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Fault Diagnosis Strategy for Complex Systems Based on Multi-Source Heterogeneous Information Under Epistemic Uncertainty

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ABSTRACT Technological innovation in modern systems has significantly improved their performance. However, fault characteristics such as epistemic uncertainty and dynamic failure modes often occur when these systems break down, which greatly raises some new challenges in fault diagnosis. A new fault diagnosis strategy for complex systems is presented based on multi-source heterogeneous information considering epistemic uncertainty in this paper. Specifically, in view of the epistemic uncertainty, the failure distribution parameters of basic events are described with interval numbers and test cost of these events are evaluated using domain experts and intuitionistic fuzzy linguistic set; Aiming at the problem of dynamic failure modes, a dynamic fault tree (DFT) is used to establish the dynamic failure model and is converted into a dynamic evidential network to calculate some reliability parameters; Furthermore, a diagnostic decision table is constructed based on multi-attribute heterogeneous information such as test cost and some reliability results; Finally, a novel fault diagnosis strategy is designed based on distance-based VIKOR algorithm, which can provide some decision support for fault diagnosis and locate the fault as quickly as possible.

INDEX TERMS Intuitionistic fuzzy linguistic set, reliability assessment, diagnosis strategy, D-S evidence theory, VIKOR algorithm.

I. INTRODUCTION

Technological improvement and innovation in modern systems significantly improve the performance and functionality of these systems. However, fault characteristics such as epistemic uncertainty and dynamic failure modes often occur when these systems break down. Besides, application of redundancy technology has also led to a continuously increasing in the complexity of these systems, which raises new challenges to fault diagnosis in these modern systems. Aiming at the unique fault characteristics of these systems, it is of great significance to establish a multi-dimensional fault diagnosis model and develop a diagnosis decision-making algorithm based on multi-source heterogeneous information in order to locate faults quickly and recover these systems as soon as possible. Fault location, which is essentially a multi-attribute decision-making optimization process, mainly determines the diagnostic sequence of each component in the system according to certain criteria [1]. For fault diagnostic strategy, current researches have provided a variety of methods to construct and analyze system fault models, mainly including correlation models, fault trees, Petri nets, signed directed graph models, neural networks and Bayesian networks. Tsai and Hsu [2] propose a correlation model to model and analyze the functional model-based system testability. The correlation between functional factors and test points of the system is also analyzed, and the fault-test correlation matrix is established. A diagnostic decision tree is generated, which provides a diagnostic method for testability of the system. A fuzzy fault diagnosis method based on directed graph model has been proposed in [3]. The main advantage is that it can diagnose multiple faults and does not need to acquire the prior failure probability of components accurately. However, this method also needs to construct a fault-test matrix, which is not applicable to the redundant systems, because the relationship between the test and the faulty unit is not a

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one-to-one in the redundant systems, but many-to-one. This makes the test effectiveness different at different test points where the information flow is available in the redundant systems. DFT [4] is developed on the basis of a static fault tree. It can capture the dynamic fault behaviors of complex systems in fault diagnosis by adding relevant dynamic logic gates. Reference [5] presents a fault diagnosis method based on the dynamic fault tree, which uses Markov chain to solve DFT and integrates sensor information to optimize the system diagnosis process. However, the solution for DFT based on Markov chain method will lead to state space explosion. For this reason, Merle *et al.* [6] proposes a priority DFT method, which solves the DFT with priority dynamic gate by directly determining the priority, without using Markov chain. In reference [7], DFT is used to model the dynamic fault characteristics, and some importance of components can be calculated and used as a basis for fault diagnosis. Reference [8] introduces a discrete-time Bayesian network to calculate some reliability parameters and update these reliability parameters by fusing sensor information to optimize the diagnosis process in a certain extent. This method can effectively avoid the state space explosion problem. However, the use of discrete-time Bayesian networks to solve DFTs is essentially an approximation method and there is a problem that the calculation accuracy and the computational complexity are contradictory. Therefore, in reference [9], an algebraic framework method is proposed to solve the structure function of the DFT, and the structure function can be simplified to a canonical form. Qualitative and quantitative analysis of a DFT can be performed directly by determining the minimum cut set/sequence of the DFT. However, this method needs to determine the minimum cut set /sequence manually from the structure function, which reduces its efficiency to a certain extent. Kabir and Papadopoulos [10] propose a stochastic Petri net based method to solve DFT, which can model and analyze the dynamic behaviors and functional dependency between components in the system. However, this method cannot analyze the large complex systems. Reference [11] used a combination of the evidential Markov chain and evidence network to construct a new dynamic evidence network to evaluate system reliability and conditional reliability. However, this method is relatively complicated and requires a large amount of calculations. Reference [12] discussed a detailed transformation from a logic tree of a fault tree to a dynamic evidence network model and an aero-engine oil system was used to verify the effectiveness of the proposed evidence network model.

Aiming at the problem of epistemic uncertainty, domain expert's evaluation can be an alternative. However, sometimes it is subjective and often leads to uncertainty. So, how to deal with uncertainty is a hot topic in fault diagnosis [13]. Sun *et al.* [14] present a possibility theory to deal with the uncertain information in fault diagnosis problems. Dempster-Shafer evidence theory (D-S evidence theory) has great advantages to handle uncertain information. D-S evidence theory was proposed by Dempster and later developed by Shafer [15]. In [16], D-S evidence theory is used to solve the problem of uncertain information that cannot be recognized in data fusion. Reference [17] proposes a fuzzy linguistic set to deal with quantitative information that can be better understood and establishes an attribute model to make decisions on evaluation information. Zhang *et al.* [18] extend the fuzzy linguistic set to the intuitionistic fuzzy domain to deal with the uncertainty information brought by expert evaluation in the multi-attribute decision making problem. Torra [19] introduces a hesitant fuzzy set and uses multiple membership degrees to represent uncertain data, which can deal with epistemic uncertainty very well. In reference [20], a fuzzy DFT analysis method based on Monte Carlo model is proposed, and triangular fuzzy numbers are used to represent the failure rate to deal with the epistemic uncertainty problem. Reference [21] introduces the Pandora temporal fault tree, which can model the dynamic fault behaviors and transform the expert's fuzzy linguistic information into quantitative information for evaluation, which not only evaluates the reliability of complex systems, but also eliminates the problem of uncertainties. This method, however, requires a lot of manual operations, which is time-consuming and expensive. Aiming at the problems in the above references, [22] proposes a HiP-HOPS analysis model based on Petri net and Bayesian network, and automatically calculates the reliability results and applies it to the actual complex dynamic system, which proves its effectiveness. However, this method assumes that the basic events in the fault tree obey the exponential distribution and the distribution parameters are crisp values, and thus cannot deal with the epistemic uncertainty. For this reason, in reference [23], linguistic fuzzy set is used to describe the distribution parameters by resorting to domain experts, and a DFT is mapped into a stochastic Petri net to calculate some reliability parameters, which are used to provide decision support for improving system performance.

As for diagnostic algorithms, many researchers have proposed many effective methods. Reference [24] incorporates the sensor information into diagnosis process and considers DIF of components and the minimum cut set to diagnose the system. However, it is impossible to make decisions on the case where DIF of the minimal cut set is large and DIF of the component is small. Furthermore, the uncertainty of the test cost is ignored. Reference [25] presents a decision-making method based on DS-VIKOR, which considers the decision-making problem of multiple experts evaluating some attributes, and obtains the final ranking scheme. However, the mass function assignment under each attribute is usually obtained by domain experts based on experience evaluation, which easily leads to subjectivity and affects the efficiency of fault diagnosis. Besides, the algorithm considers only the single data type of crisp value. Reference [26] presents a dynamic fault diagnosis method based on DFT and Bayesian network. Firstly, a DFT is used to construct a system fault model, and then the fuzzy sets and domain experts are used to obtain the fuzzy failure rate of components. After that, reliability parameters are calculated and

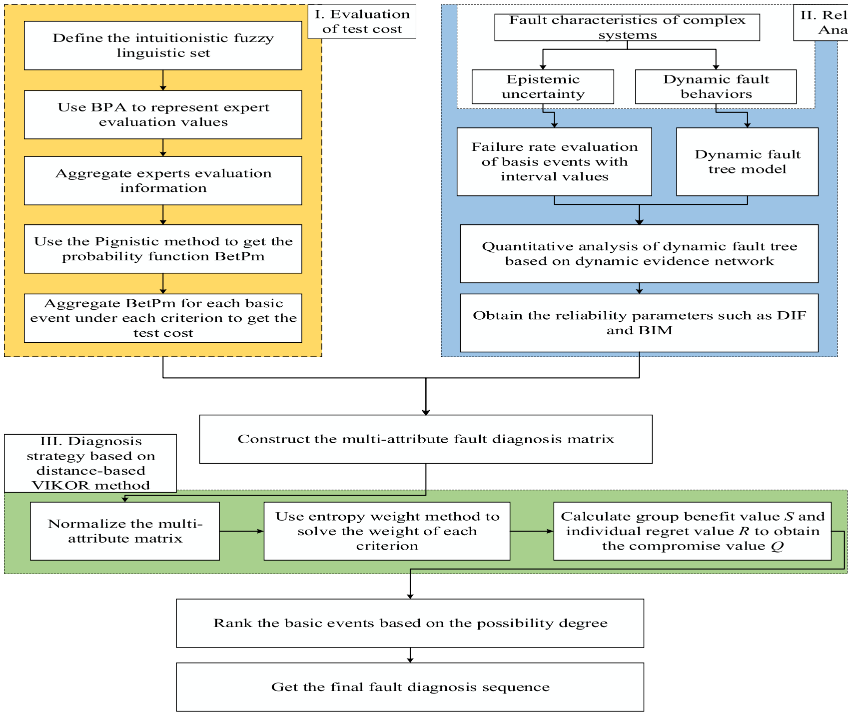

FIGURE 1. **A fault diagnosis strategy for complex systems based on multi-source heterogeneous information considering epistemic uncertainty.**

updated by sensors data. Finally, an efficient diagnostic decision tree can be generated to guide maintenance personnel to locate faults quickly using a TOPSIS algorithm. Nevertheless, the multi-attribute decision-making algorithm is still based on crisp value. Based on the above research [27] proposes a multi-attribute fault diagnosis method based on a dynamic evidence network. This method uses the system reliability results to construct the interval numbers multi-attribute diagnosis decision table, and the optimal diagnosis strategy is obtained based on a VIKOR algorithm. To some extent, this approach can improve the diagnostic efficiency, but the diagnostic decision tables belong to the same type of data (that is, the interval number) and cannot process heterogeneous information. To this end, a dynamic diagnostic strategy is proposed based on reliability analysis and an improved VIKOR algorithm [28], [29]. This method can deal with epistemic uncertainty and heterogeneous information. However, it ignores the uncertainty of the test cost and to some extent, has some influence on the diagnosis efficiency. Reference [30] presents a hybrid multi-attribute decision-making method, which considers the uncertainty of language assessment by decision makers and uses interval numbers to represent the language evaluation grades. This method has small information loss in the fusion process and can effectively overcome the defects of traditional methods.

Motivated by the problems mentioned above, this paper presents a fault diagnosis strategy for complex systems based on multi-source heterogeneous information such as test cost and reliability results shown in Fig. 1. Multiple factors are considered to construct the DFT model of complex systems. Interval numbers are used to describe the failure distribution parameters of basic events and test cost of these events are evaluated using the domain experts and intuitionistic fuzzy linguistic set to deal with epistemic uncertainty; Aiming at the problem of fault correlation, a DFT is used to establish the dynamic failure model and is converted into a dynamic evidential network to calculate some reliability parameters; Furthermore, a diagnostic decision table is constructed based on multi-attribute heterogeneous information such as qualitative evaluation information and quantitative reliability parameters; Finally, a novel fault diagnosis strategy is designed based on distance-based VIKOR algorithm, which can provide some decision support for fault diagnosis and locate the fault as quickly as possible.

The rest of the paper is arranged as follows. Section II introduces the concept of D-S evidence theory, VIKOR algorithm and interval numbers ranking method based on the probability degree. Section III presents the fusion rules of basic probability assignment (BPA), test cost evaluation method of basic events based on domain experts and D-S evidence theory. In section IV, the reliability analysis method and reliability parameters are introduced. Section V shows the fault diagnosis strategy based on multi-source heterogeneous information in detail. In section VI, an example of a specific braking system to illustrate the effectiveness of the proposed method. Finally, section VII draws conclusions and offers the further work suggestions.

II. PRELIMINARIES

A. INTUITIONISTIC FUZZY LINGUISTIC SET

Definition 1: Let $S = \{s_i \,|i = 1, 2, \ldots, 2t, s \in N\}$ be a limited set of linguistic terms [31]–[33]. s_i represents the combination of possible value sets of language variables with the following properties:

1) $s_i \geq s_j$, when $i \geq j$
2) $Min\{s_i, s_j\} = s_j$, when $i \geq j$
3) $Max\{s_i, s_j\} = s_i$, when $i \geq j$

Intuitionistic fuzzy language set S is an extension of linguistic term set, that is, the possible values of all its variables are represented by intuitionistic fuzzy numbers, $S = \{[s_i^-, s_i^+]|i = 1, 2, \ldots, 2t,\ s \in N\}$.

B. D-S EVIDENCE THEORY

Definition 2: D-S evidence theory [34], [35] is also called D-S theory. For a proposition that needs to be judged, the set of all the combinations of judgment hypotheses is limited. The set of these combinations of judgment hypotheses can be recorded as Θ and called Θ as the frame of discernment of this proposition [36].

$$\Theta = \{\theta_1, \theta_2, \ldots, \theta_i, \ldots, \theta_N\} \tag{1}$$

where all the elements in Θ are mutually independent and mutually exclusive, and contain all possible assumptions of the proposition. Since all the calculations of the evidence theory are carried out on the power set, the power set is defined as 2^Θ.

$$2^\Theta = \{\phi, \{\theta_1\}, \{\theta_2\}, \ldots, \{\theta_n\}, \{\theta_1, \theta_2\}, \ldots, \{\theta_1, \theta_n\}, \{\theta_1, \theta_2, \theta_3\}, \ldots, \Theta\} \tag{2}$$

Definition 3: When the frame of discernment is determined, the mass function m is defined as:

$$m : 2^\Theta \rightarrow [0, 1] \tag{3}$$

In D–S theory, a mass function is also called a BPA [37], which satisfies the following conditions:

$$m(\phi) = 0 \tag{4}$$

$$m(X) \geq 0 \tag{5}$$

$$\textstyle\sum_{X\in 2^\Theta} m(X) = 1 \tag{6}$$

Definition 4: Suppose m_1 and m_2 are two mass functions. Dempster's rule denoted by $m = m_1 \oplus m_2$ is defined as:

$$m(A) = \frac{\sum_{B\cap C=A} m_1(B)m_2(C)}{1 - K} \tag{7}$$

where K is the conflict coefficient between different evidences,
$K = \sum\limits_{B\cap C\neq\phi} m_1(B) \cdot m_2(C) = 1 - \sum\limits_{B\cap C=\phi} m_1(B) \cdot m_2(C)$, that is $K < 1$.

C. ENTROPY WEIGHT METHOD

In multi-attribute decision-making problems, the weights of evaluation attributes may be different, and their weights may also be unknown. The entropy weight method is a more objective evaluation method, which can obtain the weight of each attribute objectively. Entropy value H_i under criterion C_i is calculated by

$$H_i = -K \sum_{j=1}^{n} m(F_{ij}) \ln m(F_{ij}) \tag{8}$$

where $K = 1/\ln n (K > 0, 0 \leq m(F_{ij}) \leq 1)$; if $m(F_{ij}) = 0$, $m(F_{ij}) \ln m(F_{ij}) = 0$.
Then, the deviation degree coefficient α_i under attribute C_i is calculated by the following equation.

$$\alpha_i = 1 - H_i \tag{9}$$

Finally, we can get the weight value of each attribute:

$$\omega_i = \frac{\alpha_i}{\sum_{i=1}^{m} \alpha_i} \tag{10}$$

where $\sum\limits_{i=1}^{n} \omega_i = 1,\ 0 \leq \omega_i \leq 1$.

D. PIGNISTIC PROBABILITY FUNCTION BETP$_m$

Definition 5: Suppose m be a BPA on θ, so its Pignistic probability function BetP_m [38] is defined as:

$$BetP_m(\omega) = \sum_{A\subseteq\theta, \omega\in A} \frac{1}{|A|} \frac{m(A)}{1 - m(\phi)}, \quad m(\phi) \neq 1 \tag{11}$$

As $m(\phi) = 0,\ A \in \Theta$, we can simplify the above formula to the following equation.

$$BetP_m(\omega) = \sum_{\omega\in\Theta} \frac{m(A)}{|A|} \tag{12}$$

where $|A|$ is the cardinality of subset A; ω is the subset proposition in A. The purpose of the above formula is to convert BPA into the probability distribution for decision-making.

E. VIKOR METHOD

Vlsekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) method was developed by Opricovic in 1998 for multi-criteria optimization of complex systems. It can rank the limited decision-making schemes, maximize the group benefit value and minimize the individual regret, and finally obtain the compromise solution acceptable to the decision-maker. VIKOR method can rank the solutions directly, and the optimal solution obtained is closer to the ideal solution. In the case of decision-making, attribute evaluation values are usually expressed by more than two types of values. In order to take advantage of the information as much as possible, this heterogeneous information needs to be processed. The basic principle of VIKOR method is based on an aggregation function Lp-metric, which can describe the distance between

TABLE 1. Intuitionistic fuzzy linguistic set and corresponding values.

Importance	Abbreviation	Linguistic judgment	Corresponding values
Very low	VL	Almost no recognition to the performance	<0.15,0.80>
Low	L	Low evaluation to the performance	<0.25,0.65>
Medium low	ML	A low and middle level of performance	<0.40,0.50>
Medium	M	The level of the performance is medium	<0.50,0.50>
Medium high	MH	A middle and high level of performance	<0.60,0.30>
High	H	High evaluation to the performance	<0.75,0.15>
Very high	VH	Almost fully recognized this performance	<0.90,0.05>

different attributes [39], [40]. The aggregation function is defined as follows:

$$L_{p,j} = \{\sum_{i=1}^{n} [\omega_i(f_i^* - f_{ij})/(f_i^* - f_i^-)]^p\}^{1/p} \tag{13}$$

where $1 \leq p \leq \alpha,\ j = 1, 2, \ldots, J; f^-$ is the worst solution; f^* is the optimal solution of ideal solution; ω_i is the weight of attribute i; The value obtained from j^{th} basic event under i^{th} attribute is denoted by f_{ij}.

F. RANKING METHOD OF INTERVAL NUMBERS BASED ON THE POSSIBILITY DEGREE

Interval numbers can be obtained based on domain expert evaluation. Nevertheless, these interval values cannot be used directly to rank components and should be converted into relative possibility degrees. This paper uses a ranking method based on the possibility degree [41].

Definition 6: Suppose $A = [a^l, a^u], B = [b^l, b^u]$ are two interval numbers, the possibility degree that A is greater than B is calculated by:

$$P_{AB} = \begin{cases} 1 - \dfrac{1}{2e^{s-1/2}}, & s \geq 1/2 \\ \dfrac{1}{2e^{s-1/2}}, & s < 1/2 \end{cases} \tag{14}$$

where $L(a) = a^u - a^l, L(b) = b^u - b^l, e = a^u - b^l, s = e/(L(a) + L(b))$.

T is obtained by adding the rows to P_{AB}, and the final sort result value is calculated by the following formula:

$$r = \frac{1}{i} - \frac{i}{2(i-1)^2} + \frac{1}{(i-1)^2 T} \tag{15}$$

where i is the rows of P_{AB}.

III. EVALUATION METHOD OF TEST COST BASED ON DOMAIN EXPERT AND D-S THEORY

Test cost of basic events is an important evaluation parameter and plays an important role in actual fault diagnosis. The optimal diagnosis strategy should be low cost and high efficiency. For different basic events, their test cost may be different, and it is generally difficult to be evaluated with crisp values because of the uncertainty. Fuzzy set theory has been widely used to deal with vague scenarios by attributing a degree to which a certain object belongs to a set. However, traditional fuzzy set theory is not able to incorporate the uncertainty or hesitation in the membership functions. Intuitionistic fuzzy set, an extension to traditional fuzzy set, is useful in defining an imprecise quantity using fuzzy set where traditional fuzzy set cannot define the quantity due to the inadequacy of available information. In this section, intuitionistic fuzzy set is used to evaluate the test cost of basic events based on expert judgment.

A. EXPERT EVALUATION

Now suppose there are $K = \{1, 2, \ldots, k\}$ experts E to make decisions on $M = \{1, 2, \ldots, m\}$ basic events A under attribute C. Each expert evaluates basic events based on his or her own experience. The intuitionistic fuzzy linguistic term set is used to represent the corresponding evaluation value under each attribute. In this paper the linguistic term set of intuitionistic fuzzy numbers [42] is used to describe decision-making information as shown in Table 1, so the uncertainty can be judged more flexibly.

As shown in Table 1 above, 7 evaluation elements are defined, and these 7 elements constitute the recognition framework, and the corresponding BPA is assigned to the basic events under each criterion. For example, there are elements A, B, C, ..., and the corresponding belief function is $a, b, c, \ldots$. If $m(A) = a$, $m(B) = b$, $m(C) = c$, the rest part is θ, so we can get $m(\theta) = 1 - a - b - c - \ldots$.

B. BPA FUSION RULE

Definition 7: Based on Definition 4 and corresponding weight W_i(BPA), a compromise mass function can be obtained before combining them, expressed as follows:

$$\begin{aligned} m_i^{\omega}(A) &= \omega_i(BPA) \times m_i(A) \\ m_i^{\omega}(\theta) &= (1 - \omega_i(BPA)) + \omega_i(BPA) \times m_i(\theta) \end{aligned} \tag{16}$$

After getting information on basic events under different criteria of each expert for subsequent criteria determination. The next step is to obtain the mass function under each expert's criteria. According to the fusion information, all the distribution of mass function under different criteria can be obtained using the following formula.

$$m_i(BPA) = \oplus_1^R m_i^{\omega}(BPA) \tag{17}$$

where $\oplus$ is an orthogonal sum symbol; R is the number of evidences.

C. TRANSFORMING BPA INTO PROBABILITY DISTRIBUTION

The mass function of each basic event under each criterion can be obtained from the previous section. BPA can be transformed into probability distribution using Pignistic probability function BetP_m. Each probability distribution can be integrated into a value according to the aggregate function.

Definition 8: Suppose the importance of linguistic term set is $I_1, I_2, \ldots, I_n$ and the corresponding values is $W = (< W_1^-, W_1^+ >, < W_2^-, W_2^+ >, \ldots, < W_n^-, W_n^+ >)^T$, the probability distribution is $P = (P_1, P_2, \ldots, P_n)$, so, the test cost of aggregate is:

$$F(I_1, I_2, \ldots, I_n) = PW = < P_1 W_1^- + P_2 W_2^- + \cdots + P_n W_n^-, \quad P_1 W_1^+ + P_2 W_2^+ + \cdots + P_n W_n^+ > \tag{18}$$

where P is the probability distribution of BetP_m; F is the test cost of basic events. The probability function BetP_m under each criterion can be aggregated into a numerical value using the equation above.

IV. RELIABILITY ANALYSIS BASED ON DYNAMIC EVIDENCE NETEORK

Interval numbers are used to describe the failure distribution parameters of basic events to deal with the epistemic uncertainty problem in this paper. A dynamic evidence network, an extension of static initial evidence network in time, can propose a solution for DFT with interval distribution parameters of basic events. For the conversion of DFT into the dynamic evidence network, it can be divided into two parts. One part is a static evidence network, and the other part is a time attribute. DFT can be converted into a static evidence network first, and then dynamic evidence network can be obtained by adding time attribute [43]. After establishing the DFT model of the system, the DFT is mapped into a corresponding dynamic evidence network according to the above method and inference algorithm can be used to calculate some importance factors. Importance refers to the degree to which system performance is affected when several components fail.

A. DIF

DIF is the cornerstone of fault diagnosis method based on reliability analysis. It distinguishes different basic events in the system from the perspective of diagnosis. Basic events with higher diagnostic importance are more important. The DIF of a basic event refers to the failure probability of a basic event when the system fails. The calculation formula is:

$$DIF_X = P(X=1|S=1) = [Bel(\{F_{X|S}\}),\ Pl(\{F_{X|S}\})] \tag{19}$$

where X is a basic event in the system; DIF_X represents the DIF of the basic event X; $P(X|S)$ represents the failure probability of the basic event X when the system S fails; $[Bel(\{F_{X_i|S}\}), Pl(\{F_{X_i|S}\})]$ indicates the interval value of the failure probability that the basic event X fails when the system S fails.

B. BIRNBAUM IMPORTANCE MEASURE (BIM)

Birnbaum first introduced the reliability importance measure of a basic event in 1969 [44]. This measure is defined as the probability that a basic event is critical to the system failure i.e. when a basic event X fails it causes the system to move from a working to a failed state. BIM of a basic event X can be interpreted as the rate at which the system's reliability improves as the reliability of the basic event X is improved [45]. Similarly, interval BIM of a basic event X can be defined by the following equation.

$$BIM_X = [Bel(\{W_S\}|\{W_X\}), Pl(\{W_S\}|\{W_X\})] - [Bel(\{W_S\}|\{F_X\}), Pl(\{W_S\}|\{F_X\})] \tag{20}$$

where $Bel(\{W_s\}|\{W_X\})$ and $Pl(\{W_s\}|\{W_X\})$ represent respectively the belief and plausibility measures that the system is functioning when it is known that the basic event X is in a working state; $Bel(\{W_s\}|\{F_X\})$ and $Pl(\{W_s\}|\{F_X\})$ denote respectively the belief and plausibility measures that the system is functioning when the basic event X is in a failed state.

V. FAULT DIAGNOSIS STRATEGY BASED ON MULTI-SOURCE HETEROGENEOUS INFORMATION

A. CONSTRUCTING DIAGNOSTIC DECISION MATRIX

Three important parameters such as DIF, BIM and test cost are used to construct the diagnostic decision matrix of complex systems. DIF of a basic event distinguishes components from the perspective of diagnosis and the more important the basic event with a higher DIF is. BIM is one of the most widely used degrees of importance, which measures the increase of the system reliability when the reliability of the basic event is improved. Considering the cost problem in actual diagnosis, we have also introduced the test cost as an important evaluation parameter. Test cost plays an important role in actual fault diagnosis. The optimal diagnosis strategy should be low cost and high efficiency.

Based on the previous analysis, DIF and BIM are both expressed in interval numbers and belong to the benefit attributes. If the attribute value of a basic event is larger, the basic event is more important to the system failure. However, test cost is expressed by an intuitionistic fuzzy number, which is a cost attribute. Similarly, the smaller cost attribute value of a basic event is more favorable for the system fault diagnosis. In a word, DIF, BIM and test cost are used to construct the diagnostic decision matrix which is used to make decisions for fault diagnosis.

B. NORMALIZING DIAGNOSTIC DECISION MATRIX

Generally, the evaluation values of different attributes have different dimensions and cannot be directly compared. Therefore, heterogeneous information from different dimensions needs to be normalized to eliminate the influence of the dimension. The normalized matrix is obtained based on the following formula.

$$\begin{cases} r_{ij}^L = \dfrac{u_{ij}^L}{\max\limits_j u_{ij}^U} \\ r_{ij}^U = \dfrac{u_{ij}^U}{\max\limits_j u_{ij}^U}, \end{cases} \quad [u_{ij}^L, u_{ij}^U] \text{ is a benefit attribute} \tag{21}$$

$$\begin{cases} r_{ij}^L = \dfrac{\min\limits_j u_{ij}^L}{u_{ij}^U} \\ r_{ij}^U = \dfrac{\min\limits_j u_{ij}^L}{u_{ij}^L}, \end{cases} \quad [u_{ij}^L, u_{ij}^U] \text{ is a cost attribute} \tag{22}$$

$$P_{ij} = \begin{cases} [\frac{1}{n}\sum_{i=1}^{n} r_{ij}^L, \frac{1}{n}\sum_{i=1}^{n} r_{ij}^U] \\ < 1 - \prod_i^n (1-u_{ij}^L)^{\frac{1}{n}}, \prod_i^n (u_{ij}^U)^{\frac{1}{n}}, \\ \prod_i^n (1-u_{ij}^L)^{\frac{1}{n}} - \prod_i^n (u_{ij}^U)^{\frac{1}{n}} > \end{cases} \tag{23}$$

where r_{ij} is a interval number; u_{ij} is a intuitionistic number; P_{ij} is the final normalized matrix.

C. HAMMING DISTANCE MEASURE OF HETEROGENEOUS INFORMATION

Based on the previous analysis, evaluation values of attributes are expressed in interval numbers and intuitionistic fuzzy numbers. Hamming distance is used to measure the distance of the heterogeneous information.

Suppose $A = [a^-, a^+]$ is an interval number, $B = [b^-, b^+]$ is its normalized number, and the hamming distance between A and B is defined as:

$$d(A, B) = (|a^- - b^-| + |a^+ - b^+|)/2 \tag{24}$$

Suppose $C = (u_1, u_2)$ is intuitionistic fuzzy number, $D = (d_1, d_2)$ is its normalized number, and the degree of uncertainty is $u_3 = 1 - u_1 - u_2$. If d_3 is its normalized number, we can calculate the hamming distance between C and D using the following equation.

$$d(C, D) = (|u_1 - d_1| + |u_2 - d_2| + |u_3 - d_3|)/2 \tag{25}$$

D. DETERMING WEIGHT OF ATTRIBUTES

In order to determine the weight of each attribute, we need to calculate the BPA of basic events under each attribute using the fusion formula proposed above. The weight of each attribute can be obtained using the entropy weight method mentioned in Section II-C. Detail steps are as follows.

Firstly, the worst value f_j^- and optimal value f_j^* of the attribute are calculated using the following equation.

$$\begin{cases} f_j^- = \min\limits_i f_{ij}^L \\ f_j^* = \min\limits_i f_{ij}^U \end{cases} \tag{26}$$

TABLE 2. Ranking comparisons between the proposed method and existing methods.

Basic events	[46]	[47]	[28]	our proposed method
X1	1	2	1	1
X2	3	3	3	3
X3	2	1	2	2

In order to get the weight, as the evaluation value is the interval number or intuitionistic fuzzy number, the distance is needed to quantize these numbers to get the weight.

Secondly, $m(F_{ij})$ is obtained using the following equation.

$$m(F_{ij}) = \frac{d_{ij}}{\sum_{i=1}^{n} d_{ij}} \tag{27}$$

Finally, substituting equation (8), equation (9), and equation (10), we can obtain the weight of each attribute.

E. DETERMING THE OPTIMAL DIAGNOSTIC SEQUENCE

The group benefit value $S_i = [\underline{S_i}, \overline{S_i}]$ and individual regret value $R_i = [\underline{R_i}, \overline{R_i}]$ can be calculated using the following equations.

$$\underline{S_i} = \sum_{j=1}^{n} \omega_j (\frac{f_j^* - f_{ij}^U}{f_j^* - f_j^-}) \tag{28}$$

$$\overline{S_i} = \sum_{j=1}^{n} \omega_j (\frac{f_j^* - f_{ij}^L}{f_j^* - f_j^-}) \tag{29}$$

$$\underline{R_i} = \max_{j \in N} \{\omega_j (\frac{f_j^* - f_{ij}^U}{f_j^* - f_j^-})\} \tag{30}$$

$$\overline{R_i} = \max_{j \in N} \{\omega_j (\frac{f_j^* - f_{ij}^L}{f_j^* - f_j^-})\} \tag{31}$$

The compromise value of $Q_i = [\underline{Q_i}, \overline{Q_i}]$ can be calculated by

$$\underline{Q_i} = v\frac{\underline{S_i} - S^-}{S^+ - S^-} + (1\text{-}v)\frac{\underline{R_i} - R^-}{R^+ - R^-} \tag{32}$$

$$\overline{Q_i} = v\frac{\overline{S_i} - S^-}{S^+ - S^-} + (1\text{-}v)\frac{\overline{R_i} - R^-}{R^+ - R^-} \tag{33}$$

where $S^- = \min\limits_i \underline{S_i}$; $S^+ = \max\limits_i \overline{S_i}$; $R^- = \min\limits_i \underline{R_i}$; $R^+ = \max\limits_i \overline{R_i}$; v is introduced as the weight for the strategy of maximum group utility, whereas $1 - v$ is the weight of the individual regret.

If the condition $v > 0.5$ is met, it means that the decision is made with the consent of the vast majority of decision makers. If the condition $v < 0.5$ is met, the decision is made with the refusal of the vast majority of decision makers. In general, v can be arbitrarily selected from 0 to 1. In this paper, taking v as 0.5 means that the optimal diagnosis scheme of the system is determined according to the maximization of group benefit

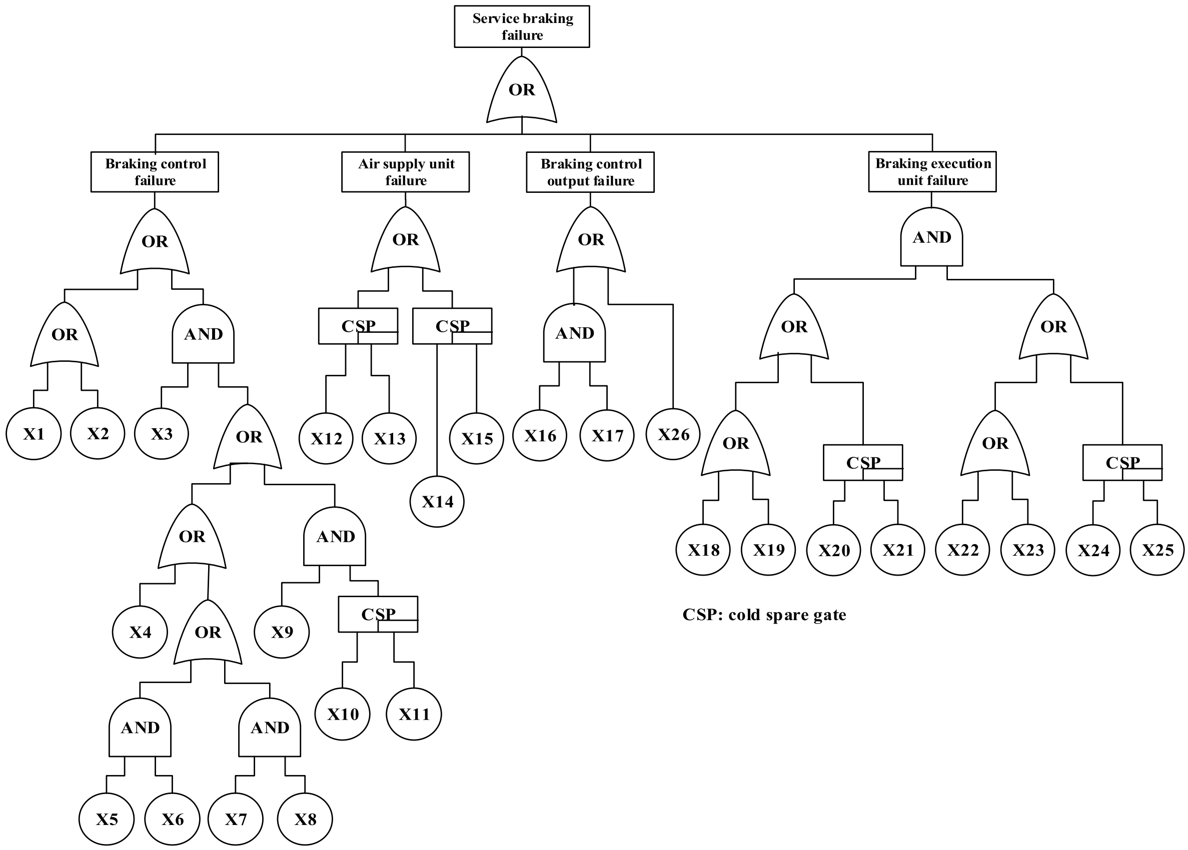

FIGURE 2. A DFT for service braking failure of a braking system.

TABLE 3. Basic events in a braking system.

Basic events	Name	Basic events	Name
X1	MBCU failure	X14	Air cylinder 1 failure
X2	EP Brake valve failure	X15	Air cylinder 2 failure
X3	Brake signal break	X16	Large diaphragm failure
X4	PWM power board failure	X17	Small diaphragm failure
X5	Digital input board failure	X18	High pressure oil seal failure
X6	Input and output board failure	X19	Low pressure oil seal failure
X7	Modulation board failure	X20	Clamp X ring 1 failure
X8	Digital output board failure	X21	Clamp X ring 2 failure
X9	PWM signal line break	X22	High pressure oil seal failure
X10	MVB network cable 1 break	X23	Low pressure oil seal failure
X11	MVB network cable 2 break	X24	Clamp X ring 1 failure
X12	Compressor 1 failure	X25	Clamp X ring 2 failure
X13	Compressor 2 failure	X26	Relay valve failure

value and the minimization of group individual regret degree. Finally, we can rank the basic events according to Q_i based on the possibility degree and obtain the optimal diagnosis sequence.

F. AN ILLUSTRATIVE EXAMPLE

To illustrate the effectiveness of the proposed multi-source heterogeneous fault diagnosis method, some existing methods are compared with our proposed method in this paper, which include Ref. [28], [46], [47]. We take the example shown in [46] so that we can compare the proposed method with existing methods.

Example:

$$(u_{ij}, v_{ij}) = \begin{pmatrix} [0.75, 0.90] & [0.60, 0.75] & <0.80, 0.20> \\ [0.80, 0.85] & [0.68, 0.80] & <0.45, 0.50> \\ [0.40, 0.55] & [0.75, 0.95] & <0.60, 0.30> \end{pmatrix}$$

TABLE 4. Interval failure rates of basic events.

Basic events	Interval failure rate /hour	Basic events	Interval failure rate /hour
X1	[2.88e-6, 4.20e-6]	X12,X13	[6.96e-6, 1.04e-5]
X3,X9	[6.08e-7, 9.12e-7]	X14,X15	[5.68e-6, 8.52e-6]
X4	[3.28e-7, 4.92e-7]	X16,X17	[5.44e-7, 8.16e-7]
X5	[1.12e-5, 1.68e-5]	X18,X19	[3.84e-5, 5.76e-5]
X6	[0.80e-6, 1.20e-6]	X20,X21	[3.84e-5, 5.76e-5]
X7	[0.88e-5, 1.32e-5]	X22,X23	[3.04e-5, 4.56e-5]
X8	[7.12e-6, 1.07e-5]	X24,X25	[3.04e-5, 4.56e-5]
X10,X11	[6.08e-7, 9.12e-7]	X26	[6.24e-6, 9.36e-6]

TABLE 5. BPA of three experts' evaluation of the basic events.

Basic events	E1	E2	E3
X1	m({MH,H})=0.3,m(θ)=0.7	m({H,VH})=0.2, m(θ)=0.8	m({VH})=0.1,m(θ)=0.9
X2	m({H})=0.4,m(θ)=0.6	m({MH})=0.3, m({H})=0.2,m(θ)=0.5	m({H,VH})=0.2, m(θ)=0.8
X3	m({H,VH})=0.2,m(θ)=0.8	m({VH})=0.3,m(θ)=0.7	m({H})=0.3,m(θ)=0.7
X4	m({VH})=0.5,m(θ)=0.5	m({M,MH})=0.4, m(θ)=0.6	m({MH,H})=0.4, m({VH})=0.1,m(θ)=0.5
X5	m({MH,H})=0.2, m({H})=0.3,m(θ)=0.5	m({H})=0.4,m(θ)=0.6	m({H,VH})=0.3, m(θ)=0.7
X6	m({MH})=0.4,m(θ)=0.6	m({H,VH})=0.3, m({θ})=0.7	m({H})=0.2, m({VH})=0.2,m(θ)=0.6
X7	m({MH,H})=0.1,m(θ)=0.9	m({MH,H})=0.4, m(θ)=0.6	m({MH})=0.2,m(θ)=0.8
X8	m({MH})=0.3, m({H})=0.1,m(θ)=0.6	m({H})=0.2,m(θ)=0.8	m({MH})=0.3,m(θ)=0.7
X9	m({H,VH})=1	m({H,VH})=0.9, m(θ)=0.1	m({H,VH})=0.3, m({VH})=0.5,m(θ)=0.2
X10	m({M,MH})=0.3,m(θ)=0.7	m({M,MH})=0.3,m({MH})=0.1, m(θ)=0.6	m({M,MH})=0.3, m({H})=0.1,m(θ)=0.6
X11	m({VH})=0.5,m(θ)=0.5	m({H})=0.5,m(θ)=0.5	m({H,VH})=0.4, m(θ)=0.6
X12	m({H})=0.1, m({VH})=0.2,m(θ)=0.7	m({H})=0.4, m({VH})=0.1,m(θ)=0.5	m({VH})=0.2,m(θ)=0.8
X13	m({MH})=0.3,m(θ)=0.7	m({MH})=0.3,m({MH,H})=0.1,m(θ)= 0.6	m({MH})=0.3, m({H})=0.1,m(θ)=0.6
X14	m({MH,H})=0.4, m({VH})=0.1,m(θ)=0.5	m({MH,H})=0.4, m(θ)=0.6	m({MH,H})=0.1, m({VH})=0.1,m(θ)=0.8
X15	m({H,VH})=0.1,m(θ)=0.9	m({VH})=0.1,m(θ)=0.9	m({H})=0.1, m({VH})=0.1,m(θ)=0.8
X16	m({VH})=0.3,m(θ)=0.7	m({H,VH})=0.2, m(θ)=0.8	m({VH})=0.2,m(θ)=0.8
X17	m({MH,H})=0.1, m({H})=0.3,m(θ)=0.6	m({MH,H})=0.2, m({H})=0.2,m(θ)=0.6	m({MH,H})=0.1, m(θ)=0.9
X18	m({H})=0.3,m(θ)=0.7	m({H})=0.2,m(θ)=0.8	m({H})=0.3,m({H,VH})=0.2,m(θ)=0.5
X19	m({M,MH})=0.4,m(θ)=0.6	m({M,MH})=0.2,m({MH})=0.2, m(θ)=0.6	m({M,MH})=0.3, m(θ)=0.7
X20	m({MH})=0.3,m(θ)=0.7	m({MH})=0.3, m(θ)=0.7	m({MH})=0.3,m({MH,H})=0.1, m(θ)=0.6
X21	m({H})=0.2,m({VH})=0.2, m(θ)=0.6	m({H,VH})=0.2, m(θ)=0.8	m({VH})=0.2,m(θ)=0.8
X22	m({H})=0.2, m({H,VH})=0.3,m(θ)=0.5	m({H})=0.2,m({H,VH})=0.3,m(θ)=0.5	m({H,VH})=0.3, m(θ)=0.7
X23	m({MH})=0.2,m(θ)=0.8	m({H})=0.2,m(θ)=0.8	m({M,MH})=0.2, m(θ)=0.8
X24	m({MH,H})=0.5,m(θ)=0.5	m({MH})=0.1,m({MH,H})=0.3,m(θ)= 0.6	m({H})=0.5,m(θ)=0.5
X25	m({MH,H})=0.3, m({H})=0.1,m(θ)=0.6	m({MH,H})=0.3, m(θ)=0.7	m({MH})=0.1,m({MH,H})=0.3, m(θ)=0.6
X26	m({MH})=0.1,m({MH,H})=0.2, m(θ)=0.7	m({MH})=0.2,m({MH,H})=0.1, m(θ)=0.7	m({MH,H})=0.2, m(θ)=0.8

where (u_{ij}, v_{ij}) represents the value of the i^{th} alternative under the j^{th} attribute.

Consider an air-condition system selection problem. Suppose there exist three air-condition systems X1, X2 and X3. Denote the alternative set by

A = {X1, X2, X3}. Suppose three attributes C1 (economical), C2 (function), and C3 (being operative) are taken into consideration in the selection problem. Values under attributes C1 and C2 are both interval numbers, and values under attribute C3 are intuitionistic fuzzy numbers. For

TABLE 6. Diagnostic decision table for fault diagnosis of the braking system.

Basic events	DIF	BIM	Test Cost
X1	[0.14233, 0.14459]	[0.91965, 0.965196]	<0.6277,0.2940,0.0783>
X2	[0.04433, 0.04496]	[0.91419, 0.961368]	<0.6607,0.2492,0.0901>
X3	[0.00124, 0.00185]	[-0.04679, 0.049173]	<0.6881,0.2384,0.0735>
X4	[0.00067, 0.00100]	[-0.04653, 0.049354]	<0.6745,0.2392,0.0863>
X5	[0.02215, 0.03304]	[-0.04770, 0.047695]	<0.6995,0.2088,0.0917>
X6	[0.00160, 0.00240]	[-0.04767, 0.047745]	<0.6714,0.2493,0.0793>
X7	[0.01745, 0.02606]	[-0.04768, 0.047724]	<0.5633,0.3532,0.0835>
X8	[0.01415 ,0.02114]	[-0.04768, 0.047734]	<0.5908,0.3202,0.0890>
X9	[0.00122 ,0.00182]	[-0.04770, 0.047695]	<0.8563,0.0813,0.0624>
X10	[0.00122, 0.00182]	[-0.04770, 0.047695]	<0.5522,0.3850,0.0628>
X11	[9.23e-7, 0.00061]	[-0.04770, 0.047695]	<0.7614,0.1644,0.0742>
X12	[0.01664 , 0.02346]	[-0.03301, 0.05561]	<0.7151,0.2099,0.0750>
X13	[0.00297, 0.00989]	[0.91843, 0.95976]	<0.5864,0.3211,0.0925>
X14	[0.00111, 0.00165]	[-0.04654, 0.048318]	<0.6510,0.2614,0.0876>
X15	[1.83e-5, 0.00056]	[0.91245, 0.959648]	<0.6212,0.3083,0.0705>
X16	[0.00112, 0.00166]	[-0.04665, 0.049183]	<0.7156,0.2220,0.0624>
X17	[0.00112, 0.00166]	[-0.04665, 0.049183]	<0.6536,0.2557,0.0907>
X18	[0.29559, 0.32213]	[0.09422, 0.228649]	<0.6904,0.2204,0.0892>
X19	[0.29559, 0.32213]	[0.09422, 0.228649]	<0.5492,0.3854,0.0654>
X20	[0.06523, 0.09322]	[-0.03775, 0.054004]	<0.5764,0.3320,0.0916>
X21	[0.00883, 0.03851]	[0.07898, 0.219255]	<0.7102,0.2204,0.0694>
X22	[0.29559, 0.32213]	[0.09422, 0.228649]	<0.7424,0.1743,0.0833>
X23	[0.29559, 0.32213]	[0.09422, 0.228649]	<0.5626,0.3601,0.0773>
X24	[0.06523, 0.09322]	[-0.03775, 0.054005]	<0.6888,0.2345,0.0767>
X25	[0.00883, 0.03851]	[0.07898, 0.219255]	<0.6322,0.2751,0.0927>
X26	[0.30735, 0.31166]	[0.91919, 0.971704]	<0.5882,0.3230,0.0888>

TABLE 7. Normalized multiple attribute decision table.

Basic events	DIF	BIM	Test Cost
X1	[0.4418, 0.4489]	[0.9464, 0.9933]	<0.0373,0.9540,0.0087>
X2	[0.1376, 0.1396]	[0.9408, 0.9894]	<0.0407,0.9480,0.0113>
X3	[0.0038, 0.0057]	[-0.0482, 0.0506]	<0.0438,0.9463,0.0098>
X4	[0.0021, 0.0031]	[-0.0479, 0.0508]	<0.0423,0.9465,0.0113>
X5	[0.0688, 0.1026]	[-0.0491, 0.0491]	<0.0452,0.9415,0.0133>
X6	[0.0050, 0.0075]	[-0.0491, 0.0491]	<0.0419,0.9480,0.0101>
X7	[0.0542, 0.0809]	[-0.0491, 0.0491]	<0.0314,0.9608,0.0079>
X8	[0.0439, 0.0656]	[-0.0491, 0.0491]	<0.0338,0.9571,0.0091>
X9	[0.0038, 0.0056]	[-0.0491, 0.0491]	<0.0719,0.9080,0.0201>
X10	[0.0038, 0.0056]	[-0.0491, 0.0491]	<0.0304,0.9640,0.0056>
X11	[2.8653e-6, 0.0019]	[-0.0491, 0.0491]	<0.0536,0.9329,0.0135>
X12	[0.0517, 0.0728]	[-0.0340, 0.0572]	<0.0471,0.9417,0.0111>
X13	[0.0092, 0.0307]	[0.9452, 0.9877]	<0.0334,0.9572,0.0094>
X14	[0.0034, 0.0051]	[-0.0479, 0.0497]	<0.0397,0.9497,0.0106>
X15	[5.6809e-5, 0.0017]	[0.9390, 0.9876]	<0.0366,0.9558,0.0076>
X16	[0.0035, 0.0052]	[-0.0480, 0.0506]	<0.0472,0.9438,0.0090>
X17	[0.0035, 0.0052]	[-0.0480, 0.0506]	<0.0400,0.9489,0.0111>
X18	[0.9176, 1]	[0.0970, 0.2353]	<0.0441,0.9435,0.0124>
X19	[0.9176, 1]	[0.0970, 0.2353]	<0.0302,0.9640,0.0058>
X20	[0.2025, 0.2894]	[-0.0388, 0.0556]	<0.0325,0.9585,0.0090>
X21	[0.0274, 0.1195]	[0.0813, 0.2256]	<0.0465,0.9435,0.0100>
X22	[0.9176, 1]	[0.0970, 0.2353]	<0.0508,0.9350,0.0142>
X23	[0.9176, 1]	[0.0970, 0.2353]	<0.0313,0.9615,0.0072>
X24	[0.2025, 0.2894]	[-0.0388, 0.0556]	<0.0439,0.9457,0.0103>
X25	[0.0274, 0.1195]	[0.0813, 0.2256]	<0.0377,0.9516,0.0107>
X26	[0.9541, 0.9675]	[0.9460, 1]	<0.0335,0.9575,0.0090>

comparison, the interval numbers under the attributes C1 and C2 need to be converted into intuitionistic fuzzy numbers in [47]. Similarly, the intuitionistic fuzzy numbers under the attribute C3 need to be converted into interval numbers in [28], [47]. Table 2 exhibits the order results of the proposed method and existing methods.

TABLE 8. Interval values of *S*, *R* and *Q* for search scheme of system fault diagnosis.

Basic events	*S* value	*R* value	*Q* value
X1	[0.1437, 0.6052]	[0.1369, 0.4513]	[0.2112, 0.7968]
X2	[0.2246, 0.6806]	[0.2138, 0.4497]	[0.3382, 0.8331]
X3	[0.5242, 0.9921]	[0.2686, 0.4482]	[0.5512, 0.9891]
X4	[0.5247, 0.9933]	[0.2685, 0.4489]	[0.5514, 0.9905]
X5	[0.5029, 0.9756]	[0.2690, 0.4475]	[0.5409, 0.9800]
X6	[0.5234, 0.9930]	[0.2690, 0.4491]	[0.5513, 0.9906]
X7	[0.4989, 0.9860]	[0.2690, 0.4542]	[0.5389, 0.9928]
X8	[0.5045, 0.9873]	[0.2690, 0.4530]	[0.5417, 0.9922]
X9	[0.5433, 0.9787]	[0.2690, 0.4345]	[0.5614, 0.9670]
X10	[0.5160, 0.9989]	[0.2690, 0.4547]	[0.5476, 0.9999]
X11	[0.5321, 0.9886]	[0.2690, 0.4434]	[0.5557, 0.9820]
X12	[0.5079, 0.9746]	[0.2667, 0.4465]	[0.5409, 0.9784]
X13	[0.2476, 0.7149]	[0.2408, 0.4532]	[0.3801, 0.8545]
X14	[0.5229, 0.9942]	[0.2688, 0.4502]	[0.5509, 0.9924]
X15	[0.2555, 0.7173]	[0.2480, 0.4516]	[0.3922, 0.8539]
X16	[0.5256, 0.9905]	[0.2686, 0.4465]	[0.5519, 0.9865]
X17	[0.5231, 0.9941]	[0.2686, 0.4500]	[0.5507, 0.9922]
X18	[0.2263, 0.7239]	[0.2163, 0.4480]	[0.3420, 0.8532]
X19	[0.2163, 0.7307]	[0.2163, 0.4548]	[0.3369, 0.8642]
X20	[0.4464, 0.9457]	[0.2672, 0.4537]	[0.5103, 0.9718]
X21	[0.4478, 0.9484]	[0.2191, 0.4468]	[0.4571, 0.9655]
X22	[0.2304, 0.7202]	[0.2163, 0.4447]	[0.3440, 0.8479]
X23	[0.2175, 0.7302]	[0.2163, 0.4543]	[0.3375, 0.8633]
X24	[0.4526, 0.9401]	[0.2672, 0.4481]	[0.5134, 0.9627]
X25	[0.4438, 0.9526]	[0.2191, 0.4511]	[0.4551, 0.9724]
X26	[0.0113, 0.4798]	[0.0081, 0.4532]	[0,0.7354]

From the ranking results given in Table 2, it can be observed that all methods show X2 is the worst choice. In addition, the ranking results obtained by our proposed method are completely consistent with [46], [28], which shows that the method proposed in this paper is effective. The inconsistent results between different methods can be understood by the different expressions of information and different weighting methods. The comparisons between the proposed method and [47] method show that there are a few differences in ranking order. The reason is that the intuitionistic fuzzy numbers are transformed into the interval numbers which can be applied in [47] and this transformation will cause some errors. Moreover, the normalization of multi-source heterogeneous matrix is different from that of the single attribute matrix, which is also the reason for the deviation of the results. The methods in [46], [47], [28] proposed essentially can only process single data type. However, our proposed method can deal with the multi-source heterogeneous information and can more accurately describe the uncertainty of complex systems.

VI. APPLICATION IN A BRAKING SYSTEM

In this section, the proposed method is applied to a braking system in urban rail transit system. DFT of the braking system is shown in Figure 2. The fault tree model is mainly composed of basic events X1 $\sim$ X26, several intermediate events and a top event, which includes logical AND gates, OR gates and cold spare gates. Table 3 lists all basic events in the braking system. It is assumed that basic event X2 follows a two-parameter Weibull distribution with parameters $\beta = 3.304$, $\eta = [4692.7, 5159.7]$ and other basic events follow the exponential distribution and corresponding failure rates expressed with interval values are given in Table 4.

In order to evaluate the test cost of 26 basic events, three experts are used to obtain BPA of three experts' evaluation of the basic events shown in Table 5 based on the intuitionistic fuzzy set. The test cost of all events can be obtained using the proposed method in section 3. Assume that the task time is 2000 hours, the DFT is converted into a corresponding dynamic evidential network. Furthermore, the DIF and BIM of all basic events can be calculated. In the end, a multi-attribute decision table and the normalized table are given in Table 6 and 7 respectively.

Based on the entropy methodology, the weights of three attributes are determined to be $\omega_1 = 0.2484$, $\omega_2 = 0.2968$, and $\omega_3 = 0.4548$. The S, R and Q values of fault diagnosis strategy can be obtained according to the improved VIKOR method, as shown in Table 8. Interval Q values are converted into definite values using the equation (15). The corresponding results are shown in Table 9. According to the Table 9,

TABLE 9. Ranking of search schemes for system fault diagnosis.

Basic events	Ranking value	Basic events	Ranking value
X1	0.0351	X14	0.04
X2	0.0363	X15	0.0369
X3	0.04	X16	0.0399
X4	0.04	X17	0.04
X5	0.0398	X18	0.0365
X6	0.04	X19	0.0366
X7	0.0399	X20	0.0393
X8	0.0399	X21	0.0387
X9	0.0399	X22	0.0365
X10	0.04	X23	0.0366
X11	0.04	X24	0.0393
X12	0.0397	X25	0.0388
X13	0.0368	X26	0.0336

the optimal diagnosis sequence is X26 $\succ$ X1 $\succ$ X2 $\succ$ X18(X22) $\succ$ X19(X23) $\succ$ X13 $\succ$ X15 $\succ$ X21 $\succ$ X25 $\succ$ X20(X24) $\succ$ X12 $\succ$ X5 $\succ$ X7(X8 X9 X16) $\succ$ X3 (X4 X6 X10 X11 X14 X17). Obviously, the first basic event to be diagnosed is X26 when the braking system fails. If X26 fails, the diagnosis process is over. Otherwise, we should diagnose the next basic event X1 until the braking system is back to normal. In order to avoid subjectivity and arbitrariness, this method uses entropy weight method to determine attribute weights. In addition, the proposed diagnosis algorithm is based on multi-source heterogeneous information and adopts a new normalization method to obtain the optimal diagnosis sequence, which can handle the epistemic uncertainty problem and dynamic fault behaviors in complex systems.

VII. CONCLUSION

This paper proposes a novel fault diagnosis strategy for complex systems based on the multi-attribute heterogeneous information, which combines reliability analysis and intuitionistic fuzzy linguistic set. A DFT is adopted to establish a system fault model to capture the dynamic failure behaviors, and interval numbers are used to represent interval distribution parameters of the basic events in the fault tree to deal with the problem of epistemic uncertainty. Furthermore, DFT is converted into a dynamic evidence network for quantitative analysis, which can effectively handle the problem of DFT solution with an interval distribution parameter. Besides, test cost of basic events is evaluated using domain experts and intuitionistic fuzzy linguistic set; In addition, a diagnostic decision table is constructed based on multi-attribute heterogeneous information such as DIF, BIM and test cost; Finally, a novel fault diagnosis strategy is designed based on distance-based VIKOR algorithm, which can provide some decision support for fault diagnosis and locate the fault as quickly as possible.

In the future, we will fuse sensor information to update the reliability results in order to optimize the diagnosis process.

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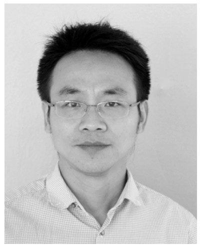

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