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RESEARCH ON FAULT DIAGNOSIS AND FAILURE RECONFIGURATION OF FLUSH AIR DATA SENSING

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Abstract

In 2018 and 2019, two Boeing 737 MAX belonging to PT Lion Mentari Airlines and Ethiopian Airlines crashed, resulting in 346 deaths. Afterward, the accident investigation revealed that the main reason was the failure of the traditional angle of attack sensor. Unlike the traditional probe-type atmospheric data sensor, flush air data sensing (FADS) employs the pressure values measured by pressure sensors that are embedded in pressure taps to deduce angle of attack α, angle of sideslip β, Mach number Ma, dynamic pressure q_c, and static pressure P_∞, which effectively overcomes the former shortcomings and deficiencies. As a result, many countries, including the United States, France, and the United Kingdom, have carried out relevant research. The chief purpose of this paper is to propose a new fault diagnosis method for FADS and carry out further research on failure reconfiguration. First, the aerodynamic knowledge under subsonic and supersonic conditions is applied to establish a high-precision aerodynamic model of the sensor. Considering the severe working environment such as low temperature and low pressure, pressure taps in FADS will inevitably fail during the process of application. To address the problem, a new fault diagnosis method for the failure of single pressure tap and simultaneous failure of multiple pressure taps is proposed with the consideration of redundant signals. Besides, to reduce the false alarm rate and improve diagnosis accuracy, the threshold of alarm times is designed with statistical knowledge. Furthermore, after the fault diagnosis of FADS is realized by using the proposed method, the next step is to make use of the remaining normal pressure taps to continue measuring atmospheric data, i.e., failure reconfiguration. In this part of the study, the fault is divided into two cases: 1) single pressure tap fails; 2) multiple pressure taps fail. When a single pressure tap fails, we start from the derivation algorithm and employ the redundancy of FADS to obtain the final measurement result by reconstructing signals. However, when multiple pressure taps fail at the same time, all the measurement signals are wrong, and the above method is invalid. To address the problem, data fitting approach is firstly adopted in FADS to estimate α. To verify the effectiveness of the method, two representative examples are adopted in this paper.

Keywords: flush air data sensing (FADS); fault diagnosis; failure reconfiguration

1. Introduction

In 2018 and 2019, two planes crashed successively, causing a total of 346 deaths. Subsequent investigations revealed that one of the main reasons was that the sensor measuring the angle of attack α failed during the flight, and the wrong signal was transmitted to flight control system, which eventually led to the two accidents [1]. Therefore, the research on air data sensor (ADS) and its fault diagnosis has always been a hot issue [2, 3].

Traditionally, the probe air data sensors are composed of pitot tube, the sensor measuring α, and the sensor measuring angle of sideslip β. Considering the low temperature, low pressure and other complex flight environment, however, the traditional ADS is prone to failure. Besides, the exposed equipment such as pitot tube can not meet the needs of modern aircraft in pursuit of stealth effect. In view of the situation, the United States, France, and the United Kingdom have successively carried out technical updates on ADS, and proposed the concept of flush air data sensing (FADS).

Different from the traditional ADS, α, β, and flight Mach M_a are derived on the foundation of pressure values that are measured by the pressure taps embedded in the body. Therefore, FADS can effectively overcome the drawbacks of the traditional ADS [4, 5]. Considering the advantages of the advanced sensor in applications, many scholars have carried out related studies. Among them, the fault diagnosis of FADS occupies an important part. In [6], Guo applied the parity equation deduced from the system model to achieve the fault diagnosis of FADS. However, the method is limited by the variance of measurement noise. To further enrich the related research, χ^2 distribution method was adopted in [7]. Similar to the above, limited by the variance of noise is a main difficulty. In [3], Atanassov's interval-valued intuitionistic fuzzy sets, belief rule base, and evidential reasoning were employed to design a fault diagnosis algorithm for FADS. To update the algorithm, Atanassov's interval-valued intuitionistic fuzzy sets were improved to interval-valued neutrosophic sets in [8]. Also, some scholars inclined to use neural network [9, 10, 11]. Although the method is particularly efficient as a fault diagnosis method due to its advantages of strong robustness and self-learning ability, there is still a lack of theoretical basis for the structure and convergence analysis. Meanwhile, this method requires enough effective training samples, which will inevitably produce a large amount of computation. In [12], comparative monitoring was firstly applied to the fault diagnosis of FADS. Compare with the other methods, the method is simple and convincing in [12]. However, only the case of single pressure tap failure was considered.

After sorting out the relevant literature, it can be found that there is thereby an urgent need to solve the fault diagnosis of FADS with a simpler idea. For addressing the problem, comparative monitoring in [12] is improved in this paper. In general, there are four innovations:

1. A high-precision aerodynamic model of FADS is established based on the aerodynamic knowledge under subsonic and supersonic conditions.
2. A new fault diagnosis algorithm is proposed on the basis of comparative monitoring to detect single and multiple pressure taps of FADS, meanwhile, the threshold of alarm times is determined with statistical knowledge.
3. After realizing the fault diagnosis of FADS, two cases of fault reconfiguration are considered. 1) When single pressure tap fails, the signals are reconstructed from the derivation algorithm. 2) When two taps fail, data fitting approach is adopted to reconstruct signals.
4. For proving the effectiveness and robustness of the proposed method, two illustrate examples are carried out in this paper.

The paper's structure is: In Section 2, the aerodynamics model and fault diagnosis problem is presented. In Section 3, the fault diagnosis algorithm based on comparative monitoring is proposed. In Section 4, the proposed method is confirmed effective using two illustrative examples. In Section 5, the conclusion is offered.

2. Problem Description

Among all FADS systems, the one installed on X-33 is the most mature and has been successfully used in actual flight. The position of each tap is shown in Fig. 1.

The surface pressure $p(\theta_i)$ of each tap can be obtained based on the potential flow model under subsonic condition and modified Newtonian flow model under the supersonic condition:

$$p(\theta_i) = q_c[\cos^2(\theta_i) + \varepsilon \sin^2(\theta_i)] + P_\infty \tag{1}$$

where ε indicates the correction coefficient. q_c and P_∞ denote the dynamic pressure and static pressure. θ represents the angle between surface normal direction and flow velocity vector direction for any surface tap. θ can be derived:

$$\cos(\theta_i) = \cos(\alpha)\cos(\beta)\cos(\lambda_i) + \sin(\beta)\sin(\phi_i)\sin(\lambda_i) + \sin(\alpha)\cos(\beta)\cos(\phi_i)\sin(\lambda_i) \tag{2}$$

where ϕ_i and λ_i represent the circumferential angle and cone angle of each tap. The values are shown in Table 1. α and β are angle of attack and angle of sideslip.

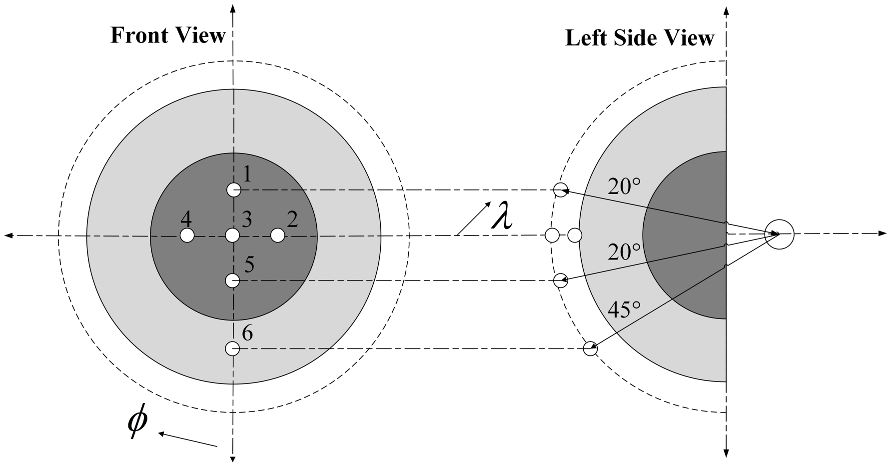

Figure 1 – Position of each pressure tap.

Table 1 – ϕ_i and λ_i of each pressure tap

The number of pressure tap i	The circumferential angle ϕ_i	The cone angle λ_i
1	180°	20°
2	270°	20°
3	0	0
4	90°	20°
5	0	20°
6	0	45°

For FADS, a widely adopted method is three-point method proposed by NASA [13]. The working principle is to select three taps from the taps in the longitudinal distribution, and then substitute the pressures p_i, p_j, and p_k into (1) and (2):

$$\frac{p_i - p_j}{p_j - p_k} = \frac{\cos^2\theta_i - \cos^2\theta_j}{\cos^2\theta_j - \cos^2\theta_k} \tag{3}$$

Considering that when α changes, the pressure values of laterally distributed pressure tapes do not change significantly. Therefore, only taps 1, 3, 5, and 6 are adopted to measure α.
Simplify (3):

$$\Gamma_{ik}\cos^2\theta_j + \Gamma_{ji}\cos^2\theta_k + \Gamma_{kj}\cos^2\theta_i = 0 \tag{4}$$

where $\Gamma_{ik} = p_i - p_k$, $\Gamma_{ji} = p_j - p_i$, $\Gamma_{kj} = p_k - p_j$.
Substitute (2) into (4):

$$\alpha = \begin{cases} \frac{1}{2}\tan^{-1}(\frac{A}{B}), & |\alpha| \le 45^\circ \\ \frac{1}{2}(\pi - \tan^{-1}(\frac{A}{B})), & |\alpha| > 45^\circ \end{cases} \tag{5}$$

where

$$A = \Gamma_{ik}\sin^2\lambda_j + \Gamma_{ji}\sin^2\lambda_k + \Gamma_{kj}\sin^2\lambda_i$$
$$B = \Gamma_{ik}\cos\phi_j\sin\lambda_j\cos\lambda_j + \Gamma_{ji}\cos\phi_k\sin\lambda_k\cos\lambda_k + \Gamma_{kj}\cos\phi_i\sin\lambda_i\cos\lambda_i$$

The final output is:

$$\alpha = \frac{1}{4}(\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4) \tag{6}$$

where α_1 is obtained from the combination of (1, 3, 5), α_2 is obtained from the combination of (1, 3, 6), α_3 is obtained from the combination of (1, 5, 6), and α_4 is obtained from the combination of (3, 5, 6).

3. Fault Diagnosis Algorithm

3.1 Working Principle

Considering that FADS is mainly applied in hypersonic vehicles and there is basically no high α requirement, so the paper only studies the case of $\alpha < 45°$. (5) can be simplified as:

$$\alpha = \frac{1}{2}\tan^{-1}\left(\frac{A}{B}\right) \tag{7}$$

The fault diagnosis algorithm is divided into two parts for analysis.

3.1.1 Single Tap Fails

Assume that tap 1 is completely damaged and the reading is $p_1 = 0$. α_1 and α_2 are adopted to illustrate the algorithm.
For α_1,

$$A_{1,3,5} = \Gamma_{15}\sin^2\lambda_3 + \Gamma_{31}\sin^2\lambda_5 + \Gamma_{53}\sin^2\lambda_1.$$

In view of $\lambda_1 = \lambda_5 = 20°$, $p_1 = 0$, and $\lambda_3 = 0$, $A_{1,3,5} = p_5\sin^2 20°$.
Similarly,

$$\begin{aligned} B_{1,3,5} &= \Gamma_{15}\cos\phi_3\sin\lambda_3\cos\lambda_3 + \Gamma_{31}\cos\phi_5\sin\lambda_5\cos\lambda_5 + \Gamma_{53}\cos\phi_1\sin\lambda_1\cos\lambda_1 \\ &= (2p_3 - p_5)\sin 20°\cos 20° \end{aligned}$$

For α_2,

$$\begin{aligned} A_{1,3,6} &= \Gamma_{16}\sin^2\lambda_3 + \Gamma_{31}\sin^2\lambda_6 + \Gamma_{63}\sin^2\lambda_1 \\ &= p_3\sin^2 45° + (p_6 - p_3)\sin^2 20°. \end{aligned}$$

$$\begin{aligned} B_{1,3,6} &= \Gamma_{16}\cos\phi_3\sin\lambda_3\cos\lambda_3 + \Gamma_{31}\cos\phi_6\sin\lambda_6\cos\lambda_6 + \Gamma_{63}\cos\phi_1\sin\lambda_1\cos\lambda_1 \\ &= p_3\sin 45°\cos 45° - (p_6 - p_3)\sin 20°\cos 20° \end{aligned}$$

Motivated by the mathematical background that the inverse tangent function in (7) is monotonically increasing. To judge the relationship between α_1 and α_2, we only need to make a difference comparison between $\frac{A_{1,3,5}}{B_{1,3,5}}$ and $\frac{A_{1,3,6}}{B_{1,3,6}}$.

$$\frac{A_{1,3,5}}{B_{1,3,5}} - \frac{A_{1,3,6}}{B_{1,3,6}} = \frac{p_5\sin^2 20°}{(2p_3 - p_5)\sin 20°\cos 20°} - \frac{p_3\sin^2 45° + (p_6 - p_3)\sin^2 20°}{p_3\sin 45°\cos 45° - (p_6 - p_3)\sin 20°\cos 20°} \tag{8}$$

According to the aerodynamics knowledge, when the airflow is distributed on the nose, the pressure value closer to the nose is greater, i.e., $p_3 > p_5 > p_6$.
In the case of (8), $\frac{A_{1,3,5}}{B_{1,3,5}} < \frac{A_{1,3,6}}{B_{1,3,6}}$ and $\alpha_1 < \alpha_2$.
The other cases are similar and will not be described here.
(1) when tap 1 fails:

$$\alpha_3 > \alpha_2 > \alpha_1 > \alpha_4 \tag{9}$$

(2) when tap 3 fails:

$$\alpha_4 > \alpha_2 > \alpha_1 > \alpha_3 \tag{10}$$

(3) when tap 5 fails:

$$\alpha_4 > \alpha_3 > \alpha_2 > \alpha_1 \tag{11}$$

(4) when tap 6 fails:

$$\alpha_4 > \alpha_1 > \alpha_3 > \alpha_2 \tag{12}$$

In the process of fault diagnosis, just match the relationship between the four signals and the above distribution characteristics, so that the fault diagnosis can be realized.

3.1.2 Two Taps Fail

Similar to the above, α_1 and α_2 are used as an example. Suppose that taps 1 and 3 fail, then $p_1 = p_3 = 0$.
For α_1, $A_{1,3,5} = p_5 \sin^2 20°$ and $B_{1,3,5} = -p_5 \sin 20° \cos 20°$.
Therefore,

$$\alpha_1 = \frac{1}{2}\tan^{-1}(\frac{A}{B}) = \frac{1}{2}\tan^{-1}\left(\frac{p_5 \sin^2 20°}{-p_5 \sin 20° \cos 20°}\right) = -10°$$

For α_2, $A_{1,3,6} = p_6 \sin^2 20°$ and $B_{1,3,6} = -p_6 \sin 20° \cos 20°$.
Then,

$$\alpha_2 = \frac{1}{2}\tan^{-1}(\frac{A}{B}) = \frac{1}{2}\tan^{-1}\left(\frac{p_6 \sin^2 20°}{-p_6 \sin 20° \cos 20°}\right) = -10°$$

The other cases are shown below.
(1) when taps 1 and 3 fail:

$$\alpha_4 > \alpha_3 > \alpha_2 = \alpha_1 = -10° \tag{13}$$

(2) when taps 1 and 5 fail:

$$\alpha_4 > \alpha_2 > \alpha_1 = \alpha_3 = 0 \tag{14}$$

(3) when taps 1 and 6 fail:

$$\alpha_2 = \alpha_3 = 12.5° > \alpha_1 > \alpha_4 \tag{15}$$

(4) when taps 3 and 6 fail:

$$\alpha_2 = \alpha_4 = 22.5° > \alpha_3 > \alpha_1 \tag{16}$$

(5) when taps 5 and 6 fail:

$$\alpha_3 = \alpha_4 = 32.5° > \alpha_2 > \alpha_1 \tag{17}$$

3.2 Threshold of Alarm Times

Given that the existence of measurement noise, α_1, α_2, α_3, and α_4 will be different even if all taps are normal. The above algorithm will inevitably lead to false detection. Therefore, the threshold of alarm times M is set to reduce the false alarm rate.
Assumed that there is a normal distribution noise with 0 mean and δ standard deviation in each tap. When the system is normal, each group of α fluctuates randomly up and down around the actual value. Therefore, the probability $P(\alpha_1 \leq \alpha_2) = P(\alpha_1 \leq \alpha_3) = P(\alpha_1 \leq \alpha_4) = P(\alpha_2 \leq \alpha_3) = P(\alpha_2 \leq \alpha_4) = P(\alpha_3 \leq \alpha_4) = \frac{1}{2}$. If these four groups of values simultaneously satisfy a particular distribution, the probability $P = (\frac{1}{2})^3 = \frac{1}{8}$. According to $(\frac{1}{8})^5 \approx 0.003\%$, which is approximately 0, the threshold M is set to be 5. For example, if $\alpha_3 > \alpha_2 > \alpha_1 > \alpha_4$ occurs five times in a row, tap 1 is considered to fail by comparing with (9).
The whole algorithm flow is shown in Fig. 2.

4. Illustrative Examples

4.1 One tap fails

4.1.1 Fault Diagnosis

Assume that the variance of noise for the taps is 100. The actual $\alpha_T = 1°$ and the actual $\beta_T = 0$. Also, the flight altitude $H = 7000$ m and velocity $V = 260$ m/s. During the first 4 seconds, the system is normal. However, tap 1 fails at the 4th second due to some unknown reason, and other taps are still normal, as shown in Fig. 3. It is emphasized that the noise of the system is only added to pressure taps and no other interference is added.
The measurement results are shown in Fig. 4. It can be seen that α_1, α_2, α_3, and α_4 fluctuate within a reasonable range around α_T in the first 4 seconds. Later, $\alpha_3 > \alpha_2 > \alpha_1 > \alpha_4$ and the number of consecutive occurrences exceeds the threshold M. According to the above algorithm, tap 1 is considered to fail in the 4th second.

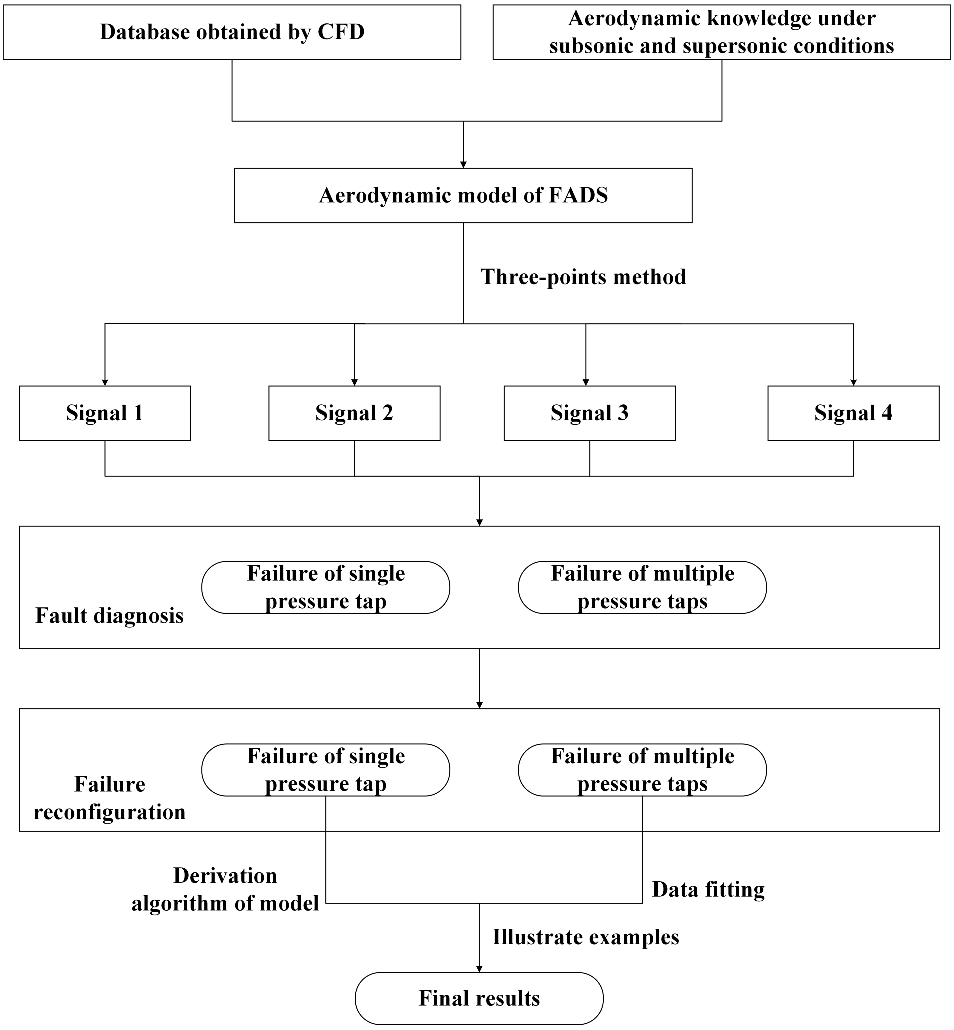

Figure 2 – The whole flow chart.

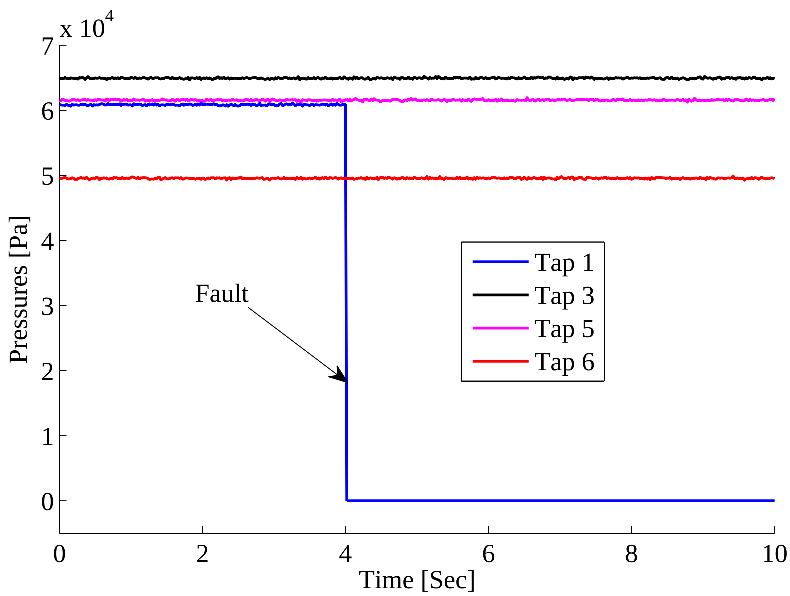

Figure 3 – Pressure of each tap.

4.1.2 Failure Reconfiguration

After the fault is detected, the next step is to reconstruct the fault, i.e., get the results according to the redundant signals. When tap 1 fails, α_1, α_2, and α_3 are not accurate. However, the process of

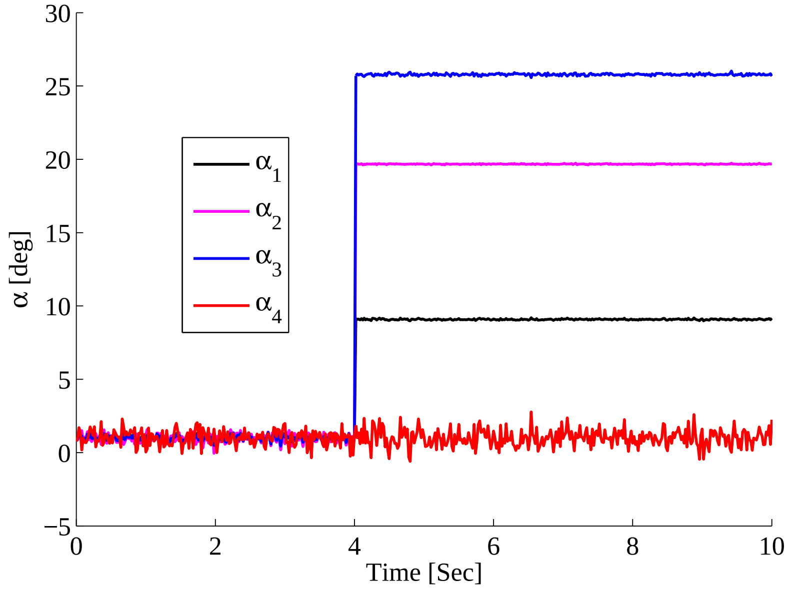

Figure 4 – Measurement results.

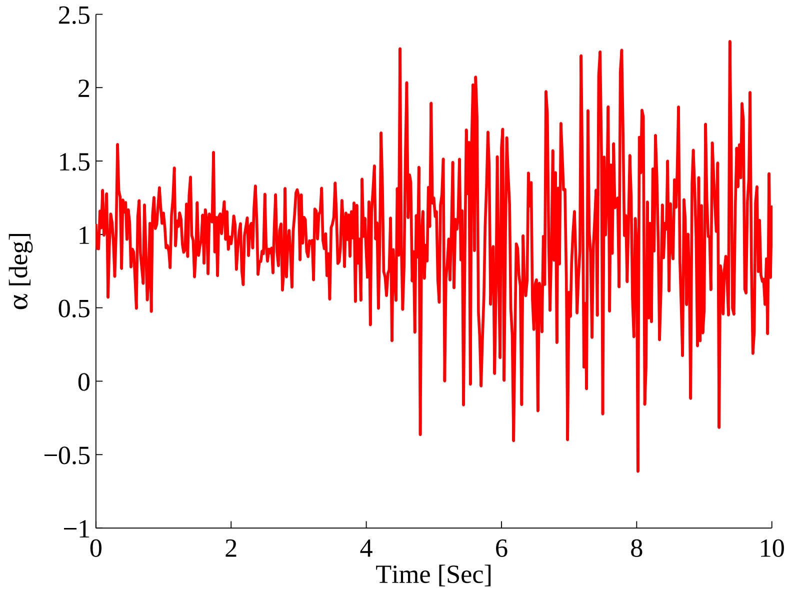

Figure 5 – Failure reconfiguration results.

obtaining α_4 does not use tap 1. Therefore, α_4 is normal and can be adopted as the final output. Results are shown in Fig. 5.

4.2 Two taps fail

4.2.1 Fault Diagnosis

Similar to the above, taps 1 and 3 fail at the 4th second. The pressure values of taps are shown in Fig. 6. From Fig. 7, it can be seen that $\alpha_4 > \alpha_3 > \alpha_2 = \alpha_1 = -10^\circ$. By matching with the rules in $(13) \sim (17)$, taps 1 and 3 are considered to fail at the 4th second, which is consistent with the actual situation. The proposed algorithm is valid.

4.2.2 Failure Reconfiguration

Different from the failure of one pressure tap, when two pressure taps fail at the same time, the four values α_1, α_2, α_3, and α_4 are all abnormal. In other words, the failure reconfiguration method in Section 4.1.2 is invalid. To address the problem, data fitting approach is firstly employed.

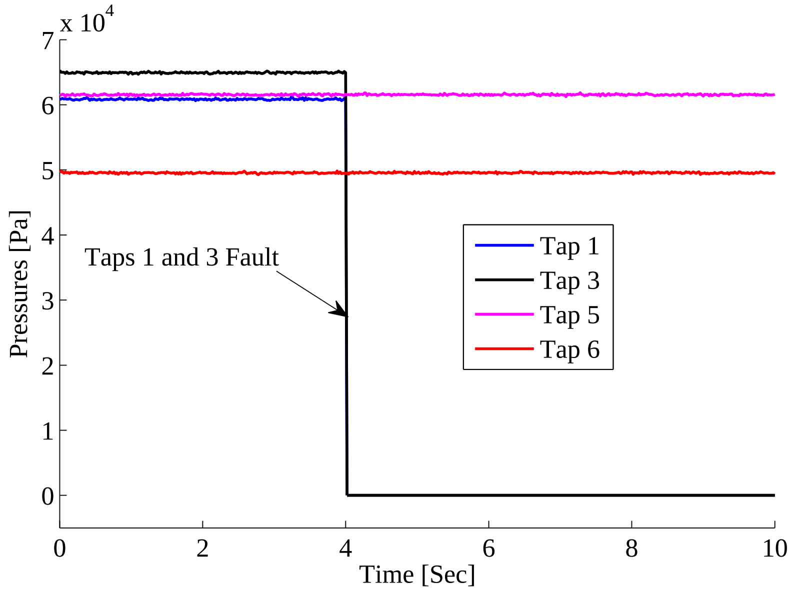

Figure 6 – Pressure of each tap.

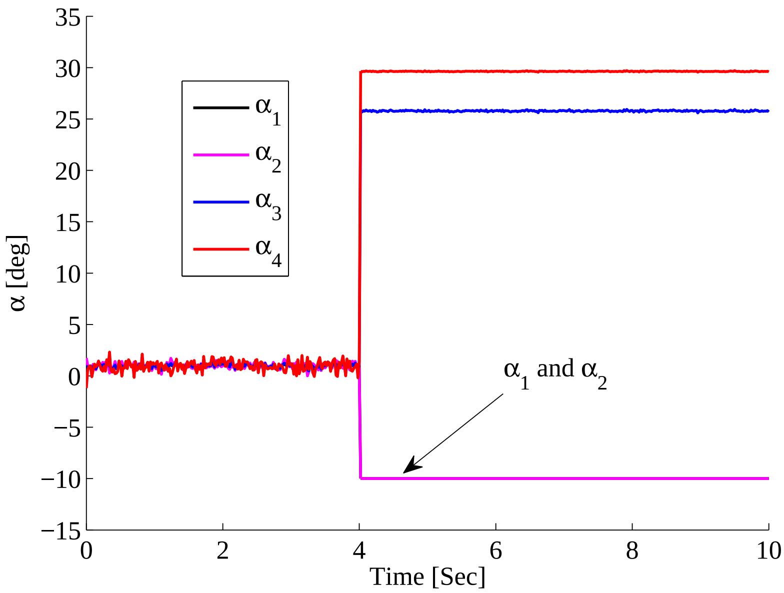

Figure 7 – Measurement results.

Assume that taps 1 and 3 fail, the values of α_1, α_2, α_3, and α_4 are shown in Table 2. Due to the existence of noise, the values are uncertain. Therefore, the data in Table 2 is the mean of α_1, α_2, α_3, and α_4. Given that α_1 and α_2 are always equal to 10°, α_3 and α_4 are adopted to map data, see Fig. 8.
The fitted equation is

$$\alpha = -6109 - 137.6\overline{\alpha}_3 + 325.9\overline{\alpha}_4 \tag{18}$$

In this example, $\overline{\alpha}_3 = 25.7778^\circ$ and $\overline{\alpha}_4 = 29.6314^\circ$. Based on (18), $\alpha = 0.8480^\circ$. Although the data is not the same as the actual value $\alpha_T = 1^\circ$, it can be used as a solution when two pressure taps fail at the same time.

5. Conclusion

In this paper, the fault diagnosis problem of FADS system is solved with a new solution. First, the high-precision model is built based on the aerodynamic knowledge. In terms of the fault diagnosis problem, a simpler and more reliable is proposed with the consideration of the uniqueness of FADS system.

Table 2 – Measurement results under different actual α

	$\alpha_T = -5^\circ$	$\alpha_T = -3^\circ$	$\alpha_T = -1^\circ$	$\alpha_T = 1^\circ$	$\alpha_T = 3^\circ$	$\alpha_T = 5^\circ$
$\overline{\alpha}_1$	-10°	-10°	-10°	-10°	-10°	-10°
$\overline{\alpha}_2$	-10°	-10°	-10°	-10°	-10°	-10°
$\overline{\alpha}_3$	25.0740°	25.2864°	25.5231°	25.7836°	26.0618°	26.3639°
$\overline{\alpha}_4$	29.3160°	29.4116°	29.5177°	29.6340°	29.7575°	29.8911°

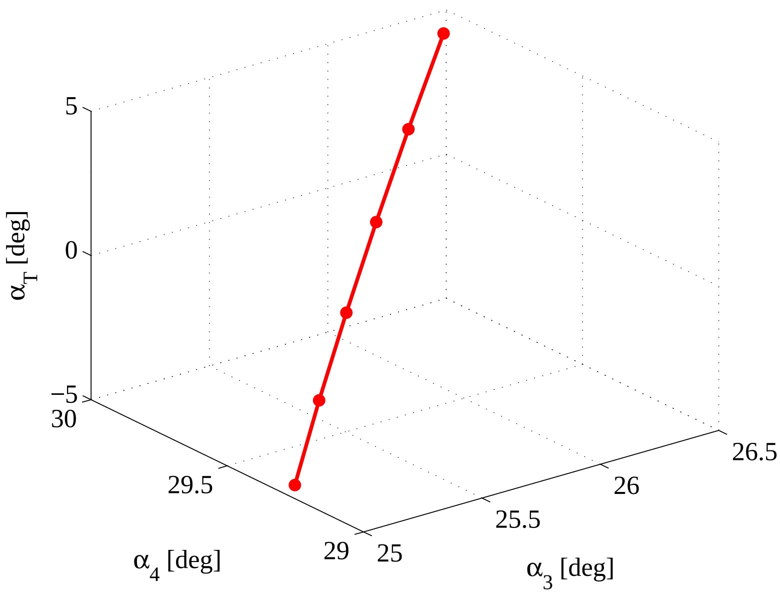

Figure 8 – Data fitting.

After that, failure reconfiguration is studied with data fitting approach. To prove the effectiveness of the proposed method, two representative examples are adopted.
Although the proposed method is valid, there are still some limitations: 1) when taps 3 and 5 fail, $A_{1,3,5} = B_{1,3,5} = 0$, $\alpha = \frac{1}{2}\tan^{-1}\left(\frac{A}{B}\right)$ is nonsense. We will carry out related research in the future.

6. Copyright Statement

Acknowledgements

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