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Engine Fault Diagnosis Based on Virtual Instrument Technology

Hashash Djalal*

Mil Tech Coll, Comp Dept, Cairo, Egypt

**corresponding author*

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Abstract: With the development of automobile technology, the function of engine detection device is more and more obvious. The introduction of virtual instrument can build a general testing system with simple hardware. The purpose of this paper is to study engine fault diagnosis with virtual instrument technology. In view of the fact that the electronic and integrated level of automobile products is constantly improving, the basic theory and technical methods of fault self-diagnosis of automobile electronic injection system are studied. BP neural network theory and virtual instrument technology are comprehensively applied to the field of engine fault self-diagnosis. By analyzing the characteristic parameters containing rich engine status information, fault characteristics are extracted, A general platform of engine intelligent fault diagnosis based on virtual instrument technology is proposed and designed. The experimental results show that the system improves the diagnosis speed and accuracy.

1. Introduction

With the constant updating and development of automotive testing equipment, innovations in mechanical equipment and all-weather engine control. Automatic testing and fault diagnosis has evolved from traditional testing based purely on human experience to digital, automated and intelligent. Virtual instrumentation combines computer resources, instrumentation and digital signal processing technology in one, allowing users to design the necessary hardware systems according to their testing needs [1].

In the traditional electric vehicle motor fault diagnosis system, the offline diagnosis is not obvious for the implicit fault diagnosis which has no obvious impact, resulting in high delay of the system [2]. For this reason, a virtual instrumentation-based electric vehicle motor fault diagnosis system has been designed. In the hardware design, a signal conditioning circuit and a virtual instrument data acquisition card are designed according to the characteristics of fault signals to achieve fault signal data acquisition; in the software design, the acquired fault signals are pre-processed and the data are accessed through a file format. Resonance demodulation was implemented for online fault diagnosis. The test results show that the designed virtual instrumentation-based electric vehicle motor fault diagnosis system has a relatively low average fault signal acquisition delay and feedback delay, meeting the system requirements for delay [3]. Some scholars have designed and developed an avionics system simulator based on the LabVIEW platform using a universal PCI interface ARINC429 communication board. The avionics system simulator can receive, analyse, display and record the operating parameters sent by the EECU and issue data commands to the EECU to control the operation, development and debugging of the EECU. The standard ARINC429 data word has been specifically defined to improve communication efficiency. The results show that the avionics system simulator is low cost, has good human-machine interaction and is stable and reliable in operation [4]. Others have used LabVIEW visualisation to process Hall sensor data via the STM32103 ARM for motor rotor fault diagnosis and developed Motor Current Spectrum Analysis (MCSA). The current motor load signal was tested, the signal conversion spectrum in the current field was analysed by Fourier transform and rotor break bar errors during engine operation were assessed [5]. There is an urgent need to improve engine diagnosis in order to improve maintenance efficiency, speed up maintenance, reduce maintenance costs and control maintenance quality [6].

This paper differs from the traditional programming method by using virtual instruments thus improving the efficiency of the fault diagnosis system and avoiding the complex coding of BP neural network algorithms with conventional programming languages. The powerful mathematical and analytical tools and sophisticated I/O hardware of LabVIEW are fully utilised, making it possible to work both in the field of automotive inspection and, in the future, in the field of marine engine testing.

2. Combining Virtual Instrumentation Technology in Engine Fault Diagnosis

2.1. Applications of Virtual Instrumentation

The current applications of virtual instrumentation are as follows:

(1) Virtual instruments significantly reduce the cost of measurement instrumentation [7]. The acquisition of a full-performance traditional measurement equipment is very expensive, usually in the price range of tens of thousands to hundreds of thousands of dollars. Under the same performance conditions, virtual instrumentation can save at least half the price [8].

(2) Virtual instruments have a broad development space in the special measurement system. Virtual instruments are suitable for all measurement occasions that require computer data transmission, processing and storage, making measurement work efficient and convenient. In addition, where technically feasible, virtual instruments can be used to acquire, store, process and analyse all measurement equipment systems. This shows that virtual instrumentation has a wide scope of application.

(3) Virtual instrumentation is also widely used in the field of industrial control and automation. Virtual instrumentation systems can meet the requirements of most closed-loop control systems for accurate sampling, timely data processing and fast data transmission [9-10].

2.2. Software Design Platform for Virtual Instruments

Virtual instrument software is the software development tool for designing toolbars, instrument drivers and common I/O interfaces [11]. Two main programming languages are available for instrument virtual software platforms.

(1) Graphical programming languages, such as LabVIEW and HPVEE.

(2) Text-based programming languages, such as VC, VB, and C.

In this paper, LabVIEW was chosen to develop and design an electronically controlled motor waveform analysis software platform and fault diagnosis system. labView has powerful network communication capabilities, allowing users to develop powerful LabViews applications and powerful remote control capabilities for network communication [12-13]. The network can be measured and managed using (1) a remote desktop with Windows, (2) data exchange using 'dalasocket' technology, (3) communication using network protocols, and (4) the most direct way of propagating NI over long distances.

2.3. Engine Signal Analysis

The electronic engine signal output by the sensor is generally an analogue signal, and signal sampling is the transformation of the analogue signal into a discrete signal in the time domain, i.e. the conversion of the analogue signal into a digital signal [14-15]. For a specific test system, the main basic link is the acquisition of data. Engine signals are divided into two main categories:

(1) signals that change slowly over time. This type of signal, such as the level of the fuel tank, the temperature of the object. As the transformation process is generally slow, a relatively low sampling frequency is used for them [16].

(2) Signals that change rapidly with time. For this type of signal, if you need to understand its waveform, you can consider it as a time domain signal. A higher sampling rate is required in this case [17-18]. For example, motor pulse signals require that the sample period signal must be smaller than the pulse period. If we want to study the increase time of a motor pulse, which is very short, we should use a higher sampling frequency. If you need to know the frequency component of the pulse signal, you can consider it as a frequency domain signal. In this case, according to Shannon's law, in order to obtain an accurate frequency signal (i.e. an accurate reproduction of the original frequency signal), the sampling frequency must be greater than twice the component of the highest frequency signal.

3. Investigation and Study of Combining Virtual Instrumentation Technology in Engine Fault Diagnosis

3.1. Remote Fault Diagnosis System Based on Virtual Instrumentation

In this paper, virtual instrument technology and computer network technology are introduced into fault diagnosis, so that the three are combined to establish a remote fault diagnosis system based on virtual instrument technology. LabvIEw software, a virtual instrument development platform, is used to write programs for the acquisition, processing, display, storage and playback of the measurements. NetMeeting is used to transmit audio and video signals, and TcP/IP and Datasocket technologies are used for remote data transmission. A local fault diagnosis expert system based on neural networks is established for general fault detection and diagnosis.

LabVIEW programs are distributed on the web using the LabvIEW web server. The following is an example of a signal generation and processing program to illustrate the implementation of the data transfer process.

This B/S based remote data transfer method requires the installation of LabVIEw software on the client side and is suitable for use on a local area network. This is because the data transfer rate on the local LAN can reach up to 1K bytes per second, which can increase the refresh rate and thus achieve better operation results.

3.2. BP Network Improvement Algorithms

Levenberg-Marquardt method, referred to as LM method. This algorithm is actually a combination of the gradient descent method and the Newton method, and its search direction is defined as:

$$S(X^{(k)}) = -(H^{(k)} + \lambda^{(k)} I)\nabla f(X^{(k)})$$
$$X^{(k)} = X^{(k)} + \eta^{(k)} S(X^{k}) \tag{1}$$

Let $\eta^{(k)} = 1$, then we have :

$$X^{(k)} = X^{(k)} + S(X^{k}) \tag{2}$$

Where the Hessian matrix H can be obtained by approximating the Jacobi matrix J. The LM algorithm requires a large amount of storage.

Table 1 lists the performance of the six neural network algorithms working with the same network topology, number of samples, network levels, number of nodes and expected error for each type of network.

As can be seen in Figure 1, the LM method, which uses a numerical optimisation-based approach, has the fastest network training and the least number of training sessions when dealing with the same problem, network structure and sampling frequency, while the adaptive learning rate method has the slowest and the most training sessions.

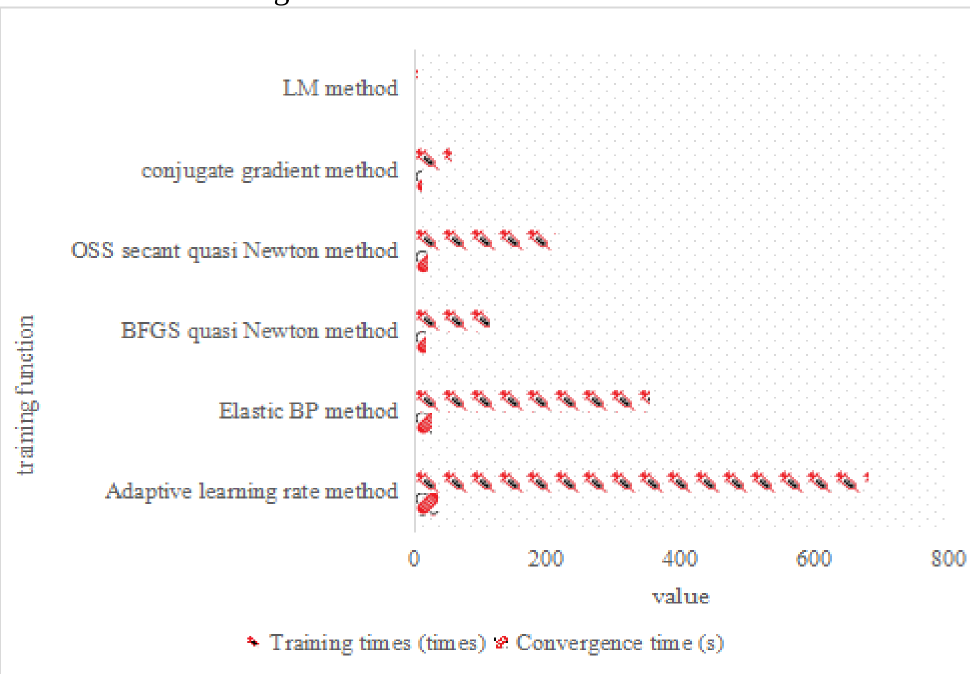

Figure 1. Algorithm comparison results

Table 1. Comparison of network performance trained by different algorithms

Training function	Improved BP algorithm	Convergence time (s)	Training times (times)
Traingdx. m	Adaptive learning rate method	34	678
Trainrp. m	Elastic BP method	26	353
Trainbfg. m	BFGS quasi Newton method	16	112
Trainoss. m	OSS secant quasi Newton method	20	211
Traincgf. m	conjugate gradient method	10	57
Trainlm. m	LM method	3	6

4. Neural Network Programming in Engine Fault Diagnosis Combined with Virtual Instrumentation Technology

The core part of the module design is the application of integrated neural network technology in the LabVIEW development environment to perform fault diagnosis and inference on the measured exhaust gas parameters, the basic flow is shown in Figure 2. The program first reads the fused exhaust gas emission parameter values and then uses MATLAB's BP neural network program to implement the diagnostic reasoning and derive the diagnostic results.

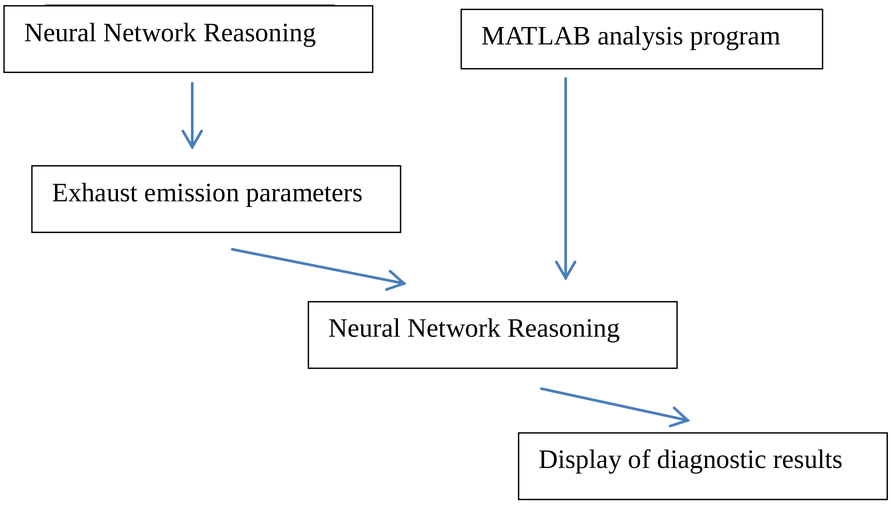

Figure 2. Test module of virtual instrument based on neural network

The design process of the exhaust emission integrated neural network diagnostic module is: first, to determine the appropriate sub-network structure, in this program an improved BP network training algorithm, namely the LM (Levenberg-Marquardt) method, is chosen; second, to determine the training samples and training parameters of the network, see Table 2; third, to build a virtual instrumentation diagnostic inference program based on the LABVIEW language.

Since the simulation training is performed under the same load, the new samples can be classified by speed. The number of classifications should be determined based on the number of new samples and the training results for each subnet after classification. After analysis, the number of classifications is 5 and the sample velocity classification interval is {0 to 600,600 to 1500, 1500 to 3000, 3000 to 4500, 4500 to 6000}. Therefore, the neural network model consists of four subneural groups of the network (i.e. NN0, NN1, NN2, NN3, NN4), with an e value of 0.2, to obtain each subnet and neural network. The connection weights and thresholds for each hidden layer of the network, the structural parameters of the two networks, the training phase and the fitted residuals are shown in Figure 3. And the convergence is fast, while the residual of neural network matching is 0.012, the convergence is slow and the error is difficult to reduce further.

Table 2. Comparison of neural network model parameters

Network model	Number of input layer cells	Number of hidden layer units	Number of output layer units	Fitting residuals
NN0	2	4	4	0.012
NN1	3	4	4	0.011
NN2	2	1	5	0.0054
NN3	3	2	5	0.0036
NN4	3	3	6	0.0014

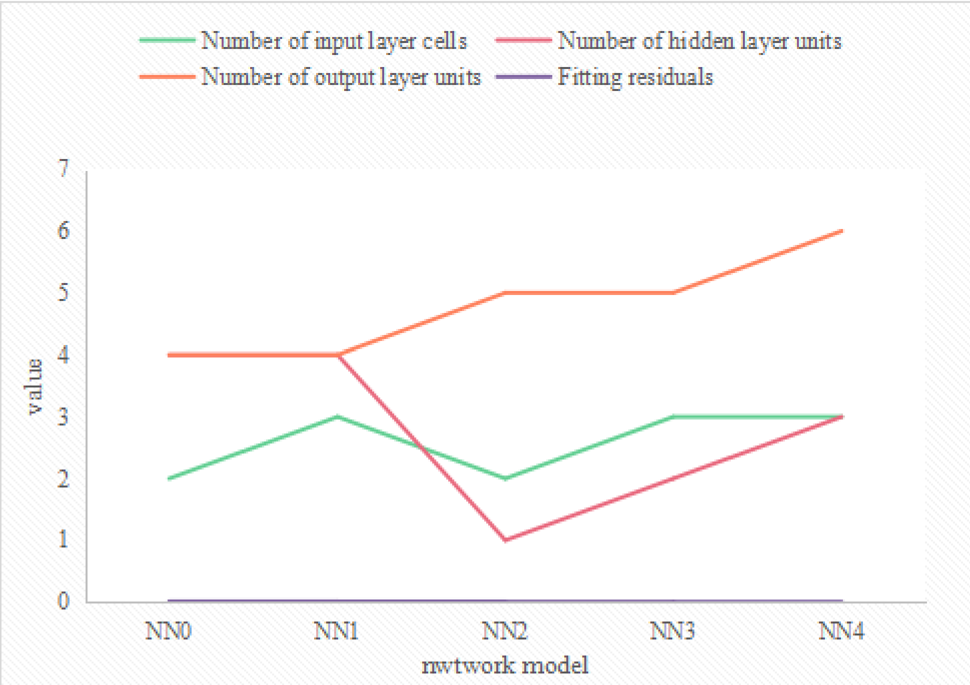

Figure 3. Structural parameters, training stages and fitting residual parameters

5.Conclusion

With the continuous improvement of computer technology, data testing technology, signal processing technology and diagnostic technology, the use of virtual instrument technology for fault diagnosis is a new trend. According to the characteristics of virtual instruments, we can easily integrate them into computer networks and use the network technology to connect test equipment with different functions in different locations, so as to realize remote diagnosis and real-time rapid diagnosis. The research in this paper is mainly to establish an engine fault diagnosis system based on BP neural network technology and virtual instrumentation, but there must still be many shortcomings in this paper. (1) The research on the mechanism of fault diagnosis in this paper is still very superficial, and the selection of testing means, instruments and computing methods is not perfect; (2) The subsequent burst of the development of the network integration and remote consultation of the diagnosis system is still lacking in due outlook and practical steps.

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Data Availability

Data sharing is not applicable to this article as no new data were created or analysed in this study.

Conflict of Interest

The author states that this article has no conflict of interest.

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