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Fault Diagnosis of Airborne Electronic Equipment Based on Dynamic Bayesian Networks

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ABSTRACT

With the rapid development of the aerospace industry, the structure of airborne electronic equipment has become more complex, which to some extent increases the difficulty of fault detection and maintenance of airborne electronic equipment. Traditional manual fault diagnosis methods can no longer fully meet the diagnostic needs of airborne electronic equipment. Therefore, this chapter uses dynamic Bayesian network to diagnose the faults of airborne electronic equipment. The basic idea of using a dynamic Bayesian network-based fault diagnosis method for airborne electronic devices is to mine data based on historical fault data of airborne electronic devices, and obtain fault symptoms and training data of airborne electronic devices. For non-essential fault symptoms, rough set theory was introduced to reduce their attributes and obtain the simplest attribute set, thereby simplifying the network model.

KEYWORDS

Airborne Electronics, Data Mining, Dynamic Bayesian Networks, Fault Diagnosis, Rough Set Theory

INTRODUCTION

As an important technical system in the aviation industry, airborne electronic equipment is the core to ensuring the efficient and safe operation of aircraft and also the key factor to ensuring the normal operation of aviation flight. However, due to the complexity of the environment and working conditions, these devices are prone to failure, which poses a great threat to the safety and performance of the aircraft. Therefore, how to diagnose the fault of airborne electronic equipment quickly and accurately has become an important research direction in the aviation field. Fault diagnosis of airborne electronic equipment based on dynamic Bayesian networks has important research value and practical application significance, which is helpful to improving flight safety and equipment reliability.

The common methods of traditional on-board electronic equipment fault diagnosis mainly include fault code-based diagnosis, fault pattern recognition, and expert system diagnosis. Among them, fault code-based diagnosis is used to judge the specific cause of the fault through the fault code generated by the on-board electronic equipment. This method is simple and direct and is only applicable to

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common types of faults. Failure mode recognition means to establish a failure mode library through long-term monitoring and data collection of on-board electronic equipment, so as to carry out diagnosis based on current failure modes. This method does recognize some complex faults but requires a large amount of data and model training. Expert system diagnosis is an inference-based diagnosis based on expert knowledge and rules, which matches fault phenomena with preset rules to infer fault causes and solutions. This method is more effective when the problem is complex and requires professional knowledge, but it requires the accumulation of fault libraries and manual knowledge modeling, which makes the diagnosis more difficult for ordinary engineers and operators. The above commonly used traditional airborne electronic equipment fault diagnosis methods all have certain limitations in the face of complex faults and data acquisition difficulties, so it is necessary to find new fault diagnosis methods to make up for the deficiencies that exist in traditional methods.

As a graphical network based on probabilistic reasoning, Bayesian networks have important research value in dealing with uncertain knowledge representation and problem reasoning and have been successfully applied in many fields. Dynamic Bayesian networks are able to flexibly deal with dynamic relationships between variables and are suitable for describing complex dynamic processes in the fault diagnosis of airborne electronic equipment. It is capable of modeling the state and faults of the equipment and can be dynamically updated based on real-time data, estimating the *a posteriori* probability of the cause of the fault through probabilistic reasoning and providing probabilistic explanations corresponding to the diagnostic results. Avoiding overly deterministic diagnostic results makes the diagnostic results more reliable. This can also continuously improve the accuracy and robustness of the model based on new fault data and train it with a large amount of historical data, so as to learn the fault patterns and fault characteristics from the data and better identify and predict faults. This is especially important when facing complex fault situations and frequent changes. The use of Dynamic Bayesian Network (DBN) for the diagnosis of airborne electronic equipment faults offers the advantages of flexibility, uncertainty modeling, fault prediction capability, and real-time performance and efficiency. These advantages make dynamic Bayesian networks an effective method to improving the accuracy and efficiency of airborne electronic equipment fault diagnosis.

RELATED WORK

With the development of industry, equipment is constantly being updated, becoming more intelligent, and performing excellently in helping humans carry out various personalized and professional activities. Therefore, many scholars are researching new fault diagnosis methods for different types of equipment (Sreedevi et al., 2022). Chen et al. (2019) proposed the use of the IQA (image quality assessment) method for mechanical equipment faults diagnosis, because IQA, as an indispensable technique in computer vision, is extensively applied to image classification and image clustering. In order to verify whether the new method is suitable for mechanical equipment fault diagnosis, this study achieved fault detection through a series of operations such as data acquisition, noise removal, and image classification. Numerous experiments have demonstrated the effectiveness and robustness of this method. Jiang et al. (2023) proposed a classification model based on integrated incremental learning for equipment fault diagnosis. The model first introduced an integrated incremental learning mechanism and imbalanced data processing technology to solve the problem of imbalanced feature extraction and classification of many new data under equipment status data as well as imbalanced sample categories. Zhang (2019) proposed the use of artificial intelligence (AI) technology for mechanical equipment fault diagnosis. Because traditional mechanical diagnostic technology cannot meet practical diagnostic requirements, AI technology has advantages in solving remote control, fault diagnosis, and nonlinear problems and can predict the remaining life of the entire equipment. The utilization of AI technology in mechanical equipment fault diagnosis is beneficial for improving equipment efficiency and reliability, reducing maintenance costs, and extending service life and can also point out the direction for the growth of mechanical fault diagnosis. Shi et al. (2021) proposed the use of the support vector machine algorithm for railway electronic equipment fault diagnosis. The study first constructed an electronic signal equipment fault diagnosis model to reduce the impact of sample data imbalance on classification accuracy. It then analyzed a large number of unstructured text information about equipment failures recorded by natural language processing, extracted semantic features, and finally classified them. Research has shown that support vector machine algorithms can effectively achieve fault diagnosis of electronic signal equipment. Through the research of scholars mentioned above, it has been found that few have studied methods for fault diagnosis of airborne electronic equipment.

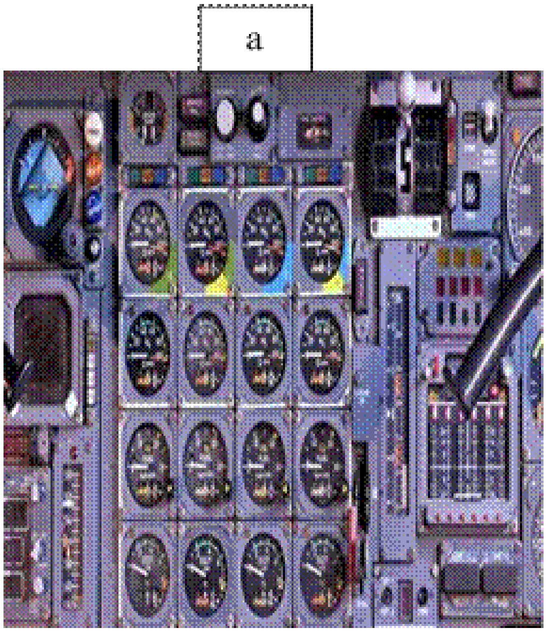
The Bayesian network technology is widely used in various fault diagnosis research studies, which has emerged in recent years. Diallo et al. (2018) applied the Bayesian network paradigm as a comprehensive data-driven diagnostic method for complex manufacturing industries, as Bayesian models can consider issues related to the surge in the number of variables and solve the problem of determining network parameters. The diagnostic program proposed using the developed Bayesian framework can provide structured data required for constructing and using diagnostic models and explain the purpose of data in terms of forward and backward traceability. Atoui and Cohen (2020) used Bayesian networks as a new method of fault detection and isolation, because Bayesian networks combine model-based and data-driven frameworks to detect and diagnose single, multiple, and unknown faults. Prior model knowledge and available data can also be utilized to provide a new perspective for detecting unknown faults, which is superior to other methods. Yu and Zhao (2019) proposed a probability set learning strategy based on Bayesian networks to alleviate the harmful effects of faults in complex systems, as Bayesian networks can integrate the advantages of different diagnostic models and accurately infer the cause of observable anomalies. In addition, Bayesian networks can effectively capture mixed fault features of multiple faults by integrating decisions from different diagnostic models. Yang et al. (2019) proposed a radial basis function feedforward neural network based on Bayesian decision theory for power transformer fault diagnosis. The radial basis function feedforward neural network optimized by the BA (Bat Algorithm) can significantly enhance the performance of fault diagnosis. Overall, Bayesian networks are suitable as methods for fault diagnosis.

Based on the above literature analysis, the innovation of this paper is the use of dynamic Bayesian networks to diagnose airborne electronic equipment faults and to obtain historical and training data on excavator electronic equipment faults, thus obtaining equipment-related fault symptoms. The rough set theory is then used to reduce the attributes of the non-essential fault symptoms, thus simplifying the model. Then the fault diagnosis network model is constructed on the basis of expert knowledge and the Bayesian neural network-based structural learning method, and the two models are fused and optimised by combining the correlation between fault symptoms. Finally, the constructed model is experimentally analysed by taking M airborne electronic equipment as an example to prove its feasibility.

COMPOSITION AND FUNCTIONS OF AIRBORNE ELECTRONIC EQUIPMENT

Airborne electronic equipment is the most important component of an aircraft. The use of onboard electronic devices can improve the safety and accuracy of aircraft operation (Liu et al., 2023). The use of airborne electronic devices can clearly obtain various information required for flight, such as meteorological conditions, terrain, air conditions, and ground building conditions, which is conducive to further ensuring the safe operation of the aircraft (Yu et al., 2023). Airborne electronic equipment refers to various types of radars installed on an aircraft, mainly divided into two parts: one is aviation instruments, and the other is aviation radio systems, as shown in Figure 1. Aviation instruments are mainly used to measure (or calculate) the flight parameters of aircraft as well as the operational parameters of engines and other devices. The aviation radio system is mainly used for aircraft communication and radio navigation.

Figure 1. Main components of airborne electronic equipment (Note. (a) Aviation instrumentation; (b) Aviation communication, navigation, and surveillance radio system; (a) shows the aviation instrument section.)



If there is a situation where the power indicator light constantly flashes “flickering”, the fault source can be locked in the power circuit section according to this situation (Feng et al., 2022). Figure 1 (b) is a part of the aviation communication, navigation, and surveillance radio system, which has a very important function of providing perception information to the driver at night or under low or zero visibility weather conditions such as rain, snow, and fog. Other important functions of airborne electronic devices are used to control and guide weapons, perform aerial surveillance and reconnaissance, and ensure accurate heading and flight safety. Airplanes cannot lack advanced onboard electronic equipment; otherwise they cannot achieve the comfort, safety, low cost, and reliability of aviation flight and cannot meet the requirements of modern warfare for military aircraft.

METHODS FOR DIAGNOSING FAULTS IN AIRBORNE ELECTRONIC EQUIPMENT

Bayesian Network

The Bayesian network is a graphical probability method based on the Bayesian formula (Wang et al., 2023). It is often utilized to address the issue of incomplete and uncertain information in the field of AI. The main elements of Bayesian network include the conditional probability table (CPT), network nodes, and directed arcs (Chen et al., 2023). The modeling of Bayesian networks mainly includes two aspects: structural learning and data learning.

The dynamic factors of system failure often appear in practice. If researchers cannot deal with these dynamic factors in time, it will result in the delay of the construction period, the increase of cost, and a low utilization of resources (Du et al., 2021). The advantages of applying Bayesian networks to analyze system faults include: firstly, it can reveal the internal relationship between fault phenomena and causes; secondly, it can quantitatively calculate the probability of occurrence of each fault cause. Compared to fault trees, Bayesian networks can be used to handle complex systems with dynamic and polymorphic problems, achieving fault diagnosis and fault component localization (Wang et al., 2018). Modifying the attribute layer weight algorithm using Bayesian network rules can obtain entropy weights that reflect the correlation of attribute layers (Hao et al., 2018).

The traditional dynamic fault tree calculation process is relatively complex and not suitable for computing large systems. It is necessary to undergo the transformation of a discrete-time Bayesian network and then redefine the initialization network and transfer network to compensate for the combinatorial space explosion caused by the large computational system (Qi et al., 2022). If a T event occurs within task time R, the occurrence interval of T must be within $\left\{\left[0,\Delta\right),\left[\Delta\ 2\Delta\right),\left[2\Delta,3\Delta\right)\cdots\left[\left(n-1\right)\Delta,n\Delta\right)\right\}$. The probability of T event occurring within task time R is:

$$Q\left(R\right)=\sum Q\left(T=\left[\left(x-1\right)\Delta,x\Delta\right)\right) \tag{1}$$

Among them, the joint probability calculation formula for $Q(T=\left[\left(x-1\right)\Delta,x\Delta\right)$ is as follows:

$$Q(T=\left[\left(x-1\right)\Delta,x\Delta\right)=\sum_{T_1-T_{i-1}} q(T_1=t_1,\cdots T_{i-1}=t_{i-1},T=\left[\left(x-1\right)\Delta,x\Delta\right) \tag{2}$$

Among them, T(1<m< $i-1$) refers to non leaf nodes, and i refers to the number of nodes. The occurrence interval of characterization T_i is within $t_i\in\left\{\left[0,\Delta\right),\left[\Delta,2\Delta\right),\left[2\Delta,3\Delta\right)\cdots\left[\left(n-1\right)\Delta,n\Delta\right),\left[R,\infty\right)\right\}$. According to the Formulas (1) and (2), the probability of T event occurring within task time R can be determined as:

$$Q\left(R\right)=\sum_{0<x\ll n}\sum_{T_1\cdots,T_{i-1}} T_1=t_1,\cdots T_{i-1}=t_{i-1},T=\left[\left(x-1\right)\Delta,x\Delta\right) \tag{3}$$

Diagnostic data processing uses a binary approach to discretise continuous values and then uses multinomial distributions for probability estimation of the discrete values to analyse and compare the performance of the fault diagnosis algorithms in terms of runtime and classification accuracy for different data sizes (Bagui et al., 2020).

Rough Set Theory

Rough set theory is a mathematical tool used to deal with uncertainty problems. Rough set theory initially deals with the imprecision, fuzziness, and uncertainty of data and is considered as an alternative to fuzzy set theory (Zhan et al., 2022). Compared to other algorithms, this algorithm does not require any prior knowledge (He et al., 2018). The internal knowledge of data itself can be directly utilized to analyze and process incomplete information and identify hidden knowledge. The rough set method can assign weights and knowledge to the extracted principal components.

In rough set theory, information systems are defined as quads (Y, S, Z, f). F (x, a) ∈ Z, where x ∈ Y and a ∈ S. If S = T ∪ J, where t∪j =∅, the information system is called a decision system, where T is the set of conditional attributes and J is the set of decision attributes (Xu, 2023).

Rough set classifies elements in the set through equivalence relation. The same division is called Equivalence class, which can be used to simplify information (Zhang et al., 2023). For ∀ a ∈ B, B ⊂ S, x ∈ Y, y ∈ Y, if $f_a\left(x\right)=f_a\left(y\right)$ is true, object x and y are equivalence relation to attribute B (also called indiscernibility relations); that is, objects x and y cannot be distinguished according to the attributes in B, which is expressed as:

$$\mathrm{IND}\left(\mathrm{B}\right)=\left\{\left(\mathrm{x},\mathrm{y}\right)\middle|\left(\mathrm{x},\mathrm{y}\right)\in \mathrm{Y}\times \mathrm{Y},\forall \mathrm{a}\in \mathrm{B},f_{a}\left(x\right)=f_{a}\left(y\right)\right\} \tag{4}$$

In Y, the set with equivalence relation is also called Equivalence class, including:

$$\mathrm{Y}\ /\ \mathrm{IND}\left(\mathrm{B}\right)=\left\{\left(\mathrm{x},\mathrm{y}\right)\middle|\left(\mathrm{x},\mathrm{y}\right)\in \mathrm{IND}\left(\mathrm{B}\right)\right\} \tag{5}$$

Among them, $\mathrm{Y}\ /\ \mathrm{IND}\left(\mathrm{B}\right)$ corresponds to a partition of domain Y.

AIRBORNE ELECTRONIC EQUIPMENT FAULT DIAGNOSIS AND MODEL CONSTRUCTION

Common Faults and Diagnostic Processes of Airborne Electronic Equipment

Electronic device failure refers to the device being in an abnormal state, causing the corresponding function of the device to malfunction or the corresponding behavior to be outside the allowable range (Jia & Li, 2023). Fault diagnosis refers to the process of identifying the root cause of faults through certain processing methods, efficiently and accurately repairing or replacing equipment components, etc., to ensure the normal operation of the system.

Common faults of airborne electronic devices include: electromagnetic relay failure of airborne electronic devices and electromagnetic interference failure between airborne electronic devices. There are many reasons for the occurrence of electromagnetic relays:

1) Product quality control technology

Electromagnetic relays mainly consist of components such as coils, steel strings, and electric shock; the quality of any of these components directly affects their working performance.

2) Electromagnetic relay pollution and aging

During long-term operation of the equipment, various impurities and aging of components can cause electromagnetic relay failures. For example, the presence of debris at the contact point, or the generation of polymer on the surface of frictional electric shock, can lead to an increase in contact resistance, a decrease in the contact surface of the contact point, an increase in contact resistance, and the phenomenon of contact disconnection.

3) Excessive voltage and current

The equipment is always in high current during operation. Long term high current causes the coil of the electromagnetic relay to melt due to heating, resulting in a short circuit in the circuit and affecting the normal operation of airborne electronic equipment.

4) Inadequate sealing

Damage to the sealing element directly leads to the entry of external impurities in the electromagnetic relay, thereby causing malfunction.

Secondly, there are many reasons for electromagnetic interference faults:

1) Electromagnetic sensitivity

It depends on the characteristics of the electronic components used in the electronic device.

2) Natural loss

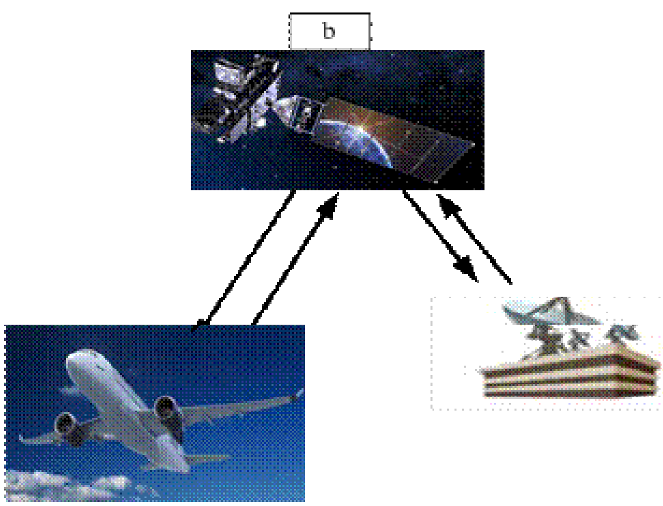
Airborne electronic equipment generally has a long production cycle and service life. During daily use and storage, the performance of some electronic components is reduced due to environmental and time factors, resulting in a decrease in radiation interference resistance and overall interference resistance.

3) wIncomplete design

At the beginning of the airborne electronic equipment design, the designers do not fully consider its electromagnetic compatibility, and the equipment can only operate normally when used alone or in a small amount. Once multiple electronic devices are used together, due to weak anti-interference ability, they are particularly prone to paralysis, which affects the normal operation of airborne electronic devices.

Usually, for faults in airborne electronic equipment, aviation staff can record the fault situation in the fault analysis file and summarize it into a fault data table. Firstly, various relevant information data contained in the fault data table are preprocessed to obtain corresponding training samples. Then, further information on the faults of electronic equipment carried by excavators is obtained, and rough set theory is introduced for attribute reduction. A Bayesian network fault diagnosis model is constructed, and finally, the fault results are output. The fault diagnosis flowchart of airborne electronic equipment is shown in Figure 2.

Figure 2. Flow chart of airborne electronic equipment fault diagnosis



The direct cause of airborne electronic equipment failure is the minimum cut set failure. The minimum cut set can be regarded as the minimum unit for diagnosis one by one (Lei et al., 2021). Based on diagnostic importance, diagnostic ranking is carried out. The minimum cut set with the highest importance is the first to be diagnosed, and the probability formula of the minimum cut set is as follows:

$$DF_{MCS_n} = Q(MCS_n \mid S) \tag{6}$$

Among them, MCS_n represents the n-th minimum cut set, and DF_{MCS_n} represents the diagnostic importance of the n-th minimum cut set. $Q(MCS_n \mid S)$ represents the probability of failure of the n-th minimum cut set when the airborne electronic equipment fails.

The diagnostic ranking of the components depends on the diagnostic importance, with the highest importance being diagnosed first. The formula is as follows:

$$DF_{C_n} = Q(C_n \mid S) \tag{7}$$

Among them, C_n represents the nth component, and DF_{C_n} represents the diagnostic importance of the nth component. $Q(C_n \mid S)$ represents the probability of the nth component failing when an airborne electronic device fails.

Data Mining for Airborne Electronic Equipment

Currently, the fault data of airborne electronic equipment is mainly described in natural language and lacks a unified structure. Therefore, the fault text information must be characterized and pre-processed to extract the metadata that can reflect the characteristics of each fault. The extracted feature information is automatically assigned to folders for storing electronic text information using a system with enhanced Bayesian classification techniques (Choo et al., 2019). Based on the airborne electronic equipment fault data table, the types and cause nodes that can reflect the fault symptoms are extracted based on the frequency and importance of fault vocabulary in the fault text information, as shown in Tables 1 and 2.

Table 1. Fault cause node table

Number	Node Name	Number	Node Name
M1	Input circuit board failure	M11	Start pulse failure
M2	Output circuit board failure	M12	13V power supply failure
M3	Program memory circuit board failure	M13	Channel selection failure
M4	Data storage circuit board failure	M14	Comparator failure itself
M5	Code - pressure circuit board failure	M15	4V power supply failure
M6	Pulse circuit board failure	M16	Pulse and frequency changer failure
M7	Matching circuit board failure	M17	Register failure
M8	Modulator circuit board failure	M18	Broken control signal wire
M9	Output pulse fault	M19	Pitch angle control circuit board failure
M10	Mobile pulse fault	M20	Pulse width modulation device failure

Table 2. Table of fault types

Number	Failure Type	Number	Failure Type
Y1	Signal processing related	Y5	Communication failure
Y2	Conversion related	Y6	Reboot circuit board failure
Y3	Matching related	Y7	Common brake faults
Y4	Logic related	Y8	Others

Construction of Diagnosis Model Based on Bayesian Networks

Firstly, the Bayesian network toolbox is used to establish a Bayesian network model based on expert knowledge. Due to the complexity of current airborne electronic devices, in order to more accurately identify the relationship between equipment failure issues and their causes, expert knowledge alone cannot be relied upon. It should also use data mining methods to actively search for internal relationships between nodes in real data. Expert knowledge and data mining are combined for Bayesian network structure learning, and a structural learning network model based on Bayesian networks is constructed. Fusion rules are used to optimize expert knowledge network models and structural learning network models but eliminate correlations between nodes in the same layer during the fusion process. In order to output the optimized Bayesian network model for fault diagnosis, the inherent correlation characteristics between each type of fault symptom are utilized to explore the potential relationships between fault symptoms, and they are integrated into the Bayesian diagnostic network model to obtain a diagnostic model with symptom correlation.

The Bayesian fault diagnosis model is divided into three layers, namely the fault type layer, fault feature layer, and fault cause layer. The corresponding relationship between fault symptom nodes is illustrated in Table 3.

EXAMPLES OF FAULT DIAGNOSIS BAYESIAN NETWORKS

Taking M airborne electronic equipment as an example, the connection tree algorithm was used to validate the fault diagnosis model constructed by Bayesian networks, and a piece of information from its fault text was selected for model experiments. The specific text information of this fault is: At 14:30, Flight V flew from L Airport to Z Airport and stopped at An Airport due to equipment output pulse failure. After the first restart, the flight continued at 14:50. At 16:40, it arrived at B Airport and chose to temporarily stop due to output pulse failure. After the second restart, the flight continued

Table 3. Corresponding relationships of fault symptom nodes

Number	Feature Words	Number	Feature Words
E1	Input circuit board failure	E9	Start pulse failure
E2	Output circuit board failure	E10	Output pulse fault
E3	Matching circuit board failure	E11	Channel selection failure
E4	Data storage circuit board failure	E12	Comparator failure itself
E5	4V power supply failure	E13	Mobile pulse fault
E6	Pulse circuit board failure	E14	Pulse and frequency changer failure
E7	Broken control signal wire	E15	Register Failure
E8	Modulator circuit board failure	E16	Pulse Width Modulation device failure

at 19:50. From the above information, it can be found that the electronic devices of Flight V contain symptoms of malfunctions such as “grounded”, “output pulse failure”, and “restart”. This set of fault symptoms has been constructed, with a and b representing occurrence and non occurrence, respectively. Then, the fault symptom set is equal to $\{a, a, a, b, b, b, b, b, b, b, b, b, b, b, b, b, b, b, b, b\}$, so the posterior probability of fault diagnosis of the output model is shown in Figure 3.

When Flight V was diagnosed by the model with three fault symptom nodes of “ground”, “output pulse fault”, and “restart”, the most likely cause of the fault was M4 (data storage circuit board fault). Figure 3 described the posterior probability obtained by the model at the fault cause node M1-M20, of which M4 had the highest probability of failure, 0.8. It can be learned that the fault diagnosis results of the model are consistent with the fault probability, indicating the high accuracy of this model.

To further verify the diagnostic ability of the fault diagnosis model constructed by Bayesian networks, symptom correlation relationships were combined in the model. The correlation model with symptoms was set as T1, and the correlation model without symptoms was set as T2. The comparison of the posterior probability of fault diagnosis between the two models is shown in Figure 4.

It can be clearly concluded from Figure 4 that both T1 and T2 were diagnosed as M4 faults. The posterior probability of M4 fault cause nodes was relatively high. The M4 fault probability of T1 was 0.9, greater than T2. This indicates that the diagnostic interference of other fault cause nodes on M4 has decreased, and it also indicates that a model of fault symptom correlation has been added, making the diagnostic results more practical.

Figure 3. Fault diagnosis posterior probability of output model

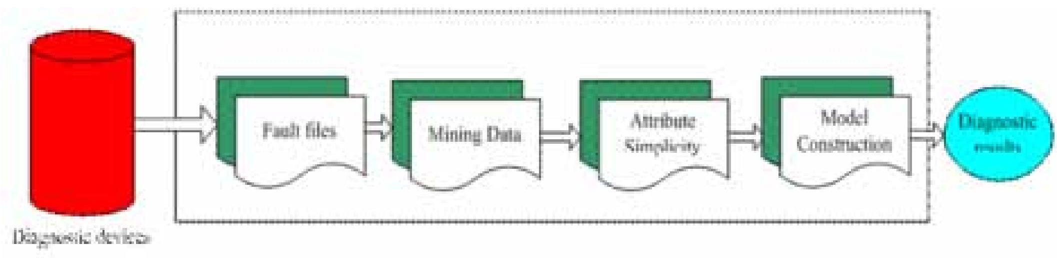


Figure 4. Posterior probability of failure in the symptom free correlation model

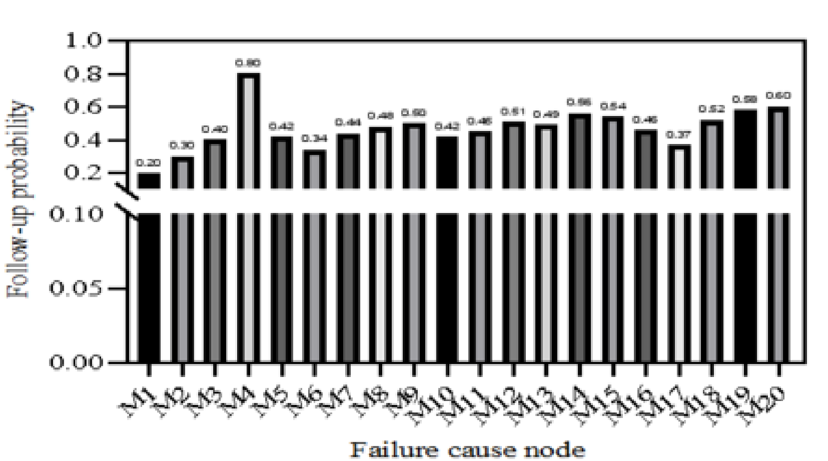


Figure 5 reflects the diagnostic accuracy of the symptom free correlation model. Among them, the accuracy of T1 was above 0.8, and the subsequent probability of T2 was between 0.6 and 0.8. The overall accuracy of T1 was greater than that of T2, and the fluctuation in accuracy was small, indicating that the diagnostic model with symptom correlation has good diagnostic effect, relatively accurate results, and high reliability. It is suitable for fault diagnosis of different fault types proposed in the article.

Finally, T1 and T2 were used for fault diagnosis of the different types of faults proposed in this article, as shown in Table 4.

Table 4 shows the actual diagnosis times of different fault types and the accurate diagnosis times of the model after using T1 and T2. Among them, T1 had the closest accuracy in diagnosing and converting related, communication faults, and other types of faults to the actual diagnosis frequency, with a difference of 1. The accuracy of T2 in diagnosing communication fault types was closest to the actual number of diagnoses, with a difference of 4. T1 had more accurate diagnoses for different types than T2, which was very close to the actual number of diagnoses. T1 fully utilizes the advantages

Figure 5. Diagnostic accuracy of the correlation model with and without symptoms

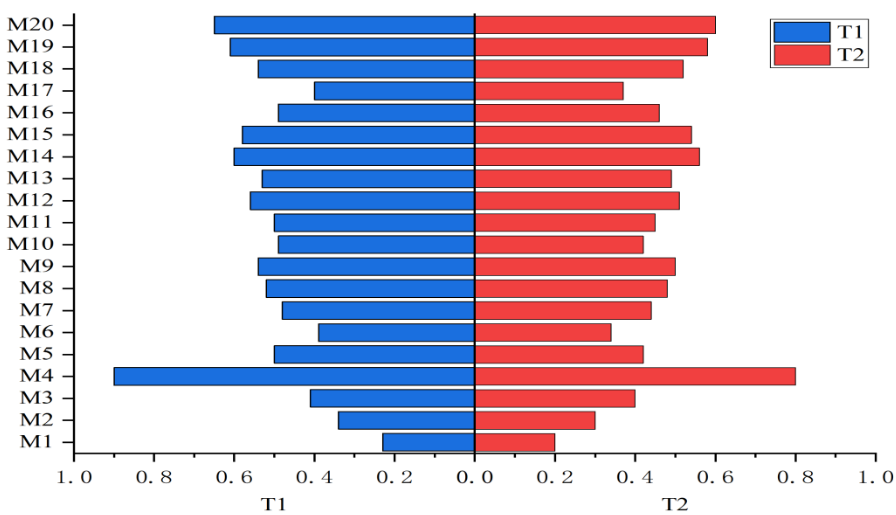


Table 4. Diagnostic accuracy of the correlation model with and without symptoms

Fault Type	Number of diagnostic faults	T1	T2
Signal processing related	67	61	57
Conversion related	84	83	78
Matching related	98	95	90
Logic related	43	40	37
Communication failure	32	31	28
Reboot circuit board failure	103	100	98
Common brake faults	56	51	50
Others	70	69	65

of Bayesian networks and symptom correlation to accurately and quickly diagnose the specific fault causes of airborne electronic equipment, save diagnostic costs, and optimize the diagnostic process.

Based on the above experiments, this paper selected three existing and commonly used airborne electronic equipment fault diagnosis models, namely the support vector machine based fault diagnosis model, the genetic algorithm based fault diagnosis module, and the random forest based fault diagnosis mode, and compared them with the models constructed in the paper. The diagnostic accuracy of each model was recorded by computer, and the number of experiments was 10 times. The use of X1 to X4 refers successively to the fault diagnosis model based on the support vector machine, the fault diagnosis model based on genetic algorithm, the fault diagnosis model based on random forest, and the fault diagnosis model based on dynamic Bayes. The diagnosis results are shown in Table 5 below.

According to the data in Table 5, it can be found that the diagnostic accuracy of X1 ranges from 0.57 to 0.77, that of X2 ranges from 0.51 to 0.79, that of X3 ranges from 0.51 to 0.75, and that of X4 ranges from 0.81 to 0.97.

Obviously, the fault diagnosis model based on dynamic Bayes has the highest diagnostic accuracy, which is above 0.8.

CONCLUSION

With the continuous development of science and technology, the on-board electronic equipment on aircraft is becoming more and more complex, and the equipment number is also increasing, which makes the maintenance of on-board electronic equipment more difficult. Therefore, by analyzing the fault characteristics of airborne electronic equipment, this paper proposed a fault diagnosis method of airborne electronic equipment based on the Bayesian network. The fault diagnosis network model is constructed by using expert knowledge and structure learning based on the Bayesian neural network. Finally, the optimized model is analyzed experimentally. The results show that the posterior probability of the diagnosis model with symptom correlation is consistent with the actual diagnosis results. In terms of diagnostic accuracy, the diagnostic model with symptom association has the highest accuracy. In different types of fault diagnosis of M-type airborne electronic equipment, there is no significant difference between the diagnosis model with symptom correlation and the actual diagnosis frequency. The feasibility and effectiveness of the fault diagnosis model of airborne electronic equipment based on Bayesian network are verified by experiments. In short, future research can further optimize and improve the modeling methods of dynamic Bayesian networks and further improve the accuracy and real-time of fault diagnosis by using big data and machine learning algorithms.

Table 5. Diagnostic accuracy of each model

	X1	X2	X3	X4
1	0.74	0.77	0.70	0.86
2	0.66	0.74	0.66	0.94
3	0.77	0.62	0.51	0.84
4	0.57	0.79	0.69	0.94
5	0.61	0.51	0.71	0.89
6	0.76	0.58	0.61	0.81
7	0.77	0.74	0.51	0.97
8	0.75	0.64	0.59	0.90
9	0.65	0.76	0.75	0.87
10	0.74	0.74	0.57	0.97

CONFLICTS OF INTEREST

These are no potential competing interests in our article. And all authors have seen the manuscript and approved to submit to your journal. We confirm that the content of the article has not been published or submitted for publication elsewhere.

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