ , x₄- HC, x₅- NO_x x₆- engine speed, x₇- position of throttle valve,x₈- air flow rate,x₉- oxygen sensor,x₁₀- air temperature sensor;
y₁-normal, y₂- nozzle fault,y₃-ignition coil fault, y₄- throttle valve sensor fault,y₅- air flow sensor fault, y₆-oxygen sensor fault

Table 5. Training data of engine accelerate to 1800r/min

Fault type	x ₁	x ₂	x ₃	x ₄	x ₅
y ₁	0	13.5	2.99	46	1397
y ₁	0	13.5	2.93	47	1590
y ₂	0	11.6	3.78	1	1115
y ₂	0	11.2	3.52	1	1487
y ₃	0.04	9.3	8.63	1	1228
y ₃	0.06	9.4	8.59	1	1215
y ₄	0.01	13.8	2.28	1	1412
y ₄	0.01	13.8	2.52	1	1027
y ₅	0.79	14.9	0.41	322	143
y ₅	0.84	14.9	0.4	356	133
y ₆	0.01	13.9	2.39	1	1675
y ₆	0.01	13.5	2.58	1	1916
Fault type	x ₆	x ₇	x ₈	x ₉	x ₁₀
y ₁	1875	957	156.2	58.6	54
y ₁	1812.5	937.4	150	58.6	54
y ₂	1875	1074.2	187.5	39.1	32
y ₂	1812.5	1054.6	181.2	39.1	32
y ₃	1875	2382.7	368.8	39.1	0
y ₃	1812.5	2382.7	406.2	39.1	0
y ₄	1718.8	39.1	150	39.1	0
y ₄	1812.5	39.1	156.2	58.6	0
y ₅	1875	917.9	0	917.9	54
y ₅	1812.5	937.4	0	937.4	54
y ₆	1781.2	937.4	156.2	39.1	32
y ₆	1718.8	839.8	156.2	19.5	32

4. Algorithm model training

4.1. BP Neural network training

BP neural network model is built using Matlab software and trained using the data. Figure 9 shows the training interface, which gives the structure of the neural network, algorithms parameters, calculates progress and

training plots. Figure 10 presents change curve of BP neural network training mean squared error with training epochs. From Figure 10(a) we can see the best validation performance is 1.49×10^{-5} at epoch 13, which mean the neural network convergence speed is very fast. Figure 11 shows the BP neural network training objective gradient curve, while Figure 12 shows the linear correlation-regression curve of a relative output of the BP neural network. The training curves of the engine are provided using different data at the idle speed and accelerate to 1800r/min respectively.

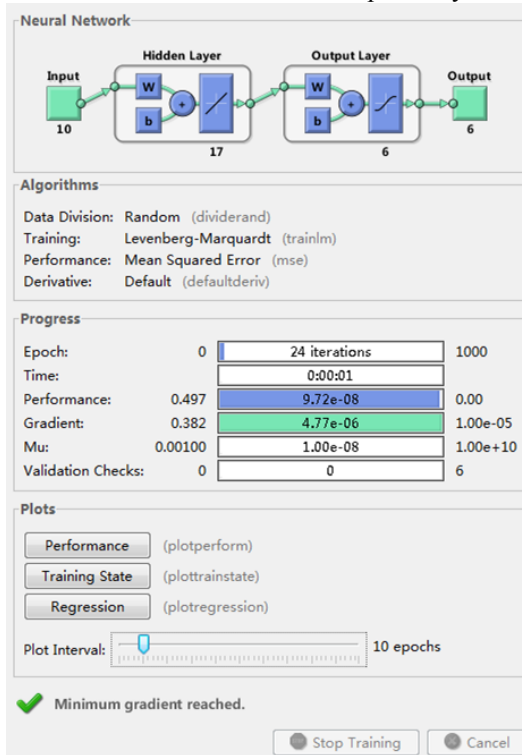
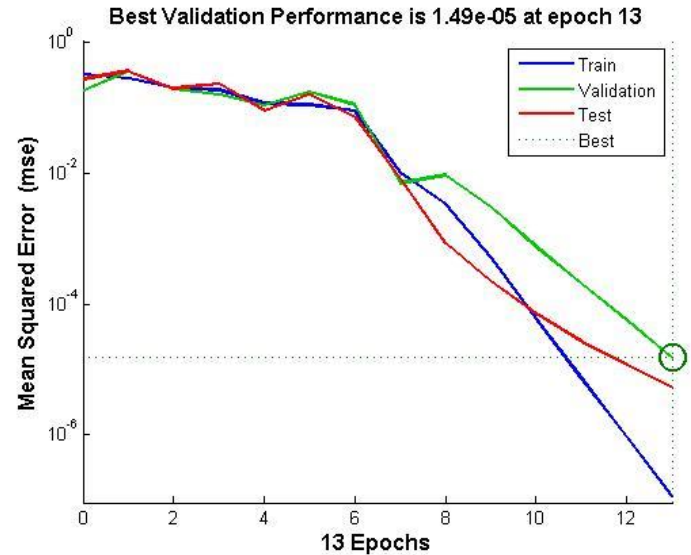


Fig. 9. Neural network training interface.

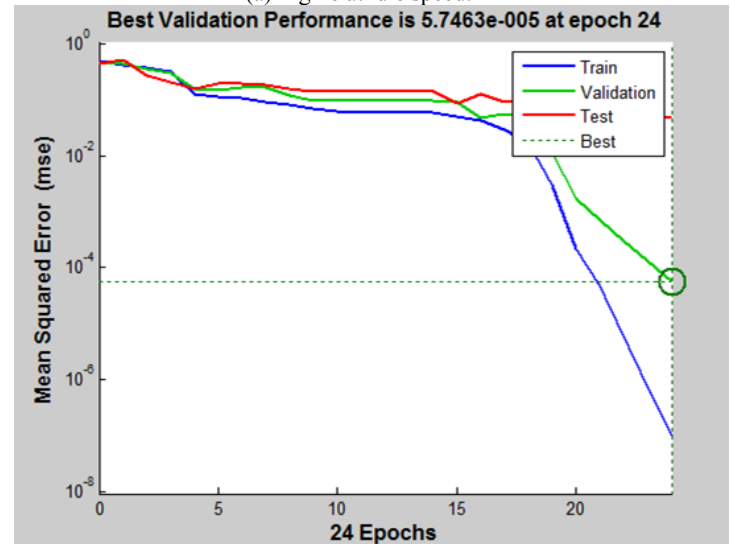
Figure 11 shows that neural network model is trained to 24 epochs by iteration, and the declining gradient can reach required minimum. Target error is in the minimum range, which can illustrate that training of neural network model is ideal. It can meet convergence requirement. It can reach the minimum gradient $1e-005$ and the minimum target error less than 0.001, which illustrate that the model can change and confirm the weights that link different layers. Figure 11(a) shows that best validation performance is $5.7463e-005$ at epoch 24.

4.2. GABP training

The best individual fitness curve and best fitness were obtained by training (showing in Figure 12). The steps of convergence GABP neural network model is shown in Figure 13.

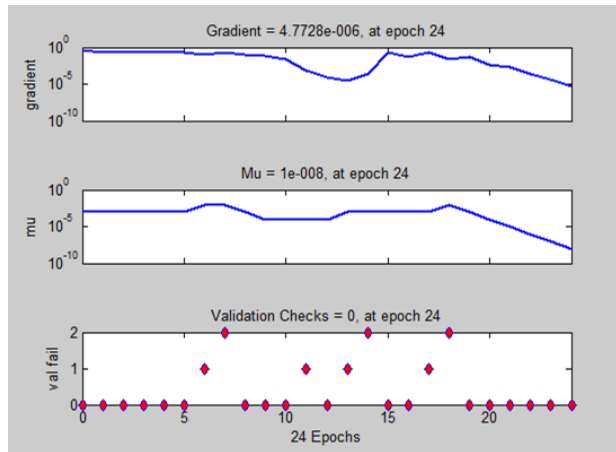


(a)Engine at idle speed.

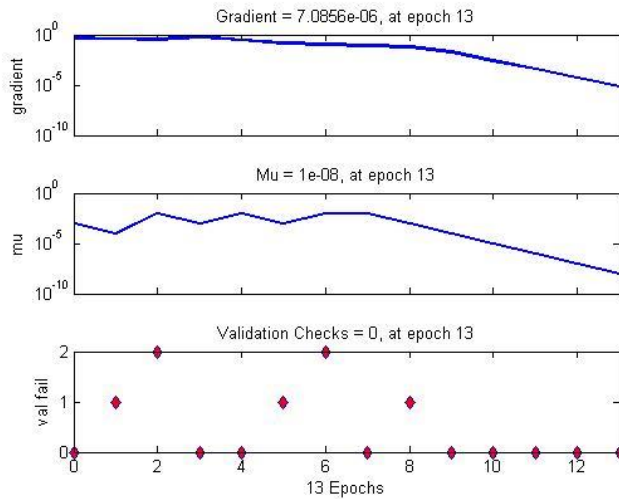


(b)Engine at accelerating to 1800r/min.

Fig. 10. The change curve of BP neural network training mean squared error with the training epoch.



(a)Engine at idle speed.



(b)Engine at accelerating to 1800r/min.

Fig. 11. BP neural network training objective gradient curve.

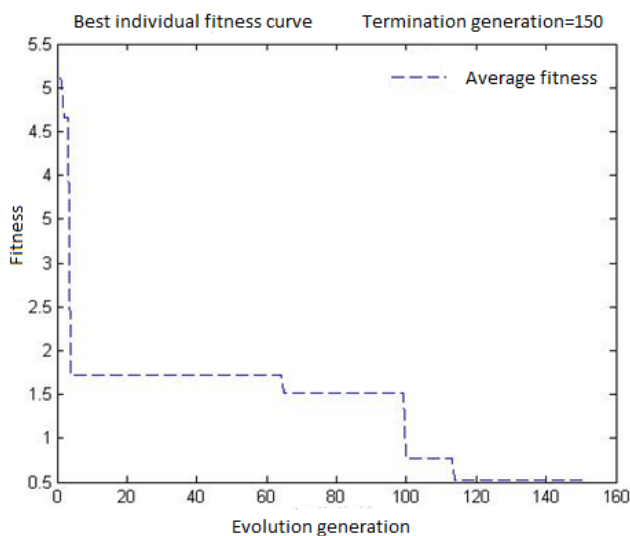


Fig. 12. Best individual fitness curve.

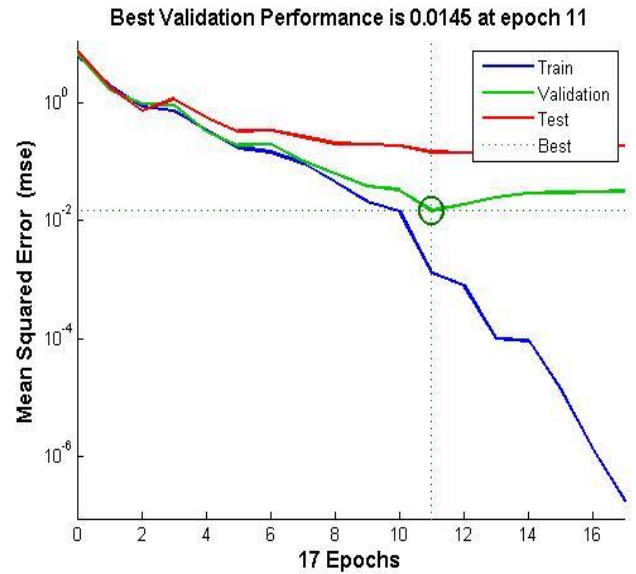


Fig. 13. Process of GABP network training.

As it can be seen from Figure 12, the best individual fitness curve stabilizes after 110 generations, which indicates that the best individual has been achieved optimizing network to 110 generations. Comparing the same structure pure BP neural network, the GABP can improve the performance of the neural network, but it also increases the training convergence time.

4.3. Test on line

We test faults diagnosis on line using the model, which has been trained BP neural network. Table 6 provides a group of data engine accelerate to 1800r/min. The data have been normalized. The normalized calculated method is shown as follows:

Within a given bounded data set there is often a large difference between the maximum and the minimum values. When normalization is applied to a data set its' upper and lower bounds are scaled to appreciably smaller magnitudes. We use the basic z-score normalization that is obtained by using Equation 6

$$x' = \frac{x - \mu(x)}{\sigma(x)} \quad (6)$$

Where $\mu(x)$ and $\sigma(x)$ denote the normal data and the standard deviation of x , respectively. This normalization produces a data set, where each point has a normal close to zero and a variance close to one.

Figure 14 provides the parameters curve when the Oxygen sensor fault is set. Table 7 provides diagnosis

results of test data. It can be seen that the real output of the neural network is close to the expected output.

Table 6. A group of test data.

	x_1	x_2	x_3	x_4	x_5
1	0.0000	0.0045	0.0012	0.0201	0.9452
2	0.0000	0.0038	0.0020	0.0000	0.7373
3	0.0001	0.0034	0.0028	0.0003	0.3983
4	0.0000	0.0048	0.0012	0.0003	0.4038
5	0.0007	0.0050	0.0001	0.3175	0.0180
6	0.0000	0.0045	0.0012	0.0003	1.0000
	x_6	x_7	x_8	x_9	x_{10}
1	0.6282	0.3182	0.0520	0.0203	0.0187
2	0.6282	0.3520	0.0650	0.0136	0.1109
3	0.6282	0.8860	0.1538	0.0136	0.0000
4	0.6282	0.0136	0.0520	0.0203	0.0000
5	0.6282	0.3317	0.0000	0.3114	0.0187
6	0.6282	0.3182	0.0520	0.0068	0.1109

Table 7. Diagnosis results.

Sample	BP neural network real output						Expected output
1	0.9886	0.1143	0.0707	0.0090	0.0903	0.0607	(100000)'
2	0.0986	0.9790	0.0789	0.0924	0.1022	0.0968	(010000)'
3	0.1018	0.1015	0.9408	0.1027	0.1428	0.1118	(001000)'
4	0.1193	0.0996	0.1175	0.9471	0.0732	0.0854	(000100)'
5	0.0617	0.0862	0.1401	0.0810	0.9181	0.0838	(000010)'
6	0.0444	0.1025	0.0132	0.0429	0.0001	0.9327	(000001)'

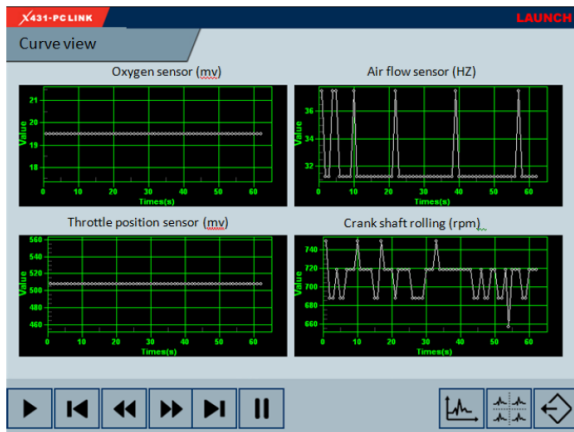



Fig. 14. Parameters curves when oxygen sensor has a fault.

5. Discussions

We used X-431 to get the test vehicle's sensors data and used the AUTO5-1 exhaust gas analyzer to get the emissions information. These data were sent to BP neural network and GABP model to train the two models then using the trained model to diagnose faults.

We test 120 groups of data, which can be diagnosed are 118 groups of data. The accuracy of diagnosis can reach 98.33%. If only use sensors data flow and exhaust emissions information the accuracy of diagnosis is 93.33 and 83.33% respectively. It means that we use sensors data flow and exhaust emissions information to diagnose engine's faults is valid and better than only use one.

We also diagnosed these data using GABP model, it can diagnose all faults accurately and the precision is higher than BP neural network, but training convergence time is increased.

It is must be pointed that  cannot guarantee the exhaust emission information keep up with the sensor data flow because they are collected using different equipment. X-431 gets the engine sensors data and then sends the data to the computer. AUTO5-1 exhaust gas analyzer gets the exhaust gas information and then sends the information to the computer. There is no connection between the two devices. They send information independently, so we cannot insure that they can get the engine's information at the same time. How can we get synchronous data is needed to research deeply. The model should be modified further for raising the accuracy of fault diagnosis on the other hand.

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