Integrated Decision Making Aided Model to Estimate the Risks of the Excavation System

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Abstract

For the last years, a bibliometric examination of risk evaluation approaches for excavating systems has been presented in this publication. To develop an early warning system, it's essential to compile a list of possible dangers that can arise during excavation. Failure Mode and Effects Analysis (FMEA) is a useful approach. Traditional risk assessment techniques have been criticized for a variety of reasons, including a lack of correlation between risk variables, difficult arithmetic operations, and a lack of correctness and preciseness in the evaluations. A unique method of risk analysis in FMEA that uses digraphs and matrix approaches underneath the Pythagorean fuzzy scenario is presented in this research. To get started, we'll defy Pythagorean fuzzy numbers in a triangle form. Both language terminology and risk factor data and information are expressed using them (inclusive of occurrence, severity, and detection). The Pythagorean fuzzy digraph thus captures the interrelationships between the risk variables and the relative importance of each one, as seen in the figure. After that, we create a Pythagorean fuzzy test indicated for each identified failure mode and compute risk priority indexes to determine risk priorities. Using a metro station excavation as a case study, the accuracy of risk assessments in excavation is improved.

Keywords: decision making; Multi-criteria; Pythagorean fuzzy; Digraph matrix; Risk Assessment; Excavation System; decision support

1. Introduction

There are now more than seven billion people on the planet, which has sped up urbanization throughout the globe and has had a significant environmental impact[1]. Especially in major cities, subways serve an important role in reducing traffic congestion as cities grow and expand their populations[2].

Many large cities have either implemented or are in the process of implementing plans for subterranean rail service[3], [4]. Due to the fast growth of cities, subterranean space is in high demand [5]. As part of the subterranean space technology, civil engineers face a significant task and various possibilities, and public safety is put at risk owing to the difficulty of the surrounding area and the uncertainty of the geological formations. Deep excavation. Deep excavation operations at metropolitan subway stations, on the other hand, come with a slew of challenges and hazards. Construction accidents involving deep excavation are common, and the resulting damage may be severe [6]. Different serious issues have developed in Chinese excavation techniques as a result of multiple risk concerns and breaches of safety regulations. In 2007, there were 80 fatalities as a result of tunnel building incidents in China[7], [8], and the risk of deaths surged to 12 in 2006 and 2014 [7], [8].

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The goal of analyzing deep excavation hazards is to provide the most precise risk estimates possible. To make things more complicated, the variables and risk profiles have a nonlinear connection. These approaches include fuzzy set theory (FST) [9], machine learning algorithms such as neural nets[10], [11], random forests (RF)[12], support vector machines (SVM) [13], and Bayesian networks (BNs) [14]–[16]to anticipate or evaluate the dangers of deep excavation. While each approach has its merits and disadvantages, determining which is the most appropriate and successful is difficult. Based on fieldwork data collecting, machine learning algorithms are better suited for estimation in excavation.

It is widely accepted that the FMEA is a very effective method for identifying and eliminating potential failures, mistakes, flaws, and defects before they reach the end-user [17]. Its primary goal is to assess risks in clearly defined modes of failure so that remedial measures may be taken against flaws whose eradication requires a greater degree of attention. The FMEA approach was first developed as a standard design methodology by the aircraft industry in the 1960s following their safety criteria (Bowles, Pelaez, 1995). Errors, Effects, and Multicriteria Analysis (FMECA) is another term for the FMEA approach used for criticality research (FMECA). As a bottom-up approach, FMEA is characterized by the division of a complex product into its basic components or subsystems. The probable failures and repercussions of each of these subsystems are progressively evaluated. Rather than reacting to a problem after it has occurred, FMEA's risk assessment is a proactive method for creating or controlling a scenario. In addition, it's important to look at the dangers that might lead to more severe failures. This study provides the facts and information ability to handle risk and make decisions. Many different sectors, such as auto, semiconductors, aviation, health care, and electromechanical, employ the FMEA approach to secure their products and ensure their designs are accurate while also reducing risk[18].

The paper is organized as follows: the related work is organized in section 2. Section 3 provides the triangular Pythagorean fuzzy sets and digraph matrix. Section 4 presented the results and application. Section 5 concludes the research.

2. Related Work

Past researches in the subject area are examined and the techniques used to evaluate their findings are evaluated, the benefits of every approach and the limits of every technique are briefly stated in this part. The OWA operator may now be obtained practically thanks to [19] work. The OWA operator and 2-tuple were combined innovatively by[20]. They found that the proposed approach could successfully address the issue of measuring ranges, and that didn't lose any experts in the process. It was found that 75 FMEA sharing information were evaluated and classified according to the strategies created to address inadequacies in conventional FMEA methodologies[21]. Using a new method based on D values and fuzzy membership projection, [22]started a new FMEA procedure for assessing risk. This approach performed better when used to assess risks and strategies. Product and technology specifications may be aligned using a TOPSIS-based approach described by [23] Using a real-world example, they were able to demonstrate that their approach was applicable.

When using fuzzy sets (FSs)[24], the flaws and shortcomings of crisp RPN approaches may be overcome. Ambiguity in practical cases has been debated using fuzzy sets. For the most part, the goal of FSs is to assign a certain degree of membership to each element. If you can't get a clear picture of the risk ratings using RPN, then the FSs come in handy. An easy method application of fuzzy OWA and a DEMATEL method was used by Chang and Cheng [25] to assess the risk ratings for types of defects. Their suggested strategy minimizes the frequency of identical RPN values and analyses the order in which severity, occurrence, and detection characteristics are affected by the method. Zhang and Chu [26] developed a fuzzy RPNs-based method for calculating the least square method.
The partial ranking approach was also used to construct the imprecision technique and generate more accurate fuzzy RPNs. Fuzzy techniques and linear programming were also examined for their ability to identify fuzzy RPNs. Fuzzy TOPSIS and fuzzy AHP were used to construct a fuzzy FMEA approach. Using this method is advantageous since it takes into account the significance of the risk variables. Experts may also use language variables to establish the risk factors for all failures. Liu,

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Liu, Liu, and Mao[27] studied a risk priority methodology based on FSs and VIKOR to determine the failures' importance rating.

To rate all possible failures, they employed the expanded VIKOR approach. Wang, Chin, Poon, and Yang [28]introduced the use of fuzzy weighted technical analysis for hazard prioritization and failure assessment in FMEA (2009). Linear programming models and -level sets are used to construct fuzzy RPNs, which are fuzzy weighted geometric averages of the fuzzy ratings for O, S, and D, respectively. Bowles and Pelaez [29] proposed a novel method for prioritizing FMECA failures based on fuzzy logic. The suggested approach addressed many issues that arose in the assessment of crisp techniques. A continuous fuzzy profi model was suggested by Alcantud, Biondo, and Giarlotta [30]to represent the creation of a political party. To facilitate the creation of new parties, they devised an algorithm. The AHP method was investigated by Ayag and Ozdemir [31] to choose machine tools. The standard AHP approaches were found to be weak, thus they used fuzzy number logic to make up for this.

Chen [32] extended the TOPSIS framework to include the fuzzy setting. For the sake of clarity, an illustration was provided to show how the suggested model's technique works. Fuzzy evidence-based reasoning and grey theory were used by Liu et al. [33] to increase the efficacy of standard methods of FMEA. They demonstrated that the suggested model can accurately capture the views of the team's specialists and rank the possible failures under various uncertainty. In Mandal and Maiti [34], fuzzy resemblance reports are available and were used to expand the application of FMEA. It was shown that the idea of possibilities may be used in decision-making by these researchers.
Introducing a fuzzy unit screening tool, Rojc and Mlakar [35] suggested a novel RGD-based examine the different optimization procedures that are completely automated. There is a major drawback to FMEA procedures that use FSs for which the discontent degree of a component is evaluated as one less the truth level, which will not adequately describe the numerous scenarios that arise in real-world events.

The concept of intuitionistic fuzzy sets (IFSs) (Atanassov, 1983), an extended version of FSs, is commonly used in FMEA to manage truth and falsity levels as independent parts of risk variables and modes of failure. In Atanassov's portrayal of FSs, he included a new ingredient that indicates the degree of falsehood or discontent. FSs reflect the extent of truth participation of an item in a particular set, but IFSs provide both an amount of truth and a level of falsehood, which are independent of everyone. Among other things, the IF mixed TOPSIS approach was developed by Liu, You, Shan, and Shao to rate failures in FMEA. Fuzzy FMEA and RPNs have their benefits and problems, however, the suggested method circumvents such shortcomings. For the first time, Agarwal, Biswas, and Hanmandlu generalized the IFSSs (GIFSSs) by including the moderator's view on the initial assessment. Conceptualized the GIFS relationship. Additional uses for GIFSSs include medical diagnostics and vendor selection. When it comes to aggregating an infinite series of IFS, Alcantud, Khameneh, and Kilicman came up with the first approach. To tackle decision-making issues, they disregarded the accuracy ratings of temporal IFSs. For the selection of suppliers in MCGDM situations, Boran, Genc, Kurt, and Akay combined the TOPSIS technique with IFSs. They used a quantifiable example of strategic sourcing to demonstrate the suggested method. This kind of analysis is not supported by the decision-making methods that use IFSs. IF membership ratings, for example, may be used to analyze dangers or fatigue damage (0.9, 0.7).
FMEA methodologies based on IFSs can't handle this kind of risk appraisal uncertainty.

Yager and Abbasov and Yager [36] first suggested the Pythagorean fuzzy set (PFS) as a novel extension of IFS to solve the constraints of IFSs. Orthopair participation classes are more relaxed in this model, requiring simplicity. Approaches that enable contributions in this approach are advantageous in later studies like[37]. A variety of tools have been created thanks to these efforts, which may be used when professionals deliver their input in a fashion that is not compatible with IFSs but is in accordance with the less stringent standards of PFS. Connotations associated with operators for PFS were presented by Yager[36]. MCDM's Pythagorean participation ratings were a way for him to convey his pleasure with the criterion. The TOPSIS approach was developed by Akram et al. [37]to tackle MCGDM issues using PF information. They used a reworked measure of proximity to rate the options and arrive at the best conclusion. The ELECTRE I approach in the PF set was suggested by Akram et al. to capture partial data in human assessments. Further instances in the fields of treatment and health safety were provided in the form of mathematical formulation.

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New criteria for image fuzzy entropy were devised by Joshi [38], who also provided new ways to make decisions using the VIKOR idea. Methods for predicting poll results and making investments were tested using the suggested technique. The indiscernible partition of the universe's set was investigated by Akram and Luqman [37] using architectures of fuzzy soft and fuzzy soft graphs. It was presented by Akram, Habib, and Alcantud [37] as a trapezoidal image fuzzy number with its visual analysis and operating rules. For a network containing trapezoidal fuzzy numbers, the Dijkstra method was suggested by the researchers.

3. Triangular Pythagorean Fuzzy and Digraph Matrix

This has been critiqued in the research for a range of factors, which has an impact on risk estimates in points of failure as well as the corrective activities that ensue.

This section proposes a more precise and reasonable model of FMEA to overcome the limits of classic and crisp FMEA procedures. Figure 1 shows the framework of the study.

This model is used to evaluate FMEA failures identified in the process. To objectively assess the topic at hand, we use PFDG and a matrix methodology that analyses the interconnectedness of n main risk R_{Fi} $(i = 1, 2, \ldots, n)$. The following model differs from typical RPN approaches in that it treats the dangers O, S, and D as PF factors and assesses them utilizing PF language words utilizing TPFNs. To begin with, the FMEA team specialists' evaluations are combined in working with stakeholders, and now the PFDG and matrix approach is used. In this way, the PF interaction matrix of all lifestyle factors R_{Fi} is obtained and the PF risk evaluation of all fail modes FM is formulated. Lastly, using the risk priority index (RPI), which is derived first from hazard functional, we can determine the relative risk of each possible mode of failure. The PFDG and grid techniques are used to prioritize all failure mechanisms in FMEA.

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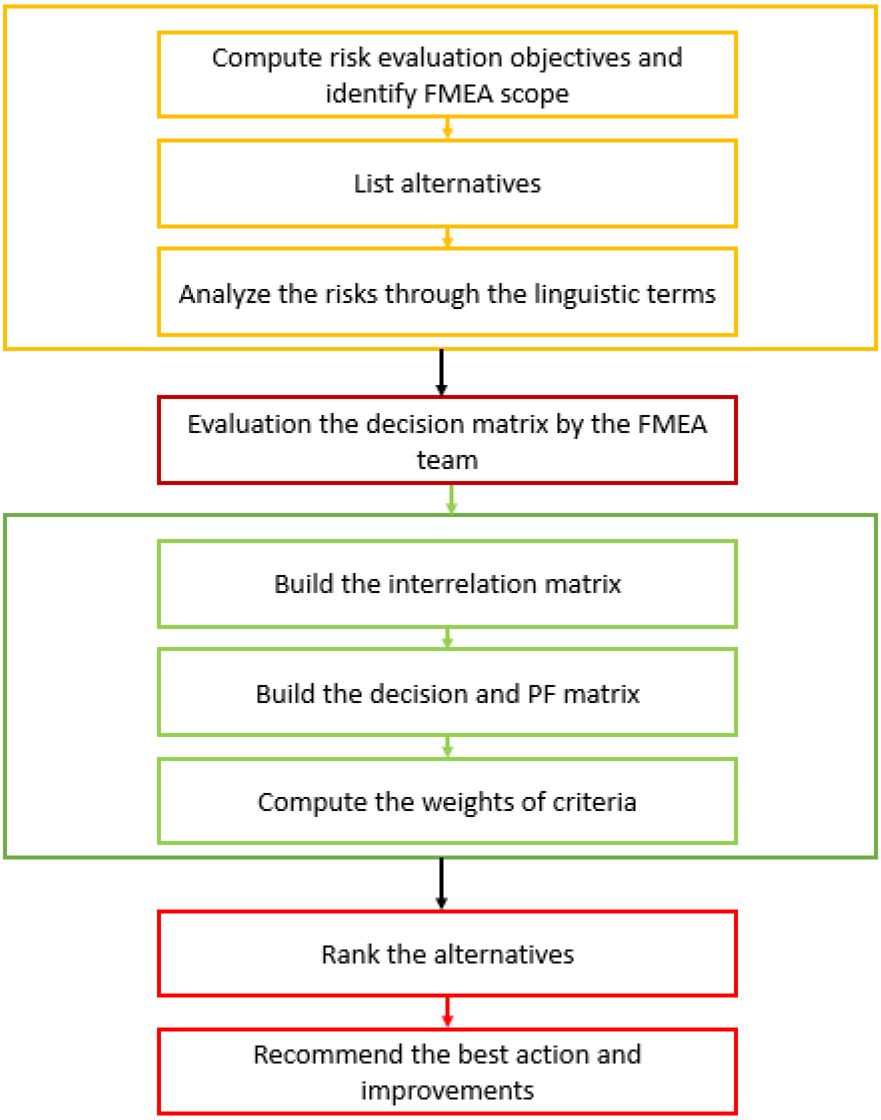

Figure 1: The framework of the study.

Step 1: For every of the risk factors, the averaged PF evaluations over all types of defects associated with that risk factor are calculated to create a PF group assessment matrix $P = (l_s)_{qr}$.

$$l_s = [(l_{s,1}, l_{s,2}, l_{s,3});\ t_{l_s}, f_{l_s}]$$

$$= \left[\left(\sum_{k=1}^{p} w_k\, {l_{s,1}}^{k}, \sum_{k=1}^{p} w_k {l_{s,2}}^{k}, \sum_{k=1}^{p} w_k {l_{s,3}}^{k}\right);\ t_{l_s}, f_{l_s}\right]$$

Similar to the PF weights w_s which are determined as follows: s = 1, 2, 3, 4,...., r risk factors

$$w_s = [(w_{s,1}, w_{s,2}, w_{s,3}); t_{w_s}, f_{w_s}]$$

$$= \left[\left(\sum_{k=1}^{p} w_k\, {l_{s,1}}^{k}, \sum_{k=1}^{p} w_k {l_{s,2}}^{k}, \sum_{k=1}^{p} w_k {l_{s,3}}^{k}\right);\ t_{w_s}, f_{w_s}\right]$$

Step 2: Finding out how risk variables are linked to one another is step two.

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The combined weights of all risk variables are first computed to build the interaction matrix. Calculated the normalized average PF weights are computed as follows

$$v_s = \frac{w_s}{\sum_{s=1}^{r} w_{s,3}}$$

$$T_s = \left[(\lambda_{s,1}, \lambda_{s,2}, \lambda_{s,3});\ t_{T_s}, f_{T_s}\right] = \frac{v_s}{\sum_{s=1}^{r} v_s}$$

Defuzzification of s yields v_s and $\sum_{s=1}^{r} v_s = 1$, which is the crisp value achieved. Risk factor interdependencies are shown using the RFPFDG. The following interaction matrix I_M indicates the relative significance of r risk factors:

$$I_M = \begin{bmatrix} R_{f_s} & R_{f_1} & R_{f_2}\ R_{f_3} & \dots & R_{f_r} \\ R_{f_1} & M_1 & m_{12} m_{13} & \dots & m_{1r} \\ R_{f_2} & m_{21} & M_2\ m_{23} & \dots & m_{2r} \\ R_{f_3} & m_{31} & m_{32}\ M_3 & \dots & m_{3r} \\ \vdots & \vdots & \vdots\ \ \vdots & \vdots & \vdots \\ R_{f_r} & m_{1r} & m_{2r} m_{3r} & \dots & M_r \end{bmatrix}$$

Where $M_s = [(1,1,1); 1,0], s = 1.2.3 \dots\dots r$

Risk factor R_{F_β}'s relative significance m_{a_β} above another risk factor R_{F_β} and m_{β_a} are generated as follows:

$$\zeta_a = \frac{T_a}{T_{a,3} + T_{\beta,3}}$$

$$\zeta_\beta = \frac{T_\beta}{T_{a,3} + T_{\beta,3}}$$

$$m_{a_\beta} = \frac{\zeta_a}{\zeta_a + \zeta_\beta}$$

$$m_{\beta_a} = \frac{\zeta_\beta}{\zeta_a + \zeta_\beta}$$

Where values of $T_a and\ T_\beta$ refer to the normalized aggregated weights.

Step 3: For every catastrophic failure, the normalized aggregate PF scores of the relevant potential cause are swapped with the major diagonal of the relationship matrix to produce the PF risk matrix. Consequently, $R_{1,1}$ is used to replace M_1 in the potential failure$F_{M_1}$and the main risk $R_{1,1}$, as follows:

$$R_{M_1} = \begin{bmatrix} R_{f_s} & R_{f_1} & R_{f_2}\ R_{f_3} & \dots & R_{f_r} \\ R_{f_1} & R_{1,1} & m_{12} m_{13} & \dots & m_{1r} \\ R_{f_2} & m_{21} & R_{1,2} m_{23} & \dots & m_{2r} \\ R_{f_3} & m_{31} & m_{32} R_{1,3} & \dots & m_{3r} \\ \vdots & \vdots & \vdots\ \ \vdots & \vdots & \vdots \\ R_{f_r} & m_{1r} & m_{2r} m_{3r} & \dots & R1,_r \end{bmatrix}$$

PF scores are combined as follows using the linear scale transformation technique.

$$R_{1,s} = \left[\left(\frac{r_{ls,1}}{\max_l r_{ls,1}}, \frac{r_{ls,2}}{\max_l r_{ls,2}}, \frac{r_{ls,3}}{\max_l r_{ls,3}}\right);\ \max_l t_{ls}, \min_l f_{ls}\right]$$

The [0, 1] area of normalized TPFNs is maintained using the transformation approach.

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Step 4: This is the step where the risk priority index (RPI) is calculated.

The permanent $P_r(R_{M_1})$ of the PF hazard is defuzzified using the scoring and reliability numbers of TPFNs, and the failure mechanisms are analyzed to get RPI_l.

Step 5: Analyzing the causes of failure:
The failure mode with the highest risk and the highest risk prioritization is indicated by the RPI's higher value. All failure modes are ranked according to their risk priority indices, therefore the overall risk priority is determined.

Step 6: Analyzing the findings and making recommendations:

The failure mechanisms with the highest risk priorities may be picked by risk managers once they have obtained the rating of all component failures according to their risk objectives. The FMEA team can better allocate resources and implement corrective measures when a specific failure mode is chosen from a list of possible failure modes. In this way, the PFDGMA-based model proposed here is an innovative FMEA approach that combines the advantages of TPFNs with those of the digraph and matrix techniques. For the construction of the RFPFDG, we use the TPFN's attributes. On this RFPFDG, the risk variables and their relationships are shown as TPFN diagrams. Once all failure modes have been calculated, the defuzzification of TPFNs utilizing such accuracy algorithms is used to prioritize distinct failure modes.

4. Empirical Finding

Accurate risk prediction and management are both necessary for preventing excavation-related incidents. In risk management, the steps of identifying, evaluating, and mitigating risk are all included.

Our presentation on steam valve systems in a power station will demonstrate the benefits and possible uses of PFDGMA in FMEA in the next section. Failure of the steam valve system may affect the precision of the whole power plant, which is regarded as a crucial element of steam turbine functioning. A steam valve system is used to monitor a rising and high-temperature carrying medium between a low-pressure cylinder and a moisture separator re-heater (MSR). There should be no issues with the steam valve when it is open or closed, as long as it is done so quickly. To ensure the precision and safety of the turbine system in the event of an eccentric operation, the steam valve must be rapidly closed to separate the water entering the LPC. Linguistic terms and score function in [39]
Four members of an FMEA analysis team were tasked with determining how to best use the little resources that had been saved. An examination of the potential consequences of many possible failure modes yields the TMk, where k equals 1, 2, 3, and 4. We came up with eight key failure mechanisms during our brainstorming session. We used four main criteria and 19 alternatives as below

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Criteria	Alternatives
Ground surface accumulative settlement RAC1 Underground accumulative water level RAC2 Safety risk level RAC3 Surface subsidence rate RAC4	RAA1
	RAA2
	RAA3
	RAA4
	RAA5
	RAA6
	RAA7
	RAA8
	RAA9
	RAA10
	RAA11
	RAA12
	RAA13
	RAA14
	RAA15
	RAA16
	RAA17
	RAA18
	RAA19

There 3 decision-makers to evaluate the criteria and alternatives in tables 1-3.

Table 1: The decision matrix 1.

	RAC_1	RAC_2	RAC_3	RAC_4
RAC_1	0.009	0.04725	0.09375	0.0585
RAC_2	0.0585	0.0585	0.09375	0.091875
RAC_3	0.09375	0.0585	0.0585	0.091875
RAC_4	0.0585	0.09375	0.091875	0.091875
RAC_5	0.0585	0.091875	0.091875	0.0585
RAC_6	0.09375	0.009	0.09375	0.0585
RAC_7	0.009	0.009	0.009	0.0585
RAC_8	0.009	0.09375	0.009	0.0585
RAC_9	0.09375	0.009	0.091875	0.0585
RAC_{10}	0.04725	0.04725	0.04725	0.09375
RAC_{11}	0.04725	0.04725	0.091875	0.09375
RAC_{12}	0.0585	0.09375	0.04725	0.09375
RAC_{13}	0.0585	0.04725	0.04725	0.09375
RAC_{14}	0.09375	0.04725	0.091875	0.091875
RAC_{15}	0.04725	0.09375	0.009	0.09375
RAC_{16}	0.04725	0.0585	0.0585	0.091875

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RAC_{17}	0.09375	0.0585	0.0585	0.09375
RAC_{18}	0.009	0.009	0.009	0.091875
RAC_{19}	0.09375	0.09375	0.09375	0.09375

Table 2: The decision matrix 2.

	RAC_1	RAC_2	RAC_3	RAC_4
RAC_1	0.009	0.009	0.009	0.009
RAC_2	0.009	0.009	0.09375	0.091875
RAC_3	0.09375	0.009	0.0585	0.091875
RAC_4	0.009	0.09375	0.091875	0.091875
RAC_5	0.0585	0.009	0.009	0.009
RAC_6	0.09375	0.009	0.09375	0.009
RAC_7	0.009	0.009	0.009	0.0585
RAC_8	0.009	0.009	0.009	0.009
RAC_9	0.09375	0.009	0.091875	0.0585
RAC_{10}	0.009	0.04725	0.04725	0.009
RAC_{11}	0.009	0.009	0.009	0.09375
RAC_{12}	0.0585	0.09375	0.04725	0.09375
RAC_{13}	0.0585	0.009	0.009	0.009
RAC_{14}	0.009	0.04725	0.091875	0.091875
RAC_{15}	0.09375	0.009	0.009	0.09375
RAC_{16}	0.04725	0.0585	0.0585	0.009
RAC_{17}	0.009	0.0585	0.0585	0.09375
RAC_{18}	0.009	0.009	0.009	0.091875
RAC_{19}	0.09375	0.009	0.009	0.009

Table 3: The decision matrix 3.

	RAC_1	RAC_2	RAC_3	RAC_4
RAC_1	0.04725	0.04725	0.09375	0.04725
RAC_2	0.0585	0.0585	0.04725	0.091875
RAC_3	0.04725	0.0585	0.04725	0.04725
RAC_4	0.0585	0.09375	0.091875	0.091875
RAC_5	0.0585	0.091875	0.091875	0.0585
RAC_6	0.04725	0.009	0.04725	0.04725
RAC_7	0.009	0.009	0.04725	0.0585
RAC_8	0.009	0.09375	0.04725	0.04725
RAC_9	0.04725	0.04725	0.091875	0.0585
RAC_{10}	0.04725	0.04725	0.04725	0.04725
RAC_{11}	0.04725	0.04725	0.091875	0.04725
RAC_{12}	0.04725	0.09375	0.04725	0.09375
RAC_{13}	0.0585	0.04725	0.04725	0.04725
RAC_{14}	0.04725	0.04725	0.091875	0.04725
RAC_{15}	0.04725	0.09375	0.009	0.09375
RAC_{16}	0.04725	0.0585	0.0585	0.04725
RAC_{17}	0.09375	0.0585	0.0585	0.09375
RAC_{18}	0.009	0.009	0.009	0.04725
RAC_{19}	0.04725	0.04725	0.04725	0.09375

They are then consolidated into TPFNs based on the independent judgments made by team specialists. To avoid the appearance of "inconsistency," we do not verify the views of the agents to see whether there are any. Instead, we assume that the agents' differing viewpoints are expressed in their differing evaluations. The PF group analyzing factors is then obtained in table 4.

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Table 4: The sum of all of the individual risk variables' ratings.

	RAC_1	RAC_2	RAC_3	RAC_4
RAC_1	0.02175	0.0345	0.0655	0.03825
RAC_2	0.042	0.042	0.07825	0.091875
RAC_3	0.07825	0.042	0.05475	0.077
RAC_4	0.042	0.09375	0.091875	0.091875
RAC_5	0.0585	0.06425	0.06425	0.042
RAC_6	0.07825	0.009	0.07825	0.03825
RAC_7	0.009	0.009	0.02175	0.0585
RAC_8	0.009	0.0655	0.02175	0.03825
RAC_9	0.07825	0.02175	0.091875	0.0585
RAC_{10}	0.0345	0.04725	0.04725	0.05
RAC_{11}	0.0345	0.0345	0.06425	0.07825
RAC_{12}	0.05475	0.09375	0.04725	0.09375
RAC_{13}	0.0585	0.0345	0.0345	0.05
RAC_{14}	0.05	0.04725	0.091875	0.077
RAC_{15}	0.06275	0.0655	0.009	0.09375
RAC_{16}	0.04725	0.0585	0.0585	0.049375
RAC_{17}	0.0655	0.0585	0.0585	0.09375
RAC_{18}	0.009	0.009	0.009	0.077
RAC_{19}	0.07825	0.05	0.05	0.0655

Then normalized the decision matrix in table 5. Table 5's other elements are calculated in the same way. Obtain the normalized averaged PF ratings for risks O, S, and D. (11). In Table 5, you'll find these numbers. The normalized aggregate weights are substituted in the diagonal of the interaction matrix, resulting in a PF hazard for each failure scenario.

Table 5: The normalized individual risk variables' ratings.

	RAC_1	RAC_2	RAC_3	RAC_4
RAA_1	0.277955	0.368	0.712925	0.408
RAA_2	0.536741	0.448	0.851701	0.98
RAA_3	1	0.448	0.595918	0.821333
RAA_4	0.536741	1	1	0.98
RAA_5	0.747604	0.685333	0.69932	0.448
RAA_6	1	0.096	0.851701	0.408
RAA_7	0.115016	0.096	0.236735	0.624
RAA_8	0.115016	0.698667	0.236735	0.408
RAA_9	1	0.232	1	0.624
RAA_{10}	0.440895	0.504	0.514286	0.533333
RAA_{11}	0.440895	0.368	0.69932	0.834667
RAA_{12}	0.699681	1	0.514286	1
RAA_{13}	0.747604	0.368	0.37551	0.533333
RAA_{14}	0.638978	0.504	1	0.821333
RAA_{15}	0.801917	0.698667	0.097959	1
RAA_{16}	0.603834	0.624	0.636735	0.526667
RAA_{17}	0.837061	0.624	0.636735	1
RAA_{18}	0.115016	0.096	0.097959	0.821333
RAA_{19}	1	0.533333	0.544218	0.698667

A relative risk, for example, has an accumulated weight as follows: Each of the four members of the FMEA team has been given a relative weight. 0.196364, 0.25974, 0.381818, 0.162078. figure 2 shows the weights of the criteria.

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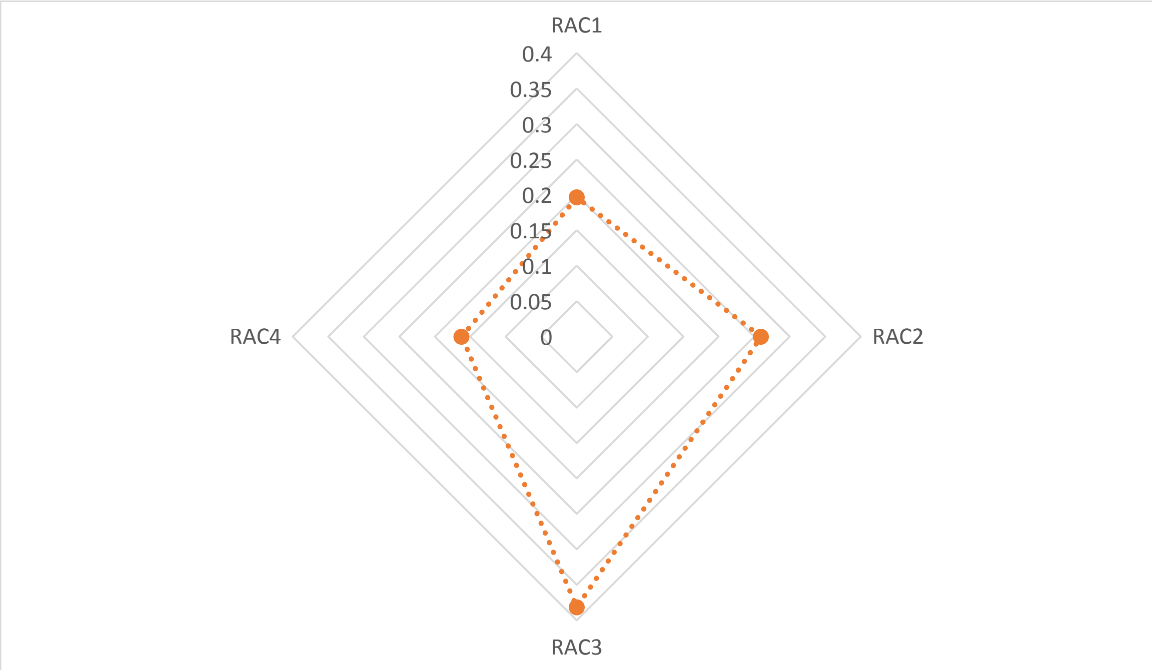

Figure 2: The weights of criteria.

Table 6 shows that the computed enchantments for all incidents are TPFNs since the risk factor weights and hazard rating are all TPFNs. Defuzzification methods such as anticipated and accuracy ratings of TPFNs are used to construct the project risk indexes for each failure scenario utilizing PF permanent values.

In Table 6, FM1 has the highest RPI and must be adjusted first, followed by FM4 and FM12 and then FM17 and then FM14, and finally FM7. Figure 3 shows the rank of risks (alternatives).

Table 5: The Indexes of risk prioritization and Pythagorean fuzzy permanent models.

	RPI	Rank
RAA_1	1.76688	4
RAA_2	2.816442	13
RAA_3	2.865252	15
RAA_4	3.516741	19
RAA_5	2.580257	10
RAA_6	2.355701	8
RAA_7	1.071751	1
RAA_8	1.458417	3
RAA_9	2.856	14
RAA_{10}	1.992514	5
RAA_{11}	2.342881	7
RAA_{12}	3.213966	18
RAA_{13}	2.024447	6
RAA_{14}	2.964311	16
RAA_{15}	2.598543	11
RAA_{16}	2.391235	9
RAA_{17}	3.097795	17
RAA_{18}	1.130308	2
RAA_{19}	2.776218	12

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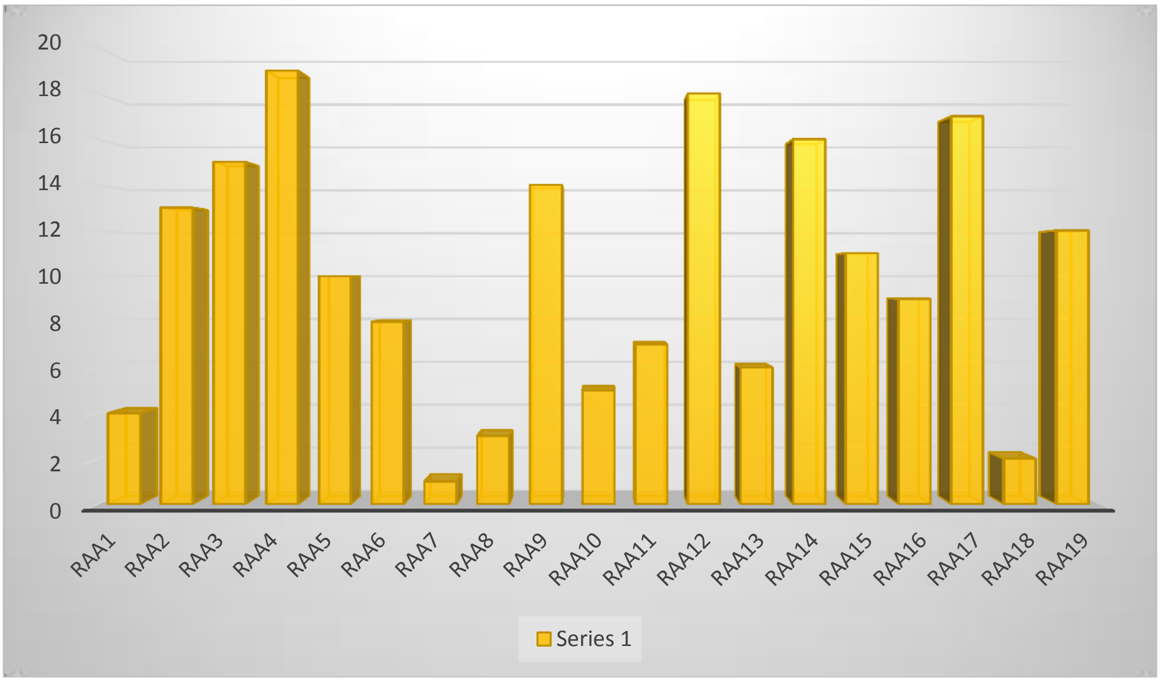

Figure 3: The rank of alternatives.

5. Conclusion

Due to the challenging geological circumstances and the rising need for complete networks and Services in recent decades, this research examined notable mishaps produced by deep excavation buildings. To lessen the harm accidents do to individuals and the planet, a reliable system of potential threat forecasting and advanced detection must be put in place. In addition, while developing an evaluation model or an early warning system, it is critical to summarise popular data foundation possible threats. Deep excavation risk assessment methodologies like fuzzy sets, which are reliant on expert opinion, have been shown to give subjective outcomes in the examination of prior research methods. By using machine learning algorithms to analyze large amounts of data acquired during fieldwork, the reliability of the excavation riskiness may be improved while still retaining some subjectivity. However, there has been just a little amount of study in this field.

To identify, detect, and eliminate potential or known problems before they reach consumers, FMEA is an effective strategy. Finding out what can be done to prevent or reduce failures is the primary goal of FMEA. To improve a structure or system's productivity and efficiency throughout manufacturing and design, professionals may use the assessment findings to discover and update flaws that have harmful or detrimental consequences on the system. TPFNs and DGMA have been used in this article to provide a novel method for determining the risk ratings of failure mechanisms in FMEAs. Conventional RPN and fuzzy approaches' flaws and weaknesses have been eliminated by the newly designed method. FMEA professionals may use it to do linguistic analyses of risk variables and their related significance. Defuzzification of the PF permanents produced in units of TPFNs was used to determine the RPIs. The interaction matrices have been used to gather critical data and information about the situation. In the FMEA procedure, the RPI produced by PF permanents has allowed the FMEA to consider all the interrelationships between risk factors.

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