

Robust Fault Detection Based on Aero Engine LPV Model

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Abstract

This paper develops an aero engine LPV mathematical model to exactly describe aero engine dynamic process characteristics, eliminate the effect of modeling error. Design FDF with eigenstructure assignment. The simulation results of turbofan engine control system sensor fault show that this method has good performance in focusing discrimination in fault signal with modeling error, enhancing the robustness to unknown input, detecting accuracy is high and satisfying real-time requirement.

1. Introduction

With the urgent demand for large thrust, long endurance and high reliability of modern aero power system. The foreign advanced aero engines all have state detection and fault diagnosis system, and takes on the trend of fire-flight-propulsion integration control. According to the special working conditions of the aero engine, the FADEC system must have rigorously considerable security and dependability, this demand sometimes seems to be more important than just improving control system performance. Once the control system runs error, it can be a disaster of the staff and financial resource.

In recent twenty years there has been growing research in fault diagnosis of the FADEC. For example, the ADIA of NASA Lewis research center^[1] etc. Many ways are analysis redundancy based on object steady linear model. But the aero engine is a typical non-linear system, its exterior and internal condition parameters quickly change in a large extent, the detection strategy lacking of robustness can't ensure engine's best reliability. How to improve the robustness of fault detection has become research focus and a lot of research works have been done^{[2][3]}. Among the various approaches that have been proposed, the fault detection filter with eigenstructure assignment can improve the unsensitivity of parameter change and has received more and more attention^[4].

The LPV (Linear Parameter Varying) object is an important type of time-varying system, its state equation is real-time measurable set and may be certain function of some time-varying parameters which can be predicted or be measured^[5]. Because the dynamic character of aero engine is characterized by non-linear and time-varying, it can be expressed by LPV model which uses thermodynamics parameter or its variety rate, the LPV model can describe aero

engine's dynamic process better. This paper uses Jacobian method to establish engine LPV model and make use of eigenstructure assignment to design the fault detection filter for detecting sensor fault and provides numerical examples.

2. The Establishment of Aero Engine's LPV Model

2.1 Linear parameter varying system

The typical linear parameter varying system's model can be described as follows:

$$\begin{cases} \dot{x}(t) = A(\rho(t))x(t) + B(\rho(t))u(t) \\ y(t) = C(\rho(t))x(t) + D(\rho(t))u(t) \end{cases} \quad (1)$$

Where

$$\begin{aligned} A(\rho(t)) &= A_0 + \sum_{k=1}^N \rho_k(t)A_k, & B(\rho(t)) &= B_0 + \sum_{k=1}^N \rho_k(t)B_k \\ C(\rho(t)) &= C_0 + \sum_{k=1}^N \rho_k(t)C_k, & D(\rho(t)) &= D_0 + \sum_{k=1}^N \rho_k(t)D_k \end{aligned}$$

state vector $x(t) \in R^n$, Output vector $y(t) \in R^p$, Input vector $u(t) \in R^m$, A_k, B_k, C_k, D_k ($k = 0, 1, \dots, N$) are the N+1 partial models. $\rho(t)$ is system parameter or exterior input (such as height, mach number etc), and is boundary closed set. If $\rho(t)$ is constant, the system is LTI and $\rho(t)$ can be replaced by ρ .

2.2 The aero engine's LPV model

The X turbofan engine is twin-duct, high thrust-weight ratio, birotary and afterburning. The engine's non-linear model as follows:

$$\begin{cases} \dot{x} = f(x, u, \rho) \\ y = g(x, u, \rho) \end{cases} \quad (2)$$

If $f(\cdot)$ and $g(\cdot)$ are differentiable in flight envelope, we can use different methods to establish the partial linear model. If we have already known the state parameter, the LVP model can be constituted through little variation of state parameter and input parameter, or through a set of input-output data identification to get a set of linear model:

$$\begin{cases} \dot{x} = A_0(x-x_0) + B_0(u-u_0) + P_0(\rho-\rho_0) \\ y - y_0 = C_0(x-x_0) + D_0(u-u_0) + Q_0(\rho-\rho_0) \end{cases} \quad (3)$$

Equation (3) expresses the feature of system (2) near the linear point, which usually is the steady balance points. This Paper uses the Jacobian method to develop model and its architecture presented in

Fig.1. To expand the non-linear model of aero engine at the point (x_0, u_0, ρ_0) by Taylor series as follows:

$$\dot{x} = \dot{x}_0 + \Delta \dot{x} = f(x_0, u_0, \rho_0) + \frac{\partial f(x_0, u_0, \rho_0)}{\partial x} \Delta x + \frac{\partial f(x_0, u_0, \rho_0)}{\partial u} \Delta u \quad (4)$$

$$= f(x_0, u_0, \rho_0) + A_0(x_0, u_0, \rho_0) \cdot \Delta x + B_0(x_0, u_0, \rho_0) \cdot \Delta u$$

Where $\Delta x = x - x_0$, $\Delta u = u - u_0$, subscript 0 represents an initial value.

Based on the partial model, use interior insert or fitting to get the coefficient matrix of Jacobian LVP model:

$$\begin{cases} \Delta \dot{x} = A(\rho) \Delta x + B(\rho) \Delta u \\ \Delta y = C(\rho) \Delta x + D(\rho) \Delta u \end{cases} \quad (5)$$

According to different ρ to adjust different A, B, C, D.

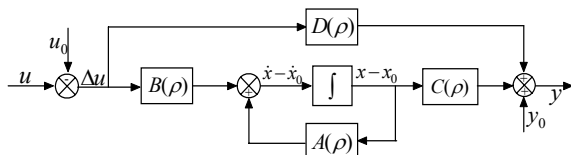


Fig.1 The Jacobian LPV model principle diagram

To solve Jacobian LPV model, the initial value x_0, y_0 and u_0 must be given. \dot{x}_0 can be non-zero value. A problem demands attention. If using the interpolation of subsection constant function at the balanced points, it is essential to use variable transform to eliminate algebra rings for output y switch among the balanced points. Computing the coefficient matrix by subsection linear interpolation through LPV model's input and output relation will be better.

In state equation, the elements may make a great difference and become ill-conditioned matrix. To avoid greater calculation error, particularly in solving inverse matrix, matrix normalization must be done.

$$\begin{cases} \dot{X}_n = A_n X_n + B_n U_n \\ Y_n = C_n X_n + D_n U_n \end{cases} \quad (6)$$

where

$$A_n = N_x^{-1} A N_x, B_n = N_x^{-1} B N_u, C_n = N_y^{-1} C N_x, D_n = N_y^{-1} D N_u.$$

Normalization matrix as follows:

$$N_x = \begin{bmatrix} x_{10} & 0 \\ 0 & x_{20} \end{bmatrix}, N_u = \begin{bmatrix} u_{10} & 0 \\ 0 & u_{20} \end{bmatrix}, N_y = \begin{bmatrix} y_{10} & 0 \\ 0 & y_{20} \end{bmatrix}$$

3. Design of Fault Detection Filter

3.1 Design principle

Consider the given system formulated explicitly in equation (7) below:

$$\begin{cases} \dot{x}(t) = [A + \Delta A]x(t) + Bu(t) \\ y(t) = Cx(t) + Du(t) \end{cases} \quad (7)$$

where the ΔA represents state matrix parameter perturbation. In order to improve the detection

robustness of uncertain input, the residual output unit add a weighting matrix.

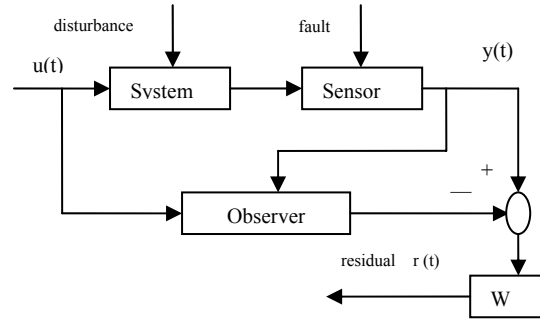


Fig.2 The fault detection filter's scheme with residual weighting matrix

Aim at the system (7), design a dynamic observer as follows:

$$\begin{cases} \dot{\hat{x}}(t) = A\hat{x}(t) + Bu(t) + K[y(t) - \hat{y}(t)] \\ \hat{y}(t) = C\hat{x}(t) + Du(t) \end{cases} \quad (8)$$

where K is the $n \times m$ dimensions gain matrix of the observer, $\hat{x}(t) \in R^n$ is state estimation vector.

$\hat{y}(t) \in R^m$ is output estimation vector.

The state estimation error $e(t)$ and weight output residual $r(t)$ are

$$\begin{cases} e(t) = x(t) - \hat{x}(t) \\ r(t) = W[y(t) - \hat{y}(t)] \end{cases} \quad (9)$$

where $W \in R^{p \times m}$ is a constant weighting matrix. Residual output equation is

$$\begin{cases} \dot{e}(t) = \dot{x}(t) - \dot{\hat{x}}(t) = (A + \Delta A)x(t) - A\hat{x}(t) - K[y(t) - \hat{y}(t)] \\ = (A - KC)e(t) + \Delta Ax(t) \\ r(t) = W[y(t) - \hat{y}(t)] = WCe(t) \end{cases} \quad (10)$$

Defining $A_c = A - KC$, the Laplace transform of shift of output residual $r(t)$ is

$$r(s) = WC(sI - A_c)^{-1} \Delta Ax(s) \quad (11)$$

Note from Eq.(10) that the effects of parameter variation can be decoupled from the residual if correctly using eigenstructure assignment by weighting matrix W and K to make Eq.(11) as output-zeroing. Designing method is summarized as follows:

- (1) Calculate residual weighting matrix W to make $WC\Delta A = 0$.
- (2) Determine the eigenstructure of the observer: the rows of $H = WC$ should be the p left eigenvectors of the observer, the $(n-p)$ left eigenvectors should to assure the rationality of model matrix.
- (3) Calculate the filter gain matrix K , satisfying the eigenstructure needs.

3.2 Fault detection

According to FDF's output error residual vector has fix-directional characteristics, the fault event vector can be detected by comparing the direction of normal vector and fault residual vector.

Defining minimal projection length of sensor fault vector:

$$MLF_j = \frac{\|r(k) - r_j^*(k)\|_2}{\|r(k)\|_2} \quad (12)$$

If $MLF_j (j = 1, 2, \dots, m)$ is least, the No. j sensor is failure.

4. Numerical Example

4.1 The LPV model verification

Establish X turbofan engine LPV model with the high-compress speed N_{ch} as adjusting variable, simulation can verify model's dynamic tracking characteristic for low-compressor speed N_{cl} . Referenced model is the engine non-linear dynamic model, input variable is the fuel of main combustion chamber, sample cycle is 10ms.

From engine non-linear model, compute matrix A and B by subsection linear interpolation and three-order polynomial fitting at different speed. Fig. 3 and Fig.4 show the contrast.

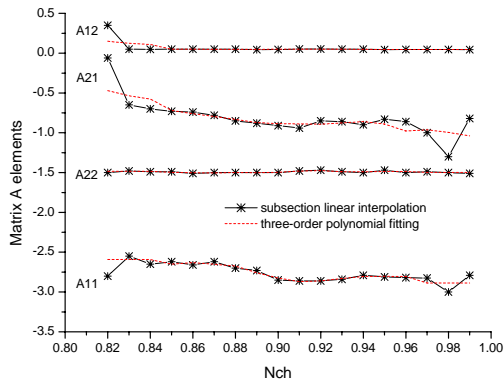


Fig.3 Matrix A elements interpolation and fitting

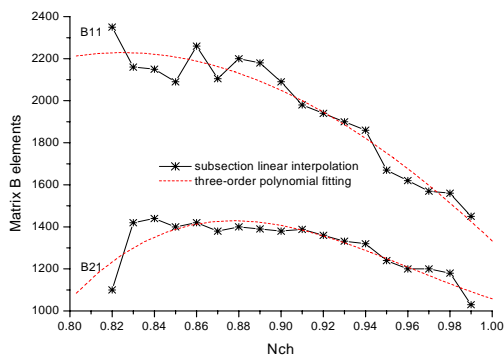


Fig.4 Matrix B elements interpolation and fitting

4.2 Sensor fault detection

Low-compressor speed sensor has occurred hard failure and soft failure, the FDF output and MLF value are shown as Fig.5 and Fig.6(State Point: $H=8.0KM$ $Ma=0.8$). n_1, n_h, p_2^*, T_4^* sensor's MLF contrast is shown as Table1.

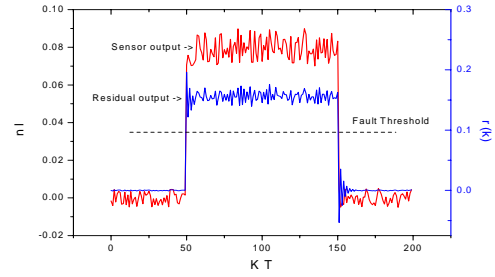


Fig.5 FDF's N_1 output with hard failure

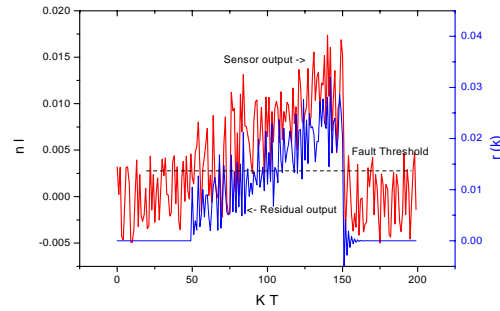


Fig.6 FDF's N_1 output with soft failure

Sensor	n_1 fault	n_h fault	p_2^* fault	T_4^* fault
MLF_1	0.0516	0.2853	0.9901	0.9991
MLF_2	0.1884	0.0733	0.9927	0.9927
MLF_3	0.4639	0.3471	0.0149	0.9993
MLF_4	0.9800	0.7181	0.9995	0.0297

Table 1 Four sensors MLF value contrast. If the sensor's MLF is least, it's in failure.

5. Conclusion

This paper provides an algorithm that designs FDF based on aero engine LPV model. From numerical simulation in the flight envelope, we can draw the following conclusions:

- (1) LPV model that comparing with ordinary non-linear model can simplify computational complexity, especially in dynamic process, meanwhile accuracy is better.
- (2) FDF based on LPV model can improve robustness in detection to unknown input and system parameters perturbation. Online fault detection time is not exceed four sampling periods.

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