Internal fault diagnosis of aircraft engine fuel metering unit based on artificial immune algorithm

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Abstract

This paper present an aircraft engine fuel metering unit internal fault diagnosis fault diagnosis method based on artificial immune algorithm. First, the overall structure and basic working principle of FMU are introduced. Then, the model of the key parts of FMU which include Electro-hydraulic servo valves (EHSV), actuator, sine-cosine revolver model and fuel flow valve model are built. With the parts model, the overall model of the FMU can be built. Then the typical faults like fuel leakage and some other faults are simulated with FMU model. Then, the fault diagnosis method based on artificial immune algorithm is introduced. At last, the FMU faults such as cylinder wall attached to the foreign body fault and resolver output circuit faults are detected with artificial immune algorithm. The diagnosis results show that the fault diagnosis method based on artificial immune algorithm is effective to FMU components failure.

Keywords: Aircraft Engine; Fuel Measuring Unit (FMU); Artificial Immune Algorithm; Fault Diagnosis

1 Introduction

With the development of aviation technology, aircraft engine control system is becoming more and more complex. In order to improve engine control efficiency and ensure flight safety, fault diagnosis and rapid identification of engine control system are very important. Full authority digital engine (or electronics) control (FADEC) is a system consisting of a digital computer, called an electronic engine controller (EEC) or engine control unit (ECU), and its related accessories that control all aspects of aircraft engine performance. Later in the 1970s, NASA and Pratt and Whitney experimented with the first experimental FADEC, first flown on an F-111 fitted with a highly modified Pratt & Whitney TF30 left engine. The experiments led to Pratt & Whitney F100 and Pratt & Whitney PW2000 being the first military and civil engines, respectively, fitted with FADEC, and later the Pratt & Whitney PW4000 as the first commercial "dual FADEC" engine [1]. FADEC monitors a variety of data coming from the engine subsystems and related aircraft systems, providing for fault tolerant engine control. Although the FAFEC is gradually replacing the Hydro mechanical Unit (HMU), the Fuel Measuring Unit (FMU) is still being used as a part of HMU. FMU is consist of fuel measuring valve (FMV), electro-hydraulic servo valves (EHSV), head sensor, bypass valve, shut-off valve and so on which can control fuel flow, pressure and prevent excessive speed when the engine was working. Once the engine stop working, it will stop supplying fuel to the combustor nozzles of the aircraft engine. If there were faults of the FMU, it will greatly reduce the engine fuel control performance or cause serious damage to the engine. For the internal structure is complex and there is no corresponding sensor to confirm which part is failure, it is very important to find a way to diagnosis the FMU internal fault timely.

Data-driven algorithms developed for aircraft engine abnormal condition detection include: pattern recognition techniques [2], expert systems [3], Bayesian belief networks [4], probabilistic neural networks [5] and artificial immune algorithm (AIA). AIA is an intelligent system imitating biological immune system, which offers the similar features to biological immune system, such as the noise tolerance, unsupervised learning, self-organization and memory mechanism. AIA is a solution to complex and distributed problems. With comparison to other intelligent optimization algorithms, AIA is of higher search succeed probability and better individual diversity [6]. Nowadays, the potential applications of the AIA can be listed: automation, data mining, pattern recognition, computer and network security. In 1992, Krishna Kumar proposed the idea of Immunized neural networks for complex identification which could solve the problem of system online identification [7]. Paul K. Harmer and Gregg H. Gunsch proposed the adaptive artificial immune system architectture to defend computer virus and check the normal network attack in 2002 [8][9].

In this paper, we present a fault diagnosis algorithm based on artificial immune algorithm that can execute aircraft engine fuel metering unit internal fault diagnosis. First, the overall structure and basic working principle of FMU are introduced. Then, the internal components model is built which can be used as the autologous samples used in AIA. At last, fault simulation was made and diagnosis result indicates that the algorithm could recognize the fault effective.

2 Composing and working logical of FMU

2.1 COMPOSING OF FMU

Fuel Metering Unit (FMU) is a part of Hydromechanical Unit (HMU) in aircraft engine which can measure the fuel flow supplying to the fuel nozzle. FMU mainly consist of fuel measuring valve (FMV), electro-hydraulic servo valves (EHSV), head sensor, sine-cosine revolver, bypass valve, shut-off valve and so on. It can ensure the minimum pressure of fuel, limit the maximum and minimum fuel flow and prevent the over speed of high pressure rotor rotational speed (N2). At the same time, it can provide the correction parameters to the other systems, such as Variable Stator Vane (VSV), Variable Bleed Valve (VBV), High Pressure Turbine Active Clearance Control (HPTACC), Low Pressure Turbine Active Clearance Control (LPTACC) and so on [10][11].

When the throttle lever angle changes, EEC will receive the throttle lever angle and it will correspondingly generate a current of 0 to 5 amperes. Then the electro-hydraulic servo valve spool displacement (EHVS) can receive the current and the actuator will drive the fuel metering valve moves and generate a mechanical angle value positive. Sine-cosine revolver will transfer the mechanical angle value to a voltage signal and feedback it back to EEC. The structure diagram of FMU is shown in Figure 1.

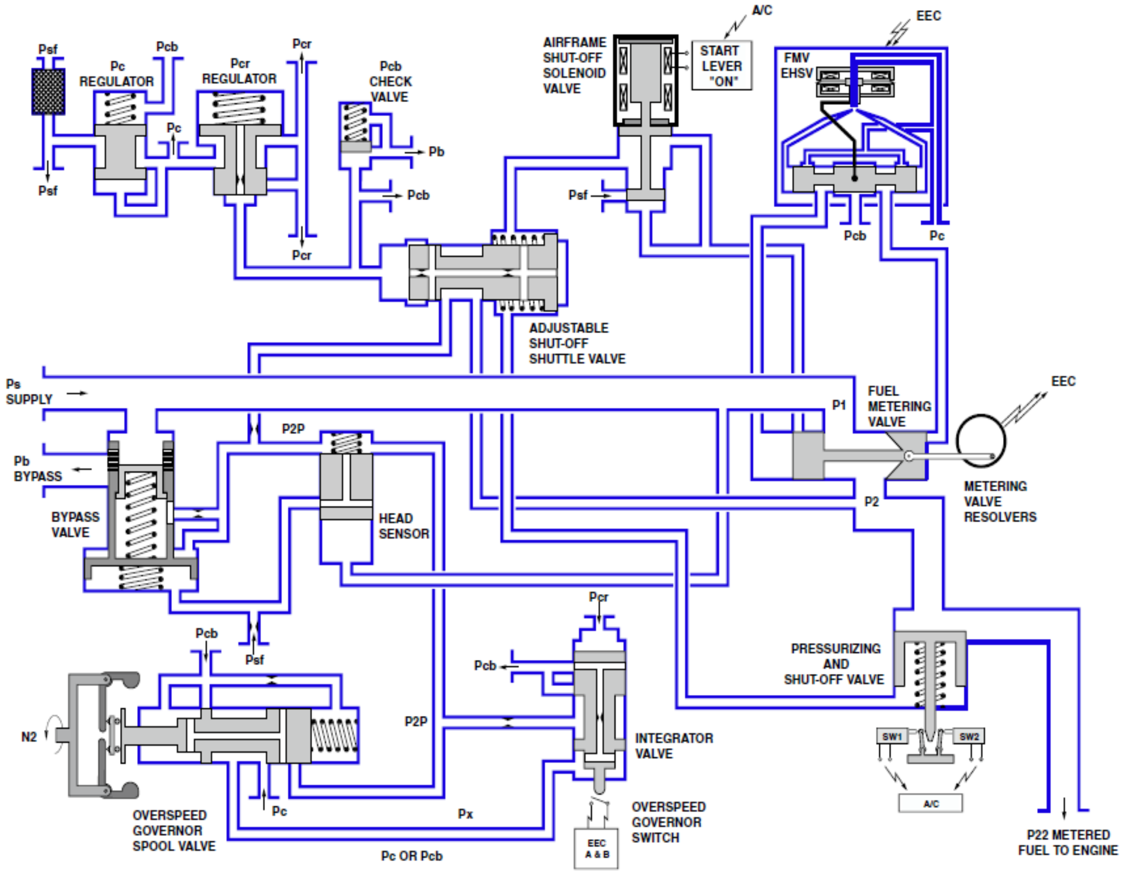

FIGURE 1 structured diagram of FMU

2.2 WORKING LOGIC OF FMU

EEC can receive all the state parameters to monitor if the FMU work normal. FMU control instruction computing is shown in Fig. 2.

N1 is the low pressure rotor speed, N2 is the high pressure rotor speed, N2K25 is corrected engine core speed, P0 is the static pressure of the environment, PS3 is the compressor Discharge Pressure, PT2 is the inlet air pressure, TAT is total air temperature, T12 is the fan in port temperature and T25 is the High pressure compressor in port temperature. In the control instruction, the other parameters represent the modified Maher number, indicator from Engine Interface and Vibration Monitoring Unit (EIVMU) and so on.

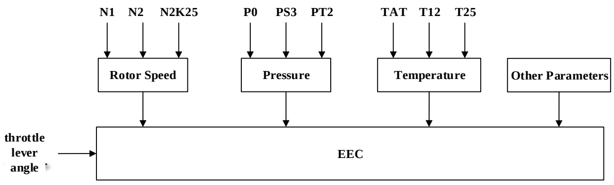

FIGURE 2 FMU control instruction computing

3 Modeling of FMU

3.1 ELECTRO-HYDRAULIC SERVO VALVES (EHSV)

EHSV is used to transfer electrical signal from EEC to hydraulic output. There is a two level valve in the EHSV which was controlled by torque motor. The first stage is fluidic amplifiers that can operate the second stage transmit the EEC control signal to torque motor. The fluidic amplifier directs high pressure fuel to ports that deliver the fuel to either side of the spool valve. A feedback spring dampens the spool valve movement when the torque motor driver provides a null position current. The spool valve directs the servo pressures to control actuator positioning. In the null position the fuel flows are equal on both sides of the spool valve. When the EEC commands the torque motor to reposition the fluidic amplifier, the armature in the torque motor deflects to position the nozzle. The nozzle can redirect the fuel flow to either side of the spool valve, which causes a servo output change. A mechanical feedback spring assures that the armature, nozzle and spool valve return to the null position after any movement of the spool valve [12][13].

So assuming the voltage signal from EEC is u_g, gain of the amplifier is K_U. u_1 and u_2 are the output of the two amplifiers. The basic voltage equation is:

$$u_1 = -u_2 = K_u u_g . \tag{1}$$

Voltage balance equation of the two coil loops can be expressed as equation (2).

$$\begin{aligned} E_b + u_1 &= i_1(Z_b + R_c + R_p) + i_2 Z_b + N_c \frac{d\Phi_a}{dt} \\ E_b + u_2 &= i_2(Z_b + R_c + R_p) + i_1 Z_b - N_c \frac{d\Phi_a}{dt} \end{aligned} , \tag{2}$$

where E_b is the required voltage value which can produce a constant current, R_c is the coil impedance. Z_b is the coil impedance of the public side. R_p is the internal resistance of the amplifier. N_c is the turns number of the coil. Φa is the magnetic flux of the armature.

Make $\Delta i = i_1 - i_2$, equation (3) can be got.

$$2K_u u_g = \Delta i(R_c + R_p) + 2N_c \frac{d\Phi_a}{dt} . \tag{3}$$

According to equation (3), we can see that the control voltage will be used to overcome the counter electromotive force produced by armature flux changes and consumed of the coil and the amplifier's resistance. Flux can be expressed as $\Phi_a = 2\Phi_g(a/l_g)\theta + (N_c/R_g)\Delta i$, so the voltage equation is:

$$2K_u u_g = \Delta i(R_c + R_p) + 2K_b \frac{d\theta}{dt} + 2L_c \frac{d\Delta i}{dt} , \tag{4}$$

where $K_b = 2aN_c\phi_g / l_g$ means back EMF constant of the coil. $L_c = N_c^{\,2} / R_g$ is the coefficient of self-inductance.

By applying Laplace transformation to equation (4), we can get:

$$2K_u u_g = (\mathrm{R}_c + \mathrm{r}_p)\Delta I + 2K_b s\theta + 2L_c s\Delta I , \tag{5}$$

$$\Delta I = \frac{2K_u u_g}{(\mathrm{R}_c + \mathrm{r}_p)(1+\frac{s}{\omega_a})} - \frac{2K_b s\theta}{(\mathrm{R}_c + \mathrm{r}_p)(1+\frac{s}{\omega_a})} . \tag{6}$$

The electromagnetic torque of the Torque motor is $T_d = K_t \Delta i + K_m \theta$.

Then the motion equation of the armature baffle assembly can be expressed by equation (7).

$$T_d = J_a \frac{d^2\theta}{dt^2} + B_a \frac{d\theta}{dt} + K_a \theta + T_{L1} + T_{L2} , \tag{7}$$

where J_a is the Moment of inertia of the armature baffle assembly. B_a is the viscous damping coefficient of the armature baffle assembly. K_a is the spring pipe stiffness. T_{L1} is the load torque generated by the liquid flow from nozzle to baffle. T_{L2} is the load torque generated by the deformation of feedback rod to baffle.

The equation of motion of the armature baffle is:

$$\theta = (K_{mf} / \frac{s^2}{\omega^2_{mf}} + \frac{2\xi_{mf}}{\omega_{mf}} s + 1) / [\mathrm{K}_t \Delta \mathrm{I} - \mathrm{K}_f(\mathrm{r}+\mathrm{b})\mathrm{x}_V - \mathrm{rA}_N \mathrm{p}_{Lp}] , \tag{8}$$

where $K_{mf} = K_{an} + (\mathrm{r}+\mathrm{b})^2 K_f$. K_{mf} is the composite stiffness and K_{an} is the net stiffness of the torque motor.

The transfer function of baffle displacement and valve displacement is:

$$\frac{x_v}{x_f} = K_{ap} A_v / s(\frac{s^2}{\omega^2_{hp}} + \frac{2\xi_{hp}}{\omega_{hp}} \mathrm{s} + 1) . \tag{9}$$

The transfer function of valve displacement and hydraulic cylinder displacement is:

$$(K_q / A_p) / s\left(\frac{s^2}{\omega_h^2} + \frac{2\xi_h}{\omega_h} s + 1\right) . \tag{10}$$

The load pressure of nozzle flapper valve is:

$$p_{Lp} = \frac{1}{A_V}\left[m_V \frac{d^2 x_V}{dt^2} + 0.43\omega(\mathrm{p}_s - \mathrm{p}_L)\,\mathrm{x}_v \right] . \tag{11}$$

Slide valve load pressure is:

$$P_L = \frac{1}{A_p} m_t s^2 x_p \tag{12}$$

So the overall control system block diagram of EHVS is shown in Figure 3.

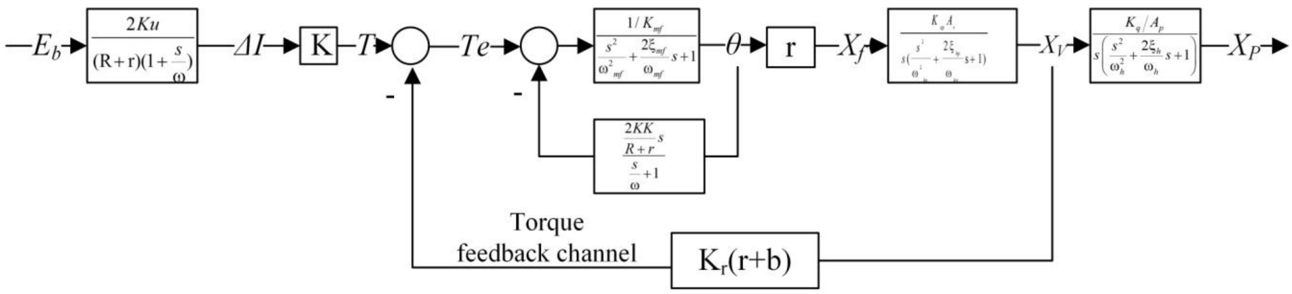

FIGURE 3 Overall control system block diagram of EHVS

3.2 ACTUATOR

Assuming the actuator pressure difference force F on both ends of the piston, there will be a displacement a. A_p is the area of the piston. M_p is the mass of the piston rod. Ad is the liquid damping. Then considering the resistance produced by liquid with the damping coefficient of K, the transfer function of the actuator can be expressed as equation (13). And the control system block diagram of actuator is shown in Figure 4.

$$H(s) = \frac{A_P}{M_p s^2 + A_p A_d s} \tag{13}$$

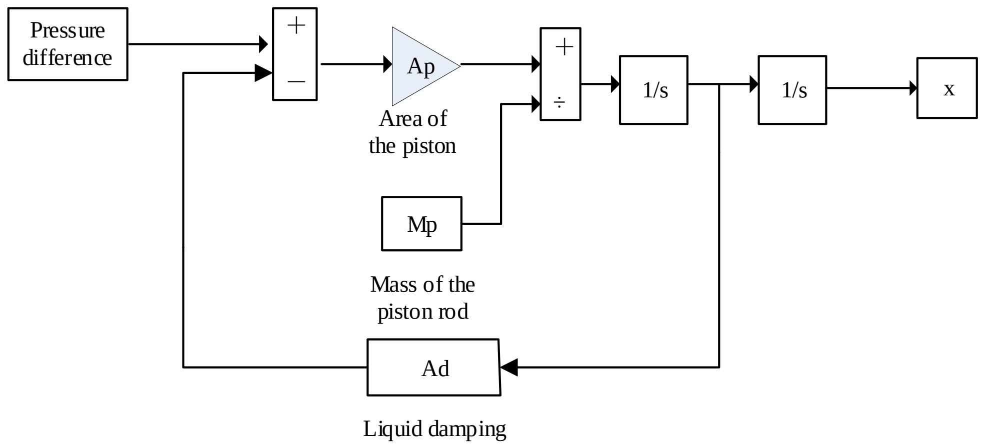

FIGURE 4 Overall control system block diagram of actuator

Other parts like sine-cosine revolver model and fuel flow valve model can also be built as above. So the overall model of the FMU is shown in Figure 5.

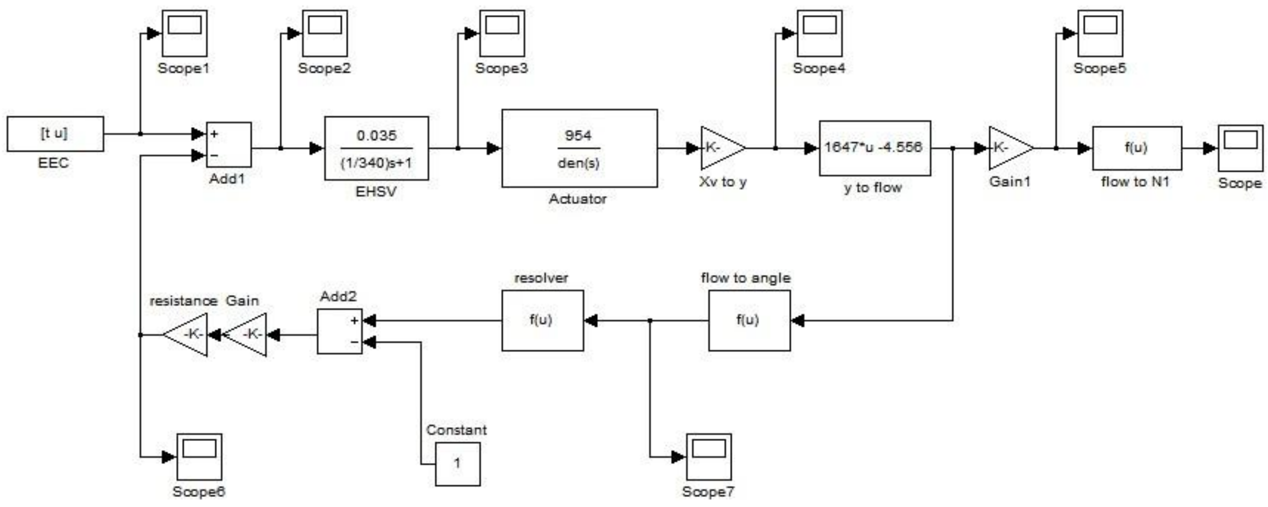

FIGURE 5 Overall model of FMU

4 Artificial Immune algorithms

The first step is antigen recognition. The object function and the restriction condition will be as antigen, and some kinds of algorithm parameters will be initialized at the same time. The next step is generating the group of initial antibodies. At the beginning, the several antibodies will be generated stochastically as the group of initial antibodies.

After calculating the affinity between antibodies and antigens, it needs to generate the new group of antibodies. If the affinity of antibodies would be bigger than the right threshold, the process of immune memory would be redirected to those antibodies with the highest rate of importance and priority to the memory-cell and put these antibodies into the new group of antibodies straight will be carried out. If the affinity of antibodies will be extracted between the left and right threshold, high frequency mutation and antibodies regrouping will be carried out. When the affinity of antibodies is smaller than the left threshold, we will delete these antibodies. Immune network regular is the last step with which can regular the degree of stimulated antibodies to reach the setting goal. So according to the general artificial immune algorithm, the three kinds of typical fault diagnosis method which include fuel leakage fault, resolver output line circuit and cylinder wall attached to the foreign body of HMU based on artificial immune algorithm flow chart is shown in Figure 6.

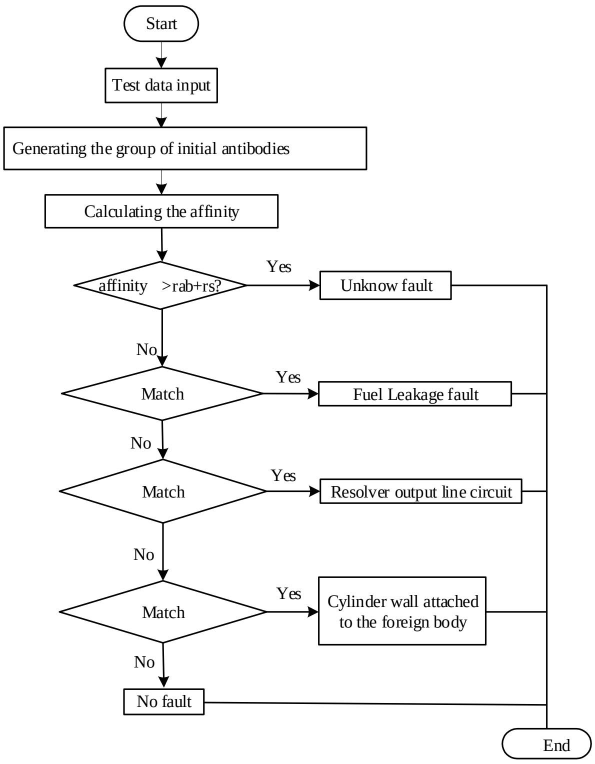

FIGURE 6 Artificial immune algorithm flow chart

5 Fault simulation and diagnosis

5.1 DATA PRE-PROCESSING

According to the Overall model of FMU, the simulation curves of FMU flow can be obtained. And the FMU flow characteristics can be got by calculating the root mean square value (RMS) and power spectral density function (PSDF) of the FMU flow. The root mean square value can be calculated by equation (14).

$$RMS = \sqrt{\frac{1}{N}\sum_{i=1}^{N} x_i^2}\,, \tag{14}$$

where x_i is the sampling point. RMS will be normalized to:

$$RMS^* = \frac{RMS - MIN_{RMS}}{MAX_{RMS} - MIN_{RMS}}\,. \tag{15}$$

Power spectral density function of FMU flow can be calculated by equation (16).

$$x(K) = \sum_{j=1}^{N} x(j) W_N^{(K-1)(j-1)}\,, \tag{16}$$

where $W_N = e^{-j\frac{2\pi}{N}}$.

Then the initial detector can be got with (RMS^*, GLP^*). And the fault diagnosis can be processed according to the artificial immune algorithm flow chart.

5.2 FUEL LEAKAGE FAULT

Servo output pressure P_c is all the pressure regulating reference of FMU. The action of Electro-hydraulic servo valve relies on the first class of differential pressure output of P_c, and amplifies the pressure difference according to P_c. So if there exists the fuel leakage fault, the correction coefficient of P_c should be reduced. So we simulate pressure reduced 5% and the value of Pc was 0.95. According to the simulation model of FMU, the relationship between the fuel flow and time under normal and fuel leakage fault condition can be got. The simulation result is shown in Figure 7 and we can see that the solid line is the normal flow and the dotted is at fault. So if there exist fuel leakage fault of FMU, the actuator actuating time would be prolonged and the fuel flow will fall down. The fault simulation output result accords with the actual situation. So the fault samples will be recorded and processed with RMS and PSDF.

Figure 8 shows the fault diagnosis result with artificial immune algorithm where "O" is the training data and "*" is the test data. We can see that the fault data is contained in the detector. The fault detector can be combined with the normal detector that can detect the fuel leakage fault successful.

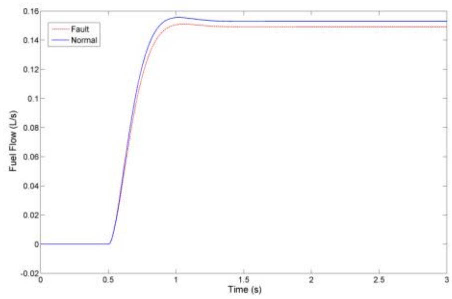

FIGURE 7 Artificial immune algorithm flow chart

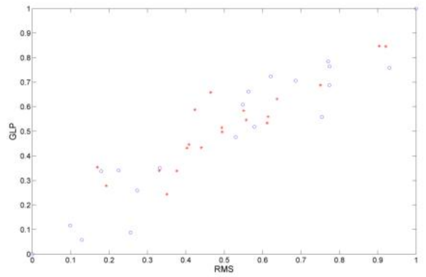

FIGURE 8 Fuel leakage fault diagnosis result with AIA

5.3 RESOLVER OUTPUT CIRCUIT

It there is fault in the resolver output circuit, there only needs to remove the circuit from the resolver to EEC. By simulation, the relationship between the fuel flow and time under normal and Resolver output circuit fault condition can be got.

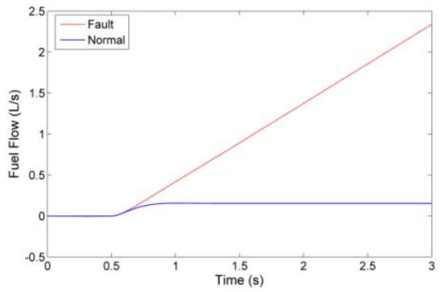

FIGURE 9 Resolver output circuit fault simulation

As we can see in Figure 9 that when the output line of the Resolver circuit breaker, EEC cannot detect angle information. If the EEC does not take measures to for the response, the piston would have been on the actuation until it reaches the maximum flow. Figure 10 shows the fault diagnosis result with artificial immune algorithm where "O" is the training data and "*" is the test data. We can see that the fault data is contained in the detector. The fault detector can be combined with the normal detector that can detect the resolver output circuit fault successful.

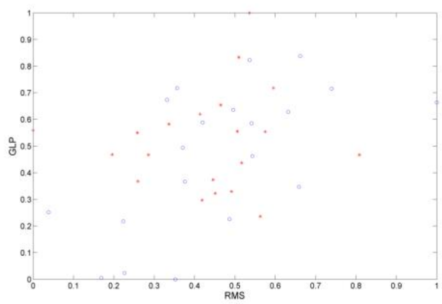

FIGURE 10 Resolver output circuit fault diagnosis result with AIA

5.4 CYLINDER WALL ATTACHED TO THE FOREIGN BODY

In actual use of FMU, the fuel is always mixed with little foreign body. When the actuator frequent actuation, there always some foreign body attached to the actuating cylinder wall which makes the inner wall of the actuator has a damping. If there would be cylinder wall attached to the foreign body fault, it will affect the liquid damping A_d. So we adjust the value of A_d, the simulation result of cylinder wall attached to the foreign body fault can be got which is shown in Figure 11. Figure 12 shows the fault diagnosis result with artificial immune algorithm where "O" is the training data and "*" is the test data. We can see that the fault data is contained in the detector. The fault detector can be combined with the normal detector that can detect the cylinder wall attached to the foreign body fault successful.

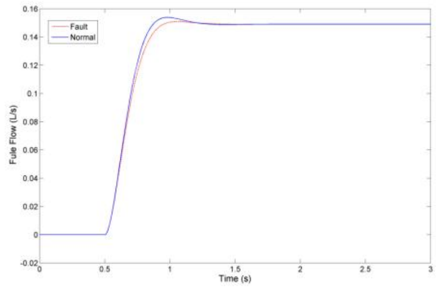

FIGURE 11 Cylinder wall attached to the foreign body fault

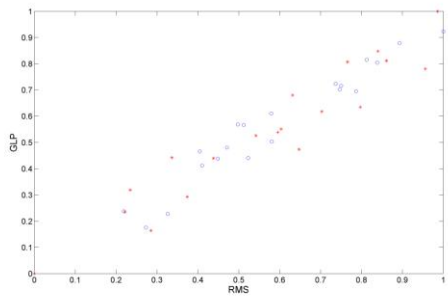

FIGURE 12 Cylinder wall attached to the foreign body fault diagnosis result with AIA

5.5 OVERALL FAULT DIAGNOSIS

So there are three kinds of detectors, where "*" denotes the fuel leakage fault detector region, "□" denotes the open circuit resolver output circuit fault detector region and "O" denotes the cylinder wall attached to the foreign body fault detector area. Figure 13 shown the summary graph of the above three kinds of fault simulation and from which we can see that each fault distribution distance is large and does not exist the different fault overlap, it will reduce the difficulty of fault identification.

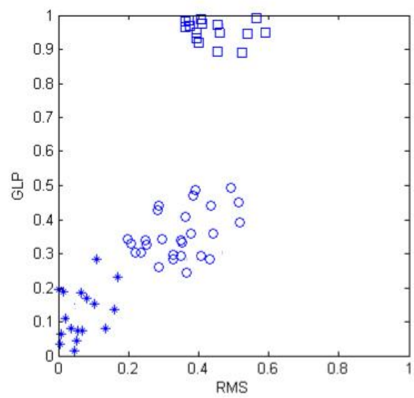

FIGURE 13 Overall fault diagnosis of FMU

For different fault types of settings will get the fault identification of different regions, different categories of recognition when the fault is when you can build more other fault types using the model.

6 Conclusion

In this paper, we present a fault diagnosis algorithm based on artificial immune algorithm that can execute aircraft engine fuel metering unit internal fault diagnosis. First, the overall structure and basic working principle of FMU are introduced. Then, the model of the key parts of FMU which include Electro-hydraulic servo valves (EHSV), actuator, sine-cosine revolver model and fuel flow valve model are built. With the parts model, the overall model of the FMU can be built. Then the typical faults like fuel leakage and some other faults are simulated with FMU model. Then, the fault diagnosis method based on artificial immune algorithm is introduced. At last, the FMU faults such as cylinder wall attached to the foreign body fault and resolver output circuit faults are detected with artificial immune algorithm. The diagnosis results show that the fault diagnosis method based on artificial immune algorithm is effective to FMU components failure.

Acknowledgments

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