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# Aircraft Engine Gas Path Fault Diagnosis Based on Fuzzy Inference

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**Abstract.** The working condition of aircraft engines is very complicated and severe. Gas path faults such as degradation of performances, decreasing of work efficiency are the most common fault patterns. In this paper, a fuzzy inference system is established. 9 measured parameters of an aircraft engine are selected as features parameters to detect 21 kinds of gas path fault patterns. The data preprocessing methods and the effect of measurement noise are also discussed.

**Keywords:** fuzzy inference system, aircraft engine, gas path, fault diagnosis

## 1. Introduction

Aircraft engine gas path faults not only reduce the economy of aircraft, but also serious threat the flight safety. It is very important to diagnose and insulate faults.

One characteristics of the description of faults is fuzzy. In this way, the fuzzy inference can be introduced into fault diagnosis system.

In Ref. [1], fuzzy concepts were introduced into fault diagnosis. The pressures, temperatures and speeds were taken as characteristics parameters of Trent-800 triple spools turbofan engine of Roll-Royce. The Matlab was used as the development tool of diagnosis system.

In Ref [2-3], the fuzzy inference technology was introduced into a gas turbine engine fault diagnosis system. The speed of high pressure spool, the temperature of exhaust gas, and the fuel flow were taken as the characteristics parameters. The result showed that the fault was the degradation of efficiency of high-pressure turbine.

In Ref [4], the fuzzy logic and the gas path parameters were adopted to diagnose a single fault of cells of engines. The effect of noise of measured parameters is concerned.

In this paper, we develop a gas path fault diagnosis system based on fuzzy inference, with 9 measured parameters and 21 kinds of faults, which is used in factory for repair test of engines.

## 2. Fuzzy Inference System

### 2.1. Structure of Fuzzy Inference System

Generally, the structure of a fuzzy inference system is shown as Fig 1. From Fig 1, it can be seen that a fuzzy inference system can be divided into four parts named as fuzzifier, fuzzy inferior, knowledge base and anti-fuzzifier[5, 6].

### 2.2. Fuzzifier

The role of the fuzzifier is mapping a determined point of the input space into a fuzzy set. The procedure is that, firstly, a scale transformation will be taken on inputs to transform them to their own domain; then, transform precise values to fuzzy values. In this procedure, fuzzy sets and corresponding membership functions are used to describe precise values. Several membership functions are commonly used such as triangle function, Gaussian distribution functions, S-curve, etc.

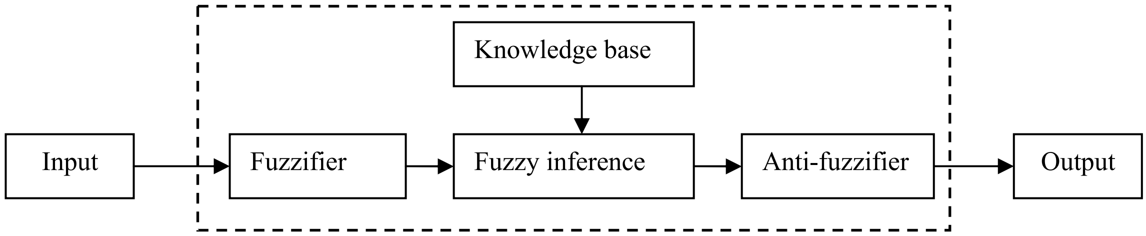


Fig. 1: The Structure of Fuzzy Inference System

### 2.3. Knowledge Base

The knowledge base is generally constructed by the membership functions of linguistic variables and inference rule library, which are usually derived from expert experiences. The knowledge base is the core of the fuzzy inference system. The main functions of rest parts of the system are to explain and use these rules to solve specific problems.

Inference rules typically have the form as following,

IF (meet a set of conditions) THEN (a set of conclusions can be introduced)

In fuzzy inference systems, rules are this kind of conditional statements. The prerequisite conditions are conditions for specific states. The conclusions are fault patterns.

### 2.4. Fuzzy Inference

The main function of fuzzy inference is to transform "IF-THEN" rules in fuzzy rule library to a specific mapping, which means mapping from input fuzzy sets to output fuzzy sets. The procedure of fuzzy inference usually includes description of "IF-THEN" rules, calculation of conjunctions, and fuzzy logic operations.

### 2.5. Anti-Fuzzifier

The result of fuzzy interference is the fuzzy quantities. While for specific problems of diagnosis, a specific fault pattern is needed. So, an anti-fuzzifier is needed. Methods are usually used by anti-fuzzifiers are the centroid of area, the bisector of area and the average maximum membership degree method.

## 3. Gas Path Fault Diagnosis

Studies of gas turbine data have shown two main features of the health signal 1) most major problems in the engine are caused by a "single fault" which is preceded by a sharp trend shift [7] and 2) long-term deterioration in the engine causes a low-order polynomial variation in the measurements with time, with a linear polynomial being a very good approximation [8].

### 3.1. Choosing Baseline Values

Aircraft engine is a complex system. Different values of condition parameters can be got with different atmosphere condition. Even with the standard atmosphere condition, different values can be got when the engine run in different conditions. So, baseline values should be chose, residuals generated by comparing measurements with the baseline values.

Generally speaking, the performance of engines is defined by NH, NL and TET of several certain thrust stages. That means when the thrust of engine is in the give section, and the NH, NL and TET are in certain sections, the engine is in normal performance.

We choose the baseline values of corrected measurements got near or in a condition in which the engine often running. Supposing $XG_0$ is the thrust in this condition, NH, NL, $M_1$, $P_2$, $T_2$, $P_3$, $T_3$, FF and TET combine to be the baseline vector $V_0$. The meanings of parameters are listed in Table 1. The baseline vector can be calculated by programs for a new type of engine or can be statistics with manufactured engines. As for an individual engine, the corrected measurements of acceptance test can be used baseline values.

### 3.2. Generating Residuals

Two kinds of residuals should be got for gas path diagnostic. One is that residuals ($V_i, i=1,\cdots,N$) which stand for standard failure patterns. That means if the measured residuals is same or similar with the residuals, the fault must be happened. This kind of residuals can be calculated with engine models or be gotten by statistical method. In our research, engine X is studied. The fault patterns of performance deterioration of components are 21 kinds. There are LP (low-pressure) compressor capacity, HP (high-pressure) compressor capacity, LP turbine capacity, HP turbine capacity, LP compressor efficiency, HP compressor efficiency, LP turbine efficiency, HP turbine efficiency, can loss, bypass duck loss and so on (Listed in Table 2). We have calculated the residual vectors of each fault patterns.

Table 1. Meanings of Measured Parameters

| No. | Symbol | Name of Parameter |
|---|---|---|
| 1 | $M_1$ | Air flow of fan |
| 2 | $P_2$ | Outlet total pressure of fan |
| 3 | $T_2$ | Outlet temperature of fan |
| 4 | NL | Speed of low-pressure spool |
| 5 | NH | Speed of high-pressure spool |
| 6 | $P_3$ | Outlet total pressure of high-pressure compressor |
| 7 | $T_3$ | Outlet temperature of high-pressure compressor |
| 8 | FF | Fuel flow |
| 9 | TET | Outlet temperature of mixer |

Table 2 Component Performance Faults

| No. | Name of Fault | No. | Name of Fault |
|---|---|---|---|
| 1 | LP compressor capacity | 12 | HP 7th stage to bypass duct |
| 2 | HP compressor capacity | 13 | HP 7th stage overboard |
| 3 | HP turbine capacity | 14 | HP turbine cooling air |
| 4 | LP turbine capacity | 15 | LP turbine cooling air |
| 5 | LP compressor efficiency | 16 | Bypass duct loss |
| 6 | HP compressor efficiency | 17 | Jet pipe loss |
| 7 | HP turbine efficiency | 18 | Can loss |
| 8 | LP turbine efficiency | 19 | Turbine exit mixer area |
| 9 | LP bleed overboard | 20 | Bypass duct mixer area |
| 10 | HP bleed overboard | 21 | Final nozzle area |
| 11 | HP bleed to bypass duct | | |

Another kind of residuals ($V_m$) is generated by comparing the measurements of an individual engine with its baseline values, which can be used for fault detection and diagnosis of the engine.

## 3.3. Fault Diagnosis

As shown in Fig. 2, normalized vectors of fault patterns are drawn on a two-dimensional plan. The horizontal axis is for the 9 measured parameters. The vertical axis is for the values of components of $V_i$. Different shapes of points stand for different fault patterns. It can be seen that for different fault patterns, the normalized vectors are not exactly equal to each other.

Let $V_m$ stands for the normalized vector of measured parameters. There are several rules for the fuzzy inference system.

$$\text{Rule}(i)\text{: IF } V_m \text{ is } V_i\text{, THEN } F_m \text{ is } F_i\text{. (i=1~21)} \quad (1)$$

The vectors write in component model will be:

$$\text{Rule}(i)\text{: IF } v_{m1} \text{ is } v_{i1} \text{ AND } v_{m2} \text{ is } v_{i2} \text{ AND … AND } v_{m9} \text{ is } v_{i9}\text{, THEN THEN } F_m \text{ is } F_i\text{. (i=1~21)} \quad (2)$$

Here, $v_{ij}$ ($i$=1, 2, …, 21; $j$=1, 2, …, 9) , a real number, is the $j^{th}$ component of normalized vector $V_i$ of fault pattern $F_i$. In fuzzy inference system, Gauss Fuzzier is adopted to map $v_{ij}$ into a fuzzy set $V_{ij}^{'}$.

For example, the first component of $V_1$ of fault pattern $F_1$, $v_{11} = 0.061857$, it can be fuzzied with Equ. 3 and shown in Fig. 2.

$$\mu_{v_{11}}(x) = e^{-(\frac{x-0.061857}{0.05})^2} \quad (3)$$

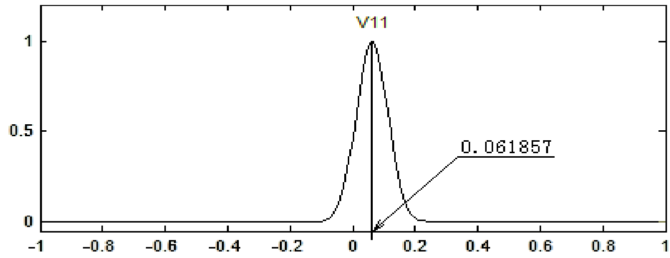


Fig. 2: Fuzzy set of vectors of fault patterns

Here, the Sugeno style fuzzy inference system is adopted. The inputs of system are 9 components of characteristic vector. One output uses constant membership functions to stand for normal state and 21 fault patterns. With Matlab, the knowledge base is constructed with 21 rules. The fuzzy inference system is shown in Fig. 3.

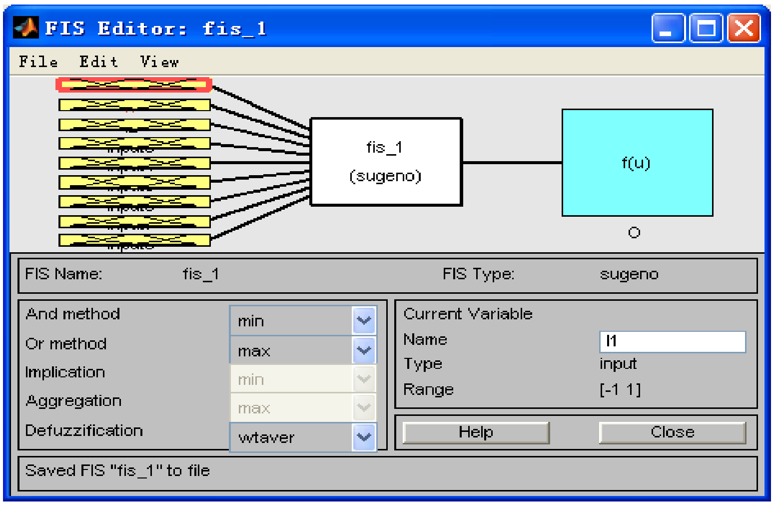


Fig. 3: The fuzzy inference system for fault diagnosis

Simulate data are generated to examine the fault diagnosis ability of the system. The data are generated in this way: take the standard values at $XG_0$ as a reference point; the range of performance degeneration of each component is 0.1~5%; for each components, a vector is selected with interval of 0.1%. For 21 kinds of faults and normal state, 1100( 1100=50×21+50) vectors are generated. Vectors with measurement noise are generated in this way: firstly, generate vectors without noise as mentioned above. Then, add Gaussian noise $N(0,\sigma_i)$ (i=1, 2, …, 9)to each component of vectors. Here, $\sigma_i$ is a third of the measurement errors.

All 1100 vectors without noise can be indentified correctly. The identification rate is 100%. 899 vectors of 1100 vectors with noise can be identified correctly. The identification rate is 81.7%. The relationship between correct identification rate and failure severity is shown in Fig. 4.

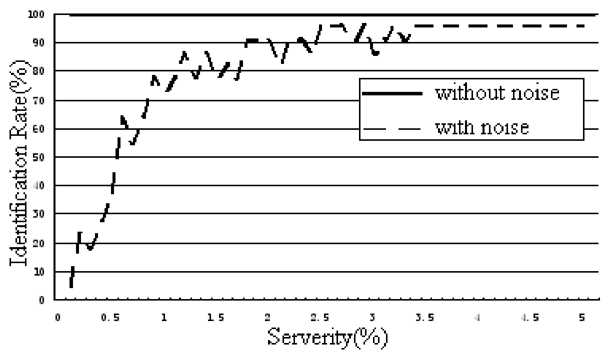


Fig. 4: Identification rate of fault diagnosis

## 3.4. Effect of Noise

It can be seen from Fig.4 that for vectors with noise, the correct rate of fault identification increases with the severity of failure. In engineering, noise of measurement is usually assumed as normal distribution

$N(0, \sigma_i)$. In certain sense, the values of noise are fixed relatively. So, when the severity of failure is small, the signal to noise rate is lower. It causes the reduction of the ability of identification.

## 4. Summaries

In the repair process of aircraft engine, it should be found out which degeneration caused the deviation of measured values to standard values. In this paper there are 21 kinds of fault patterns of components performance degeneration. 9 measured parameters are selected as feature signals. A fuzzy inference system is established to indentify the fault pattern. Examples show that all failures can be identified if the data without noise. Serious degeneration is easier to identified if the data with measurement noise. It is same to intuition

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