Article citation info:
Gan W. A fault detection method for automated industrial equipment based on multi attribute decision fusion in knowledge graph. Diagnostyka. 2024;25(4):2024407. https://doi.org/10.29354/diag/192496.

DIAGNOSTYKA, 2024, Vol. 25, No. 4

e-ISSN 2449-5220
DOI: 10.29354/diag/192496

A FAULT DETECTION METHOD FOR AUTOMATED INDUSTRIAL EQUIPMENT BASED ON MULTI ATTRIBUTE DECISION FUSION IN KNOWLEDGE GRAPH

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Abstract

Automated industrial equipment is an important production equipment in modern industry, but the occurrence of equipment failures may seriously affect production capacity. A method based on multi-attribute decision fusion was studied and designed for fault detection of automation industrial equipment. During the process, a mapping structure between the data layer and the pattern layer of the knowledge graph was designed. Knowledge extraction was performed on unstructured and semi-structured texts, and the fault knowledge graph was established through knowledge verification operations. Then, the fault alarm data was processed using Cypher query language, and the semantics were blurred using fuzzy set theory. Finally, the correctness of the fault chain was analyzed through attribute weights and attribute value matrices. Then it searched for the source fault node of the fault. The experimental results showed that the research method maintains an average accuracy of 0.8046 or above in the mean accuracy test when the number of traceability fault chains is 17-18. In the analysis of actual fault detection effectiveness, the research method focused on the fault detection time of the 8-station robotic arm swing plate robot when the number of fault nodes involved increased to 12, which was only 72ms. This indicated that the research method can effectively detect faults in automated industrial equipment and has more accurate detection accuracy.

Keywords: automation equipment, fault detection, knowledge graph, multi attribute decision-making, relative closeness

1. INTRODUCTION

In the trend of vigorously developing intelligent manufacturing in various countries around the world, automated industrial equipment that combines electrical systems, mechanical structures, and intelligent systems has become an important research and development object [1]. However, during the operation of automated industrial equipment, it may be affected by external environments or its own instructions may be disrupted, leading to malfunctions. Stopping production due to malfunctions will reduce output and cause economic losses to the factory. When a malfunction occurs, the system of automated industrial equipment will leave fault information [2]. However, automated industrial equipment that involves multiple functions and operations leaves a lot of fault information, making it difficult for technical personnel to quickly extract key content from these fault information [3]. There are certain difficulties in detecting faults in automated industrial equipment. At present, there are methods for industrial equipment fault detection through unsupervised learning, neural network and other technologies. However, some of these methods require extensive learning of fault information during operation, resulting in insufficient work efficiency, while others require examples for comparison and lack generalization for complex fault type combinations. Knowledge graphs can be extracted using natural language processing techniques, connecting entities and constructing chains of fault occurrence [4]. Knowledge graphs have natural advantages in representing complex relationships among entities. Compared with traditional relational databases, knowledge graphs can represent and manage the relationships between entities more intuitively and flexibly, which is particularly important for the fault detection of automated industrial equipment, because equipment failures often involve complex interactions between multiple components and systems. Multi attribute decision-making technology can trace the source of events through the attribute values of different information, thereby obtaining the source information of faults. In this context, the knowledge graph technology is applied to the fault detection field of automatic industrial equipment, and the fault information is organized and mined efficiently by

Received 2024-04-02; Accepted 2024-08-21; Available online 2024-10-25

constructing fault knowledge graph. In addition, compared with other existing methods that only construct knowledge graph or consider multiple factors, this study innovatively considers multiple factors and attributes in the fault detection process by integrating multi-attribute decision-making technology. And a complete set of fault detection process is constructed, from fault information collection, knowledge extraction to fault chain construction and analysis, in order to provide a certain technical reference for the development of automation equipment through the innovation of technical ideas.

The research mainly consists of four parts. The first part discusses the relevant research results of equipment fault detection methods and multi-attribute decision fusion technology. The second part is the design of an automated industrial equipment fault detection method based on multi-attribute decision fusion in the knowledge graph. The third part is to analyze the effectiveness of the research method. The fourth part discusses and summarizes the entire text.

2. RELATED WORKS

With the rapid development of the manufacturing industry, more and more scholars have begun to realize the importance of fault detection technology for automated industrial equipment used in the manufacturing industry. Some scholars have conducted research on equipment fault detection methods. Zhan et al. proposed a chip level gate sensing carbon based FET gas sensor method for real-time detection of H_2S and early fault diagnosis to address the potential damage caused by SF_6 gas decomposition products to power equipment. The results show that the detection limit of the sensor can reach 20 ppb, and the response deviation does not exceed 3% [5]. Dong and Bi proposed an effective method for quickly detecting mechanical faults in load cells through simulation experiments to address the lack of mechanical fault diagnosis methods for weighing sensors. It used a sliding window to obtain the ratio of the standard deviation relative to the normal output as the testing basis. The experimental results show that this method can monitor the operating status of multiple devices in real time [6]. Ghods and Faiz analyzed the performance of permanent magnet vernier generators under healthy and different mechanical fault conditions. This study used two-dimensional and three-dimensional time stepping finite element methods to predict the performance of generators. It compared healthy and faulty generators by developing analytical models to estimate air gap permeability and induced voltage. Accurate evaluation of PMVG performance has been achieved, providing reliable power supply for traffic law enforcement cameras and driving applications [7]. Nguyen and Huang proposed a deep learning method based on sound analysis for machine fault detection. By preprocessing and feature extraction of sound signals generated by machines under different operating conditions, convolutional neural networks were used to automatically learn the required features for classification. The results show that the model exhibits high accuracy in fault detection of known and unknown machines, proving its good performance in machine fault detection [8].

Some scholars have also conducted research on multi-attribute decision fusion technology. Mahmood and Ali proposed a complex q-order orthogonal fuzzy set method based on the Hamiltonian aggregation operator to address environmental conflicts in gold mining development. Through comparative analysis and sensitivity analysis, it is shown that the multi-attribute group decision-making problem method has high reliability [9]. Xie et al. focused on the key issue of determining the resolution coefficient in grey entropy correlation analysis and studied the effect of discarded bricks on their properties through mixed recycled coarse aggregate experiments. It used indoor experiments and grey entropy theory to analyze the correlation between performance indicators and mechanical properties. The results show that the resolution coefficient can be within a range of values, providing guiding conclusions [10]. Lan addressed the challenges of water resource management in the Mekong River Basin and used the Analytic Hierarchy Process to analyze and evaluate water resource development plans. The research results provide a reference for the analysis method to formulate appropriate water resource policies based on the best cooperation plan [11]. Researchers such as Liu et al. proposed an analysis method based on fuzzy comprehensive evaluation to address the spatiotemporal complexity of roadway failure in deep metal mines. The results indicate that the accuracy of the method is close to 90%, achieving quantitative assessment of the risk of large-scale regional tunnel damage [12]. Liu and Liang addressed the issue of evaluating the humanistic literacy of medical laboratory students by using the entropy weight method to determine the weights of each factor, and combined with the fuzzy comprehensive evaluation method to scientifically rank the importance of humanistic literacy. The results show that this method provides a scientific, objective, and comprehensive evaluation system for the humanistic literacy of medical laboratory students [13].

In summary, although multi-attribute decision fusion technology has been studied and applied in many fields, there is still relatively little research on fault detection in automated industrial equipment. In view of this, the study attempts to apply multi-attribute decision fusion technology to the fault detection of automated industrial equipment and design a detection method. This is to provide feasible technical references for the automation industry.

3. DESIGN OF FAULT DETECTION TECHNOLOGY BASED ON MULTI ATTRIBUTE DECISION FUSION IN KNOWLEDGE GRAPH

The fault detection technology for automated industrial equipment helps industrial technicians to maintain and repair equipment more quickly [14-15]. This section elaborates on the technical means used in the automated industrial equipment fault detection method based on multi-attribute decision fusion in the knowledge graph of research and design.

3.1. Establishment of knowledge graph for automation industrial equipment faults

Automated industrial equipment, as an important processing and production equipment in modern industry, has a large number of electronic components and control systems working simultaneously during operation [16-17]. During operation, equipment systems may malfunction and generate corresponding data alerts [18-19]. Knowledge graphs can analyze the connections between alert data. This study uses knowledge graphs as the foundation for fault detection in automated industrial equipment. The knowledge graph can contain many types of entities, such as the cause of failure, involved modules, fault levels, fault consequences, treatment methods, and the fault itself. These entities are organized through predefined patterns, forming a complete view of the chain of failure occurrence. In addition, knowledge graph can integrate information from different data sources, including historical fault records, operation logs, device parameters, etc., to provide comprehensive data support for fault detection. Knowledge graph can express various types of relationships between entities, which define the logical sequence and dependencies of the fault occurrence chain. There is a complete chain of faults that occur during the operation of automated industrial robots. Based on the fault occurrence chain, this study sets up six types of knowledge entities: fault antecedents, involved modules, fault levels, fault consequences, handling methods, and faults. The six types of entities use CF, FM, EL, FE, EL, and FD as marking symbols. The mapping structure between the data layer and the pattern layer of the designed knowledge graph is shown in Figure 1.

As shown in Figure 1, there are three main types of relationships between different entities in the data layer and pattern layer of the knowledge graph: triggering, processing, and occurrence. A complete chain of fault occurrence is formed by triggering the fault entity before the fault, and then causing the consequences of the fault or triggering other fault entities again. It evaluates the fault level based on the final manifestation of the fault. The pattern layer is an induction of the structure and data categories contained in the data layer, and the content between the two layers is bi-directional mapped. The design of the pattern layer is determined by the data structure of the text contained in the original data. It first designs the pattern layer during construction, and then determines the content of the data layer based on the pattern layer. When extracting knowledge, text preprocessing is necessary to obtain data with standardized formats. In order to reduce noise interference in the data and minimize the impact between data, this study used text sharding to process semi-structured text and text annotation to process unstructured text. When extracting knowledge from semi-structured text, it obtains knowledge triplets as shown in equation (1).

$$G = \langle E, A, V \rangle \quad (1)$$

In equation (1), G represents a knowledge triplet. E represents the entity. A represents attribute. V represents the attribute value. The attribute values are obtained by combining historical alarms of automated industrial equipment with manual calibration results. When extracting knowledge from unstructured text, it uses a Transformer based bidirectional encoding model for entity recognition. In the bidirectional encoding model based on Transformer, the Encoder plays a crucial role, and the Encoder structure is shown in Figure 2.

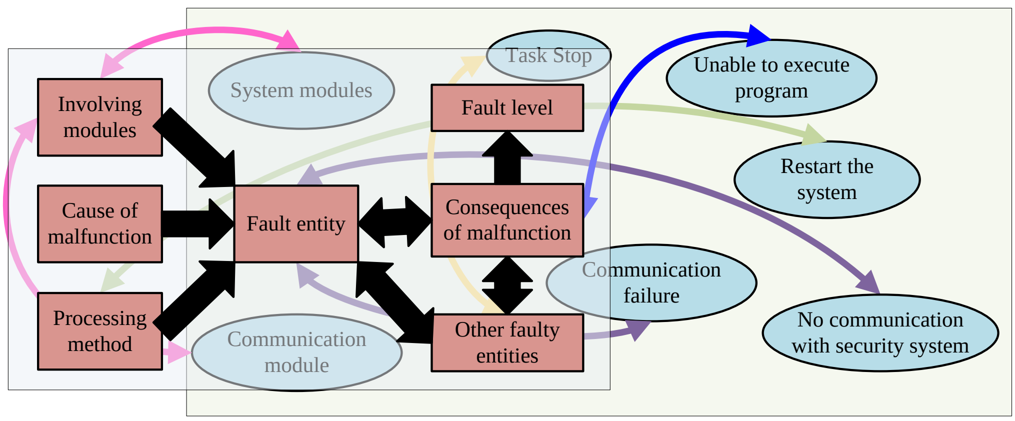


Fig. 1. Knowledge graph mapping structure

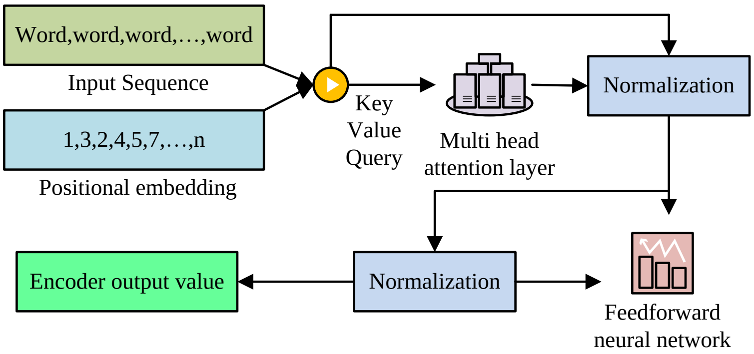


Fig. 2. Encoder structure

As shown in Figure 2, the Encoder starts with an Embedding, which includes two operations: positional embedding and input sequence. The input sequence takes the signal word used for each fault alarm as the basic unit, sets appropriate word dimensions, and expresses them mathematically. Position embedding expresses the order of words, and the encoding at even numbered positions is shown in equation (2).

$$PE_{(pos,2i)} = sin\left(pos/10000^{2i/d_{model}}\right) \quad (2)$$

In equation (2), $PE_{(pos,2i)}$ represents even position encoding. pos represents the position of the word. d_{model} represents dimension. $2i$ represents the total number of positions. The encoding at odd positions is shown in equation (3).

$$PE_{(pos,2i+1)} = cos\left(pos/10000^{2i/d_{model}}\right) \quad (3)$$

In equation (3), $PE_{(pos,2i+1)}$ represents odd position encoding. After Embedding, it becomes a multi head attention layer, where Embedding inputs Key, Value, and Query into the multi head attention layer. The multi head attention mechanism obtains multiple sets of matrices from three matrices and maps them. The calculation of attention value is shown in equation (4).

$$Attention(Q,K,V) = soft\,max\left(\frac{QK^T}{\sqrt{d_k}}\right)V \quad (4)$$

In equation (4), $Attention(Q,K,V)$ represents attention value. Q represents the Query vector. K^T represents the Key matrix. V represents the Value vector. d_k represents the number of Key vectors. $softmax$ represents normalized calculation. Both multi head attention and feedforward neural networks are connected to a normalization layer. The input of the feedforward neural network is a matrix compressed from normalized multi head attention, which is processed and normalized again to obtain the Encoder output value. Finally, it undergoes another knowledge validation, as shown in Figure 3.

As shown in Figure 3, the data used for knowledge validation consists of the knowledge set produced by the current project's knowledge extraction and the knowledge set produced from other sources. It first performs pattern layer rule validation that includes relationship rules and verification pattern layer structures. It then performs knowledge triplet category validation, which includes triplet sentence vector expression and category validation. After completing knowledge validation, the output of the knowledge set to be updated is used to classify sentence vectors using cosine similarity calculation, as shown in equation (5).

$$S_{cos} = \frac{\sum_{i=1}^{n}(x_i y_i)}{\sqrt{\sum_{i=1}^{n}(x_i)^2} \times \sqrt{\sum_{i=1}^{n}(y_i)^2}} \quad (5)$$

In equation (5), S_{cos} represents cosine similarity. x_i, y_i represent the two sentence vectors that need to be compared, respectively. It updates the knowledge set through sentence vectors and establishes a fault knowledge graph.

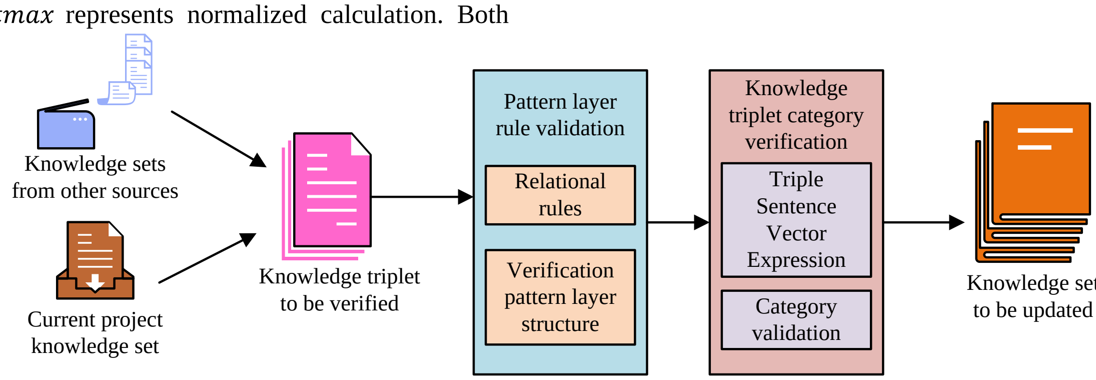


Fig. 3. Knowledge verification process

3.2. Fault detection technology for automated industrial equipment based on multi-attribute decision-making

After a malfunction occurs in automated industrial equipment, the system will generate an alarm message [20]. The research and design of automated industrial equipment fault detection technology rely on the alarm information of knowledge graphs to search for the relationship direction of information and find the complete fault triggering chain. In order to achieve information retrieval, the Neo4j graph database is used as the storage location for knowledge graphs, and the Cypher query language is used for data processing. The main query code for the research design is shown in Figure 4.

As shown in Figure 4, during the query process, six basic operations were studied and designed, and complex operations were all expanded and extended based on these six operations. The basic operations cover querying ordinary paths between entities and querying multiple deep relationships between entities. The path obtained from the query operation is the mining result obtained from fault tracing in the knowledge graph. By supplementing the attribute and entity information in the path, a fault tracing path structure is established as shown in Figure 5.

As shown in Figure 5, when conducting fault tracing, the complete fault tracing path includes fault nodes, fault consequence nodes, module nodes, fault cause nodes, and fault level nodes. Automated industrial equipment failures may involve multiple entities pointing to the same fault or one entity pointing to multiple faults. This study integrates multi-attribute decision-making with knowledge graphs to analyze fault alarms. To ensure the feasibility and independence of fault detection operations, a fault chain decision attribute tree is established, which includes three primary branches: fault path relationships, fault path entities, and fault traceability entities. The fault path relationship includes the frequency of path occurrence and the length of the path. The fault path entity includes the

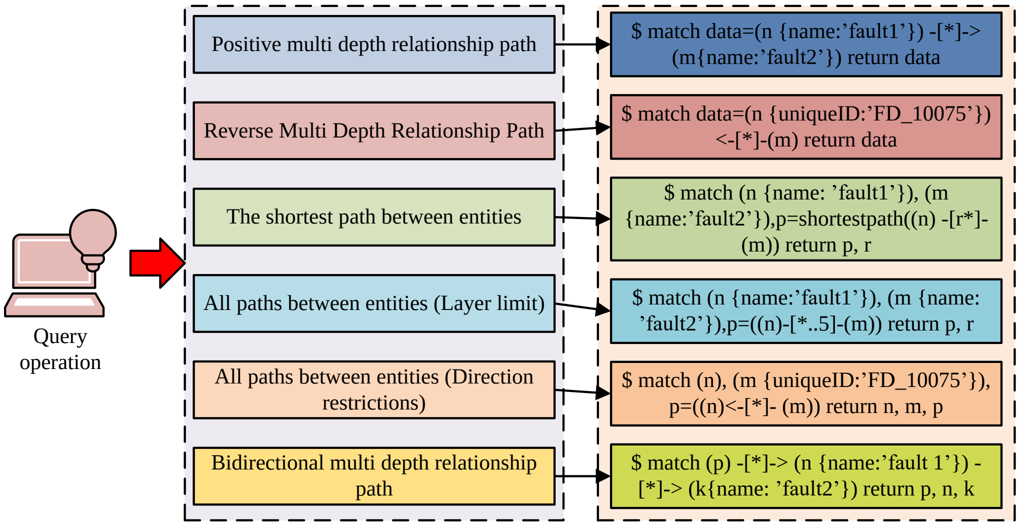


Fig. 4. Main query operations and codes

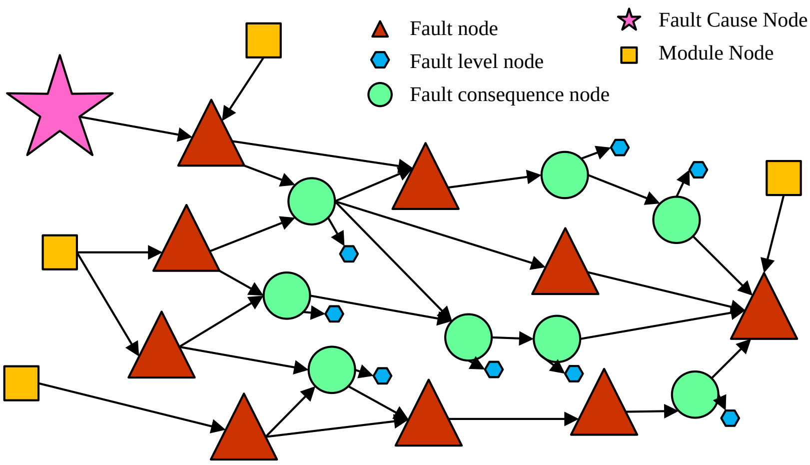


Fig. 5. Fault tracing path structure

semantic value of fault level, entity semantic value, and entity occurrence frequency. The fault tracing entity includes the semantic value of the source fault, the discrimination degree of the head and tail entity modules, and the frequency of source fault occurrence. However, some semantics do not have exact numerical values, and research is conducted using fuzzy set theory for semantic fuzziness. Fuzzy set theory is particularly suitable for dealing with fuzziness and uncertainty problems, which are often encountered in automatic industrial equipment fault detection. Fuzzy sets provide an intuitive way to quantify the semantic value concept of faults, whereas Artificial Neural networks may require more complex feature engineering in this regard. It uses a triangle membership function to quantify the semantic values of the text, as shown in equation (6).

$$\mu_s(x) = \begin{Bmatrix} 0, x \le s^l \\ \frac{x-s^l}{s^t-s^l}, s^l < x \le s^t \\ \frac{x-s^u}{s^t-s^u}, s^t < x \le s^u \\ 0, x > s^u \end{Bmatrix} \tag{6}$$

In equation (6), $\mu_s(x)$ represents the membership degree value. x represents the element. s^l, s^t, s^u represent triangular fuzzy numbers. It sets seven levels of semantic intervals for language variables, and determines the semantic attributes of entities based on membership values, completing semantic fuzzification. Then, the weight allocation of the attributes of the fault chain is carried out through the multiplication analysis method. It constructs a judgment matrix based on the fault chain decision attribute tree, and then uses the set averaging method to calculate the attribute weights, as shown in equation (7).

$$w_i = \frac{\left[\prod_{j=1}^{n}\left(p_{ij}/\sum_{j=1}^{n} p_{ij}\right)\right]^{\frac{1}{n}}}{\sum_{i=1}^{n}\left[\prod_{j=1}^{n}\left(p_{ij}/\sum_{j=1}^{n} p_{ij}\right)\right]^{\frac{1}{n}}}, i = 1,2,\dots,n \tag{7}$$

In equation (7), w_i represents the weight vector. p_{ij} represents the elements of the judgment matrix. It uses the consistency index to test the error situation of the judgment matrix, as shown in equation (8).

$$CI = \frac{\sum_{i=1}^{n}\frac{[PW]_i}{nw_i} - n}{n-1} \tag{8}$$

In equation (8), CI represents the calculated consistency index. P represents the judgment matrix. W represents the eigenvector of the judgment matrix. w_i represents the ith value of W. n represents the order of the judgment matrix. After adjusting the matrix based on the error, a comprehensive evaluation calculation is carried out by approximating the ideal solution ranking method. It defines the attribute value matrix for a fault chain, as shown in equation (9).

$$Y = \left(y_{ij}\right)_{m\times n} \tag{9}$$

In equation (9), Y represents the attribute value matrix. y_{ij} represents the value of the j -th decision attribute in a fault chain. Afterwards, the decision attributes are normalized and the cost attribute values are calculated as shown in equation (10).

$$z_{ij} = 1/y_{ij} \tag{10}$$

In equation (10), z_{ij} represents the cost type attribute. The calculation of intermediate attributes is shown in equation (11).

$$z_{ij1} = 1 - \frac{y_{ij}-y_{best}}{max\{|y_{ij}-y_{best}|\}} \tag{11}$$

In equation (11), z_{ij1} represents the intermediate type attribute. y_{best} represents the median value. It normalizes each column attribute, calculates relative closeness, and calculates relative closeness through Euclidean distance. The calculation of Euclidean distance is shown in equation (12).

$$\begin{cases} D^+ = \sqrt{\sum_{j=1}^{n} w_i\left(v_{ij} - v_j^+\right)^2} \\ D^- = \sqrt{\sum_{j=1}^{n} w_i\left(v_{ij} - v_j^-\right)^2} \end{cases} \tag{12}$$

In equation (12), D represents the Euclidean distance. v represents the ideal solution. The calculation of relative closeness is shown in equation (13).

$$C = \frac{D^-}{D^+ + D^-} \tag{13}$$

In equation (13), C represents relative closeness. When evaluating and analyzing, the closer the relative closeness is to 1, the higher the correctness of the analyzed fault chain. The complete process of fault detection for automated industrial equipment is shown in Figure 6.

As shown in Figure 6, when conducting fault detection for automated industrial equipment, the first step is to trace the source of the fault node through a knowledge graph. After obtaining the fault chain, it performs attribute queries and selection. The attribute query obtains the decision attribute value, and after fuzzification, the semantic quantification value is obtained. The decision attribute system is obtained through attribute selection, and the weight vector is obtained through weight allocation. By combining decision attribute values, weight vectors, and semantic quantification values, a comprehensive evaluation is conducted to obtain the source fault node and complete automated industrial equipment fault detection.

4. EFFECTIVENESS ANALYSIS OF FAULT DETECTION TECHNOLOGY BASED ON MULTI-ATTRIBUTE DECISION FUSION IN KNOWLEDGE GRAPH

Intelligent fault detection technology is one of the important technologies in the development of automated industrial equipment. This section analyzes the effectiveness of the research and design of automated industrial equipment fault detection technology from two aspects: performance testing and application analysis.

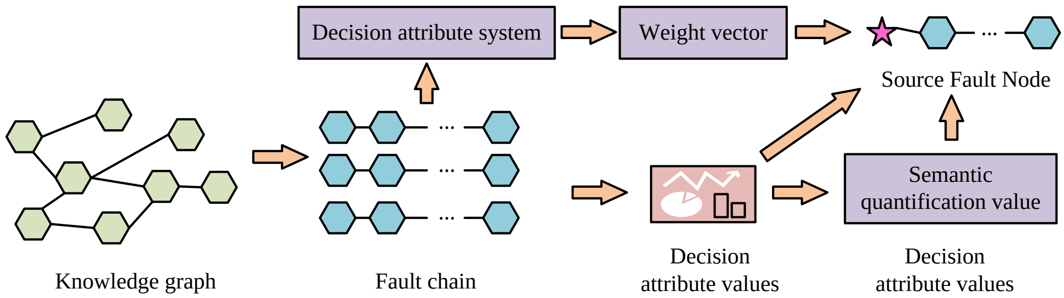


Fig. 6. Fault detection process for automated industrial equipment

4.1. Performance testing of fault detection technology based on multi-attribute decision fusion in knowledge graphs

In order to test the performance of the automated industrial equipment fault detection technology designed for research, 2000 sets of knowledge triplets were selected, of which 60% were positive samples and 40% were negative samples. It is evenly divided into two test sets, each containing 1000 sets of knowledge triplets, called Alpha and Bravo, respectively. The abbreviated research method is the Fusion of Multiple Attributes (FMA) method. A test was conducted on a fault in Alpha, and the results are shown in Table 1.

As shown in Table 1, FMA extracted 8 possible fault chains during fault testing. Among the 8 fault chains, the maximum positive ideal solution distance is the fault chain numbered 6, reaching 0.3679. The smallest positive ideal solution is the fault chain numbered 7, which is 0.1387. Among the 8 fault chains, the maximum negative ideal solution distance is the fault chain numbered 7, reaching 0.3203. The smallest negative ideal solution is the fault chain with number 4, which is 0.1289. Through calculation, it was found that the fault chain with the highest relative closeness among the 8 fault chains is numbered 7, which reaches 0.6981. The fault chain with representative number 7 is the detected fault. This indicates that the research method can smoothly carry out fault detection of automated industrial equipment. It tests the average accuracy and compares it with Knowledge Graph Relationship Decision Making (KGRDM) and Fuzzy Entity Semantic Decision making (FESD), as shown in Figure 7.

As shown in Figure 7, the average accuracy of different methods decreases as the number of traceability fault chains increases. As shown in Figure 7 (a), in the Alpha dataset, the average accuracy of KGRDM decreases to 0.6091 when the number of traceability fault chains reaches 17-18.

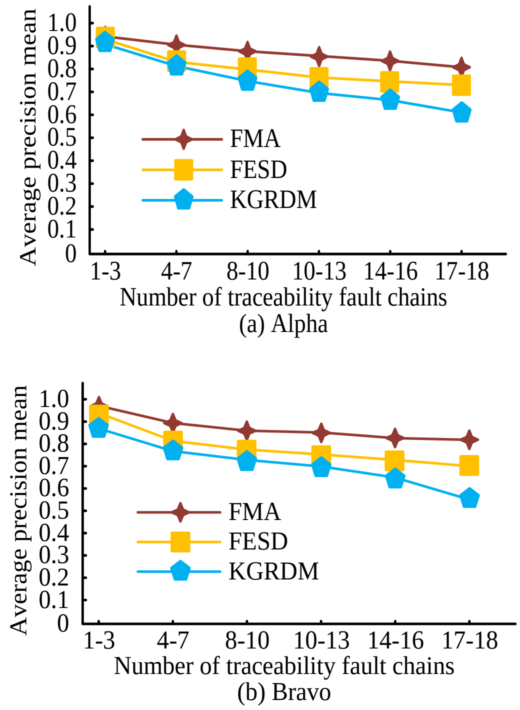


Fig. 7. Average precision mean

Table 1. Fault testing

Fault chain number	Positive ideal solution distance	Negative ideal solution distance	Relative closeness	Fault chain correctness ranking
1	0.3041	0.2222	0.4221	4
2	0.3209	0.1911	0.3730	6
3	0.1955	0.2975	0.6032	2
4	0.3081	0.1289	0.2961	7
5	0.2633	0.2137	0.4479	3
6	0.3679	0.1411	0.2772	8
7	0.1387	0.3203	0.6981	1
8	0.2811	0.1711	0.3791	5

The average accuracy of FMA is 0.9356 when the number of traceability fault chains is 1-3. When tracing the number of faulty chains from 17 to 18, it dropped to 0.8046. As shown in Figure 7 (b), in the Bravo dataset, the average accuracy of FESD decreases to 0.6913 when the number of traceability fault chains reaches 17-18. The average accuracy of FMA is 0.9703 when the number of traceability fault chains is 1-3. When tracing the number of faulty chains from 17 to 18, it dropped to 0.8216. This indicates that the research method has better detection accuracy for positive ideal solutions. Its test normalized cumulative gain of loss is shown in Figure 8.

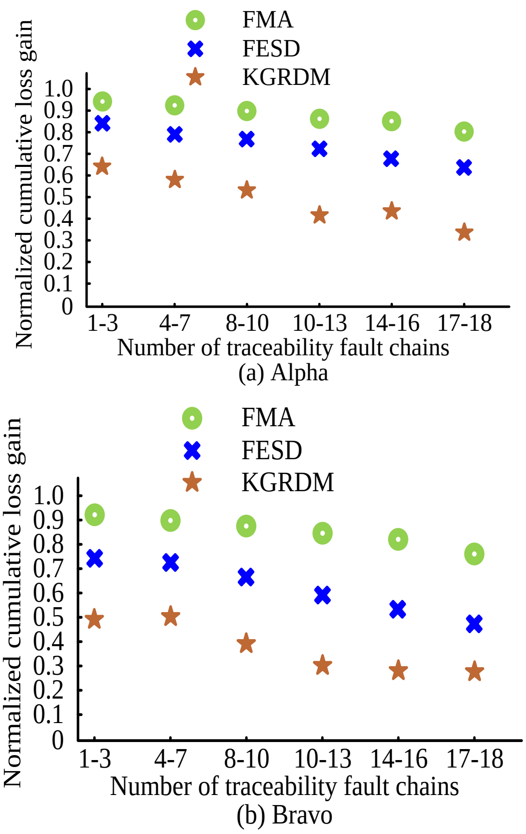


Fig. 8. Normalized cumulative loss gain

As shown in Figure 8, the cumulative gain of normalized loss for different methods decreases as the number of fault chains traced increases. As shown in Figure 8 (a), in the Alpha dataset, the normalized cumulative loss gain of FESD decreases to 0.6421 when the number of traceability fault chains reaches 17-18. The normalized cumulative loss gain of FMA is 0.9429 when the number of traceability fault chains is 1-3. When tracing the number of faulty chains from 17 to 18, it drops to 0.8104. As shown in Figure 8 (b), in the Bravo dataset, the normalized cumulative loss gain of KGRDM decreases to 0.2721 when the number of traceability fault chains reaches 17-18. The normalized cumulative loss gain of FMA is 0.9274 when the number of traceability fault chains is 1-3. When tracing the number of faulty chains from 17 to 18, it dropped to 0.7635. The research method can achieve more accurate fault chain sorting.

4.2. Application analysis of fault detection technology based on multi-attribute decision fusion in knowledge graph

In order to further determine the practical feasibility of the fault detection technology designed in the study, the practical application of the research method is studied under actual industrial conditions. In order to ensure the consistency of other conditions during testing as much as possible, the actual industrial application scenario is two automated industrial equipment on a precision stamping parts production line. One of the two automatic industrial equipment is an 8-station robotic arm swing robot, the main working parts are servo motor, cylinder, optical fiber probe. The other is a 4-station cutting machine, the main working parts are cylinder, pressure sensor, position sensor, stepper motor. It analyzes the time and accuracy of fault detection in the swinging robot, as shown in Figure 9.

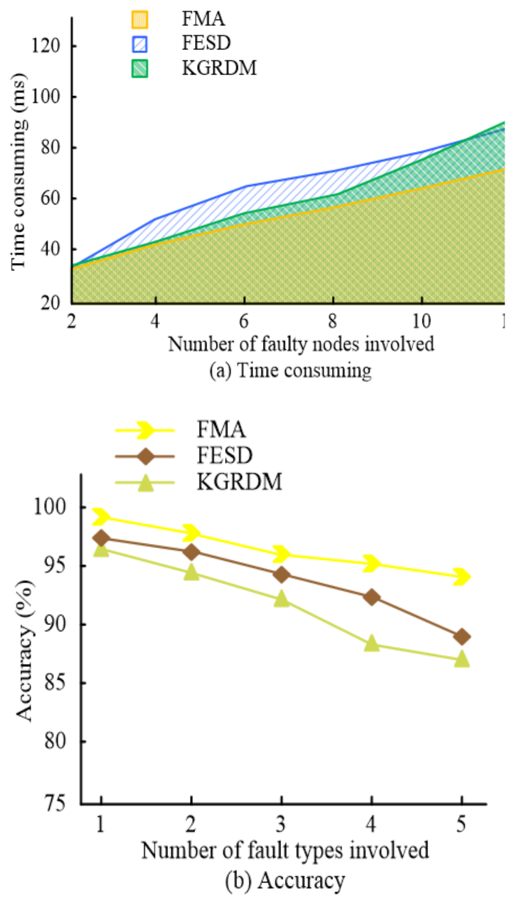
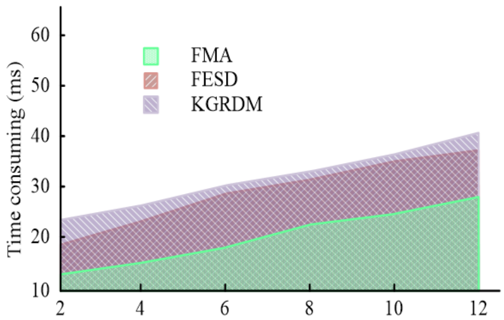


Fig. 9. Fault detection effect of swinging robot

Figure 9 shows that different methods have similar trends in the effectiveness of fault detection for the oscillating disc robot. As shown in Figure 9 (a), when conducting detection time analysis, the three methods all take around 33ms when involving 2 faulty nodes. When the number of faulty nodes increases to 12, the time consumption of FESD increases to 88ms, KGRDM increases to 91ms, and FMA increases to 72ms. As shown in Figure 9 (b), in the analysis of detection accuracy, the detection accuracy of FESD decreases to 89.1% when the number of fault types involved increases to 5. The detection accuracy of KGRDM decreases to 86.6%. The detection accuracy of FMA is 99.3% when the number of fault types involved is 1. When the number of fault types involved increases to 5, it is 94.1%. It analyzes the time and accuracy of fault detection in the cutting machine, as shown in Figure 10.



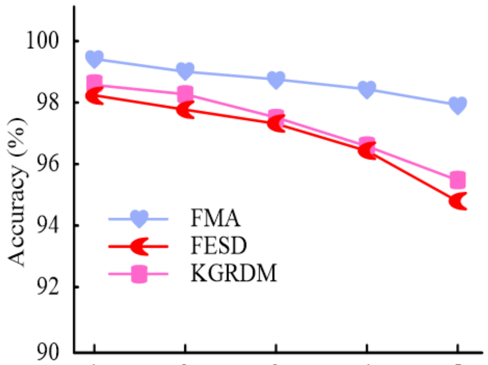
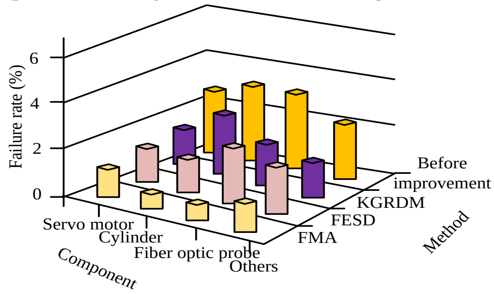


Fig. 10. Cutting machine fault detection effect

As shown in Figure 10, different methods also exhibit similar trends in the effectiveness of fault detection for cutting machines. As shown in Figure 10 (a), when conducting detection time analysis, the three methods all take less than 25ms when involving 2 faulty nodes. When the number of faulty nodes increases to 12, the time consumption of FESD increases to 37ms, KGRDM increases to 41ms, and FMA increases to 28ms. As shown in Figure 10 (b), in the analysis of detection accuracy, the detection accuracy of FESD decreases to 94.8% when the number of fault types involved increases to 5. The detection accuracy of KGRDM decreases to 95.6%. The detection accuracy of FMA is 99.4% when the number of fault types involved is 1. When the number of fault types involved increases to 5, it is 97.9%. The research method is more efficient and accurate in fault detection. Based on the fault detection results of 50 hours, the equipment is improved and the failure rate of the improved equipment is analyzed, as shown in Figure 11.



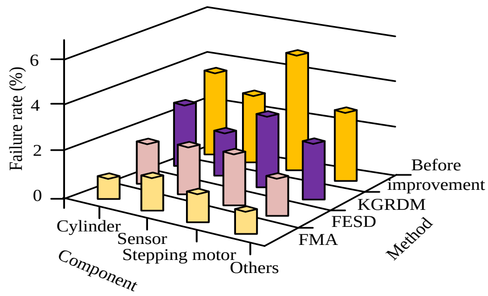


Fig. 11. Machine failure rate after maintenance

As shown in Figure 11, different methods effectively improve the machine's failure rate. Figure 11 (a) shows that the component with the most significant improvement effect of FESD in the pendulum robot is the cylinder, which reduces the failure rate from 3.2% to 1.5%. The component with the most significant improvement effect of KGRDM is the fiber optic probe, which reduces the failure rate from 3.2% to 1.7%. FMA reduces the failure rate of fiber optic probes from 3.2% to 0.8%. Reduce the cylinder failure rate from 3.2% to 0.7%. Figure 11 (b) shows that the component with the most significant improvement effect of FESD in the cutting machine is the stepper motor, which reduces the failure rate from 5.0% to 2.3%. The component with the most significant improvement effect of KGRDM is also the stepper motor, which reduces the failure rate from 5.0% to 3.0%. FMA reduces the cylinder failure rate from 3.5% to 0.8% and the stepper motor failure rate from 5.0% to 1.2%. The research method can provide better assistance for the maintenance of automation industrial equipment. In order to more clearly summarize the performance of the research method, the research results from Figure 7 to Figure 11 are presented in a Table, as shown in Table 2.

Table 2. Comprehensive analysis of results

Average precision mean		
Number of traceability fault chains	1-3	17-18
Alpha	0.9356	0.8046
Bravo	0.9703	0.8216
Normalized cumulative loss gain		
Number of traceability fault chains	1-3	17-18
Alpha	0.9429	0.8104
Bravo	0.9274	0.7635
Fault detection effect of swinging robot		
Number of faulty nodes involved	2	12
Time consuming (ms)	33	72
Number of fault types involved	1	5
Accuracy (%)	99.3	94.1
Cutting machine fault detection effect		
Number of faulty nodes involved	2	12
Time consuming (ms)	25	28
Number of fault types involved	1	5
Accuracy (%)	99.4	97.9
Machine failure rate after maintenance		
swinging robot	0.8%	
Cutting machine	1.2%	

As can be seen from Table 2, the research method has shown good performance in terms of Average precision mean and Normalized cumulative loss gain. In practical application, the research method completes the automatic equipment fault detection with high accuracy and high efficiency, which proves the effectiveness of the research method.

5. CONCLUSION

There are a large number of automated industrial equipment running in modern factories, which also generate a large amount of system data during operation. A fault detection method based on multi-attribute decision fusion in a knowledge graph was studied and designed to obtain fault information of automated industrial equipment from system data. During the process, six types of entities were used to construct the chain of fault occurrence. A Transformer based bidirectional encoding model was used for knowledge extraction from unstructured text. The knowledge set was updated through sentence vectors. Then, a system information query code was designed and a fault tracing path structure was established. The source fault node was determined by relative closeness, and the effectiveness of the research method was analyzed. The experimental results showed that the research method successfully extracted 8 possible fault chains in fault detection and calculated the corresponding relative closeness. In the normalization loss cumulative gain test, the research method maintained a value of 0.7635 or above when the number of traceability fault chains was 17-18. When conducting actual operation on a 4-station cutting machine, the research method achieved an accuracy of 97.9% when the number of fault types involved increased to 5. The research method reduced the failure rate of the fiber optic probe of the 8-station robotic arm swing disk robot from 3.2% to 0.8%. The research method can complete automated industrial equipment fault detection at a faster speed, and can better guide technical personnel in equipment improvement based on the detection results. Current methods have shown good performance in dealing with small scale automated industrial equipment, but in the face of very large and complex industrial systems, how to ensure the construction and update efficiency of knowledge graph, and how to optimize the query and analysis process to meet the needs of large data volumes, is a problem that needs further research. With the expansion of system scale, the balance between real-time requirements and computing resources becomes a challenge. Future research is needed to explore more efficient algorithms and optimization strategies to ensure fast and accurate fault detection in resource-limited situations.

Source of funding: *This research received no external funding.*

Author contributions: *Wufang Gan conducted experiments, recorded data, analyzed the results, and wrote a manuscript. Wufang Gan agreed to the published version of the manuscript.*

Declaration of competing interest: *The author declares no conflict of interest.*

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