University of Pannonia
Doctoral School of Business and Management

Thesis summary

Supply chain risk analysis

Author:

István Mihálcz

Supervisor:

Prof. Dr. habil. Zsolt Tibor Kosztyán

June 3, 2024

1 Introduction

In our interconnected globalized world, supply chains play a crucial role, impacting not only businesses but also everyday citizens. Disasters like earthquakes, floods, and fires can disrupt supply chains, affecting products and services worldwide. Risk analysis and management are essential to mitigate these dangers, including external events, like natural disasters, cyber-attacks, and pandemics; or internal ones, like materials handling, storing, incomming process, incomming ispection, labeling, picking, moving to production area etc. Organizations must understand the implications of these risks to maintain stability and resilience in their supply chains (Yacob Khojasteh; Geske; Henke; Huang et al., 2020).

The challenges faced by Tier 1 or 2 suppliers who view their supply chains as proprietary and restrict visibility pose significant risks. Despite these challenges, systematic techniques can address identified risks. Thorough evaluations of suppliers through audits and the risk of suppliers inaccurately assessing themselves must be considered. The objective of the dissertation was to create a user-friendly risk assessment instrument for supply chain decision-makers. The study focuses on the challenges of Failure Mode and Effects Analysis (FMEA), explores the appropriate number of risk factors, and emphasizes implementing warning systems across departments and management systems.

2 Research objectives and research questions

In my dissertation, I aimed to develop and present a methodology that allows especially for supply chain a more effective risk analysis methodology, which can help them to easily establish the potential risk. In this regard, my research questions were formulated as follows:

R.Q.1. In what ways can a risk management framework tailored to supply chains be constructed to offer a more precise and straightforward estimation than the existing systems?

The methods described in the literature determine the level of risk based on a predetermined set of factors. The writers utilize different individual aggregation functions, however there is a lack of analysis of the optimal aggregation risk function or framework, as well as the potential for using combinations that have not been previously explored. My objective is to create a comprehensive risk assessment system that is capable of managing uncertain risk elements.

R.Q.2. In the supply chain, risks must be mapped and estimated for several areas/domains. What method can be used to bring these alarm levels together?

Warnings are crucial in the assessment of risks. Numerous endeavors have been made to enhance the risk evaluation warning system. Existing methods in the literature fail to account for warning events that arise from several levels, such as factor, effect, mode, and process. These methods do not provide specific warning criteria for each risk factor individually at each level. The objective was to create a multi-level warning system that can be integrated with the previously indicated comprehensive risk assessment framework.

R.Q.3. Which aggregation method is the most optimal for supply chain?

While there are numerous publications on risk, only a small number specifically analyze risks in the supply chain. The primary cause is a deficiency in comprehending the proper implementation of a risk assessment system, such as the Failure Mode and Effects Analysis (FMEA), which is widely employed in Supply Chain Management (SCM) within a supply chain setting. An easy methodology should be developed for this purpose, utilizing the previously indicated universal risk assessment framework.

3 Literature review and research assumptions

In the following, I highlight the scholarly findings on which I formulated my research assumptions.

In risk analysis or in used methods, authors use a limited to a fixed number of risk factors (Liu et al., 2013a). In addition, during literature investigation can be seen that authors calculate with risk factors, as they are independent (Liu et al., 2013a). One potential reason for disregarding new risk factors is the need to acknowledge their interdependence. These problems require innovative solutions that can effectively tackle the interdependence of risk variables and an unlimited number of risk factors. In literature, predetermined scales with identical factor numbers are commonly utilized.

Risk aggregation plays an important role in various risk assessment process (Bani-Mustafa et al., 2020; Bjørnsen and Aven, 2019). Aggregation can be considered a method for combining a list of numerical values into a single representative value (Pedraza and Rodríguez-López, 2020, 2021). Traditionally, the risk value is calculated based on a fixed number of risk components. Failure mode and effect analysis (FMEA), which is a widely used risk-assessment method, includes three risk components: the occurrence (O), detectability (D), and severity (S) (Fattahi and Khalilzadeh, 2018; Liu et al., 2013b; Spreafico et al., 2017). According to Huang et al. (2020) keyword analysis orisk-related literature over the past 20 years confirms that the FMEA remains the most commonly utilized tool for evaluating risks.

The shortcoming of FMEA was presented by several authors Liu et al. (2013a); Lolli et al. (2015); Malekitabar et al. (2018); Wu and Wu (2021). A summary can be seen in the table below (Table 1).

Table 1: Shortcomings of old FMEA (based Wu and Wu (2021)), and comparison with the new FMEA (2019).

The shortcoming of the traditional FMEA	**Improvements and representative articles**	**Comparison with new FMEA**
1. The relative importance between O, S and D was not considered. It is assumed that these three factors are of equal importance, but this may not be the case when considering the practical application of FMEA.	Weights are assigned to three factors based on various weighting methods, such as OWA [20], IFWA [21], BWM [22], and FWE[23].	Solved with introduction of AP (action priority) level matrix, based on factors level
2. Different O, S and D rating sets may produce exactly the same RPN values, but their hidden risk implications may be completely different. This issue may result in wasted resources and time, or, in some cases, high-risk failure modes were not widely known.	The introduction of factor weights reduces and avoids the confusion caused by the same RPN results in different failure modes.	The RPN removed, instead appears AP levels (Low, Medium, High)
3. RPN calculation considers only three risk factors, mainly safety, and ignores other important factors such as quality and cost.	Cost [4], quality [7], and other factors [24] are added to improve the theoretical basis of the RPN evaluation.	Not improved, still consider just 3 factors (O, S and D)
4. The RPN approach does not consider the direct/indirect relationship between failure modes and is flawed for systems with many subsystems and components. When one failure causes several other failure modes, that failure should be prioritized for corrective action.	The FTA [25], Bayesian network [16], and other methods are used to present the interactions and relationships of various failures.	AP levels are a bit better, but the level H require corrective action, level M require or corrective action or a justification why not need any action, L means not needs any action.
5. The three risk factors O, S, and D are evaluated on a discrete ordinal scale. However, the multiplication is not meaningful on the ordinal scale. Thus, the results obtained are not only meaningless, but also in fact misleading.	Few articles discuss the ordinal scale and multiplication issues. Alternatively, MCDM methods, such as TOPSIS [26] and DEMATEL [27], are used to prioritize the failure modes directly.	Still not improved
6. The three risk factors are often difficult to determine accurately. FMEA team members often provide different types of assessment information for the same risk factor, and some of the assessment information may be inaccurate, uncertain, and incomplete due to time constraints, inexperience, and insufficient data.	Introduce uncertainty assessment methods, such as fuzzy theory, rough theory, evidence theory, and probability theory into the FMEA analysis (see Section 2.2).	Still not improved
7. The mathematical form used to calculate RPN is very sensitive to changes in the assessment of risk factors.	Few articles discuss this issue	Still not improved
8. The rating transitions for the three components of the FM are different. The relationship between the probability table for O and O is nonlinear, whereas the relationship between the probability table for D(S) and D(S) is linear.	Few articles discuss this issue	Still not improved
9. The results of RPNs are discrete, and many holes are there.	Few articles discuss this issue	Instead of RPN are used 3 levels

In 2019 was published the new FMEA (AIAG), called AIAG-VDA FMEA 1st edition.

Changes:

- The RPN (Risk Priority Number) was eliminated and replaced with Action Priority level defined in related Table,
- Use a seven steps approach (planning, structure analysis, function analysis, failure analysis, risk analysis, optimization and documentation of results),
- Use as a measurable of the FMEA effectiveness and efficiency,
- Higher emphasis on error-proofing,
- Appears a new chapter: Monitoring and System Response.

Regrettably, the AP's introduction cannot be utilized for risk level comparison due to its inadequate "compression" into three levels. Therefore, a numerical or ordinal representation corresponding to the RPN is necessary to aid risk assessors in comprehending which hazards are substantial.

Several methods and analyses have been proposed for aggregating risk. It can be observed from one of the most recent reviews of FMEA conducted by Liu et al. (2013a) that the fuzzy rule-based system is the most popular method for prioritizing failure modes. The fuzzy rule-based FMEA approach uses linguistic variables to prioritize failures in a system to describe the severity, detection and occurrence as the riskiness of failure (Tay and Lim, 2006; Petrović et al., 2014; Bowles and Peláez, 1995; Cardiel-Ortega and Baeza-Serrato). The writers employ various singular aggregation functions, but analysis about the best aggregation risk function, or a framework, what whether there is the possibility to use their combinations that have not been previously used.

Based on these, I formulated my first assumption

A.1. Conventionally employed three-factor risk analysis systems (e.g., FMEA) yield a less precise risk estimation than multi-factor systems. Increasing the number of factors (higher, than 3), carefully selecting them, can be achieved a more precise risk estimation.

arnings play a vital role in risk evaluation (Khan et al., 2015; Øien et al., 2011). Conventional risk evaluation has the disadvantage of having rigor (Kalantarnia et al., 2009), repeatedly adopting a single index (Zheng et al., 2012) or a list of warning indicators (Øien et al., 2011) to signal warning events and failing to capture meaningful failures. There have been many efforts to develop the warning system of risk evaluation. Ilangkumaran et al. (2015) proposed a hybrid technique (Liu et al., 2015; Panchal et al., 2019) for assessing work safety in hot environments including a warning rating and safety grade at the risk factor level. Øien et al. (2011) have developed a set of risk indicators that can provide warnings about potential major accidents. Zheng et al. (2012) proposed an early warning rating system for hot and humid environments calculating safety indexes at the factor and sub-factor levels. In addition, Xu et al. (2002) suggested two levels of warnings. In the scientific literature, the risk hierarchy is occasionally mixed with risk level; e.g., Chen et al. (2012); Manuele (2005) use the action levels as risk hierarchies, and no real hierarchy levels are used.

Liu et al. (2013a); Shaker et al. (2019) conclude that objective and combination weighting methods should be applied in risk evaluation because they evaluate relative importance objectively without decision makers.

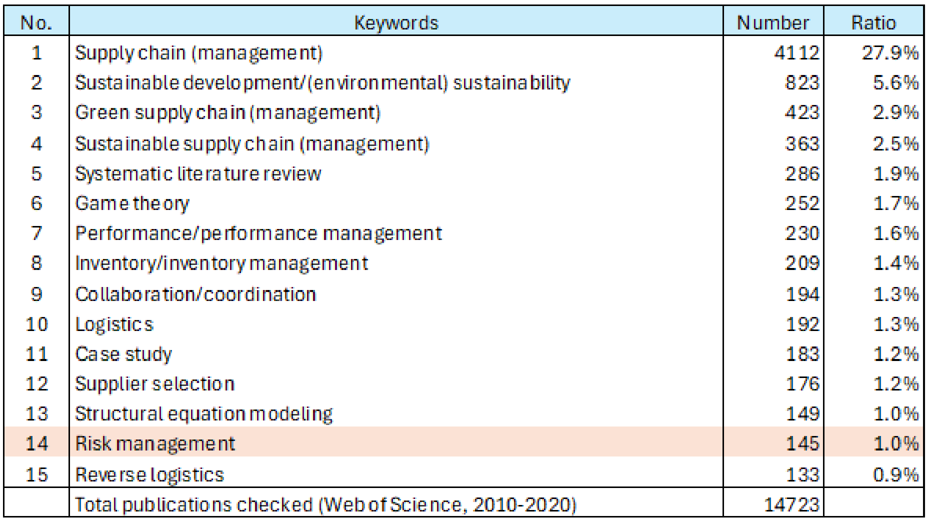
Domains such as health and safety, quality or environment can be considered in risk evaluation with different weights. To conclude, priorities and demands can be different by domains, which calls for flexible risk aggregation. As Kanes et al. (2017) stated, it is important to focus on the area of flexible risk evaluation, as a way forward for improving current risk evaluation methodologies. O'Keeffe and his team also emphasized that a risk evaluation process should be recursive rather than linear, flexible rather than rigid and pluralist not binary (O'Keeffe et al., 2015).

This summary shows that methods developed in the literature do not address warning events originating from multi-levels such as factor, effect, mode, and process in order to specify unique warning rules for each risk factor separately at each level.

A.2. Alert/warning limits per domain provide management or staff with a more precise depiction of potential risks, as they will blend in with the other values if they only occur once in a set. By emphasizing them and assigning them a limit value, management can be made aware of their significance and impact.

Supply chain risk factors can significantly impact a company's operations and overall performance (Zhao et al.). Multiple authors (Sime Curkovic, 2013; Wagner, 2016; Vodenicharova, 2017) have examined the reasons behind the limited use of FMEA and other risk analysis methods in the supply chain. The researchers conducted an analysis and successfully identified the main factors: the main difficulty impeding wider deployment appears to arise from a lack of understanding of how to apply FMEA within a supply chain environment. A pertinent, functional, and adaptable instrument for performing supply network risk assessment is currently non-existent. It is imperative that supply chain managers and risk analysts have easy access to simple instrument or tool, considering the aforementioned activities and global developments that have an impact on the supply chain.

Fang et al. literature review is very interesting , because they made a bibliometric keywords analysis on 14723 SCM related publications published between 2010 and 2020, to examine the primary concerns of authors and research trends. The result can be seen on Table 2.



No.	Keywords	Number	Ratio
1	Supply chain (management)	4112	27.9%
2	Sustainable development/(environmental) sustainability	823	5.6%
3	Green supply chain (management)	423	2.9%
4	Sustainable supply chain (management)	363	2.5%
5	Systematic literature review	286	1.9%
6	Game theory	252	1.7%
7	Performance/performance management	230	1.6%
8	Inventory/inventory management	209	1.4%
9	Collaboration/coordination	194	1.3%
10	Logistics	192	1.3%
11	Case study	183	1.2%
12	Supplier selection	176	1.2%
13	Structural equation modeling	149	1.0%
14	Risk management	145	1.0%
15	Reverse logistics	133	0.9%
	Total publications checked (Web of Science, 2010-2020)	14723	

Table 2: Keyword analysis on Web of Science between 2010-2020, based on Fang et al. data

As indicated in Table 2, the risk assessment ranks a mere fourteenth in terms of significance within the publication.

Multiple authors (Sime Curkovic, 2013; Wagner, 2016; Vodenicharova, 2017) have examined the reasons behind the limited use of FMEA and other risk analysis methods in the supply chain. The researchers conducted an analysis and successfully identified the main factors: the main difficulty impeding wider deployment appears to arise from a lack of understanding of how to apply FMEA within a supply chain environment.

It may be inferred from the existing body of research that the supply chain industry uses risk analysis methods that closely resemble those employed in various other domains. The authors exclusively employ the FMEA (Ewa Kulinska and Dendera-Gruszka, 2021; Ebadi et al., 2020; Indrasari et al., 2021) assessment technique, or a modified version of FMEA with factors limited to 5 levels instead of 10 (Aleksic et al., 2020). Alternatively, they utilize mixed evaluation techniques such as Fuzzy-FMEA (Mustaniroh et al., 2020; Trenggonowati et al., 2021; Lu Lu and de Souza, 2018; Wu and Wu, 2021; Petrović et al., 2014), Fuzzy-AHP Trenggonowati et al. (2020); Canbakis et al. (2018), FMEA-ANP (Zammori and Gabbrielli, 2012), or Fuzzy Bayesian-based FMEA (Indrasari et al., 2021). Fuzzy FMEA (Petrović et al., 2014) is considered the second most often utilized risk analysis technique, following the FMEA method. The three membership functions commonly utilized in Fuzzy FMEA are triangular, trapezoidal, and Gaussian (Ling, 2004; Kubler et al.; Johanyák and Kovács, 2004).

The conventional approach for assessing supply chain risk predominantly involves employing the FMEA framework, which incorporates three key factors: Severity, Occurrence, and Detection. A limited number of authors argue against the adequacy of three factors and instead propose the utilization of models that incorporate either four (expense, time, flexibility, and quality) (Zhu et al., 2020) or five (likelihood, consequence of time/delay, consequence of additional expense, consequence of damage to quality, and visibility) (Wan et al., 2019) factors.

A.3. By carefully choosing the appropriate aggregation function and arranging them in a certain sequence, the evaluation of risks can yield an ideal outcome. This outcome can effectively communicate to top management which risks should be prioritized for mitigation.

4 Research Findings and Theses

Several authors acknowledged in the preceding chapter that three factors are insufficient for a comprehensive risk assessment. As the number of factors increases, the aggregation function becomes more intriguing. The same limitations that are evident in the FMEA become apparent when employing multiplicative aggregation, which is the same logic as the aggregation function in the FMEA. As a result, the research investigates the criteria that define an aggregation function, the various types of aggregation functions that can be employed, and the benefits and drawbacks of these functions in the context of risk assessment.

For this reason were defined the aggregation function criterias, like validity, monotonicity, sensitivity, symmetricity, linearity, scale fit, and scale endpoint identity (Grabisch et al., 2009; Zahedi Khameneh and Kilicman).

Several instances of aggregation functions S are as follows, along with their respective output ranges:

- $S_1(\mathbf{f}) = \prod_{i:=1}^{n} f_i$ is the product of risk factors. If $n = 3$, and the factors can be the severity, occurrence, and detection, resulting the original RPN (risk priority number) from the FMEA. $S_1(\mathbf{f}) \in [1, 10^n] \in \mathbb{N}$
- $S_2(\mathbf{f}) = \sqrt[n]{\prod_{i:=1}^{n} f_i}$ is the geometrical mean. The range $S_2(\mathbf{f}) \in [1, 10] \in \mathbb{R}$
- $S_3(\mathbf{f}) = Median(\{\mathbf{f}\})$ is the median (middle element) in a sorted list of risk factors. $S_2(\mathbf{f}) \in [1, 10] \in \mathbb{N}$
- $S_4(\mathbf{f}) = \frac{1}{n} \sum_{i:=1}^{n} f_i$ is the average of risk factors. $S_3(\mathbf{f}) \in [1, 10] \in \mathbb{R}^+$
- $S_5(\mathbf{f}) = \sqrt{\sum_{i:=1}^{n} f_i^2}$ is the generalized n-dimensional radial distance of risk factors. $S_4(\mathbf{f}) \in [\sqrt{n}, 10\sqrt{n}] \in \mathbb{R}^+$
- $S_6(\mathbf{f}) =$ Aggregation of Fuzzy membership functions based on rule base. In this case, the output function range depends on the defuzzyfication function established by user, and can be in any prespecified range.

Other aggregation functions, such as *Sum*, *Geometrical mean*, and *Logaritmic*, are available in the literature; however, their behavior is comparable to that of the functions previously described.

The risk assessment framework, known as Kosztyán et al. (2020), has undergone an expansion to incorporate a fuzzy module. This addition has been implemented to effectively address the issue at hand.

Typically, Fuzzy FMEA utilizes three to seven linguistic variables (Kozarević and Puška; Cardiel-Ortega and Baeza-Serrato).

At the beginning and end of the interval, the sigmoid function was implemented:

$$\mu(x,a,b)_{sigu} = \begin{cases} 0, \ x \leq a \\ \frac{1}{1+e^{a(x-b)}}, & \text{any other case} \end{cases} \tag{1}$$

$$\mu(x,a,b)_{sigd} = \begin{cases} 1 - \frac{1}{1+e^{a(x-b)}}, \ x \leq a \\ 0, & \text{any other case} \end{cases} \tag{2}$$

where a is the steepness of function, and b is the inflection point.

For each range within the interval, the bell/splay function is applied:

$$\mu(x,a,b,c)_{spl} = \frac{1}{1+\left|\frac{x-b}{a}\right|^{2c}} \tag{3}$$

where b is the center of function, a is the width of curve and c is the steepness of function.

Both the splay and bell are Gaussian membership functions that were selected due to their smoothness, non-zero value at all point intervals, continuous differentiability, and mathematical and computational tractability (Johanyák and Kovács, 2004).

As illustrated in Figure 1, for $n = 5$ (5 linguistic levels), in accordance with its original score or crisp, each component is converted into the sum of n membership functions.

$S_i(\mathbf{f_i}) = \sum_{i:=1}^{n} \mu_i(x)$, $x \leq 10$ and $x \in \mathbb{R}^+$, other variables of membership functions are constants (a, b, c).

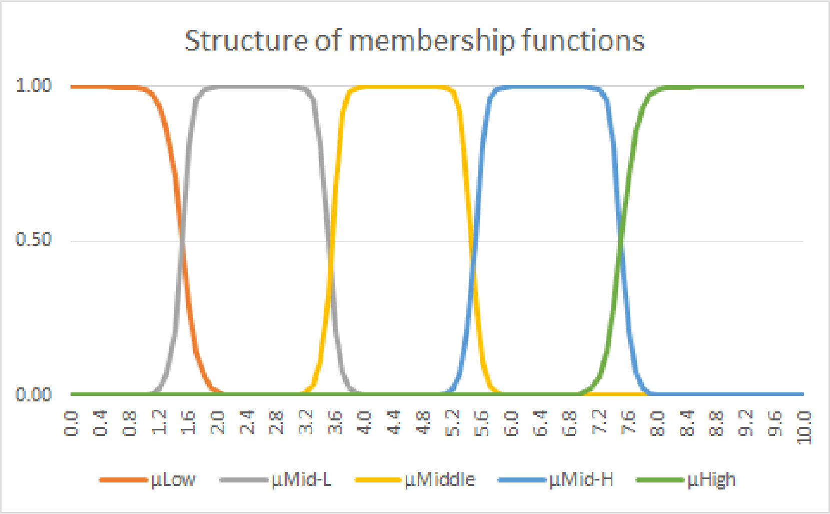


Figure 1: The structure of Fuzzy membership functions for each factor.

An analogy can be drawn between the sum of the fuzzy membership functions and the accumulation of factors comprising the fuzzy rule base. An instance of this can be described as follows:

$$W_i(\mathbf{S_i}) = S_1(\mathbf{f_i}) \otimes S_2(\mathbf{f_j}) \otimes \ldots \otimes S_n(\mathbf{f_n}) \tag{4}$$

where $\otimes$ is the aggregation protocol. The final phase entails the transformation of the amount of risk from a fuzzy state to a crisp state. In this phase, the determination of risk level will be achieved by converting the membership functions in real numbers.

An inherent characteristic of all aggregation functions is their failure to differentiate among factors; rather, they treat them as equivalent. This means that a flexible system should be able to weigh the importance of different aspects.

Let $\mathbf{f} = [f_1, f_2, .., f_n]^T$, $(n \geq 2,\ n \in \mathbb{N})$ be the vector of risk factors, and let $\mathbf{w} = [w_1, w_2, .., w_n]^T$ be the weight vector of risk factors $(w_i \in \mathbb{R}^+)$. Denote $r = S(\mathbf{f}, \mathbf{w})$ as a **resulting risk value**, where S is a monotonous aggregation function. Denote $(\mathbf{f}, \mathbf{w}, S)$ as the **risk aggregation protocol** (RAP).

- $S_1(\mathbf{f}, \mathbf{w}) = \prod_{i:=1}^{n} f_i^{w_i}$ is the weighted geometric mean of risk factors.
- $S_2(\mathbf{f}, \mathbf{w}) = max(\{f_1 w_1, .., f_n w_n\})$ is the weighted maximum value of risk factors.
- $S_3(\mathbf{f}, \mathbf{w}) = Median(\{\mathbf{f}, \mathbf{w}\})$ is the weighted median of risk factors.
- $S_4(\mathbf{f}, \mathbf{w}) = \sqrt{\sum_{i:=1}^{n} w_i f_i^2}$ is the weighted radial distance of risk factors.
- $S_5(\mathbf{f}, \mathbf{w}) =$ Aggregation of Fuzzy membership functions based on rule base. The weighting can be applied in the last, defuzzyfication step.

In the case of $w_i = 1/n$ for s S_1, S_3 and S_4, and $w_i = 1$ for S_2 produces the unweighted multiplicative, unweighted median and unweighted radial distance and unweighted maximum of risk factors.

4.1 Evaluating the Results of Used Aggregation Functions

Two approaches appeared viable for comparing the outcomes produced by the aggregating functions.

- One is when the **range of output arguments of functions is set to be identical**; this is typically resolved by multiplying the values by a constant. This was promptly abandoned due to the potential complexity that the behavior of the functions would have introduced to the situation.
- An alternative approach entails **comparing the output values** generated by distinct aggregating functions in the same order in which they assign equivalent risks.

This second methodology will be further implemented, elucidated in the validation methodology, and will be applied in the case study. In order to achieve this, it is necessary to employ ranking techniques.

4.1.1 Rank correlation

The Spearman's rank correlation coefficient is a statistical measure that quantifies the strength and direction of the association between two variables:

$$r_s = 1 - \frac{6\sum_{i=1}^{N}(R_{Xi} - R_{Yi})^2}{N(N^2 - 1)} \tag{5}$$

where R_{Xi} and R_{Yi} represent the ranks of the first and second variables, respectively. The Spearman's rank correlation coefficient is a statistical measure that quantifies the strength and direction of the association between two variables. The sign and magnitude of the value both fall within the range of $[-1; +1]$.

4.1.2 TOPSIS (Technique for Order Preference by Similarity to Ideal Solution)

The application of a multi-criteria decision analysis technique will be employed to evaluate a set of alternatives and ascertain the ranking of the risk analysis models implemented. The TOPSIS method chooses the alternative that has the shortest geometric distance from a positive ideal solution and the greatest geometric distance from a negative ideal solution (Chakraborty).

Let A represent the pairwise comparison matrix for factors as follows:

$$A = \begin{pmatrix} a_{11} & \dots & a_{1n} \\ \dots & \dots & \dots \\ a_{n1} & \dots & a_{nn} \end{pmatrix} \tag{6}$$

where a_{ij} are the judgement scores, considering $a_{ij} = 1/a_{ji}$, and $a_{ii} = 1$. This matrix is normalized with:

$$k_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \tag{7}$$

The local weight resulting:

$$w_i = \sum_{j=1}^{n} \frac{k_{ij}}{n} \tag{8}$$

The variables h_i are used to represent the risk incidents, where i ranges from 1 to n. Similarly, the variables f_j are employed to designate the TOPSIS evaluation criteria, with j ranging from 1 to m. The numerical outcomes of the alternative h_i with respect to the criteria f_j are represented by the variable x_{ij}.

The formula for the normalized decision matrix can be expressed as follows:

$$d_{ij} = \frac{x_{ij}}{\sqrt{\sum_{j=1}^{m} x_{ij}^2}} \tag{9}$$

The weighted normalized decision matrix elements can be generated:

$$V_{ij} = w_i \times d_{ij} \tag{10}$$

The ideal best solution V_j+ and ideal worst solution V_j- are determined by aggregating the highest and lowest values of each criterion.

For beneficial criteria:

$$V_j^+ = max[V_{ij}] \quad V_j^- = min[V_{ij}] \tag{11}$$

For non-beneficial criteria:

$$V_j^+ = min[V_{ij}] \quad V_j^- = max[V_{ij}] \tag{12}$$

Euclidian distances are measured from the ideal best (S_i^+) and ideal worst (S_i^-) values:

$$S_i^+ = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^+)^2} \quad S_i^- = \sqrt{\sum_{j=1}^{m} (V_{ij} - V_j^-)^2} \tag{13}$$

The performance score (relative closeness to the ideal solution) can be calculated:

$$P_i = \frac{S_i^-}{S_i^+ + S_i^-} \tag{14}$$

The ranked options are subsequently arranged in descending order as the final step.

This methodology is suitable for pairwise correlation analysis, specifically when the number of variables being compared does not exceed seven. Implementing this strategy gets problematic in situations where there are more than ten hazards, which is a frequently seen phenomenon in real-world scenarios. An illustration depicting the initial use of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) may be observed in the Bognár and Hegedűs context.

When evaluating a case that involves more than seven significant individual hazards, it is recommended to engage a team of experts who possess comprehensive expertise regarding the consequences associated with each risk. The individuals possess the capability to produce a matrix that facilitates the rating of effects, dangers, and impacts, alongside another matrix that enables the evaluation of results. One can utilize RSTUDIO to input both matrices and calculate their ranks using the TOPSIS algorithm (Yazdi).

4.2 Evaluation of aggregation functions

Five risk aggregation methods, which consider five factors as input and employ multiplicative, average, median, modified Euclidean distance, and fuzzy functions, are very interesting. The utilization of the frequency perspective in the assessment process can prove to be useful. The Crystal Ball application developed by Oracle, which is an add-in for Microsoft Excel, was employed for this purpose. For the examination of three variables, specifically for the conventional FMEA, the trial number was established at 10,000. In this particular case, the sensitivity for each element was 33.3 %. In the case of evaluating five factors, the trial numbers were set to 100,000 to achieve equal sensitivity for each element, with each factor accounting for 20 % of the total.

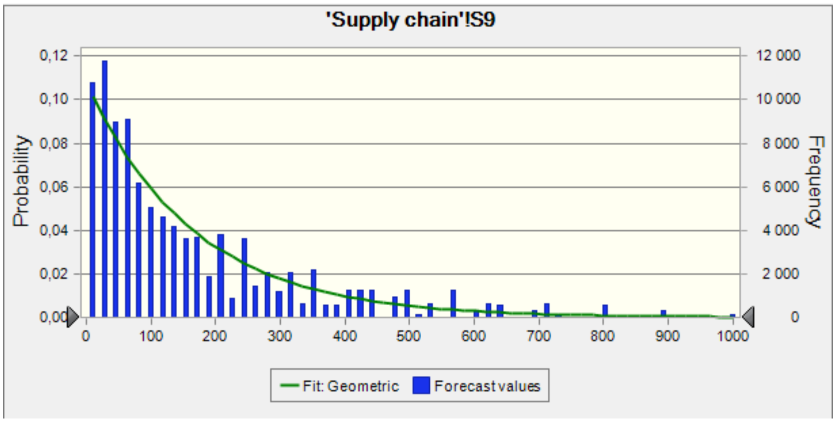


Figure 2: Standard FMEA frequency/values distribution.

The related sensitivity for the standard FMEA (with 3 factors, O, S D) can be seen in Figure 3

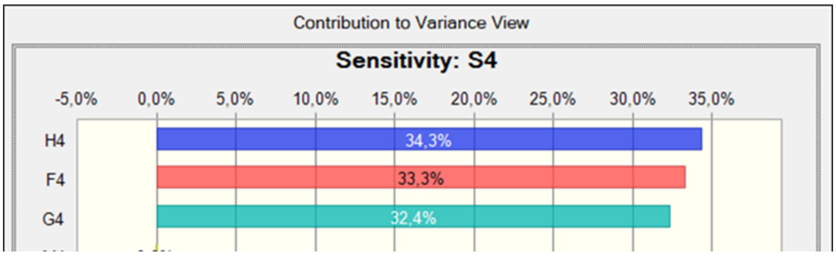


Figure 3: Standard FMEA sensitivity distribution for its 3 factors (O,S,D).

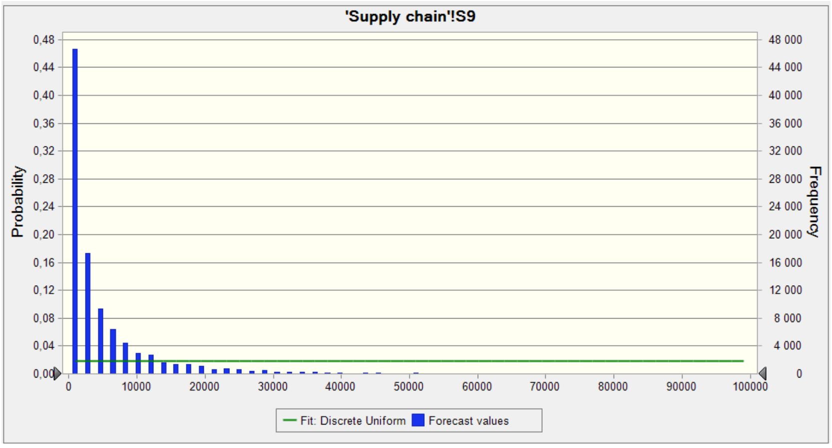


Figure 4: TREF Multiplication frequency/values distribution

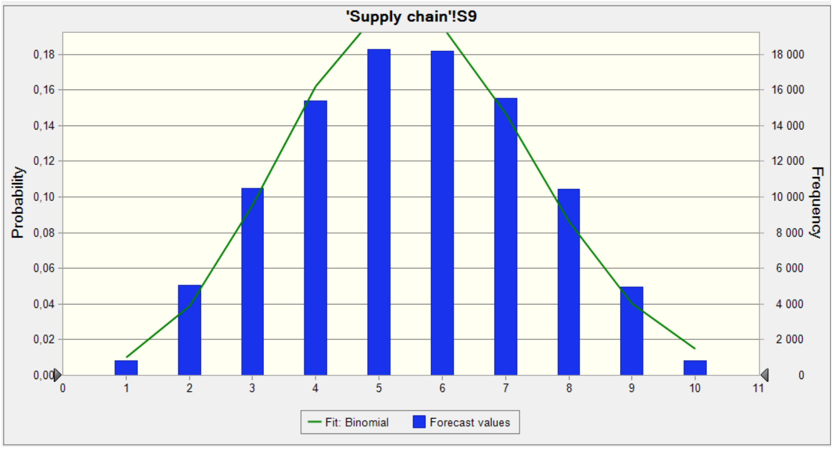


Figure 5: TREF Average frequency/values distribution

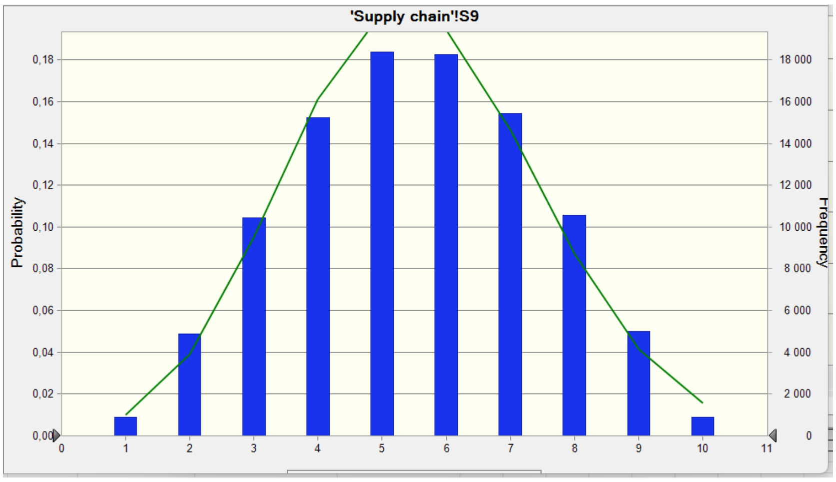


Figure 6: TREF Median frequency/values distribution

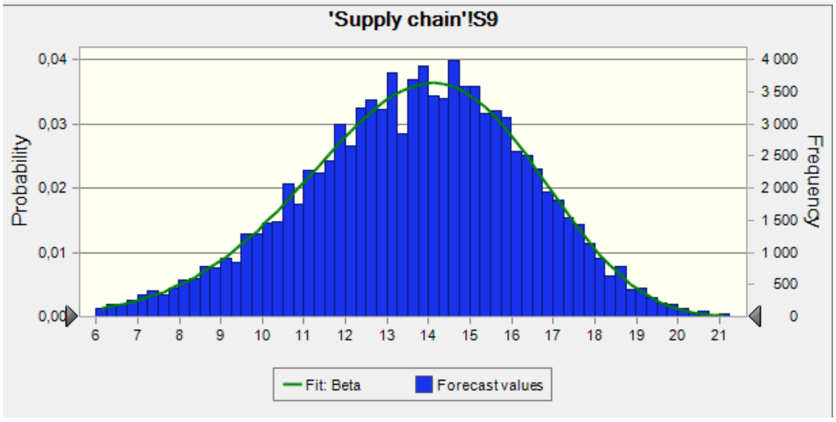


Figure 7: TREF Euclidean Distance frequency/values distribution

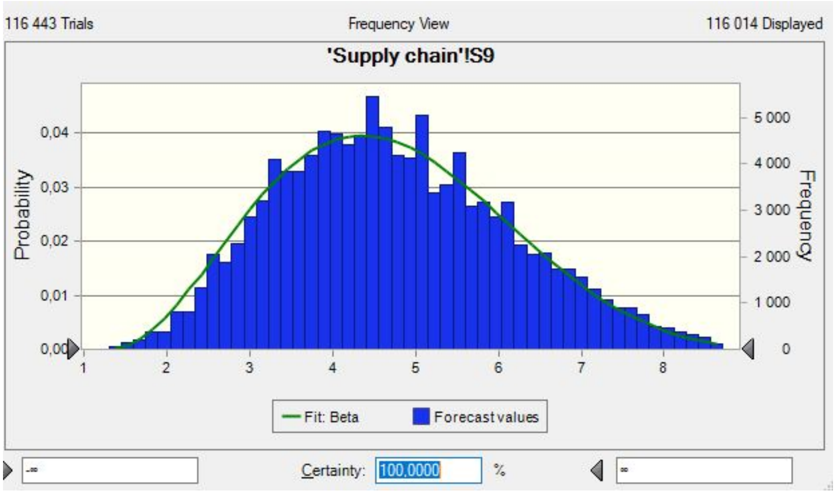


Figure 8: TREF Geometrical mean frequency/values distribution

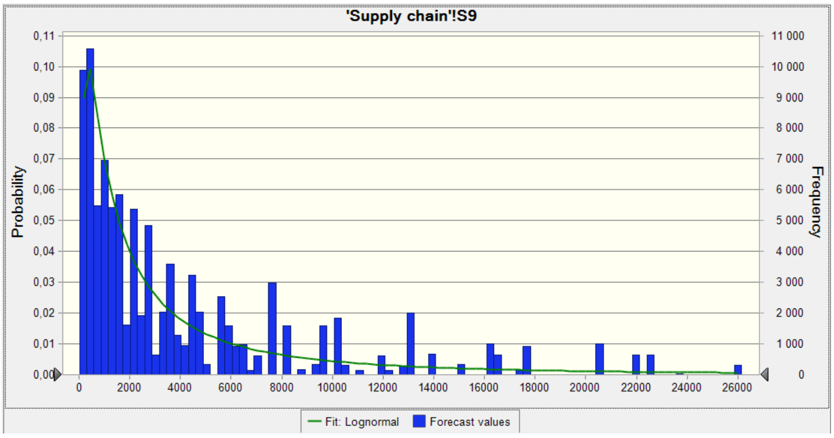


Figure 9: TREF Fuzzy frequency/values distribution

The sensitivity in case of 5 factors distribution (Figures 4 - 9 looks like Figure 10. Figure 10 represents the sensitivity for the TREF Multiplication case, but for other aggregations functions with 5 factors the deviation are within 2.4%. A trial count of 100,000 was chosen for 5 parameters in order to attain almost identical sensitivity values.

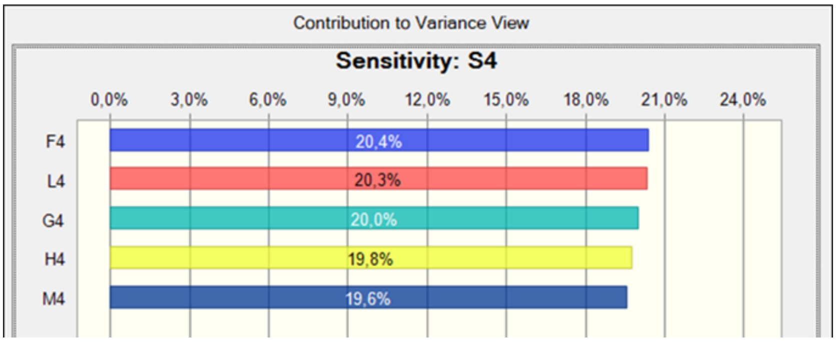


Figure 10: Standard FMEA sensitivity distribution for its 3 factors (O,S,D).

A comprehensive summary of the simulations conducted using Oracle's Crystal Ball is provided in Table 3.

Table 3: Characteristics of different aggregation methods for 5 factors including the standard FMEA with 3 factors.

Item	**FMEA**	**TREF Multi**	**TREF Aver**	**TREF Median**	**TREF EucDist**	**TREF Fuzzy**
Factors	3	5	5	5	5	5
Skewness	1.66	3.34	-.0025	-.003	-.32	3.28
Kurtosis	5.77	18.84	2.36	2.37	3.02	17.91
Min	1	1	1	1	2	8
Max	1000	100000	10	10	22	77348

The Skewness in Table 3 pertains to the absence of symmetry in the dataset, whereas the Kurtosis assesses whether the data exhibit heavy (positive values) or light (negative values) tails relative to a normal distribution.

Upon examination of the simulation Figures 2 to 9, it is evident that:

- The results obtained via the **Multiplication Aggregation Method**, as depicted in Figure 4, exhibit a level of comparability to those obtained from a conventional FMEA. However, it should be noted that the former method involved the consideration of five components, whereas the latter method typically considers three components. The linearity of the Multiplication technique and the standard FMEA is commendable. Consequently, the outcome for a scenario including n factors will yield a range of $[1, 10^n] \in \mathbb{N}$ for each factor, where the range of each factor is $[1, 10] \in \mathbb{N}$. The concerns of FMEA are equally relevant in this particular case. This is the most commonly used aggregation method. It is crucial to highlight that this aggregation function solely utilizes a small number of values within the range of $[1, 10^n]$. For instance, when considering 3 factors only 120 values are used from a range of $[1, 1000] \in \mathbb{N}$, for 4 factors only 274 values are used from a range of $[1, 10000] \in \mathbb{N}$, and for 5 factors only 546 values are used from a range of $[1, 100000] \in \mathbb{N}$. There are a total of seven unique values in the upper third part for all three cases. In the upper half, there are 7 distinct values for three factors (from 1000), 21 for four factors (from 10,000), and 23 for five factors (from 100,000). There are positive and negative aspects to this issue. Negative: only a few numbers from a substantial range are utilized. To the contrary, the high-risk procedures are notably emphasized.

- The input range and output range for the **Average aggregate** in Figure 5 are identical, spanning from 1 to 10. This method demonstrates strong linearity and is very easy to calculate. The components/factors range must be measured on the same interval scale. The presence of extreme values can pose challenges in some scenarios. In that case if one factor attains its maximum value and the remaining factors maintain low values, the resulting output will nevertheless fall below the midpoint of the output range. In this particular scenario, the presence of low-value components effectively mitigates the impact of any extreme values, hence impeding the identification and analysis of potential risks.

- The **Median aggregation** yields the lowest Skewness score, as depicted in Figure 6, suggesting that the data exhibits a high degree of symmetry. The Kurtosis score of our dataset is rather low, suggesting a moderate level of customization in the data. The resulting scale is the same as the components' scale, and this function can also be used on ordinal scales. The calculation is not easy in practice. The scale is relatively rough and can be considered correct only for homogeneous risk components. This situation bears resemblance to the Average aggregation approach.

- The linearity is only average and the computation is challenging in the case of the **Euclidean distance (generalized) aggregate** (see Fig. 7). Interpretation is challenging in n-dimensional space where $n > 3, n \in \mathbb{N}$. In the case of n factors, the output will be $[\sqrt{n}, 10\sqrt{n}] \in \mathbb{R}^+$ for each factor's range of values of $[1, 10] \in \mathbb{N}$. The linearity of the Euclidean distance (generalized) aggregate is only average, and its computation is problematic, as depicted in Figure 7.
- The outcome data for the **Fuzzy aggregation method** (refer to Figure 9), which is determined by the used membership and defuzzification functions, exhibit similarities to those of the TREF Multiplication. The calculation is very complex, and needs experience. However, it is important to note that the output consists of just five primary groups (see Figure 1).

In conclusion, it is important to acknowledge that aggregations utilizing multiplication approaches, such as FMEA, generalized TREF Multiplication, and TREF Fuzzy with respect to defuzzification, yield the most unfavorable distribution. However, their significant contributions become essential in situations when elements exhibit elevated levels of risk. Their advantage is, in the upper level of output range make a significant differentiation of risk levels, and this property making them usable in risk evaluation.

Given the intricacy of the Fuzzy function, it can be inferred that the multiplicative evaluation approach, which involves an increasing number of components, is the simplest method among the analyzed aggregating functions.

T.1. I have demonstrated that the suggested method for total risk evaluation offers a more comprehensive assessment of risk levels compared to existing methods. It provides the option to

select more than three elements and utilize various aggregation algorithms. This affirmation is validated via the first case study made at an EMS company

4.3 Proposed Warning Systems

The warning system signals to the risk evaluation team or related decision makers where critical failures are, and this team can see the general conditions of the processes. Corrective/preventive actions are scheduled if a risk factor is not lower than a threshold **W1**, but also corrective/preventive actions are scheduled if the aggregated value is not lower than a threshold **W2**. The warning system can proposes an extra output factor, for example **criticality**, to allow the risk evaluation team to specify corrective/preventive actions **W3**, even if the aggregated risk value is lower than the specified threshold. If its value is 1, corrective or preventive actions should be specified.

Let $(\mathbf{R}^{(N)}, \mathbf{W}^{(N)}, S)$ and $(\mathbf{R}^{(N-1)}, \mathbf{W}^{(N-1)}, S)$ $(N \geq 1)$ be risk aggregation protocols. Additionally, denote $Cr^{(N-1)} \in \{0, 1\}$ as the criticality value in hierarchy level $N-1$. Let $\mathbf{T}^{(N)}, \mathbf{T}^{(N-1)}$ be threshold vectors, where $\forall i, j, T_i^{(N-1)}, T_j^{(N)} \in \mathbb{R}^+$. Denote the intervention function in level N for factor i

$$K_i^{(N)} = \begin{cases} 1, & R_i^{(N-1)} \geq T_i^{(N-1)} \\ 0, & \text{otherwise} \end{cases} \tag{15}$$

A ***warning event*** has occurred if

(W1) $\sum_i K_i^{(N-1)} \geq n^{(N-1)}$ (at least $n^{(N-1)}$ of risk factors are not lower than the specified threshold);

(W2) $\sum_j K_j^{(N)} \geq n^{(N)}$ (at least $n^{(N)}$ aggregated risk values are not lower than the specified threshold);

(W3) $Cr^{(N-1)} := 1$ (a risk factor is decided as critical).

The thresholds and the rule of thresholds can be specified as arbitrary, based on the company experts. Generally, warning thresholds are specified based on former experiences, but standards can also provide a threshold. (In our case study, because the company had to follow more than one standard requirement, the minimum value of the experts' opinions was the threshold.) In addition, the dependence of risk factors can also be addressed by specifying different thresholds for each single risk factor separately.

We can say that a risk effect is a **failure effect** if at least one of the conditions (W1)–(W3) is satisfied.

an be concluded that it is important to replace RPN with another number that can generally indicate the risk level. This will be the TPRN (total risk priority number).

It is important to note that the proposed risk aggregation protocol does not require existing (predefined) scales. Scale values can be a result of a pairwise comparison (see e.g. Merrick et al., 2005).

Applying the *risk aggregation protocol* iteratively, the risk values can be specified in a higher hierarchy level.

Let $(\mathbf{R}^{(N)}, \mathbf{W}^{(N)}, S)$, $(\mathbf{R}^{(N-1)}, \mathbf{W}^{(N-1)}, S)$ be risk aggregation protocols. Denote $TRPN_i^{(N)} = R_i^{(N)} = S\left(\mathbf{R}_i^{(N-1)}, \mathbf{W}_i^{(N-1)}\right)$ as the **total risk priority number** i in the hierarchy level N.

If TRPNs are calculated for the total process tree (see Fig. 11), thresholds should be specified for all levels.

Based on the proposed iterative bottom-up calculation method (see Definition 4.3), through the process hierarchy or an acyclic process graph, risk values can be calculated for each hierarchy level.

Contrary to traditional FMEA and fuzzy FMEA, TREF allows the specification of more than one effect to be assigned to a cause (see Fig. 11). However, different failure modes and risk effects may have the same causes (common causes) (see Fig. 12). The only restriction is to avoid cycles in the process hierarchy.

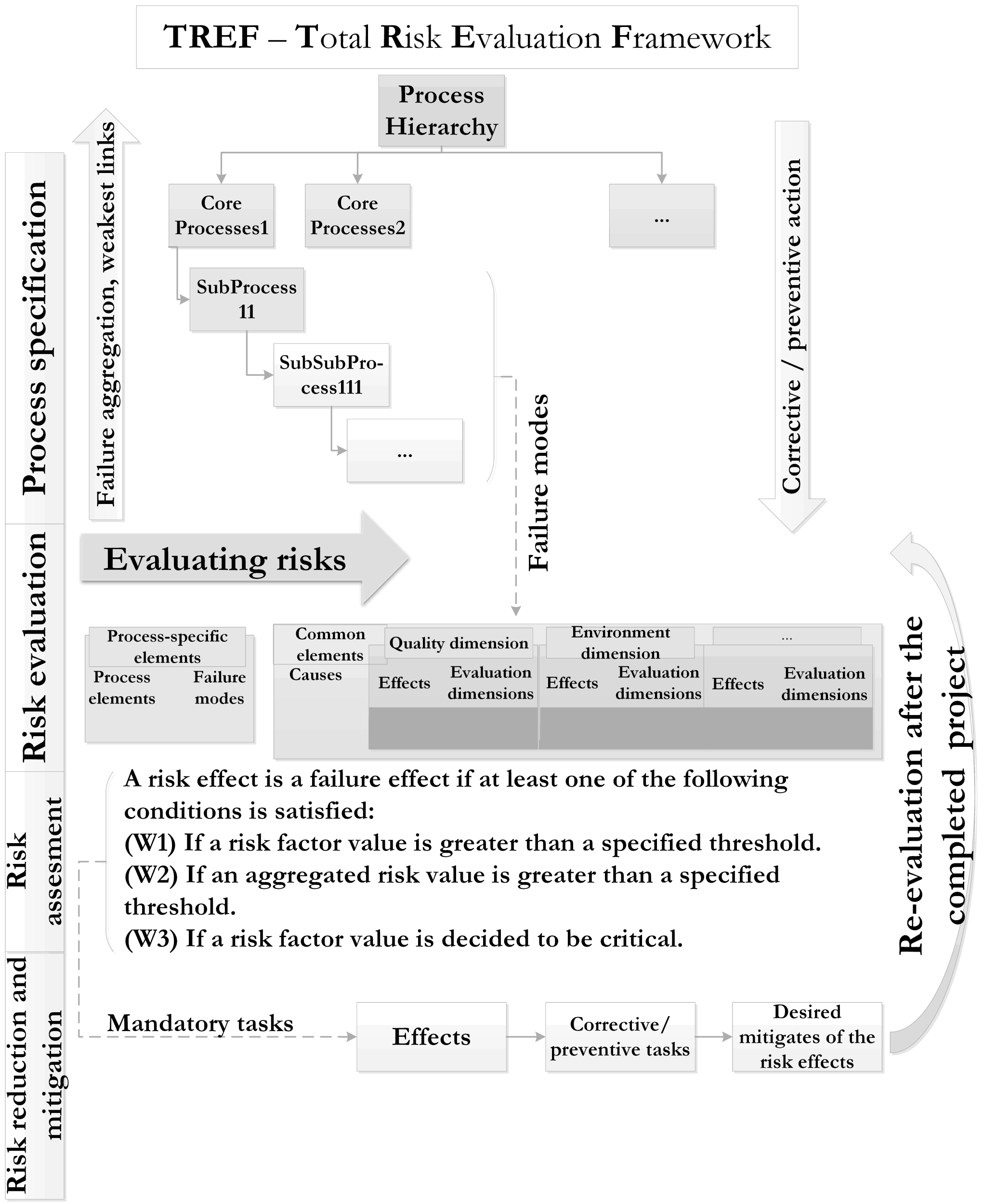


Figure 11: The proposed Total Risk Evaluation Framework (TREF)

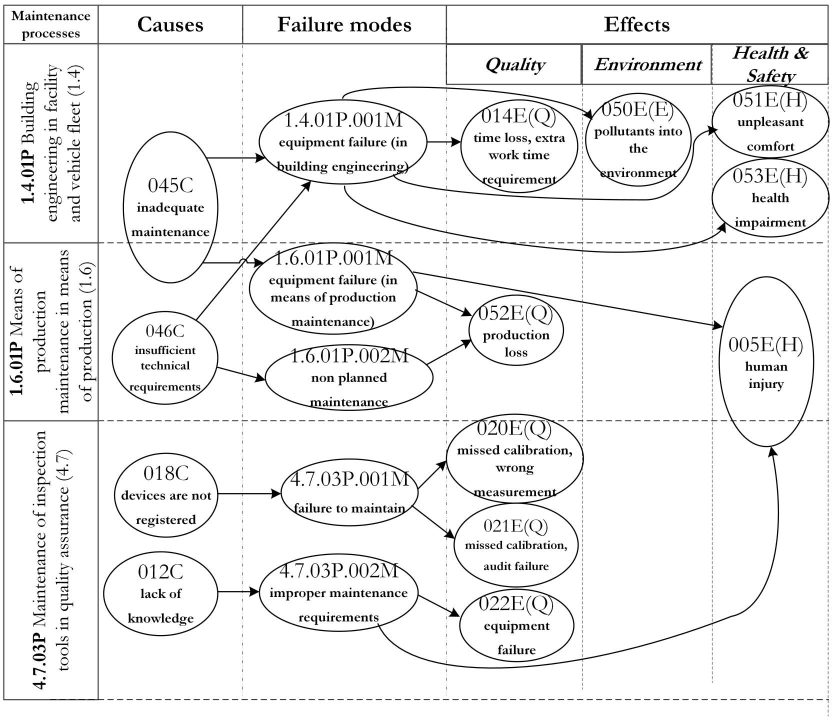
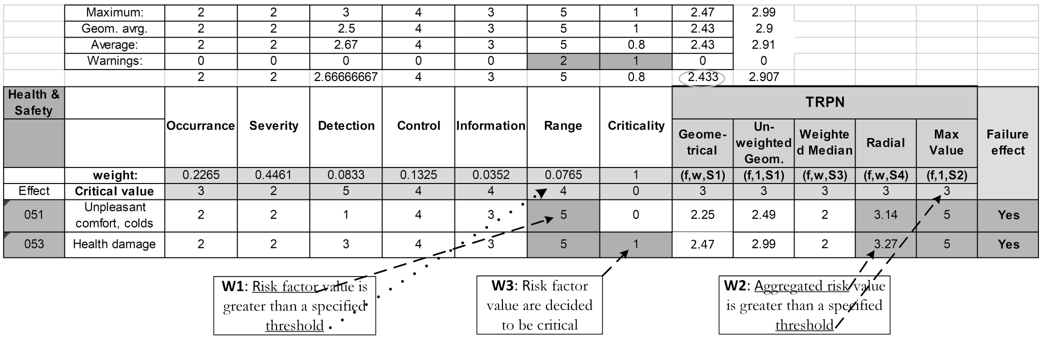


Figure 12: The TREF graph for evaluating the risk maintenance process: the chain of causes, failure modes and effects

Fig. 13 shows the TRPN of each effect. The value of range is not lower than the critical value (threshold); therefore, corrective/preventive actions have to be specified to mitigate both (051E(H), 053E(H)) range effects (see (W1) in Section 4.3). Fig. 13 also shows that despite average TRPNs ($\text{TRPN}_{051\text{E,H}}$ and $\text{TRPN}_{053\text{E,H}}$) that are lower than the specified threshold, 053E(H) is critical (see (W3) in Section 4.3), and the risk evaluation team specified corrective/preventive actions to avoid this risk effect.



	Maximum:	2	2	3	4	3	5	1	2.47	2.99				
	Geom. avrg.	2	2	2.5	4	3	5	1	2.43	2.9				
	Average:	2	2	2.67	4	3	5	0.8	2.43	2.91				
	Warnings:	0	0	0	0	0	2	1	0	0				
		2	2	2.66666667	4	3	5	0.8	2.433	2.907				
Health & Safety		**Occurrance**	**Severity**	**Detection**	**Control**	**Information**	**Range**	**Criticality**	**TRPN**					**Failure effect**
									Geome-trical	**Un-weighted Geom.**	**Weighted Median**	**Radial**	**Max Value**	
	weight:	0.2265	0.4461	0.0833	0.1325	0.0352	0.0765	1	**(f,w,S1)**	**(f,1,S1)**	**(f,w,S3)**	**(f,w,S4)**	**(f,1,S2)**	
Effect	**Critical value**	3	2	5	4	4	4	0	3	3	3	3	3	
051	Unpleasant comfort, colds	2	2	1	4	3	5	0	2.25	2.49	2	3.14	5	**Yes**
053	Health damage	2	2	3	4	3	5	1	2.47	2.99	2	3.27	5	**Yes**

W1: Risk factor value is greater than a specified threshold

W3: Risk factor value are decided to be critical

W2: Aggregated risk value is greater than a specified threshold

Figure 13: The evaluation of TRPN for failure mode (1.4.01P.001M) effects (051E(H) and 053E(H))

T.2. The proposed warning system can be integrated in the above mentioned total risk evaluation model, and can define thresholds on different levels (factors, risk evaluation levels), or different relations between factors and risk evaluations.

In summary, the proposed total risk evaluation framework allows for a more accurate estimation of risk. Additionally, this framework can incorporate a warning system that can identify risk levels in various domains or managing systems such as quality, environmental, health and safety, energy saving, and cyber security. This is particularly useful in situations where these domains are not integrated into a unified risk assessment system within a company or corporation.

To make this process properly, is necessary 2 things:

- a risk assesment or FMEA team, including as member an FMEA moderator
- a regular review of risk assessment process based on PDCA methodology

Fortunately, both items exist (are mandatory!) in an automotive company. In other organizations, those should be established.

In addressing the third research question of my dissertation, I aimed to extend the proposed method developed within the first and second research question to be effectively applicable in supply chain.

4.4 Designing Steps for Practical Implementation

Figure 14 illustrates the steps of evaluation, which are utilized in both the subsequent analysis of the theoretical framework and the case study.

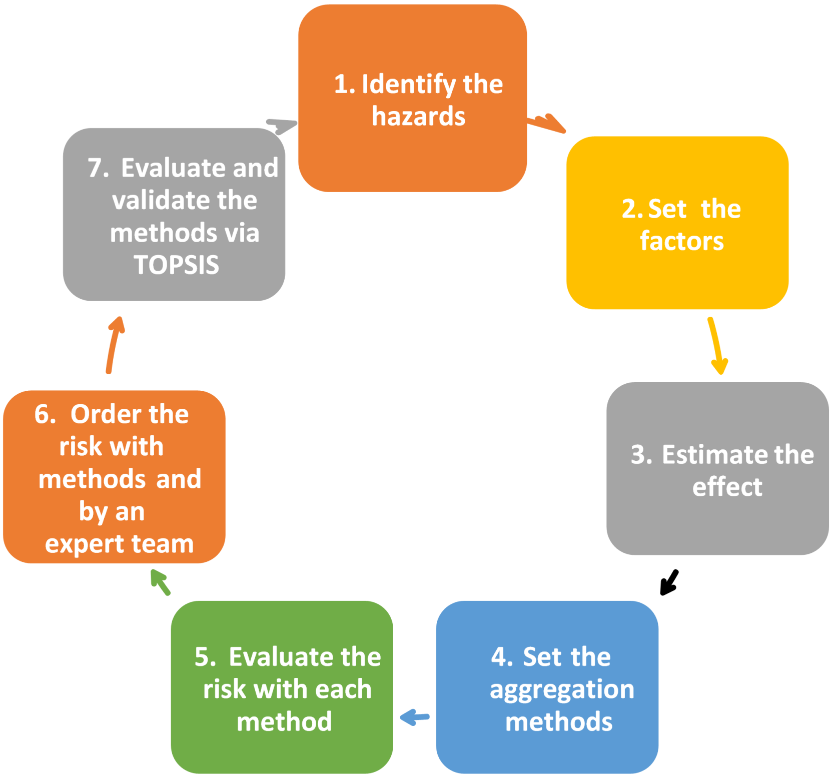


Figure 14: Determination of the appropriate risk evaluation method.

Step 0—Forming the Team: An assemblage of experts with specialized knowledge in logistics, quality management, risk assessment, evaluation, and mitigation, including all relevant departments such as finance/controlling or others, should be formed.

Step 1—Hazards identification: This step is a comprehensive gathering of all supply chain concerns, encompassing claims, losses, and delays.

Step 2—Factors and scales setting: The list from Step 1 should be used to identify the most accurate factors that describe the risk of organization, department, or process. This phase is exceptionally challenging. The factors included in the FMEA, namely detectability, severity, and occurrence, serve as a solid foundation. However, if there are other elements within these that can enhance our ability to precisely characterize the associated risk, they should be incorporated. In addition to the three previously mentioned factors, supply chains also utilize various other elements such as quality, time, cost, intensity, consequence, effect, cause, and measure. The quantity of factors is contingent upon the intricacy of the business or logistic procedures, traffic patterns, business affiliations, and other pertinent considerations (ex. sustainability, energy saving, cyber security, . . .). It is imperative to assess these factors on a case-by-case basis for each company, as the level of risk may vary depending on factors such as geographical location, supply chain network pattern, technological infrastructure, workforce availability and expertise, environmental conditions, core technological capabilities, political/economical/regional stability, etc. If a novel component can enhance the risk analysis from the perspective of the organization's functioning, it is recommended to utilize it. It is important to note that the elements should be linked to specific levels, which are ideally defined by the organization. However, it is recommended that the number of levels should be an even number. Typically, 10 levels are employed, although there is flexibility to differ from this standard.

Step 3—Risk assessment: In this section, is determined the levels of the factors for each risk.

Step 4—Set aggregation methods: This step involves the selection of the aggregating functions that were intended to be utilized for the purpose of analysis.

The standard FMEA will be utilized as a fundamental framework and point of comparison. Due to the inclusion of three levels (L, M, and H) in the revised FMEA, it is important to note that these levels serve solely as indicators for subsequent evaluation and are not intended for the purpose of risk prioritization. Due to this rationale, the analysis will not incorporate the new FMEA.

Every organization has the autonomy to make a decision regarding whether to accept, mitigate, or acknowledge specific hazards. Based on the aforementioned information, the management of the company or the risk assessment team of experts can ascertain the specific aspects that accentuate the level of risk.

Step 6—Order the results via TOPSIS method and by the experts: This pertains to the arrangement of outputs resulting from aggregating functions. This step comprises two components: the application of the TOPSIS algorithm for ordering and the ordering process conducted by the expert team members.

Step 7—Evaluation and validation: The assessment of outcomes carries considerable significance at this phase, and requires meticulous and strategic preparation. The risk evaluation expert team was asked to form a committee including the most experienced individuals to assign incidents, disregarding the rankings already published or the outcomes of the risk assessment. This indicates that the indicated persons have a deficiency in understanding the output values of TOPSIS ranking and the results of the aggregation functions.

This committee will make a ranking effect matrix and the impact matrix using their respective scores. The precision of these matrices is of utmost importance as it exerts a substantial influence on the final result. This implies that the perspectives of a specific cohort of specialists with substantial expertise in evaluating the relative effects of each approach should be considered.

The validation of the method involves comparing the results of the committee with the ranking made via TOPSIS. If it coincides, that will be the best aggregation function that can be used by the organization.

The risk assessment is conducted using individuals, thereby yielding qualitative data. Applying any aggregating function to these values yields a qualitative outcome, irrespective of the mathematical functions used to rank the data, such as AHP, TOPSIS, etc. Nevertheless, by conducting the same comparison using the most seasoned experts from the risk analysis team and employing the aforementioned comparative mathematical tools, the outcome should be identical. The occurrence of human error can be mitigated by conducting this study again with the group. Using this method, the most appropriate aggregating function for risk analysis within the organization.

4.5 Setting the warning levels

This is a more difficult assignment because, while several firms utilize the so-called integrated management system with a risk-based approach, they really operate their quality, environmental, energy-saving, and data protection management systems separately. In certain cases, integration means that the certification is issued by the same certification authority, typically for budgetary reasons.

In this situation, decision makers receive many reports from various management system auditing groups but lack a consistent basis for risk comparison. It appears practical to examine the occurrence and the consequent harm in value, but this is not a clear basis for decision making because it does not address the total impacts of damages, only those connected to the related management system.

The evaluation methodology is almost same.

hile the calculation of risk values and the thresholds should be calculated by the bottom-up iterative formula, the operating of the monitoring system can follow both the bottom-up but also the top-down approach.

Bottom-up approach At the 0-th hierarchy level, risk factors are evaluated. A warning event has occurred if a risk factor is not lower than the threshold (W1) or a criticality value is set to be 1 (W3). For maintenance, this monitoring system shows which risk effect (in which domain) of process mode caused a failure mode and which factor(s) are not lower than a threshold; therefore, a ***specific corrective/preventive action*** must be prescribed to mitigate the value of the risk factor. If a specific corrective/preventive action is not prescribed but the aggregated risk value is not lower than a threshold, a ***general corrective/preventive actions*** should be prescribed (W2) to mitigate the aggregated risk values. General corrective/preventive actions should contain the set of specific tasks, which mitigates the values of risk factors. This bottom-up approach can be extended to the higher hierarchy levels, where general activities in a hierarchy level N should contain specific tasks to mitigate risk factors or risk values in the lower hierarchy.

Top-down approach The top-down or *managerial approach* can be specified if in addition to the aggregating risk values the number of failure effects are calculated for all hierarchy levels. If there is a warning event on hierarchy level N, a general corrective/preventive action is specified, which, similarly to the bottom-up, may (but in this case not necessarily) contain a (detailed) corrective/preventive action to mitigate risk factors. The number of failure effects in every level helps management to drill down and specify the set of corrective/preventive actions.

T.3. The proposed model's usability was effectively evaluated for supply chain networks. It is important to note that the study of SCM risks is often overlooked in comparison to other risk assessment methods.

The estimated outcome was compared to the result obtained by the expert team, and it was determined that they are identical.

T.3.a. [Flexibility] New factors and alternative aggregation functions can be chosen, which effectively emphasize the risk for the associated supply chain.

T.3.b. [Simplicity] The multiplicative aggregation method is nearly as straightforward as the FMEA (Failure Mode and Effects Analysis), yielding highly satisfactory outcomes and being easily implementable.

T.3.c. [Process steps] Using the presented process steps, easily can be implemented the whole methodology in case of risk evalu-

ation and also in case of warning systems.

These results offer a new perspective on the implementation of supply chain risk analysis, proposing a simple method to evaluate risks, including the warning system implementation possibility in case, when the risk should be compared from different domains.

At the end of my thesis I presented a intuitive method of comparison of effectiveness od the new risk assesment via Alluvian graphs.

The last one presents an ordering change after implementing the last 2 factors (in total 5 factors) ofrisk evaluation (sse Figure 15):

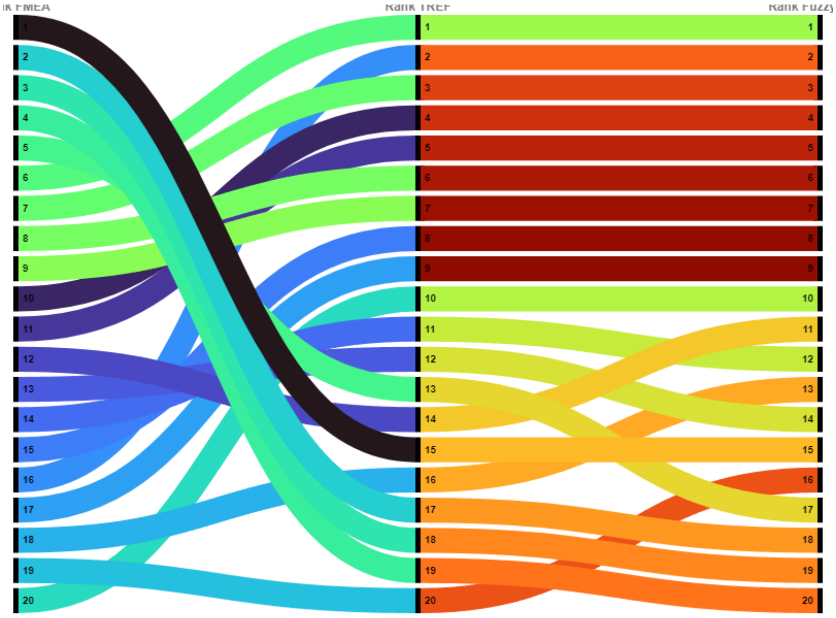


Figure 15: FMEA - TREF Multiplicative - TREF Fuzzy

5 Summary

In my dissertation, I conducted a study of the factors, scales, and aggregation functions utilized in the risk analysis of supply chains. The behavior of the aggregating functions was analyzed in order to evaluate them. All aggregating functions were assessed, including the Fuzzy FMEA, which is one of the most often used ones. The proposed approaches were tested through two case studies conducted in diverse environments: supply chain and maintenance. The latter was utilized in several domains to emphasize the significance of a warning system. Also via the case study was presented the implementation method and validation of models, using the expert teams and PDCA methodology.

5.1 Contribution to the literature

Iurrently, there is no commonly approved method for aggregating, as indicated by the literature analysis. The writers utilize different unique aggregation functions, nevertheless, an examination of the optimal aggregation risk function or framework is necessary to establish the feasibility of employing previously unused combinations. Furthermore, the literature includes studies on risk including more than 3 risk factors (namely 4 and 5). However, there is currently no universally applicable approach for aggregating an indefinite number of elements.

This thesis presents a novel risk evaluation framework that provides a guideline for selecting additional components. It also includes examples that demonstrate the necessary aggregation function when more than three risk factors are utilized.

The existing literature on warning systems fails to address warning events that arise from several levels, such as factor, effect, mode, and process. This means that there is no provision for creating distinct warning rules for each risk factor independently at each level.

The risk warning system proposed is a comprehensive one that may effectively address the deficiencies mentioned earlier. In a case study, the methodology presented is tested in practice and yields positive results.

5.2 Practical applicability

The practical use and utilization of this proposed technique was a primary emphasis of this thesis and was implemented in practice at two companies.

The primary objective was to provide a straightforward approach for SCM decision makers, as the literature review revealed that SCM is the most overlooked domain in risk analysis.

The implementation was successful in both cases.

It is possible to conclude that the introduction of the two new factors substantially prolonged the identification of actual risks, i.e., risks that cause substantial damage emerged. The methodology that was demonstrated, as well as explained in the Case Study, is readily implementable by SCM decision-makers. This aids them in identifying the fundamental risks that require preparation and consequently facilitates the identification of such risks. The comprehensive exposition of the method's implementation steps in the case study renders them universal, and applicable to sectors and industries beyond supply chain management.

Examples were shown in the case of a warning system, demonstrating how multiple management systems (such as quality and health and safety) might interact. These interactions can effectively identify and bring attention to high-risk concerns in maintenance activities, providing valuable information for decision makers.

6 Publications

Publications in Hungarian and international refereed journals:

- Zsolt Tibor Kosztyán, Tibor Csizmadia, Zoltán Kovács, Mihálcz István: Total risk evaluation framework, International Journal of Quality and Reliability Management, Emerald, Vol. 37, No.4, 2020, pp.575-608, ISSN: 0265-671X, doi:10.1108/IJQRM-05-2019-0167
- Zoltán Kovács, Tibor Csizmadia, István Mihálcz, Zsolt Tibor Kosztyán: Multipurpose Aggregation in Risk Assesment, Special Issue Mathematical Methods and Operation Research in Logistics, Project Planning, and Scheduling, Mathematics 2021, 10, 3166, MDPI, pp.1-20, ISSN: 2227-7390, doi: 10.3390/math10173166
- Kovács Zoltán, Csizmadia Tibor, Mihálcz István, Kosztyán Zsolt Tibor: A vállalati kockázatkezelésben használt aggregálófüggvények jellemzése (The characterization of aggregation functions in enterprise risk management˙), STATISZTIKAI SZEMLE 100 (9), 821-853 ISSN: 0039-0690, doi: 10.20311/stat2022.9.hu0821
- István Mihálcz, Zsolt Tibor Kosztyán: REF - A Risk Evaluation Framework on Supply Chain, Special Issue Mathematical Methods and Operation Research in Logistics, Project Planning, and Scheduling, 2nd Edition, Mathematics 2024, 12, 841, MDPI, pp.1-23, ISSN: 2227-7390, doi: 10.3390/math12060841

Conferences:

- Istvan Mihalcz, Dr. Zsolt Tibor Kosztyán: Total Risk Evaluation networks, as a flexible risk analysis tool, 19th ANNUAL ENBIS CONFERENCE, Budapest, Hungary, 02-04.09.2019. pp. 100, ISBN/ISSN: 978-963-489-146-8

- Istvan Mihalcz, Dr. Zsolt Tibor Kosztyán: Risk assessment of corporate processes, Industry Days Conference ”Challenges and Lessons in Management. Focus on Process Management - Industry 4.0 Challenges Conference, Debrecen, Hungary, 07-08.11.2019. pp. 62,
- Istvan Mihalcz: Risk Analysis in Supply Chain Using Fuzzy Functions, New Trends and Challenges in Management - Special Focus on Industry 4.0, Conference, Debrecen, Hungary, 31.03-01.04.2022.

References

(AIAG), A.I.A.G., 2019. Failure Mode and Effects Analysis - FMEA Handbook. volume 1. 1. ausgabe, korrigierter nachdruck ed., AIAG-VDA. URL: https://www.aiag.org/store/publications/details?ProductCode=FMEAAV-1.

Aleksic, B., Djekic, I., Miocinovic, J., Memisi, N., Smigic, N., 2020. Application of FMEA analysis in the short cheese supply chain. Meat Technology 61, 161–173. doi:10.18485/meattech.2020.61.2.6.

Bani-Mustafa, T., Zeng, Z., Zio, E., Vasseur, D., 2020. A new framework for multi-hazards risk aggregation. Safety science 121, 283–302.

Bjørnsen, K., Aven, T., 2019. Risk aggregation: What does it really mean? Reliability Engineering & System Safety 191, 106524.

Bognár, F., Hegedűs, C., . Analysis and consequences on some aggregation functions of PRISM (partial risk map) risk assessment method 10, 676. doi:10.3390/math10050676.

Bowles, J.B., Peláez, C., 1995. Fuzzy logic prioritization of failures in a system failure mode, effects and criticality analysis. Reliability Engineering & System Safety 50, 203 – 213. URL: http://www.sciencedirect.com/science/article/pii/095183209500068D, doi:http://dx.doi.org/10.1016/0951-8320(95)00068-D.

Canbakis, S.K., Karabas, M., Kilic, H.S., Koseoglu, S., Unal, E., 2018. A risk assessment model for supply chains. Pressacademia 7, 122–125. doi:10.17261/Pressacademia.2018.866.

Cardiel-Ortega, J.J., Baeza-Serrato, R., . Failure mode and effect analysis with a fuzzy logic approach 11, 348. doi:10.3390/systems11070348.

Chakraborty, S., . TOPSIS and modified TOPSIS: A comparative analysis 2, 100021. doi:10.1016/j.dajour.2021.100021.

Chen, Y., Song, G., Yang, F., Zhang, S., Zhang, Y., Liu, Z., 2012. Risk assessment and hierarchical risk management of enterprises in chemical industrial parks based on catastrophe theory. International Journal of Environmental Research and Public Health 9, 4386–4402. doi:10.3390/ijerph9124386.

Ebadi, A., Keyghobadi, A.R., Motadel, M.R., Yeganegi, M.R., 2020. The analysis of sustainable supply chain risks based on the fmea method in the oil and gas industry and factors affecting risk management. Petroleum Business Review 4. doi:10.22050/pbr.2020.115177.

Ewa Kulinska, D.M., Dendera-Gruszka, M., 2021. New pplication of FMEA nalysis in the eavy ndustry Supply Chain. techreport vol. XXIV, issue 2B, 600-616. European Research Studies Journal. URL: https://www.ersj.eu/journal/2312/download.

Fang, H., Fang, F., Hu, Q., Wan, Y., . Supply chain management: A review and bibliometric analysis 10, 1681. doi:10.3390/pr10091681.

Fattahi, R., Khalilzadeh, M., 2018. Risk evaluation using a novel hybrid method based on fmea, extended multimoora, and ahp methods under fuzzy environment. Safety Science 102, 290–300. doi:https://doi.org/10.1016/j.ssci.2017.10.018.

Geske, S.K..W...M., . Supply Chain Resilience: Insights from Theory and Practice. Springer International Publishing. doi:10.1007/978-3-030-95401-7.

Grabisch, M., Marichal, J.L., Mesiar, R., Pap, E., 2009. Aggregation functions. volume 127 of *Encyclopedia of mathematics and its applications*. Cambridge University Press. URL: http://www.cambridge.org/9780521519267. includes bibliographical references (p. 428-453) and index.

Henke, O.K..H..Z.., . Supply Chain Resilience: Reconceptualizing Risk Management in a Post-Pandemic World. Springer International Publishing. doi:10.1007/978-3-031-16489-7.

Huang, J., You, J.X., Liu, H.C., Song, M.S., 2020. Failure mode and effect analysis improvement: A systematic literature review and future research agenda. Reliability Engineering & System Safety 199, 106885. doi:10.1016/j.ress.2020.106885.

Ilangkumaran, M., Karthikeyan, M., Ramachandran, T., Boopathiraja, M., Kirubakaran, B., 2015. Risk analysis and warning rate of hot environment for foundry industry using hybrid MCDM technique. Safety Science 72, 133–143. doi:10.1016/j.ssci.2014.08.011.

Indrasari, L.D., Vitasmoro, P., Pariyanto, A.Y.T., 2021. FMEA approach to risk factors as a factor in implementing green supply chain management (study in PT. gresik cipta sejahtera). Journal of Physics: Conference Series 1858, 012069. doi:10.1088/1742-6596/1858/1/012069.

Johanyák, Z., Kovács, S., 2004. On the right selection of the fuzzy membership function. GAMF Journal XIX, 73–84. URL: http://johanyak.hu/files/u1/publi/J_K_A_Fuzzy_Tagsagi_Fuggveny_GAMFK_2004.pdf.

Kalantarnia, M., Khan, F., Hawboldt, K., 2009. Dynamic risk assessment using failure assessment and bayesian theory. Journal of Loss Prevention in the Process Industries 22, 600–606. doi:10.1016/j.jlp.2009.04.006.

Kanes, R., Marengo, M.C.R., Abdel-Moati, H., Cranefield, J., Véchot, L., 2017. Developing a framework for dynamic risk assessment using bayesian networks and reliability data. Journal of Loss Prevention in the Process Industries 50, 142–153. doi:10.1016/j.jlp.2017.09.011.

Khan, F., Rathnayaka, S., Ahmed, S., 2015. Methods and models in process safety and risk management: Past, present and future. Process Safety and Environmental Protection 98, 116–147. doi:10.1016/j.psep.2015.07.005.

Kosztyán, Z.T., Csizmadia, T., Kovács, Z., Mihálcz, I., 2020. Total risk evaluation framework. International Journal of Quality & Reliability Management , 575–608doi:https://doi.org/10.1108/IJQRM-05-2019-0167.

Kozarević, S., Puška, A., . Use of fuzzy logic for measuring practices and performances of supply chain 5, 150–160. doi:10.1016/j.orp.2018.07.001.

Kubler, S., Robert, J., Derigent, W., Voisin, A., Traon, Y.L., . A state-of the-art survey &amp testbed of fuzzy AHP (FAHP) applications 65, 398–422. doi:10.1016/j.eswa.2016.08.064.

Ling, W.K., 2004. Nonlinear Digital Filters. Elsevier Ltd, Amsterdam Boston London.

Liu, H.C., Liu, L., Liu, N., 2013a. Risk evaluation approaches in failure mode and effects analysis: A literature review. Expert Systems with Applications 40, 828 – 838. URL: http://www.sciencedirect.com/science/article/pii/S0957417412009712, doi:http://dx.doi.org/10.1016/j.eswa.2012.08.010.

Liu, H.C., Liu, L., Liu, N., 2013b. Risk evaluation approaches in failure mode and effects analysis: A literature review. Expert systems with applications 40, 828–838.

Liu, H.C., You, J.X., Ding, X.F., Su, Q., 2015. Improving risk evaluation in fmea with a hybrid multiple criteria decision making method. International Journal of Quality & Reliability Management 32, 763–782.

Lolli, F., Ishizaka, A., Gamberini, R., Rimini, B., Messori, M., 2015. FlowSort-GDSS – a novel group multi-criteria decision support system for sorting problems with application to FMEA. Expert Systems with Applications 42, 6342 – 6349. URL: http://www.sciencedirect.com/science/article/pii/S0957417415002584, doi:http://dx.doi.org/10.1016/j.eswa.2015.04.028.

Lu Lu, R.Z., de Souza, R., 2018. Enhanced fmea for supply chain risk identification, in: Hamburg University of Technology (TUHH), I.o.B.L., Management, G. (Eds.), The Road to a Digitalized Supply Chain Management: Smart and Digital Solutions for Supply Chain Management,, epubli. pp. 311–330. URL: https://econpapers.repec.org/bookchap/zbwhiclch/209355.htm, doi:10.15480/882.1783.

Malekitabar, H., Ardeshir, A., Sebt, M.H., Stouffs, R., Teo, E.A.L., 2018. On the calculus of risk in construction projects: Contradictory theories and a rationalized approach. Safety Science 101, 72–85. doi:10.1016/j.ssci.2017.08.014.

Manuele, F.A., 2005. Risk assesment & hierarchies of control. Safety Management , 33–39URL: https://aeasseincludes.assp.org/professionalsafety/pastissues/050/05/030505as.pdf.

Merrick, J.R.W., van Dorp, J.R., Singh, A., 2005. Analysis of correlated expert judgments from extended pairwise comparisons. Decision Analysis 2, 17–29. doi:10.1287/deca.1050.0031.

Mustaniroh, S.A., Murod, F.A.I.K., Silalahi, R.L.R., 2020. The risk assessment analysis of corn chips supply chain using fuzzy FMEA. IOP Conference Series: Earth and Environmental Science 475, 012052. doi:10.1088/1755-1315/475/1/012052.

Øien, K., Utne, I., Herrera, I., 2011. Building safety indicators: Part 1 – theoretical foundation. Safety Science 49, 148–161. doi:10.1016/j.ssci.2010.05.012.

O'Keeffe, V.J., Tuckey, M.R., Naweed, A., 2015. Whose safety? flexible risk assessment boundaries balance nurse safety with patient care. Safety Science 76, 111–120. doi:http://dx.doi.org/10.1016/j.ssci.2015.02.024.

Panchal, D., Chatterjee, P., Yazdani, M., Chakraborty, S., 2019. A hybrid mcdm approach-based framework for operational sustainability of process industry, in: Advanced Multi-Criteria Decision Making for Addressing Complex Sustainability Issues. IGI Global, pp. 1–13.

Pedraza, T., Rodríguez-López, J., 2020. Aggregation of l-probabilistic quasi-uniformities. Mathematics 8, 1980.

Pedraza, T., Rodríguez-López, J., 2021. New results on the aggregation of norms. Mathematics 9, 2291.

Petrović, D.V., Tanasijević, M., Milić, V., Lilić, N., Stojadinović, S., Svrkota, I., 2014. Risk assessment model of mining equipment failure based on fuzzy logic. Expert Systems with Applications 41, 8157 – 8164. URL: http://www.sciencedirect.com/science/article/pii/S0957417414003832, doi:http://dx.doi.org/10.1016/j.eswa.2014.06.042.

Shaker, F., Shahin, A., Jahanyan, S., 2019. Developing a two-phase qfd for improving fmea: an integrative approach. International Journal of Quality & Reliability Management .

Sime Curkovic, Thomas Scannell, B.W., 2013. Using fmea for supply chain risk management. Modern Management Science Engineering 1, 251–256. URL: https://www.researchgate.net/publication/263733916_Using_FMEA_for_Supply_Chain_Risk_Management.

Spreafico, C., Russo, D., Rizzi, C., 2017. A state-of-the-art review of fmea/fmeca including patents. computer science review 25, 19–28.

Tay, K.M., Lim, C.P., 2006. Fuzzy fmea with a guided rules reduction system for prioritization of failures. International Journal of Quality & Reliability Management 23, 1047–1066. doi:10.1108/02656710610688202.

Trenggonowati, D.L., Bahauddin, A., Ridwan, A., Wulandari, Y., 2021. Proposed action of supply chain risk mitigation air compressor type l unloading

$\frac{1}{4}$ HP using the fuzzy – FMEA and fuzzy – AHP method in PT. XYZ. Journal of Innovation and Technology 2, 10–17. doi:10.31629/jit.v2i1.3204.

Trenggonowati, D.L., Ulfah, M., Arina, F., Lutfiah, C., 2020. Analysis and strategy of supply chain risk mitigation using fuzzy failure mode and effect analysis (fuzzy fmea) and fuzzy analytical hierarchy process (fuzzy ahp). IOP Conference Series: Materials Science and Engineering 909, 012085. doi:10.1088/1757-899x/909/1/012085.

Vodenicharova, M., 2017. Opportunities for the applications of FMEA model in logistics processes in bulgarian enterprises. Logistics & Sustainable Transport 8, 31–41. doi:10.1515/jlst-2017-0003.

Wagner, S.C.T.S.B., 2016. ManagingSupply Chain Risk, Integrating with Risk Management. CRC Press, Taylor Francis Group, LLC. URL: https://www.ebook.de/de/product/24417566/sime_curkovic_thomas_scannell_bret_wagner_managing_supply_chain_risk.html.

Wan, C., Yan, X., Zhang, D., Qu, Z., Yang, Z., 2019. An advanced fuzzy bayesian-based FMEA approach for assessing maritime supply chain risks. Transportation Research Part E: Logistics and Transportation Review 125, 222–240. doi:10.1016/j.tre.2019.03.011.

Wu, X., Wu, J., 2021. The risk priority number evaluation of FMEA analysis based on random uncertainty and fuzzy uncertainty. Complexity 2021, 1–15. doi:10.1155/2021/8817667.

Xu, K., Tang, L., Xie, M., Ho, S., Zhu, M., 2002. Fuzzy assessment of fmea for engine systems. Reliability Engineering & System Safety 75, 17 – 29. URL: http://www.sciencedirect.com/science/article/pii/S0951832001001016, doi:10.1016/S0951-8320(01)00101-6.

Yacob Khojasteh, Henry Xu, S.Z., . Supply Chain Risk Mitigation: Strategies, Methods and Applications. Springer International Publishing. doi:10.1007/978-3-031-09183-4.

Yazdi, M.M., . TOPSIS method for multiple-criteria decision making (MCDM). URL: https://CRAN.R-project.org/package=topsis.

Zahedi Khameneh, A., Kilicman, A., . Some construction methods of aggregation operators in decision-making problems: An overview 12, 694. URL: https://www.mdpi.com/2073-8994/12/5/694#:~:text=Therearethreemainconstruction,handledbyeachofthem., doi:10.3390/sym12050694.

Zammori, F., Gabbrielli, R., 2012. Anp/rpn: a multi criteria evaluation of the risk priority number. Quality and Reliability Engineering International 28, 85–104. URL: http://onlinelibrary.wiley.com/doi/10.1002/qre.1217/abstract, doi:10.1002/qre.1217.

Zhao, L., Huo, B., Sun, L., Zhao, X., . The impact of supply chain risk on supply chain integration and company performance: a global investigation 18, 115–131. doi:10.1108/13598541311318773.

Zheng, G., Zhu, N., Tian, Z., Chen, Y., Sun, B., 2012. Application of a trapezoidal fuzzy AHP method for work safety evaluation and early warning rating of hot and humid environments. Safety Science 50, 228–239. doi:10.1016/j.ssci.2011.08.042.

Zhu, Q., Golrizgashti, S., Sarkis, J., 2020. Product deletion and supply chain repercussions: risk management using FMEA. Benchmarking: An International Journal 28, 409–437. doi:10.1108/bij-01-2020-0007.