# Anomaly Detection in Airliner Centrifugal Compressor Using Sensor Data during the Climb Phase

Sadanari Shigetomi[1], Makoto Imamura[2], Naoya Kaido[3], Makoto Taniguchi[4], Masaru Nishiwaki[5], Junichiro Kaya[6]

[1,3,4,5,6]*Engineering and Maintenance, ALL NIPPON AIRWAYS CO., LTD., Tokyo, Japan*
*s.shigetomi@ana.co.jp*
*n.kaido@ana.co.jp*
*mako.taniguchi@ana.co.jp*
*ken.nishiwaki@ana.co.jp*
*j.kaya@ana.co.jp*

[2]*Department of Embedded Technology, Tokai University, Tokyo, Japan*
*imamura@tsc.u-tokai.ac.jp*

## ABSTRACT

Predictive maintenance using sensor data has been attracting attention to improve the efficiency of aircraft operations. However, analyzing sensor data for aircraft systems can be challenging due to their limited sensors and dependence on various operational modes. Furthermore, explainability is crucial for applying the results of an analysis to actual maintenance operations. In this study, we propose an anomaly detection method for Cabin Air Compressors (CACs) in the Boeing 787-9 air conditioning system, using a causal graph and neural network. Our evaluations on real sensor data of the CACs show that our method detected 38% of air-bearing degradation cases with explainable visualization of degradation trends.

## 1. INTRODUCTION

Safety and punctuality are fundamental values that every airline seeks to uphold. From the perspective of aircraft maintenance, it is necessary for better operational efficiency to reduce aircraft downtime while lowering operational cost. The 2022 International Air Transport Association [IATA] report showed that the commercial aircraft maintenance cost in global MROs amounted to approximately $62 billion and is predicted to double in 2030. The digitalization and integration of recent aviation electronics, or avionics, is one solution to improve maintenance productivity that enables the condition monitoring of aircraft systems and diagnosing the anomalies with vast and various sensor data during flights. The acquired sensor data is also expected to be utilized for predictive maintenance using data analytics and machine learning to improve fleet-wide reliability. However, the application of predictive maintenance to aircraft systems can be challenging due to limited sensors and dependence on various operational modes by integrated digital controls.

The recent papers in the field of predictive maintenance to the aircraft systems mainly target jet engines. Aydin and Guldamlasioglu (2017) applied LSTM to predict the remaining useful life (RUL) of a turbofan engine. Mathew, Toby, Singh, Rao, and Kumar (2017) also compared ten machine-learning models for RUL prediction. The distinctive points of these papers are; (1) A simulation-based dataset from the NASA data repository was used as benchmark, (2) The output does not have explainability. Luo, Zhao, and Xiong (2021) analyzed real sensor data of air conditioning system that has been acquired from an airline company to demonstrate the anomaly detection using a statistical approach. The proposed method can detect anomalies in several case studies but the fleet-wide performance is not discussed.

In this paper, multivariable real sensor data is analyzed to detect anomalies in the Boeing 787-9 CACs. The proposed method utilizes both domain knowledge and machine learning to visually explain the degradation of the air-bearing in the CACs. Moreover, fleet-wide analysis using a simple threshold was also demonstrated to evaluate the performance of the proposed method. This research aims to contribute towards the application of anomaly detection in the airline industry to maximize operational efficiency.

## 2. PROBLEM DESCRIPTION

In this section, we will describe the functions and features of the CACs, which is the target of anomaly detection in this study.

## 2.1. Overview of the CAC

### 2.1.1. Function

The CAC is a centrifugal compressor in the Boeing 787 aircraft air conditioning (Pack) system. The CAC compresses outside air and supplies high-temperature and high-pressure air to the downstream Pack system. The appearance of the CAC is shown in Figure.1. The CAC consists of a rotating shaft and impeller that compresses air, as well as a three-phase electric motor. Variable Diffuser Vanes (VDVs) are also equipped in the CAC to prevent compressor surging by adjusting the angle of stator vanes. All components are housed in the metal casing.

Figure 1. External view of the CAC

As shown in Figure.2, two CACs are installed in parallel in one set of the Pack system for safety reasons. Add Heat Valves (AHVs) returns the CAC outlet flow to the inlet, to raise the outlet temperature especially in low-temperature environments. The Boeing 787 aircraft is equipped with two sets of Pack systems, Left and Right, and four CACs are installed per aircraft, consisting of Left-1, Left-2, Right-1, and Right-2. Additionally, the Pack systems are centrally controlled by Pack Control Unit (PCU). The PCU controls the Pack systems while responding to meteorological conditions from the ground to the upper atmosphere to efficiently regulate cabin conformity, such as cabin temperature and pressure.

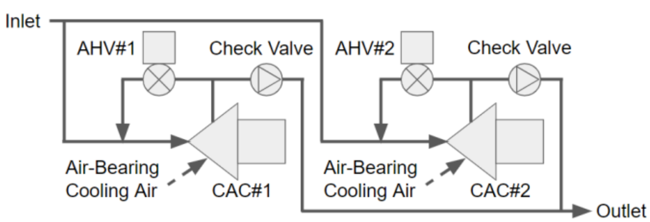


Figure 2. CACs in the Pack system

### 2.1.2. Effects of Failure

When the PCU detects a failure of the CAC, the PCU automatically shuts down the affected CAC and continues to operate the Pack system with the other CAC to maintain a safe and comfortable environment in the cabin. At the same time, fault messages are shown on the flight deck, and aircraft mechanics perform a system check after arrival. When a failure of a CAC is confirmed, mechanics can repair the Pack system by replacing the faulty CAC. The repair work can be postponed within a certain period based on Minimum Equipment List (MEL) provided by the aircraft manufacturer, which allows the aircraft to continue operation without immediate grounding. However, unexpected arrangements of parts and manpower are required. For these reasons, predictive maintenance of CAC is highly expected.

### 2.1.3. Failure Modes

Based on the 75 repair reports of CAC that failed during the 39 months from June 2016, Table.1 shows the failure modes and effects of the CAC.

Table 1. Failure modes and failure effects of the CAC

| Failure Modes | | | Failure Effects | |
|---|---|---|---|---|
| No. | Detail | Event Rate | No. | Detail |
| A | Degradation of air-bearings | 55% | A-1 | Minor wear and/or scratch on air bearing surface. |
| | | | A-2 | Rotating shaft eccentricity and/or impeller rubs to casing. |
| | | | A-3 | Biting of air bearing foils. |
| B | Insulation failure of motor | 40% | B | Imbalance resistance between three-phase motor. |
| C | Others | 5% | C | Such as foreign object damage or no fault found |

The primary failure mode of the CAC is a degradation of air-bearings. As shown in Figure.3, an air-bearing consists of an inner foil sandwiched between the top foil and outer housing. The pressurized airflow lubricates the bearing by forming a thin layer between the top foil and the outer housing.

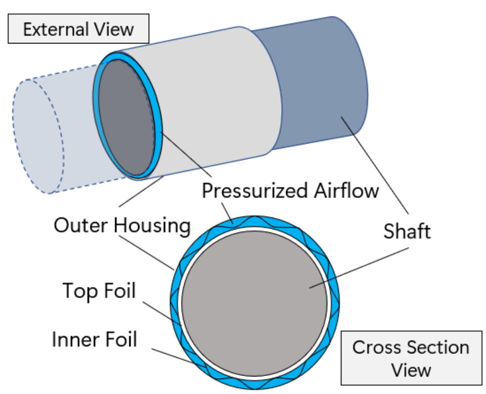


Figure 3. Typical structure of air-bearing (journal bearing)

The pressurized airflow passing through the air-bearing in the CAC comes from heat exchangers, which is installed downstream of the CAC. Since this pressurized air flow is not filtered, atmospheric particles gradually accumulate inside the air-bearing, becoming the starting point of wear and scratch on the bearing surface. As the air-bearing wear progresses, the observed effects change in the order of A-1 to A-3 in Table.1. A-1 is a stage in which only minor wear on the air-bearing is confirmed, and no trouble is found in other areas. A-2 is a stage in which deterioration of the air-bearing has progressed, and the impeller and casing are in contact due to the eccentricity of the rotating shaft. A-3 is a situation where further deterioration of the air-bearing has occurred, and the internal foil is bitted between the casing and the rotating shaft, causing the CAC not to rotate.

The domain knowledge and inspection results suggest that the rotation resistance of the shaft may have been increased as the air-bearing deteriorated, which might increase the power consumption of the three-phase electric motor. However, the CAC is controlled according to meteorological conditions and flight paths and exhibits various operational modes, making it difficult to evaluate its long-term degradation.

## 2.2. Sensor Data

The Boeing 787 has a function to acquire time-series sensor data called Continuous Parameter Logging (CPL). In this study, 44,118 flights of the Boeing 787-9 aircraft (5 aircraft with domestic seat configuration and 35 aircraft with international seat configuration) operated by an airline from January 2021 to 25 months were analyzed. The time-series sensor data was acquired from engine start to engine shut-down with 1 Hz sampling frequency.

## 2.3. Features of CACs

The following factors make anomaly detection difficult among the structural and functional features of the CAC.

### Individual Performance Errors

The performance of machine accessories such as compressors may differ slightly due to manufacturing and assembly errors.

### Interaction of CACs Running in Parallel

Figure.2 shows two CACs are installed to operate in parallel with a shared inlet and outlet for one Pack system. The PCU controls these two CACs and adjusts the airflow output to the target value. Therefore, if the performance of one CAC deteriorates, it may also affect the other CAC.

### Operational Modes

The CACs have various operation modes during flights in response to the external environments and the target cabin temperature and pressure. Especially, external conditions such as the meteorological conditions and flight paths are always different depending on the flight conditions which make the anomaly detection difficult.

## 3. Proposal Method

This study proposes a method for predicting the time-series power consumption during climb flight and detecting anomalies when there is an error between the predicted and actual power consumption.

## 3.1. Feature Selection

Based on the disclosed information to operators, we organized a causal graph of parameters around a CAC into a diagram shown in Figure.4.

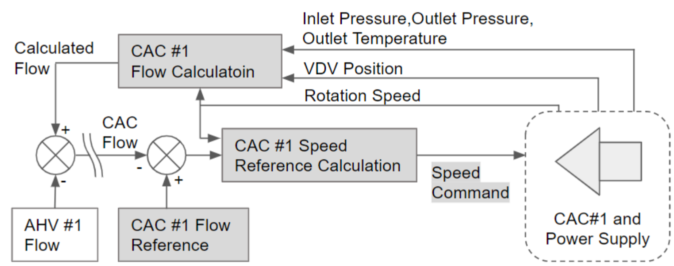


Figure 4. Causal graph of CAC power consumption

The gray boxes represent parameters that cannot be acquired using the CPL. We have selected three explanatory variables shown in Table.2 to estimate the CAC power consumption based on Figure.4.

## 3.2. Region of Interests

We mainly focused on the climb phase of the flights, in which the CAC is rotating at a low speed, making the air-bearing lubrication pressure relatively low. For confidentiality reasons, specific methods have been omitted from this paper.

## 3.3. Anomaly Detection Method

### 3.3.1. Benchmarks

We evaluated the actual power consumption of CAC during the climb phase using three different benchmarks:

- The actual power consumption of the other CAC running in parallel.
- The predicted power consumption by a neural network model derived from a typical Pack system (typical model).
- The predicted power consumption by a neural network model derived from the subject Pack system (subject model)

Comparison with the other parallel CAC is a simple method to offset the meteorological condition differences. In addition, we also developed a power consumption estimation model under the conditions shown in Table.2. The typical power consumption model was trained using the oldest 500 flights after the aircraft delivery in which no Pack system-related failure has yet to be experienced. In comparison, the subject Pack systems' power consumption model was trained using the first 100 flights after the CAC installation, and we updated the model every time the CACs were replaced in the subject Pack system.

Table 2. CAC power consumption model

| | |
|---|---|
| Objective variable | CAC power consumption |
| Explanatory variables | CAC rotation speed, CAC inlet pressure, AHV position |
| Network Type | Nonlinear input-output network |
| Hidden layer | Single layer / 10 Nodes |
| Time delay | 1 Second |
| Error function | Mean Square Error (MSE) |
| Division of data | Training: 70%<br>Validation: 15%<br>Test: 15% |
| Early stopping | Until the validation error increases consecutively for six iterations or 1000 iterations. |

### 3.3.2. Error Functions

We evaluated the actual power consumption $p$ in size of $n$ time-series samples during a single climb flight with the benchmarks using Eq. (1) and Eq. (2), where maximum and minimum functions are used to assess the increase and decrease of the power consumption, respectively.

$$MSE_{pos} = \frac{1}{n}\sum_{t=0}^{n}\{max(p(t) - \hat{p}(t), 0)\} \quad (1)$$

$$MSE_{neg} = -\frac{1}{n}\sum_{t=0}^{n}\{min(p(t) - \hat{p}(t), 0)\} \quad (2)$$

## 4. Experiment Result and Discussions

### 4.1.1. Case Studies

Figure.5 and 6 show the evaluation results of the power consumption of the CACs on the two different aircraft, JA872A and JA830A. The left side of the figure represents CAC#1, and the right side represents CAC#2, with each point representing the evaluation results of the power consumption errors for one flight, while the colored area in the bottom row shows the training period of the subject models. The top, middle and bottom row represents the evaluation results with the other parallel CAC, the typical model, and the subject model, respectively. The vertical solid line represents the replacement of the faulty CAC, and the broken vertical line represents the replacement timing of the other CAC running in parallel. Table.3 shows the inspection results of the CACs based on the aircraft maintenance records and the repair reports.

Focusing on the failure case No.2 in Table.3 and Figure.5, the $MSE_{pos}$ of Left-2 CAC using the subject model has been slightly increasing since July 2022 and exceeded 0.75 just before the failure. Based on the repair report of the CAC, we have concluded that the air-bearing degradation and the contact between the impeller and the casing may have caused the increase in power consumption. Figure 5 also shows that the evaluation using the subject model is smaller than the typical model results. The results suggest that the typical model is not able to absorb the individual performance errors and the subject model can be used for anomaly detection of the air-bearing degradation. On the hand, the $MSE_{pos}$ of Left-1 CAC using the subject model has also been slightly increasing similar to the Left-2 CAC. The results show that the Left-1 CAC may have been affected by the degradation of the Left-2 CAC since the PCU controls both CAC to achieve the outlet pressure and temperature target. In anomaly detection, the CAC with the higher increase in power consumption is considered anomalous.

In Figure.6, we can observe that the seasonal trend both in $MSE_{pos}$ and $MSE_{neg}$ in all benchmarks. Although the failure modes and effects were the same between the failure case No.2 and 3 in Table.3, the periodic trends in the prediction errors make anomaly detection difficult. These trends are a common characteristic observed in aircraft with domestic seat configurations. It means the proposed methods can be affected by the differences between domestic flights and international flights.

### 4.1.2. Fleet-wide Anomaly Detection

Based on the previous analysis, an abnormal increase in power consumption compared to the subject model, as stated in Eq. (3), was used to detect anomalies. The five aircraft with domestic seat configuration was excluded from the evaluation. Where $N$ represents the number of flights in the past 21 days, and $MSE_{pos\_sub}$ represents the evaluation result of the power consumption compared with the subject model.

$$\frac{1}{N}\sum_{i=0}^{N} MSE_{pos\_sub\ i} > 0.35 \quad (3)$$

In case parallel CACs satisfied Eq. (3) simultaneously, only the one with a higher power consumption was considered anomalous.

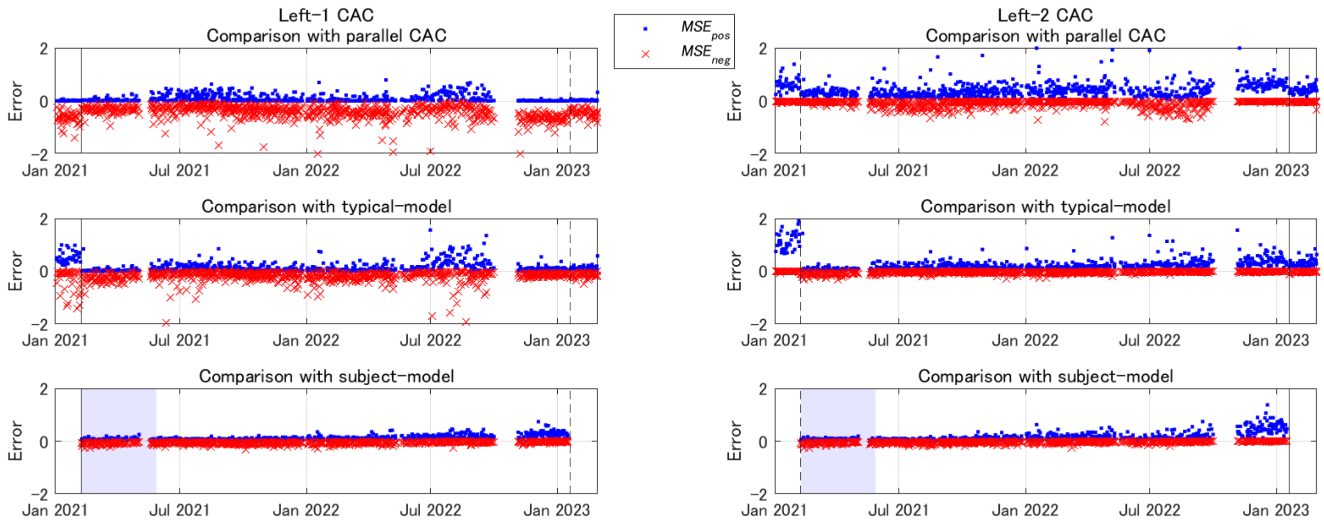


Figure 5. Evaluation results of CAC power consumption
aircraft registration: JA872A (with international seat configuration)

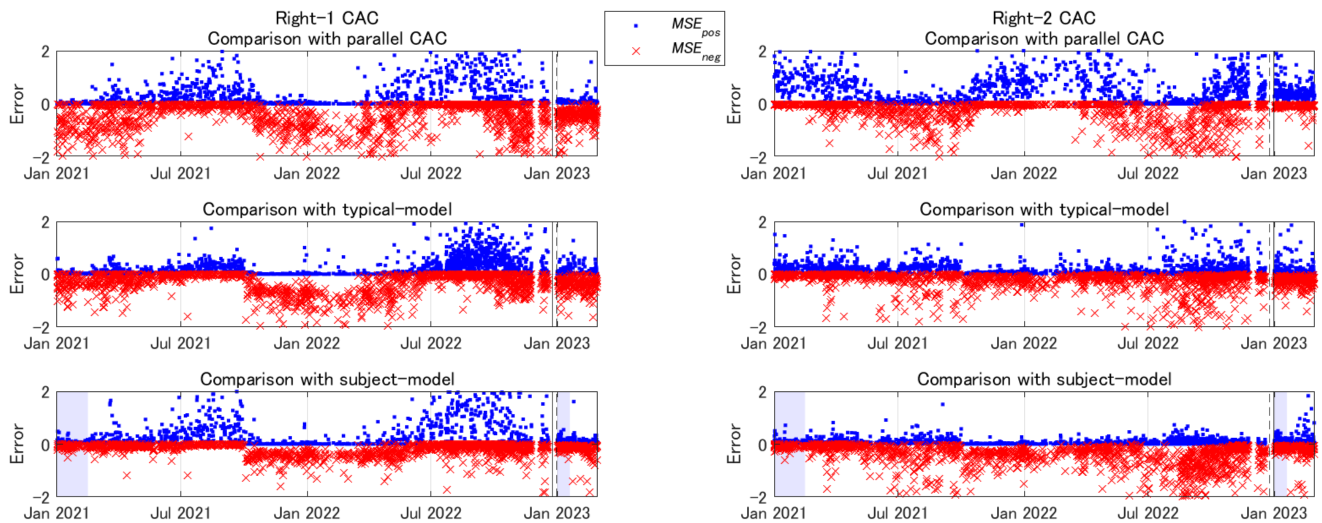


Figure 6. Evaluation results of CAC power consumption
aircraft registration: JA830A (with domestic seat configuration)

Table 3. CAC removals in case studies

| No. | Aircraft | Position | Removal date | Confirmed effects | | |
|---|---|---|---|---|---|---|
| | | | | A-1 | A-2 | A-3 |
| 1 | JA872A | Left-1 | Feb.08.2021 | YES | NO | NO |
| 2 | JA872A | Left-2 | Jan.20.2023 | YES | YES | YES |
| 3 | JA830A | Right-1 | Dec.26.2022 | YES | YES | YES |
| 4 | JA830A | Right-2 | Jan.01.2023 | YES | NO | NO |

Table 4. Results of anomaly detection

| | Observed failure modes and effects | | | Total |
|---|---|---|---|---|
| | A-1 | A-2 | A-3 | |
| Cases where anomalies were predicted: $a$ | 3 | 7 | 8 | 18 |
| Cases where anomalies were NOT predicted: $b$ | 7 | 15 | 7 | 29 |
| False positives: $c$ | - | - | - | 9 |
| Recall: $a/(a+b)$ | 30% | 32% | 53% | 38% |
| Precision: $a/(a+c)$ | - | - | - | 67% |

Table.4 shows the results of the anomaly detection of CACs caused by air-bearing failures. The proposed method detected 38% of air-bearing anomalies before their occurrence. When comparing the recalls by the type of effects of air-bearing degradations, A-3 had the highest rate, followed by A-2 and A-1. The results imply that the A-3 failure mode is most susceptible to the proposed method, as it represents the most advanced stage of air-bearing degradation. However, there are nine false positives in which the CAC failures were not confirmed within six months of anomaly detection.

## 5. Conclusions

An anomaly detection method was proposed using real sensor data of the Boeing 787-9 CACs. The proposed method aims to detect degradation of air-bearings, which is the primary failure mode of the CACs.

The case studies revealed that the benchmark using the neural network model trained by the sensor data of subject systems can be useful for anomaly detection. At the same time, the other two benchmarks explain the interactions between the two CACs running in parallel. The seasonal trend of power consumption error in the aircraft with domestic seat configuration is a problem that needs to be investigated.

The fleet-wide evaluation revealed that the proposed method detected 38% of air-bearing degradation cases and the recall increased as the effect of air-bearing degradation progresses. When considering the brake-even point between inspection costs and the effectiveness of predictive maintenance, the accuracy of the anomaly detection method proposed in this study has room for improvement.

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**Sadanari Shigetomi** works for Component Operation Management & Maintenance, Engineering and Maintenance, All Nippon Airways Co., Ltd. He graduated from the Master’s course of the Department of Aeronautics and Astronautics at the Graduate School of Engineering, Kyushu University, in 2015. He is involved in aircraft condition monitoring and data analysis for predictive maintenance.

**Makoto Imamura** received B.S. and M.E. degrees in Applied Mathematics and Physics from Kyoto University and a Ph.D. in Information Science and Technology from Osaka University. After working for Mitsubishi Electric Corp., he became a full professor at Tokai University in April 2016. His research interests include time series analysis, data mining, and PHM. He is a member of IEEE and ACM.

**Naoya Kaido** also works for Component Operation Management & Maintenance, Engineering and Maintenance, All Nippon Airways Co., Ltd. He graduated from the Master’s course of the Department of Marine Engineering at the Graduate School of Maritime Science, Kobe University, in 2017. He is involved in aircraft component repair management and technical analysis.

**Makoto Taniguchi** also works for Component Operation Management & Maintenance, Engineering and Maintenance, All Nippon Airways Co., Ltd. He graduated from the Bachelor’s course of the Department of Aeronautics & Astronautics at the Faculty of System Design, Tokyo Metropolitan University, in 2005. He is involved in aircraft condition monitoring and flight data analysis for predictive maintenance.

**Masaru Nishiwaki** works for e.Team ANA Production System & Innovation, Engineering and Maintenance, All Nippon Airways Co., Ltd. He graduated from the Bachelor’s course of the Department of Electrical and Electronic Engineering at the Faculty of Engineering, Chiba University, in 1986. He is involved in aircraft engineering and digital transformation.

**Junichiro Kaya** works for Component & Supply-chain Management, Engineering and Maintenance, All Nippon Airways Co., Ltd. He graduated from the Bachelor’s course of the Department of Electrical Engineering and Electronics at the Faculty of Science and Engineering, Aoyama Gakuin University in 1993. He is involved in the supply chain management of aircraft components.