# **Intelligent Engine**

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In recent years, on-condition maintenance has been generally applied to aircraft engines. On-condition maintenance is the methodology to repair the equipment only when the maintenance is actually necessary by observing the state of the system periodically. Aiming at the further reduction of maintenance costs, engine health monitoring technology was developed to evaluate the deterioration of the engine and to isolate the fault module if any failure is detected. The engine electronic control unit module utilizing multifunctional electronic devices was also developed to reduce the cost increase associated with this additional monitoring function. This article introduces these technologies.

### 1. Introduction

The on-condition maintenance method has been introduced to the maintenance of civil aviation aircraft engines in recent years. In the on-condition maintenance method, an engine is inspected as it is mounted on an airframe, and it is demounted from an airframe and serviced only if a defect has been found in the engine or the engine is suspected of malfunctioning. For further reduction of the engine maintenance cost, the acquisition of accurate information on each engine is key for deciding appropriate maintenance plans and parts supply plans and maintaining operational reliability. Specifically, the technology for grasping the tendency in the deterioration of engines and identifying the parts that require servicing as early as possible must be established at a low cost.

In this research and development project, we developed model-based monitoring technology that allows diagnosis of the state of deterioration of each engine module, detection of malfunctions, and identification of faulty modules by monitoring the state of quantities inside an engine. We also developed low-cost ECU (Electronic Control Unit) design technology to reduce the cost associated with building an intelligent aircraft engine maintenance system.

This paper describes the technologies developed to build the intelligent aircraft engine maintenance system at low cost.

#### 2. Model-based monitoring

# 2.1 **Purpose of the technical development**

The technology was developed for diagnosing the state of deterioration of characteristics of each module comprising an engine, detecting a fault, and isolating the fault to a specific module. An aircraft engine is comprised of five modules: FAN, LPC (Low Pressure Compressor), HPC (High Pressure Compressor), HPT (High Pressure Turbine), and LPT (Low Pressure Turbine). Each module has two characteristics: the adiabatic efficiency and flow rate coefficient. Therefore, deterioration and fault diagnoses are performed on a total of 10 characteristics (2 characteristics  $\times$  5 modules).

#### 2.2 Diagnostic method

#### 2.2.1 Basic principle of diagnosis

In this research and development project, the weightedleast-squares method was used to evaluate the characteristics of each module based on measurements using an engine model. This method was developed and made practical by an overseas engine manufacturer. <sup>(1)</sup> We made some improvements to this method to further increase the diagnostic accuracy. The basic principle of this method, which is explained in detail in reference (1), is outlined as follows:

(1) Basic principle

Generally, a deviation  $\Delta x$  from the normal condition xB (for example, characteristics of a standard engine) of a module characteristic x (adiabatic efficiency  $\eta_{FAN}$  of a fan, flow rate

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coefficient  $Wc_{FAN}$  of a fan, adiabatic efficiency  $\eta_{LPT}$  of LPT, flow rate coefficient  $FF_{LPT}$  of LPT, flow rate coefficient  $FF_{HPT}$  of HPT, etc.) of an engine can be affiliated with a deviation  $\Delta z$  from the normal condition zB of a measured value z (high pressure spool rotational speed Ng, exhaust gas temperature EGT, etc.) by using equation (1) in which the sensitivity matrix S determined according to a specific engine model is included.

$$\Delta z = S \cdot \Delta x + err$$

$$S = \begin{pmatrix} \frac{\partial Ng}{\partial \eta_{FAN}} & \frac{\partial Ng}{\partial Wc_{FAN}} & \cdots & \frac{\partial Ng}{\partial FF_{HPT}} & \frac{\partial Ng}{\partial \eta_{LPT}} & \frac{\partial Ng}{\partial FF_{LPT}} \\ \frac{\partial EGT}{\partial \eta_{FAN}} & \frac{\partial EGT}{\partial Wc_{FAN}} & \cdots & \frac{\partial EGT}{\partial FF_{HPT}} & \frac{\partial EGT}{\partial \eta_{LPT}} & \frac{\partial EGT}{\partial FF_{LPT}} \\ & \cdots & \\ \frac{\partial z_{J-2}}{\partial \eta_{FAN}} & \frac{\partial z_{J-2}}{\partial Wc_{FAN}} & \cdots & \frac{\partial z_{J-2}}{\partial FF_{HPT}} & \frac{\partial z_{J-2}}{\partial \eta_{LPT}} & \frac{\partial z_{J-2}}{\partial FF_{LPT}} \\ \frac{\partial z_{J-1}}{\partial \eta_{FAN}} & \frac{\partial z_{J}}{\partial Wc_{FAN}} & \cdots & \frac{\partial z_{J}}{\partial FF_{HPT}} & \frac{\partial z_{J-1}}{\partial \eta_{LPT}} & \frac{\partial z_{J-1}}{\partial FF_{LPT}} \\ \frac{\partial z_{J}}{\partial \eta_{FAN}} & \frac{\partial z_{J}}{\partial Wc_{FAN}} & \cdots & \frac{\partial z_{J}}{\partial FF_{HPT}} & \frac{\partial z_{J}}{\partial \eta_{LPT}} & \frac{\partial z_{J}}{\partial FF_{LPT}} \\ \frac{\partial z_{J}}{\partial \eta_{FAN}} & \frac{\partial Z_{J}}{\partial Wc_{FAN}} & \cdots & \frac{\partial z_{J}}{\partial FF_{HPT}} & \frac{\partial z_{J}}{\partial \eta_{LPT}} & \frac{\partial z_{J}}{\partial FF_{LPT}} \\ \frac{\partial z_{I}}{\partial \eta_{FAN}} & \frac{\partial Wc_{FAN}}{\partial Wc_{FAN}} & \cdots & \frac{\partial Z_{J}}{\partial FF_{HPT}} & \frac{\partial z_{J}}{\partial \eta_{LPT}} & \frac{\partial z_{J}}{\partial FF_{LPT}} \\ \frac{\partial z_{I}}{\partial \eta_{EAN}} & \frac{\partial Wc_{FAN}}{\partial Wc_{FAN}} & \cdots & \frac{\partial Z_{J}}{\partial FF_{HPT}} & \frac{\partial z_{J}}{\partial \eta_{LPT}} & \frac{\partial z_{J}}{\partial FF_{LPT}} \\ \frac{\partial z_{I}}{\partial \eta_{EAN}} & \frac{\partial Wc_{FAN}}{\partial Wc_{FAN}} & \cdots & \frac{\partial Z_{I}}{\partial FF_{HPT}} & \frac{\partial Z_{J}}{\partial \eta_{LPT}} & \frac{\partial Z_{J}}{\partial FF_{LPT}} \\ \frac{\partial z_{I}}{\partial \eta_{EAN}} & \frac{\partial Wc_{FAN}}{\partial Wc_{FAN}} & \cdots & \frac{\partial Z_{I}}{\partial FF_{HPT}} & \frac{\partial Z_{I}}{\partial \eta_{LPT}} & \frac{\partial Z_{J}}{\partial FF_{LPT}} \\ \frac{\partial Z_{I}}{\partial \eta_{EAN}} & \frac{\partial Z_{I}}{\partial Wc_{FAN}} & \cdots & \frac{\partial Z_{I}}{\partial FF_{HPT}} & \frac{\partial Z_{I}}{\partial \eta_{LPT}} & \frac{\partial Z_{I}}{\partial FF_{LPT}} \\ \frac{\partial Z_{I}}{\partial \eta_{EAN}} & \frac{\partial Z_{I}}{\partial Wc_{FAN}} & \cdots & \frac{\partial Z_{I}}{\partial FF_{HPT}} & \frac{\partial Z_{I}}{\partial \eta_{LPT}} & \frac{\partial Z_{I}}{\partial FF_{LPT}} \\ \frac{\partial Z_{I}}{\partial \eta_{EAN}} & \frac{\partial Z_{I}}{\partial Wc_{FAN}} & \cdots & \frac{\partial Z_{I}}{\partial QC_{I}} & \frac{\partial Z_{I}}{\partial Q$$

where

err : Measurement error

J : The number of sensors that can be used for diagnosis

Because measurement errors *err* caused by bias, noise, etc., are included in the equation (1), the module characteristic  $\Delta x$  cannot be calculated absolutely from the measured value  $\Delta z$ . Therefore, the module characteristic that allows the evaluation function *RE* shown in equation (2) to become the smallest should be adopted as the solution of the highest degree of certainty. The weight coefficient should be empirically adjusted to obtain appropriate diagnostic results.

$$RE = \left\{ \sum_{i} \left( \frac{\Delta x_{i}}{\sigma_{x,i}} \right)^{2} + \sum_{j} \left( \frac{err_{j}}{\sigma_{z,j}} \right)^{2} \right\}$$
.....(2)

where

- $\sigma_{x,i}$ : Weight coefficient for evaluating the module characteristic  $\Delta x_i$
- $\sigma_{z,j}$ : Weight coefficient for evaluating sensor error  $err_j$

In performing a diagnosis using this weighted least squares method, the number of sensors does not necessarily need to be equal to the number of module characteristics to be diagnosed. To properly diagnose each module characteristic, however, it is desirable to use the number of sensors equal to the number of module characteristics. In this research and development project, a total of 10 sensors including control and diagnostic sensors were used to take 10 measurements.

(2) Fault detection

If a module or sensor is faulty, the result of diagnosis widely deviates from the trend component. By monitoring the amount of deviation, the occurrence of a fault can be detected.

According to a generally known detection method, a fault is judged to have occurred if the fault diagnosis indicator calculated by equation (3) exceeds a certain threshold value.<sup>(1)</sup>

$$RE' = \left\{ \sum_{i} \left( \frac{\delta \Delta x_i}{\sigma_{x,i}} \right)^2 + \sum_{j} \left( \frac{\delta err_j}{\sigma_{z,j}} \right)^2 \right\}$$

where

 $\delta \Delta x_i = \Delta x_i$  - a trend component of  $\Delta x_i$  $\delta err_j = err_j$  - a trend component of  $err_j$ (3) Fault isolation

If a fault has been detected, the fault must be isolated to a specific module or sensor. Although there may be a case where it is difficult to identify a faulty module or sensor in a definite manner, a definite judgment must be made as to whether or not to demount an engine.

A fault should be isolated as described below by following the instructions given in reference (1):

If a single fault occurs, only deviation  $\delta \Delta x_{iF}$ or  $\delta err_{jF}$  from the trend component of the characteristic  $\Delta x_{iF}$  of a faulty module or from the trend component of the sensor error  $err_{jF}$  becomes large, while deviation  $\delta \Delta x_i$  or  $\delta err_j$  from trend components of other modules or sensors remains small. Therefore, although RE' is large when a single fault occurs, the indicator  $RE'_F$  obtained by multiplying the weight coefficient of a faulty module or sensor by 100 is small, as expressed by the equation (4).

$$RE'_{F} = \left\{ \sum_{i \neq iF} \left( \frac{\delta \Delta x_{i}}{\sigma_{x,i}} \right)^{2} + \left( \frac{\delta \Delta x_{iF}}{100 \times \sigma_{x,iF}} \right)^{2} + \sum_{j \neq iF} \left( \frac{\delta err_{j}}{\sigma_{z,j}} \right)^{2} + \left( \frac{\delta err_{jF}}{100 \times \sigma_{x,jF}} \right)^{2} \right\}$$

On the assumption that a certain module or sensor goes faulty, the evaluation function  $RE'_F$  was established and a solution  $\delta \Delta x_i$  was calculated using equation (1) in such a way that the evaluation function  $RE'_F$  becomes the smallest. If  $RE'_F$ , obtained as a diagnostic result, is smaller than a threshold value, the assumption should be considered to be right and there is a high probability that the module or sensor is faulty. Conversely, if  $RE'_F$  is larger than a threshold value, the assumption should be considered to be wrong and the module or sensor is not faulty. This way, a search can be performed through modules and sensors to locate the faulty ones. If more than one module or sensor is found to be faulty, evaluation functions  $RE'_F$  of each module or sensor should be compared, and it is highly probable that a module or sensor with a smaller evaluation function  $RE'_F$  is faulty.

#### 2.2.2 Technical problems and countermeasures

In diagnosing the state of deterioration, two technical problems related to fault detection and fault isolation were noted, and the countermeasures for these problems were developed in this research and development project as described below.

(1) Fault detection

Diagnostic results ( $\Delta x$ , *err*) are interfered with by the effect of measurement noise. To detect a fault with a high degree of accuracy, a deviation from the trend component occurring as a result of a fault must be detected with a high level of sensitivity in this disturbed condition.

To detect a fault with a higher level of sensitivity in this research and development project, individual fault diagnosis indicators  $(\delta \Delta x_i / \sigma_{x,i})^2$  and  $(\delta err_j / \sigma_{z,j})^2$  in addition to that calculated by equation (3) were monitored, and a fault was judged to have occurred if any of these indicators exceeds a threshold value.

(2) Flight conditions

The sensitivity matrix S in equation (1) depends on flight conditions (atmospheric pressure (altitude), atmospheric temperature, flight speed, and the number of fan revolutions). Subsequently, diagnostic errors also depend on flight conditions. Therefore, if flight conditions vary, dispersion of diagnostic results will increase. To increase the sensitivity of fault detection and isolation, dispersion of diagnostic errors must be minimized. In this research and development project, the dependence of diagnostic results on flight conditions was clarified by time-series multiple regression analysis, and this dependence was removed.

#### 2.3 Test results

#### 2.3.1 Purpose of the test and test method

A survey was experimentally conducted to see whether it is possible to diagnose the state of deterioration with a high degree of accuracy, to detect a fault with a high level of sensitivity, and to isolate a fault with a high degree of certainty while eliminating the effects of flight conditions by the diagnostic method described in Section 2.2.

Tests were conducted in the form of simulations. An engine model of a small-size ECO engine was used. By simultaneously changing all module characteristics built

into this ECO engine model, a state of deterioration was simulated. A single-module fault was simulated by changing the characteristics of a faulty module in steps at a certain point of time. By setting the module characteristics in this manner and solving an engine model under given flight conditions, theoretical values of measurements under the influence of the deterioration of a module characteristic or a fault can be calculated. Measurement noises simulated by normal distribution random numbers were superposed on these theoretical values to simulate the actual values measured by sensors. Moreover, when simulating a single sensor fault, values measured by this faulty sensor were changed in steps. Using the values measured by the sensor simulated in this way, a diagnosis was performed using the method described in Section 2.2, and diagnostic performance was examined.

#### 2.3.2 Test results

(1) Deterioration diagnosis

Figure 1 shows an example of the result of a deterioration diagnosis performed with changing flight conditions (3 atmospheric conditions  $\times$  3 atmospheric temperature conditions  $\times$  4 fan revolution number conditions = 36 conditions). In this simulation, a fault was not simulated. Figure 1-(a) shows true value of module performance, diagnostic results obtained by using the method under 2.2.1 (1), and corrected value of diagnosis result values obtained by removing the dependency







Fig. 1 An Example of Deterioration Diagnosis

on flight conditions using the method under 2.2.2 (3). Figure 1-(b) shows the trend components obtained by performing a time-series multiple regression analysis on the diagnostic results shown in Fig. 1-(a) with flight conditions defined as explanatory variables. Trend components are concentrated to form some trend lines, which indicates the dependence of diagnostic errors on flight conditions. As shown in Fig. 1-(a), corrected diagnostic result values are in good agreement with true values, in terms of the degree of deterioration as against initial module characteristics. It is also evident from Fig. 1-(a) that the removal of the dependence on flight conditions contributes to decreasing dispersion of diagnostic results.

It was verified from all these results that the state of deterioration can be properly diagnosed using the proposed method.

#### (2) Fault diagnosis

If variation in measured values occurring as a result of a fault is small, it is buried in measurement noises, making it difficult to detect or isolate the fault. By changing the amount of a change in the characteristics of a faulty module, tests were conducted to simulate a case where the amount of variation in measured values occurring as a result of a fault becomes twice, 3.5 times and 5 times as large as a standard deviation of measurement noise.

Table 1 shows the results of fault diagnosis tests. If the amount of variation in measured values occurring as a result of a fault was 3.5 or more times as large as the standard deviation of measurement noise, a fault was detected with no problem, and a correct judgment was made as to which system the faulty module belongs, a high-pressure system or low-pressure system. Although a faulty module could be identified if the module was in a highpressure system, it was difficult to distinguish a fan fault in a low-pressure system from a fault of the LPT. If the amount of variation in measured values was only twice as large as the standard deviation of measurement noise, a fault could be detected with a high level of sensitivity although it was difficult to isolate the fault to a specific module or sensor. Figure 2 shows the fault diagnosis indicator in a case

Table 1	Results	of	Fault	Diagnosis
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True value of	Result of faulty part isolation			
faulty part	Amount of variation $2\sigma$	Amount of variation $3.5\sigma$	Amount of variation $5\sigma$	
FAN	FAN	LPT	LPT	
LPC	LPC	LPC	LPC	
HPC	HPC	HPC	HPC	
HPT	LPT	HPT	HPT	
LPT	LPC	FAN	FAN	

(Note) The amount of variation  $N\sigma$  shows that the amount of variation in measured values occurring as a result of a module fault is *N* times as large as the standard measurement noise deviation  $\sigma$ .

(a) Normal fault diagnosis indicator

200 400 600 800 1 000 Number of flights (Cycle)





Fig. 2 Fault Index for the Case of FAN Fault

where the amount of variation in measured values occurring as a result of a fault of a fan is twice as large as the standard deviation of measurement noise. As shown in **Fig. 2**, the sensitivity of fault detection can be increased by monitoring the state quantities using not only *RE'* but also individual  $(\delta \Delta x_i / \sigma_{x,i})^2$ and  $(\delta err_j / \sigma_{z,j})^2$  as fault diagnosis indicators.

(3) Summary of test results

It was verified that the accuracy of deterioration diagnosis and the sensitivity of fault detection can be increased by improving the diagnostic techniques using the weighted-least-squares method which are actually being used by an overseas engine manufacturer. In the future, the reduction of the number of sensors is to be studied.

#### 3. Low-cost ECU

# 3.1 Purpose of this technical development and problems to be solved

As aircraft engines are becoming more intelligent, it becomes necessary to provide the ECU with not only the control input but also the input for model-based monitoring. In designing the ECU with the capability to accept both inputs, circuit scale become large, and costs will subsequently increase.

Since the cost of electronic components accounts for the majority of ECU costs, the technology for realizing circuitry with a smaller number of components than are used in existing ECU hardware must be developed in order to reduce costs.

#### 3.2 Technology for reducing costs

We conducted research and development on singlechip technology as the purpose for realizing circuitry with a smaller number of components than are used in the existing ECU hardware. The single-chip technology aims to integrate analog signal conditional circuits comprised of multiple electronic components into a single chip and thereby reduce the number of components while maintaining the same circuit functions.

In this research and development project, we verified the viability of applying the MCU (Micro Controller Unit) and Analog FPGA (Field Programmable Gate Array), which fall in the category of multi-function devices configurable through programming to perform various functions, to the ECU.

The MCU is a product in which a CPU (Central Processing Unit), memory, input output signal conditional function, etc., are built into a single chip. The Analog FPGA has multiple analog circuit blocks, including an operational amplifier, comparator, etc., with block-to-block wiring and variable gain.

**Figure 3** shows the internal configuration of the lowcost ECU to which the MCU and Analog FPGA are applied. **Figure 4** shows how the number of components can be reduced by introducing multi-function electronic components. If these multi-function electronic components can be applied to the ECU, it becomes possible to decrease production costs and the packaging area to about a half.

#### 3.3 Test results

# 3.3.1 Purpose of the test and testing method

The Analog FPGA was evaluated with respect to the accuracy of input and output signal processing, linearity, response, etc., to verify whether it can be applied to the ECU. In this evaluation, an ECU evaluation board for multi function devices (FPGA) having each sensor and signal conditional circuit for actuator of the actual ECU was designed and fabricated using the Analog FPGA. Element tests were conducted on this board by connecting dummy inputs and dummy loads to each circuit in this board.

The applicability of the MCU to the ECU was evaluated in two phases: the element test phase and composite test phase. If the ECU performs many input and output signal conditional tasks at the same time, switching from one task to another takes time and, as a result, processing operations cannot be completed within a specified time, and overall processing time measured becomes longer than the processing time calculated by totaling the time to process each individual task. This raises the concern over the possible occurrence of malfunction or deterioration in the accuracy of measurement.

In the element test, individual functions performed by the MCU were evaluated to verify whether the MCU can be applied to the ECU. In evaluating the A/D conversion function, for example, the A/D conversion speed and the accuracy of conversion to digital signals were evaluated.

In the composite test, the MCU was made to execute multiple input and output signal conditional tasks at once each time an interrupt was generated at certain intervals by the timer interrupt function evaluated in the element test, in the same manner as the ECU. Data was taken, and output externally using the communication function. The data was then compared with data measured when a malfunction occurred and data collected in the element test.

As objects to be subjected to these element and composite tests, an ECU multi-function component evaluation board (MCU) and low-cost ECU prototype module (**Fig. 5**) were designed and fabricated. A testing set to be used to test these objects was also designed and fabricated: an ECU multi-function electronic component evaluation testing set. Element and composite tests were conducted on the combined board and module using this testing set.

#### 3.3.2 Test results

In the element test conducted on the Analog FPGA, it was verified that the input and output signal conditional circuit for processing temperature sensor signals, position sensor signals, actuator output signals, etc., has the signal conditional accuracy, linearity, and response appropriate for the control of an engine.

In the element test conducted on the MCU, the MCU was evaluated with respect to the memory access function, arithmetic function, timer interrupt function, and input signal conditional functions including the A/D conversion function, and output signal conditional functions. It was verified that the MCU meets the ECU performance requirements.



Fig. 3 The block diagram of the ECU utilizing multi function devices

(a) Before multi-function electronic components are introduced

(b) After multi-function electronic components are introduced



Fig. 4 The component reduction through the multi function devices



Fig. 5 Tested module of ECU

In the composite test, it was verified that simultaneous processing of many signals does not affect the processing time and that each function works without malfunctioning and no deterioration in the accuracy of measurement occurs. It was concluded from these results that the ECU configuration with integrated FPGA and MCU meets basic performance requirements for the ECU.

# 4. Conclusion

In this research and development project, the results described below were achieved. Although the monitoring technology still remains to be validated based on data obtained through servicing of actual engines and there are many other problems to be solved, the foundation of the technology for making aircraft engines intelligent to reduce aircraft engine maintenance costs while holding down manufacturing cost increase of ECU hardware associated with this intellectualization has been established. We will further improve the technology for actual aircraft engine application.

- (1) It was verified that the accuracy of deterioration diagnosis and the sensitivity of fault detection of the model-based monitoring can be increased by making improvements to the diagnostic technique using the weighted-least-squares method that is in practical use by an overseas engine manufacturer. In the future, the reduction of the number of sensors is to be studied.
- (2) It was verified through evaluation tests that a low-cost ECU can be realized using single-chip technology, specifically by integrating the MCU and Analog FPGA into the ECU to form a singlechip ECU. This demonstrates the effectiveness

of the system design using these multi-function components. Because the number of components can be decreased while maintaining the level of functionality equivalent to that of the current ECU, the prospect of reducing the packaging area and production costs to about a half looks favorable.

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# REFERENCES

 David L. Doel : Interpretation of Weighted-Least-Squares Gas Path Analysis Results ASME GT-2002-30025