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Hierarchical Storage Model and Priority Ranking Method of Rules in Rule-based Reasoning System

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Abstract

It is very difficult to create the fault trees based on components framework for some complex equipment. So a multi-hierarchy diagnosis method based on fault categories is proposed in this paper. The according storage model of rules is designed, and the concept of rule priority is introduced. Then, a rule priority ranking method based on fuzzy multi-attribute group decision making method is proposed. Finally, the uncertainty diagnosis reasoning flow and the credibility transfer algorithm based on the proposed multi-hierarchy diagnosis reasoning method and rule priority ranking method are detailed. The application case and analysis show that the proposed method has a good performance on the aspect of conflict resolution, and can improve diagnosis efficiency markedly.

Keywords: rule priority ranking; hierarchical fault diagnosis; fuzzy multi-attribute group decision making (FMAGDM); uncertainty reasoning; decision support system

1. Introduction

The Fault diagnosis for complex equipment has many unique features, which mainly implies that there are usually complex nested faults between parts and components because of powerful function and complex structural relations. A fault is often caused by many factors, among which there are very complex linkages; and the weight of each factor contributing to the final fault is very vague, which has typical characteristics such as relevance and uncertainty.[1] If using a simplify method to process the weight, it cannot accurately reflect the characteristics of the complex equipment fault diagnosis. Therefore, it is extremely difficult to diagnose the fault of complex equipment.

Currently, the reasoning method widely used in the fault diagnosis expert system is the diagnostic tree method based on hierarchical decomposition of devices, which determines there is or not a fault by retrieving the rules of component nodes.[1-10] If there is a fault, the diagnosis process should turn into a certain child node of the component node. Otherwise, the diagnosis process should sequentially turn into the next node at the same layer, until all nodes in the same layer are retrieved.

For complex equipment, because of the foregoing characteristics, it is difficult to effectively create a diagnostic tree based on hierarchical decomposition of devices. So a multi-hierarchy diagnosis method based on fault categories is proposed, and the according storage model of rules is designed. Such a reasoning

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strategy is based on the available fault symptoms and all relations among the faults and need not further consider the position relationships and functional relationships among the components.

In the rule-based reasoning system, it is probable to generate clash or ambiguity when retrieving and matching rules or sub-goals. That is so-called matching conflicts. Therefore, the rule-based fault diagnosis system must have the conflict resolution mechanism. A usual method is to determine directly the retrieval order according to the credibility of rules, but the simple method cannot improve the efficiency of matching rules. For that reason, all factors that can affect the matching efficiency should be considered. Liu [2] presented the concept of rule priority, according to which the retrieving and executing orders of rules can be determined.

In different fault diagnosis fields, the factors that affect the rule priority may not be the same exactly, and the importance of each factor may be different. Besides the credibility of rules, the common factors also include the credibility of premises, the probability of fault symptoms (premises), the weight of premises, the difficulty of getting the property values of premises, etc. Therefore, when determining the rule priority, we need as synthetically as possible to consider the factors such as the manifestations of equipment faults, the fault signal detection methods, analysis and processing methods, the probabilities of faults, the consequences caused by faults, the credibility of rules, the credibility of fault symptoms, and the judging characteristics of field experts. Lai[11] considered the credibility of rules and the credibility of fault symptoms, Liu[1] and Dou[4] considered the fault probability, diagnostic time-consuming, complexity, and so on.

When determining the rule priority by considering synthetically various factors, it is feasible to use the multi-attribute decision making (MADM) theory and method. The values of some factors such as the credibility of rules are often given by experts in the form of the vague language subjectively. The experts differ possibly on the importance of the foregoing factors because of the differences in people's subjective knowledge. For that reason, in this paper, we propose the method of determining the rule priority by using the fuzzy multi-attribute group decision making (FMAGDM).

FMAGDM theory is already used in the fault diagnosis field, but it is not widespread up to now. Such studies are still in their initial phase. Refs. 4-5 and 12 described one kind of expert systems based on the priority diagnostic tree for the fault diagnosis of mechanical equipment. Here the fuzzy group multiple attribute decision making method was applied to fault diagnosis, and see Refs. 11-15 for more details. Du[4] proposed the fault diagnosis model of power transformers based on the combination of fuzzy multiple attribute decision making method and D-S evidence theory. Yao[5] introduced the fault diagnosis method of electronic devices controlling missile launch based on the fuzzy group multiple attribute decision making. Wu[12] realized the fine diagnosis fault by analyzing the status information of rotating machineries based on fuzzy multi-attribute decision making method. Each of the aforementioned cases used the classic Zadeh fuzzy set theory to deal with fuzziness. From the perspective of decision makers, they were mainly based on the individual decision making or the simply summation of the multiple decision making. In fact, the application of determining the rule priority usually requires more than one expert to participate in decision-making, which belongs to the application field of FMAGDM. Group decision-making is very different from the individual decision-making in these respects of decision-making process and evaluation criteria. Therefore, there are many limitations in using the individual decision making method to deal with the group decision making problem.

For this reason, a rule priority ranking method based on the fuzzy multi-attribute group decision making is proposed in order to ensure the rationality of rule priority ranking and improve the ranking quality.

2. Hierarchical Diagnosis Strategy and Storage Model of Rules

2.1. *Basic idea about the hierarchical diagnosis strategy*

The basic idea about the strategy is to divide all rules into several diagnostic hierarchies according to fault characteristics, fault categories, and the relations among them, and each hierarchy has several fault categories. Each fault category in the different hierarchy has a set of diagnosis rules, and the execution sequence of these diagnosis rules is determined by the rule priority. The conclusion of the executed rule can be taken as a premise of these rules in the next hierarchy. According to the complexity of the equipment fault, the number of the diagnostic hierarchy should be different for diverse equipment. Fig.1 is a demonstration of three diagnostic hierarchies. The three hierarchies can be respectively named for fault detection hierarchy, fault location hierarchy, and final diagnostic conclusion hierarchy.

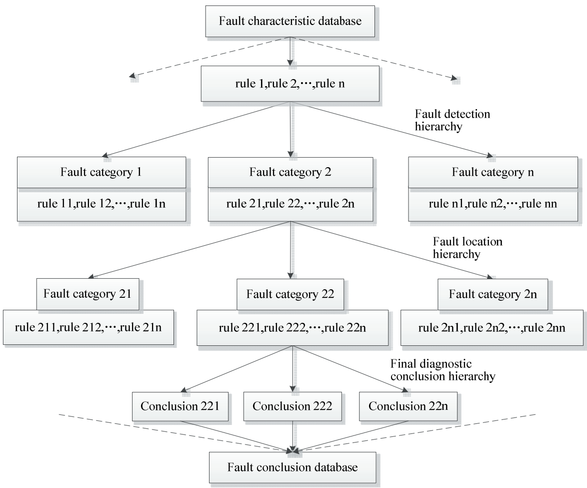

Fig.1. The organization chart of the hierarchical diagnosis strategy

2.2. *The storage model of rules*

We designed a kind of storage model for the rule in accordance with the multi-hierarchy diagnosis strategy. The key of the storage model is that the rule database table has the hierarchy field and the fault category field. The storage structure of rules is shown as Table 1. Each rule has at most three fault symptoms as the precondition. When the conditions are more than three, they can be split into two or more rules. It can avoid the problem that the rule database and the diagnostic process are too complicated. But these split rules can have the same conclusion, each rule has only one conclusion code field. The category attribute field (CA) is used to explain which fault category the rule belongs, it and the conclusion code field (Conclusion ID) together can determine the hierarchy position of the rule in the entire diagnostic process.

3. Rule Priority Ranking Method Based on FMAGDM

According to the above, each fault category in a different hierarchy contains a set of diagnosis rules, and the execution orders of these diagnosis rules are determined by priority ranking.

The main factors affecting the rule ordering are the credibility of rules, the credibility of premises, the weight of each premise (when multiple premises), the probability of fault symptoms (premises), and so on. These influencing factors are called the attributes of rules, which affect the priority ranking in different weights. Among them, the credibility of rules and the weight of premises are the most important attributes, which should have greater weights. And their values are generally given by experts in the form of vague languages directly. The credibility of premises is given either by users directly or by the transfer algorithm based on uncertain reasoning (when the premise is the conclusion of these rules in the upper layer). The probability of premises is determined based on statistical information. Because of the differences of subjective judgments, different experts or users must have disagreements about the importance of the same attribute. Therefore, we propose a rule priority ranking method based on fuzzy multiple attribute group decision making.

Table 1. The table structure in the rule base.

Field name	Explanation	Data type	Length	Null value?
Rule ID	Rule code	Int	4	No
Symptom ID1	Corresponding fault symptom code	Int	4	No
Symptom ID2	Corresponding fault symptom code	Int	4	Yes
Symptom ID3	Corresponding fault symptom code	Int	4	Yes
Conclusion ID	Corresponding conclusion code	Int	4	No
CF(E)	Certainty factor of the precondition	Real	4	No
CF	Certainty factor of the rule	Real	4	No
CA	Category attribute of the rule	Varchar	16	No

3.1. *An approach to transforming fuzzy languages into fuzzy numbers*

Of all attributes of rules, some are qualitative attributes expressed in vague languages, like the credibility factor, some are quantitative attributes expressed in exact numbers, like the probability of fault symptoms. Only when the various forms of decision-making information are unified will the assembly process of group decision-making be completed. Considering the fuzzy numbers have greater advantages than the language values in the computing and processing, we provide a method to transform the attribute values of linguistic information into the fuzzy numbers. The operations of general fuzzy numbers are very difficult, so we use the trapezoidal fuzzy number in this paper. In fact, the triangular fuzzy number and interval-valued fuzzy number (rectangular fuzzy number) are special forms of the trapezoidal fuzzy number. The general form of trapezoidal fuzzy numbers is $M = (a, b, c, d)$, which means a real number about between *b* and *c*, obviously the values of *a, b, c* and *d* determine the characteristics of the trapezoidal fuzzy number.

In order to have a better partition degree, we utilize nine fuzzy language judgment indexes in this paper, which are Absolute good, Best, Better, Good, General, Bad, Worse, Worst and Absolute bad. The more indexes to use, the more accurate the experts offer the fuzzy language values. On the other hand, the meaning expressed in two adjacent indexes should not be absolutely different, since it is a vague expression. In consideration of subjective factor, even if various experts offer the same index, there are not identical meanings in the index. Another angle, the meaning of adjacent indexes should have some degree of overlap. So, the values of these trapezoidal fuzzy numbers need the ability to express the differences of adjacent indexes.

In this paper, we simplified the procedure of determining the values of *a, b, c* and *d*, so these values are inerratic and equally spaced, as shown in Table 2 and Fig.2. In fact, the values should be determined by communicating with the fault diagnosis experts in the relevant field.

The nine trapezoidal fuzzy numbers have original values between 0 and 30, which can well indicate the fuzzy relation between the nine level indexes. For convenient for comparing, these original values need to be normalized to have values between 0 and 1. Based on the transform relations in Table 2, we can convert the vague language attribute values into the normalized trapezoidal fuzzy numbers, and then utilize the fuzzy number algorithms for computing and processing.[16]

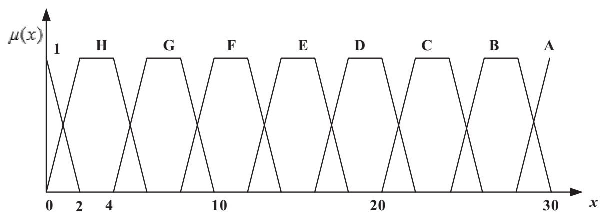

Fig.2. Utilizing trapezoidal fuzzy numbers to express the fuzzy language judgment indicators

3.2. *Ranking indexes of fuzzy numbers*

There are three kinds of common ranking indexes for fuzzy numbers, which are Kim-Park method, barycenter method and Li Rongjun method.[16-18] We adopt the barycenter method here.

Definition 1. Let F_x and σ_x be the mean value and the variance of a fuzzy number *X*, represented as follows respectively[19]:

Table 2. The transform relations between the nine fuzzy language judgment indexes and the normalized trapezoidal fuzzy numbers.

Grade	Language judgment indexes	Trapezoidal fuzzy numbers	Normalized trapezoidal fuzzy numbers
A	Absolute good	(28, 30, 30, 30)	(0.933, 1, 1, 1)
B	Best	(22, 24, 26, 28)	(0.8, 0.867, 0.933, 1)
C	Better	(20, 22, 24, 26)	(0.667, 0.733, 0.8, 0.867)
D	Good	(16, 18, 20, 22)	(0.533, 0.6, 0.667, 0.733)
E	General	(12, 14, 16, 18)	(0.4, 0.467, 0.533, 0.6)
F	Bad	(8, 10, 12, 14)	(0.267, 0.333, 0.4, 0.467)
G	Worse	(4, 6, 8, 10)	(0.133, 0.2, 0.267, 0.333)
H	Worst	(0, 2, 4, 6)	(0, 0.067, 0.133, 0.2)
I	Absolute bad	(0, 0, 0, 2)	(0, 0, 0, 0.067)

$$F_x = \frac{\int x\mu(x)dx}{\int \mu(x)dx} \quad (1)$$

$$\sigma_x = \left[\frac{\int x^2\mu(x)dx}{\int \mu(x)dx} - F_x^2\right]^{\frac{1}{2}} \quad (2)$$

then, the fuzzy number ranking index based on the barycenter method can be expressed as follows:

$$F_{1x} = F_x - \rho\sigma_x \quad (3)$$

where ρ is the expert's uncertainty preference coefficient in group decision-making, $\rho = 0$ indicates the expert is uncertainty neutral decision-making, $\rho > 0$ indicates the expert is uncertainty averse decision-making, $\rho < 0$ indicates the expert is uncertainty preference decision making.

Specially, the mean value $F_m$and the variance σ_m of the trapezoidal fuzzy number $M = (a, b, c, d)$ can be respectively defined as follows:

$$F_m = \frac{c^2+d^2-a^2-b^2-ab+cd}{3(c+d-a-b)} \quad (4)$$

$$\sigma_m = \left[\frac{c^3+d^3+cd^2+c^2d-a^3-b^3-ab^2-a^2b}{6(c+d-a-b)} - \frac{(c^2+d^2+cd-a^2-b^2-ab)^2}{9(c+d-a-b)^2}\right]^{\frac{1}{2}} \quad (5)$$

Eq. (4) and Eq. (5) simplify the calculation of means and variances for trapezoidal fuzzy numbers.

3.3. *Ranking method based on FMAGDM*

Definition 2. Let $S = \{s_1, s_2, s_3, \dots s_m\}$ be a rule set, and it has *m* rules, each rule has *n* attributes effecting its ordering, the *n* attributes form an attribute set $P = \{p_1, p_2, p_3, \dots p_n\}(n \geq 2)$, and let *s* experts take part in the decisions, the *s* experts form an expert set $E = \{e_1, e_2, e_3, \dots e_s\}$, then, according to the judgment values given by the experts for the attributes, an information system *J* can be expressed as follows:

$$\mathrm{J} = \langle E, S \times P, V_{S\times P}, g\rangle \quad (6)$$

where *E* is a set denoting all experts involved in the decision-making, *S* is a rule set, *P* is an attribute set denoting all attributes which effect the rule ordering, and

$$S \times P = \{\langle s_i, p_j\rangle : i = 1,2,3, \dots, m; j = 1,2,3, \dots, n\}$$

where $\langle s_i, p_j\rangle$ denotes an expert's judgment value to the attribute p_j of the rule s_i, $V_{S\times P}$ is a fuzzy set denoting all judgment values given by one expert for all attributes of all rules (the trapezoidal fuzzy number is used in this paper).

Mapping $g: \mathrm{E} \times (S \times P) \to V_{S\times P}$ denotes $\forall e_k \in E$, $\forall \langle s_i, p_j\rangle \in S \times P$, then $\mathrm{g}(e_k, \langle s_i, p_j\rangle) \in V_{S\times P}$.

Let $V_k = \left(V_{ij}^k\right)_{m\times n}$be a fuzzy decision matrix offered by the expert e_k , and $\forall i \in \{1,2,3, \dots, m\}$, $\forall j \in \{1,2,3, \dots, n\}$. Thus, the rule ranking model based on fuzzy multiple attribute group decision-making is established. As mentioned, it is noteworthy that some of attribute values are given by experts in fuzzy languages, some attribute values are determined by the statistics or the calculation. The fuzzy language values should be transformed into the normalized trapezoidal fuzzy numbers. In the following, we consider the expert weights and the attribute weights.

3.4. *Determine the expert weights*

As mentioned above, different experts or users must have disagreements about the importance of the same attribute, the given attribute values may be different. So, we need to consider the expert weights during the comprehensive judgment.

According to Eq. (6), let the number μ_k represent the weight of the experte_k, and meet the normalization requirement $\mu_k > 0$, $\sum_{k=1}^{s} \mu_k = 1$. The number μ_k is a synthetic weights based on the subjective weight and the objective weight, given directly according to the actual situation.[15, 20]

3.5. *Determine the attribute weights of rules*

Attributes such as the credibility of rules, the credibility of premises, and the weight of premises, influence the rule priority ranking in varying degrees. So, we introduce the attribute weights during the comprehensive judgment. The weight of each attribute is given by experts in fuzzy language variables.

Definition 3. Let $L = (L_{kj})_{s\times n}$be a fuzzy language decision matrix composed of all attribute weight values given by *s* experts for *n* attribute of one rule, and let $F = (F_{kj})_{s\times n}$ be the corresponding fuzzy number decision matrix by transforming matrix *L*, the group evaluation fuzzy number vector of the attribute weight $F^A = \left(F_j^A\right)_{1\times n}$can be expressed as follows:

$$F^A = \sum_{k=1}^{s} \mu_k F_{kj} \quad (7)$$

Every element in the vector F^A is a fuzzy number, whose ranking index can be calculated by using the barycenter method, based on Eq.(3), Eq.(4) and Eq.(5). Thus the exact number vector, whose form is $F^B = \left(F_j^B\right)_{1\times n}$, is got, and by the normalization processing, the final attribute weight vector F^N can be expressed as follows:

$$F^N = \left(F_j^N\right)_{1\times n} = \left(F_j^B\right)_{1\times n} / \sum_{j=1}^{n} F_j^B \tag{8}$$

3.6. *The comprehensive judgment of the rule ranking based on FMAGDM*

According to the fuzzy decision matrix $V_k = \left(V_{ij}^k\right)_{m\times n}$ that is defined in Definition 2, the expert weight μ_k and the attribute weight F^N, the comprehensive judgment index of the rule ranking based on FMAGDM can be expressed as follows:

$$U_i = \sum_{j=1}^{n} \sum_{k=1}^{s} \mu_k V_{ij}^k F_j^N \tag{9}$$

where $i = 1,2,3, \dots, m$.

Because V_k is a fuzzy matrix, U_i is a fuzzy number. Likewise, the ranking index value of the fuzzy number U_i can be calculated by using the barycenter method, based on Eq.(3), Eq.(4) and Eq.(5), also known as the ranking index value of the rule.

4. Reasoning Strategy

The premises and rules are only some degree of credibility, so the conclusion is not entirely credible in the hierarchical fault diagnosis. And for this reason, the reasoning process is actually the transfer process of an uncertainty. In the multi-hierarchy reasoning process, the conclusion of the executed rule is taken as one of the premises of the rules in the next hierarchy. For the fault diagnosis of a complex device, maybe such progression reasoning is required repeatedly in order to obtain the final diagnosis conclusion.

4.1. *Representation of the uncertainty rule*

Definition 4. Let the uncertainty rule be defined as follows:

IF $E_1\{t_1\}$ *AND* $E_2\{t_2\}$ *AND … AND* $E_n\{t_n\}$
THEN H WITH CF

where

- $E = \{E_1, E_2, \dots, E_n\}$ denotes the premise set or fault characteristic set. Rules can have a single premise, can also have a composite premise;
- E_i denotes a single premise.
- *H* denotes the conclusion. The above representation is a case having a single conclusion, of course, multi-conclusions is also feasible.
- $t_i (i = 1,2,3, \dots, n)$ denotes the premise credibility of the premise E_i, the range (0,1]. Its value is given by experts in the field in the form of vague languages. The value of t_i is 1 if the premise is a hard fact.
- *CF* denotes the rule credibility which indicates the degree of support that the conclusion *H* is true, the range (0, 1]. Its value is given by experts in the field in the form of vague language.

The initial credibility values are in the forms of fuzzy languages. Firstly, transform the values into the fuzzy numbers and normalize them, then get the ranking indexes of the fuzzy numbers with Eq. (3). The ranking index values are regarded as credibility values.

When multiple premises are used in a rule, the weight of different premise is different. The weight subset corresponding with the premise subset can be expressed as $a = \{a_1, a_2, a_3, \dots, a_n\}$, which must meet the following conditions:

$$\sum_{i=1}^{n} a_i \le 1, \quad i = 1,2,3, \dots, n$$

where *n* is the number of premises, a_i are real number between (0, 1] for the weight values, which are provided by experts in the forms of fuzzy languages. We can determine a_i in the same way that is used to determine the attribute weights.

4.2. *Credibility transfer algorithm*

As above, t_i denotes the credibility of the premise E_i. The total credibility of the premises $CF(E)$ can be expressed as follows[16]:

$$CF(E) = CF(E_1 \wedge E_2 \wedge \dots E_n) = min\{t_1, t_2, \dots t_n\} \tag{10}$$

The conclusion credibility of the rule can be calculated by the following equation.

$$CF(H) = CF \cdot CF(E) \tag{11}$$

where *CF* represents the rule credibility, $CF(E)$ represents the total credibility of the premise, $CF(H)$ represents the conclusion credibility. If a conclusion is confirmed by two rules, the final credibility of the conclusion can be calculated by the following equation:

$$CF(H) = CF(H)_1 + CF(H)_2 - CF(H)_1 \cdot CF(H)_2 \tag{12}$$

where $CF(H)_1$ and $CF(H)_2$ represent the conclusion credibility of two rules, respectively.

In the hierarchical diagnosis, the conclusion of upper hierarchy is a premise for the next hierarchy. For complex equipment fault diagnosis, the reasoning among the hierarchies may experience many times for obtaining the diagnosis conclusion. The progressive diagnosis process is actually an uncertain reasoning process. In the situation, the conclusion credibility of rules can be got by the credibility transfer algorithm. The transfer formula is as follows:

$$\begin{cases} CF(H) = CF \cdot CF(E) \\ CF(E) = min\{CF(H^*), t_1, t_2, \dots\ t_n\} \end{cases} \tag{13}$$

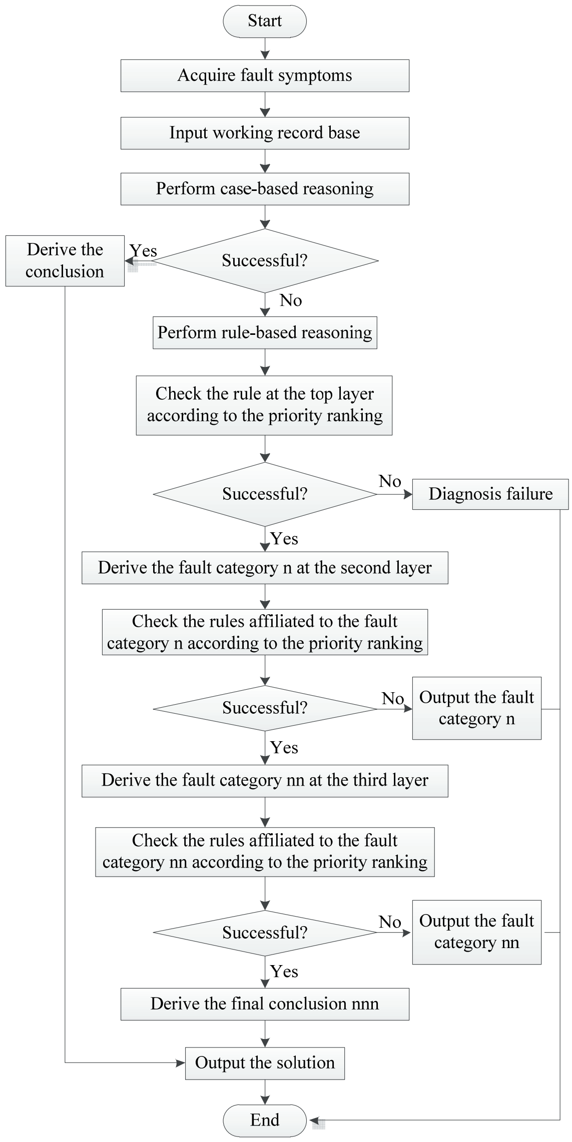

Fig. 3. The flow chart for the inference engine

where $CF(H^*)$is the conclusion credibility of the upper rules.

4.3. *Uncertain reasoning process in the hierarchical fault diagnosis*

When the diagnosis reasoning is executed, it retrieves and matches these rules on the top layer firstly, the reasoning process progresses into the next hierarchy if the match is successful, otherwise, it goes into the intervention situation, which corrects the diagnosis process through the human-computer interaction. When the diagnosis process goes into the next hierarchy, the conclusion corresponds to a fault category, and it is actually the premise of the set of rules that belong to the fault category. So the premise credibility must be corrected by Eq. (13), and the credibility of the final diagnosis conclusion is got by Eq. (13). Obviously, diagnostic credibility will reduce with increasing the diagnosis hierarchy. Therefore, planning reasonably the diagnostic hierarchies is very important to improve the reliability of the diagnosis conclusion.

In retrieving rules, first of all, it matches the premise of every rule according to the fault cases and related parameters, if the premises of some rules fit well with the currently inputted fault characteristic parameters, the matching are successful. Then the ranking index values of all matching rules are computed by using the comprehensive judgment method of the rule ranking based on FMAGDM, and the rule with the highest index value will be executed. The conclusion credibility of the executed rule is calculated by using Eq. (13), and then which is compared with the thresholds designated for each fault category, the diagnosis process goes into the next hierarchy if it is greater than the threshold, otherwise, the next rule will be executed and compared sequentially according to their index values. If all rules in the current fault category are matched but do not succeed, the diagnosis process is over and the current fault category is regarded as the diagnostic conclusion, or turns into the model of human-computer interaction, as shown in Fig.3.

5. The Application and Performance Analysis

5.1. *Brief Information about the software system*

We developed a fault diagnosis expert system for intelligent instruments by applying the diagnosis reasoning strategy given in the aforementioned sections.

In fact, the system is an updated version of the previous system, [11] of which major improvements are in the rule storage model and the reasoning strategy that are elaborated in this paper. Its function structure is shown in Fig.4. We elaborated the system structure, knowledge base and reasoning strategy of the previous system in the Ref. 11. The system is open and extensible, at present, which is effective to 9 kinds of equipment such as comprehensive measurement class (TX6392 communication synthetically testing instrument etc.), waveform measurement class (TEK2245A multi-functional oscilloscope etc.), signal source class (QF1022 low-frequency signal generator etc.), characteristic parameters measurement class (SD4130 automatic modulation testing instrument etc.). Among them, the multifunctional oscilloscope has 3 diagnostic hierarchies, a total of 157 rules, which are stored in 16 data tables according to fault categories. In addition to the rule base, the system also includes case library, fault characteristics base, diagnosis conclusion base, troubleshooting knowledge base and working record base, a total of 6 databases. In the diagnosis, the case-based reasoning is done firstly, if no case match, the diagnosis enters into the rule-based reasoning process. Similarity method is adopted for the conflict resolution in case-based reasoning, by which the cases can be ranked according to the similarity values among them and the given fault characteristic information.[21-22] The rule-based reasoning adopts the conflict resolution strategy introduced above, namely, the diagnosis reasoning method combining the multi-hierarchy diagnosis and the rule priority ranking method.

5.2. *Performance analysis*

The availability of the diagnosis reasoning strategy has been demonstrated through the software system developed by us for a certain air unit. Since the system was used, more than 300 diagnosis cases (including dozens of instrument equipment) statistically show that the diagnostic accuracy rate is more than 91percent.

The diagnostic accuracy is directly related to the number of rules and the credibility values given by experts, therefore it cannot fully reflect the performance of the diagnosis reasoning strategy. And setting different matching threshold has an effect to the diagnosis results in some extent. For that reason, we illustrate the performance of this diagnosis reasoning strategy by comparing the human-computer interaction frequency between the existing system and the original system. Human-computer interaction is more, the amount of information required to provide is greater, and the time needed for diagnosis is longer, which reflect the diagnosis efficiency is lower, and the performance of reasoning strategy is poorer.

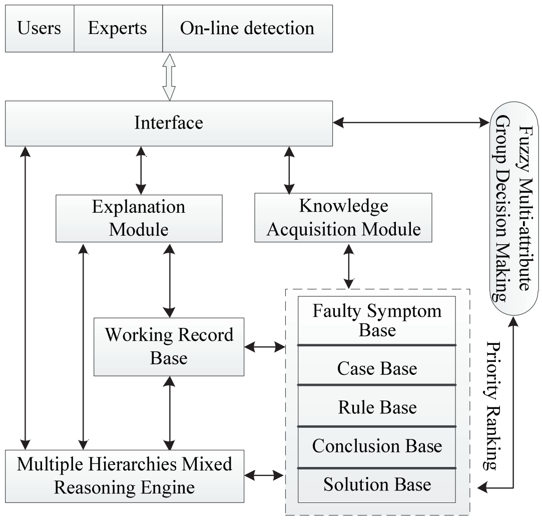

Fig.4. The framework of the fault diagnosis expert system

In order to facilitate comparison, we select 90 cases from more than 100 actual diagnosis cases belonging to two kinds of equipment, which have been verified correct diagnostic conclusions can be drawn in the two systems. Table 3 shows the comparison results that the performance of this system is 20 percent higher than the original system from the point of view of the number of interactions alone, for functions more, fault model more complex HP8656B signal generator, the performance

Table 3. Human-computer interaction frequency and performance contrast.

Name of equipment	The number of cases	The number of interactions of this system	The number of interactions of original system	The difference of the number of interactions	Performance improvement
Multifunctional oscilloscope	38	75	83	8	9.6%
Signal generator	52	117	137	20	14.6%
Comprehensive comparison	90	192	220	28	12.7%

improvement is more obvious relatively.

Because there is no need to retrieve all rules, the reasoning speed is greatly improved in the multi-hierarchy diagnosis reasoning.

6. Conclusion

This paper introduces a kind of fault diagnosis method based on the multi-hierarchy diagnosis reasoning strategy; these rules in the same fault category are retrieved according to their priority ranking index values which are determined by using the fuzzy multi-attribute group decision making. Such a diagnosis reasoning strategy is particularly suitable for the situation of complex device diagnosis that it is difficult to effectively create a diagnostic tree based on hierarchical decomposition of devices. Using such a diagnosis reasoning method combining the multi-hierarchy diagnosis and the rule priority ranking method, the system do not need to search the entire rule base, so the retrieval speed and diagnosis efficiency have a great improvement. Application examples show that the reasoning strategy and the priority ranking method of rule can effectively reduce the number of human-computer interaction, and the accuracy of diagnostic conclusions can be significantly improved.

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