Aircraft System State Recognition and Fault Prediction Based on a Test Diagnostic Model

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Abstract. The existing testability models for fault prognosis of aircraft systems limit the implementation of prognosis and health management systems. This paper develops a test diagnosis modeling method and relevant algorithms to support dynamic testing and to evaluate fault prognostic ability during aircraft system design. According to the system principles and the complex function structure of aircraft systems, a test diagnostic model is established by integrating testing and prognostic information with a test diagnostic skeleton model using multi-signal flow. New test indexes are identified to assess the testability and prognostic ability of aircraft systems. Relevant state recognition and fault prediction algorithms are established by fusing the improved particle swarm optimization algorithm and Hidden Semi-Markov Model. The feasibility and validity of the test diagnostic modeling method and relevant algorithms are verified in an aircraft’s engine bleed air system. Training and test show that the model can support analysis and estimation, and the algorithms can ensure accurate results after training the HSMM using improved PSO algorithm.

1. Introduction

Flight safety is a common goal of the global civil aviation industry. Airlines strive to minimize operating costs and increase economic efficiency while safeguarding aircraft operation for passengers and crew. Aircraft economic efficiency can be improved by reducing diagnostic and maintenance costs [1, 2]. Manufacturers use design for testability (DFT) to reduce the cost of a product during its design and life cycle and to limit additional investment in test equipment. Maintenance efficiency is improved by using built-in test (BIT) coverage methods [3]. DFTs can improve system fault diagnosis ability and fault coverage by adding sensors and tests in the design stage of the system. Most of the test designs focus on professional microcosmic fields, such as test problems of large-scale integrated circuits and self-built test problems [4].

DFT uses two methods [5, 6] based on either empirical engineering weights or models. Model-based DFT has been widely used in engineering and have resulted in many testability models. The most widely used models are logic models, hybrid diagnosis models, information flow models, and multi-signal (flow graphs) [7]. In the 1980s, Data Sciences International (DSI) developed a logic model based on correlation, which is the earliest applied testability model [8]. Later, DSI researched the hybrid diagnostic modeling technology that expressed the function and the failure mode in the same correlation model [9]. In the 1990s, express, test design software based on a hybrid diagnostic model, came out [10]. In the multi-signal flow model, the fault and the test are not directly related, and the correlation information is expressed through the signal propagation relationship [11]. Hybrid
diagnostic models and later information flow and multi-signal flow models are all improvements of the logic model, the essence of which can be called the correlation model [12, 13, 14, 15]. At present, multi-signal flow models are commonly used to improve the testability of the product in the design stage [16, 17, 18, 19].

The existing testability models obtain the test parameters such as the fault detection rate and the fault isolation rate, and can evaluate and optimize the fault detection ability and fault isolation ability of the product [20]. However, the existing testability models have the following limitations: (a) Much of the test and diagnostic information is lost during the modeling process. The diagnosis ability and the dynamic development progress of faults cannot be described in detail. (b) The established model cannot evaluate the prediction ability of the system. The information cannot meet the requirements of system dynamic test and fault prognosis.

With the development and application of new technology and new equipment, the causes of aircraft faults are increasing. The parameters, which need to be monitored to ensure the operational safety of the aircraft, are also increasing. The testability of aircraft systems has greatly increased the complexity of aircraft diagnosis and repair, and has become a critical factor that affects the entire life cycle cost of aircraft systems. Aircraft maintenance costs are high primarily because aircraft system designs lack fault prediction capability [21].

Considering these limitations, this paper develops a new test diagnostic modeling method based on the system principles and multi-signal flow to test aircraft systems and predict faults. The model integrates system test and fault prognosis information. The relevant state recognition and fault prediction algorithms are used for the developed test diagnostic model. An aircraft engine’s bleed air system is used as an example to demonstrate the developed modeling method and verify the test analysis and evaluation algorithms.

2. Test diagnosis modeling
The test diagnosis modeling process is shown in figure 1. Firstly, a skeleton model was established based on aircraft system principles and multi-signal flow by applying the functional structure of the hierarchy analysis method. The test, fault, and status information was then obtained based on testability design data and the predictable properties through failure modes and effects analysis. Finally, the test, fault, status, and other information was dynamically related with the skeleton model to establish a test diagnostic model.

![Test diagnosis modeling process](image-url)
2.1. Skeleton modeling based on system theory and multi-signal flow

The test diagnostic skeleton model is defined as FS:

\[ FS = (M, E, D, I, O) \]

where M is the module and can be divided into different levels of system, subsystem, least replaceable unit (LRU), and other layers, expressed as:

\[ M = [m_1, m_2, \ldots, m_l] \]

E represents the set of directed edges of each node, indicating the connection between each node and the propagation direction of each variable, expressed as \( E = [e_{ij}] \). D is the functional description to specify the function of the unit in the system. I represents the input variable, describing all input variables of the functional unit. O represents the output variable, describes all the output variables of the functional unit, and is also the input variable of the subsequent functional unit. The model can be optimized to improve system-level diagnosis and prediction by adding and deleting test points and optimizing test methods based on the testability skeleton model.

2.2. Information modeling based on test diagnostic skeleton model

In order to support fault prognosis, relevant fault prognosis information and test information were added to the test diagnostic skeleton model. The failure mode and failure mode attributes of each module are related to the nodes of the skeleton model.

The fault prognosis information model is defined as follows:

\[ Fa = (F_l, F_m, F_r, F_{fs}, F_p, F_S) \]

where \( F_l \) indicates the location of the fault, \( F_m \) is the failure mode, \( F_r \) indicates the fault occurrence rate, \( F_{fs} \) represents the function of each failure mode function, \( F_p \) is the predictability of the fault, and \( F_S \) expresses the fault status.

The test information model is defined as follows:

\[ Te = (T_l, T_d, T_i, T_r, T_{dp}, T_p, T_v, T_c) \]

where \( T_l \) is the location of the test point, \( T_d \) is the functional text description, \( T_i \) is the input signal, \( T_r \) is the signal feature extraction method, \( T_{dp} \) is the output of the test, \( T_p \) is the ability to predict the test, and \( T_v \) and \( T_c \) are the test time and cost of testing, respectively.

The fault prognosis information Fa and test information Te were set as the attributes of the relevant test nodes of the skeleton model according to the correlation between information and nodes. The relationship between the signal and the behavior of the test node was described by the directed edge. Finally, the test prognostic model with test information and prognosis information was established to satisfy the requirements of dynamic fault testing by changing the attributes of the nodes.

2.3. Test analysis and evaluation

Hypothesis fault \( f_i \) is related to test \( t_j \), and the occurrence of fault \( f_i \) will cause test \( t_j \) to fail. This relationship is the correlation between failure and testing and can be expressed by a binary matrix \( FT_{m \times n} \) [19, 22].

\[ FT_{m \times n} = \begin{bmatrix}
    ft_{i1} & \cdots & ft_{in} \\
    \vdots  & \ddots & \vdots  \\
    ft_{ml} & \cdots & ft_{mn}
\end{bmatrix} \]

The value of \( ft_{ij} \) is 0 or 1. If \( ft_{ij} = 1 \), then fault \( f_i \) is related to test \( t_j \), that is, fault \( f_i \) can be detected by test \( t_j \). If fault \( f_i \) has nothing to do with test \( t_j \), the fault \( f_i \) cannot be detected by test \( t_j \), assuming there are \( m \) failure modes and \( n \) tests in the model.

The developed test diagnostic model adds fault prediction properties to describe the development process of the fault. In order to evaluate the model’s testability and prognosis, this paper develops a new concept of predictable fault coverage.

Definition 1. Predictable fault

Predictable fault means that the fault mode itself supports fault prediction, and the existing testing methods can meet the requirements of its fault prediction.

Definition 2. Predictable fault coverage.
Predictable fault coverage indicates the ratio of the number of faults that can be predicted by the system’s existing methods to the total number of predictable faults under the given conditions.

$$\gamma_{FSi} = \frac{N_{PSi}}{N_{PSi}}$$  \hspace{1cm} (6)

The predictable fault and predictable fault coverage are combined with traditional testability parameters, i.e., fault detection rate, fault isolation rate, unmeasured fault, and fuzzy group, and are set as test indexes. The model’s testability and prognostic ability are evaluated using these indexes to identify design deficiencies.

3. State recognition and fault prediction based on PSO and HSMM

Normally, the function of aircraft system from normal to failure does not happen instantaneously. It will go through a series of different fault states before failure. There is a gradual transition relationship between different fault states, and the fault states are hidden. The specific state must be determined by the collected test data. In the developed test diagnosis modeling process, the predictable attributes of the fault are defined, and different fault states of the same failure mode are divided, so that the test diagnosis model can well support the identification and prediction of fault states. Considering that the Hidden Semi-Markov Model (HSMM) focuses on fault development and evolution, and has the advantages of strong state classification capabilities, it is suitable for system state identification and prediction[25]. The hidden semi-Markov model is used to identify and effectively evaluate the fault state of aircraft systems, and to predict the remaining service life of the system.

According to the relevant definitions of HSMM, the HSMM model parameters are defined as follows [24]:

$$\lambda = (\pi, A, B, D, N, M)$$  \hspace{1cm} (7)

where D represents the state dwell time probability distribution. Assuming that the system will experience failure states from the initial normal state to the final complete fault, is the expected dwell time of the system in the fault state \((i=1, 2, \ldots, n-1)\). Set as observed variable, RUL as the left life of system, then:

$$RUL = d_i^* + \sum d_i$$ \hspace{1cm} (8)

$$d_i = \mu_i + \rho \sigma_i^2$$

$$\rho = (T - \sum_{i=1}^{N} \mu_i) / \sum_{i=1}^{N} \sigma_i^2$$

$$d_i^* = p(i|\nu)d_i$$ \hspace{1cm} (9)

The recognition and fault prediction steps are as following:

Step 1. According the life cycle test data of all fault states of the system, estimate the parameters of HSMM model, such as the transition probability matrix, the dwell time of the fault states, and the variance so on. A model library including all fault states of the system is established.

Step 2. Input the real-time characteristic data of the object system into the model library established by HSMM for fault status identification.

Step 3. Calculate the dwell time and the left dwell time of the system state.

Step 4. Calculate the RUL.

In above steps, parameter estimation is a very important and difficult step of solving with HSMM. Baum-Welch algorithm [27] is used to solve the parameter estimation of HSMM model at present. Baum-Welch algorithm trains the HSMM model converging to a local optimum. In order to converge to system’s global optimal, this paper combines the improved particle swarm optimization (PSO) algorithm [28] with the original training algorithm to train HSMM. The process of HSMM training algorithm combined with improved particle swarm is as follows:

Step 1. Initialize the position and velocity of each particle, and set the iteration termination conditions. Let the original number of iterations \(t=0\). 

\[ d_i^* = p(i|\nu)d_i \]
The dynamic adjustment of inertia weight variables $\omega$ according to the exponential decrease is introduced into the standard particle swarm algorithm.

$$\omega[t] = \exp\left(-\frac{t}{\text{maxt}}\right)$$ (10)

Step 2. Estimate the HSMM parameters using the sample data and Baum-Welch algorithm, and let the parameters as the initial positions of the particles in the particle swarm.

Step 3. Calculate observation sequence probability $P(O|\lambda)$ of the model parameter $\lambda$ using the following formula:

Herein, $(O_1 O_2 \cdots O_{t-d})$ is the observed variable of the state $i$ at time $t-d$, and $(O_{t-d} O_{t-d+1} \cdots O_t)$ the observed variable of the state $j$ at time $t$.

$$P(O|\lambda) = \sum_{i=1}^{N} \sum_{j=1}^{N} \alpha_{t-d}(i) \alpha_{j} P_{i,j}^{(d)} \prod_{j=1}^{t} b_{j}(O_{j}) \beta_{t-1}(j)$$

$$\alpha_{i}(t) = P(O_{1} O_{2} \cdots O_{t}|\lambda)$$

$$\beta_{t}(i) = \sum_{j=1}^{N} \sum_{d=1}^{D} \beta_{t+d}(j) \alpha_{i} P_{i,j}^{(d)} b_{j}(O_{t+d|t})$$ (11)

Step 4. Update the local and global optimal positions of each particle according to the formula of the improved particle swarm algorithm.

$$V_{i}(t) = \omega(t) V_{i}(t-1) + c_1 r_1 (P_{i}(t-1) - X_{i}(t-1)) + c_2 r_2 (P_{i}(t-1) - X_{i}(t-1))$$ (12)

$$c_1, c_2 \in (0,2)$$

$$r_1, r_2 \in (0,1)$$

In the above algorithm, $c_1, c_2, r_1, r_2$ are random number, and $\omega(t)$ is weight of inertia. Learning factor $c_1$ and $c_2$ delegate the acceleration weight of particles advancing to their own extreme value and global extreme value.

Step 5. Determine whether the above parameter estimate meet the requirements. If not, set $t = t + 1$, go back to step 2.

4. Application

An engine bleed air system of certain type aircraft is selected as the typical application to verify the test diagnostic modeling method. According to the system principle of the engine bleed air system, its components can be divided into several LRU-level components, namely one-way control valve IPCV, high pressure valve HPV, pressure regulating shut-off valve PRSOV, pre-cooler PCE, fan control valve FAV, Bleed-air Temperature sensor BTS and PESOV downstream pipe. Through analysis, the engine bleed air system has 7 modules, expressed using set of $M$, which is defined as $\{m_1, m_2, \cdots, m_7\}$.

Further analysis of input and output variables, the connection between the engine bleed air system nodes and the propagation of each variable direction, expressed as $E = [e_{ij}]$. Input and output variables of engine bleed air system are shown in table 1. The engine bleed air system testability skeleton model is established in figure 2.

Where $m_1$ is the medium pressure one way valve IPCV, $m_2$ is the high pressure valve HPV, $m_3$ is the pressure regulating shut off valve PRSOV, $m_4$ is the PRSOV downstream piping, $m_5$ is the pre-cooler PCE, $m_6$ is the temperature sensor BTS, $m_7$ is the fan air valve F.

| Table 1. Formatting sections, subsections and subsubsections. |
|---------------------------------------------------------------|
| **Modules (D)** | **Input variable (I)** | **Output variable (O)** |
| Intermediate pressure control valve (IPVC) | Engine bleed air selection command / $C_{HPV}$ | IPCV opening degree / $V_{IPVC}$ |
High pressure valve (HPV)  
Engine bleed air selection command/CHPV  
High pressure upstream pressure/PHPV-IN  

Pressure regulation shut-off valve (PRSOV)  
PRSOV inlet pressure/PPRV-IN  
Bleed air pressure adjustment value/PPIPS  

PRSOV downstream pipeline  
PRSOV outlet pressure/P_{PRV-OUT}  

Fan air valve (FAV)  
FAV Torque current/I_{PRV}  
FAV powered by/W_{FAV}  

Pre-cooler engine (PCE)  
Precooling module inlet pressure/P_{PPS}  
FAV opening degree/V_{FAV}  

Bleed-air Temperature Sensor (BTS)  
PCE hot edge outlet temperature/T_{PCE}  
Engine bleed air temperature/T_{BTS}  

**Table 2.** Engine bleed air system fault mode and associated signals.

| Fault location F₁ | Fault mode Fₘ | Fault characteristic parameters Fₖ | Whether to support forecasting Fₚ |
|-------------------|--------------|-----------------------------------|----------------------------------|
| Intermediate pressure control valve IPCV | IPCV On position failure | IPCV opening degree/V_{IPCV} | Yes |
| | IPCV Off position failure | HPV outlet pressure/P_{HPV-OUT}, IPCV opening degree/V_{IPCV} | Yes |
| HPV | HPV On/Off position failure | HPV opening degree/V_{HPV} | Yes |
| Test number | Test name                                | Detection signal | Pass condition | Whether to support forecasting |
|-------------|------------------------------------------|------------------|----------------|-------------------------------|
| t₁          | IPCV open view                           | $V_{IPCV}$       | $C_{HPV}=1, V_{IPCV} =0/ C_{HPV}=0, V_{IPCV} =1$ | No                            |
| t₂          | HPV open view                            | $V_{HPV}$        | $C_{HPV}=1, V_{IPCV} =1/ C_{HPV}=0, V_{IPCV} =0$ | No                            |
| t₃          | PRSOV open view                          | $V_{PRV}$        | $C_{HPV}=1, V_{PRV} =1/ C_{HPV}=0, V_{PRV} =0$ | No                            |
| t₄          | PRSOV outlet pressure monitoring         | $P_{PRV-OUT}$    | [2.8, 3.3] bar gauge | No                            |
| t₅          | PRV downstream pressure monitoring       | $P_{PIPS}$       | [2.8, 3.3] bar gauge | No                            |
| t₆          | PCE hot side outlet temperature monitoring| $T_{PCE}$       | [190,260] ° C | No                            |
| t₇          | Engine bleed air temperature monitoring  | $T_{BTS}$       | [190,260] ° C | No                            |
| t₈          | FAV open view                            | $V_{FAV}$        | $+I_{FAV} \rightarrow +V_{FAV}$ | No                            |

**Table 3.** Engine bleed air system fault mode and associated signals.
Through testing and diagnosis analysis of the engine bleed air system, the fault detection rate and fault isolation rate of the established model all equal to 100%, the predictable fault coverage is just 16.667%. The pressure regulating shut-off valve PRSOV has four open position fault status, i.e. normal status $S_0$ at open degree 0° position, degenerating status $S_1$ at open degree 60° position, deterioration status $S_2$ at open degree 120° position, failure status $S_0$ at open degree 180° position. In order to verify the developed state recognition and fault prediction method based on PSO and HSMM, training and test samples of different states are collected, shown in figure 4. The test samples are put into the HSMM model library, and test data recognition results under different fault conditions are calculated in table 5.

![Figure 3. Test diagnosis skeleton model of engine air bleed subsystem](image)

**Figure 3.** Test diagnosis skeleton model of engine air bleed subsystem

**Table 4.** HSMM train and test samples of PRSOV.

| Fault status | $S_0$ | $S_1$ | $S_2$ | $S_3$ |
|--------------|-------|-------|-------|-------|
| Samples      | Train | Test  | Train | Test  | Train | Test  | Train | Test  |
|              | 10    | 2     | 12    | 2     | 12    | 2     | 10    | 2     |

**Table 5.** Fault status recognition results.

| Likelihood probability | $T_1$ | $T_2$ | $T_1$ | $T_2$ | $T_1$ | $T_2$ | $T_1$ | $T_2$ |
|------------------------|-------|-------|-------|-------|-------|-------|-------|-------|
| HSMM$_0$               | -17.647 | -17.042 | -325.156 | -341.164 | -378.655 | -370.164 | - | - |
| HSMM$_1$               | -359.249 | -364.189 | -23.975 | -347.165 | -342.785 | -389.154 | -394.454 |
| HSMM$_2$               | -425.189 | -465.187 | -378.156 | -379.145 | -34.265 | -36.131 | -278.487 | -285.486 |
| HSMM$_3$               | - | - | -398.154 | -400.564 | -301.165 | -298.575 | -12.545 | -14.543 |
According to the magnitude of the log-likelihood probability, the fault state with the largest output value is the current fault state. It can be seen from table 5 that all test samples have the largest output value in the HSMM in its original state, so the fault state recognition rate based on HSMM is 100%. HSMM is trained based on an improved PSO algorithm training method. The maximum number of iterative steps in the training process is set to 50, and the algorithm's convergence error is 0.0001. Therefore, the fault state recognition method based on HSMM is accurate. Full-life history data of PRSOV is used as a training sample for HSMM. Using the HSMM training method in this paper, the failure state transition probability, the expected time, mean and variance of the fault status are obtained, shown in table 6 and table 7. Therefore the system fault state identification and remaining life prediction can be obtained on developed method. Taking the data of a certain observation point in S1 as an example, the fault state recognition probability can be calculated. The probability that it is in S1 is 0.8536. According to the remaining life calculation equation (8), the remaining life of the system is 11.6121.

Table 6. Transition matrix for four fault states of PRSOV.

| Fault state | S_0  | S_1  | S_2  | S_3  |
|-------------|------|------|------|------|
| S_0         | 0.9063 | 0.0937 | 0.0000 | 0.0000 |
| S_1         | 0     | 0.6955 | 0.3045 | 0.0000 |
| S_2         | 0     | 0    | 0.9145 | 0.0855 |
| S_3         | 0     | 0     | 0     | 1     |

Table 7. Expected dwell time for four fault states of PRSOV.

| Fault state | S_0     | S_1     | S_2     | S_3     |
|-------------|---------|---------|---------|---------|
| mean        | 10.4515 | 7.1256  | 5.5483  | 5.4275  |
| variance    | 1.2864  | 0.7256  | 0.6384  | 0.2548  |
| d_i         | 10.4764 | 7.1456  | 5.5617  | 5.4924  |

5. Conclusions

This paper presents a test diagnosis modeling method and relevant algorithms to support dynamic testing and evaluate the ability of fault prognosis. A test diagnostic model was developed to support analyzing and evaluating the ability of test and prognosis simultaneously during system testability design. Considering the requirements of test and fault prognosis, the test information and prognosis information were added to a skeleton model as attributes. New testability indicators based on test diagnostic models were developed to evaluate system fault diagnosis and prediction capabilities.

In order to achieve effective identification of system fault states and estimate the remaining service life of the system during testability design, state recognition and fault prediction algorithms on HSMM are established. Because HSMM training is easily trapped in local extreme values, the improved PSO algorithm is used to converge to system’s global optimal in the training process of HSMM. Finally, a test diagnostic model of an aircraft’s engine bleed air system was established to verify the developed model.

Through test and diagnosis analysis of the engine bleed air system, the fault detection rate and fault isolation rate of the established model all equal to 100%, the predictable fault coverage is only 16.667%. The system fault state identification and remaining life prediction of the engine bleed air system can be obtained using the developed state recognition and fault prediction method. The algorithm's convergence error is just 0.0001. Therefore, the fault state recognition and fault prediction algorithms based on PSO and HSMM are accurate. The developed modeling method is helpful for optimizing system testability design and implementing prognosis and health management for improved system design.

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