

SOLENOID VALVE FAILURE DETECTION FOR ELECTRONIC DIESEL FUEL INJECTION CONTROL SYSTEMS

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Abstract: Possible faults existing in electronic diesel fuel injection control (EDC) systems include rack deformation, solenoid valve failure, and rack-travel sensor malfunction. Among these problems, the solenoid failure is the most likely to occur for in-use diesel engines. This paper focuses on developing the algorithm that can clearly classify the usability of a solenoid valve without disassembling the fuel pump of the EDC system. Key parameters to feature the failure of the solenoid valve are determined. And a detection algorithm is discussed. Experimental results show that the proposed algorithm can identify the solenoid valve failure precisely. *Copyright © 2005 IFAC*

Key words: Diesel engines, Fault diagnosis, Actuator.

1. INTRODUCTION

The control of road vehicles emissions has become an important issue globally. Fuel injection control system directly affects the fuel efficiency and emissions of diesel engines. Recently, the advancement in electronics and measurement technologies has led to substantial improvement of engine fuel injection control, both in hardware configuration and control methodology. A typical example is the BOSCH electronically controlled P-EDC in-line fuel-injection pump. In this system, a linear solenoid valve instead of conventional mechanical governor is used to actuate the control rack of the fuel pump to regulate the injected fuel quantity. A rack-travel sensor is used in the pump to measure the rack position. The rack position is related to the injected fuel quantity through a calibrated map. The electronic control unit (ECU) controls the rack position to achieve desired fuel quantity.

Possible faults in the diesel fuel injection control system include rack deformation, solenoid valve

failure, and rack-travel sensor malfunction. The solenoid failure is most likely to occur due to those factors such as long period of usage, lubricant degradation and over heat. According to manufacturer's specification, the acceptable values of the coil resistance and plunger clearance are 0.6-0.9 Ω and 0.12mm, respectively. However, the plunger clearance is difficult to measure in situ because the solenoid is mounted inside the pump. To improve vehicle repairability and serviceability, a method for detecting the solenoid failure without disassembling the pump is needed.

Component fault detection and diagnosis (FDD) for vehicles has been studied for two decades. The resulting methodologies support both on-board and service applications. Examples include the observer-based approaches (Patton et. al., 1989; Patton and Chen, 1991; Ge and Fang, 1988) and parameter-estimation method approaches (Isermann, 1984; Freyermuth, 1991; and Bloch et al, 1995). These methods have been proven to be capable of detecting certain types of system faults. However, most of the previous works focused on diagnosing

the circuit faults for sensors or actuators. The work for mechanical fault diagnosis of actuator is limited.

The present paper is intended to develop the technique that detect the solenoid valve failure presented in the diesel fuel injection control system without disassembling the system. Generally, failed solenoid valves in the EDC system are difficult to ascertain, because there exists no evident mechanical or electrical damages on it. Only the plunger clearance can be used for reference to diagnose. Since excessive plunger clearance indicates worn plunger or sleeve, it is suspected that the solenoid valve failure may be caused by plunger wear. Thus in this study, we first investigated how the wear condition relates to malfunction to the system. Then the system's parameters were identified to characterize the wear. Finally, a neural network based classifier was applied to diagnose the fault.

2. SYSTEM MODELING

In EDC systems, the dynamic equation for its rack motion can be expressed as follows:

$$m\ddot{x} + c\dot{x} + kx + F_f(\dot{x}, F_m) = F_m \quad (1)$$

where x is the rack position (measurable), $F_f(\dot{x}, F_m)$ includes the friction force and other unmodeled forces, k is the elasticity coefficient of the spring, c is the damping coefficient, m is the mass of the moving parts, F_m is the driving force of the solenoid valve. When the solenoid is excited by a voltage, u , the developed current in its coil windings is governed by:

$$L \frac{di}{dt} + iR_c = k_A u(t), \quad (2)$$

where R_c is coil resistance, L is coil inductance, and k_A is the gain of power amplifier. Linearizing F_m about the operation point of the system yields

$$F_m = -k_x x + k_i i. \quad (3)$$

In general, the most significant friction components in a servo-mechanical system are the static friction (F_0), the Coulomb friction (F_c), and the viscous friction, i.e.,

$$F_f(\dot{x}, F_m) = F_0(\dot{x}, F_m) + F_c \operatorname{sgn}(\dot{x}) \quad (4)$$

The viscous friction depending on the velocity is not included, because its effect is combined into the damping behavior of the system.

3. PARAMETER IDENTIFICATION AND FAULT DIAGNOSIS

This section is intended to investigate how the wear condition of the solenoid valve relates to malfunction of the EDC system and then identify the system's parameters to characterize the wear.

The study is proceeded by driving the rack of the EDC system steadily using a sinusoidal reference input. To guarantee stable tracking, a feedback controller is applied. Then the parameters are identified through feedforward path of the system. The proposed method is shown in Fig.1. Here, G_4 denotes the dynamics of the plant corresponding to the time domain models (1) and (3), G_3 the dynamic characteristics of the current through the coil of the actuator corresponding to Eq.(2), G_2 the feedback controller, G_1 the feedforward model, r the position reference, x the position output of the control plant, u_1 the output of G_1 , and u_2 the output of the feedback controller. In addition to G_1 , the feedforward path also includes the friction compensation (F_{comp}). From Fig.1, the displacement response, x , of the rack is determined by

$$x = \frac{G_3 G_4 (G_1 + G_2 + F_{\text{comp}}) r + G_4 F_f}{1 + k_0 G_2 G_3 G_4} \quad (5)$$

and the tracking error, e , is

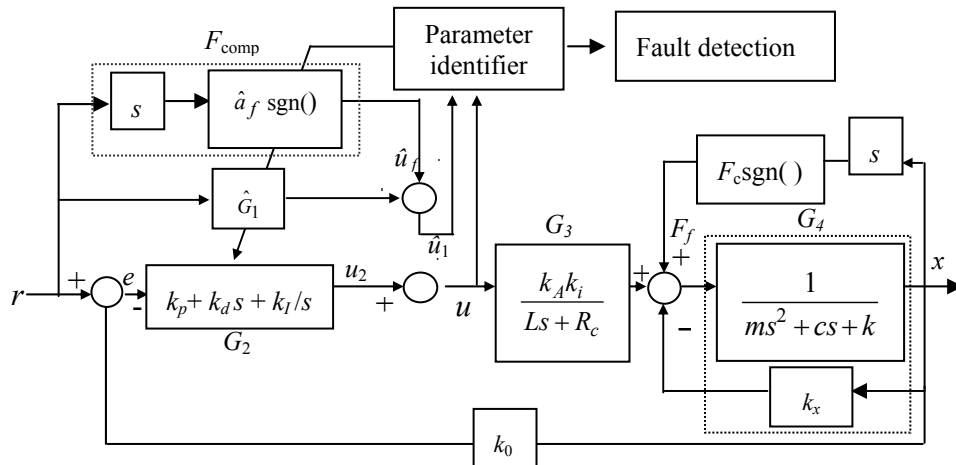


Fig. 1. Block diagram of the proposed diagnostic system

$$e = \frac{[1 - k_0(G_1 + F_{\text{comp}})G_3G_4]r - k_0G_4F_f}{1 + k_0G_2G_3G_4}. \quad (6)$$

Since the output of the feedback controller G_2 is $u_2 = G_2(s)e$, we can obtain the relation among u_2 , F_f and r as:

$$u_2 = \frac{[G_2 - k_0(G_1 + F_{\text{comp}})G_2G_3G_4]r + k_0G_2G_4F_f}{1 + k_0G_2G_3G_4} \quad (7)$$

If the parameters in G_1 and F_{comp} are identified properly such that the characteristics of the controlled plant and the associated friction are captured, i.e., if the conditions

$$G_1 = (k_0G_3G_4)^{-1} \quad (8)$$

$$u_f = F_{\text{comp}}r = \frac{1}{G_3}F_f \quad (9)$$

are satisfied, then the pump rack will perfectly track the desired trajectory determined by the position reference with zero state errors. Consequently the feedback controller effort will become $u_2 = 0$ such that $u = u_1$.

Based on this idea, the parameter identification algorithm is proposed as follows. The output of the friction compensation in Eq.(9) can be approximated by

$$\frac{1}{G_3}F_f \approx \frac{R_c}{k_Ak_i}F_c \text{sgn}(\cdot) = a_f \text{sgn}(\cdot). \quad (10)$$

G_1 can be expanded as

$$G_1 = a_3s^3 + a_2s^2 + a_1s + a_0. \quad (11)$$

where s being the Laplace variable. Thus the total feedforward effort becomes

$$u_1 = G_1r + a_f \text{sgn}(\cdot). \quad (12)$$

Using Eqs. (10)-(12), the estimation of total feedforward output can be obtained as:

$$\hat{u}_1 = \hat{a}_3\ddot{r} + \hat{a}_2\dot{r} + \hat{a}_1\dot{r} + \hat{a}_0 + \hat{a}_f \text{sgn}(\dot{r}), \quad (13)$$

where \hat{a}_f and \hat{a}_{0-3} are the parameters to be identified. The true values of \hat{a} 's are related to the physical parameters by the following equations:

$$a_f = \frac{R_c}{k_Ak_i}F_f, a_3 = \frac{Lm}{k_Ak_i k_o}, a_2 = \frac{mR_s + Lc}{k_Ak_i k_o}, \quad (14)$$

$$a_1 = \frac{L(k - k_x) + R_sc}{k_Ak_i k_o}, a_0 = \frac{R_s(k - k_x)}{k_Ak_i k_o}, \quad (15)$$

If all the parameter are identified properly so as to make \hat{a} 's = a 's, then $u_1 = u$ will be obtained. In other words, we estimate the parameters in model (13) to make u_1 equal to u . Thus the parameter identification can be accomplished by defining the following estimating error equation:

$$e_2 = u - u_1 = W\hat{a} - Wa = W\tilde{a}, \quad (16)$$

where $W = [\ddot{r} \ \dot{r} \ r \ \text{sgn}(\dot{r})]^T$ and $\hat{a} = [\hat{a}_3 \ \hat{a}_2 \ \hat{a}_1 \ \hat{a}_0 \ \hat{a}_f]^T$. With these notations, the gradient method can be applied to obtain the following on-line parameters estimator:

$$\dot{\hat{a}}(t) = -PW(t)e_2(t), \quad (17)$$

where the scalar gain matrix P is positive definite called the estimator gain. This on-line algorithm allows us to update the estimate \hat{a} easily. By starting with an initial estimate $\hat{a}(0)$ and the corresponding $e_2(0)$, we can sequentially update \hat{a} while new data are continuously obtained. It is noted that, in this algorithm, only the reference data are included in W . Thus the identification is not sensitive to disturbance.

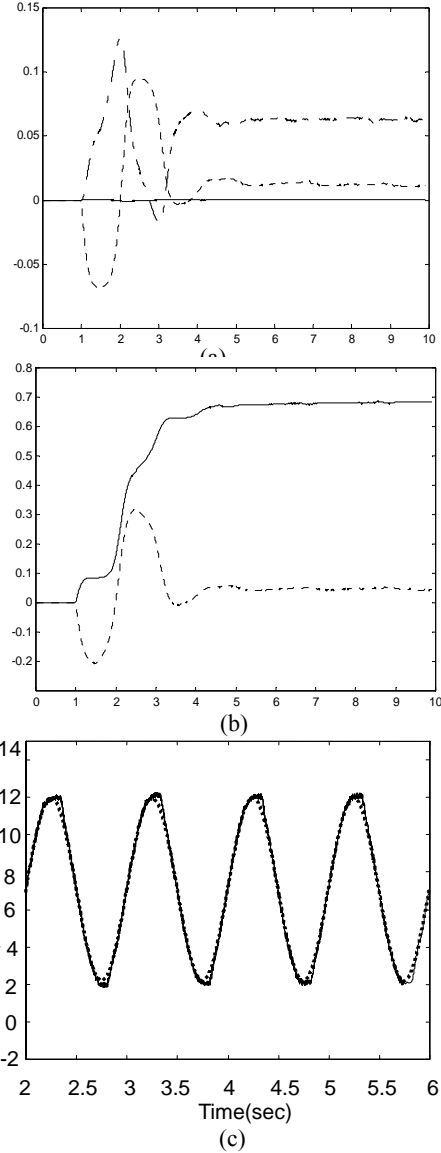


Fig. 2. Identification for valve V_1 . (a) \hat{a}_3 : solid line, \hat{a}_2 : dot-solid line, \hat{a}_1 : dot line; (b) \hat{a}_0 : solid line, \hat{a}_f : dot line; (c) the tracking signal (solid line) and the reference input (dot line) during identification.

Also note that the feedforward effort \hat{u}_1 in Fig.1 is not introduced into the controlled system. This is especially important to the system with a failure solenoid valve. Because the system with a failure solenoid valve is always in the state of marginally stable, the transient in updating the parameters in \hat{a} would increase the chance of destabilizing the system. As a result, the elements in gain matrix P in Eq.(17) should be selected as small as possible. Consequently, the convergent speed of the estimate of \hat{a} will be decreased. However, with the idea without the introduction of \hat{u}_1 into the controlled system, this situation can be avoided. More importantly, the selection of the parameters in the gain matrix P will become more flexible.

4. EXPERIMENTS

To study how the wear condition relates to malfunction to EDC systems, several experiments were carried on a BOSCH P-EDC fuel pump. Seventeen different solenoid valves collected from diesel fuel pump service shops were used for the test. Among these solenoid valves, four were brand new while thirteen had different worn conditions. Experimental apparatus includes a power amplifier, a controller, and a BOSCH P-EDC fuel pump equipped with LVDT type position sensor. The controller was a personal computer using Matlab XPC real time control software, which consisted of the feedback controller, feedforward parameter identifier, and a digital filter with bandwidth of 20Hz. A 0.5Hz sinusoidal pattern was used for the desired motion near the middle stroke of the solenoid.

The algorithm as shown in Fig.1 is implemented as follows. The conventional PID controller is adopted as the feedback controller G_2 . Initially, G_1 was set to be zero and the gains in G_2 were adjusted such that a stable rack motion can be achieved. Then the parameters in G_1 were identified using Eqs.(16) and (17). The tests were performed on the pump for respective solenoid with different degrees of wear using the same controller gains in G_2 . Before each test, the coil resistance and the clearance between plunger and sleeve of the solenoid were measured. According to the manufacturer's specification, the acceptable values of the coil resistance and plunger clearance are 0.6-0.9 Ω and 0.12mm, respectively. In the experiments, all the resistances of the solenoid valves were acceptable, but the measured plunger clearances showed large variations depending on their usage period. In the followings, three critical cases are presented for demonstration.

Figure 2 shows the first case for a brand new solenoid valve (denoted by V_1). The plunger clearance and the coil resistance were measured with 0.09mm and 0.7 Ω , respectively. It can be seen that

the estimated values rapidly converge to its final value with

$$\hat{a}_{V_1}=[0.0001,0.0630,0.0118,0.6819,0.0469]^T.$$

Although equipped with a brand new solenoid valve, the overall system still exists small extent of friction ($\hat{a}_f=0.0469$) caused by other mechanical components. With this solenoid valve, Fig.2(c) shows that the rack tracks the reference input satisfactorily.

Figure 3 shows the identification results for the pump equipped with a worn solenoid valve (denoted by V_2). The coil resistance and the plunger clearance were measured with 0.7 Ω and 0.25mm, respectively. It was disassembled from a vehicle whose idle speed still could be stabilized but produced a certain amount of smoke emission. The parameters are obtained as:

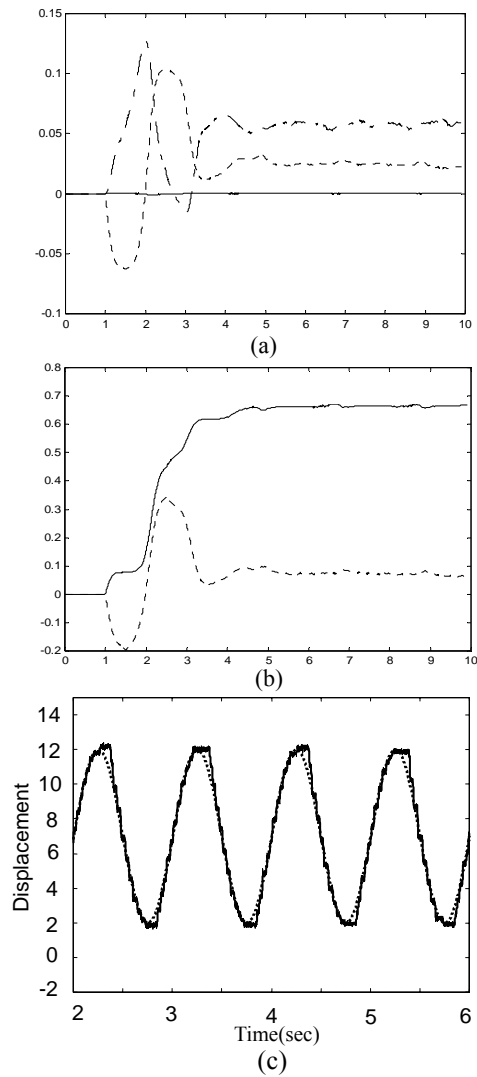


Fig. 3. Parameter identification for valve V_2 . (a) \hat{a}_3 : solid line, \hat{a}_2 : dot-solid line, \hat{a}_1 : dot line; (b) \hat{a}_0 : solid line, \hat{a}_f : dot line; (c) the tracking signal (solid line) and the reference input (dot line) during identification.

$$\hat{a}_{V_2} = [0.0001, 0.0583, 0.0239, 0.6649, 0.0715]^T.$$

Due to the wear, the plunger clearance increase to 0.25mm and the identified friction coefficient (\hat{a}_f) increases to 0.0715. The effect of the increased friction can be clearly seen in Fig.3(c), where the rack trajectory (solid line) and the reference input (dot line) are shown. Due to the friction force, the rack motion exhibits chattering phenomenon.

Figure 4 indicates the identification results for a more serious case. Here a faulty solenoid valve (V_3) with service life over 97000km is used. The parameters were measured to be 0.7 Ω and 0.2mm for coil resistance and plunger clearance, respectively. The smoke emission level from the diesel engine was too high to pass the EPA standard in Taiwan; and furthermore, a hunting phenomenon occurs with it. When this solenoid valve is fitted on the test pump, the identified parameters are obtained as:

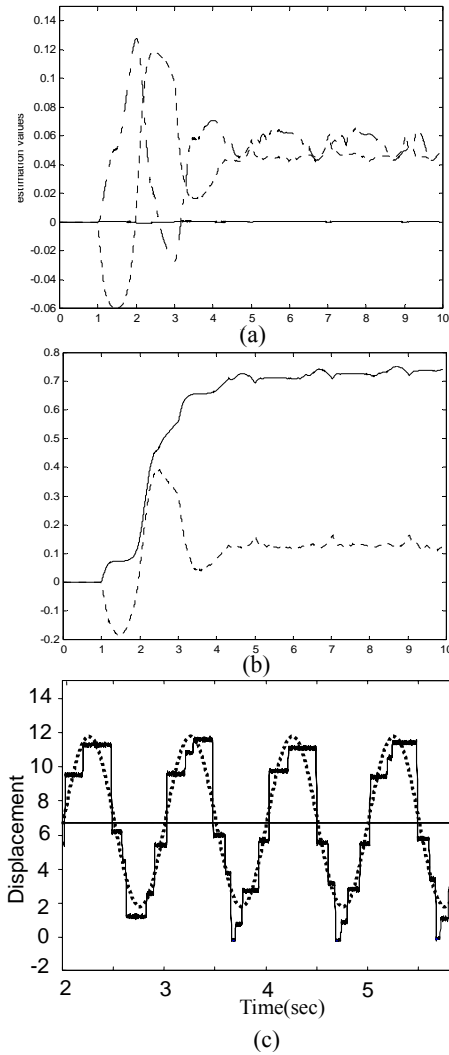


Fig. 4. Parameter identification for valve V_3 . (a) \hat{a}_3 : solid line, \hat{a}_2 : dot-solid line, \hat{a}_1 : dot line; (b) \hat{a}_0 : solid line, \hat{a}_f : dot line; (c) the tracking signal (solid line) and the reference input (dot line) during identification.

$$\hat{a}_{V_3} = [0.0001, 0.0546, 0.0471, 0.7321, 0.1284]^T.$$

Although the plunger clearance (0.2 mm) was less than that of the V_2 , it still produced a greater frictional force ($\hat{a}_f = 0.7321$). It is believed that the rough surface between the plunger and sleeve of the solenoid valve due to uneven wear attributes to the increase in friction. As can be seen from Fig.5(c), the chattering phenomenon is shown more violently.

By comparing the identified parameters of the worn solenoid valves (V_2 and V_3) with that of the brand new one (V_1), the percentage increases on $\hat{a}_{0,3}$ as well as \hat{a}_f were obtained as listed in table 1. Here, only the two critical cases are shown for simplicity; the other cases were shown having the same trend as these two cases in our experiments. From this table, it is seen that, in addition to \hat{a}_f , the wear of the solenoid valve also induces the changes on \hat{a}_1 significantly. The changes on \hat{a}_0 , \hat{a}_2 , and \hat{a}_3 are not clear. This is because that the wear of the solenoid valve also increases the damping force of the valve plunger resulting in the increase of \hat{a}_1 . Therefore the fault of pump rack control system are mainly due to the solenoid valve wear, and this kind of fault can be diagnosed by monitoring the values of \hat{a}_f and \hat{a}_1 .

Table 1 List of parameter changes

	Solenoid V_2	Solenoid V_3
$\Delta\hat{a}_f/\hat{a}_f$	52.45%	100.74%
$\Delta\hat{a}_0/\hat{a}_0$	-2.5%	7.36%
$\Delta\hat{a}_1/\hat{a}_1$	102.5%	316.9%
$\Delta\hat{a}_2/\hat{a}_2$	-7.46%	-13.3%

5. NEURAL NETWORK BASED FAULT DIAGNOSIS

As presented in section 4, since the vector (\hat{a}_f, \hat{a}_1) can feature the wear condition of the solenoid valve, the failure of solenoid valve wear can be diagnosed by monitoring its variation. Thus the diagnostic work becomes focusing on the value of (\hat{a}_f, \hat{a}_1) instead of all the system parameters. This reduces the dimensionality of the input data for diagnosis; and the computation time can then be reduced significantly. It is noted that the changes in the physical parameters are still unable to be detected, since the number of model parameters is less than that of the physical parameters. For diagnostic application, however, it is not necessary to display the changes in the physical parameters. Only a malfunction signal to trigger an alert is needed. In other words, we need a decision boundary to classify fault component. This leads to the two-dimensional two-classes classification problem.

In this section, a neural network classifier was used for this purpose. The network was a three layers (including the input and output layers) feedforward

network with nonlinear hidden and output units in which the weights were assigned using the generalized back propagation algorithm. The neural network training was performed off-line utilizing a previously generated training data, which consisted of input patterns (\hat{a}_f, \hat{a}_1) and the corresponding output being the 0/1 Boolean value to indicate whether the solenoid is abnormal or not. Six solenoids were utilized to train the network, where two were with severe worn conditions and four were brand new solenoids. Using these solenoids, a total of 18 input/output patterns were obtained by performing three tests for each solenoid.

After training, a decision boundary which partitions the input space (\hat{a}_f, \hat{a}_1) into regions corresponding to normal and abnormal components was obtained as shown in Fig.5. Another eighteen old solenoids were used to test the effectiveness of the classification, where ten of them were reusable and eight were faulty. In this figure, the solenoids classified as normal are marked as "O", while the abnormal solenoids are "+". Since every solenoid were tested three times, the three data points belong to the same solenoid were circled by a dash line. As can be seen in this figure, the ten reusable solenoids were classified into normal region. For the eight faulty solenoids, seven are successfully classified into the abnormal region except for the one near the decision boundary. Two data points of this solenoid are classified into abnormal region while one is in normal region. This indicates that its wear condition is not so severe as the others but should also be classified as an abnormal component. By observing the data points belong to the same solenoid, the closeness of these data points reveals the repeatability of parameter identification.

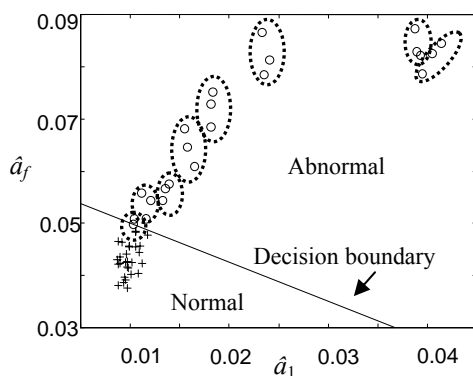


Fig. 5. The decision boundary in (\hat{a}_f, \hat{a}_1) space.

6. CONCLUSIONS

This paper proposes a method to detect the solenoid valve failure for electronic diesel fuel injection control systems without the need of disassembling the pump. The proposed diagnostic algorithm comprises a feedback controller, a parameter identifier, and a neural network classifier, which is found acceptably accurate through experiments. The genuine idea of this work is helpful for the design of a diagnostic device used to monitor the operation of the solenoid valve. If the solenoid valve is found to be abnormal, the device will generate an alarming signal. This improves the vehicle reparability and serviceability in the field.

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