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Fault Diagnosis and Fault-Tolerant Control for Manifold Absolute Pressure Sensor (MAP) of Diesel Engine Based on Elman Network Observer

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Abstract: Fault diagnosis (FD) and fault-tolerant control (FTC) of automotive diesel engines are important for efficient repair and maintenance. The construction of an accurate model for a diesel engine intake system is difficult due to its strong nonlinearity, and bias fault and precision degradation fault of Manifold Absolute Pressure Sensor (MAP) of diesel engine can't be diagnosed easily using model-based methods. In this paper, a FD-FTC system is developed for the diesel engine intake system. The system is based on Elman neural network observer, and active fault-tolerant control strategies are constructed. A short analysis reveals Elman neural network observer is suitable to prediction of the intake pressure of diesel engine, which is more accurate than Back Propagation (BP) network. In this FD-FTC system, four types of MAP failures are considered, complete failure fault, bias fault, precision degradation fault and drift fault. The results of simulations of the proposed FD-FTC system show that MAP failures can be diagnosed and the engine can be effectively protected with fault-tolerant control system.

Keywords: Neural networks, Diesel engine, Intake system, Fault diagnosis, Fault-tolerant control.

1. INTRODUCTION

The functions of an automotive engine are entirely dependent on the performances of the installed sensors. The faults of any sensors can lead to the degradation of engine efficiency. Therefore, fault diagnosis (FD) and fault-tolerant control (FTC) techniques can pave a new way for increasing the reliability of the complex processes. Besides, due to the strict legislative regulations defined in OBD (on-board diagnosis), and a growing end-user demand of fuel economy during automotive operations, fault-free, fuel-efficient and environmental-friendly vehicles are always preferred. Currently, the focus has shifted to the vehicles driven by diesel engines. OBD system is necessary for all diesel-driven cars in Europe and will soon be required also for heavy vehicles in USA and EU (Mattias Nyberg, 2002). In China, a set of relatively complete vehicle emission standards named GB18352.3-2005 is issued by Ministry of environmental protection. According to GB18352.3-2005, not only fault associated with emissions but also fault of sensors, actuators and circuit should be diagnosed in OBD system (Huang, G. L et al., 2009). All vehicles on sale in Beijing must be equipped with OBD system from 2006 and it began to implement in whole china from 2008 (Wu et al., 2008).

According to the requirements in OBD, one important part of a diesel engine is air intake system. The sensors in the air system play vital roles in monitoring the health of the system. The manifold absolute pressure sensor (MAP) is installed for measuring engine working load, whose signals are generally used for the calculation of engine's air intake flow and thus the fuel injection quantity. The sensor faults would lead to the degradation of process performances, or even worse, a catastrophic failure.

Many researchers have been working in the diagnosis field. A diagnosis system based on the model of an automotive air-intake system was constructed (Mattias Nyberg et al., 2004), in which the model-based approach and the framework of structured hypothesis tests were used. A model-based fault diagnosis method of the diesel engine's intake system was presented, and the fault diagnosis strategy based on detection observer was formulated (Sun, Y. L et al., 2013). A signal- and process model-based diagnosis method for the combined intake system was developed (Kimmich, F et al., 2005), in which the wavelet signals of the injection system and the combustion process were used. A fault diagnosis based on hybrid observer was proposed to apply on Spark Ignition (SI) engine for misfire fault detection and built a hybrid model (Akram, M. A et al., 2014). The similarities among these methods include the calculation of residuals and the application of residuals for fault detection and isolation. For each study, a detailed dynamic model was identified so that the residual could be generate. So, researchers pointed out that only the failures under steady-state conditions were considered in these literatures (Franchek Matthew et al., 2007). Some researchers reckoned that the model-based diagnosis method is only applicable to specific faults under some working conditions, and the accuracy of model depends on the calibration of data because the parameters are fixed through data fitting. When conditions or fault locations are changed, it is hard to achieve a high diagnostic accuracy; moreover, and the stability of the fault system is not good (Duyar, A, V et al., 1994).

In recent years, the development of neural network has provided a new research direction for fault diagnosis in various fields (Samadani, M et al., 2014; Madaeni, S. S et al., 2015; Jia, H et al., 2015). Some supervision systems based on artificial neural networks approach were developed to generate defects indicators for our examined industrial control valve (Hassani, V et al., 2014; Xue, SF et al., 2014; Hafaifa, A. et al., 2013). Several researchers gained a lot of achievements in fault diagnosis of engine. A neural-network-based model was built for the detection of misfires in a diesel engine (Liu B. et al., 2013). An explicit back propagation neural network model was developed to identify diesel combustion misfire according to the general operating parameters. A fault diagnosis model for internal combustion engines based on extension neural network (ENN) was presented, in which ENN is used as a feature classification tool for the extraction of features (Shatnawi, Y. et al., 2014). In these literatures, ANNs were used to solve model-free nonlinear problems.

The intake-manifold system of diesel engine is a nonlinear system, with a quite complex relation between input and output. In addition, the external and internal parameters have great certainties, and thus the construction of appropriate models for the system is difficult. In this paper, neural network observer was selected to predict the intake pressure of diesel engine.

Elman neural network (ENN) is a partial recurrent network model first proposed by Elman in 1990 (Elman, J. L.1990). Owing to its distinguished dynamical characteristics, it has widely applied for identification (Liu, H. et al., 2015) and control of dynamical (Lin, C. H. 2013). Generally, it lies somewhere between a classic feedforward perception and a pure recurrent network. The feedforward loop consists of the input layer, hidden layer, and output layer, in which the weights connecting two neighboring layers are variables. In contrast to the classical feedforward loop, the backforward loop employs context layer that is sensitive to the history of input data, therefore, the connections between the context layer and hidden layer are fixed. Owing to the context neurons and local recurrent connections between the context layer and the hidden layer, it has certain dynamical advantages over static feedforward network and it is widely used in dynamic system identification. (Lin, W. M. and Hong, C. M., 2011).

Fault-tolerant control can be classified into passive FTC and active FTC (Zhou Donghua et al., 2000). The passive control deals with the robustness problem of faults using the similar tools as those used for the robustness of uncertainties and disturbances. On the other hand, when active approaches are employed, faults should be detected and diagnosed (in terms of location and identification) by FD systems as quickly as possible. The choice of the best FTC strategy mainly depend on the capabilities of diagnosis procedure. The latter must detect and isolate the faults when different uncertainties originated from the inputs, the measurements, and the system model.

Among the recent studies regarding FTC methods on vehicles, a robust and adaptive fault-tolerant tracking control strategy was proposed (Chen H. et al., 2011), in which the actuator failures were taken into account. A passive fault tolerant control strategy for the diesel engine air path is proposed (Mohamed G. et al., 2014). The strategy is carried out under the concept of Higher Order Sliding Mode Control (HOSMC), then additive and loss-of-effectiveness faults are considered. A passive fault tolerant control was performed when the sensor faults appeared (Oubellil, R. et al., 2014). An adaptive integral sliding mode control (AISMC) was proposed for the purpose of regulating the ICE air path (M Guermouche et al., 2014), and the simulation results show that it can satisfy fault tolerant performances against parametric uncertainties and actuator faults. The faults of actuator or sensor were considered in most of these studies.

In this paper, a FD-FTC system for air-intake system of a diesel engine was constructed based Elman Neural network observer. Fig. 1 displays the overview of the proposed FD-FTC system, in which two dotted boxes represent the FD system and FTC system, respectively. In FD system, an Elman Neural network observer was developed for air-intake system of diesel engine. Residuals are calculated in the module of Residual Generation by comparing the measured values of intake pressure with the output values of the Elman Neural network observer. According the results of Residual Evaluation module, diagnosis results can be received from Decision module. The fault-tolerance schemes of control system are classified into three categories in the paper, i.e., reconfiguration, alarm and stop. If fault is serious, FTC system will alarm and send out the stop signal; else, the system start to reconfiguration. The proposed diagnosis strategy is based on residuals and the active FTC system was selected.

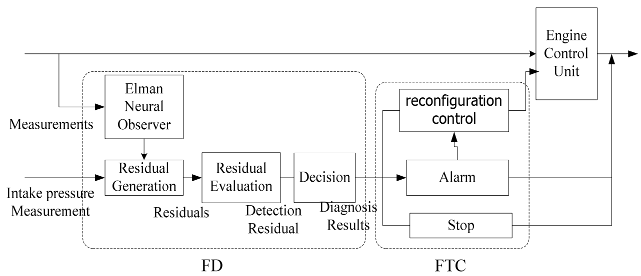

Fig. 1. Overview of the proposed FD–FTC system.

In this paper, the proposed FD-FTC approach can provide an early detection of the faults and guarantee the safe reconfiguration of system control. The FD-FTC technique was developed based on the MATLAB simulation platform.

2. FAULT DIAGNOSIS BASED OA ELMAN NEURALNETWORK OBSERVER

2.1 Experimental setup

In this study, experimental research was conducted on an eight-cylinder electronic control diesel engine, and the diesel engine with double turbocharger was installed in a heavy vehicle. Sensor information and some important parameters acquired by controller were transmitted between computer by CAN bus, and monitored by LABVIEW.

The intake-manifold pressure is important in the electronic control system of diesel engine since it indicates whether the intake-manifold system operates in a normal condition or not. Therefore, many researchers have gained a deep insight into this parameter (Matthew A et al., 2007; Low, S. C et al., 1981; Benson, R. S, 1982; Chapman, M et al., 1982, Winterbone,

D. E et al., 2000; Lakshminarayanan, P.A et al., 1979; Takizawa, M et al., 1982; Meisner, S. et al., 1986). The intake-manifold pressure is affected not only by the characteristics of the engine itself such as rotating speed, the mass of fuel, the intake temperature and the exhaust temperature, but also by some external elements such as ambient pressure, the property of turbo, and *etc*.

Through the analyses of the diesel engine air-intake system, the parameters which influence MAP were concluded and listed inTable.1

Table 1. Parameters of the training sample.

Serial Number	Parameter
1	Engine speed N_e (r/min)
2	Exhaust temperature T_{exh} (□)
3	Intake temperature T_{inlet} (℃)
4	Cycle fuel injection quantity q
5	Ambient pressure p_{am} (MPa)
6	Intake pressure p_{inlet} (ba)

2.2 Elman Neural Network

The Artificial neural networks (ANNs) were proposed under the inspiration of biological neural networks. ANNs can learn the desired input-output mapping based on training examples, without looking for an exact mathematical model.

Due to the feedback, time-delay structure and dynamic behavior characteristics, Elman neural network has a very strong computing ability, which can also be regarded as a kind of dynamic neural network. Unlike Radical Basis Function (RBF) network, Back Propagation (BP) network and other forward neural network include input layer, hidden layer and output layer, Elman network adds a context layer in the hidden layer. The structure of Elman neural network is shown in Fig. 2. The input layer only plays the role of linear weighted. The hidden layer plays the role of relationship mapping between the input layer and output layer. The undertake layer is used to remember the previous output of hidden layer. So Elman network has the ability to deal with dynamic information.

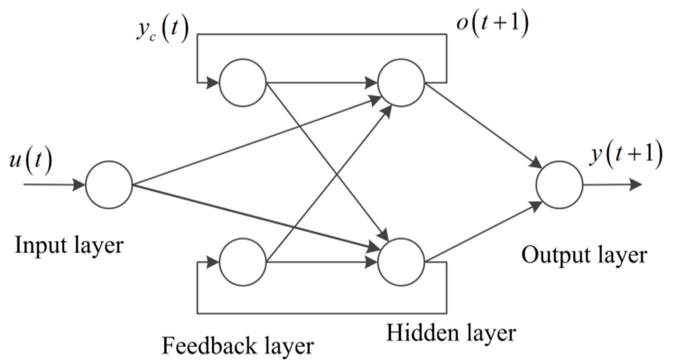

Fig. 2. Structure of an Elman neural network.

As shown in Fig. 2, We described time series outside the network as *u(t)*, the feedback layer output as $y_c(t)$, the output of the network as *y(t)*, and $y_1(t)$ and $y_2(t)$ are described as the transfer functions of hidden layer and output layer respectively, ${}^1W$, ${}^HW$ and ${}^2W$ are connection weight matrixes of input layer to hidden layer, feedback layer to hidden layer and hidden layer to output layer respectively. Eq. (1) expresses the relation between input and output.

$$\begin{cases} x_o(t+1) = {}^{\mathbf{H}}\mathbf{W}y(t+1) + {}^{\mathbf{1}}\mathbf{W}u(t) + {}^1\theta \\ y_c(t) = o(t-1) = f_1(x_o(t-1)) \\ y(t) = f_2({}^{\mathbf{2}}\mathbf{W}u(t) + {}^2\theta) \end{cases} \tag{1}$$

In the present study, linear transfer function was selected as the function of output layer neurons, and "S" type function was selected as the function of hidden layer neurons. This neural network can approximate any nonlinear arbitrary precision dynamic process by adjusting the number of network layers and the number of neurons in layers (Zhang, L. Y. et al., 2005).

2.3 Fault diagnosis system

Figure 3. presents the fault diagnosis system based on neural networks observer. There are two ways of applying neural network on fault diagnosis. One way is to use the ability of neural network that can approximate any continuous bounded nonlinear function and thus it can build a non-linear model for fault diagnosis; the other is to use the powerful classification capabilities of neural network and it can perform fault pattern classification and learning and then diagnose the failures. This article focuses on how to use neural networks as a nonlinear function estimator for fault diagnosis.

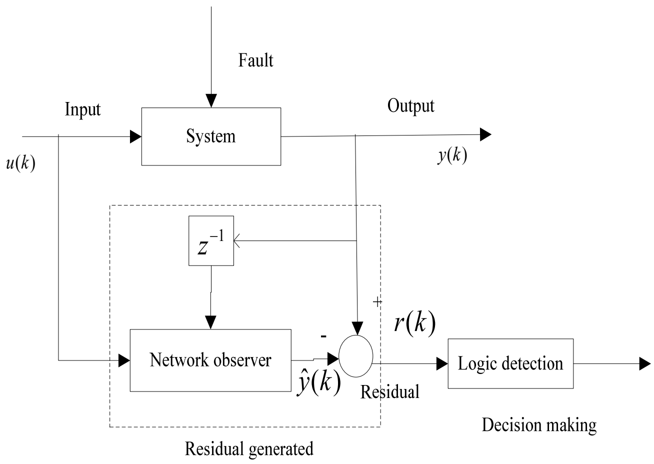

Fig. 3. Fault diction and isolation scheme based on neural network observer.

2.4 Selection of training samples and test samples

1 Acquisition of training samples

2162 groups of data were selected as the training sample in the neural network, with the sampling time is 0.025 s. The acquired training samples are shown in Figure4.

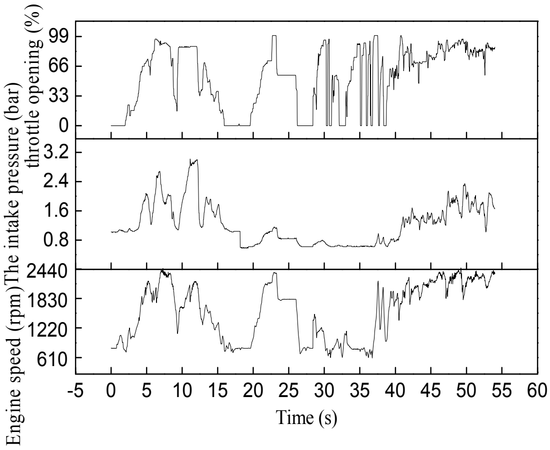

Fig. 4. Data of training samples.

2 Acquisition of test samples

Considering the continuity of the feedback network, the amount of validation sample data should not be too small, so the number of sample data in this experiment should be more than 50 groups in each sample. In this paper, validation samples were acquired under five different operating conditions. To be specific: (1), the driver stepped on the accelerator slowly and gradually increased the engine speed, during which the engine load was always small and totally 258 sets of data were obtained; (2)The driver quickly stepped on the accelerator pedal, during which the collected data were a set of throttle mutation data and totally 250 sets of data were collected; (3) the driver stepped on the accelerator to 100% rapidly, during which the engine speed reached a maximum and totally 310 sets of data were collected; (4)the data were collected under the plateau environment(with the ambient pressure of 58 KP) and the driver depressed the accelerator quickly, during which the engine speed rapidly increased and totally 201 sets of data is gained; (5)the sample data were collected in dynamic response processes when the engine operated at a high speed, during which the accelerator-pedal position at most time was maintained above 80% and totally 201 sets of data were collected.

2.5 Selection of an Elman neural network observer

1 *Type of neural network*

Intake-manifold pressure of the engine has a time lag, i.e., the prediction of engine is influenced by the previous engine working conditions. Therefore, Elman network with feedback was selected, which includes 5 input nodes and 1 output node. Engine speed, exhaust temperature, intake temperature, cyclic oil volume and ambient pressure were adopted as the input vectors of neural network while intake pressure was the output vector of neural network. The intake pressure of engine had a time lag, that is to say that each engine prediction was influenced by previous engine working condition, so Elman network with feedback and BP network are considered to select.

The main work is to decide the number of nodes in the hidden layer. In this paper, the number of nodes in the hidden layer follows the Kolmogorov's theorem (KOLMOGOROV A N et al., 1957), namely that the number of nodes in the hidden layer is at least 2n + 1, where n is the number of nodes in the input layer

The setting parameters of the neural network are listed in Table 2.The MSE (Mean Square Error) function is used as error function. Eq. (2) gives the expression of the MSE function:

$$E_{mse} = \frac{1}{mn} \sum_{i=1}^{n} \sum_{j=1}^{m} (t_{ij} - y_{ij})^2 \tag{2}$$

where m is the number of input nodes; n is the number of training samples; t_{ij} is the expected output and y_{ij} is the actual output.

Table 2. Parameters of the neural network.

Function types	BP network	Elman network
Hidden layer number	single	single
Transfer function	tansig()	tansig()
Training fuction	traingdx	traingdx
MSE function	mes	mes

In this paper, the hidden layer nodes are selected as 45, the accuracy of training goals is selected as 0.01–0.025. Compared Fig. 5 with Fig. 6, the sampling error of BP network is much bigger than that of Elman network, but worse in error fluctuation. The sampling error of BP network is smaller when the training accuracy is controlled within 0.014 5–0.016 5, but it is above 0.2; the sampling error of Elman network is smaller when the training accuracy is controlled within 0.015 0–0.017 5, but it is less than 0.07.

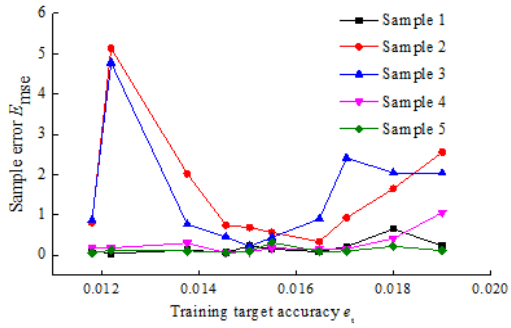

Fig. 5. Verification result of BP network with a single hidden layer.

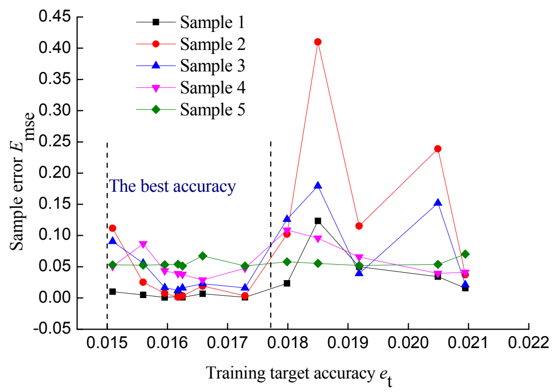

Fig. 6. Verification result of Elman network with a single hidden layer.

2 Number of hidden layer and Number of hidden layer

Based on a lot of training experimental results, Elman network with a single hidden layer or double hidden layers can also achieve the desired training results.

In this paper, the number of hidden layers is discussed. Elman network with a single hidden layer and Elman network with double hidden layers are mainly studied. In the study, the node number in single hidden layer was between 20 and 53 and that in double hidden layers was between 15 and 40.

From the research results, Compared Fig. 7with Fig. 8, it can be seen that Elman network with a single hidden layer with the nodes between 43 and 47 has a better training effect; Elman network with double hidden layers with the nodes between 23 and 27 has a better effect.

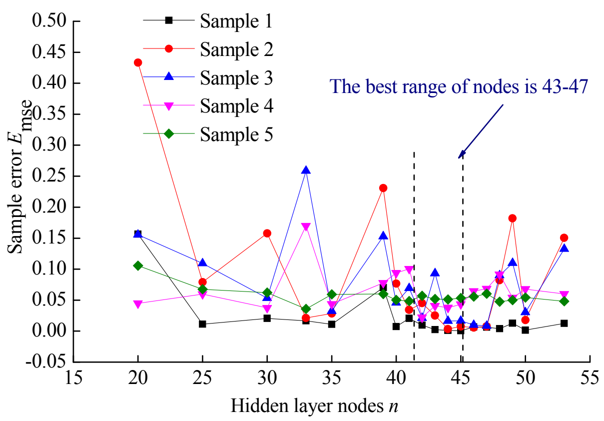

Fig. 7. Result of Elman network with a single hidden layer.

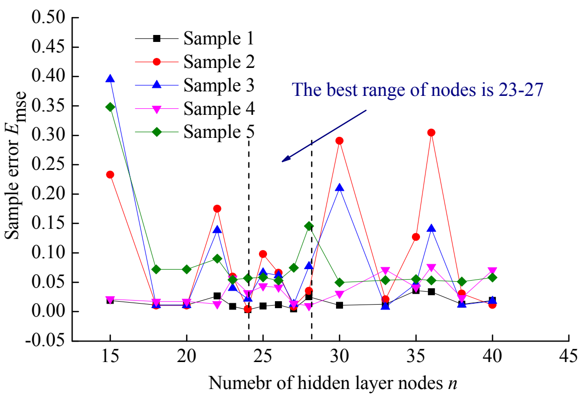

Fig. 8. Result of Elman network with double hidden layers.

3 Stability of Elman network with hidden layer

Based on a lot of training experimental results, Elman network with a single hidden layer or double hidden layers can also achieve the desired training results. Five groups of training samples were used to calculate the standard deviation for the judgment of stability. As shown in Fig. 9, the Elman network with single hidden layer and 44 nodes has higher stability than the Elman network with double hidden layers and 24 nodes. Therefore, the Elman network with a single hidden layer and 44 nodes was used in the present study.

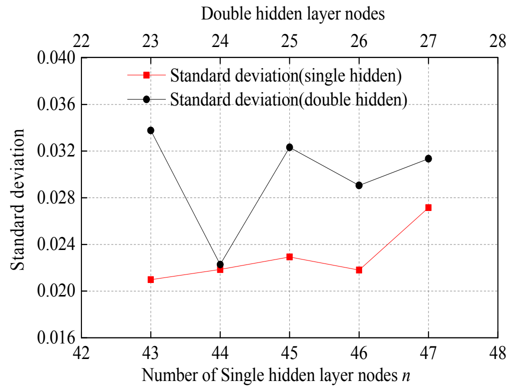

Fig. 9. Stability of the results using the Elman network with a single hidden layer nodes and double hidden layers, respectively.

2.6 Results of Elman neural network observer

Five groups of test samples were selected for verifying the above-described Elman neural network. In this paper, test sample 4 is listed as example. The verification results are listed in Fig. 10, in which the red straight dash line represents the real inlet pressure value, the black straight solid line denotes the inlet pressure observation, and blue solid lines shade denotes the relative error of observation.

As shown in Fig. 10, the observation results at idle are higher than those measured in the plateau, with the relative error below 10%.

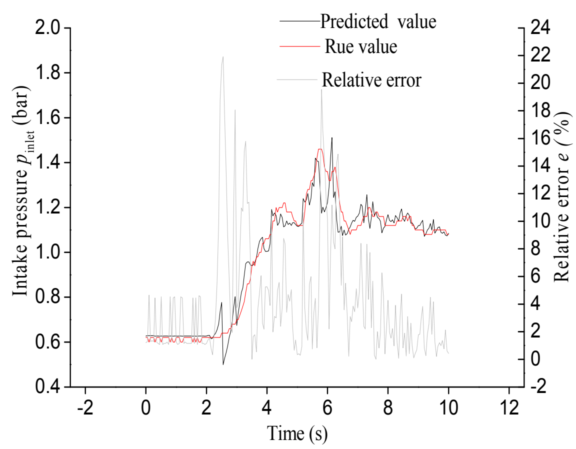

Fig. 10. Predicted results of sample 4.

As shown in Table 3, using the designed observer, the relative errors between inlet air pressure values and predict observations at the various conditions remain below 20%.

Table 3. Relative errors of five samples.

Sample types	Relative errors(maximum)
Sample 1	5%
Sample 2	10%
Sample 3	12%
Sample 4	18%
Sample 5	20%

2.7 Fault diagnosis strategy and fault diagnosis results

In this paper, fault diagnosis strategy was proposed based on the residuals. The simulated values of air intake pressure were calculated through Elman network observer under different conditions, and the difference between output value of intake air pressure sensor and the simulated intake pressure value was regarded as the residual value. Whether the fault occurs in intake pressure sensor and which fault occurs were determined based on the residuals characteristics. Confidence interval was achieved through the analysis of residuals using mathematical statistics, and, finally the sensor fault threshold was gained.

Seven fault status of intake pressure sensor can be attributed to four forms--complete failure, bias fault, precision degradation fault and drift Fault. Specific fault diagnosis strategy was described in detail (Wang, Y., et al. 2016).

When a certain sensor fault occurs, the fault diagnosis system should the output fault code which represents different fault using diagnosis strategy. Table 4 lists the fault codes corresponding to different sensor faults. The diagnoses were performed using stateflow, a finite state machine tool in MATLAB.

Table 4. Relationship between fault code and fault.

Fault types	Fault code
Short-circuit fault	1
Open circuit fault	2
Normal degradation fault	3
Bias fault	4
Precision degradation fault	5
Virtual joint failure	6
Drift fault	7

1 Complete fault

According to the sensor fault code, the input data of speed and load were randomly set in air intake system model by the simulation module failure. Fault parameters are shown in Table 5.

Table 5. Fault type and fault parameters.

Fault types	Sensors voltage value u_s （V）
Open circuit fault	5
Short-circuit fault	0
Normal precision degradation fault	1.5
	3

Four different faults were set. When 20 groups of abnormal data appear, it can be determined that fault occurs. The obtained curves of intake pressure are displayed below.

Four different faults were set. When 20 groups of abnormal data appear, it can be determined that fault occurs. The obtained curves of intake pressure are displayed below.

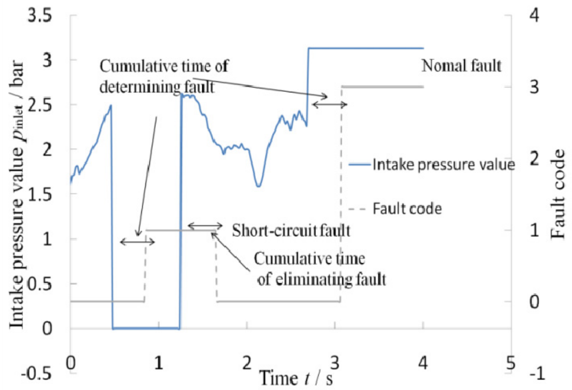

Fig. 11a. Curve of intake pressure of the sensor with normal fault.

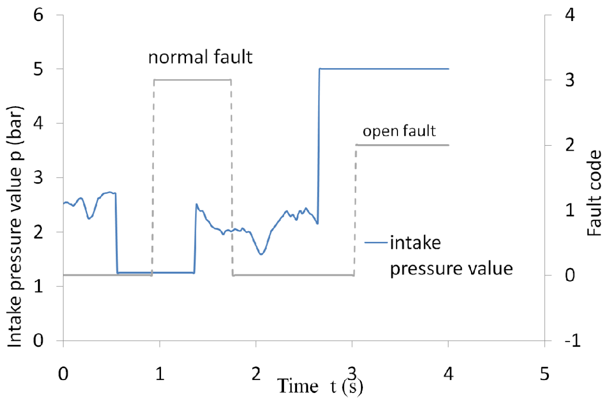

Fig. 11b. Curve of intake pressure of the sensor with open fault.

As shown in Fig. 11a, when the sensor fails completely, the output of the inlet pressure remains at a constant value for different failure modes. The sensor fault information can be accurately output by diagnosis system. According to the experimental data, the inlet pressure is stable when the engine is idle running, which may be on account of the possibility of miscalculation. However, this point can be neglected in the present study. When the engine does not operate at an idle speed, if the actual inlet pressure values remain unchanged, the complete failure occurs in the sensor complete; when the inlet pressure value is 0 bar, sensor short-circuit fault occurs; in Fig. 11b, when the inlet pressure value is 5 bar, open circuit fault occurs.

2 Bias fault

According to the sensor fault code, sensor bias fault was set. When five groups of abnormal data appear, it can be considered that sensor bias fault occurs, and the set deviation voltage values were 0.2 V higher, 0.3 V higher and 0.5 higher than the normal value, respectively. The obtained fault curves by simulation are presented in Fig. 12a and Fig. 12b.

As shown in Fig.12, residual value is above deviation threshold in 1s to 1.5s and 2.3s to 2.8s period for each fault, and the sensor can be diagnosed as bias fault.

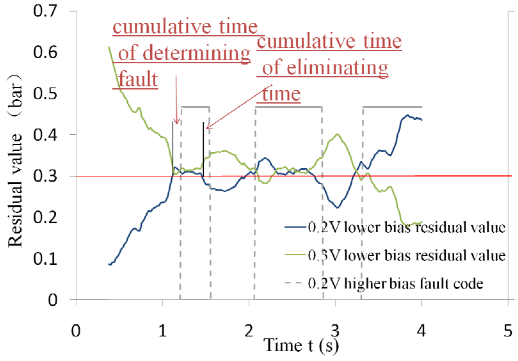

Fig. 12a. Curve of intake pressure of the sensor with 0.2V bias fault.

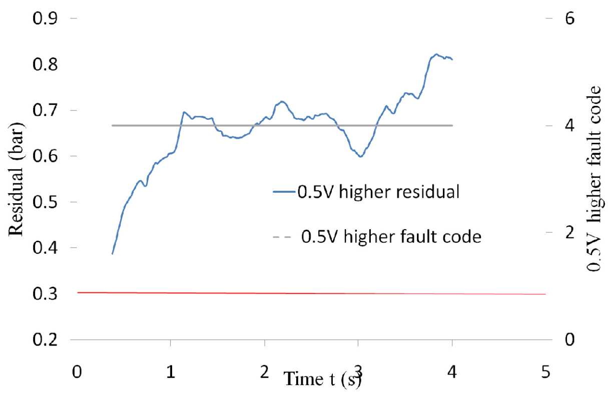

Fig. 12b. Curve of intake pressure of the sensor with 0.5V bias fault.

3 Drift Fault

Drift fault was set in intake pressure sensor model, and the simulations were conducted in a quick change trend. In simulations, the sample time interval was set as 0.02 s, the average value among 30 sampling points was calculated, and the judge proportion was set as 60%. Decision criteria can be expressed as: when six increasing average values appear in 6 s, the drift fault can determined in the sensor. Fig.13 displays the simulations results.

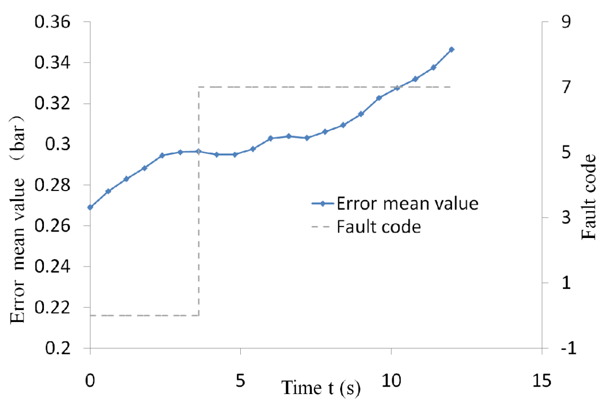

Fig. 13. Curve of intake pressure of the sensor with drift fault.

As shown in Fig.13, drift fault can be accurately diagnosed in simulation experiment; however, in practical applications, the diagnosis strategy is affected by fault changing trend.

According to diagnosis strategy and experimental results, when a certain sensor fault occurs, multiple sensor faults may be diagnosed since the data contained multiple sensor fault characteristics. Further analysis shows that when a variety of fault characteristic appear, the fault diagnoses can be judged in the following order: precision degradation fault → virtual joint failure → bias fault→ sensor complete failure, open circuit fault and short-circuit fault→ drift fault. The fault appears earliest should be regarded as the real fault of sensor.

The experimental results show that the diagnosis strategy has accurate results for short-circuit fault, open circuit fault, bias fault and the decrease of precision. On the other hand, drift fault requires a large number of long-term targeted experiments to determine the diagnosis strategy.

3. FTC SYSTEM AND RESULTS OF FAULT TOLRANT CONTROL

3.1 Fault-tolerant control strategy

When the failure of intake pressure sensor occurs, faults should be diagnosed through control system, and moreover, reasonable fault-tolerant control operation should be given simultaneously. In this paper, the failures in MAP is under the assumption that the other sensors work normally.

In Fig.14, the proposed fault-tolerant control strategy is shown.

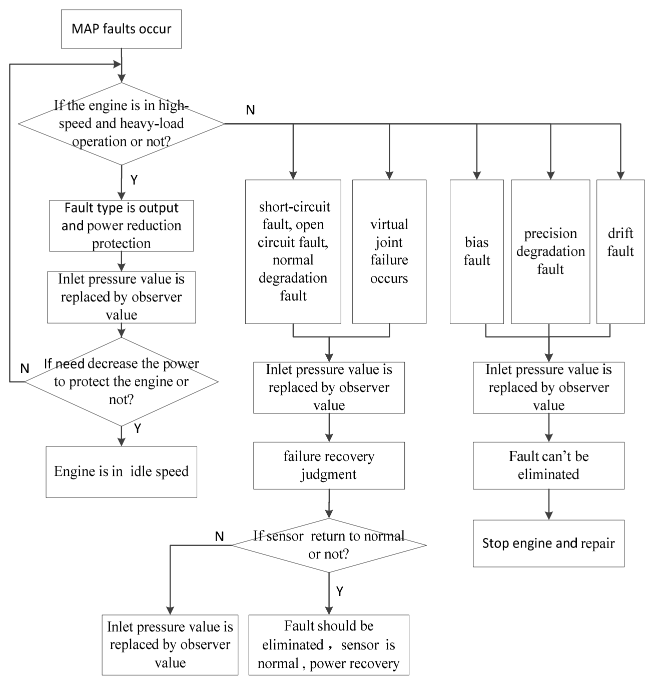

Fig. 14. Overview of proposed fault-tolerant control strategy

As shown in Fig.14. The fault-tolerant control strategies is described below.

When the failure of intake pressure sensor occurs, the control system sends alarm information and the following operations should be conducted:

1. If the engine runs under the operating condition with high speed and heavy load, it should decrease the power to protect the engine and inlet pressure value was replaced by the value predicted by the observer.

2. For the high-power diesel engine, power reduction protection can be divided into two kinds--gradient power reduction strategy and emergency power reduction strategy.

3. The inlet pressure values when the engine operates under the conditions without high speed and external characteristic were simulated and an alarm is given for the case when the power exhibits no reduction.

4. Different fault-tolerant control strategies were applied according to different failures. When the short-circuit fault, open circuit fault, normal degradation fault or virtual joint failure occurs, it may be induced by some occasional factors such as the disconnection of connectors and external disturbance and the sensor after return to normal has a high reliability. In these cases, the failure recovery judgment should be conducted and the failures should be eliminated after the requirements are satisfied. When bias fault, precision degradation fault or drift fault occurs, it may be induced by some unrecoverable reasons such as the damages and aging of the sensor. In these cases, the sensor failures cannot be eliminated and the engine should be repaired or changed when it stops operating.

FD—FTC simulation system was constructed on an eight-cylinder diesel engine based on MTALAB simulation experiment platform.

As shown in Fig. 15. It consists of six modules--engine intake system, intake pressure sensor system, intake pressure observer, filtering module, FD module and FTC module. Engine intake system is modelled with mean value model; intake pressure sensor model in intake pressure sensor system is used for the simulation of sensor failures; intake pressure observer is based on Elman network; the filtering module is used for the filtering processing of the inlet pressure value measured by the observer so that the measured results can be more accurate; FD module and FTC module is built in above.

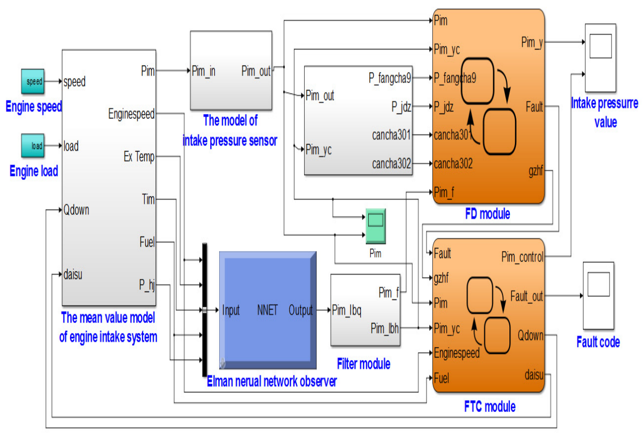

Fig. 15. FD_FTC system of diesel engine based on neural network observer.

3.2 Selection of the parameters of fault-tolerant strategies

Using the above-described engine model, fault-tolerant strategies are verified through simulation. The selection of parameters of fault-tolerant strategies are described as follows:

(1) When the engine operates at a speed of 2100 RPM and under a heavy load, the fuel-injection quantity remains at 200 mg/(cyl*cyc), which is adopted as the critical value of high-speed and heavy load.

(2) Power reduction using gradient method is used as the power reduction of engine power control, and the power was reduced by lowering the fuel injection quantity in a gradient way. According to the high inlet pressure protection strategy using on the real vehicle, power reduction strategy is set below, the fuel-injection quantity of external characteristic was reduced by 5% every 10 s, which can be expressed as:

$$q_j = q_{inject}\cdot\left[1-INF\left(\frac{t}{10}\right)\times 0.05\right] \tag{3}$$

(3)As shown in Eq. (3), fuel-injection quantity equals to 70% of the external characteristic fuel injection quantity after 1 min, which can meet the general protection requirements. Therefore, 60 s is decision condition of emergency power reduction.

(4) Intake pressure is high when the engine operates under the conditions with high speed and heavy load, the high intake pressure will affect the combustion in cylinder, and may result in the inlet pipe leakage fault. Therefore, if engine still operates under the conditions with high speed and heavy load after the engine power is reduced after 1 min, the engine should be forced back into the idle speed. (5) The critical conditions for resuming data acquisition is that no fault signal appears and lasts more than 1 min.

As shown in Fig. 16, fault-tolerant strategy is using Stateflow simulation tool. Different fault is set as fault code as shown in table 3.

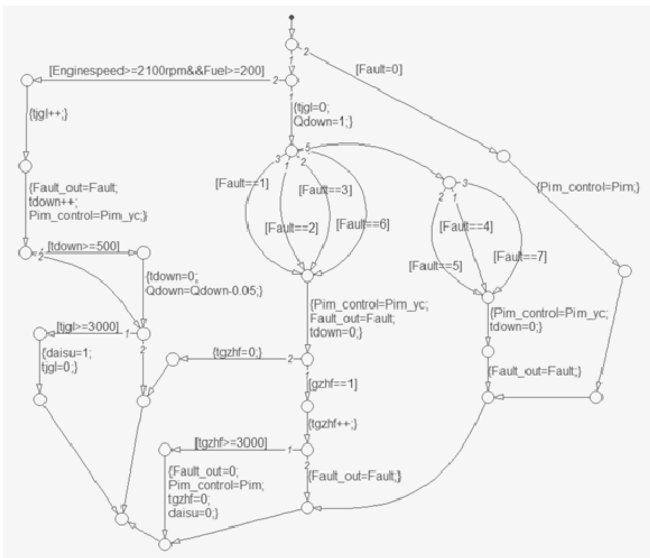

Fig. 16. Fault-tolerant control logic diagram.

3.3 Results of fault tolerant control

Short circuit fault, open circuit fault and sensor bias fault were set to verify fault-tolerant control strategy. During the simulation process, the engine operates under a stable condition, and fault determining time can be extended appropriately so as the accuracy of diagnosis can be ensured. In the following simulations, fault determining time in bias fault was sets as 5 s, the values in short circuit fault and open circuit fault were set as 1 s, and the fault recovery time was set as 1 min.

1 Results of short circuit fault and open circuit fault

As shown in Fig.17, when the actual intake pressure is zero bar, short-circuit fault is detected and fault code 1is generated. At the same time, the simulated value of air intake pressure is used to replace the fault pressure value as the output. Then short-circuit fault code disappears when the sensor returns back to normal more than 1 min, and simultaneously, the actual pressure value is output and sensor begins to collect data again. When open circuit fault occurs, sensor can be shielded in time using fault-tolerant control strategy and the fault can be fault-tolerant.

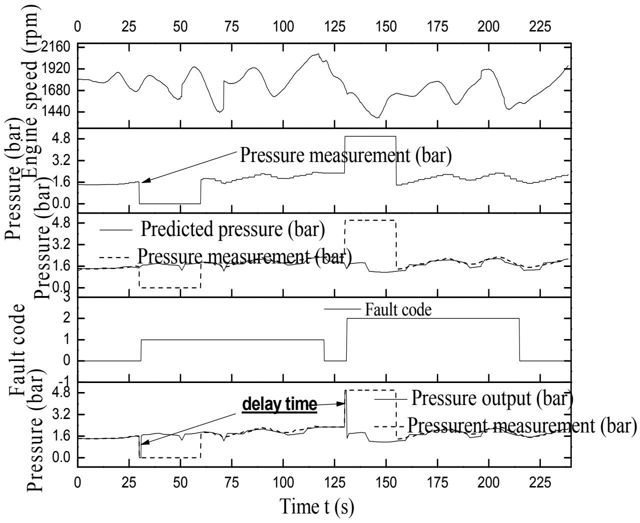

Fig. 17. Fault tolerance simulation of short circuit fault and open circuit.

2 Results of bias fault

As shown in Fig.18, sensor is normal before 40 s and the bias fault occurs at 40 s. According to the residual value, when the intake pressure deviation exceeds 0.4 bar for 5 s, bias fault is detected and the fault code 4 is generated. Meanwhile, fault-tolerant control begins, and the simulated pressure value is used to replace the actual pressure value. The engine operates at a high speed and with heavy load, and power reduction control is used during the output of fault code. Since the external fuel characteristics are restricted, fuel quantity is less than the limited value at that moment; in a period after fault is detected, engine power has no obvious drop. At 65 s, engine power begins to decline, and simultaneously, engine speed and inlet pressure decrease.

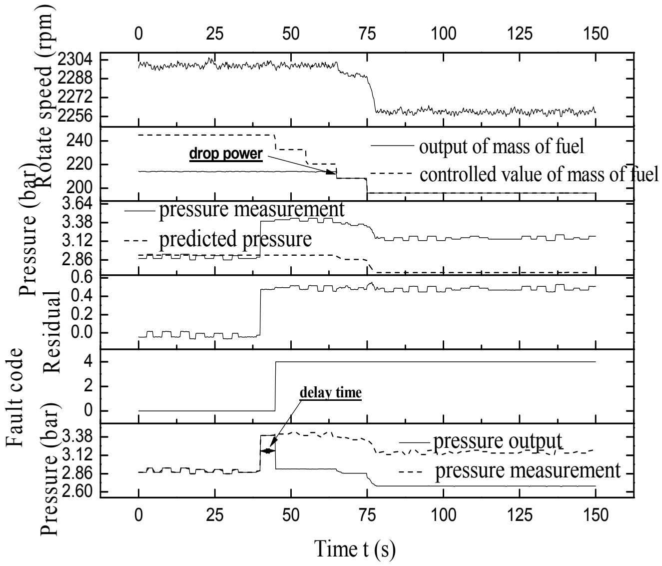

Fig. 18. Fault tolerance simulation of base fault

4. CONCLUSIONS

In this paper, a novel fault detection(FD)system and active fault-tolerant control (FTC) strategies of diesel engine MAP were constructed, based on Elman neural network observer. The structure of Elman neural network observer was established by simulation. The strategies were established on active fault-tolerant control and used for the protection of engine. The designed FD-FTC system was validated by simulation and experimental results. The following conclusions can be reached.

(1) According to characteristics of diesel engine intake system, fault diagnosis method based on Elman neural network observer was proposed. Experimental results demonstrate that the proposed fault diagnosis method is suitable to fault diagnosis for intake system of diesel engine, which is independent with the mathematical model of intake system.

(2) Comparing BP network with Elman neural network, Elman neural network observer is suitable to prediction of the intake pressure of diesel engine, which is more accurate than BP network.

(3) By analysing the characteristics of residuals in each fault mode and the relation between confidence interval and fault modes, the fault diagnosis strategies of complete failure, bias fault and drift fault were presented. Experimental results demonstrate that complete failure, bias fault and drift fault can be diagnosed using the proposed residual-based fault diagnosis strategies.

(4) Active fault-tolerant control (FTC) strategies in a closed-loop were proposed based on neural network observer. Different strategies were designed for the engine's different operating conditions, and power gradient reduction method was proposed. It can be concluded from the experimental results that short circuit fault, open circuit fault and sensor bias fault can be diagnosed and the engine can be effectively protected using the proposed fault-tolerant control strategies.

(5) The proposed FD and FTC methods is applied in simulation. It provides theoretical reference and simulation verification for practical applications in future. Future studies will consider optimization stability of the FTC system and application of the current design methods on-line in automotive diesel engine.

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