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A Maintenance and Troubleshooting Method Based on Integrated Information and System Principles

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ABSTRACT Newly developed equipment is occasionally disturbed by unknown faults during operation; however, it is difficult to diagnose unknown faults based on existing fault diagnostic models or knowledge. In addition, it is time-consuming to frequently and interactively check information related to a certain fault from numerous manuals. To address the maintenance and troubleshooting of faults, this paper develops an innovative method based on integrated information and system principles. Multi-source, distributed, and heterogeneous information integration methods based on ontology and ant colony are presented, and an information integration model based on system principles and graph theory is established. A theoretical system based on the information integration model is then designed and developed. To verify the effectiveness and the feasibility of the above methods and applications, the developed methods are applied to an air source system. The results show that the developed theories support the fault diagnosis of newly developed equipment and advance the efficiency of maintenance and troubleshooting.

INDEX TERMS Complex system, fault diagnosis, information integration, maintenance, troubleshooting.

I. INTRODUCTION

The accuracy and efficiency of maintenance and troubleshooting of complex systems is increasingly challenged by the complexity and intelligence of modern equipment. The influence of single factors on complex systems is also growing, which means a small fault in a complex system can produce a domino effect, leading to the fault of the entire system ultimately. Maintenance and troubleshooting technologies are important for ensuring the safety of equipment during operations. Maintenance and troubleshooting include two major steps: fault diagnosis and troubleshooting. The current methods focus solely on fault diagnosis, maintenance, or troubleshooting. However, fault diagnosis, maintenance, and troubleshooting are a continuous work process in engineering practice.

This paper develops a theory and method of maintenance and troubleshooting based on information integration and system principles that supports a continuous work process of fault diagnosis, maintenance, and troubleshooting. Firstly, the innovative idea is presented. Secondly, an information integration method based on ontology and ant colonies for integrating semantic and heterogeneous information is studied in depth to improve the utilization rate of maintenance and troubleshooting information. Then, the information integration modeling method based on system principles and graph theory is presented to support fault diagnosis, maintenance, and troubleshooting. To realize intelligent fault diagnosis and actively provide maintenance information on the established integrated information flow model, a fault diagnosis algorithm based on information entropy and a maintenance information push algorithm based on fuzzy theory and a neural network are given. Finally, the above methods are applied to an air source system of an aircraft based on a self-developed maintenance and troubleshooting system. The methods are then validated.

Current fault diagnostic methods can be divided into three categories: mathematical modeling methods, signal-based methods, and knowledge-based methods [1]. A fault diagnostic method based on a mathematical model needs to establish

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a precise mathematical model for fault diagnosis by using the internal knowledge of the object system [2]. However, it is difficult to develop a precise mathematical model for complex systems that can ensure high reasoning efficiency. Fault diagnosis based on signal processing is unnecessary for the establishment of precision but is widely applied in the field of nonlinear systems [3], [4]. Compared with methods based on signal processing, a fault diagnostic method based on knowledge can greatly improve decision-making correctness in the diagnostic process because it introduces information about the diagnostic object and has certain self-reasoning abilities [5].

II. RELATED WORK

With the continuous development of big data and network information technology, knowledge-based fault diagnosis has apparent advantages due to its ability to process knowledge. There are several typical fault diagnostic methods based on knowledge, i.e., pattern recognition [6], artificial neural network [7], fault tree [8], fuzzy theory [9], expert system [10], or graph theory model [11].

The graph theory model shows strong vitality and potential applications due to its ability to predict new faults and deal with large and complex systems [12]. At present, graphical modeling methods [13], including Petri net models [14], bond graph models [15], sign-directed digraph models [16], and fault tree models [17], [18], have all been applied to fault diagnostic modeling. A multi-signal diagnostic model with nodes as a component unit and lines as a function connecting links between nodes was established based on a hierarchical modeling method and a graphical modeling method [19], [20]. An extended ambiguous Petri net model was developed based on Petri theory and fuzzy theory [21], [22]. A process dynamic digraph model was presented based on a symbolic digraph model and the system structure model [23], [24]. A hybrid bond graph model was developed by adding finite state variables to the traditional bond graph model [25]. A fault tree model and a Bayesian network model were established using a diagnostic Bayesian network [26]. The existing diagnostic methods based on the graph theory model are usually established for the fault diagnosis system. The necessary information of systems for diagnostic reasoning cannot be fully established in the existing graph theory model to improve diagnostic accuracy.

As equipment becomes more complex, fault diagnosis and maintenance decision techniques have been increasingly associated with testing, diagnostics, maintenance troubleshooting, and security. Maintenance and troubleshooting bring great economic benefits for the lifecycle cost of equipment, but the processes are time-consuming and costly. During maintenance and troubleshooting, technical manuals guide maintenance personnel to carry out certain tasks. However, it is extremely time-consuming for maintenance personnel to consult various forms and structures of technical information from a plethora of technical manuals. Researchers have studied new technical forms of

TABLE 1. Term abbreviations and mathematics symbols used in this paper.

Abbreviation/ Symbol	Meaning	Abbreviation/ Symbol	Meaning
RDF	resource description framework	s_i	the main body
IETMs	interactive electronic technology manuals	p_i	predicate
TO	transition ontology	o_i	object
FO	final ontology	r_i	degree of acceptance
FFA	unction fault analysis	ρ	pheromone volatilization coefficient
FMEA	failure mode and effect analysis	$\tau(0)$	the value of the initial pheromone
SDG	signed directed graph	$\tau(k)$	he value of the k^{th} declared pheromone
TF	test/fault	G	directed graphs
FIM	fault isolation manual	Φ	TF correlation matrix
AMM	aircraft maintenance manual	Ψ	fault-maintenance mapping
EICAS	engine indication and crew alerting system	TFM	test, fault, and maintenance

documentation known as interactive electronic technology manuals (IETMs) to replace printed manuals and support equipment maintenance [24]. Table 1 presents abbreviations and symbols used in this paper.

With the development of IETMs and information integration technology, the realization of multi-source, distributed, heterogeneous maintenance and troubleshooting information integration has become a research hotspot [27]–[31].

Existing information integration methods can barely integrate information with varied semantic structures. Ontology, however, describes semantic concepts accurately and establishes a relationship between the concepts. The ontology-based approach provides a unified standard of semantic expression and can be used to handle semantic heterogeneity in maintenance and troubleshooting information integration.

Ontology has been used to establish an information model for the fault diagnosis of aircraft control surfaces in aircraft systems [32]. Complex equipment maintenance and fault cases have been modeled using ontology modeling [33]–[36]. A fault ontology model for aircraft was built based on ontology knowledge by analyzing the characteristics of the knowledge in the field of aircraft maintenance [37], [38].

Existing ontology modeling processes are usually carried out by a single person. Multi-sourced, distributed, heterogeneous aircraft maintenance and troubleshooting information, however, will miss important mapping features and greatly impact information integration accuracy if only a single person constructs the maintenance and troubleshooting information ontology. Additionally, constructing an ontology model involves a heavy workload, thus it is difficult to update an ontology model. Therefore, it is necessary to study ontology optimization modeling to achieve multi-sourced, distributed, heterogeneous information integration.

III. MAINTENANCE AND TROUBLESHOOTING BASED ON INTEGRATED INFORMATION AND SYSTEM PRINCIPLES

The goal of the maintenance and troubleshooting method based on integrated information and system principles is to realize the collaborative optimization of fault diagnosis and troubleshooting. To realize this goal, firstly, system operation principles, system reliability design, and maintenance technical manuals are comprehensively analyzed to obtain low-dimensional information, e.g., test information, fault information, and maintenance information. Then, the three sorts of low-dimensional information are integrated into a high-dimensional information integration model based on system function structure through test-fault correlation and fault-maintenance mapping based on system function structure.

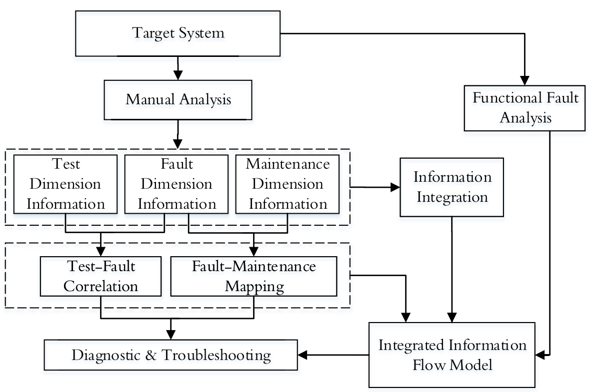

FIGURE 1. **Overall technical route.**

The overall method is shown in Fig. 1. The maintenance and troubleshooting method based on integrated information and system principles is divided into four parts: (1) information optimization integration based on ontology and ant colonies; (2) integrated information flow modeling based on the system function structure; (3) fault diagnosis based on integrated information flow models; and (4) an information push method based on integrated information flow model for maintenance and troubleshooting. Among them, information optimization integration is the foundation that directly affects the integrity of diagnostic, maintenance, and troubleshooting knowledge. Diagnosis and troubleshooting are conducted on integrated information flow models. The key technologies are the model-based fault diagnosis algorithm and the maintenance and troubleshooting information push algorithm.

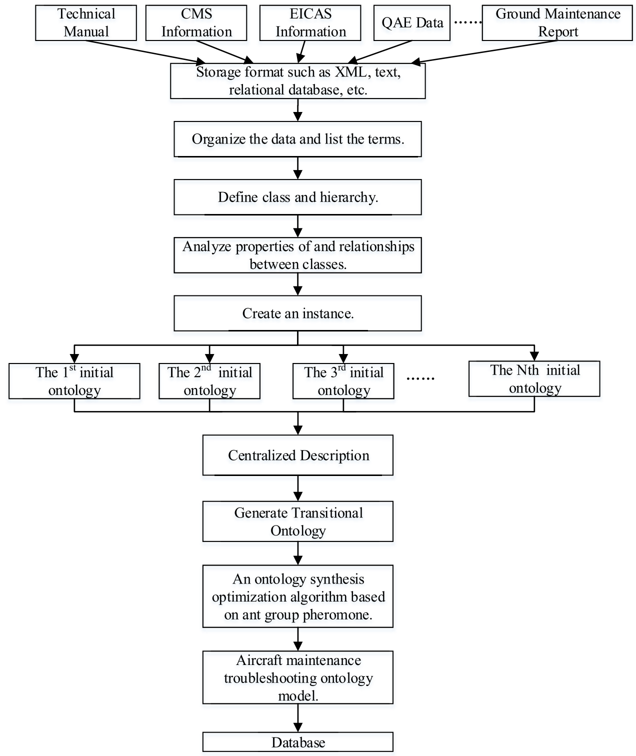

FIGURE 2. **Information integration based on ontology and ant colonies.**

IV. INFORMATION OPTIMIZATION INTEGRATION BASED ON ONTOLOGY AND ANT COLONIES

To achieve information optimization integration, we use ontology to solve the integrated modeling problem of multi-source heterogeneous information. Considering the difficulty of updating during ontology construction, collaborative generation algorithms are studied to handle large modeling workloads and models. The integration of maintenance and troubleshooting information is divided into two steps, as shown in Fig. 2. The first step is to build the initial ontology model of maintenance and troubleshooting information. The second step is to establish the ontology synthesis and optimization algorithm to optimize the initial ontology models; a maintenance information ontology model is generated. The ontology is utilized as the data organization structure to store the troubleshooting information in a relational database.

In order to build the integrated information flow model, an information initial ontology of test, fault, and maintenance information must be constructed. The specific construction steps are as follows:

Step 1: Determine the domain scope of ontology and the purpose of ontology construction and update the maintenance method of the ontology model. Reuse existing ontologies in the domain, if possible. At present, there is no other research on integrated ontology of test, fault, and maintenance, thus, no existing ontology could be used. We built the integrated ontology for future utilization.

Step 2: Analyze the information in the domain category and enumerate all terms. Do not consider whether there will be semantic or attribute duplication between the terms at this point. Test area terms include test point location, test point name, test type, test means, and test of auxiliary information. Fault area terms include fault mode, fault impact, and fault code. Maintenance area terms include maintenance level, maintenance tools, and maintenance steps.

Step 3: Define the hierarchy of classes. By collecting the relevant test, fault, and maintenance information and by considering test, fault, and maintenance as the core concepts of the top level, the knowledge in each area can be sorted and analyzed using the top-down method.

Step 4: Describe the class attributes as an internal structure of class and a representation of the semantic relationships between classes, including Object Properties and Data Properties.

This relationship between classes (e.g., a mapping between classes) is the core function of ontology. It can be considered either a binary group function or a multiple group function. The values of the function domain and range are the objects of the class and subclass defined for test, fault, and maintenance. Domain (intersection) sub-properties in the Object Properties attribute are used to set the domain, and Range (intersection) sub-properties set the range.

Step 5: Define the "side" of the class attribute. The attribute side is the rule of the attribute values, including the number of attribute values and the range of permissible values.

Step 6: Finally, when creating an instance of classes, add the instance and its property value.

To improve the credibility and accuracy of the ontology model, this paper synthesizes and optimizes several initial ontologies based on the initial ontology construction. There are only two states in a traditional resource description framework (RDF) statement (i.e., presence and absence), however, when the actual ontology is built, the recognition of RDF statements is a continuous process. The present invention is based on the original RDF triples and another attribute of recognition. Recognition indicates the degree of acceptance of an RDF declaration by various ontology builders. The value of recognition is between 0 and 1. The steps for maintenance troubleshooting information ontology synthesis optimization are as follows:

Step 1: Build the initial maintenance troubleshooting information ontology. The constructed initial ontology (IO) can be expressed as:

$$IO = \{(s_1, p_1, o_1, r_1), (s_2, p_2, o_2, r_2), \cdots, (s_i, p_i, o_i, r_i), \cdots, (s_n, p_n, o_n, r_n)\} \quad (1)$$

where $1 \leq i \leq n$, $\boldsymbol{n}$ denotes the number declared in the ontology RDF model, s_i represents the main body, p_i is the predicate, o_i is the object, $\boldsymbol{r}_i$ is the degree of acceptance, and the initial recognition is set to 0.

Step 2: Generate the maintenance troubleshooting information transition ontology.

The transition ontology (TO) is a collection of all declared triplets in m initial ontologies. It is expressed as:

$$TO = \bigcup_{k=1}^{m} IO_k \quad (2)$$

Here, IO_k represents the k^{th} initial ontology. Moreover, you need to keep the same triples in the generation of transitional ontologies, such as:

$$IO_1 = \{(s_1, p_1, o_1, r_1), (s_2, p_2, o_2, r_2), (s_3, p_3, o_3, r_3)\}$$
$$IO_2 = \{(s_3, p_3, o_3, r_3), (s_4, p_4, o_4, r_4)\}$$

then:

$$TO = \{(s_1, p_1, o_1, r_1), (s_2, p_2, o_2, r_2), (s_3, p_3, o_3, r_3), (s_3, p_3, o_3, r_3), (s_4, p_4, o_4, r_4)\}$$

In TO the number of declarations u is calculated when s is equal to o but not to p, and the number of declarations v is calculated when s is equal to o and p.

Step 3: G enerate the final ontology of the troubleshooting information.

The final ontology (FO) is generated based on the ontology synthesis optimization algorithm. The FO is the set of TO subsets that meets the algorithm conditions.

This paper suggests an ontology synthesis optimization algorithm based on ant colony pheromones and the initial ontology of aircraft maintenance troubleshooting. The feature of ontology information modeling is combined with maintenance troubleshooting, the local pheromone renewal strategy is introduced, and the ontology synthesis information element is developed for ontology synthesis optimization. Ontology synthesis pheromone τ represents the ratio change of different predicates p with the same s and r. The ontology synthesis pheromone can be calculated by Eq. (3).

$$\begin{aligned} \tau(0) &= \rho \ (0 \leq \rho \leq 1) \\ \tau(k+1) &= (1-\rho)\cdot\tau(k) + \rho\cdot\eta \\ \eta &= \begin{cases} \dfrac{v_{\mathrm{k}}}{u_{\mathrm{k}}}, & \text{if statement k has the same} \\ & \quad \text{s \& o as other statements} \\ 0, & \text{otherwise} \end{cases} \end{aligned} \quad (3)$$

where $\tau(0)$ represents the value of the initial pheromone, $\tau(k)$ represents the value of the k^{th} declared pheromone, and ρ is the pheromone volatilization coefficient. To avoid the unlimited accumulation of information, the range of volatility coefficient ρ is set as [0, 1].

Threshold ε is set after calculating acceptance value r.

(s, p, o) is inserted into the final ontology only when $r > \varepsilon$. The range of threshold ε is (0.5, 1). The larger the threshold ε is, the more accurate final generated ontology will be.

A larger acceptance value statement is selected if there are multiple declarations that satisfy the approval value $r > \varepsilon$ when s and o have the same statement and p has a different statement. Only s, p, and o remain in the final ontology without recognition r. The algorithm is shown in Fig. 3.

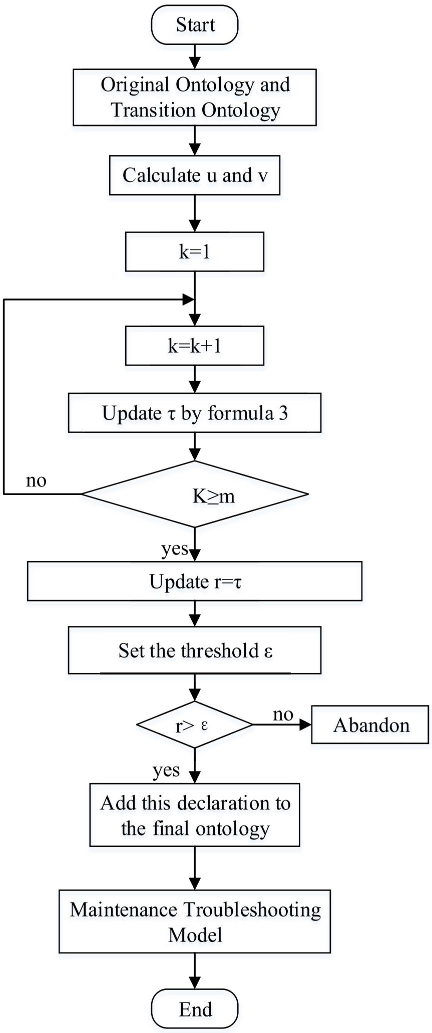

FIGURE 3. Ant colony-based pheromone ontology synthesis optimization algorithm.

V. INTEGRATED INFORMATION FLOW MODELING BASED ON SYSTEM PRINCIPLES AND GRAPH THEORY

The integrated information flow method in this paper decomposes the information on the fault propagation path into three kinds of information: test, fault, and maintenance.

The three information dimensions are integrated based on the system function structure according to the relationship between test/fault information and fault/maintenance information. The process for establishing integrated information flow models for maintenance and troubleshooting is shown in Fig. 4. A function structure skeleton model is established via function fault analysis (FFA) based on failure mode and effect analysis (FMEA) report target system and system principles. After analyzing the aircraft system principles and various technical manuals comprehensively, test, diagnosis, and maintenance information is obtained. Then, an information integration method based on ontology and ant colonies is adopted to integrate the three dimensions of heterogeneous information in a single function structure skeleton model. A correlation matrix is established for test and fault information using the multi-signal flow graph method. The mapping relationship between fault and maintenance information is obtained using the ontology mapping method based on a Bayesian network. Finally, the ontology information is added to a system function skeleton model to build the integrated information flow model. The advantages of establishing the integrated information flow model based on the system functional structure are as follows: (1) it can reflect the structure and hierarchy of test, fault, and maintenance information; (2) it meets the requirements of small-scale updates when the information changes; and (3) it is versatile.

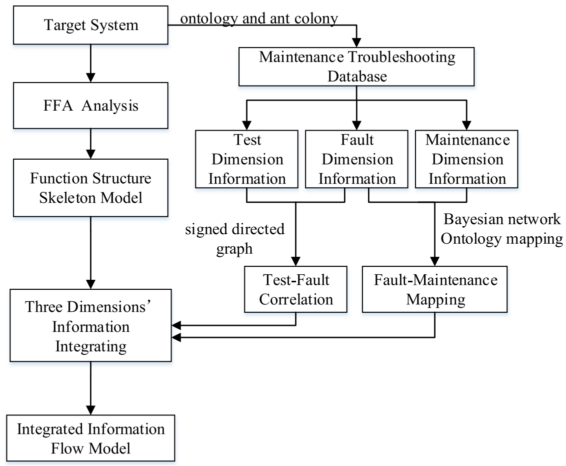

FIGURE 4. Integrated information flow modeling based on the functional structure.

The integrated information flow model can be defined as a combination of directed graphs G, function Φ, and function Ψ, i.e., (G, Φ, Ψ). Directed graph G is quintuple (V, T, F, M, E), where $V = \{v_1, v_2, \ldots, v_n\}$ represents a collection of nodes, T is the test dimension element set, F is the fault dimension elements collection, M is the maintenance dimension elements collection, and E is convergent set $E = (V \times V)$. Function Φ represents the test/fault correlation matrix. Function Ψ represents the fault-maintenance mapping.

As the basic structure of the integrated information flow model, the function structure skeleton model needs to reflect the functional structure of the system and include fault modes and fault propagation knowledge. To meet the above requirements, this paper uses the graph modeling approach and the FFA method, because symbolic digraph is good at describing the causal relationship and the large amount of information in dynamic systems.

Due to the complicated structure and diversified functions of modern equipment, there are a variety of fault modes and causes. To establish the function structure skeleton model, the FFA method is used to analyze the system and obtain the functional structure and fault mode information. FFA is a qualitative analysis method that can be used to analyze the system hierarchy, function information, and fault information. The system analysis steps are as follows:

Step 1: Collect technical information, e.g., technical manuals, FMEA reports, historical experience, and case studies.

Step 2: Partition the components of the system. A complex system is gradually decomposed into several subsystems, sub-subsystems, and components. The basic principles of component division are as follows: components (1) reflect the structural hierarchy of the original system; (2) reflect the diagnostic data attributes (including the diagnosis of the object structure, function and behavior); and (3) meet the demands of a small node update when test and fault knowledge change.

Step 3: List the capabilities of the components. During FFA, faults are defined as the loss of a particular function. Listing the relevant functions of components helps explain the causes and consequences of the fault.

Step 4: Select the input and output variables of the components. Based on the capabilities of the components, the input and output state variables are selected to reflect the feature changes of the capabilities. The causal relationship between state variables is analyzed according to system principles.

Step 5: Fault mode analysis. Based on the system FMEA report, the possible fault effects and conditions that may occur for a particular fault mode are analyzed, thus, fault modes, fault mechanisms, and fault effects of each component in the system are obtained.

The signed directed graph (SDG) model is similar to the basis of the physical structure, and the flow of the function is expressed in a directed graph. We build a function structure skeleton model by using the SDG model method, which is given below:

Step 1: Establish a system structure model, which will be presented in the last part of the paper (Figs. 8, 10, and 11). An open square, "□", is used to represent the components and establish the structural model of the system.

Step 2: Establish a functional model. Based on the system structure model, an open circle, "◯", is used to represent the state variables and establish the functional model. The input node is displayed on the left frame of the module, and the output node is displayed on the right frame of the module.

Step 3: Add fault mode nodes to the components. In this paper, the fault is divided into two types: the endpoint fault and the underlying fault. An endpoint fault is at the component level, using "⦸" in the model. Underlying faults represent signs that a component is in a faulted state due to an internal component fault, using a solid circle, "●", in the model after adding the fault mode node.

Step 4: Connect the fault mode to the corresponding state variable node with a link.

In order to add test information and eventually generate the final integrated information flow model, the relationships between test and fault information, and fault and maintenance information are studied.

This paper analyzes the influence of the relationship between fault and test variables and establishes a test/fault relationship matrix. Set test $T = \{t_1, t_2, \ldots, t_n\}$ and fault $F = \{f_1, f_2, \ldots, f_n\}$. The test/fault relationship matrix is a Boolean matrix as follows:

$$TF_{m\times n} = \begin{array}{c} \\ T_1 \\ T_2 \\ \vdots \\ T_m \end{array} \begin{array}{c} \begin{array}{cccc} F_1 & F_2 & \cdots & F_n \end{array} \\ \begin{bmatrix} tf_{11} & tf_{12} & \cdots & tf_{1n} \\ tf_{21} & tf_{22} & \cdots & tf_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ tf_{m1} & tf_{m2} & \cdots & tf_{mn} \end{bmatrix} \end{array} \tag{4}$$

where tf_{mn} is the correlation between test t_m and fault f_n, $tf_{mn} = 1$ can be judged according to test information t_m, f_n fault, and $tf_{mn} = 0$ indicates that test information t_m cannot determine fault f_n. The m^{th} row vector $T_m = \left[tf_{m1}\ tf_{m2} \cdots tf_{mn} \right]$ represents all faults that test information t_m can detect; the n^{th} column vector $F_n = \left[tf_{1n}\ tf_{2n} \cdots tf_{mn} \right]$ represents all the test information that can indicate fault f_n occurred.

Based on the function structure skeleton model, which reflects the hierarchy of system structure, a test information point is added for each state variable node or fault mode node. All test information points are represented by a shaded circle, "◯", in the graph model.

In this paper, maintenance information from the integrated information database is added to the fault mode node through mapping based on similarity calculations. We use the ontology Bayesian network (OBN) for mapping:

$$OBN = \{N, E, P, I, A, \theta_{ST}\} \tag{5}$$

where the set of conceptual nodes $N = \varphi(C)$ (where C is the set of elements in the ontology to be mapped) and edge set $E = \varphi(R)$ (where R is the set of relations between the elements) constitute the model framework, $I = \varphi(I)$ represents a node instance set, $P = \varphi(F)$ (where F is the set of functions in the ontology to be mapped) represents the attribute set of the model node, $A = \varphi(A)$ represents the axiom set of the node, and the similarity set is represented by θ_{ST}. We use a simple similarity calculation algorithm based on the nodes' name as follows:

$$Sim_{\text{name}}(x, y) = \max\left(0, \frac{\min(|x|, |y|) - ed(x, y)}{\min(|x|, |y|)}\right) \tag{6}$$

where $|x|$ and $|y|$ are the length of characters x and y, respectively, $\min(|x|, |y|)$ is the length of the shorter characters in x and y, and $ed(x, y)$ is the minimum number of steps required to convert x to y. The available operations include replacement, insertion, and removal.

To obtain a perfect mapping relationship, we utilize an iterative mapping reasoning process to discover the mapping relationship. The steps for implementation are as follows:

Step 1: Set threshold δ $(0 < \delta < 1)$. Find all concept node pairs whose node similarity value in the on-body Bayesian network model is greater than the threshold value δ and put them in the queue to be mapped.

Step 2: Randomly remove a pair of concept nodes from the to-be-mapped queue. Assume that is (x_1, y_1), establish a corresponding mapping relationship, and add the mapping relationship to set M, which is a mapping set with an initial value of null.

Step 3: According to the set of edges E and P of the ontology network model, develop adjacency concept node sets n and n' for two concept nodes in (x_1, y_1). Sets n and n' are divided into a parent node set $\left(f, f'\right)$, a child node set $\left(c, c'\right)$, and a predicate node set $\left(w, w'\right)$ based on the relationships between nodes in sets n, n' and (x_1, y_1).

Step 4: Update the similarity of the parent node set, child node set, and predicate node set.

Step 5: Return to the first step.

The iterative processes end when there is no concept node pair in the queue to be mapped. The global mapping relational table of ontology mapping can be obtained by organizing the final mapping set M.

VI. FAULT DIAGNOSIS ALGORITHM BASED ON INFORMATION ENTROPY

Based on the test/fault (TF) matrix, the optimized information entropy algorithm is used to deal with the TF matrix to obtain a better test diagnostic strategy and accurate fault diagnostic results. The basic steps of the algorithm are as follows.

Step 1: Calculate the global information entropy of the TF matrix.

Global information entropy is the basis for dividing the TF matrix, and the size of the information contained in the test is the main concern. The formula for global information entropy is:

$$H\left(t_m\right) = -\sum_{k=1}^{d}\left(\frac{N_m^1}{l}\log_2\frac{N_m^1}{l} + \frac{N_m^0}{l}\log_2\frac{N_m^0}{l}\right)_k \tag{7}$$

where d is the number of matrices after splitting, $d \leq 2^p$, p is the number of tests that have been selected, l is the number of fault modes of the TF correlation matrix, and N_m^1, N_m^1 represent the number of elements 1 and the number of elements 0 in matrix column vector c, respectively. Compare the size of the entropy calculated for each row to find $\max H\left(t_m\right)$ and select the first test item.

Step 2: Calculate the local entropy after segmentation.

The TF matrix is divided into TF_n^0 and TF_n^1 after $\max H\left(t_m\right)$ is obtained, and local information entropy $H'\left(t_m\right)$ is calculated using the local information entropy algorithm formula:

$$H'\left(t_m\right) = -\left(\frac{N_m^1}{l}\log_2\frac{N_m^1}{l} + \frac{N_m^0}{l}\log_2\frac{N_m^0}{l}\right) \tag{8}$$

After all local information entropies are calculated by Eq. 8, their sizes are compared and the maximum local information entropy $\max H'\left(t_m\right)$ is found.

Step 3: Determine the relationship between $\max H\left(t_m\right)$ and $\max H'\left(t_m\right)$.

When $\max\left(H\left(t_m\right)\right) = \sum_{n=1}^{d}\max\left(H'\left(t_m\right)_n\right)$, the value of global information entropy is equal to the sum of all the largest local information entropies. At this time, t_m items are selected to segment the TF matrix.

When $\max\left(H\left(t_m\right)\right) = \sum_{z=1}^{c}\max\left(H'\left(t_m\right)_z\right) + \sum_{n=1}^{d-c}H'\left(t_m\right)_n$ $1 \leq c < d$, the maximum global information entropy is equal to the sum of c local maximum entropies and $d - c$ local information entropies. In this case, t_m and $\bigcup_{m=1}^{d-c}\max H'\left(t_m\right)_n$ are selected to segment the TF matrix.

When $\max\left(H\left(t_m\right)\right) = \sum_{n=1}^{d}H'\left(t_m\right)_n$, all the local maximum information entropy is not the maximum global information entropy. At this moment, select $\bigcup_{m=1}^{d}\max H'\left(t_m\right)_n$ to segment the TF matrix.

Step 4: Repeat the above steps. When all F elements in the TF matrix are single-row matrices, the algorithm ends. The output is expressed as a diagnostic tree.

VII. INFORMATION PUSH ALGORITHM BASED ON AN INTEGRATED INFORMATION FLOW MODEL

The acquisition of information is an integral part of the maintenance process. It is possible to locate the source of a known fault directly by referring to the manual to obtain information on maintenance and troubleshooting. To diagnose unknown faults and determine the possible causes of fault, this paper makes full use of the information in the fault isolation manual (FIM) and aircraft maintenance manual (AMM) to locate the fault and obtain corresponding maintenance and troubleshooting information. To improve efficiency, this paper studies the troubleshooting information push algorithm based on a fuzzy genetic neural network and a semantic relevance search and establishes a two-dimensional information mapping model. For each fault, the dynamic prediction algorithm based on a fuzzy neural network and the genetic algorithm is adopted to establish a corresponding dynamic model, and the automatic push of the information is arranged according to the information of the fault, as shown in Fig. 5.

The specific procedures are as follows:

Step 1: Collect information related to a single fault, including troubleshooting experience and historical maintenance procedures. Then, a dynamic prediction algorithm based on a fuzzy neural network and the genetic algorithm is used to establish a dynamic prediction model of information for troubleshooting. Update information according to changes in the troubleshooting situation of maintenance personnel.

Step 2: Push the filtered troubleshooting information to the maintenance personnel according to their needs.

Step 3: The maintenance personnel provide the automatically received troubleshooting information to the dynamic

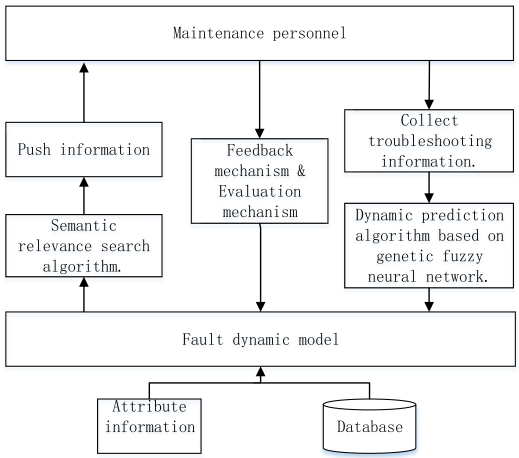

FIGURE 5. Troubleshooting information push process.

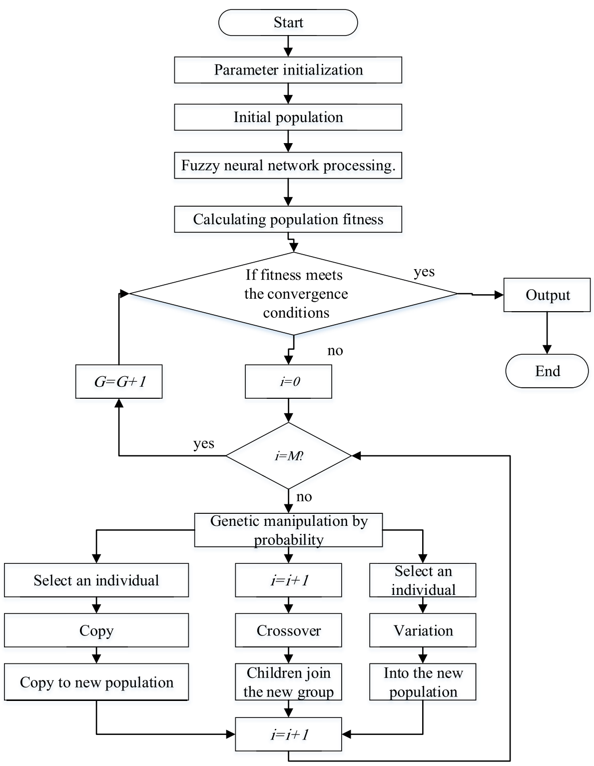

FIGURE 6. Dynamic prediction algorithm based on a fuzzy neural network and the genetic algorithm.

prediction model so that the model can be continuously updated and optimized.

The basic steps of the dynamic prediction algorithm are shown in Fig. 6, where M is the largest number of individuals in each generation and G is the current algebra. Assuming X is the data to be calculated, including one dependent variable and n independent variables, the relationship between them is nonlinear. The fuzzy function in fuzzy theory handles dependent variables and independent variables, and the mapping relationship between them is obtained; a neural network is established based on this relationship. The number of input nodes of the neural network is n, and the number of hidden nodes is determined according to sample size. There is only one output node in each neural network, and the genetic algorithm is used to optimize the output value weight network.

The basic steps to find the associated search algorithm with concept instance X are as follows:

Step 1: Set degree of association $R = \lambda$; the result set is V. The greater the degree of association is, the greater the traversal depth of the algorithm search and the larger the number of search results are. However, when the degree of relevance is too high, there will be too many invalid results from the search, which will affect the overall quality of the search results. According to the study, a relevance with an upper limit of 6 is most appropriate.

Step 2: $R = R - 1$; when $R = -1$, end the algorithm; otherwise, go to Step 3.

Step 3: $V = V + \{X\}$; find node X_i associated with X that is not inset V. If there is a value for X_i, set $X = X_i$ and go to step 2. If it does not exist, end the algorithm.

VIII. CASE STUDY

The feasibility of the above theory and method is verified using the air source system of a certain aircraft as an object. As part of the aircraft ring control system, the main function of the air source system is to control and monitor the distribution of gas from the engine, APU, or high-pressure air source. According to the characteristics of fault propagation analysis and the air source system function relationship, the air source system is divided into five subsystems: APU bleed air system, engine bleed air system, ground air bleed air system, loss valve of the gas monitoring system, and the control system.

A fault isolation manual and a maintenance manual of an air source system were integrated to verify the accuracy of the integration method based on ontology and ant colonies. The AS-FIM and AS-AMM of the air source system of a certain type of aircraft were analyzed, and the information was described in terms of conceptual description and hierarchy. The results are shown in Table 2. The information ontology model of the maintenance platoon was based on this analysis. In this paper, the original ontology is collected from 8 maintenance troubleshooting manuals. These manuals were transformed into an RDF structure, and the final maintenance troubleshooting ontology was built by using an ontology synthesis optimization algorithm based on ant group pheromone. The basic structure of the final ontology is shown in Fig. 7.

Analyze the levels and functions of each subsystem in the air source system, with "□" as the component, "◯" as the state variable, "●" as the bottom fault, and "⦸" as the endpoint fault and the air source system subsystem level function structure skeleton model, shown in Fig. 8.

To acquire the value of each node variable in the test, fault, and maintenance (TFM) skeleton model, a test/fault two-dimensional information relationship is established. By analyzing the fault propagation mechanism of aircraft systems based on functional structure, we obtain all the test points and fault mode information.

TABLE 2. **Information concept description and hierarchy of air source system maintenance troubleshooting.**

Knowledge Domain	Class	Subclass	Significance
AS-FIM	FIM task	FIM task number	FIM task number
		Possible reason	Possible reason
		Procedure	Fault isolation procedure
	Engine indication and crew alerting system (EICAS) code		EICAS fault code
	Maintenance information		Maintenance information
AS-AMM	AMM task	AMM task number	AMM main task number
		Subtasks	Subtasks
	Button position		Button position
	Consumables/ parts		Consumable parts
	Position/ cover	Position number	Location number

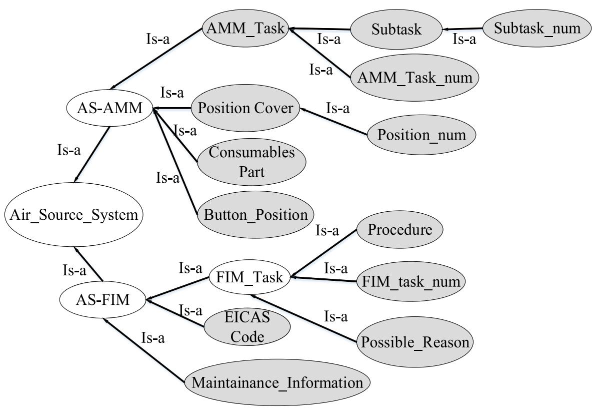

FIGURE 7. **Basic structure of the information ontology model of air source system maintenance troubleshooting.**

The test/fault correlation matrix *TF* is applied to obtain the real matrix of the air source system (see Table 3). Using a certain type of TFM skeleton model, the test information point is represented by "◯", the test point test/fault relation is added to the skeleton model in Fig. 8, and the established ontology relationship is ascertained, as shown in Fig. 9.

To verify the validity and feasibility of the fault diagnosis and troubleshooting information push algorithm based on the integrated information flow model above, this paper uses C# and the SQL Server 2008r2 database on the Visual Studio 2010 platform to design the maintenance and troubleshooting systems based on integrated information flow. The system includes five modules: a component tree display module, a system function structure skeleton model display module, a diagnostic information input module, a diagnostic result display module, and a maintenance troubleshooting information push display module. As shown in Fig. 10, after inputting the fault description and state variable values, a possible cause of

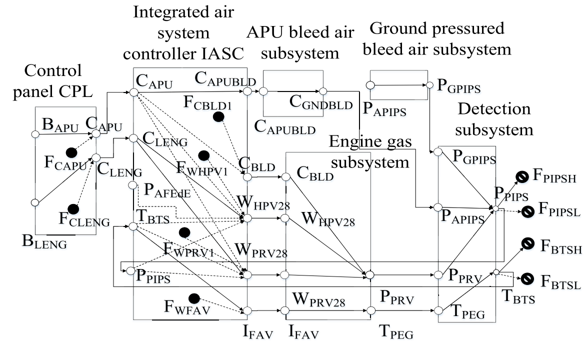

FIGURE 8. **Subsystem level of the skeleton model of the air source system.**

TABLE 3. ***TF*** **matrix of air source system.**

	F_1	F_2	F_3	F_4	F_5	F_6	F_7	F_8	F_9	F_{10}	F_{11}
T_1	1	0	0	0	0	0	0	0	0	0	0
T_2	1	1	1	0	0	0	0	0	0	0	0
T_3	0	1	0	0	0	0	0	0	0	0	0
T_4	1	1	1	1	1	0	0	0	0	0	0
T_5	1	1	1	1	1	0	1	0	0	0	0
T_6	1	1	1	1	1	1	1	0	0	0	0
T_7	1	1	1	1	1	1	1	1	1	1	0
T_8	1	1	1	1	1	1	1	1	1	1	1
T_9	0	0	0	0	0	0	0	0	1	0	0
T_{10}	0	0	0	0	0	0	0	0	0	0	0
T_{11}	0	0	0	0	0	0	0	0	0	0	0
T_{12}	0	0	0	0	0	0	0	0	0	0	0
T_{13}	0	0	0	0	0	0	0	0	0	0	0
T_{14}	0	0	0	0	0	0	0	0	0	0	0
T_{15}	0	0	0	0	0	0	0	0	0	0	0
T_{16}	0	0	0	0	0	0	0	0	0	0	0
T_{17}	0	0	0	0	0	0	0	0	0	0	0

(Continued)

	F_{12}	F_{13}	F_{14}	F_{15}	F_{16}	F_{17}	F_{18}	F_{19}	F_{20}	F_{21}
T_1	0	0	0	0	0	0	0	0	0	0
T_2	0	0	0	0	0	0	0	0	0	0
T_3	0	0	0	0	0	0	0	0	0	0
T_4	0	0	0	0	0	0	0	0	0	0
T_5	0	0	0	0	0	0	0	0	0	0
T_6	0	0	0	0	0	0	0	0	0	0
T_7	1	1	1	0	0	0	0	0	0	0
T_8	1	1	1	0	0	0	0	0	0	1
T_9	1	1	1	0	0	0	0	0	0	0
T_{10}	0	1	0	0	0	0	0	0	0	0
T_{11}	0	0	0	1	0	0	0	0	0	0
T_{12}	0	0	0	1	1	0	0	0	0	0
T_{13}	0	0	0	1	1	1	1	0	0	0
T_{14}	0	0	0	1	1	1	1	1	0	0
T_{15}	0	0	0	0	0	0	0	0	1	0
T_{16}	0	0	0	0	0	0	0	1	1	1
T_{17}	0	0	0	0	0	0	0	0	0	1

fault is determined. Combined with the possible reasons for the fault and background database maintenance experience, the system obtains keyword information through a dynamic prediction algorithm and then automatically displays maintenance troubleshooting information on the display interface. Fig. 11 is an example of fault diagnosis and troubleshooting information push results.

In order to simplify the relationship between fault information and maintenance information, only the ontology mapping relationship of 1 to 1 was considered. However,

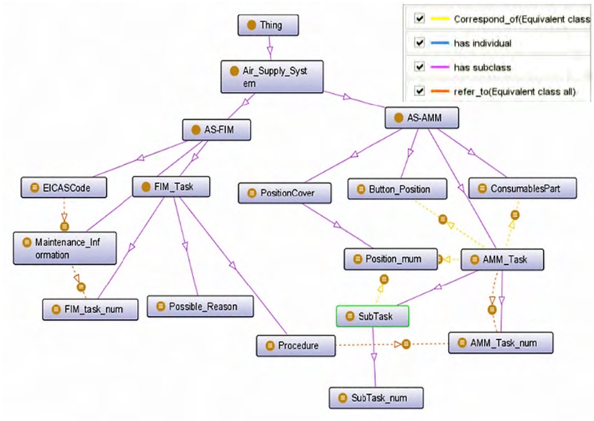

FIGURE 9. Maintenance troubleshooting body diagram of air source system.

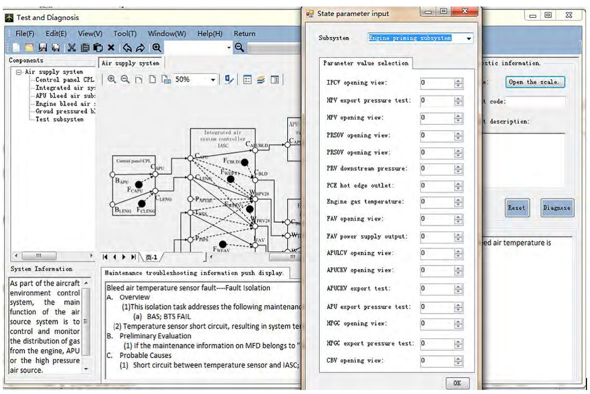

FIGURE 10. Diagnostic information input.

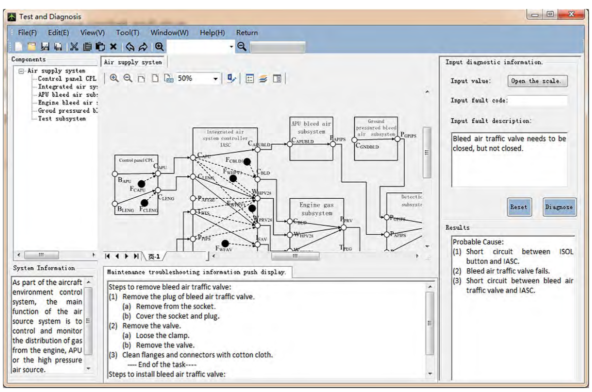

FIGURE 11. Fault diagnosis and troubleshooting information push.

because the structure of fault information and maintenance information is complex and diverse, other relationship ratios such as 1 to N and N to 1 also should be researched. Further study could complete the system to get better functionality, such as adding maintenance tool management, maintenance decisions, and spare parts management, which are indispensable for the maintenance and troubleshooting phase and could be further developed on the basis of the original system. The system could be used in portable repair systems in the future to enable remote expert guidance at the repair site. Existing electronic versions of the AMM and FIM share interactive indexes and do not actively present information for specific faults or maintenance work flow. The information push function is for the fault and its maintenance task flow, and realizes the active information flow to be presented to the maintenance engineer. The electronic information query system created in this paper will greatly increase the efficiency compared with traditional electronic manuals because it provides relevant information connected directly with a specific fault.

IX. CONCLUSION

Interactive querying of numerous technical manuals increases the difficulty of the troubleshooting process and affects the efficiency of maintenance. This article is based on the maintenance troubleshooting process and intelligently pushes the relevant information of technical manuals for specific faulty software systems, so maintenance staff no longer need to query electronic manuals interactively. Existing graph theory-based diagnostic methods have poor versatility and low diagnostic accuracy. This paper adds information about the auxiliary diagnosis in the nodes of the model, and applies information integration technology to the process of graphical modeling.

Table 2 shows that the results of the integration method based on ontology and ant colony applied to a fault insolation manual (AS-FIM) and aircraft maintenance manual (AS-AMM) for an air source system are consistent with the actual situation, showing the accuracy of the method. The case study shows that the developed system saves time while conducting inquiries. The user only needs to make a couple of clicks to get all the relevant information compared with searching numerous technical manuals, which is beneficial because systems are becoming more complex and the requirement for accuracy is increasing. Through analyzing the established model in the case study, the fault detection rate of the model was greater than 95%, and the fault isolation rate was greater than 93%, while the mean time to detect was less than 1 s. The system is expected to be loaded on a portable maintenance system for remote expert guidance at the repair site.

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