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Research on Fault Diagnosis and Intelligent Maintenance Technology of Airborne Electronic Equipment

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Abstract: With the increasing integration and complexity of avionic systems, fault diagnosis and intelligent maintenance technologies for airborne electronic equipment have become critical supports for ensuring flight safety and improving equipment integrity. This paper systematically reviews the research status and development context of fault diagnosis technologies for airborne electronic equipment. It summarizes major research achievements and technological advances in the field from the perspectives of traditional fault diagnosis methods, integrated intelligent diagnosis strategies, artificial intelligence-driven technologies, data-driven methods, and intelligent maintenance assistance systems. On this basis, core bottlenecks in current research are analyzed, including data dependency, poor model interpretability, and insufficient generalization ability. Future development directions are prospected, such as few-shot learning, explainable AI, digital twin, and edge intelligence.

Keywords: Airborne electronic equipment; Fault diagnosis; Intelligent maintenance; Artificial intelligence; Data-driven; Integrated diagnosis

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1. Introduction

At present, discussions on fault diagnosis and intelligent maintenance of airborne electronic equipment show diverse viewpoints in domestic and foreign academic circles. Extensive debates and important theoretical achievements have been made focusing on the intelligence level of diagnosis methods, multi-source information fusion strategies, and the balance between real-time performance and accuracy [1]. The intelligent transformation of fault diagnosis for airborne electronic equipment has become a research focus worldwide. Foreign studies mainly concentrate on model-based reasoning, data-driven methods, and artificial intelligence algorithms, while domestic research adopts a path of integrated intelligent diagnosis and multi-method fusion [2].

With the extensive application of power electronic equipment on aircraft, the failure and repair rates of airborne avionic equipment have increased significantly [3]. Electronic equipment in modern aircraft and advanced weapon systems imposes higher requirements on the intelligence and efficiency of fault diagnosis technologies during design, production, and maintenance [3]. Mechanical equipment is an important carrier for national economic development and national defense construction, while mechanical faults are "potential killers" for the safe service of equipment, and fault diagnosis is a critical technology to ensure safe and reliable operation [4]. Therefore, research on intelligent fault diagnosis and maintenance technologies for airborne electronic equipment is of great theoretical value and engineering significance for improving equipment readiness, reducing support costs, and guaranteeing continuous airworthiness of aircraft throughout their life cycle.

2. Overview of fault diagnosis technologies for airborne electronic equipment

2.1. Basic connotation of fault diagnosis

Fault diagnosis of airborne electronic equipment refers to the process of monitoring and analyzing equipment operating status information to determine whether a fault occurs, identify fault types, locate fault positions, and predict fault development trends. As shown in **Table 1**, a fault diagnosis system usually includes four core modules: signal acquisition, feature extraction, fault identification, and decision output [5].

Table 1. Basic architecture of fault diagnosis system

Core Process Module	Module Function	Typical Input / Technical Means	Output / Function
Signal Acquisition	Real-time acquisition of raw operating status data of airborne electronic equipment	Voltage / current, temperature / vibration, various status parameters	Provide raw data foundation for subsequent analysis
Feature Extraction	Extract effective features reflecting equipment health status from raw signals	Time-domain features, frequency-domain features, wavelet coefficients	Eliminate redundant information and extract fault-sensitive features
Fault Identification	Judge equipment faults and locate fault types based on extracted features	Pattern recognition, classification decision, neural networks and other intelligent algorithms	Output fault diagnosis conclusions and complete fault determination
Decision Output	Provide actionable operation and maintenance solutions based on diagnosis results	Maintenance suggestions, fault location, replacement schemes	Guide equipment repair and maintenance to ensure safe operation

Fan (2023) pointed out that most common fault diagnosis technologies are based on advanced technologies such as computers and artificial intelligence, which can fully meet the automatic detection requirements of airborne systems and facilitate the rapid restoration of equipment safety and reliability [6]. With the advancement of modern science and technology, the types of airborne electronic equipment have become increasingly diverse, and regular maintenance and management are key to ensuring safe and stable operation [7].

2.2. Fault characteristics of airborne electronic equipment

Airborne electronic equipment features high integration, strong coupling, and harsh working environments, leading to complex and diverse fault modes. According to [8], the Aircraft Auto-Transformer Rectifier Unit (ATRU), an important secondary power supply in aircraft power supply and distribution systems, faces challenges in fault diagnosis such as difficulty in nonlinear system modeling and severe coupling of fault features. Hu (2019) further noted that airborne electronic systems are fundamental to the normal operation of aircraft. As their internal structures become more complex and functions more powerful, maintenance of reliability and stability becomes more critical [9].

3. Traditional fault diagnosis methods and their limitations

3.1. Main method types

Traditional fault diagnosis methods mainly include model-based reasoning, rule-based methods, and fault tree analysis. Zhang *et al.* (2006) systematically introduced intelligent fault diagnosis methods for electronic equipment, including rule-based methods, fault tree analysis, fuzzy diagnosis, artificial neural networks, and information fusion fault diagnosis (**Table 2**) [10].

Table 2. Comparison of traditional fault diagnosis methods

Method Type	Basic Principle	Advantages	Limitations
Rule-based	IF-THEN rule reasoning	Intuitive and easy to implement	Knowledge acquisition bottleneck, unable to handle unknown faults
Fault Tree	Deductive reasoning, logic gate analysis	Clear logic, easy to trace	Large tree structure, difficult to handle probabilistic dependence
Fuzzy Diagnosis	Membership function, fuzzy reasoning	Handle uncertain information	Membership function design relies on experience
Neural Network	Nonlinear mapping, self-learning	Strong fault tolerance, no precise model required	Requires large amounts of data, poor interpretability
Information Fusion	Multi-source data integration	Information complementarity, strong robustness	Difficult data alignment and fusion

3.2. Common limitations of traditional methods

Comprehensive analysis shows that traditional fault diagnosis methods have unique characteristics and respective limitations. A single reasoning method can hardly meet the diagnosis requirements of multi-fault mode and high uncertainty of airborne electronic equipment [11]. Specifically, several details are as follows:

(1) Rule-based methods suffer from knowledge acquisition bottlenecks and cannot adapt to new faults;
(2) Fault tree analysis encounters structural explosion in complex systems and is difficult to maintain;
(3) Fuzzy diagnosis is sensitive to membership function design and highly subjective;
(4) Neural network methods require massive training data and lack interpretability;
(5) Information fusion methods face challenges in alignment and fusion of multi-source heterogeneous data. These limitations have driven the development of integrated intelligent diagnosis technologies.

4. Integrated intelligent fault diagnosis system

4.1. Proposal of integrated diagnosis strategy

Integrating multiple diagnosis methods to compensate for the defects of single reasoning methods is an important development direction in the field of airborne electronic equipment fault diagnosis. Based on the current situation of aircraft field maintenance and shop overhaul, Li and Qin (2002) designed an integrated intelligent fault diagnosis system for airborne electronic equipment. As shown in **Table 3**, the system adopts an integrated intelligent diagnosis strategy to overcome the shortcomings of single reasoning methods and enhance fault diagnosis capability [12].

Table 3. Structure of integrated intelligent fault diagnosis system

Level	Module Name	Core Function / Component	Role Positioning
Upper Layer	Diagnosis Strategy Control Center	Overall scheduling and decision management	Formulate integrated diagnosis strategies, coordinate reasoning modules, realize multi-method collaboration and process control
Middle Layer	Model-based Reasoning Module	Model-driven fault analysis	Conduct fault simulation, prediction and location using mathematical / mechanism models of equipment
Middle Layer	Rule-based Reasoning Module	Expert experience-driven decision	Perform logical reasoning and diagnosis based on fault rules summarized by domain experts
Middle Layer	Case-based Reasoning Module	Historical experience-driven matching	Retrieve typical historical fault cases and deduce current fault causes through similarity analysis
Middle Layer	Neural Network Reasoning Module	Data-driven learning and classification	Learn fault features from massive data and realize pattern recognition and fault classification
Middle Layer	Other Reasoning Modules	Supplementary diagnosis methods	Include fuzzy reasoning, Bayesian network, D-S evidence theory and other auxiliary methods
Lower Layer	Comprehensive Database / Knowledge Base	Data storage and knowledge management	Store equipment operation data, fault cases, diagnosis rules, model parameters, etc., to support each module

Nie (2006) further discussed the development of intelligent fault diagnosis for avionic equipment and proposed key technologies such as integrated diagnosis, comprehensive test and diagnosis strategies, machine learning methods, and software tool development [13]. Practice has shown that the integrated intelligent fault diagnosis system plays a positive and effective role in fault diagnosis and maintenance of airborne electronic equipment.

4.2. Multi-agent intelligent diagnosis system architecture

Guided by the idea of integrated diagnosis, researchers have further explored distributed intelligent diagnosis architectures. Shi and Chen (2013) took a certain submarine fire control radar as the research object and designed an overall structure of a multi-agent-based intelligent fault diagnosis system. The system can dynamically adjust according to equipment structure changes and be conveniently applied to other equipment through technologies such as separation of knowledge base and diagnosis inference engine, and dynamic generation and management of diagnosis agents [14].

The structure of the multi-agent-based diagnosis system is shown in **Table 4**:

Table 4. Structure of multi-agent-based fault diagnosis system

Level	Role / Module	Function Positioning	Specific Responsibilities
Upper Layer	Management Agent	Core of system coordination and scheduling	Responsible for task allocation, multi-agent coordination, and global communication management
Lower Layer	Transmitter Agent	Equipment functional unit agent	Correspond to transmitter module, responsible for fault diagnosis and condition monitoring of the unit
Lower Layer	Receiver Agent	Equipment functional unit agent	Correspond to receiver module, responsible for fault diagnosis and condition monitoring of the unit
Lower Layer	Antenna Agent	Equipment functional unit agent	Correspond to antenna module, responsible for fault diagnosis and condition monitoring of the unit
Lower Layer	Power Supply Agent	Equipment functional unit agent	Correspond to power supply module, responsible for fault diagnosis and condition monitoring of the unit
Lower Layer	Display Agent	Equipment functional unit agent	Correspond to display module, responsible for fault diagnosis and condition monitoring of the unit

Application results on shipborne radar by a domestic research team show that the multi-agent-based intelligent diagnosis system has good scalability and adaptability. The current domestic research on integrated intelligent diagnosis of airborne electronic equipment is evolving from single method to multi-method collaboration, and from static architecture to dynamically configurable architecture, which is also one of the current research hotspots.

4.3. Bayesian network diagnosis model

Bayesian network is one of the most effective theoretical models in uncertain knowledge representation and reasoning. Li (2002) took a certain helicopter airborne equipment as the research object, especially suitable for decisions conditionally dependent on multiple control factors adopted Bayesian network as the fault diagnosis and maintenance decision model, and deeply studied Bayesian network-based fault diagnosis and maintenance decision methods [15].

The study proposed a diagnostic Bayesian network model based on fault hypothesis–observation–maintenance action node structure, as shown in **Table 5**. Among them, fault hypothesis nodes (H) represent possible fault causes, observation nodes (O) represent detectable fault symptoms, and maintenance action nodes (R) represent executable maintenance actions.

Table 5. Basic structure of diagnostic Bayesian network

Node Type	Symbol Identification	Node Meaning	Structural Position
Fault Hypothesis Node	H (e.g., H_1, H_2, H_3)	Represent possible fault causes of equipment	Top layer of the network, as the starting point of reasoning
Observation Node	O (e.g., O_1, O_2, O_3)	Represent detectable fault symptoms / phenomena	Middle layer of the network, connect fault hypotheses and transmit observation evidence
Maintenance Action Node	R (e.g., R_1)	Represent executable maintenance actions / decision schemes	Bottom layer of the network, output maintenance strategies based on fault hypotheses and observation evidence

Through Bayesian probabilistic reasoning, the posterior probability of each fault hypothesis can be calculated given observation evidence. The basic formula of Bayesian reasoning is:

$$(H_i \mid E) = \frac{P(E \mid H_i)P(H_i)}{\sum_j P(E \mid H_j)P(H_j)}$$

Where H_i represents the i-th fault hypothesis, E represents the observed evidence set, $P(H_i \mid E)$ is the posterior probability, $P(H_i)$ is the prior probability, and $P(E \mid H_i)$ is the likelihood function.

Studies have shown that Bayesian networks have the ability to consistently express and fuse multi-source information, perform bidirectional parallel reasoning, and integrate prior information and sample information to make reasoning results more accurate and reliable [16].

5 .Artificial intelligence-driven fault diagnosis technology

5.1. Neural network diagnosis method

Artificial neural networks have been widely used in fault diagnosis of airborne electronic equipment due to their strong nonlinear mapping ability and self-learning characteristics. Yang (2026) focused on the research and application of artificial intelligence technology in electronic equipment fault diagnosis, analyzed the core technical system of AI fault diagnosis, and dissected specific implementation paths and application effects in typical scenarios such as circuit board detection, predictive maintenance of communication equipment, and self-diagnosis of consumer electronic products [17].

As shown in **Table 6**, a typical three-layer feedforward neural network structure includes input layer, hidden layer, and output layer:

Table 6. Structure of three-layer feedforward neural network

Network Layer	Layer Description	Structural Characteristics
Input Layer	Layer receiving external input data	Correspond to the leftmost neurons, responsible for transmitting raw data (such as fault features, sensor signals) into the network without calculation
Hidden Layer	Core layer for feature extraction and nonlinear transformation	Located between input and output layers, complete feature learning through connection weights between neurons, key to complex mapping ability
Output Layer	Layer outputting final calculation results	Correspond to the rightmost neurons, output fault diagnosis results, classification labels and other target values based on hidden layer features

The mathematical model of a neuron can be expressed as:

$$y = f\left(\sum_i w_i x_i - \theta\right)$$

Where x_i is the input signal, w_i is the connection weight, θ is the threshold, $f(\cdot)$ is the activation function, and y is

Lin (2022) adopted a radial basis function neural network algorithm based on fast Fourier transform to diagnose faults of ATRU, a complex nonlinear system. The method first extracted the spectrum characteristics of the system output voltage as the basis for fault diagnosis, and built and trained the RBF network model using the Matlab neural network toolbox. Test results show that the optimized network model can realize classification and recognition of complex fault modes of ATRU.

5.2. Feature extraction and data preprocessing

Feature extraction is a key link in data-driven fault diagnosis. Si (2020) proposed a median-based weighted principal component analysis (WPCA) algorithm for feature extraction aiming at the fault diagnosis of large aircraft PDU components. The core idea is weight features by calculating the contribution of each dimension to classification, and replace the mean with the median in centralization preprocessing to suppress noise.

The basic process of weighted principal component analysis is as follows:

(1) Centralize the original data set;

(2) Calculate the covariance matrix;

(3) Calculate the contribution weight of each dimension feature:

$$w_j = \frac{\lambda_j}{\sum_{k=1}^{n} \lambda_k}$$

Where λ_j is the j-th eigenvalue of the covariance matrix.

Perform weighted transformation on the data, then conduct PCA dimensionality reduction.

Simulation verification on the TE data set shows that the proposed feature extraction method improves the dimensionality reduction performance of traditional PCA on the premise of ensuring efficient algorithm operation, and the processing results can highlight the main features or dimensions of the original data.

5.3. Data-driven fault classification method

At the level of fault diagnosis methods, Si (2020) proposed an improved clustering algorithm-based fault diagnosis method, diagnostic set clustering distribution map method. By constructing a standard feature sample set and forming a diagnostic set with the samples to be diagnosed as the input of the clustering algorithm, the method realizes the intuitive embodiment of fault detection and diagnosis results on the clustering result map.

Common clustering algorithms and their characteristics are shown in **Table 7**:

Table 7. Comparison of commonly used clustering algorithms

Algorithm	Principle	Advantages	Disadvantages
K-Means	Partition-based iterative clustering	Simple, efficient and easy to implement	Need to preset K value, sensitive to initial centers
Hierarchical Clustering	Bottom-up or top-down merging	No need to preset category number, good visualization	High computational complexity
FCM	Fuzzy partitioning, membership matrix	Handle samples with fuzzy boundaries	Need to preset category number, sensitive to noise

$$d\left(x,y\right)=\sqrt{\sum_{i=1}^{n}\left(x_i-y_i\right)^2}$$

Evaluation indicators of clustering effect include classification coefficient F and average fuzzy entropy H:

$$F=\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}u_{ij}^2$$

$$H=-\frac{1}{N}\sum_{i=1}^{c}\sum_{j=1}^{N}u_{ij}logu_{ij}$$

Where u_{ij} represents the membership degree of sample j belonging to the i-th category, c is the number of categories, and N is the total number of samples. The closer F is to 1 and H is to 0, the better the clustering effect.

6. Intelligent maintenance and maintenance assistance technology

6.1. Technical framework of intelligent maintenance

With the extension of fault diagnosis technology from "detection" to "maintenance", intelligent maintenance has become an important development direction of the field. Yang and Du (2025) studied fault diagnosis and intelligent maintenance of power system communication SDH equipment using advanced intelligent technologies.

Gao *et al.* proposed a distributed, loosely coupled, scalable and maintainable integrated management and control scheme for intelligent security of information production. The scheme applies URL rewriting technology and MQTT message broker to realize loosely coupled, low-latency and high-concurrency information interaction between information systems.

6.2. Augmented reality-assisted maintenance system

Augmented reality technology provides a brand-new interaction paradigm for airborne equipment maintenance. Aiming at the problems of numerous maintenance steps, difficult manual consultation, and human errors in airborne equipment maintenance, Ruan (2020) developed an intelligent maintenance assistance system for airborne equipment based on augmented reality. As shown in **Table 8**, on the one hand, the system uses AR to mix virtual assistance information into the real working environment to guide maintenance personnel; on the other hand, it intelligently analyzes maintenance status spontaneously through the image detection and recognition module.

Table 8. Architecture of AR-based intelligent maintenance assistance system

System Name	**AR Intelligent Maintenance Assistance System**		
Core Modules	Image Detection and Recognition	Target Location	AR Information Rendering
Module Functions	• EAST text detection • LSTM text recognition • Template matching graphics	• Image feature matching • Spatial coordinate transformation • Spatial anchor stability	• 3D model overlay • UI information display • Real-time interactive feedback

Spatial coordinate system transformation is the core of AR rendering, and its transformation relationship can be expressed as:

$$M_{MVP} = P \times V \times M$$

Where M is the model matrix, V is the view matrix, and P is the projection matrix.

The system helps reduce maintenance difficulty and improve maintenance efficiency and quality.

7. Current challenges and future prospects

7.1. Analysis of core bottlenecks

Although intelligent fault diagnosis technology for airborne electronic equipment has made considerable progress, it still faces several core bottlenecks. Evaluation and analysis by Yang (2026) pointed out that current AI diagnosis models suffer from core bottlenecks such as data dependency, model black-box problem, and insufficient generalization ability as follows:

(1) Data dependency: Deep learning models require a large amount of labeled fault data for training, while fault data of airborne electronic equipment is costly and time-consuming to obtain, and fault samples, especially rare fault samples, are seriously scarce;

(2) Poor model interpretability: The diagnosis and decision-making process of “black-box” models such as neural networks is difficult to explain, which is a severe challenge in the field of aviation safety;

(3) Insufficient generalization ability: Diagnosis models trained under one aircraft type or working condition often experience significant performance degradation when transferred to other aircraft types or working conditions.

7.2. Future research directions

Looking forward, fault diagnosis and intelligent maintenance technologies for airborne electronic equipment will develop in the following directions:

(1) Few-shot learning: Aiming at the scarcity of fault data, technologies such as meta-learning, transfer learning, and generative adversarial networks are expected to realize effective diagnosis with a small number of labeled samples;

(2) Explainable artificial intelligence: Improve the transparency and understandability of the decision-making process of diagnosis models through attention mechanism, knowledge distillation and other methods;

(3) Digital twin technology: Build digital twin models of airborne electronic equipment to realize real-time interaction and collaboration between physical entities and virtual models;

(4) Edge intelligence and federated learning: Deploy lightweight diagnosis models on airborne edge computing platforms, and realize cross-aircraft collaborative training under the premise of protecting data privacy through federated learning framework.

8. Conclusion

Fault diagnosis and intelligent maintenance technologies for airborne electronic equipment are key supports for ensuring the safe and reliable operation of aviation equipment. This paper systematically reviews the development context of the field from traditional diagnosis methods, integrated intelligent diagnosis, artificial intelligence-driven technologies to intelligent maintenance assistance systems. Studies show that single diagnosis methods have limitations, and intelligent diagnosis strategies integrating multiple methods can effectively improve the comprehensive performance of diagnosis systems; artificial intelligence technologies represented by neural networks and Bayesian networks show significant advantages in complex fault mode recognition; data-driven feature extraction and classification methods provide new technical paths for fault diagnosis; intelligent maintenance assistance technologies such as augmented reality promote the extension from diagnosis to maintenance, forming a closed-loop system of “diagnosis-decision-maintenance”. At present, the field still faces challenges such as data dependency, insufficient model interpretability, and limited generalization ability. In the future, emerging technologies such as few-shot learning, explainable AI, digital twin, and edge intelligence will provide new solutions for more intelligent, reliable and efficient fault diagnosis and intelligent maintenance of airborne electronic equipment.

Disclosure statement

The authors declare no conflict of interest.

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