Research on Predictive Maintenance Architecture of Experimental Aircraft Based on Digital Twins

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Abstract. With the rapid development of industrial technology and the new generation of information technology, the integration and intelligence of aircraft equipment continue to improve, increasing the probability of experimental aircraft malfunction and functional failures, resulting in a significant increase in flight test maintenance costs. To reduce downtime and maintenance costs, this article proposes a new predictive maintenance model for experimental aircraft based on digital twin technology, established a predictive maintenance process architecture for digital twin driven experimental aircraft, and elaborated on the operational mechanism of this architecture in detail. Taking twin data as the core, the information collection scheme and multidimensional virtual model scheme are constructed, and the fault diagnosis, fault trend prediction and maintenance scheme decision based on artificial intelligence are studied. A predictive maintenance process for experimental aircraft based on digital twins is presented, and key artificial intelligence algorithms are analyzed. This technology will help experimental aircraft improve flight efficiency, reduce equipment maintenance costs, and ensure the safety and reliability of the aircraft.

Keywords: digital twin, predictive maintenance, artificial intelligence algorithms, fault diagnosis, fault prediction

1 Introduction

In recent years, with the development of data analysis and Internet of Things, as well as the aviation management system and continuous innovation of high - tech, predictive maintenance of aircraft has become a hot topic in the aviation industry at home and abroad. Various machine learning algorithms and artificial intelligence technologies have significant advantages in improving aircraft operational safety, reducing unplanned downtime, and lowering maintenance costs in predictive maintenance. However, currently, experimental aircraft maintenance work still relies on manual operations, making it difficult to achieve real-time intelligent control of predictive maintenance based on actual or expected future situations. Moreover, if decision-making errors occur, significant safety hazards may arise.

Digital twin technology is a system model established by combining data acquisition, transmission, processing and simulation of the experimental aircraft with data

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analysis visualization and artificial intelligence.[1]With the aid of artificial intelligence algorithms and High-performance computing technology, these data are processed and analyzed in a large scale, and real operating data are provided within the expected time through simulation scenarios, enabling maintenance personnel of the experimental aircraft to take real-time measures based on actual needs, helping maintenance personnel detect potential fault problems in advance. At the same time, through model updates and iterations, intelligent maintenance solutions are made more accurate and maintenance costs are reduced. The digital twin technology is of great significance for the future development of experimental aircraft maintenance and operation, and deserves our attention and in-depth research. In terms of model implementation methods, relevant technical methods and tools are showing a diversified development trend. At present, the digital twin modeling language mainly include AutomationML, UML, SysML and XML, etc. Some models are developed using general modeling tools such as CAD, while more models are based on specialized modeling tools such as FlexSim and Qfsm, etc[2] .

Lu Han studied the trusted evaluation framework of equipment digital twin; Han Zhoupeng studied the continuous casting roller driven by digital twin and the optimization framework of health monitoring and assembly; Fan Weijun studied the whole life cycle management of power battery driven by digital twin; Dai Chengyuan studied the dynamic scheduling of prefabricated building construction process based on digital twin; The predictive maintenance of the experimental aircraft has not been theoretically analyzed, so this paper is to study.

This article mainly studies the overall framework of digital twin technology in predictive maintenance of experimental aircraft. A large amount of data is obtained through new sensing technologies such as sensors, and data analysis and artificial intelligence technology are used for data processing and feature extraction. Various components of the aircraft are modeled, and their historical data and environmental factors are analyzed to predict potential future faults and plan maintenance plans in advance. By analyzing the maintenance history data of the aircraft and considering factors such as cost and feasibility of different maintenance plans, the best maintenance decision support plan is provided.

2 Predictive Maintenance Architecture for Experimental Aircraft Based on Digital Twins

2.1 Design objectives

In order to improve the efficiency and accuracy of aircraft maintenance and avoid safety accidents and economic losses caused by equipment failures, this paper proposes the use of digital twin technology, the use of Physical system and mathematical models to establish a connection. Through the construction of a new perception technology of maintenance status information collection scheme, the construction of fault diagnosis, trend prediction technology, intelligent predictive maintenance strategy of artificial intelligence algorithm, monitor and analysis of aircraft operation status in real time and extract of parameters and features. Early maintenance based on predicted results, reduce downtime and maintenance costs and achieve aircraft fault prevention and scientific maintenance, as well as providing more accurate maintenance data and decision support, providing strong guarantee for further improving the quality of test flights. This article constructs a predictive maintenance framework for digital twin experimental aircraft based on the following design objectives:[3]

1) Based on digital twin technology, different modules can be compatible and interact with each other to ensure smooth data transmission within the framework without data loss, and to meet the collaborative work between different modules;

2) The digital twin model can achieve real-time mapping of data with physical entities, always maintaining virtual and real synchronization, in order to facilitate real-time data collection, storage, and processing, and achieve visual monitoring of the experimental aircraft;

3) Introducing artificial intelligence algorithms under digital twin technology can provide reference for fault diagnosis, fault trend prediction, and intelligent maintenance decision-making of experimental aircraft.

2.2 Overall Architecture

Based on the concept of a digital twin five-dimensional model,[4] as shown in equation (1):

$$M_{DT} = (PE, VE, Ss, DD, CN)$$

which PE represents a physical entity, VE represents a virtual entity, Ss represents a service, DD represents twin data, CN represents the connection of various components. A digital twin is constructed for predictive maintenance of the experimental aircraft.[5] The specific architecture is shown in Figure 1:

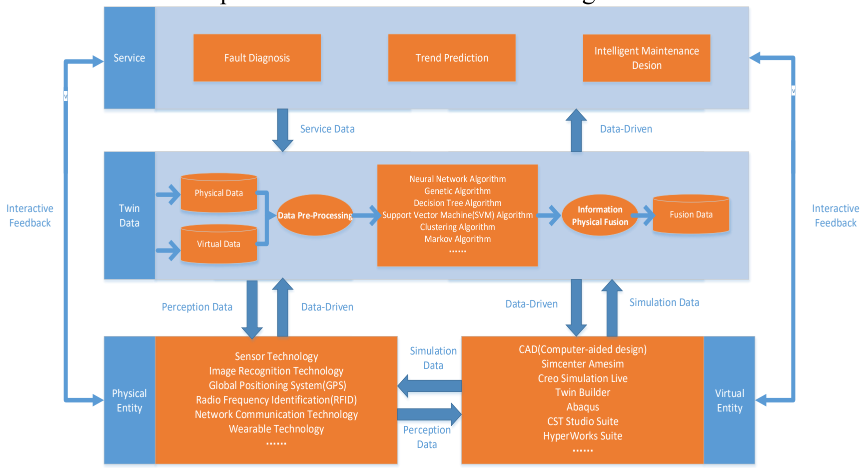

Fig. 1. Predictive Maintenance Framework for Experimental Aircraft Based on Digital Twins

3 Maintenance status information collection scheme based on new perception technology

It is crucial to design an effective information collection scheme for experimental aircraft with highly complex systems. By using new sensing technologies to connect these sensing device data to a collaborative management system, real-time transmission of device status data is carried out for statistics, analysis, and diagnosis, thereby promoting product reliability and improving maintenance efficiency. The following is a list of information collection solutions for experimental aircraft with new sensing technologies:

1) Sensor technology: include various sensors such as temperature, pressure, vibration and so on, which can monitor these parameters in real-time during flight and convert them into digital signals;

2) Image recognition technology: use laser radar, infrared cameras and so on to collect images or three-dimensional spatial information, and to inspect and judge the surface defects and losses of aircraft;

3) Global Positioning System (GPS): obtain real-time data on the position, speed, and heading of aircraft, and accurately record their trajectory and motion status;

4) Radio Frequency Identification (RFID): track the maintenance history, installation time, and predict repair needs of components. By attaching RF tags to items and using a reader for scanning during flight, the original information is captured and stored at the same time;

5) Network communication technology: include wired communication technology and wireless communication technology, mainly through means such as the Internet, satellites, or the Internet of Things, to achieve real-time transmission and sharing of aircraft data;

6) Wearable technology: install sensors, displays or other electronic devices on equipment commonly worn by pilots, connect various devices during the whole flight, cooperate to complete real-time monitoring during the flight, and record important vital sign parameters such as pilots' heartbeat, pulse, blood pressure, respiratory rate, etc.

4 Construction of multi-dimensional virtual models

Virtual entities depict and describe the experimental aircraft from multiple dimensions, spatial scales, and temporal scales through various software and tools. Commonly used, including CAD (Computer-aided design), can be used to design and draw the geometric shape and structure of products, including parts and system equipment; Simcenter Amesim supports systems and simulations in multiple fields such as physics, liquids, gases, and electronics; Creo Simulation Live enables designers to evaluate design solutions and optimize them faster by using real-time simulation technology in CAD; Twin Builder provides a new solution by combining models and simulations for designing, operating, and analyzing different types of systems such as electronics, machinery, and fluids; SIMULIA includes Abaqus and CST Studio Suite, among others. The former is used for solid/structural analysis, fluid and thermal simulation, while the latter is suitable for electromagnetic simulation and micro wave circuit simulation;

HyperWorks Suite integrates functions such as finite element analysis, multi-physics simulation simulation, modeling and visualization.

5 Research on Predictive Maintenance Algorithm Based on Artificial Intelligence

Predictive maintenance based on artificial intelligence is a method of fault diagnosis, fault trend prediction, and intelligent maintenance decision-making based on machine learning, data mining, and other technologies. It aims to improve the reliability of experimental aircraft, reduce fault rates and maintenance costs. By analyzing historical data and real-time monitoring information, it predicts possible future faults of equipment or systems, and makes intelligent decisions based on these predictions, in order to take appropriate measures as soon as possible to prevent the occurrence of faults. This paper considers the following Al predictive maintenance algorithms, including but not limited to: regression model based algorithms, support vector machine (SVM) based algorithms, KNN (K-neighborhood algorithm), decision tree based algorithms, clustering based algorithms, time - series analysis based algorithms, neural network based algorithms such as CNN (volume and neural network) and RNN (Recurrent neural network), algorithm based on GAN (confrontation generation network), algorithm based on Markov processes, genetic algorithms, fuzzy logic algorithms, etc.

5.1 Fault Diagnosis of Experimental Aircraft Based on Artificial Intelligence

By organizing the above artificial intelligence algorithms, some solutions for artificial intelligence algorithms in fault diagnosis of experimental aircraft are provided:

i. Engine fault diagnosis system based on neural network: train neural network models using aircraft monitoring data to achieve fast and accurate diagnosis of engine faults;

ii. Fault diagnosis of flight control system based on decision tree: by constructing a decision tree of the flight control system, the equipment is judged layer by layer to determine if there are problems and ultimately determine the cause of the fault;

iii. Air data computer fault diagnosis based on genetic algorithm: use genetic algorithm to search and optimize multiple possible factors to find the most suitable fault diagnosis model for the actual situation;

iv. Airborne Electrical fault diagnosis based on support vector machine (SVM): through collecting the monitoring data under different states of the airborne power system, use SVM to establish a classification model, so as to achieve rapid fault diagnosis.

5.2 Fault Trend Prediction of Experimental Aircraft Based on Artificial Intelligence

Through the organization of artificial intelligence algorithms, the following are some solutions for predicting the fault trend of experimental aircraft using artificial intelligence algorithms:

i. Engine fault prediction based on neural network: this method uses deep learning technology to extract features from multiple data sources, constructing a neural network model based on these features, and use historical data to predict future faults. The model can also be continuously learned and optimized to improve its accuracy and stability;

ii. Equipment life prediction based on time series analysis: use regression models to predict the life of key components or systems, while considering the impact of different environments and consumption factors in order to achieve more accurate equipment maintenance, more efficient component replacement, and more reasonable resource allocation;

iii. Fault prediction of airborne electronic equipment based on Markov process: select appropriate states to describe the health status of equipment, such as "normal", "warning", "fault", use historical data to estimate the transition probability from one state to another, build a state-transition matrix, and establish a trend prediction model of airborne electronic equipment in combination with HMM (Hidden Markov model) or MC (Markov chain), predict the next state based on the current state and transition probability;

iv. Trend prediction based on fuzzy logic algorithm can be applied to the following aspects: a)maintenance priority ranking, which analyzes various indicators (such as fault severity, impact range, time urgency, etc) for different maintenance tasks, classifies and summarizes, and determines the priority sequence of maintenance tasks; b) Fault pattern recognition: in consideration of many confounding (such as flight environment, region, aircraft type difference, etc), a fault recognition system is built to quickly and accurately identify and determine unknown or similar abnormalities; c) The demand for maintenance materials, combined with factors such as equipment usage frequency, material characteristics, and supply cycle, has been modified to develop relevant models to predict the types and quantities of materials that may be used in maintenance.

The following is an example of predicting the trend of airborne electronic devices towards the next state based on HMM (Hidden Markov Model):

Using Python software and the hmmlearn library, the HMM model is implemented. Based on the given transition state matrix $\begin{bmatrix} 0.7 & 0.3 \\ 0.4 & 0.6 \end{bmatrix}$ and observation matrix $\begin{bmatrix} 0.8 & 0.2 \\ 0.1 & 0.9 \end{bmatrix}$, the HMM model is initialized and the transition probability and observation probability are set. Then, the probability distribution of the next state is calculated based on the current state. Finally, a state transition probability histogram is drawn as shown in Figure 2.

Firstly, a DevicePredictionModel class was defined, which includes methods for training models and predicting states. Then a DevicePredictionModel object was created and observations were provided as input data.Train the model using observations and obtain the optimal state sequence. Next, use the last state to predict the next state. Finally, use the Matplotlib library to plot the changes in observed values and predicted states over time. The red dots represent the observed values, and the blue lines represent the predicted state as shown in Figure 3.

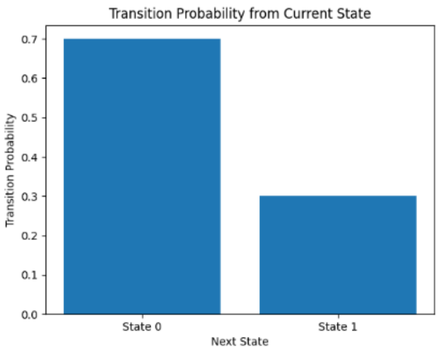

Fig. 2. Transition Probability from Current State

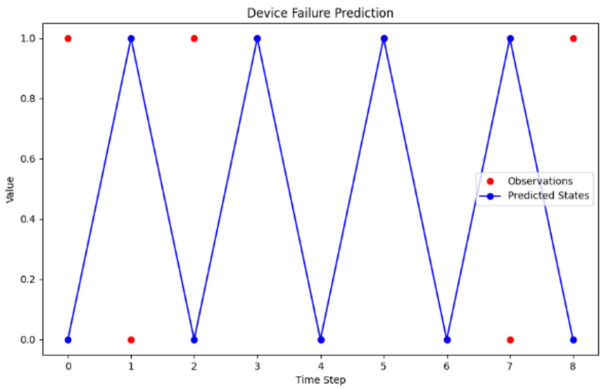

Fig. 3. Device Failure Prediction

5.3 Maintenance Plan Decision Based on Artificial Intelligence

Use sensors and detection equipment to collect real-time information data, and transmit the data to virtual entities, including vibration, temperature, electronic parameters and other types of data.[6] After completing data collection, use artificial intelligence algorithms, rely on big data analysis and human-computer cooperation processing modules, process and analyze the data, determine whether the equipment has faults, and determine whether there is a fault according to the historical data environmental characteristics and other relevant data are used to predict trends and identify potential fault issues in advance. Continuously conducting flight tests using a large number of artificial intelligence algorithms and data fusion methods to adjust the model parameters and methods of the twin data layer.[7] The experimental aircraft runs and interacts with virtual entities synchronously, and evaluates maintenance plans based on various factors such as maintenance quality and standards, controlling costs and risks, and ultimately finding the best maintenance plan. At the same time, the plan can be optimized and adjusted in a timely manner based on real-time analysis and predict result, and automated predictive maintenance process can be constructed.

In short, digital twin technology can develop efficient maintenance plans, reduce equipment failure losses, achieve higher safety guarantees, and performance, and continuously improve its maintenance accuracy and intelligence level through continuous updates and evolution.[8]

6 Conclusion

Digital twin technology has a wide range of application scenarios in predictive maintenance of experimental aircraft. Through the combination of digital twin technology and maintenance of experimental aircraft, it can quickly analyze and predict which predictive maintenance operations the experimental aircraft needs to carry out to minimize the possibility of failure, estimate the life of different component, and then develop corresponding plans and means to extend the life of component.[9,10] In addition, it can also guide the daily flight, timely maintenance, and unplanned maintenance of the experimental aircraft. This technology will improve the flight efficiency of the experimental aircraft, optimize human resources, and reduce equipment maintenance costs. Driven by the upgrading of the digital economy, future digital twin technologies will deepen data analysis and modeling, further optimize predictive maintenance effects, and improve the efficiency and safe operation of experimental aircraft.

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