Article

An Intelligent Fault Analysis and Diagnosis System for Electromagnet Manufacturing Process Based on Fuzzy Fault Tree and Evidence Theory

Jihong Pang ¹, Jinkun Dai ² and Yong Li ²,*

¹ College of Business, Shaoxing University, Shaoxing 312000, China; pjh@usx.edu.cn
² College of Mechanical and Electrical Engineering, Wenzhou University, Wenzhou 325035, China; 194611471207@stu.wzu.edu.cn
* Correspondence: lyre@wzu.edu.cn; Tel.: +86-577-8668-9138

Abstract: Because an electromagnet has a complex structure and manufacturing process, it is difficult to analyze the overall failure of the electromagnet. In order to solve this problem, a fault intelligent analysis and diagnosis system based on fuzzy fault tree and evidence theory is proposed in this paper. First, the failure structure and fuzzy fault tree are generated according to the experience. Second, the probability of failure caused by basic events is obtained based on the data statistics of the insufficient holding force of the electromagnet in the past. Then, the probability of the basic events is given by using the synthesis rules of evidence theory. Next, the belief interval of the basic event is set as the fuzzy number, and the intelligent analysis is completed by using the calculated fuzzy importance. Finally, the validity and feasibility of the proposed method is proved by using the failure of insufficient retention force in the electromagnet manufacturing process as an example.

Keywords: fuzzy fault tree; evidence theory; intelligent analysis; diagnosis system; electromagnet manufacturing process

MSC: 62P30

1. Introduction

Fault analysis and diagnosis are the most critical steps in quality and reliability optimization of the manufacturing process; therefore, many studies have focused on intelligent methods. The products’ manufacturing process is the stage with the highest frequency of faults being generated, because the products have a complex structure and require high equipment accuracy. With the rapid development of advanced technology, many scholars have carried out extensive research on numerical techniques and analyses to solve mathematical models arising in all fields of science and engineering [1]. Therefore, the question of how to guarantee product quality and reliability has been an important research direction, and one which utilizes the technology of numerical simulation and experiment. The reliability of a product or system can be improved quickly based on the analysis of the fault analysis [2]. The electromagnet is a product that generates magnetic force through an energized coil to drive the movable iron core to complete the specified action. The advantage which is different from other mechanical structures is that the electromagnet can indirectly control the execution and strength of the action without manual operation. Because electromagnets have their own advantages and defects, electromagnet products are often used in some important fields such as transportation, medical security, and aerospace [3]. Compared with other mechanical structures, the structure of electromagnet products is more complex due to the interaction between electricity and magnetism in the working process. Once a fault of an electromagnet product occurs, it will cause very serious consequences. It is difficult to analyze its fault. Therefore, we should pay more attention in
analyzing the realization of test tools, test processes, and methods of fault diagnosis. The rank sum method can be used to analyze the importance degree of fault influence factors and diagnosis methods; therefore, it is of great practical value in a statistical manner in many aspects [4]. At present, most of the fault analysis methods of electromagnet products are based on characteristic data of product failure and subjective analysis by engineers. The characteristic data come from a large number of experiments with a long time for fault analysis. A subjective analysis will lead to the inaccurate determination of the influencing factors of faults. Therefore, in order to solve the problem of fault analysis, this paper proposes a fault intelligent analysis method for the electromagnet manufacturing process based on fuzzy fault tree and evidence theory. Moreover, the intelligent diagnosis system will have great application prospects and practical significance.

On the one hand, the technology and methods of fault analysis have been widely applied in manufacturing process condition monitoring and reliability analysis. At present, the research methods of the intelligent fault analysis of complex systems include the binary decision diagram (BDD) [5], Petri net analysis [6], the Markov system [7], fault tree analysis [8], the Bayes network [9] and other methods, which are often used for fault analysis in combination with databases and experience. However, due to the obvious upper and lower-level relationship between electromagnet fault and influencing factors, and because there is a priority relationship between the influencing factors, the fault tree analysis method is often used for the fault analysis of electromagnets. The traditional fault tree analysis is based on the hierarchical relationship between the fault and its underlying influencing factors, until all influencing factors are found. The traditional fault is characterized by intuitive, clear thinking and strong logic. It can be used for qualitative analysis or quantitative analysis. Because of the unique characteristics of traditional fault, it is applied in many fields as a classic method. However, with the development of modern technology, some limitations have been found in the existing research of the traditional fault; for example, some mechanical mechanisms are not “or”, “and”, or “but” of a progressive relationship. The traditional fault tree cannot express this relationship. It has its limitations not only in a logic gate, but also in quantitative analysis. Take the electromagnet as an example; some electromagnet faults are not due to the complete failure of the parts, but due to the partial failure of parts or the failure to complete the specified action, so there is no definite failure rate for the influencing factors. In view of the defects of the traditional fault tree, many scholars have used scientific methods to improve standards. Yao Chengyu et al. [10] proposed a Takagi-Sugeno (T-S)-based dynamic fault tree analysis method for the defects of the traditional dynamic fault tree logic gate, which used the T-S gate based on the occurrence rules of the T-S model to optimize the dynamic fault. Then, the continuous time T-S dynamic fault tree analysis was proposed, the T-S dynamic door fault rules describing the failure caused by the continuous time operation of parts were defined, and the dynamic fault tree was further improved [11]. For the optimization of the fault tree, in addition to logic gates, some scholars have used fuzzy numbers as the language of the fault tree evaluation to form a new fault tree and fuzzy fault tree analysis method, which was used to deal with uncertain fault forms. Its advantage is, for example, that it can analyze and diagnose faults for some incomplete information systems. To understand the distinctions among different types, the fuzzy fault tree analysis method has been successfully applied in the all fields of the electric multiple unit (EMU) train [12], industrial robot [13], automobile, and so on [14,15].

On the other hand, the fuzzy fault tree is directly combined with the intelligent analysis database to determine the fault, which will cause any judgement attempts to fail with the ambiguous data. Therefore, some scholars have combined other methods with fuzzy fault tree analysis to improve the short board of traditional fault analysis methods. XiaoPing Bai et al. [16] established a new nonlinear programming mathematical optimization model based on the fuzzy number and grey correlation method to solve the problem of the dynamic reliability optimization of complex systems. The grey correlation was used between the occurrence law of underlying events and the occurrence trend of
faults to judge the correlation [17]. In order to improve the reliability of the multifunctional sensors, Yang J [18] and others proposed a new data verification strategy, based on K-nearest neighbor (KNN) and grey model GM (1,1), which deals with independent variables and related variables, respectively. It can be seen from the above documents that for the analysis of the fuzzy fault system, the combination of fault structure description and the uncertain information processing method is often used, but it can be seen that there is a gap in the information fusion of multiple information sources. For multiple information fusion, especially incomplete information, it is more reasonable to use the evidence theory for information fusion by Xiaowei Wang et al. [19]. Based on the evidence theory and fault tree, an adaptive fault detection method for a small current grounding system is proposed. Firstly, the current change data when the fault occurs is obtained, and then the importance of the basic events of the fault tree analysis is calculated through D–S (Dempster–Shafer) evidence theory. Finally, the fault comprehensive belief value is obtained, and the selection result is outputted, which is verified by simulation. The fault diagnosis method is accurate and reliable. Shang H et al. [20] proposed a fault diagnosis method based on a hypersphere multiclass support vector machine (HMSVM) and the improved D–S evidence theory. The improved D–S evidence theory combines the advantages of various diagnosis methods to improve the accuracy of fault diagnosis. In addition, many scholars apply the evidence theory to multi-attribute decision-making [21] and the multi-criteria evaluation method [22].

Based on the two methods of fuzzy fault tree analysis and evidence theory, this paper proposes an intelligent fault analysis and diagnosis system for the manufacturing process of electromagnets, to solve the problem that the failure rate of the electromagnets is unknown and cannot be analyzed. First, the failure structure of the electromagnet is expressed by using the information of the experience base, and the basic events that affect the fault are found. After the fuzzy fault tree of the electromagnet was formed, the problem of the fault analysis of the complex structural system will be solved. Then, based on the basic events obtained by the fuzzy fault tree analysis method, the identification model of the evidence theory is constructed, and the probability of failure caused by the basic events in the identification model is fused by using the evidence theory to obtain the belief interval of the basic events. Second, the belief interval of the basic events is used as the fuzzy number in the fault tree analysis, which solves the problem of too much subjectivity in the process of fuzzy fault tree analysis. Finally, the fuzzy importance of the electromagnet failure structure is calculated and sorted, and then the electromagnet is repaired to complete the fault intelligent analysis of the complex devices.

The research structure of this paper is as follows. The research background and significance of the product fault analysis and diagnosis methods are described briefly in Section 1. Section 2 introduces each module of the electromagnet fault intelligent analysis and diagnosis system and its function. In addition, it also describes the related concepts and calculation formulas of the fuzzy fault tree and evidence theory. Section 3 explains some of the details in the calculation process of the system through an example of the intelligent fault analysis of an electromagnet product. Section 4 verifies the objectivity of the analysis results of the system through simulation experiments. Section 5 summarizes the content of this paper.

2. Intelligent Analysis and Diagnosis System for Electromagnet Fault

The fault intelligent analysis system proposed in this paper can be divided into the four steps of data acquisition, data processing, intelligent diagnosis, and result processing, which are shown in Figure 1.
Figure 1. Framework and function of fault intelligent diagnosis system in electromagnet manufacturing process.

First of all, the production workshop is mainly responsible for data collection. The production process is divided into several quality collection points, according to certain production processes. Sensors, high-speed cameras, and recording equipment are arranged in the quality acquisition point to collect text, photos, data, and other information. Second, the collected data are processed and fused. Then, the intelligent analysis platform performs the intelligent analysis based on historical database, evidence theory, and fuzzy fault tree analysis. Finally, the analysis results are verified by simulation and transmitted to the workshop management system to issue the adjustment task.

On the other hand, the experience base divides the top events into levels and structures, making qualitative analyses to determine the basic events affecting the fault during the intelligent analysis. If the bottom events cannot be obtained, the scope of division needs to be reduced until all basic events are found. Secondly, according to the cause analysis data of previous failed electromagnets, the basic probability of the electromagnet failure caused by each basic event is determined. Then, the belief interval of the basic events is obtained through the synthesis rules of evidence theory, and the belief interval is set as the fuzzy number of basic events in the fuzzy fault tree. Finally, the quantitative analysis algorithm of the fuzzy number and fuzzy fault tree is combined to obtain the fuzzy importance of each basic event by ranking its importance, and then the repair of the overall fault of the electromagnet can be performed.
2.1. Fuzzy Fault Tree

(1) Probability expression of fuzzy fault tree

The fuzzy number finally obtained in this paper is the belief interval obtained by the fusion of the evidence theory, which describes the fault occurrence probability through triangular fuzzy numbers or other fuzzy numbers. Therefore, this paper directly combines the occurrence probability of basic events between logic gates in the fuzzy fault tree.

Suppose bottom event \( X_i \) fuzzy number is \((a_i, b_i)\), the calculation expression in a logic gate is as follows:

The probability expression in or gate is:

\[
P(O) = \left\{ 1 - \prod_{i=1}^{n} \left[ 1 - (a_i + (b_i - a_i)) \right], 1 - \prod_{i=1}^{n} \left[ 1 - (b_i - (b_i - a_i)) \right] \right\}
\]  
(1)

where \( i = 1, \cdots, n \).

The probability expression in and gate is:

\[
P(A) = \left\{ (a_i + (b_i - a_i)), (b_i - (b_i - a_i)) \right\}
\]  
(2)

The operation rules of multiplication, addition, and subtraction used in Equations (1) and (2) are shown in the following:

If \( X_1 = (a_1, b_1) \), \( X_2 = (a_2, b_2) \), then

\[
X_1 \ast X_2 = [\min(a_1 \ast a_2, a_1 \ast b_2, b_1 \ast a_2, b_1 \ast b_2), \max(a_1 \ast a_2, a_1 \ast b_2, b_1 \ast a_2, b_1 \ast b_2)]
\]  
(3)

\[
X_1 + X_2 = [a_1 + a_2, b_1 + b_2]
\]  
(4)

\[
X_1 - X_2 = [|a_1 - b_2|, |b_1 - a_2|]
\]  
(5)

If \( X_1 \) in Equations (3)–(5) is 1, it is recorded as \( X_1 = (1, 1) \), similarly \( X_2 \) is the same, but if it is 0, it will not participate in the calculation.

(2) Qualitative and quantitative analysis of fuzzy fault tree

The purpose of qualitative analysis is to find the law of fault occurrence and its factors, that is, qualitative analysis. The main content is to calculate the minimum cut set, and then conduct qualitative analysis according to the order of the minimum cut set and the number of bottom events, so as to obtain the weak points of the whole system [23].

The quantitative analysis is to quantify the whole fault structure by introducing relevant fault data as support after the qualitative analysis. On the one hand, the probability of the top event is calculated according to the logical relationship of the logic gate. On the other hand, the importance of each bottom event is calculated, and the weak links of the system are improved according to the importance, so as to make the protection in the product manufacturing process more targeted [24].

2.2. Evidence Theory

Evidence theory, also known as D–S evidence theory, is a series of papers published by A.P. Dempster, a mathematician at Harvard University. His student G. Shafer further popularized and developed the evidence theory and formed a set of mathematical methods using “evidence” and “combination” to deal with uncertain problems. Because the prior probability required by evidence theory is more intuitive and easier to obtain than other probabilistic reasoning methods, and the Dempster synthesis rule can summarize and calculate the data of multiple information sources, it is suitable for incomplete information fusion, multi-attribute decision-making, intelligence analysis, and other fields [25].

(1) Basic concepts of evidence theory

The following concepts need to be pointed out in evidence theory, namely basic probability assignment (BPA), belief function (BEL), plausibility function (PL), and belief interval [26].
(i) Basic Probability Assignment

The BPA of recognition framework or hypothetical space $\Theta$ is a function $m$ of $2^\Theta \in [0, 1]$. The function $m$ is called mass function, and is also known as the basic probability assignment function, satisfies $m(\emptyset) = 0$ and $\sum_{A \subseteq \Theta} m(A) = 1$, where $m(A)$ is the basic probability number of $A$. $A$ is called the recognition framework or the hypothesis space $\Theta$ of the focal element in the work of [27].

(ii) Belief Function

In recognition framework $\Theta$, the belief function of $m(A)$ based on BPA on is:

$$\text{Bel}(A) = \sum_{B \subseteq A} m(B)$$ (6)

B in Equation (6) is a subset of focal elements $A$, $m(B)$ is the basic probability of $B$.

(iii) Plausibility Function

In recognition framework $\Theta$, the plausibility function of $m(A)$ based on BPA on is:

$$\text{Pl}(A) = \sum_{B \cap A \neq \emptyset} m(B)$$ (7)

The set B in Equation (7) refers to any set whose intersection with focal element $A$ is not an empty set, $m(B)$ is the basic probability of $B$.

(iv) Belief interval

In evidence theory, for the identification framework $\Theta$, the focal element is $A$. According to BPA, the belief function $\text{Bel}(A)$ and plausibility function $\text{Pl}(A)$ of the focal element are calculated to form the belief interval $[\text{Bel}(A), \text{Pl}(A)]$, respectively, which represent the credibility of focal element $A$.

(2) Synthesis rules of evidence theory

Evidence theory synthesis rules, also known as the Dempster synthesis formula, are defined as follows: in the identification framework or hypothesis space $\Theta$, for $\forall A \subseteq \Theta$. Now identify the framework or hypothetical space $\Theta$ which has two pieces of evidence, $m_1$ and $m_2$ [28]. Then the Dempster synthesis rule of $m_1(A)$ and $m_2(A)$ on the two pieces of evidence is:

$$m_1 \oplus m_2(A) = m_{1,2}(B) + m_{1,2}(C) = \frac{1}{K} \sum_{B \cap C = \emptyset} m_{1,2}(B) \ast m_{1,2}(C)$$ (8)

where $m_{1,2}(B)$ and $m_{1,2}(C)$ indicate basic probability of $B, C$ of evidence $m_1$ and $m_2$, respectively. The two intersections are the set basic probability of focal element $A$, $K$ is the normalization constant. The calculation formula is as follows:

$$K = \sum_{B \cap C \neq \emptyset} m_{1,2}(B) \ast m_{1,2}(C) = 1 - \sum_{B \cap C = \emptyset} m_{1,2}(B) \ast m_{1,2}(C)$$ (9)

If $\forall A \subseteq \Theta$ identify frames or hypothetical spaces $\Theta$ and have $m_1, m_2, \cdots$ evidence, then Dempster composition rule is:

$$(m_1 + \cdots + m_n)(A) = \frac{1}{K} \sum_{A_1 \cap A_2 \cap \cdots \cap A_n = A} m_1(A_1) \ast \cdots \ast m_n(A_n)$$ (10)

where $m_n(A_n)$ represents evidence $m_n$, intersections of $n$ are the set basic probability of focal element $A$, $K$ is the normalization constant for evidence. The calculation formula is as follows:

$$K = 1 - \sum_{A_1 \cap \cdots \cap A_n = A} m_1(A_1) \ast \cdots \ast m_n(A_n)$$ (11)
2.3. Composite of Fuzzy Fault Tree and Evidence Theory

Importance refers to the impact on the top event when each bottom event or minimum cut set in the fault tree fails. Generally speaking, the greater the importance of the bottom event or minimum cut set, the easier it is to cause the top event to fail. On the other hand, importance also makes up for the subjective errors of engineers when building the fault tree. Due to the different understandings or different workflows, there will be some subjective errors such as different level settings or a different number of bottom events. Therefore, the introduction of the concept of importance can improve this situation to a certain extent. This paper uses fuzzy importance (FIM) to judge the importance of each bottom event. Before calculating the fuzzy importance, it is necessary to calculate the probability of the top event. The calculation formula is as follows [29]:

\[ P(\alpha) = P_1 \times P_2 \times \cdots \times P_n \]  

where \( P_n \) represents the occurrence probability of the basic event \( n \).

Secondly, calculate the probability of the top event when \( X \) event does not occur, expressed by \( P(X) \), and its calculation formula is as follows:

\[ P(X) = P_1 \times P_2 \times \cdots \times P_n \]  

Equation (13) is to assume \( P(X) = 0 \) when Equation (12) is used to solve the probability of the top event occurrence. The result is the probability of the top event occurrence when \( X \) event does not occur.

Ultimately, the exact probability of the top event occurrence is required in the importance analysis, so the fuzzy probability of the top event occurrence should be clarified. The commonly used clarification methods are maximum subordination method, maximum subordination average method, area average method, and center of gravity method, among which the maximum subordination average method is the simplest and most convenient. Therefore, this method is used to clarify the fuzzy probability of the top event; assuming that the fuzzy probability of the top event occurrence is \( \alpha = (a, b) \), then the maximum mean subordination formula is [30]:

\[ \text{MOM} = \frac{a + b}{2} \]  

Equation (14) is to assume \( P(X) = 0 \) when Equation (12) is used to solve the probability of the top event occurrence. The result is the probability of the top event occurrence when \( X \) event does not occur.

In Equation (15), \( P(\alpha) \) refers to the failure rate of the top event and \( P(X) \) refers to the failure rate of \( X \) the event. Because the final importance ranking results need to be simulated and checked in this paper, the operation guide of the simulation software is given, as described in [33].

3. A Case Study

In this case study, an electronic technology company is expected to produce a rotating electromagnet for medical blood collection instruments. The specific part drawing and finished product drawing are shown in Figure 2. This rotating electromagnet is normally open. When it is energized in the forward direction, it is opposite to the magnetic pole of the permanent magnet. According to the principle of opposite repulsion, the movable iron core will start to move and reach the specified position. The opposite occurs when it is energized in the reverse direction. In the same manner as the magnetic pole of the permanent magnet, according to the principle of mutual attraction in the same direction, the movable iron core will return to the original position, and the rotating electromagnet will complete one action.
The current fault is that the movable iron core cannot reach the specified position or reach the specified position when it is energized in the forward direction, but returns to the original position when it is not energized in the forward direction (i.e., insufficient retention force). After analyzing the fault, the engineer believes that there may be two reasons: one is the problem in the design of the permanent magnet, and the other is the problem in the external coordination relationship of the permanent magnet. The specific size or fit relationship is shown in Figure 3.

The flow chart of the electromagnet manufacturing process fault analysis, based on the fuzzy fault tree and D–S evidence theory, is shown in Figure 4.
According to the experience base, the analysis interval of the fault is determined as the coordination relationship between the permanent magnet and the external permanent magnet. Then, the causes affecting the fault are divided hierarchically in the interval until

**Figure 4.** Flow chart of electromagnet manufacturing process fault analysis based on fuzzy fault tree and D–S evidence theory.
According to the experience base, the analysis interval of the fault is determined as the coordination relationship between the permanent magnet and the external permanent magnet. Then, the causes affecting the fault are divided hierarchically in the interval until all the basic events are found, and the appropriate logic gate is selected for connection to draw the fault tree of the rotating electromagnet fault, as shown in Figure 5.

Figure 5. Fault tree of insufficient holding force of rotating electromagnet.

The intermediate events and basic events represented by the symbols in the electromagnet fault tree in Figure 5 are shown in Table 1.

Table 1. Meaning of symbols in fault tree of rotating electromagnet.

| No. | Event                                      | No.  | Event                                      |
|-----|--------------------------------------------|------|--------------------------------------------|
| Y   | Insufficient holding force of rotating electromagnet | X3(B) | Width of permanent magnet                  |
| Y1  | Design dimension of permanent magnet        | X4(G) | Distance between permanent magnet and guide rod |
| Y2  | Improper external fit of permanent magnet  | X5(F) | Distance between permanent magnets         |
| X1(A)| Length of permanent magnet                 | X6(D) | Distance between permanent magnet and coil  |
| X2(C)| Thickness of permanent magnet              | X7(E) | Included angle between permanent magnets    |

According to the production records of similar products from the first quarter to the fourth quarter of 2021, the engineers have obtained the basic probability of failure caused by each basic event, based on the cause database of insufficient retention. The statistical method is used to export the required data directly through the company’s customer complaint website by using data statistical analysis. In order to rule out the possibility that some other products caused the failure, the engineers count two similar products as $E_1$ and $E_2$, and the statistical data are shown in Table 2. For example, the number of $E_1$ failures of product $E_1$ in the four quarters is 9800, 9978, 9659, and 9119, respectively, with a total of 38,556. Other data can be obtained in the same way. It should be noted here that if the customers are not sure about the cause of the faults, the company’s website will ask them to upload the failure reason, and then the engineers of the company should analyze the failure reason to understand the specific failure mode. Because the annual output of $E_1$ and $E_2$ products is more than 70 million, the data sample is large, which can ensure that the analysis results are more objective. Similar products refer to the mature products similar to the design, structure, materials, manufacturing, and performance of the rotating electromagnets. In the product development stage, the statistics of the similar products are the most commonly used method for reliability prediction and fault analysis.
Table 2. Similar product statistics.

| Basic Events | Number of Faults |
|--------------|-----------------|
|              | E1              | E2              |
| X1           | 38,556          | 71,540          |
| X2           | 38,097          | 25,404          |
| X3           | 37,638          | 25,988          |
| X4           | 84,272          | 71,540          |
| X5           | 28,688          | 37,843          |
| X6           | 29,192          | 37,318          |
| X7           | 38,786          | 49,465          |
| (X4,X5)      | 29,215          | 71,598          |
| (X4,X6)      | 20,426          | 26,222          |
| (X4,X7)      | 20,012          | 49,465          |
| (X5,X6)      | 19,967          | 25,638          |
| (X5,X7)      | 18,911          | 25,930          |
| (X6,X7)      | 29,606          | 37,726          |

From Table 2, the basic events of X4 and X5 indicate that the fault cause is caused by both X4 and X5 events, and the intermediate events Y1 and Y2 are set as two identification frames or hypothesis spaces \( \Theta_1 \) and \( \Theta_2 \). So, \( \Theta_1 = \{ X1, X2, X3 \} \), \( \Theta_2 = \{ X4, X5, X6, X7 \} \), then calculate the failure rate of the basic events. For example, in the similar product E1, the failure rate of the basic event X1 is \( P(X1) = \frac{38,556}{459,000} = 0.08 \).

Similarly, the failure rate of the other basic events can be obtained, as shown in Table 3.

Table 3. Failure rate of basic events.

| Basic Events | Failure Probability |
|--------------|---------------------|
|              | E1                  | E2                  |
| X1           | 0.08                | 0.12                |
| X2           | 0.08                | 0.04                |
| X3           | 0.08                | 0.04                |
| X4           | 0.18                | 0.12                |
| X5           | 0.06                | 0.06                |
| X6           | 0.06                | 0.06                |
| X7           | 0.08                | 0.08                |
| (X4,X5)      | 0.06                | 0.12                |
| (X4,X6)      | 0.04                | 0.04                |
| (X4,X7)      | 0.04                | 0.08                |
| (X5,X6)      | 0.04                | 0.04                |
| (X5,X7)      | 0.04                | 0.04                |
| (X6,X7)      | 0.06                | 0.06                |
| \( \Theta_1 = \{ X1, X2, X3 \} \) | 0.04 | 0.04 |}
| \( \Theta_2 = \{ X4, X5, X6, X7 \} \) | 0.06 | 0.06 |

According to Table 3 and the re-combination Equation (9), we can produce:

\[
K_1 = \frac{\sum_{X1 \cap X2 \cap X3 \neq \emptyset} m(X1) \cdot m(X2) \cdot m(X4)}{m(E1) \cdot m(E2)}
\]

\[
= 1 - \frac{\sum_{X1 \cap X2 \cap X3 \neq \emptyset} m(X1) \cdot m(X2) \cdot m(X4)}{m(E1) \cdot m(E2)}
\]

\[
= 1 - \left[ m_{E1 X1} \cdot m_{E2 X2} + \cdots + m_{E2 X3} \cdot m_{E1 X2} \right]
\]

\[
= 1 - (0.08 \cdot 0.04 + 0.08 \cdot 0.04 + 0.08 \cdot 0.12 + \cdots + 0.04 \cdot 0.08)
\]

\[
= 0.930
\]
Similarly, \( K2 \) is obtained by the same calculation. In the above calculation, \( m_{E1X1} \) represents the basic probability distribution of the similar product \( E1 \) at \( X1 \). Similarly, \( m_{E2X1} \) represents the basic probability distribution of the similar product \( E2 \) at \( X1 \). From the combined Equation (7), \( K1 \) and \( K2 \) are obtained. The mass function value of the mass function fused with each basic event can be calculated; for example, the combined mass function of \( X1 \) is:

\[
m(X_1) = m(E1X1) + m(E2X1) \\
= \frac{1}{X} \sum_{E1X1 \cap E2X2 = X1} m(E1X1) \ast m(E2X1) \\
= \frac{1}{X} \left[ m_{E1X1} \ast m_{E2X1} + \cdots + m_{E2X1} \ast m_{E101} \right] \\
= \frac{1}{0.930} \left[ 0.08 \ast 0.12 + \cdots + 0.12 \ast 0.04 \right] \\
= 0.032
\]

The combined mass function of the other focal elements is calculated in the same way as the combined mass function of \( X1 \). The results are shown in Table 4.

**Table 4.** Combination results of mass functions.

| Basic Events | Combination Results |
|--------------|---------------------|
| X1           | 0.032               |
| X2           | 0.013               |
| X3           | 0.014               |
| X4           | 0.151               |
| X5           | 0.052               |
| X6           | 0.042               |
| X7           | 0.063               |
| (X4,X5)      | 0.032               |
| (X4,X6)      | 0.011               |
| (X4,X7)      | 0.018               |
| (X5,X6)      | 0.032               |
| (X5,X7)      | 0.032               |
| (X6,X7)      | 0.019               |
| \( \Theta_1 \) = \{X1, X2, X3\} | 0.002               |
| \( \Theta_2 \) = \{X4, X5, X6, X7\} | 0.005               |

According to the concepts of Equations (6) and (7) of the belief function and plausibility function, the belief function values of \( X1 \) are \( Bel(X1) = 0.032 \), \( Pl(X1) = 0.057 + 0.002 = 0.034 \), so the belief interval of \( X1 \) is \( (0.032, 0.034) \). Similarly, the belief interval for other basic events can be obtained, as shown in Table 5.

**Table 5.** Basic Event Trust Interval.

| Basic Events | Belief Interval |
|--------------|-----------------|
| X1           | (0.032, 0.034)  |
| X2           | (0.013, 0.015)  |
| X3           | (0.014, 0.016)  |
| X4           | (0.151, 0.217)  |
| X5           | (0.052, 0.153)  |
| X6           | (0.042, 0.109)  |
| X7           | (0.063, 0.137)  |

Because the fault trees of this fault are connected by “or” gates, according to Equations (1) and (12), the probability of the top event is:

\[
P(Y) = 1 - \prod_{i=1}^{n} [1 - P(X_i)] = 1 - (1 - P(Y_1)) \ast (1 - P(Y_2))
\]

(16)
Then the fuzzy importance of the top event is as follows: Table 6. Fuzzy importance of each basic event.

| Basic Events | Fuzzy Importance |
|--------------|------------------|
| X1           | 7.02%            |
| X2           | 0.47%            |
| X3           | 0.07%            |
| X4           | 14.48%           |
| X5           | 1.28%            |
| X6           | 2.46%            |
| X7           | 0.07%            |

It can be seen from the fuzzy importance that the importance of each basic event to the top event is as follows:

\[ X_4 > X_1 > X_6 > X_5 > X_2 > X_7 = X_3 \]
These results show that $X_4$ is the most important event, and the working principle of the product is used to the magnetic pole generated by the permanent magnet magnetic pole and the energizing coil. The same pole repels each other, and the different pole attracts each other. If the position of the permanent magnet moves up or down, the magnetic induction lines generated by the coil cannot act on the permanent magnet, and the retention force naturally cannot meet the design requirements. In addition, according to the assembly drawing, the permanent magnet is embedded in the plastic mold when the enterprise is not sure of the cause of the fault. After the distance between the permanent magnet and the guide rod was checked, the inspection is convenient and fast, and the fault data can be uploaded without identifying the possible causes of the failure of the permanent magnet. Moreover, the results from the working principle and subsequent simulation experiments showed that $X_4$ is the most important event.

4. Results Analysis

4.1. Simulation Experiment Verification

In this paper, the JMAG-designer20.0 simulation software is used to analyze and verify the calculation results. The simulation test is carried out by controlling a single variable. The range of the simulation division of each basic event is shown in Table 7.

| Type                      | Parameter | Original Size | Parameter Range |
|---------------------------|-----------|---------------|-----------------|
| Permanent magnet size     | A (mm)    | 13.5          | (12.5–13.5)     |
|                           | B (mm)    | 6             | (5.5–6.5)       |
|                           | C (mm)    | 3.8           | (3–4)           |
| Permanent magnet position | D (mm)    | 0.8           | (0.2–1.2)       |
|                           | E (°)     | 20            | (15–20)         |
|                           | F (mm)    | 2.1           | (1.6–2.6)       |
|                           | G (mm)    | 7.4           | (6.9–7.9)       |

The codes are shown in Table 7, A = Permanent magnet length, B = Permanent magnet width, C = Permanent magnet thickness, D = Distance between magnet and coil, E = Angle between magnets, F = Distance between magnets, and G = Distance between magnet and guide rod.

In the simulation test, except for the single variable controlled, the other variables are the original size. For the single variable controlled, divide the size into several data of equal proportion within the reference range to participate in the simulation. The material of each component in the simulation test is shown in Table 8.

| Spare Parts            | Material |
|------------------------|----------|
| Coil                   | Copper   |
| Iron frame             | SPCC     |
| Upper cover            | SPCC     |
| Magnetic conductive disc| SPCC   |
| Permanent magnet       | N48H     |
| Fixed core             | S10C     |

Set the supply voltage of the electromagnet product to 24 V, the turns of the coil to 636 turns, the resistance to 38.4 Ohm, the switch to closed for the first 3 seconds and open for the last 3 seconds, and the size of the grid to 0.01 mm, as is shown in Figure 6.
The parameter is calculated, which is the holding force after the parameter changes minus the variable and divided into 11 sizes of $3, 3.1, 3.2, \ldots, 4$. The remaining variables are designed as the original size. When the thickness of the permanent magnet is 3 mm, the first simulation experiment, the thickness of the permanent magnet is set as a single variable and divided into 11 sizes of $3, 3.1, 3.2, \ldots, 4$. The remaining variables are designed as the original size. When the thickness of the permanent magnet is 3 mm, the simulation results are shown in Figure 7.

Through the simulation test, the size of the retaining force and the total change of the difference of the retaining force under each parameter are calculated. For example, in the first simulation experiment, the thickness of the permanent magnet is set as a single variable and divided into 11 sizes of $3, 3.1, 3.2, \ldots, 4$. The remaining variables are designed as the original size. When the thickness of the permanent magnet is 3 mm, the simulation results are shown in Figure 7.

![Meshing diagram of rotating electromagnet.](image)

**Figure 6.** Meshing diagram of rotating electromagnet.

![Change in retention force when permanent magnet thickness is set to 3 mm.](image)

**Figure 7.** Change in retention force when permanent magnet thickness is set to 3 mm.

Similarly, the other simulation results are obtained and shown in Table 9.

The codes in Table 9 have the same meaning as those in Table 7. In Table 9, the force refers to the holding force of the electromagnet under the specified conditions. For example, in Table 9, the holding force in the second row is the result under the parameter $A$ in the first row. In Table 9, the unit of the distance is mm, the unit of the angle is degrees, and the unit of the holding force is $N$.

Then the absolute value of the difference between the holding forces under each parameter is calculated, which is the holding force after the parameter changes minus the minimum holding force in the parameter. The calculation results are shown in Table 10.

| Code | Distance (mm) | Angle (°) | Holding Force (N) |
|------|--------------|----------|-------------------|
| A1   | 5            | 0        | 100               |
| A2   | 7            | 15       | 106               |
| A3   | 8            | 30       | 114               |
| A4   | 9            | 45       | 121               |
| A5   | 10           | 60       | 122               |
| A6   | 11           | 75       | 121               |
| A7   | 12           | 90       | 116               |

![Retaining force](image)

| Time (ms) | Retaining Force (N.M) |
|-----------|-----------------------|
| 0         | 5                     |
| 0.5       | 100                   |
| 1         | 53                    |
| 1.5       | 78                    |
| 2         | 91                    |
| 2.5       | 106                   |
| 3         | 109                   |
| 3.5       | 114                   |
| 4         | 121                   |
| 4.5       | 122                   |
| 5         | 121                   |
| 5.5       | 116                   |
| 6         | 78                    |
Table 9. Retaining force under each parameter.

| Test Design | Test No |
|-------------|---------|
| Parameter A | 12.5 12.6 12.7 12.8 12.9 13.0 13.1 13.2 13.3 13.4 13.5 |
| Parameter B | 5.5 5.6 5.7 5.8 5.9 6.0 6.1 6.2 6.3 6.4 6.5 |
| Parameter C | 3.0 3.1 3.2 3.3 3.4 3.5 3.6 3.7 3.8 3.9 4.0 |
| Parameter D | 0.2 0.3 0.4 0.5 0.6 0.7 0.8 0.9 1.0 1.1 1.2 |
| Parameter E | 15.0 16.0 17.0 18.0 19.0 20.0 21.0 22.0 23.0 24.0 25.0 |
| Parameter F | 1.6 1.7 1.8 1.9 2.0 2.1 2.2 2.3 2.4 2.5 2.6 |
| Parameter G | 6.9 7.0 7.1 7.2 7.3 7.4 7.5 7.6 7.7 7.8 7.9 |
| Retention Force F1 | 35.01 90.03 115.30 136.30 174.20 177.20 223.20 235.70 246.00 271.60 288.60 |
| Retention Force F2 | 134.60 137.60 143.80 152.40 152.80 156.60 159.00 167.90 172.40 169.30 176.60 |
| Retention Force F3 | 121.80 169.80 197.80 195.00 220.60 244.40 278.70 298.80 286.60 263.70 243.80 |
| Retention Force F4 | 55.01 80.03 105.30 133.50 156.10 176.60 201.00 221.60 248.80 267.00 290.60 |
| Retention Force F5 | 203.50 236.60 216.40 200.40 189.70 185.80 176.60 171.40 166.50 159.20 145.40 |
| Retention Force F6 | 85.32 98.23 112.80 137.70 145.70 187.60 225.30 244.70 252.30 287.70 310.50 |
| Retention Force F7 | 14.89 51.81 95.00 115.70 134.30 176.60 204.50 235.10 269.20 298.60 356.20 |

Table 10. Total variation of retention force difference under each parameter.

| Parameter | Sum of Difference |
|-----------|-------------------|
| Magnet size (thickness) | 980.77 |
| Magnet size (length) | 1608.05 |
| Magnet size (width) | 242.28 |
| Distance between magnet and coil | 1330.39 |
| Distance between magnets | 1149.12 |
| Angle between magnets | 452.61 |
| Distance between magnet and guide rod | 1788.16 |

From the sum of the differences, it can be seen that the influence of various parameters on the retention force is ranked (from large to small) as the distance between the magnet and guide rod, magnet size (length), magnet and coil distance, distance between magnets, and magnet size (thickness), as well as including the angle between the magnets and the magnet size (width). This is roughly the same as the result calculated by this method, only the ranking of the last two factors is slightly different, and the error is within the control range.

4.2. Result Discussion

In this paper, we find that the new intelligent fault analysis and diagnosis system based on the fuzzy fault tree and the evidence theory can better solve the dilemmas faced by the electromagnet manufacturing process. This paper also comes to a good conclusion, which corresponds to the actual case. Moreover, applying these theories and methods to open the complicated connection of actual production data and the electromagnet manufacturing process is the value of this article.

Furthermore, the situation without any information fusion means that only lots of failed products with determined failure modes are used to calculate the importance of each bottom event, as shown in Table 11. It can be seen that the final calculation results with the approved method show a very good agreement with the failure rules in reality. Compared to other methods, the new method has many advantages. The experimental results for the electromagnet manufacturing process indicate that the proposed method improves the fault analysis and diagnosis performance as compared with other related methods. Moreover, the method in this paper has the advantages of a simple algorithm, short run time, and high efficiency. The analysis results also have preferable regularity, and this may be referenced for other related engineering and technical personnel. Therefore, the new method obtained through comparative analysis is practical and objective.
Table 11. Importance of events without information fusion.

| Basic Events | Fuzzy Importance |
|--------------|------------------|
| X1           | 26.69%           |
| X2           | 15.69%           |
| X3           | 15.72%           |
| X4           | 38.33%           |
| X5           | 16.23%           |
| X6           | 16.23%           |
| X7           | 21.54%           |

5. Conclusions

Compared with the traditional fault tree, the fuzzy fault tree retains the advantage of intuitively describing the overall structure of the fault mode. Moreover, the fuzzy fault tree can reduce the loss of data effectiveness in the process of information conversion, and it is also possible to analyze faults based on fuzzy data without converting the fuzzy data into definite data. For electromagnet products, it is difficult to describe the faults with accurate data because of coil wrapping and other process fault problems. In this paper, the fuzzy fault tree can play a good role in different test environments during the electromagnet product manufacturing stage.

On the other hand, the evidence theory can be used to fuse the data of similar products with the poor processing data in the product manufacturing process. The D–S evidence theory is one of the most common means in data fusion, and its objectivity is beyond doubt. In this paper, the D–S evidence theory is combined with the fuzzy fault tree to solve the defect of the subjective division of the fuzzy interval. Moreover, the evidence theory can integrate the occurrence probability of basic events between similar products to ensure objectivity and credibility.

Furthermore, the intelligent analysis and diagnosis system can be proved to have a high reference value based on the case analysis and a large number of simulation test results. Moreover, the new fault analysis system can cope with the complex assembly environment to ensure the assembly accuracy in an increasingly complex manufacturing environment. In addition, the fault analysis system can reduce the time of the simulation verification for the fault diagnosis at the product manufacturing phase. This approved method can also be applied to the fault analysis of different kinds of electrical products.

Author Contributions: Data curation, J.D.; Methodology, Y.L.; Project administration, J.P. and Y.L.; Software, J.P. and J.D. All authors have read and agreed to the published version of the manuscript.

Funding: This work was supported by the National Natural Science Foundation of China (No. 72071149, 71671130), Provincial Natural Science Foundation, Zhejiang, China (No.LY20G010014).

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

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