A Fault Diagnosis and Maintenance Decision System for Production Line Based on Human-machine Multi-Information Fusion

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ABSTRACT

In this paper, we describe the importance of the operation and maintenance in manufacturing systems for Manufacturing Enterprises. Through the mining of enterprise fault detection information by data mining method, we obtain the probability of machine failure. The importance of each machine in the manufacturing system is evaluated by the FUZZY FMEA method, and the importance information of the machine is obtained. Moreover, based on the D-S evidence theory, the contradictory and conflict information is merged in this paper, and a machine fault operation and maintenance decision-making system based on human-machine multi-information fusion is constructed. The feasibility of the decision-making system is verified by industrial case.

CCS Concepts

• Information systems → Information systems applications → Decision support systems → Data analytics

Keywords

Decision Support Systems; Information Fusion; Operation & Maintenance

1. INTRODUCTION

For manufacturing companies, an efficient and stable manufacturing system is the key element of a company's long term development. The manufacturing of multi-process products is usually done by multiple machines, and the quality of the machine will determine the quality of products[1]. In order to detect possible failures of machine as early as possible, most manufacturing companies have deployed various types of fault alarm devices in the manufacturing system to detect machine failures[2]. The number of alarms is related to the tolerance of sensor's error. If the tolerance of sensor's error is set to be too large, it will not offer any efficient early warning. Conversely, a sensitive sensor error range will result in a large number of alarm prompts, making useful fault information submerged in massive alarm messages. Therefore, most of the machine alarm systems will classify the level of alarm according to the content and type of the actual alarm, and prioritize fault alarms. Such an alarm handling mechanism typically focuses on these alarms that have an impact on the quality of the currently produced product, and does not consider the machine itself to be the subject of fault handling. However, with the advent of personalized customization, more and more manufacturing systems need to face the test of production tasks of small batches and multiple types of products This fault handling mode for current production products makes it difficult to calibrate the types of alarms in multi-product manufacturing processes and cannot meet the actual needs of multi-product manufacturing. At the same time, product-oriented fault handling mode can't exploit critical but easily overlooked critical faults in manufacturing systems. For example, if there are two alarm prompts in the manufacturing system at a certain moment, one is the low priority fault of the critical equipment, and the other is the high priority fault of the secondary equipment. Then, due to the trigger mechanism of the system, the maintenance worker will be recommended to solve the problem of the secondary equipment. The alarm system will not care that if a critical equipment fails, it may even cause a large area of production to stagnate. Therefore, it is necessary to comprehensively consider the above two kinds of information. On the one hand, it is necessary to obtain the abnormality of the alarm information detecting device from the existing manufacturing system manufacturing process, and on the other hand, it is necessary to obtain the influence of each device itself on the manufacturing system from the experience or the expert system. Then, combining these two kind of information may help us build a more useful and stable fault diagnosis and maintenance decision system.

Section 2 of this paper will take the manufacturing and processing machine in the manufacturing system as research object, and introduce how to model the alarm information of the actual industrial production line and the expert information of the machine importance. Section 3 mainly introduces how to adopt the improved D-S evidence theory to obtain a comprehensive human-machine joint decision-making system to guide the daily maintenance of the production line machine failure. Section 4 will apply the aforementioned theoretical method to analyze an actual production line example to explain how to build a more useful and stable fault diagnosis and maintenance decision system On a certain production line. The conclusion and prospect will be presented in Section 5.

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2. INFORMATION MODELING

The purpose of this section, information modeling, is to map all kinds of information in the manufacturing system to the attributes that can be utilized by the machine operation and maintenance. The main consideration here is the modeling of alarm information and the modeling of expert information on machine importance.

2.1 Alarm Information Modeling

The alarm information is the most direct response to the local anomaly in the manufacturing system, and includes various types of information such as alarm codes, alarm levels, alarm machine information, and time of alarm occurrence. There are a large number of alarm types generated in actual industrial production lines, which can make it difficult to locate from an alarm to an abnormal machine. According to a survey conducted in the enterprise, we found that similar alarm codes usually occur on similar machines, and in most cases, alarms with similar time also represent the same machine. Therefore, the two dimensions of alarm codes and alarm occurrence time can be taken for analysis. Based on the similarity consideration, *k*−means method can be used for clustering in these two dimensions. After clustering, the machines corresponding to each subclass are reversed according to the main alarm in the sub-class. The probability of each machine's suspected failure is synthetically assigned by the number of alarms and the importance of each type alarms in each sub-class.

Clustering algorithm involves clustering validity, which is the problem of the optimal number of clusters. There are some uncertain but unknown noises in alarm information, so it is difficult to build the reference standards and measure the consistency of clustering results and by external methods to evaluate the excellent clustering results. According to the Calinski−Harabasz (*CH*) Index[3-4], the geometric structure of the data samples can be quantitatively described, and the clustering results can be evaluated by using the data set itself and the statistical characteristics of the clustering results. *CH* index can be expressed as follows:

$$CH = \frac{[traceB/(k-1)]}{[traceW/(n-k)]}$$

Where *B* and *W* are the inter-class variance matrix and the intraclass variance matrix, respectively, *n* is the number of all machine alarms, and *k* is the number of sub-classes.

Actually, CH index, a function of k ,*n*, can be expressed by CH(k,*n*). The variables k and *n* are all integers. In alarm modeling, *n* takes 10 to represent the 10 machines. Hence, the CH function is transformed into a unary function of k. By taking different values for k, the corresponding CH value can be calculated. The k at the highest CH value is the number of clusters.

The *k*−means clustering is performed according to the number of best sub-classes obtained by the *CH* index, then sub-classes of each alarm can are obtained. For each sub-class *j*, the number of alarms can be weighted by the alarm importance score to determine the category i, and can compute score S_{ij} of the jth alarm sub-class for the ith machine. So, the probability of a suspected failure of the machine is:

$$\mathrm{p(j)} = \frac{\sum_i S_{ij}}{\sum_i \sum_j S_{ij}}.$$

2.2 Machine Importance Modeling

The determination of the importance of the machine mainly depends on the engineer's effective experience judgment on the manufacturing activities. By establishing the $FUZZY\ FMECA$, the importance degree of each machine is mapped to the influence weight on the manufacturing system. $FMECA$ [5-6] comprehensively considers the importance of each machine in the production line from the machine failure frequency, machine failure severity, machine failure detection possibility and the degree of difficulty in machine failure maintenance. The $FUZZY$ method[7] is used to reduce the irrationality of subjective evaluation by experts and enhance the consistency of evaluation ranking.

The following are the main processes for establishing *FUZZY FMECA*:

$Step\ 1$: Establish Factor Set

Factor set is a collection of factors that affect an assessment object, usually expressed as U:

$$U = \{u_1, u_2, \dots, u_i, \dots, u_n\},$$

Where u_i represents the ith influential factor.

For machine failure problems, we consider each machine from four factors: Failure Probability Level, Fault Severity Level, Difficulty in Fault Detection, and Degree of Difficulty in maintenance.

$Step$ 2: Establish Evaluation Level Set

Evaluation Level Set is a collection of evaluation results that may be made to an evaluation object, usually expressed as V:

$$V = \{v_1, v_2, \dots, v_j, \dots, v_m\},$$

Where v_j represents the jth evaluation factor.

We divide the evaluation results into 1 to 4 levels to evaluate. The level "1" represent the lowest degree and "4" highest degree. Next, we can do fault analysis for each machine by filling the following table for each machine according to historical experiences and expert suggestions.

Table 1. Fuzzy factor evaluation matrix

Factor Set	level			
	1	2	3	4
Failure Probability				
Fault Severity Level				
Degree of Difficulty in Fault Detection				
Degree of Difficulty in maintenance				

$Step$ 3: Establish Factor Set

In the fuzzy comprehensive evaluation and analysis process of the faulty machine, we use r_{ij}^k to represent the membership of the ith factor to the evaluation level j in kth machine. and the membership degree of each factor is evaluated. The commonly used evaluation method is to set up an expert evaluation group composed of h people. Each member evaluates one evaluation level v_j for each influential factor u_i^k. If there are h_{ij}^kpeople in the h group members evaluating that u_i^k belongs to v_j, then we get the evaluation set of u_i^kas:

$$\boldsymbol{R_i^k} = \left\{\frac{h_{i1}^k}{h}, \frac{h_{i2}^k}{h}, \dots, \frac{h_{im}^k}{h}\right\} = \{r_{i1}^k, r_{i2}^k, \dots, r_{im}^k\},$$

$$\sum_{j=1}^{m} \boldsymbol{r_{ij}^k} = 1.$$

Next, the evaluation level of each factor in the kth machine is written as the level evaluation matrix of the machine fuzzy factor:

$$\boldsymbol{R^k} = [R_1^k \ R_2^k \ \dots \ R_n^k]^T = \begin{bmatrix} r_{11}^k & r_{12}^k & \cdots & r_{1m}^k \\ r_{21}^k & r_{22}^k & \dots & r_{2m}^k \\ \vdots & \vdots & & \vdots \\ r_{n1}^k & r_{n2}^k & \dots & r_{nm}^k \end{bmatrix}$$

***Step* 4: Determine the Set of Weights for Each Influential Factor**

Use AHP (Analytical Hierarchy Process) to solve weights [8-9]. First, the relative importance value of the influential factor u_i to u_j is represented by a_{ij},and the value of a_{ij} can be selected according to the following table.

Table 2. Judgment of factor importance degree

Meaning	a_{ij}
u_i is as important as u_j	1
u_i is slightly more important than u_j	3
u_i is obviously more important than u_j	5
u_i is strongly more important than u_j	7
u_i is definitely more important than u_j	9

Then, Construction judgment matrix:

$$\boldsymbol{A} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{21} \\ \vdots & \vdots & & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{bmatrix}$$

According to the judgment matrix $\boldsymbol{A}$, the largest eigenvalue λ_{max} and its corresponding eigenvector $\xi = [x_1 \ x_2 \ \dots \ x_n]$ are calculated. Then, perform a consistency test and calculate the consistency ratio R_c:

$$R_c = \frac{I_c}{I_R},$$

Where I_c is the consistency indicator:

$$I_c = \frac{\lambda_{max} - n}{n-1}.$$

I_c represents the average random consistency index of the judgment matrix. For 1 ~ 13 rank judgment matrix, the value of I_R can refer to the following table:

Table 3. I_R of 1 ~ 13 rank judgment matrix

n	I_R	n	I_R
1	0.00	8	1.41
2	0.00	9	1.45
3	0.58	10	1.49
4	0.90	11	1.52
5	1.12	12	1.54
6	1.24	13	1.56
7	1.32		

When $R_c < 0.1$, it is considered that the consistency of the judgment matrix is acceptable, otherwise the judgment matrix should be appropriately modified. Taking x_i in corresponding eigenvector as the importance degree coefficient w_i of the factor u_i, normalize the feature vector ξ as a weight if necessary.

Assuming that the factor weighting term of the machine k is w_i^k, then the factor weight set of the machine k is $W^{\boldsymbol{k}} = \{w_1^k, w_2^k, \dots, w_n^k\}, 0 < w_i^k < 1$, and the normalization condition is satisfied: $\sum_{\boldsymbol{i=1}}^{\boldsymbol{m}} w_i^k = 1$.

***Step* 5: Establish Level-One Fuzzy Comprehensive Evaluation**

Rewrite the set of factor weights of the machine to a vector form:

$$\boldsymbol{B^k} = \boldsymbol{W^K} \cdot \boldsymbol{R^K}$$

$$= [w_1^k \ w_2^k \ \dots \ w_n^k]^T \cdot \begin{bmatrix} r_{11}^k & r_{12}^k & \cdots & r_{1m}^k \\ r_{21}^k & r_{22}^k & \dots & r_{2m}^k \\ \vdots & \vdots & & \vdots \\ r_{n1}^k & r_{n2}^k & \dots & r_{nm}^k \end{bmatrix}.$$

In the formula, $\boldsymbol{B^k}$ is the fuzzy comprehensive evaluation vector of the machine.

***Step* 6: Determination for Comprehensive Importance Level**

In order to see the results more intuitively, the weighted average method will be used to obtain a simple numerical value to indicate the comprehensive importance level as following formula.

$$\boldsymbol{C^k} = \boldsymbol{B^k} \cdot \boldsymbol{V^T}$$

***Step* 7: Normalized Machine Comprehensive Importance**

Through the above calculations, it is concluded that the importance of each machine is $\boldsymbol{C^k}$. By weighting all the importance degrees, the machine importance of the entire manufacturing system can be normalized. The relative importance of each machine can be computing by the following formula:

$$C_{norm}^k = \frac{C^k}{\sum_{i=1}^{k} C^k}$$

and C_{norm}^k satistified:

$$\sum_{i=1}^{k} C_{norm}^k = 1.$$

3. INFORMATION FUSION DECISION

At this point, the probabilities of suspected failures of the machine and the relative importance of the normalization of the machine have been obtained. The following considerations are how to integrate the information obtained by data mining with the experience of human experts to provide decision-making basis for the final machine operation and maintenance. In the consideration of information fusion, the contradiction and conflict between information should be considered. In this section, we will discuss how to overcome the contradictions and conflicts in the information fusion process through the improvement of D-S (Dempster-Shafer) evidence theory.

3.1 D-S Evidence Theory

The D-S evidence [10-12] theory first defines a space X, called the recognition framework, consisting of some mutually exclusive and exhaustive elements. Any proposition A in the problem domain should be included in 2^X. The definition map, m: $2^X \to [0,1]$, is a Basic Probability Assignment Function (BPAF), which m satisfies: (1) $m(\emptyset) = 0$; (2) $0 \le m(\emptyset) \le 1, \forall A \subset X$; (3) $\sum_{A \subset X} m(A) = 1$. If $A \subset X$,and $m(A) > 0$, A is called a focus element. In the D-S evidence theory, the description of the event uses intervals $[Bel(A), Pl(A)]$, Bel and Pl is called the trust function and the likelihood function.

D-S evidence theory provides an evidence formula that can be synthesized from multiple sources of evidence. The definition is as follows:

$$\boldsymbol{m(A)} = \frac{\boldsymbol{1}}{\boldsymbol{1-k}} \sum_{\boldsymbol{A_i \cap B_j \cap C_l \cdots = A}} \boldsymbol{m_1(A_i) \cdot m_2(B_j) \cdot m_3(C_l)} \cdots$$

In this formula, $k = \sum_{A_i \cap B_j \cap C_l \cdots = \emptyset} m_1(A_i) \cdot m_2(B_j) \cdot m_3(C_l) \cdots$.

The value of k represents the degree of evidence conflict. The coefficient $1/(1-k)$ is called the normalization factor, and its purpose is to avoid assigning a non-zero probability to the empty set during synthesis.

3.2 Improved D-S Evidence Theory

The traditional D-S evidence theory method will not be able to fuse evidence in the case of extreme conflicts and contradictions. Therefore, the D-S evidence formula needs to be improved [13-14].

Suppose the evidence set corresponding to $m_1, m_2, \ldots, m_n$ is $F_1, F_2, \ldots, F_n$, and the conflict between the evidence sets i and j is k_{ij}, then:

$$k_{ij} = \sum_{\substack{A_i \cap A_j = \Phi \\ A_i \epsilon F_i, A_j \epsilon F_j}} m_i(A_i) \cdot m_j(A_j)$$

Defining ε is the credibility of the evidence, $\varepsilon = e^{-k}$,where $k = \frac{1}{n(n-1)/2} \sum_{i<j} k_{ij}$, $i, j < n$, n is the number of evidence sources. k is the average of the sum of each pair of evidence sets in n evidence sets, which reflects the degree of conflict between two evidences. k is the decreasing function of n, reflecting the credibility of the evidence, that is, when the conflict between the evidences increases, the credibility of the evidence will decrease.

The new synthesis formula is defined as follows:

$$m(\phi) = 0$$

$$m(A) = p(A) + k * \varepsilon * q(A), A \neq \phi, X$$

$$m(X) = p(X) + k * \varepsilon * q(X) + k(1-\varepsilon)$$

where

$$p(A) = \sum_{\substack{A_i \epsilon F_i \\ \cup_{i=1}^{n} A_i = A}} m_1(A_1) m_2(A_2) \cdots \cdot m_n(A_n)$$

$$q(A) = \frac{1}{n} \sum_{i=1}^{n} m_i(A)$$

The formula also can be rewritten as follows:

$$m(A) = (1-k) \frac{p(A)}{1-k} + k * \varepsilon * q(A).$$

The first term of this formula is the D-S evidence synthesis formula. Therefore, the new synthesis formula is actually a weighted sum form, $(1-k)$ and k are weighting coefficients. When k is small, the evidence conflict is small, the first term plays a major role, and the synthesis result approximates D-S synthesis result. When $k = 0$, the new synthetic formula is equivalent to the synthetic formula of D-S. When k $\rightarrow$ 1, at that time, the evidence is highly conflicting. The synthesis result will be mainly determined by $* q(A)$. ε is the credibility of the evidence, and, $q(A)$ is the average support for the evidence pairs.

Therefore, for highly conflicting evidence, the composite results will be determined primarily by the product of the evidence's credibility and the evidence's average support.

3.3 Information Fusion

In the information fusion of operation and maintenance decision-making system, we use each machine on the production line as the problem recognition framework, and use the above-mentioned alarm information and machine importance information as important evidence for the operation and maintenance of the machine. Put the probability of suspected failure of the machine and the normalized relative importance of the machine into the problem recognition framework for information fusion. Then, the improved D-S method is used to neutralize the contradiction, and the maintenance order of the machine is prioritized.

4. Case of Study

4.1 Background

Consider a practical industrial case. Enterprise Y is a manufacturer of electronic equipment materials, using multimachine production line to manufacturing. Enterprise Y currently have a relatively mature equipment failure warning system. In the long-term machine maintenance process, the degree of importance for the alarm code is gradually divided. At the same time, Enterprise Y has a number of experienced senior engineers who are familiar with the use of various equipment on the production line. But for enterprise Y, there is not a long-term fixed machine maintenance team due to the large number of people moving. Due to the large number of alarms, inexperienced maintenance workers generally only focus on important warning information and carry out maintenance. And, there are ten machines on the production line.

4.2 Machine Alarm Analysis

1) Preprocess the raw data.

Observing the alert data of manufacturing system in enterprise Y, we found that the alert code was originally a hexadecimal number. To facilitate clustering, we need to convert it into a decimal number.

The original system time is year / month / day / hour / minute / second, which needs to be uniformly processed into a second format.

2) Clustering

After 0-1 standardization of alert and system data, the CH index can be used to determine the appropriate number of sub-classes. After the calculation of the CH index, the best sub-class number is shown in Figure 1. The clustering algorithm should be divided into ten sub-classes.

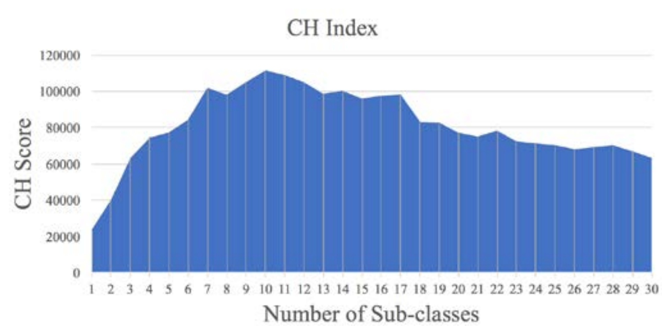

Figure 1. Result of Computing CH index.

Considering that it is a two-dimensional cluster, and the number of clusters is also known, the clustering result can be visualized using two-dimensional coordinates. Using k-means to cluster, the clustering results are shown in Figure 2 below.

3) Suspicious probability generation

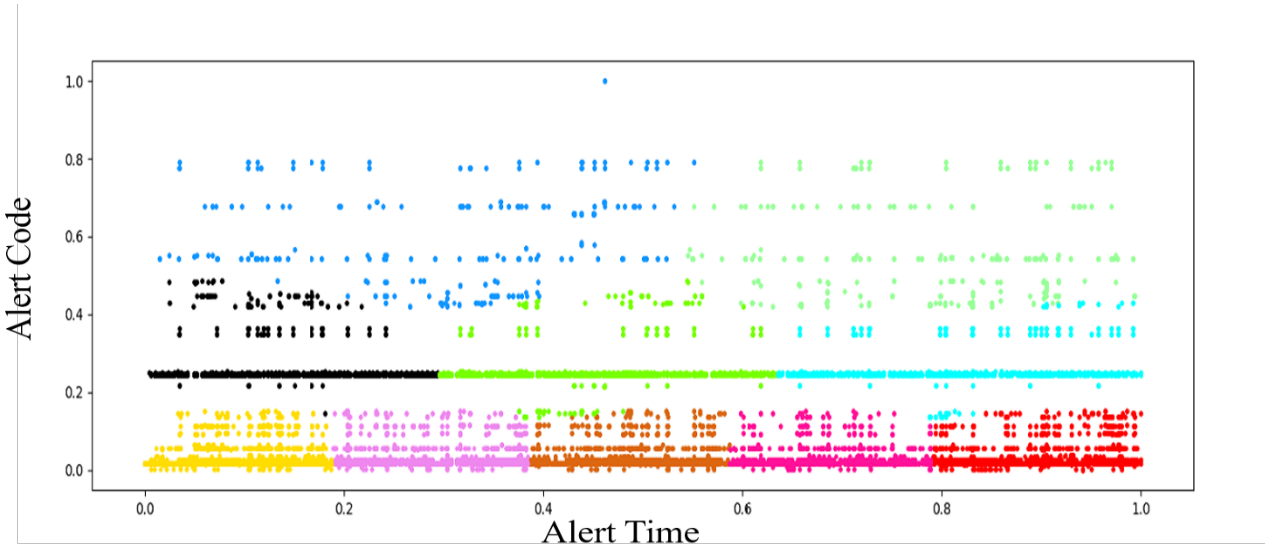

Figure 2. Clustering by k-means.

Take the alarm level "L" to 1, and "H" to 2, and score the points for each alarm class. Then, obtain the probability of machine failure by using the above formula. The result is below:

Table 4. The probability of machine failure

Order	*Probability*	*Order*	*Probability*
1	0.330857	6	0.037647
2	0.317637	7	0.009189
3	0.171331	8	0.008302
4	0.079313	9	0.005408
5	0.037647	10	0.002667

4.3 Machine Importance Modeling

With the fuzzy FMEA method, the evaluation of 10 machines on the production line can be calculated by the above method. Then, the relative importance of each device on the production line can be obtained.

Since there are too many calculation processes, the specific calculations are not listed here. But, the final degree of relative importance results are given.

Table 5. The probability of machine failure

Order	*Probability*	*Order*	*Probability*
1	0.254678	6	0.021658
2	0.145601	7	0.023461
3	0.131532	8	0.154332
4	0.002123	9	0.012201
5	0.211138	10	0.043276

4.4 Information Fusion & decision-making

Taking the machine as the problem recognition framework, the improved D-S evidence theory is used to calculate and obtain the final operation and maintenance importance.

Table 6. the final operation and maintenance importance

Order	*Probability*	*Order*	*Probability*
1	0.289043	6	0.021556
2	0.208258	7	0.011634
3	0.128457	8	0.058160
4	0.028649	9	0.006224
5	0.094957	10	0.016183

Based on the final result, comparing the three tables, it is easy to see that the original No. 5 machine does not have a high probability of alerting in the alarm message. However, according to the importance of comprehensive operation and maintenance obtained after the joint decision of man and machine, the importance of the fifth is reflected.

In an actual industrial production system, the importance of each machine itself generally does not change. Enterprises can gradually perform FMECA analysis on existing equipment according to actual conditions, and obtain the comprehensive importance level of each machine. At the same time, an assessment of comprehensive importance level is carried out for each new machine that is put into production. Integrate old and new machines and establish a database of importance information for each production in enterprise. When the machine enters a production line for operation, the importance level of the machine well be normalized to obtain the relative importance level of this machine.

The machine alarm of the production line is a variable that changes with time. A time period T can be selected as the sampling period to modeling machine alarms, and the probability of the suspected fault machine is modeled in the time period T. Combine with the importance of the machine, information fusion can be performed in real time to make decisions for operation and maintenance.

5. CONCLUSION AND PRESPECTIVE

In this paper, the alarm information and machine importance information are modeled, and the results are fused by D-S evidence fusion method. A machine fault operation and maintenance decision system based on human-machine multi-information fusion is constructed. At the same time, the actual industrial case is analyzed and the feasibility of the method is verified. This paper regards the decision-making process as the process of evidence fusion, thus making the decision-making system more scalable. Once some information is added to the decision-making system, it only needs to be added as a new piece of evidence to carry out the original information fusion process to support the decision-making. The research of this method is due to the current enterprise's enthusiasm for intelligent manufacturing and digital factories. For enterprises with higher degree of digital networking, more information will be generated to wait for further exploration of its value. How to use these newly generated information effectively and turn it into useful operation and decision-making information is the next step in this research work.

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