Civil Aircraft Health Management Research based on Big Data and Deep Learning Technologies

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***Abstract*—the coupling and correlation degree between aircraft systems is higher, and the diagnosis and prognosis of aircraft are more complex. Building a platform for storing and analyzing the aviation big data becomes an important task for civil aviation. This paper proposes a civil aircraft health management big data architecture. The civil aircraft health management system includes airborne PHM, ground PHM, remote diagnosis system, portable maintenance assistant system, maintenance center, automatic test equipment, special test equipment. Airborne PHM collects data from multiple types of data sources. Ground PHM provides decision making support for civil aircrafts including real-time alarm, health management, maintenance plan, spare parts. The paper introduces deep learning algorithm and aircraft fault diagnosis and prognosis implementation.**

Keywords-civil aircraft; health management; big data; deep learning

I. INTRODUCTION

Aircraft Prognostics and Health Management (PHM) is a system for aircraft detection, monitoring, diagnosis, forecasting and decision-making. It is based on testing technology, computer technology, information technology and fault diagnosis technology. It is mainly used for real-time forecasting of aircraft failure, aircraft condition and remaining useful life by means of data acquisition, signal processing and data analysis. It is the technical basis of Condition-Based Maintenance (CBM) and Autonomic Logistic (AL).

Because of the high integration of aircraft systems and the using of high-tech, the coupling and correlation degree between aircraft systems is higher, and the testing and diagnosis of aircraft are more complex. The types and quantity of aircraft real-time monitoring data's size are sundry and huge, and the health management technologies cannot meet the current situation. We propose an aircraft health management big data architecture, and we study the fault diagnosis technologies based on deep learning. It can achieve the health management of the system-level or components-level. It can solve the problem of low fault coverage, low fault isolation rate, high false alarm rate and low maintenance efficiency. It can effectively improve the viability of aircraft and improve maintenance efficiency. In addition, it is becoming more and more difficult to extract and select the fault features by experts' experience or signal processing technologies. Therefore, it is urgent to study a new method to adapt to the challenge of diagnosis system. Deep learning has a strong ability to extract features from a sample and transform features, and it can automatically extract the essential characteristics of aircraft monitoring data, mining the hidden information in the big data, improve the accurateness and effectiveness of fault diagnosis.

The rest structure of the paper is as follows. Section 2 introduces the related work of the study. Section 3 details the concepts of the civil aircraft health management big data architecture. Section 4 gives an example of the civil aircraft PHM big data frame. Section 5 introduces the concepts of deep leaning. Finally, Section 6 summarizes the conclusion and the future work.

II. RELATED WORK

Prognostics and Health Management system has been applied in the military and civil. Black Hawk helicopters, F35 and other military aircraft have been installed on the PHM system [1]. Among them, the most mature PHM system is the double-deck architecture of F35 aircraft. The system includes the airborne intelligent real-time monitoring system and the ground integrated health management system. Using the multi-stage system, the airborne system integrates the airplane airborne information, and sends the information to the ground. The integrated health management system determines the safety of aircraft and realizes the state management and maintenance guarantee.

In civil aircraft integrated health management system, Aircraft Health Management System (AHM) and Aircraft Maintenance Analysis System (AIRMAN) are representative [2] [3]. The main function of the AHM system is collecting and analyzing the aircraft flight data, monitoring the aircraft state. The long-term reliability of the fleet is supported by identifying faults and responding in advance. Through the analysis of operational history data and knowledge, the AHM system can accurately locate the fault, identify the maintenance plan, and improve the maintenance efficiency of the fleet. The main function of the AIRMAN system is continuously monitoring the status of the aircraft and transmitting the monitored faults or warning messages to the ground control station. Rely on the early information, maintenance personnel can clearly determine the fault before the plane landed. By real-time monitoring of aircraft operational status and electronic troubleshooting, AIRMAN can reduce flight delays and cancellations, improve aircraft availability, save maintenance and operating expenses. Then, Airbus has introduced an aircraft real-time health monitoring system (AiRTHM). The system can provide

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support for real-time troubleshooting, guide spares provisioning, monitor system health, and achieve fault prediction.

In addition, many engines have installed the health management system for real-time monitoring of engine conditions. For example, the health management system of Rollo's T900 engine consists of airborne system and ground station. The airborne system mainly realizes data acquisition, data preprocessing, data storage, condition monitoring and alarm. The ground station mainly realizes the engine fault diagnosis and prediction.

GE proposed the "Industrial Internet" and improved the efficiency of aircraft engines by statistics and analysis for mass data. Later, GE launched the world's first cloud service platform for industrial data analysis-Predix cloud platform. At present, the data of 35,000 engines was transferred to the Predix. The Predix handles the hundreds of millions of data generated by the engine fleet and determines the level of warnings [4]. For monitoring thousands of Trent engines in real time, Rolls-Royce's Global Engine Health Monitoring Center has established the Engine Health Management System (EHM). In order to achieve the mass of aviation operations data summary and integration, Rolls-Royce and Microsoft will jointly establish a new digital function, and apply it to the Microsoft Azure cloud platform. Using Microsoft's advanced big data analysis technology, the center can analyze the mass data, propose personalized solutions [5].

Airbus and Oracle established a big data processing system based on Hadoop technology and flight simulation data analysis software, and the company set up a data processing and flight test integration center. The center collects and analyzes the flight test data, and uses Google's MapReduce technology to improve the efficiency of data access and processing. Boeing and Carnegie Mellon University built a Boeing/Carnegie Mellon Aerospace Data Analytics Lab for a comprehensive upgrade of Boeing aircraft using artificial intelligence and the big data technology. Use machine learning to optimize the flight mode of the aircraft, and use the results of data analysis to guide the future design, manufacture and operation [6]. COMAC launched a "big data application demonstration project for improving the aircraft development capability", established a data analysis platform. The functions of the platform include high-speed acquisition of massive, structured/unstructured aviation big data, distributed storage, processing, display, aircraft data value mining.

As a machine learning method, deep learning uses massive data for adaptive learning. With its powerful automatic feature extraction, deep learning has achieved brilliant results in the field of image and speech recognition [7] [8] [9]. Due to the complexity of the aircraft system and the diversity of the collected signals, the aircraft PHM is still a complex problem. More and more researchers use deep learning methods for aircraft fault diagnosis, and obtain good diagnostic effects. In deep learning algorithms, Deep belief network (DBN) has excellent feature extraction and training algorithm, and successfully solves the problems of information retrieval, dimension reduction and fault classification.

P. Tamilselvan applied the DBN method to the health diagnosis of aircraft wings and engine structures, and the results showed that the DBN has a higher detection rate [10]. For the aircraft engine fault diagnosis, P. Tamilselvan proposed a multi-sensor fault diagnosis method based on DBN. Finally, the DBN was compared with four diagnostic methods, the validity of the method was verified [11]. Van Tung Tran fused DBN and Teager-Kaiser energy operation (TKEO) algorithm, and achieved a higher fault recognition rate in the fault diagnosis of reciprocating compressor valve [12]. Xue Sen Lin diagnosed the engine rotating components using ad_ DBN, DBN, LS-SVM, BP and RBF. By comparing the diagnostic results, it is shown that among the algorithms, ad_ DBN has the highest diagnostic accuracy [13]. For rolling bearing fault diagnosis, Particle Swarm Optimization (PSO) is combined with DBN. In the absence of a priori fault information, the method still achieved a better identification accuracy [14]. Li C proposed a multimodal deep support vector classification (MDSVC) method to improve the accuracy of gearbox fault identification under a single vibration source [15]. Using the deep neural network (DNN), Jia F directly performed fault feature extraction and recognition from the frequency domain signal of the rotating bearing, and achieved good results [16].

Therefore, it is urgent to study the civil health management framework based on big data. In addition, the study of fault diagnosis based on depth learning also greatly increases the detection rate of PHM, improves the maintenance efficiency of civil aircraft and increases the dispatch rate.

III. CIVIL AIRCRAFT HEALTH MANAGEMENT BIG DATA ARCHITECTURE

The focus of aircraft health management is to prognosis, diagnose, monitor and manage the state of the aircraft. Diagnosis includes fault monitoring and fault location. It refers to determine the causes, nature, location of the fault. Prognosis refers to diagnose the state of an aircraft component or system in advance by sensor information and historical information using algorithms and intelligent models. It determines the remaining life of the component or normal working time. Health management is the ability to make appropriate decisions about maintenance activities based on diagnostic / forecasting information, available resources and usage requirements.

According to the OSA-CBM standard, the PHM system includes 7 functional parts: data acquisition, data processing, state monitoring, health assessment, fault prognosis, reasoning decision and human-machine interface [17].

- Data acquisition and transmission: The data collection and transmission of the system was achieved through the traditional sensors, intelligent sensors and data bus.
- Data processing: Get and process input data from sensors and control systems. Processing methods include filtering, averaging, statistical analysis, spectral analysis.
- State monitoring: Monitor the status of the aircraft system/component and detect abnormal alarms.

- Health assessment: Determine the current health status of a system, subsystem, or component based on state monitoring information and historical status.
- Fault prognosis: Predict the remaining life based on the current health status of the system, subsystem, or component.
- Reasoning decision: Provide maintenance and protection decisions based on health assessment and fault prognosis.
- Human-machine interface: Show the results of the modules.

In this paper, the civil aircraft health management system is divided into the airborne PHM and the ground PHM. The airborne PHM includes data acquisition, data processing, state monitoring, the ground PHM includes Health Assessment, Fault Prediction, Reasoning Decision, Man-Machine Interface. In addition, the civil aircraft health management system includes some auxiliary decision support systems, such as remote diagnosis system, portable maintenance assistant (PMA) system, maintenance center, automatic test equipment, special test equipment. Fig. 1 shows the civil aircraft health management big data architecture.

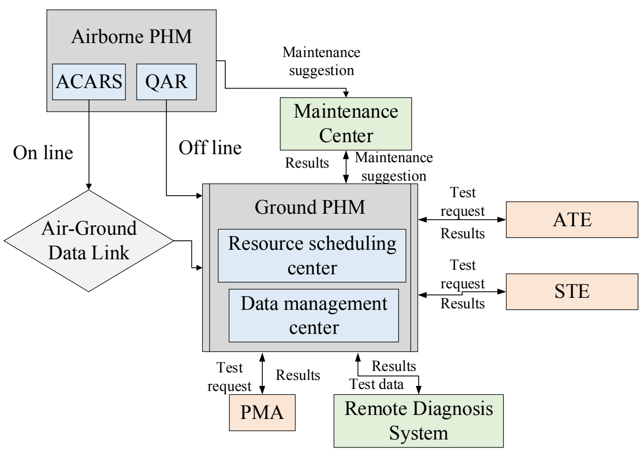

Fig. 1 Civil Aircraft Health Management Big Data Architecture

A. Airborne PHM

Airborne PHM is classified into aircraft PHM, system PHM, subsystem PHM, aircraft structure and airborne PHM classification as shown in Fig 2. Aircraft includes airframe, power plants, electronic devices, environmental control systems, electromechanical systems. The airframe includes the fuselage, the wing, the tail, and the landing gear. The power plants include the engine, the auxiliary power units. The electronic devices include the communication, the navigation, and the flight control instrument system. The electrical system includes the power supply, the power distribution system. The environment control system includes oxygen, the air-conditioning, and the supercharging system. Electromechanical systems include fuel systems, power supply and hydraulic systems.

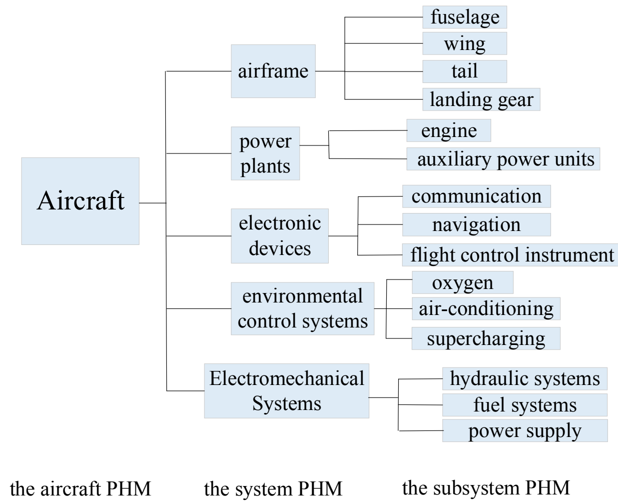

Fig. 2 Aircraft structure and airborne PHM classification

The main function of the aircraft PHM is to receive the system PHM analysis, to comprehensive analysis combined with the cascade relationship between the systems, to get the results of the aircraft PHM, and send the results to the ground PHM and the maintenance center. The main function of the system PHM is to receive the subsystem PHM analysis, to comprehensive analysis combined with the cascade relationship between the subsystems, to get the results of the system PHM, and send the results to the aircraft PHM. The main function of the subsystem PHM is to collect monitoring data, data preprocessing, feature extraction, to comprehensive analysis combined with the cascade relationship between the parts, to get the results of the subsystem PHM, and send the results to the system PHM.

B. Ground PHM

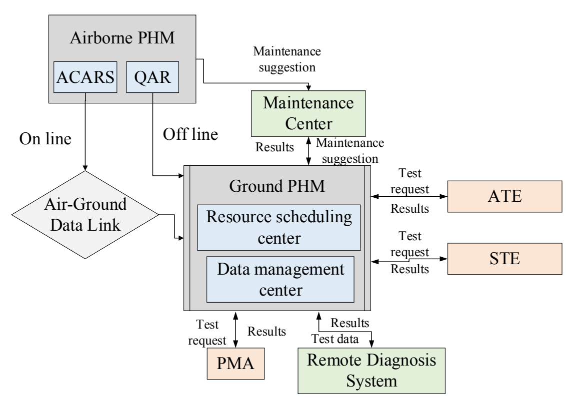

Fig. 3 The ground PHM structure

Fig. 3 shows the ground PHM structure. The ground PHM includes fault diagnosis module, fault prognosis module, reasoning decision module, resource scheduling center and data management center. Ground PHM receives on-line/off-line acquisition data and analysis conclusions, as well as the test results and the diagnosis results sent by test equipment. All the resources are analyzed offline and the results were sent to the ground maintenance center. Using the conclusions of airborne PHM, the resource scheduling center determines test resource and data, and sends test request / test data to PMA, automatic test equipment, remote diagnosis system. The function of data management center is to store and manage aircraft big data.

1) Diagnostic methods for fault diagnosis：

- Fault diagnosis based on analytic model: To use accurate mathematic model and observed quantity, the fault is generated by residual signal. Diagnostic methods include State Estimation Method, Parameters Estimation Method, and Parity Space Method.

- Fault diagnosis based on data driven: Based on the analysis of historical data and real-time monitoring information, various intelligent models are used to realize the system fault diagnosis. Diagnostic methods include Machine Learning Method, Multivariate Statistical Methods, and Information Fusion Methods.

- Fault diagnosis based on knowledge: With some qualitative analysis tools and expertise, fault diagnosis was achieved through analysis of continuity. Diagnostic methods include Expert System Method and Stereotyped Simulation Method.

- Fault diagnosis based on deep learning: Using the original time-domain signal, deep learning is developed and intelligent diagnosis is completed. The method can free man from the dependence of the feature extraction technology, and enhance the intelligence of the identification process. Diagnostic methods include deep belief networks, convolutional neural networks.

2) Prognosis methods for fault prognosis：

- Fault prognosis based on statistics: Prognosis methods include Bayesian technique, Hidden Markov Model and Proportional Hazards Model.

- Fault prognosis based on data driven: By analyzing the relationship between input/output and state parameters, the mapping relations between input and output is learned from historical data, and the fault prognosis model is established. Prognosis methods include time-series, neural network, and filter.

- Fault prognosis based on failure-physics model: Reliability is assessed using product life cycle loads and failure mechanism knowledge.

3) Reasoning Decision：

Comprehensive fault diagnosis and fault prediction conclusion, using decision-making information fusion algorithm or fuzzy theory algorithm, aircraft health status was analyzed, decision support is obtained.

4) Man-Machine Interface

Including the display of alarm information and the representation of data information, data information is from the health assessment, prediction and decision support modules.

C. Automatic Test Equipment (ATE)

The main function of the automatic test equipment is to receive test request sent by the ground PHM, carry out test according to test request, and return test result to the ground PHM. Automatic test equipment consists of measuring instruments, adapter, testing interface and testing software. It is mainly used for test of aircraft electronic system, flight control system, and power system.

D. Special Test Equipment (STE)

The main function of the special test equipment is to receive test request sent by the ground PHM, carry out test according to test request, and return test result to the ground PHM. Refers to general test equipment, special test equipment can complete some special test content, such as oil spectrum analysis, ferrographic analysis, nondestructive examination, and ultrasonic inspection.

E. Portable Maintenance Assistant (PMA)

PMA is mainly used for aircraft in-situ detection and fault diagnosis. It can detect the possible failure promptly and accurately, solve the problems that test equipment is difficult to be carried in the field or in the narrow space, short maintenance time and improve maintenance efficiency. Maintenance personnel run interactive electronic technical manual (IETM) and testing process (TP/TPS) to complete automatic test diagnosis of measured object. PMA receive test request sent by the ground PHM, carry out test according to test request, and return test result to the ground PHM.

F. Remote Diagnosis System

The remote diagnosis system includes fault diagnosis inference module and remote data transmission module. The function of fault diagnosis inference module is to analyze and calculate fault information, feedback fault conclusion and processing scheme to the ground PHM. The remote data transmission module is responsible for the transmission of fault information between the remote diagnosis system and the ground PHM.

G. Maintenance Center

The maintenance center is mainly used to receive maintenance recommendations from the ground PHM and the airborne PHM, to develop a maintenance plan based on maintenance recommendations, to carry out a maintenance implementation process, and to return the results to the ground PHM.

IV. EXAMPLE

Taking hydraulic system as an example, this paper describes the application of civil aircraft health management big data architecture.

Airborne PHM includes aircraft PHM, electromechanical system PHM, and hydraulic system PHM, as shown in Figure 4. The aircraft PHM is installed on the aircraft central maintenance computer. The electromechanical system PHM and the hydraulic system PHM are installed on the electromechanical management computer.

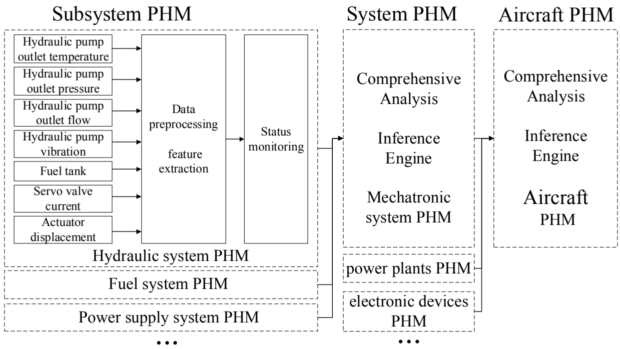

Fig. 4 The airborne PHM structure

The main function of the hydraulic system PHM is to collect the hydraulic system sensor data, including the hydraulic pump outlet temperature, outlet pressure, outlet flow, hydraulic pump vibration, fuel tank, servo valve current, actuator displacement. The data are preprocessed and characterized. The features include time domain features such as mean, RMS, kurtosis, and frequency domain features such as spectrum and power spectrum. According to the given threshold, the hydraulic system PHM determines the state of the system parameters, and sends the data and the analysis results to the electromechanical system PHM. The electromechanical system PHM integrates the analysis results and data sent from the hydraulic system PHM, the fuel system PHM, the power system PHM, considers the connection between the subsystems. The PHM obtains the electromechanical system PHM conclusion based on the inference engine comprehensive analysis, sends to the aircraft PHM. The aircraft system PHM integrates the analysis results and data sent from the electromechanical system PHM, the airframe PHM, the power plants PHM, the electronic devices PHM, the environmental control system PHM. The aircraft system PHM considers the connection between the systems. The airborne PHM obtains the aircraft PHM conclusion based on the inference engine comprehensive analysis, sends to the ground PHM.

Based on the analysis results of the ground PHM, the resource scheduling center decides which resource to call. Figure 5 shows the resource scheduling center logic of the hydraulic system test.

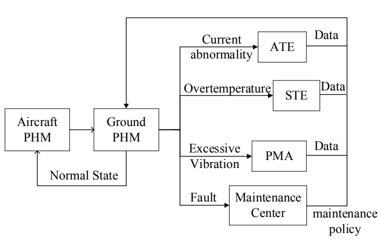

Fig. 5 The hydraulic system test resource scheduling center logic

- Normal state: the aircraft system status is normal, the airborne PHM system continues to monitor aircraft status in real time.
- Current abnormality: the hydraulic system servo valve current is abnormal. After the plane landed, the ground PHM resource scheduling center calls ATE. ATE performs off-line test according to test requirements provided by the ground PHM, and returns the test results to ground PHM.
- Overtemperature: the hydraulic pump outlet overtemperature. The ground PHM resource scheduling center calls STE. STE performs off-line test according to test requirements provided by the ground PHM, such as hydraulic oil test, iron chip test, and returns the test results to ground PHM.
- Excessive vibration: the hydraulic pump vibration is excessive. The ground PHM resource scheduling center calls PMA. PMA performs a separate off-line test of the hydraulic pump and returns the test results to ground PHM.
- Fault: the hydraulic system failure. The airborne/ ground PHM sends the fault mode, maintenance recommendations to the maintenance center, the maintenance center develops maintenance strategies and maintenance plans, and returns the repair results to ground PHM.

The ground PHM receives and stores the airborne PHM information and other equipment test information, and analyzes the data using the fault diagnosis and the fault prediction algorithm, realizes the aircraft fault diagnosis, fault isolation, maintenance decision and life prediction.

V. Aircraft Fault Diagnosis based on Deep Learning

A. *Common Models of Deep Learning*

1) Convolutional neural networks (CNNs)

CNNs is a multi-layer neural network, each layer consists of multiple two-dimensional plane, and each plane consists of multiple independent neurons. A convolutional neural network includes the input layer, the convolutional layer, the pooling layer, and the fully-connected layer.

The training of the CNNs consists of forward propagation phase and backward propagation phase.

2) Deep belief networks (DBNs)

DBNs is a probabilistic generative model, and it is stacked by a number of Restricted Boltzmann Machines (RBM). The RBM includes the visible layer and the hidden layer. The bottom of DBNs receives the input data and converts the input data to the hidden layer via RBM. Between the RBMs, the input of the higher layer comes from the output of the lower layer.

The training of the DBNs consists of unsupervised training and supervised fine-tuning.

B. Aircraft Fault Diagnosis and Prognosis Deep Learning Algorithm Implementation

Aircraft fault diagnosis deep learning algorithm can be divided into four steps:

Step 1: Obtain big data (sensor data, switch data, equipment data, event data) for aircraft fault diagnosis and prognosis.

Step 2: Fault making.

Step 3: Calculate using deep learning algorithm.

Step 4: Calculate fault diagnosis and prognosis results.

Compared with the traditional method, fault making cannot be omitted, because we use a supervised method, and this method must have lots of labeled samples. What makes it different is that the labeled samples were trained directly with deep learning algorithm to get the final result of fault diagnosis and prognosis. Deep learning eliminates feature extraction. We learn from the original data through deep learning without expert guidance. Deep learning methods can even learn features that are not known to experts, or that cannot be expressed. The effect of deep learning model is better than the traditional model. However, deep learning requires massive data.

VI. Conclusion

The types and quantity of aircraft real-time monitoring data are huge. In this paper, we propose an aircraft health management big data architecture, and study the fault diagnosis technology based on deep learning. It can solve the problem of low fault coverage, low fault isolation rate, high false alarm rate and low maintenance efficiency. The platform provides management and analysis of aircraft operating around the world. The platform monitors the aircraft operational health status in real time, and reduces operating costs. In the future, we will focus on the following work: (1) the big data-based aircraft diagnosis and prediction algorithms; optimization of the algorithms using deep learning methods; (2) construction of big aircraft data analysis center, particularly the security of the platform. We will focus on investigating enhanced security of aviation data sharing using the block chain technology.

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