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Optimization of Logistics System with Fuzzy FMEA-AHP Methodology

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Abstract: The COVID-19 pandemic broke out and the global logistics industry suffered severe losses; therefore, the Fuzzy FMEA-AHP (Fuzzy Failure Mode and Effects Analysis-Analytic Hierarchy Process) method is proposed to analyze the failure reasons of the logistics system in the COVID-19 pandemic. In this article, we have made an optimization on the basis of the FMEA method: the fuzzy is integrated into the FMEA algorithm, referred to as F-RPWN (fuzzy risk priority-weighted number). Meanwhile, the AHP is used to determine the weights of risk indicators. In this article, we consider new logistics failures, such as the failure modes and failure reasons of the logistics system under the COVID-19 pandemic. There are 12 failures that have been determined, and relevant preventive and corrective measures have been recommended to cut off the path of failure propagation and reduce the impact of failures. In addition, the proposed method can help logistics firms, their supply chain partners, and customers with risk management issues during the COVID-19 pandemic.

Keywords: logistics risk; failure analysis; Fuzzy FMEA-AHP; COVID-19; optimization

Citation: Jin, G.; Meng, Q.; Feng, W. Optimization of Logistics System with Fuzzy FMEA-AHP Methodology. *Processes* **2022**, *10*, 1973. https://doi.org/10.3390/pr10101973

Academic Editors: Chia-Nan Wang, Thanh-Tuan Dang and Ngoc Ai Thy Nguyen

Received: 29 July 2022
Accepted: 21 September 2022
Published: 30 September 2022

1. Introduction

The sudden outbreak of COVID-19 has brought huge problems to people's lives. For the logistics industry, logistics companies have suffered huge losses [1]. In China, strong mobilization capabilities and prevention and control efforts are advanced, and experience in fighting the epidemic is more abundant.

Compared with 2003, the level of socialization of logistics in China is now relatively mature, and socialized enterprises or platforms with strong logistics capabilities such as Cainiao, JD Logistics, and SF Express have emerged (Cainiao is a logistics company launched in 2013 by Chinese e-commerce giant Alibaba Group). In this epidemic, the mature logistics operation mechanism is medical equipment and other emergency materials have played a significant role in the supply and deployment of emergency materials. The trust of the government, enterprises, and consumers in logistics has been further strengthened, which has provided a good foundation for the in-depth development of the logistics industry. All aspects now support the logistics industry to give priority to the resumption of work and break through the logistics bottleneck. It also shows that everyone has realized the supporting role of logistics on the social economy and provides a better business environment for the logistics industry. Therefore, after the epidemic is controlled in time and normal life and production order are restored, the logistics industry's self-rescue and recovery capabilities will be much stronger than in 2003. There is also confidence to effectively control the impact of the epidemic on logistics revenue and costs.

However, most scholars from various countries have studied logistics systems based on natural disasters such as earthquakes and floods. They did not take into account the large-scale infection of disease control of infectious diseases such as COVID-19. It has appeared that people must be involved in low-level transportation [2]. Contact with each other increased the risk of infectious diseases, etc., and led to an extreme shortage of epidemic prevention materials and medical supplies at the beginning of the epidemic, which caused heavy losses to the country's economy and people's lives and health, and exposed the logistics in the context of the epidemic. Therefore, for all the shortcomings above, it is urgent for relevant workers to undertake in-depth thinking and research on this in order to improve the logistics industry's ability to respond to such risks in the future, and at the same time, protect the property safety and life and health of the people.

Hence, in this paper, we consider the impact of large-scale infectious diseases (taking COVID-19 as an example) in the logistics system and the optimization of the system. The specific process is as follows: we use the AHP (Analytic Hierarchy Process) method first to calculate the weights of the evaluation criteria S, O, and D to evaluate the risk, and then make optimizations on the basis of the fuzzy FMEA to establish a new F-RPWN (fuzzy risk priority-weighted number), which includes weight analysis. This allows us to optimize the identified risks, and the final results are more convincing.

2. Literature Review

Failure Mode and Effects Analysis (FMEA) was first proposed in the aerospace industry in the 1960s and applied to the Grumman Aircraft Corporation's naval aircraft flight control system [3]. FMEA is a group-oriented, structured, and active reliability management technology used to identify hidden failure modes in products, processes, and services, and allocate limited resources to implement improvements. If a critical analysis includes an effect and criticality analysis (FMECA), then this is also known as failure mode. Generally, the risk priority order of the identified failure modes is defined by the risk priority number (RPN) method. RPN is the product of the occurrence (O), severity (S), and detection (D) of three risk factors, where O and S represent the occurrence and severity of the failure, and D is defined as the failure to be detected before the failure reaches the customer probability [4]. In conventional FMEA, every risk factor is scored on a 10-point scale (the higher the value, the worse the situation). Failure modes with larger RPN values are considered more important, so more attention should be paid to risk mitigation. Nowadays, FMEA is an approach that identifies the various shortcomings in a product design stage and their influences on the overall system or even a holistic level [5]. It is carried out through the use of various subjective and dimensionless instruments. FMEA combines subjective assets such as severity, incidence, and detection to evaluate a subjective and dimensionless metric, the Risk Priority Number (RPN), which represents each potential failure.

FMEA is used to identify logistics systems [6–8]. The reason for failure is also one of the most important ones, especially now that under the influence of the COVID-19 pandemic, some failure reasons that did not exist or were very low in the past have been added. Previous [9,10] research papers pointed out that some technological errors are likely to occur in the production process of the equipment, which will cause the equipment to fail to operate normally. Some scholars [1] believe that the COVID-19 pandemic has had a huge influence on the supply chain. The supply chain is a link in the logistics system, which will eventually affect the logistics system. Therefore, in the research part of this article, we combine previous studies to analyze failure models, failure causes, and effects caused by failures.

However, the shortcomings of FMEA have been criticized [11]: (1) the three risk factors (severity, occurrence, and detection) are not distinguished in RPN, because their relative importance is considered to be equal. (2) The combination of various risk factors may cause the same RPN value to hinder the determination of the risk level. Therefore, traditional FMEA may not be sufficient to determine the risk level of failure.

Fuzzy logic [12–14] is an appropriate technique for estimating output responses from given input data. Business commentators use fuzzy logic systems for a number of reasons, including:

1. The concept of fuzzy logic is easy to understand. The mathematical basis is also simple in fuzzy interface systems.
2. It is flexible and can tolerate the data if any inappropriacy exists in the datasets.

3. This technique enables the modeling of complex nonlinear functions in a short period of time. This approach can also build up the experience of specialists without the need of additional training.
4. This technique will work on top of simple natural language.

By improving the conventional FMEA method so that it is not restricted by the above conditions, and is suitable for research and analysis of the logistics system under the pandemic situation, this paper proposes a Fuzzy FMEA-AHP method. The innovations of this article are as follows:

1. Calculate the weight of each factor in the FMEA using Analytic Hierarchy Process (AHP).
2. Make a new definition of the scoring standards of FMEA's various factors to apply to the logistics system.
3. The COVID-19 pandemic will become normal, so it is more practical to study the failure model in the pandemic situation.
4. To overcome the shortcomings of FMEA, a method called fuzzy FMEA is therefore proposed.

This paper conducts a logistics system risk analysis based on the ISO31000 standard [15], and it is shown in Figure 1.

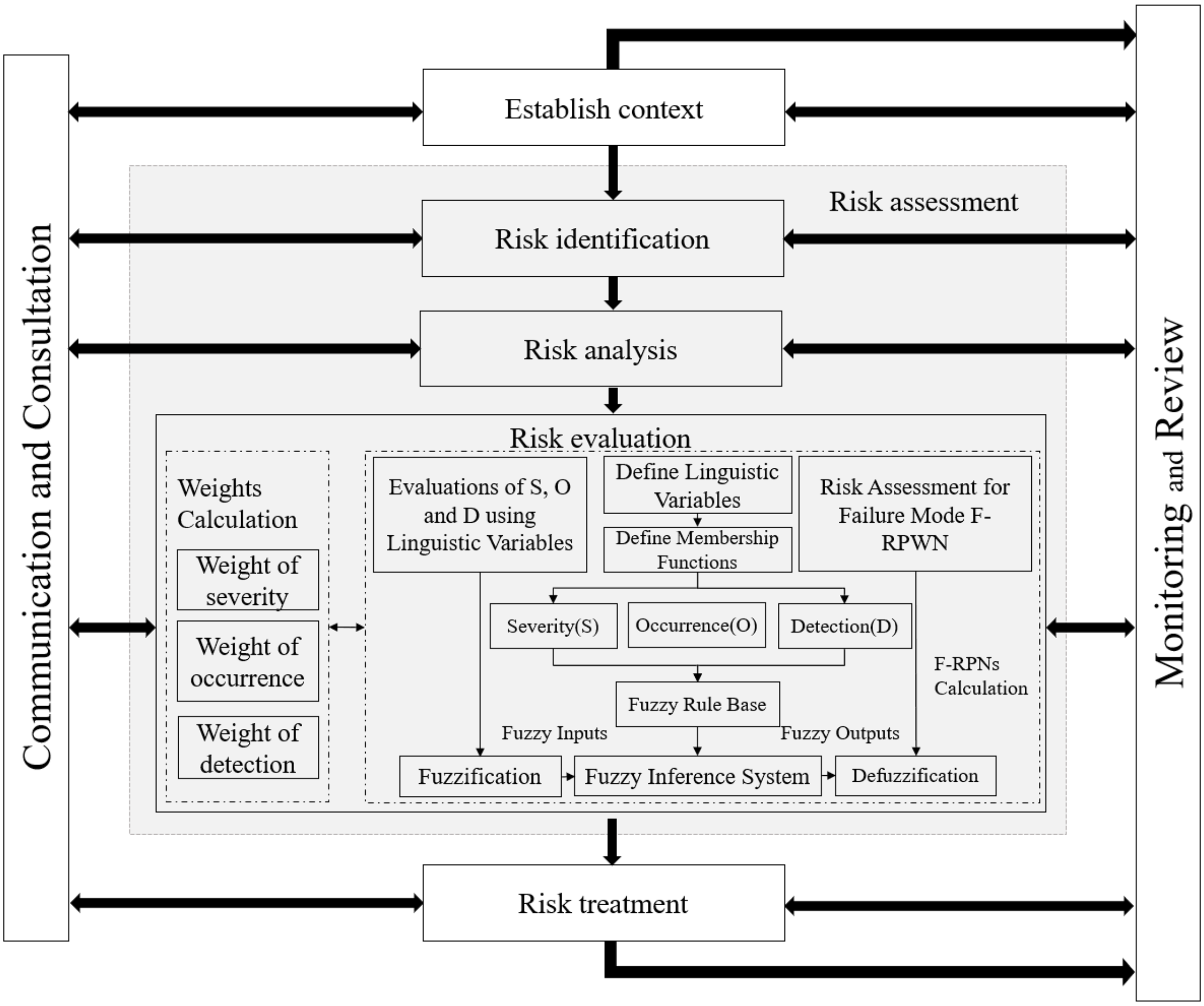

Figure 1. The procedure of implementing the proposed method.

3. Methodology

The fuzzy method [16] is an important theory for dealing with information decomposition. In Fuzzy-FMEA [17,18], risk index parameters, such as severity (S), occurrence (O), and detection (D), are fuzzed using appropriate membership functions. This is a knowledge-based approach that can be created with proficiency and knowledge in the form of fuzzy IF-THEN rules [19]. More informed and appropriate knowledge-based models can be built using expert knowledge and decision-making. The fuzzy conclusions are then defuzzied to obtain the RPN value.

The Fuzzy FMEA-AHP technique is a combination of the proposed algorithm and the AHP method. It allows the generation of a Failure Risk Index (F-RPN) by considering the severity, occurrence detection, and weight of the dataset. The process driving the proposed Fuzzy FMEA-AHP method is shown in Figure 1.

As shown in Figure 1, risk assessment is the most important step. The first step is system identification. We need to determine the parts the logistics system to be studied consists of. This is followed by a system analysis, and then, we analyze the logistics system and decompose it into three categories. The third step is to perform a risk evaluation: including weight calculation and F-RPN calculation, the weight W and F-RPN are combined using the Fuzzy FMEA-AHP method proposed in this paper, and finally, F-RPWN is obtained. Finally, risk management is carried out in the fourth section of this paper, the proposed Fuzzy FMEA-AHP method is used for case analysis. The ranking of each risk can be visually observed through calculation, and then analyzed and processed based on this.

3.1. System Identification

In the initial research [20–26], we confirm the risk classification of the logistics system and the components of each type of risk. This includes business risks, safety risks, and special issues (see Figure 2).

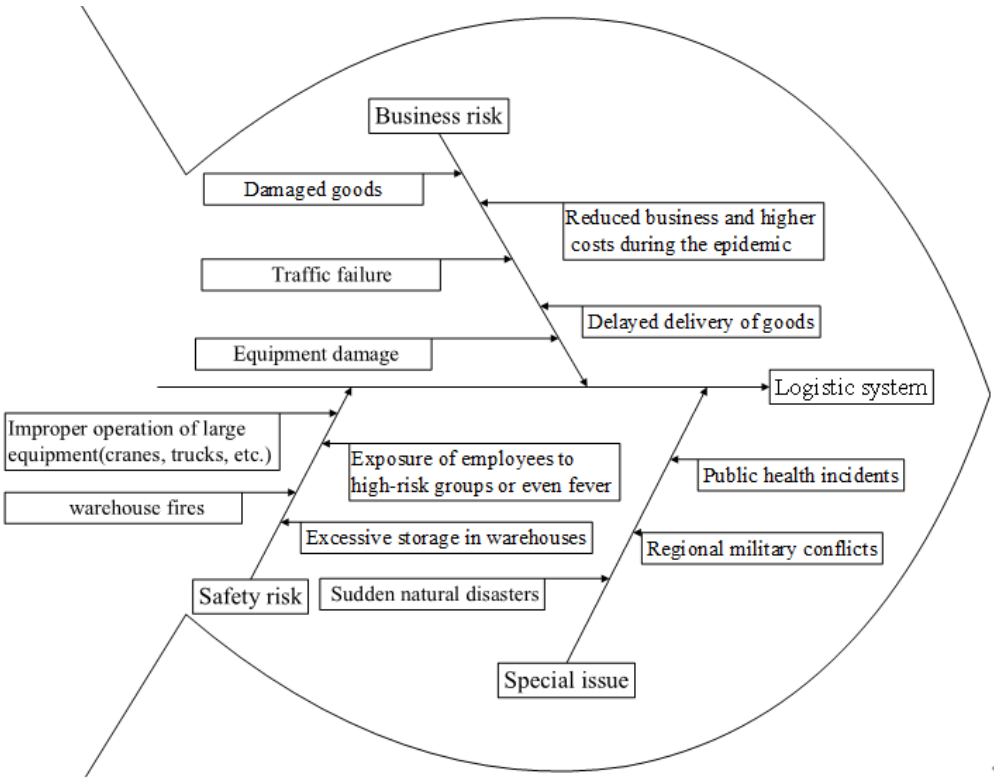

Figure 2. Logistic System Classification.

3.2. Failure Collection

The consistency and standardization of their ratings are ensured by the use of a unified rating guidance, see Table 1 [27,28].

Table 1. The rating guidance of risk factors.

Rating	Severity	Description
1	Very low	Based on the extent of each company's operational interruption and property damage.
2	Low	
3	Moderate	
4	High	
5	Very high	
Rating	**Occurrence**	**Description**
1	$P < 10^{-5}$	Occurs once in more than three years
2	$10^{-5} < P < 4 \times 10^{-4}$	Occurs every one to three years
3	$2 \times 10^{-3} < P < 1 \times 10^{-2}$	Occurs once a year
4	$4 \times 10^{-3} < P < 0.2$	Occurs every six months to a year
5	$P > 0.33$	Occurs every three to six months
Rating	**Detection**	**Description**
1	Very high	Error prevention technology is adopted in the process/design
2	Moderate	Detection of abnormalities by mechanical means and prevent subsequent failure modes
3	Low chance	Detection of failure modes by the operator using relevant equipment
4	Remote	The operator detects the failure mode through visual/tactile/auditory
5	No chance, no inspection	There is currently no relevant process control

The detailed description of Table 1 can be seen as follows: A five-point Likert scale was used to conduct a questionnaire survey to collect the severity of risk, risk occurrence, and detection degree. For severity, the numbers 1, 2, 3, 4, and 5 indicate the degree of operational disruption and property damage, respectively. For the risk occurrence, the number 1 means "occurs once in more than three years", 2 means "occurs every one to three years", 3 means "occurs once a year", 4 means "occurs every six months to a year", and 5 means "occurs every three to six months". For the detection degree, 1 means "error prevention technology is adopted in the process/design", 2 means "detection of abnormalities by mechanical means and prevent subsequent failure modes", 3 means "detection of failure modes by the operator using relevant equipment", 4 means "the operator detects the failure mode through visual/tactile/auditory", 5 means "there is currently no relevant process control".

In addition, the pairwise comparisons of various risk factors are performed using the AHP method [29], see Table 2:

Table 2. Pairwise comparisons of AHP method.

Number of Importance	Description	Number of Importance	Description
1	Equal Importance	7	Very Strong Importance
3	Medium Importance	9	Utmost Importance
5	Strong Importance	2, 4, 6, 8	Intermediate Importance

After consulting the relevant information, the reasons for the failure models and the effects of the failure were determined, see Table 3.

Table 3. Failure modes and reason of the Logistic System.

Code	Failure Modes	End Effects	Failure Causes
#1	Damaged goods	Customer complaints and compensation	Shock during transportation Unstable stacking, damp
#2	Delayed delivery of goods	Customer complaints and compensation	Inventory backlog
#3	Equipment damage	Business interruption	Manufacturing error Insufficient protection

Table 3. *Cont.*

Code	Failure Modes	End Effects	Failure Causes
#4	Reduced business and higher costs	Business interruption, bankruptcy	Financial market turmoil
#5	Traffic failure	Delayed delivery of goods	Major accident
#6	Improper operation of large equipment (cranes, trucks, etc.)	Staff injured	Training is not up to standard
#7	Warehouse fires	Staff injured and loss of goods	Aging of fire-fighting equipment Improper use of fire by staff
#8	Exposure of employees to high-risk groups with fever	Business interruption	Failure to take protective measures
#9	Excessive storage in warehouses	Staff injured	Warehouse management errors
#10	Sudden natural disasters	Business interruption	Natural variation Human influence
#11	Public health incidents	Business interruption	Natural variation Human influence
#12	Regional military conflicts	Business interruption	Human influence

3.3. Risk Evaluation

3.3.1. Weights Calculation

The assignment of each scale in the judgment matrix in the AHP method is very arbitrary. Therefore, in order to avoid this situation, we evaluate and test the consistency when selecting the sample, and finally select the valid sample as the case of this article.

We use AHP to calculate the weight of the severity, occurrence, and detection of each failure model. First, we establish a judgment matrix for each failure model, as shown below.

$$A = \begin{pmatrix} c_{11}, & c_{12}, & c_{13} \\ c_{21}, & c_{22}, & c_{23} \\ c_{31}, & c_{32}, & c_{33} \end{pmatrix} \quad (1)$$

We suppose that the elements of the judgment matrix are c_{ij}. Here, we use the sum-product algorithm to calculate the standard weight.

We normalize each column of the judgment matrix:

$$c_{ij} = \frac{c_{ij}}{\sum_{i=1}^{n} c_{ij}} (j = 1, 2, \ldots, n) \quad (2)$$

To obtain the judgment matrix normalized by column, we sum by row:

$$W = \sum_{j=1}^{n} c_{ij} (i = 1, 2, \ldots, n) \quad (3)$$

W represents the weight value. We normalize the vector $W = [W_1, W_1, \ldots, W_N]$:

$$\overline{W} = \frac{W}{\sum_{I=1}^{W} W_I (I = 1, 2, \ldots, n)}) \quad (4)$$

We calculate the maximum eigenvalue:

$$\lambda_{\max i} = \frac{\sum_{i=1}^{n} (AW)_i}{nW_i} \quad (5)$$

We calculate the consistency index (Consistency Index, CI):

$$CI = \frac{\lambda \max - n}{n - 1} \tag{6}$$

When the judgment matrix is completely consistent, $\lambda_{max} = n$, then CI = 0.

When the Consistency Index is larger, the consistency of the matrix is worse.

In order to test whether the judgment matrix is satisfactory and consistent, it is necessary to compare the Consistency Index with the average random index (Random Index, RI).

We find the corresponding average random consistency index RI, which is listed in Table 4.

Table 4. Average random consistency index value of RI.

Matrix order	1	2	3	4	5
Random Index	0	0	0.58	0.90	1.12
Matrix order	6	7	8	9	10
Random Index	1.24	1.32	1.41	1.45	1.49

3.3.2. F-RPWNs Calculation

Risk priority number (RPN) is a product of the occurrence, severity, and detection level of an event. It is called the risk factor or the risk sequence number. The higher the value, the more severe the potential problem. It is used to measure possible process defects to take possible preventive actions, reducing critical process variations, and making the process more reliable.

The conventional risk priority number sets the overall level of risk. We calculate it using Equation (7)

$$RPN = FS * POF * PFD \tag{7}$$

where: FS—failure severity; POF—probability of occurrence of failure; PFD—probability of failure detection.

In the following, we set three factors (S, O, D) as input factors of the fuzzy system and evaluate them using the "If-Then" rule defined by the fuzzy logic tool. Membership functions were originally exported to generate fuzzy rule bases. With the "If-Then" rule viewer left open, it is used to access the member function editor and the rule editor, the function rule editor is used to edit the list of rules that describe the behavior of the framework, and the Fuzzy Interface System (FIS) can be used to add input variables/member functions.

The value output of the fuzzy RPN is divided into 5 categories: Very High—5, High—4, Moderate—3, Low—2, Very Low—1. The membership function of the output variable and its parameters can be determined according to the type of curve used.

Fuzzy rules ("If-Then" rules) are formulated by considering that the severity value is the most decisive input to the fuzzy RPN value, so if the severity (S) value is very high (1), the fuzzy RPN value is also very high (1), independent of the values obtained for Occurrence (O) and Detection (D). The resulting fuzzy RPN value represents the priority of the risk to be addressed. A high ambiguous RPN value indicates that a risk should have a higher priority. We use "If-Then" to calculate the Fuzzy RPN value.

The input variables used in the analysis were the severity, occurrence, and detectability of failure modes (Figure 3). Depending on the significance level, the severity scale should be assigned on a scale from 1 to 5. The level in the severity scale can be estimated based on proficiency of the FMEA expert. Occurrence is the probability of an exact failure occurring during the time period considered. This can be estimated based on the frequency of failures. Occurrence was also graded in severity using a 1 to 5 scale. A value of 5 indicates the highest probability of occurrence, and similarly, a value of 1 indicates the lowest probability of occurrence. Detectability defines the probability of detecting failure modes and can also be expressed as the ability of a person to detect potential failure modes and their consequences [30]. Detectability can also be estimated using a score from 1 to 5. A minimum detectability value can be assigned when the failure mode has no current control action. These parameters can be used to estimate the Risk Priority Number (RPN). The criticality of components can be determined based on the priority of failure modes [31].

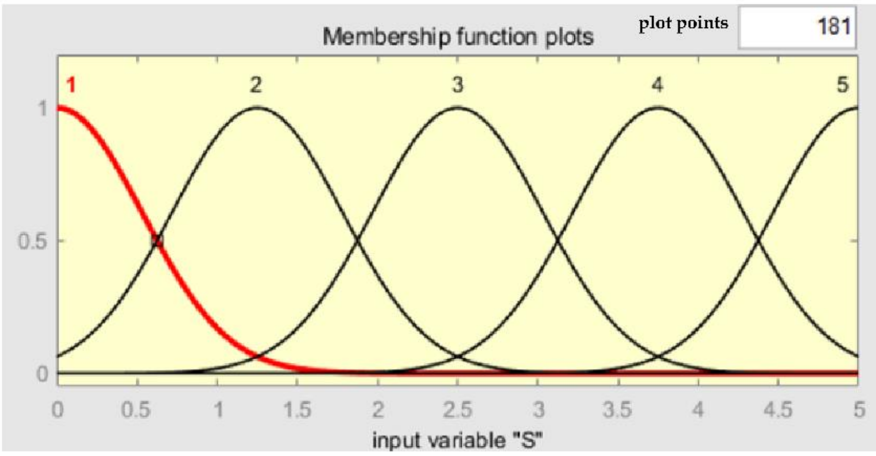

Figure 3. Membership function editor.

The Rule Editor is an "If-Then"-based logical unit that facilitates adding rules in linguistic format. The dependencies of the output parameters should depend on the input data in the given linguistic format. The training process is performed on the created combination of input rules in an "If-Then"-based fuzzy analysis. The combination of this FMEA fuzzy rule base is as Table 5.

Table 5. The combination of this FMEA fuzzy rule base.

Severity	Occurrence	Detection	F-RPN
4	3	3	3
4	3	2	1
4	4	3	5
4	3	4	4
3	4	3	3
4	3	3	3
5	2	2	2
5	3	4	5
3	2	3	1
5	2	5	4
5	1	4	2
3	2	2	1

We use the MATLAB command plotfm (fis) to help view the dependency of the output on one or two of the inputs, such as severity and detection. In this analysis, the presented surface viewer is a three-dimensional mapping view with severity, detection, and FRPN, see Figure 4.

At last, in this article, we establish a new coefficient F-RPWN (Fuzzy Risk Priority Weighted Number), which adds a weight calculation on the basis of F-RPN, and is also the core of this article Fuzzy FMEA-AHP. The F-RPWN of the Fuzzy FMEA-AHP method can be calculated as:

$$\mathrm{F-RPWN} = \mathrm{FRPN} * \mathrm{W_{Si}} * \mathrm{W_{Oi}} * \mathrm{W_{Di}} \quad (8)$$

The average F-RPWN can be calculated as:

$$\overline{\mathrm{F-RPWN}} = \frac{\sum_{i=1}^{n} \mathrm{F-RPWN_i}}{n} \quad (9)$$

where: $RPWN_i$ of failure model i

The normalized average F-RPWN can be calculated as:

$$\text{NOR}\ \overline{F-RPWN} = \frac{\overline{F-RPWN}}{\sum_{I=1}^{W} \overline{F-RPWN}_i (I = 1, 2, \ldots, n)} \tag{10}$$

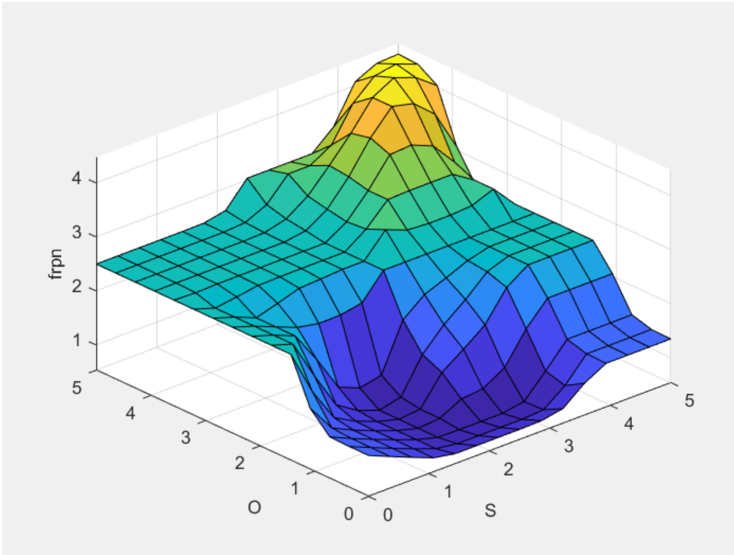

Figure 4. Severity, Detection, and FRPN 3D Map View.

4. Result

In this example, we make the questionnaire survey to collect the scoring results of each expert, among the experts interviewed and consulted, including the staff at the grass-roots level of the logistics system, as well as decision-makers in the logistics industry. The results are universal, but the influence of subjective factors cannot be ruled out. Here, this case is used as an analysis to verify the feasibility of the proposed method. We select the results that pass the consistency test, and calculate the average value. Equations (3) and (4) are used to calculate the weights of S, O, D. The weights of all factors are calculated according to the above method, and the codes are sorted according to Table 3, and the final weight result obtained can be seen in Table 6 below.

Table 6. Weight calculation result (W_{Si}, W_{Oi}, W_{Di} denote the weight values of S, O, and D).

Code	W_S	W_O	W_D
#1	0.648	0.122	0.230
#2	0.637	0.105	0.258
#3	0.429	0.143	0.428
#4	0.637	0.105	0.258
#5	0.634	0.192	0.174
#6	0.581	0.110	0.309
#7	0.443	0.388	0.169
#8	0.400	0.400	0.200
#9	0.558	0.122	0.320
#10	0.594	0.157	0.249
#11	0.594	0.157	0.249
#12	0.594	0.157	0.249

Note: W_S, W_O, W_D represent the weight of S, O, and D, respectively.

After calculating the weights of S, O, D using the AHP method, we use Equation (8) to calculate the F-RPN of the failure model i. The calculation results and experts' scores of FS, POF, and PFD can be seen in Table 7.

Table 7. Weight, FS, POF, PFD, F-RPN, F-RPWN, and their ranking of failure mode.

Code	W_S	W_O	W_D	FS	POF	PFD	F-RPN	F-RPWN	Rank
#1	0.648	0.122	0.230	4	3	3	3.09	0.056185	7
#2	0.637	0.105	0.258	4	3	2	2.5	0.043141	10
#3	0.429	0.143	0.428	4	4	3	4.34	0.113953	2
#4	0.637	0.105	0.258	4	3	4	3.7	0.063848	4
#5	0.634	0.1920	0.174	3	4	3	3	0.063542	5
#6	0.581	0.110	0.309	4	3	3	2.5	0.04937	9
#7	0.443	0.388	0.169	5	2	2	1.47	0.042701	12
#8	0.400	0.400	0.200	5	3	4	4.23	0.13536	1
#9	0.558	0.122	0.320	3	2	3	2.5	0.054461	8
#10	0.594	0.157	0.249	5	2	5	3.72	0.086383	3
#11	0.594	0.157	0.249	5	1	4	2.5	0.058053	6
#12	0.594	0.157	0.249	3	2	2	1.85	0.042959	11

We calculate the average F-RPWN for each failure type according to Table 7, using Equations (9) and (10). See Table 8.

Table 8. F-RPWN and $\overline{\mathrm{F-RPWN}}$ of each failure type and RPWN of each failure model.

Failure Type	Failure Mode	Code	F-RPWN	NOR $\overline{\mathrm{F-RPWN}}$
Business risk	Damaged goods	#1	0.056185	0.338853
	Delayed delivery of goods	#2	0.043141	
	Equipment damage	#3	0.113953	
	Reduced business and higher costs	#4	0.063848	
	Traffic failure	#5	0.063542	
Safety risk	Improper operation of large equipment	#6	0.04937	0.350487
	Warehouse fires	#7	0.042701	
	Exposure of employees to high-risk groups with fever	#8	0.13536	
	Excessive storage in warehouses	#9	0.054461	
Special issue	Sudden natural disasters	#10	0.086383	0.31066
	Public health incidents	#11	0.058053	
	Regional military conflicts	#12	0.042959	

Finding out the key links of the logistics system helps understand the nature of failure models and arrange solutions such as failure warning and diagnosis, inspection, and preventive planning.

The critical rank of the logistics system is shown in Figures 5–7. Therefore, among the failure types of the logistics system, the safety risk is considered the most critical risk of the logistics system, NOR $\overline{\mathrm{F-RPWN}}$ is 0.350487, followed by business risks (0.338853) and special problems (0.31066). Furthermore, Figure 7 also concludes that the safety risk is the most critical, because the RPWN of the failure model #8 (exposure of employees to high-risk groups with fever) is the highest (0.13536), which also shows that the COVID-19 pandemic has a great influence on the logistics system. Secondly, the NOR $\overline{\mathrm{RPWN}}$ of the business risk is second only to safety risks because it contains more failure models; special issue is more men-made, therefore, it is easier to prevent in advance.

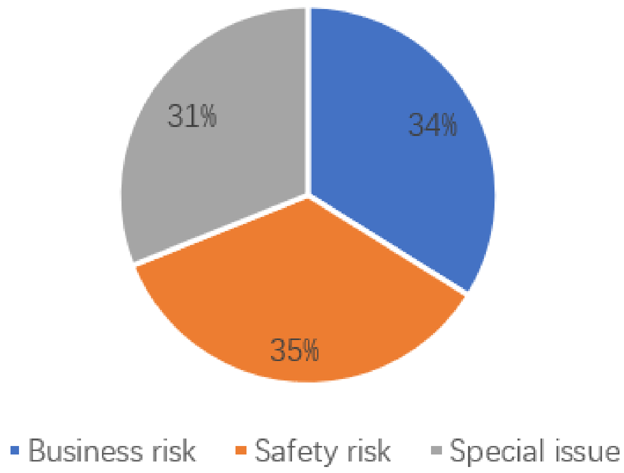

Figure 5. Failure type NOR $\overline{\mathrm{F}-\mathrm{RPWN}}$ pie chart.

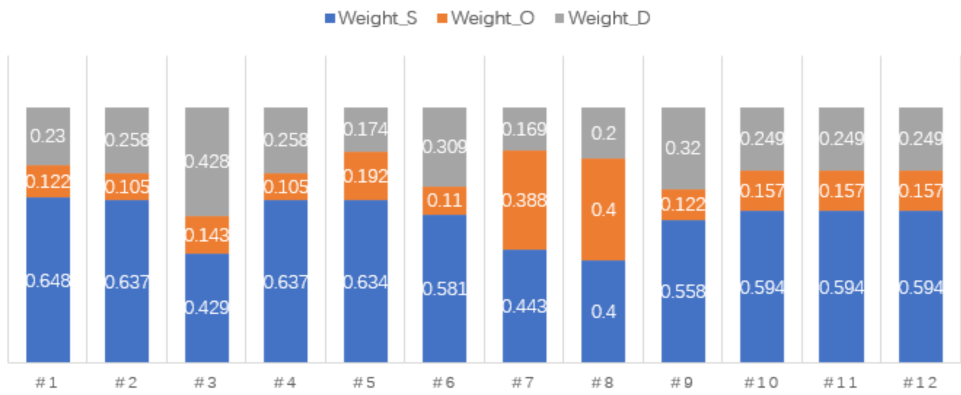

Figure 6. S, O, D weight of each failure mode.

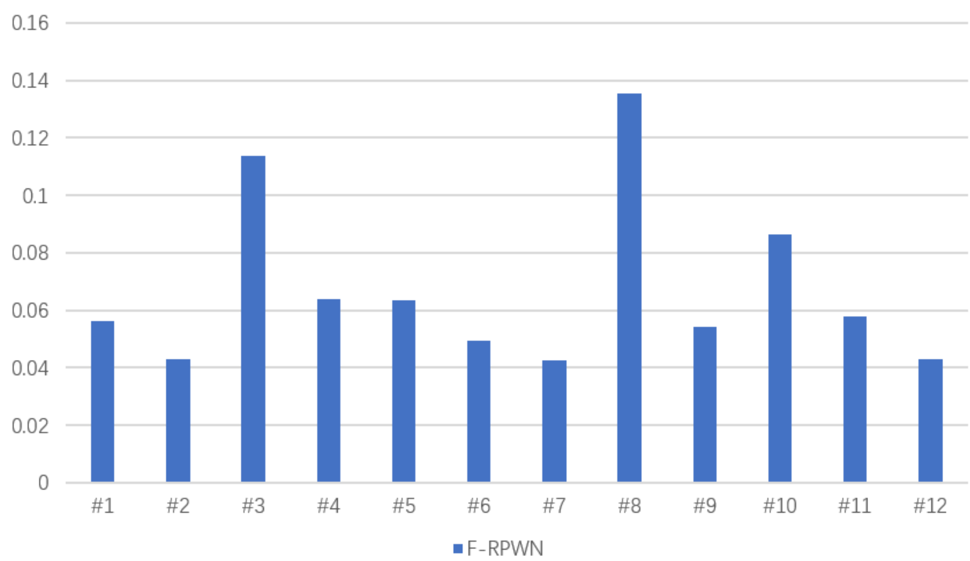

Figure 7. Each failure mode F-RPWN.

Overall, 12 failure models in the logistics system are analyzed. Among them, #8 is considered the weakest link in the logistics system because it has the highest RPWN value, as seen in Figure 7. According to Figures 6 and 7: #1 (Damaged goods) has the highest severity weight (0.648), but the probability of occurrence is not high compared to other failure models, so the impact on the entire logistics system is moderate, ranking seventh.

This shows that even though this failure model brings the highest severity, it does not have the greatest impact on the entire logistics system. In Figure 6, the severity, occurrence, and detection degree of #7 (Warehouse fires) and #8 (Exposure of employees to high-risk groups with fever) are the closest (0.169 and 0.2, 0.388 and 0.4, 0.433 and 0.4, respectively), but the final F-RPWN is quite different (0.042701 and 0.13536). Therefore, just by looking at the weights of S, O, and D, we cannot get the most accurate results. Instead, we need to combine FMEA to get the most accurate results.

The proposed Fuzzy FMEA-AHP(F-RPWN) method is compared with Fuzzy FMEA(F-RPN), FMEA-AHP(RPWN), traditional FMEA(RPN) method, and the data are normalized as shown in Table 9. According to the ranking of each failure model, it can be seen that compared with other methods, the proposed method can distinguish failure models with equal ranking, resulting in more accurate results.

Table 9. Fuzzy FMEA-AHP, Fuzzy FMEA, FMEA-AHP, traditional FMEA ranking comparison.

Code	F-RPWN	Rank	F-RPN	Rank	RPWN	Rank	RPN	Rank
#1	0.069367966	7	0.087288136	5	0.069488648	7	0.088235294	4
#2	0.053263387	10	0.070621469	7	0.043921069	10	0.058823529	5
#3	0.140690358	2	0.12259887	1	0.13367282	2	0.117647059	3
#4	0.078828973	4	0.104519774	4	0.087842139	4	0.117647059	3
#5	0.078451175	5	0.084745763	6	0.080946319	5	0.088235294	4
#6	0.060953928	9	0.070621469	7	0.075429663	6	0.088235294	4
#7	0.052720148	12	0.041525424	9	0.061638022	8	0.049019608	6
#8	0.167120189	1	0.119491525	2	0.203691916	1	0.147058824	1
#9	0.067239455	8	0.070621469	7	0.0415871	11	0.044117647	7
#10	0.106651472	3	0.105084746	3	0.123169955	3	0.12254902	2
#11	0.071674264	6	0.070621469	7	0.049225546	9	0.049019608	6
#12	0.053038684	11	0.052259887	8	0.029386802	12	0.029411765	8

The contributions of this article are as follows:

1. Compared with traditional FMEA, fuzzy FMEA uses suitable membership functions to fuzz the risk index parameters such as severity (S), occurrence rate (O), and detection rate (D), and the resulting F-RPN can be prioritized for failure modes. Severity ranking provides guidance and can be used to minimize the occurrence of severity levels and failure modes.
2. After combining the AHP technology, it can also help determine the priority of the failure mode more accurately when two or more have equal F-RPNs. From Table 6, it is found that for 2#, 6#, 9#, 11#, the F-RPNs are equal, both 2.5. However, because each FMEA factor is weighted differently, it can be ranked accurately.
3. In this article, the Fuzzy FMEA-AHP technique is used to rank the identified failure modes. The technique also takes into account obscured data in the evaluation process. The final conclusion is that the Fuzzy FMEA-AHP analysis using rules provides strong evidence that the proposed method is logically useful for prioritization of F-RWPN values. This approach not only identifies the RPN-related limitations of traditional FMEA methods, but also addresses the issue that FMEA may not be sufficient to determine the level of failure risk. In addition, when there is a lot of fault information, the fuzzy rule base should also be modified or updated.
4. This method is designed to optimize the risk analysis of the logistics system. In this case, the proposed Fuzzy FMEA-AHP is used for analysis. Compared with the traditional method, this method can accurately calculate the degree of risk and is universal.

5. Conclusions

This paper proposes an optimization method based on the traditional method: the Fuzzy FMEA-AHP method to complete the failure analysis of the logistics system. The proposed method uses AHP technology to calculate the severity, occurrence, and detection importance of the logistics system failure model. Therefore, the weights of these risk factors can be extracted to facilitate the implementation of the proposed Fuzzy FMEA-AHP method. Security risk is the most critical type in the logistics system, followed by commercial risks and special issues. Subsequently, damage to goods and 11 other failure modes were determined as risky failures. This article then distinguished the critical failure causes such as manufacturing errors, human errors, insufficient protection, economic turbulence, and environmental factors, and proposed relevant preventive and corrective measures to prevent the logistics system from being affected by failures. Similarly, related logistics enterprises can also refer to the points presented in this article to reduce the operating costs of enterprises under the COVID-19 pandemic situation, so as to achieve the highest work efficiency. The comparison results show that there are differences in the F-RPWN obtained by different experts, indicating that FMEA is a subjective method, and personal judgment affects the results; the choice of experts is reasonable because their backdrops are diverse; the correctness of the Fuzzy FMEA-AHP results is determined by conventional methods. The results of the method are confirmed.

The method proposed in this paper still has certain limitations: FMEA and AHP itself are subjective methods, and the results obtained by different experts may be different. Although, adding Fuzzy can reduce the subjective impact, it still needs to be improved. This paper is an analytical method for optimizing risk management, which is universal, and therefore, in future work, the authors plan to continue to optimize such methods to minimize the impact of subjectivity on the results.

Author Contributions: Writing—original draft preparation, Q.M.; supervision, G.J.; conceptualization, Q.M. and G.J.; writing—review and editing, G.J. and W.F.; funding acquisition, G.J.; methodology, Q.M. All authors have read and agreed to the published version of the manuscript.

Funding: This research was funded by Dalian Maritime University (China), grant number 02502329. This research was also funded by the Fundamental Research Funds for the Central Universities, grant number 3132022291.

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

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