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RISK EVALUATION OF WAREHOUSE OPERATIONS BY USING FMEA AND COMBINED AHP-TOPSIS APPROACHES UNDER FUZZY ENVIRONMENT

*[1]Muhammad Nazam, [2]Jiuping Xu, [3]Dr. Zhimiao Tao, [4]Jamil Ahmad and [5]Dr. Muhammad Hashim

[1,2,3,4] Uncertainty Decision-Making Laboratory, Business School, Sichuan University, Chengdu 610064, P. R. China

[5]Department of Business Administration, National Textile University, Faisalabad, Pakistan

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ABSTRACT

In this study, we investigate the effects of supply chain operations and supply chain risks on supply chain performance. Operationally, warehouse processes contain various risks which lead to a poor supply chain performance. In order to avoid supply chain breakdown, risk analysis in warehouse operations is a challenging task to enhance both the supply chain efficiency and the customer satisfaction. In this context, failure mode and effects analysis (FMEA) is a useful risk assessment tool and therefore, this study is a novel approach towards risk evaluation of warehouse operations. In traditional (FMEA) the risk priorities of failure modes are determined by using crisp risk priority number (RPN), which has been criticized due to several limitations. In this article a fuzzy multi-criteria group decision making (MCGDM) approach, allowing a group of experts to use linguistic variables for identifying three risk factors namely; severity (S), occurrence (O), and detection (D), is considered for FMEA by applying fuzzy technique for order performance by similarity to ideal solution (TOPSIS) integrated with fuzzy analytical hierarchy process (AHP) in the food retail chain. Finally, a case study which evaluates the risk of warehouse process is presented with sensitivity analysis to demonstrate the application of the proposed model effectively under fuzzy environment.

INTRODUCTION

In today's world, an important feature of the rapidly flourishing business environment, spurred on by massive technology shifts, innovation, global competitions and communication technologies, is the increasing prevalence of risk in most of the industrial activities (Wu, 2009; Yang *et al.*, 2014). Risk is an inherent activity and it occur because we can never predict explicitly that what will happen tomorrow or in the near future. The organizations can use the optimal forecasting techniques or tools and conduct every possible analytical solution, but there are more chances of uncertainty exists about future events (Waters, 2007; Lewis, 2003). This uncertainty creates a gap between what really happens and what a firm has planned for and consequently causes losses due to the sequence of failures or causal events. This uncertainty eventually causes losses due to the sequence of failures or errors.

Corresponding author: Muhammad Nazam
Uncertainty Decision-Making Laboratory, Business School, Sichuan University, Chengdu 610064, P. R. China

However, as the risk can create troubles for a big loss, therefore industries have to evaluate the potential for such a sequence of failures or causal events. In the risk management mechanism of warehouse operations, the crucial component is the timely quantification and evaluation of risk to satisfy the customer needs. This mechanism involves understanding the conditions that create potential problems, and then evaluating the consequences of likelihood and negative impact of such problems (Wakolbinger and Cruz, 2011; Silbermayr and Minner, 2014). The result of this process will be information regarding situational risks upon which strategic decisions can be made. However, as risk has the potential for loss, organizations must assess the potential for such a sequence of failures. A crucial element of the risk management process is the identification and assessment of risk (Tapiero, 2007; Vilko and Hallikas, 2012). Nowadays, uncertainties or ambiguities about a situation can often indicate risk, which is happening or non-happening of loss, damage, disaster or any other undesirable event. The risk can be defined as an uncertain event or set of circumstances which should it occur, will have an impact on achievement of one or more objectives according to the Association of the Project Managers. In this definition, the core concepts namely the purposes, the probability of occurrences and their impact are emphasized (Tuncel and Alpan, 2010; Thun and Hoenig, 2011). In supply chain risk management (SCRM) point of view, risk sometimes interpreted as unreliable and uncertain resources creating supply chain interruption, whereas uncertainty can be explained as matching risk between supply and demand in supply chain processes (Tang and Musa, 2011; Hoffmann *et al*., 2013). Therefore, warehouse processes in supply chain operations contain risks which deteriorate supply chain performance and customer satisfaction. Delanuay *et al*. (2007) specify four types of errors or risks in supply chain of warehouse operations: firstly, the permanent shrinkage in the physical stock due to embezzlement or destruction. Secondly, the misplacement, which is temporary shrinkage in the physical stock that can be replaced after material handling or counting after every period. Thirdly, the more or less production capacity of supplier which is the long-lasting deficit or surplus in the physical inventory due to supplier failure or errors.

And finally the most significant fourth one is the transaction type error that affects the management information system differently than the first three errors, which modify the physical inventory. In most of the cases, due to these types of errors, the accuracy rate in handling inventory decreases and a big gap happens between the actual level of inventory and system inventory in the shipment store of the company. Due to these reasons, the supply chain performance and thereby the customer service level decrease in warehouse processes. Therefore, the companies have to calculate the risks of warehouse operations to reach the required customer service level and increase the supply chain performance (Hallikas *et al*., 2004; Diabat, 2012; Lavastre *et al*., 2012). A typical process of risk management contains four basic steps risk identification, risk assessment, risk management and risk monitoring in supply chain operations. The most well-known method for risk assessment, failure mode and effects analysis (FMEA) is an analysis method of reliability which can identify potential failure modes and its effect. FMEA has been extensively used for examining potential failures in products, processes, designs and services.

In FMEA method, risk rating of failure modes is estimated by risk priority numbers (RPN) and correction measure is decided in order to increase the reliability. Traditional FMEA determines the risk priorities which require the risk factors like the occurrence (O), severity (S) and detection (D) of each failure mode to be precisely evaluated (Wang *et al*., 2009). The traditional FMEA has some drawbacks so that affect the risk evaluation and corrective actions. It is not very easy for three risk factors to be evaluated exactly. Additionally, traditional FMEA doesn't deliberate the relative importance of three risk factors. The more critical issue is that same (RPN) can be obtained by different combination of three risk factors (Huadong and Zhigang, 2009). Therefore, to deal with these problematic issues fuzzy logic is introduced to overcome all the problems in traditional FMEA (Wang *et al*., 2009; Hua *et al*., 2009). The main obstacle in managing and analyzing risks comes from the fact that due to globalization there is a lot of subjectivity involved. The experts input to solve the multi-criteria problems mainly comes in the form of subjective judgments. This necessitates the practice of theories such as fuzzy or grey analysis which are capable of dealing with subjectivity and ambiguity. To deal with these situations, two extensively popular tools previously used are fuzzy analytical hierarchy process (AHP) and fuzzy technique for order preference by similarity to the ideal solution (TOPSIS). These two methodologies have the benefit of combining approaches like fuzzy theory, which by its very nature is built to handle subjective assessments, with fuzzy analytical technique such as fuzzy AHP, which is a acceptable tool for managing multi criteria decision making (MCDM) problems in various sectors (Karsak and Tolga, 2001; Zayed *et al*., 2008; Chan and Kumar 2007). The resulting techniques give us the advantage to make prompt decisions and at the same time be imprecise while giving inputs. Samvedi *et al*. (2013) proposed a risk-oriented assessment model for quantifying risks in a supply chain through integration of fuzzy AHP and fuzzy TOPSIS methods in Indian textile and steel industry. That is why techniques such as fuzzy AHP and fuzzy TOPSIS are becoming increasingly popular today.

In this study, the fuzzy FMEA is used to analyze and assess the risks of warehouse operations. Ten failure modes are determined for risk evaluation in warehouse operations of a food retail distributor. We classified the warehouse risks into two main categories, the first five cause permanent shrinkage of products, the second five are related to the processes. According to best of our knowledge, it is noticed that there has not been any published research article which considers risk factors under fuzzy environment for evaluation of warehouse operations. In this context, our research work has the originality of applying the fuzzy FMEA method through integration of fuzzy AHP-TOPSIS approaches that evaluates most serious failure modes considering risk factors for warehouse operations to address this research gap. The rest of the paper is organized as follows: The brief summary of problem statement by categorizing risks in warehouse operations is given in Section 2. An overview of fuzzy FMEA and combined fuzzy AHP-TOPSIS methodologies is explained in Section 3. Section 4 formulates the proposed risk-oriented assessment model in warehouse operations of food distributor company and Section 5 presents the application of the proposed methodology with numerical results and sensitivity analysis. Finally, conclusions and future work are provided in section 6.

Key Problem Statement

In this problem, a risk analysis is conducted to solve the disruptive issues for a warehouse of a food retail distributor. In today's scenario, supply chain risks can be classified in various different ways and from different viewpoints, such as from a corporate governance or logistics risk agenda, or supply chain failures or even in terms of a multi-layer complicated system (Christopher and Peck, 2004). Supply chain failure's one simple categorization can be external and internal risks. Some interesting examples in such classification can be natural unanticipated events (external) and supplier's insolvency problems (internal). When classified in such a way, things are streamlined and can be understood better, but practically this fails to assign responsibility to individual organizations for tackling risks. In this study, we treat internal risks as one, namely process risk and shrinkage risk of food Distributor Company. For this purpose, ten failure modes are determined for warehouse operations. The first five are related to the processes and second five cause permanent shrinkage of products. We believe that it makes situations simpler to understand and also control risks are anyway part of the process decisions and thus they can be integrated. All the risk factors should be considered and calculated by the distributor company to increase the supply chain performance and the customer satisfaction. The detailed categorization and explanation of risks in warehouse operations is shown in Fig. 1.

Processing Risks of the Products

Receiving errors (FM1): This is one of the risks internal to the chain but is external to the warehouse in focus, such as wrong or missing items from supplier. These risks relate to the irrelevant order quantities arising due to lack of good buyer-supplier relationship, leading to a gap between demand and supply, thus affecting the warehouse operations. There can be various reasons for these risks. Any change in the supplier's personnel or information system can also trigger these risks. For example, a wrong order allocation of any essential commodity being exhausted will create panic and send the demand for that product soaring. These kinds of errors can never be totally removed but can be managed within limits and proper supervision.

Misplacement errors (FM2): These are the risks which are internal to the distributor company, and emanate from the put-away errors in the flow of the product through the different processes within a warehouse. For example, the products may be misplaced by the warehouse personnel, sothere is a temporary shrinkage in the physical stock.

Pick-up errors (FM3): These errors refer to the risks emanating from the problems of wrong pickup or miss some products by the warehouse personnel.

Transportation errors (FM4): Transportation errors refer to the shipment risk emanating from the problems in a smooth flow from the downstream side. In this case, the personnel could deliver the products to wrong customer address or they could miss some products to deliver.

Transaction type errors (FM5): The personnel may input wrong data into the warehouse information system. Transaction type errors affect the information system differently than the first two types of errors, which modify the physical inventory.

Shrinkage Risks of the Products

Theft risk (FM6): The products may be stolen or lost in the warehouse due to mismanagement of the security personnel. There can be various reasons for these kind of risks in warehouse operations. Any change in the internal infrastructure can also trigger these risks.

Expiration risk (FM7): The products can pass the expiration date and it cause severe loss for the Distributor Company. It is the most significant financial failure for the distributor company.

Obsolescence risk (FM8): These are the risks which are internal to the firms and emanate from the disturbances in the smooth flow of products within a warehouse. For example, the most of the products may be damaged due to the careless physical movement of products during operational activities. Therefore, the personnel must be vigilant and sincere with their job assignment.

Fire risk (FM9): Sometimes due to inadequate fire safety equipment and lack of personnel training, fire may break out in warehouse which eventually causes huge loss.

Biochemical risk (FM10): The perishable food items may spoil due to biological or chemical factors. These kind of risks severely effect on the supply chain performance of the distributor company.

The evaluation and prioritization procedure of the above referred ten supply chain failure modes with respect to risk factors expressed with analytical results and sensitivity analysis in the practical application section.

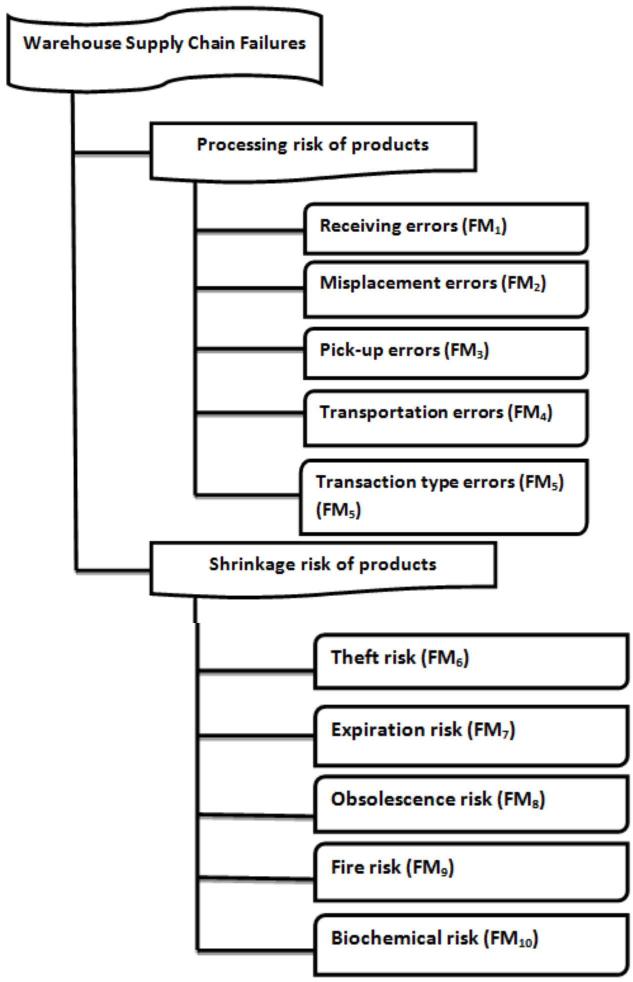

Figure 1. Classification of warehouse supply chain failures

MATERIALS AND METHODS

In this study, Fuzzy FMEA will apply to determine the risk factors and combined Fuzzy AHP-TOPSIS structure the decision-making problem and to compute the weights of the criteria, and TOPSIS will be used for the aggregation of the criteria, ranking of the alternatives, and sensitivity analysis. Fuzzy FMEA and combined Fuzzy AHP-TOPSIS are detailed mathematically and theoretically in the following sub-sections.

Formulating a Fuzzy (MCGDM)

For Evaluating Risk in Warehouse Supply Chain Breakdown

Fuzzy FMEA

Failure mode and effects analysis (FMEA) is a widely used risk assessment tool for defining, identifying, and eliminating potential failures or problems in products, process, designs, and services. In traditional FMEA, the risk priorities of failure modes are determined by using risk priority numbers (RPNs), which can be obtained by multiplying the scores of risk factors like occurrence (O), severity (S), and detection (D). Despite of all these factors, the crisp (RPNs) method has been criticized to have several limitations. For instance, when the typical traditional FMEA and the fuzzy approaches are compared, the fuzzy approach has an edge of allowing the conduction of risk evaluation and prioritization based on the knowledge of the experts (Tay and Lim, 2006). Xu *et al.* (2002) explain the causes for considering the fuzzy logic approach as following:

- All FMEA-related information is taken in natural language which is easy for fuzzy logic to handle with as it is based on human language and can be built on top of the experience of decision makers.
- Fuzzy logic allows imprecise data usage so it enables the treatment of many states.
- The relative importance among the three risk factors probability of occurrence, severity, and likelihood of detection is not considered as they are accepted equally important.

Furthermore, fuzzy FMEA allows both quantitative data and vague and qualitative information to be used and managed in a consistent manner and makes it possible for the combination of severity, occurrence and detect-ability in a more exible structure (Braglia *et al*., 2003). Based on the literature review, previous researchers have viewed supply chain failures as a multi-criteria decision problem (Schoenherr *et al*., 2008; Neiger *et al*., 2009). The multi-attribute decision making technique is often used to solve this problem. However, this research considers this type (operational risk) of warehouse problem as a (SCRM) problem; few researchers have focused on this field but the research in this area is still nascent. Pillay and Wang (2003) found that the result of the FMEA could assist managers in making the right decisions in the face of supply chain risk. In practice, the FMEA has been used in product design and manufacturing improvement. Therefore, introducing the FMEA into the risk evaluation of warehouse operations is highly feasible.

Fuzzy AHP

The fuzzy AHP methodology extends by Saaty's AHP by combining it with fuzzy set theory and fuzzy sets. Fuzzy ratio scales can be utilized to express the relative importance of the factors in corresponding criterion. Therefore, in the following, Chang's extent analysis method is explained to structure the decision hierarchy and for identification of criteria weights. Let $X = x_1, x_2 \ldots n$ be an object set, and $U = u_1, u_2 \ldots u_n$ be a goal or objective set. According to the method of extent analysis, each object is taken and extent analysis for each goal is performed, respectively. Hence, m extent analysis values for each object can be obtained, with the following signs:

$\tilde{M}_{gi}^{1}, \tilde{M}_{gi}^{2}, \ldots, \tilde{M}_{gi}^{j}$ where all the $\tilde{M}_{gi}^{j}\left(i = 1,2,3,\ldots,n \text{ and } j = 1,2,3,\ldots,m\right)$ and are triangular fuzzy numbers (TFNs). These (TFNs) are used for warehouse supply chain failure's criteria and utilized as weights for linguistic assessment of fuzzy TOPSIS method.
The steps of extent analysis can be given as in the following:

Step 1: Fuzzy synthetic extent calculation: The value of fuzzy synthetic extent with respect to the *ith* object is defined as

$$\tilde{S}_i = \sum_{j=1}^{m} \tilde{M}_{gi}^{j} \otimes \left[\sum_{i=1}^{n} \, , \sum_{j=1}^{m} \tilde{M}_{gi}^{j} \right]^{-1} \qquad (1)$$

To obtain g_i perform the fuzzy addition operation of m extent analysis values for a particular matrix such that

$$\sum_{j=1}^{m} \tilde{M}_{gi}^{j} = \left[\sum_{j=1}^{m} l_j, \sum_{j=1}^{m} m_j, \sum_{j=1}^{m} u_j \right]^{-1} \qquad (2)$$

And to obtain $\sum_{i=1}^{n} \sum_{j=1}^{m} \tilde{M}_{gi}^{j}$ the fuzzy addition operation $\tilde{M}_{gi}^{j}\left(j = 1,2,\ldots,m\right)$ values is performed such as

$$\sum_{i=1}^{n} \sum_{j=1}^{m} \tilde{M}_{gi}^{j} = \left(\sum_{i=1}^{n} l_i, \sum_{i=1}^{n} m_i, \sum_{i=1}^{n} u_i \right) \qquad (3)$$

And the inverse of the above vector is computed in such as

$$\left[\sum_{i=1}^{n} \sum_{j=1}^{m} \tilde{M}_{gi}^{j} \right] = \left(\frac{1}{\sum_{i=1}^{n} u_i}, \frac{1}{\sum_{i=1}^{n} m_i}, \frac{1}{\sum_{i=1}^{n} l_i} \right) \qquad (4)$$

Step 2: Comparison of fuzzy values: As $\tilde{M}_1$ and $\tilde{M}_2$ are two triangular fuzzy numbers, the degree of possibility of $\tilde{M}_2 \leq \tilde{M}_1$ is defined as

$$V\left(\tilde{M}_2 \geq \tilde{M}_1\right) = \sup_y \geq x\left[\min \mu_{\tilde{M}_1}(x), \min \mu_{\tilde{M}_2}(y)\right] \quad (5)$$

And can be equivalently expressed as follows:

$$V\left(\tilde{M} \geq \tilde{M}_1\right) = \mu(\mathrm{d}) = \begin{cases} 1, & if \quad m_2 \geq m_1, \\ 0, & if \quad l_2 \geq u_{2,} \\ \dfrac{l_2 - u_2}{(m_2 - u_2) - (\mathrm{m}_{1-}\mathrm{l}_1)} & otherwise. \end{cases} \quad (6)$$

Where d is the ordinate of the highest intersection point D between $\mu_{\tilde{M}_1}$ and $\mu_{\tilde{M}2}$ as shown in Fig.2. To compare $\tilde{M}_1$ and $\tilde{M}_2$, we need both values of $V\left(\tilde{M}_2 \geq \tilde{M}_1\right)$ and $V\left(\tilde{M}_1 \geq \tilde{M}_2\right)$

$$d'(A_i) = \min V\left(\tilde{S}_i \geq \tilde{S}_k\right) \quad (7)$$

Step 3: Priority weight calculation: The degree of possibility for a convex fuzzy number to be greater than k convex fuzzy numbers $\tilde{M}_i$ can be defined by

$$V(\tilde{\mathrm{M}} \geq \tilde{\mathrm{M}}_1, \tilde{\mathrm{M}}_2, ..., \tilde{\mathrm{M}}_k) = \min \mathrm{V}(\tilde{\mathrm{M}} \geq \tilde{\mathrm{M}}_i) \quad (8)$$

Where i=1,…,k. assume that

$$d'(A_i) = \min V\left(\tilde{S}_i \geq \tilde{S}_k\right) \quad (9)$$

For k=1, 2,…, ; $k \neq i$. Then the weight vector is given by

$$W' = \left(d'(\mathrm{A}_1), d'(\mathrm{A}_2), ..., d'(\mathrm{A}_n)\right)^T$$
(10)

Where $A_i\left(i = 1,2,3,...,n\right)$ are n elements.

Step 4: Calculation of the normalized weights: Via normalization, the normalized weight vectors are

$$W = \left(d(\mathrm{A}_1), d(\mathrm{A}_2), ..., d(\mathrm{A}_n)\right)^T \quad (11)$$

Where W is a non-fuzzy number. Weight vector of risk factors can be obtained by either directly assigning or indirectly using pair-wise comparisons. Here, it is suggested that the decision makers use the linguistic variables in Table 1to evaluate the weight vector risk factors. After comparison is made, it is necessary to check the consistency ratio of the comparison. To do so, the graded mean integration approach is utilized for defuzzifying the matrix. According to the graded mean integration approach, a fuzzy number $\tilde{M} = \left(m_1, m_2, m_3\right)$ can be transformed into a crisp number by employing the below Eq. (12):

$$P\left(\tilde{M}\right) = M = \frac{m_{1+}4m_{2+}m_3}{6} \quad (12)$$

After the deffuzification of each value in the matrix, 'consistency ratio' (CR) of the matrix can easily be calculated and checked whether CR is smaller than 0.10 or not.

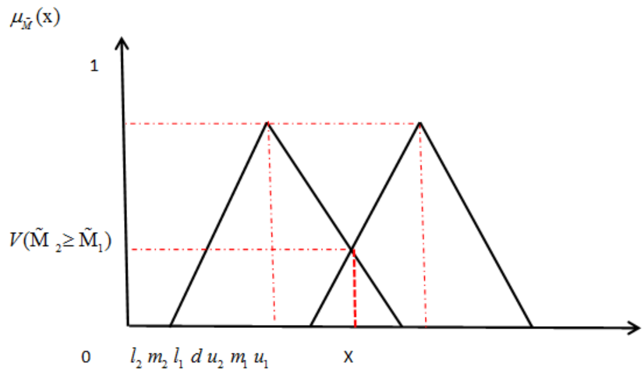

Figure 2. The intersection between $\tilde{M}_1$ and $\tilde{M}_2$ fuzzy terms

Fuzzy Tops is

Fuzzy set theory can be used to solve multi-criteria decision making problems. For this reason, the fuzzy TOPSIS methodology is very suitable for solving real life application problems under a fuzzy environment. In the following, Chen's fuzzy TOPSIS method is explained briefly. Chen (2000) extends the TOPSIS approach to fuzzy multi-criteria group decision making situations by considering triangular fuzzy numbers and defining crisp Euclidean distance between two fuzzy numbers.

Table 1. Fuzzy evaluation score for calculating the weight vector

Linguistic variables	Notations	Fuzzy score (L,M,U)
Absolutely strong	AS	(2.00,2.50,3.00)
Very strong	VS	(1.50,2.00,2.50)
Fairly strong	FS	(1.00,1.50,2.00)
Slightly strong	SS	(1.00,1.00,1.50)
Equal	E	(1.00,1.00,1.00)
Slightly weak	SW	(0.66,1.00,1.00)
Fairly weak	FW	(0.50,0.66,1.00)

Table 2. Fuzzy evaluation score for rating the alternatives

Linguistic variables	Notations	Fuzzy score (L,M,U)
Very poor	VP	(0.00,0.00,1.00)
Poor	P	(0.00,1.00,3.00)
Medium poor	MP	(1.00,3.00,5.00)
Fair	F	(3.00,5.00,7.00)
Medium good	MG	(5.00,7.00,9.00)
Good	G	(7.00,9.00,10.0)
Very good	VG	(9.00,10.0,10.0)

In Chen's fuzzy TOPSIS, linguistic preferences can easily be transformed to fuzzy numbers which are allowed to be used in calculations (Ekmekioglu *et al*., 2010; Onut and Soner 2008;

Kutlu and Ekmekioglu, 2010a; Kannan *et al.*, 2014; Choudhary and Shankar, 2012). It is suggested that the experts utilized linguistic variables to evaluate the ratings of alternatives with respect to criteria. Table 2 gives the linguistic scale for evaluation of the alternatives. Assuming that a decision group has K people, the ratings of alternatives with respect to each criterion can be calculated as

$$\tilde{x}_{ij} = \frac{1}{K}\left[\tilde{x}_{ij}^{1}(+)\tilde{x}_{ij}^{2}(+)...(+)\tilde{x}_{ij}^{k}\right] \quad (13)$$

Where $\tilde{x}_{ij}^{k}$ is the rating of the *Kth* decision maker for *ith* alternative with respect to *jth* criterion (Chen, 2000). Obtaining weights of the criteria and fuzzy ratings of alternatives with respect to each criterion, the fuzzy multi-criteria decision-making problem can be expressed in matrix format as

$$\tilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} \dots \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} \dots \tilde{x}_{2n} \\ \vdots & \vdots \quad \dots \quad \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} \dots \tilde{x}_{mn} \end{bmatrix}, \qquad \tilde{W} = \left[\tilde{w}_1, \tilde{w}_2, ..., \tilde{w}_n\right] \quad (14)$$

Where $\tilde{x}_{ij}$ is the rating of the alternative A_i with respect to criterion j (i.e. C_j) and w_j denotes the importance weight of C_j . These linguistic variables can be described by triangular fuzzy numbers: $\tilde{x}_{ij} = a_{ij}, b_{ij}, c_{ij}$. To avoid the complicated normalization formula used in classical TOPSIS, the linear scale transformation is used here to transform the various criteria scales into a comparable scale. Therefore, we can obtain the normalized fuzzy decision matrix denoted by $\tilde{R}$.

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m \times n} \quad (15)$$

Where B and C are the set of benefit criteria and cost criteria, respectively, and

$$\tilde{r} = \left(\frac{\tilde{a}_{ij}}{c_j^*}, \frac{\tilde{b}_{ij}}{c_j^*}, \frac{\tilde{c}_{ij}}{c_j^*}\right), \qquad j \quad \varepsilon \quad B; (16)$$

$$\tilde{r} = \left(\frac{a_j^-}{c_{ij}}, \frac{b_j^-}{b_{ij}}, \frac{c_j^-}{a_{ij}}\right), \qquad j \quad \varepsilon \quad C; (17)$$

$$c_j^* = \max_i c_{ij} \qquad if \quad j \quad \varepsilon \quad B; (18)$$

$$a_j^- = \min_i c_{ij} \qquad if \quad j \quad \varepsilon \quad C_i \, (19)$$

The normalization method mentioned above is to preserve the property that the ranges of normalized triangular fuzzy numbers belong to [0; 1]. Considering the different importance of each criterion, we can construct the weighted normalized fuzzy decision matrix as

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m \times n,} \qquad i = 1, 2, 3, ..., m; \quad j = 1, 2, 3, ..., n \quad (20)$$

$$\tilde{v}_{ij} = \tilde{r}_{ij}\left(.\right) d\left(C_j\right) (21)$$

According to the weighted normalized fuzzy decision matrix, we know that the elements ~vij8; j are normalized positive triangular fuzzy numbers and their ranges belong to the closed interval [0, 1]. Then, we can define the fuzzy positive-ideal solution (FPIS, A^*) and fuzzy negative-ideal solution (FNIS, A^-) as

$$A^* = \left(\tilde{v}_1^*, \tilde{v}_2^*, ..., \tilde{v}_n^*\right) \quad (22)$$

$$A^- = \left(\tilde{v}_1^-, \tilde{v}_2^-, ..., \tilde{v}_n^-\right) (23)$$

Where

$$\tilde{v}_j^* = \left(1, 1, 1\right) \quad and \quad \tilde{v}_j^- = \left(0, 0, 0\right) \quad (24)$$

The distance of each alternative form A^* and A^- can be currently calculated as

$$d_i^* = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^*\right), \qquad i = 1, 2, ..., n \quad (25)$$

$$d_i^- = \sum_{j=1}^{n} d\left(\tilde{v}_{ij}, \tilde{v}_j^-\right), \qquad i = 1, 2, ..., n \, (26)$$

Where d (.) is the distance measurement between two fuzzy numbers calculating with the following formula:

$$d(\tilde{\rho}, \tilde{\tau}) = \sqrt{\frac{1}{3}\left[\left(\rho_1 - \tau_1\right)^2, \left(\rho_2 - \tau_2\right)^2, \left(\rho_3 - \tau_3\right)^2\right]} \, (27)$$

$$CC_i = \frac{d_i^-}{d_i^- + d_i^+} \, (28)$$

Obviously, an alternative A_i is closer to the (FPIS, A^*) and farther from (FNIS, A^-) as CC_i approaches to 1. Therefore, according to the closeness coefficient, we can determine the ranking order of all alternatives and select the best one from among a set of feasible alternatives. In this study, we employed fuzzy FMEA based combined AHP-TOPSIS to prioritize the supply chain failures. It has been extensively argued that the potential risk factors probability of occurrence (O), severity (S), and likelihood of detection (D) are not easy to be exactly assessed and the traditional FMEA takes no account of the relative importance of the risk factors (Gargama and Chaturvedi, 2011; Liu *et al.*, 2011; Zhang and Chu, 2011). Fuzzy logic is the useful tool for transforming the ambiguities of human thinking and recognition and its decision-making ability into a precise mathematical formula. It also provides

logical representation of quantification for uncertainties and vague ideas expressed in natural language. So due to these reasons a fuzzy multi-criteria decision making framework is preferred instead of crisp decision making methods to tackle the FMEA procedure (Kutlu and Ekmekioglu, 2012b).
In this paper, for identifying the importance of supply chain failure modes a modified fuzzy approach proposed by Ekmekioglu *et al*. (2010) is developed to prioritize the most serious failure modes. A systematic approach to apply the TOPSIS is proposed to determine the risk priorities of supply chain failure modes under a fuzzy environment in this section. The structural flow of proposed fuzzy FMEA and combined AHP-TOPSIS model has been presented in Fig. 3 and main steps are discussed here. Firstly, a group of experts identify the risk assessment objective and determine the supply chain failure modes in warehouse processes. Second, a pair-wise comparison matrix for risk factors is constructed, and Chang's fuzzy AHP is utilized to compute the weight vector of these risk factors. Later, expert's qualitative or linguistic evaluations of each failure mode with respect to risk factors are aggregated to get a mean value. Then fuzzy decision matrix is formulated by using the linguistic scores of risk factors for each failure modes for the implementation of fuzzy TOPSIS. After that, by using the weight vector of risk factors and the fuzzy decision matrix weighted normalized fuzzy decision matrix is constructed. Eventually, (FPIS*) and (FNIS$^-$) and the distance of each supply failure mode from (FPIS*) and (FNIS$^-$) are calculated, respectively. Finally, at last step of Chen's fuzzy TOPSIS closeness coefficients (CC_i) of processes are obtained. According to the (CC_i), the ranking order of all failure modes is determined.

Step 2: Arrange the group of FMEA experts, list the potential supply chain failure modes and describe a finite set of relevant risk factors.

Step 3: Determine the necessary linguistic variables for risk factors and Chang's fuzzy AHP approach is utilized to obtain the weights of the risk factors. A pair-wise comparison matrix for severity, occurrence, and detect ability is formulated, and expert's linguistic evaluations are aggregated to get a mean value for each pair-wise comparison.

Step 4: Evaluate the importance of the risk factors and the ratings of failure modes with respect to each risk factor using the linguistic variables. Consistency of pair-wise comparison matrix for S, O, and D is checked after the defuzzification of each value in the matrix according to graded mean integration approach.

Step 5: Chen's fuzzy TOPSIS is utilized to obtain the closeness coefficient value. In order to obtain this value the expert's linguistic evaluations of each failure mode with respect to risk factors are aggregated to get a mean value.

Step 6: After the aggregation of fuzzy decision matrix the most important step is the formulation of normalized fuzzy decision matrix for the implementation of TOPSIS and then set the values between the range [0,1]. After that, weighted normalized fuzzy decision matrix is constructed.

Step 7: The distance of each supply chain failure mode from (FPIS*) and (FNIS$^-$) are calculated respectively.

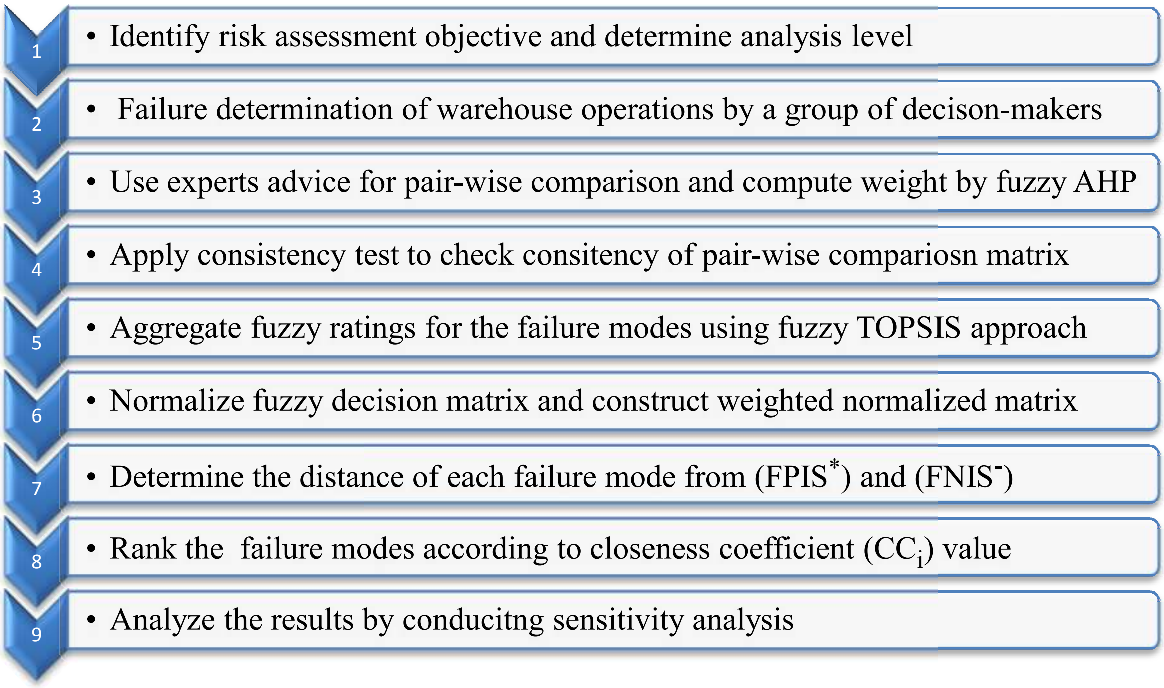

Figure 3. Flow of the proposed methodology

To sum up, the risk priorities of failure modes are determined through the following steps:

Step 1: Identify the objectives of the risk assessment process and determine the analysis level of supply chain failures in the warehouse operations of a food distributor company.

Step 8: Ranking of supply chain failure modes will be finalized according to the closeness coefficient CC_i values calculated by fuzzy TOPSIS in descending order.

Step 9: Analyze the results by conducting sensitivity analysis and recommend corrective actions.

Practical Application

The proposed model has been applied to the warehouse risk management of a food retail distributor which wants to prevent and reduce internal risk of warehouse operations. As warehouse processes in supply chain operations contain risks which deteriorate supply chain performance. Therefore, we practically analyze the risk of general warehouse process because its higher level of risk. The application is based on nine steps provided in previous section and computational procedure for risk assessment can be defined as follows:

Presentation of the Problem

Nowadays, more and more food retail distribution companies realize that risk management plays an important role in business success and that timely risk evaluation in supply chain is becoming a core activity. Few retail distribution companies have implemented risk management practices in integration with supply chain. But the success rate is very less due to sudden supply chain breakdown of food warehouses. To improve the success rate it is essential to identify these failures and solutions to overcome them. It is difficult to identify all failures at the same time. Hence, it is essential to prioritize these solutions of risk evaluation in supply chain; hence, perishable food retail distribution companies can concentrate on the high rank supply chain risks and evaluate them in a stepwise manner.

Case Solution

The food retail distributor desires to identify several most serious supply chain failure modes during general warehouse process to take appropriate measures correspondingly in advance and prevent the incidence of operational errors. After preliminary screening, ten potential failure modes are identified by a group of decision-makers in a warehouse operations as receiving errors (FM_1), misplacement errors (FM_2), pick-up errors (FM_3), transportation errors (FM_4), transaction type errors (FM_5), theft risk (FM_6), expiration risk (FM_7), obsolescence risk (FM_8), fire risk (FM_9) and biochemical risk (FM_{10}). A group of three experts (E_1), (E_2) and (E_3) has been established to assess the most serious failure modes. The risk factors, Occurrence, Severity, and Detection, have been defined according to the historical data and the questionnaire answered by all experts. Three experts use the linguistic variables given in Table 1 to formulate the pair wise comparison matrix for the risk factors. By using fuzzy AHP method, the weight vector of the risk factors is determined as (0.393, 0.294, 0.313) and shown in Table 3.The experts choose the linguistic rating values for the failure modes with respect to risk criteria and the scale for solution rating is given in the Table 2. The evaluations of experts in linguistic variables for the risk factors with respect to each failure modes are shown in Table 4. In the next step, we formulate the fuzzy evaluation matrix and aggregated fuzzy decision matrix by using Eq. (13) and their calculation process as shown in Table 5-6.

Table 3. Fuzzy evaluations of experts in linguistic terms and computation of the weights for risk factors

	Severity (S)	Occurrence (O)	Detection (D)	Weight	Consistency value
Severity (S)	E,E,E	SS,FS,VS	SS,SS,E	0.393	λ max=3.0367
Occurrence (O)	-	E,E,E	SS,FW,SS	0.294	CI=0.0183
Detection (D)	-	-	E,E,E	0.313	CR=0.0353

Table 4. Fuzzy linguistic evaluations of experts for risk factors with respect to each potential failure modes

Failure modes	Severity (S)	Occurrence (O)	Detection (D)
FM_1	MP,F,P	VG,MG,F	VP,MP,P
FM_2	F,MP,P	G,VG,F	MG,MP,VP
FM_3	F,F,MP	F,MG,MP	G,MG,G
FM_4	P,MP,F	MG,F,MG	F,MP,MP
FM_5	MG,MP,VP	VG,VG,VG	VP,MP,P
FM_6	F,P,G	VP,MP,F	G,VG,VG
FM_7	VP,P,MP	VP,VP,VP	P,MP,MG
FM_8	P,VP,VP	F,MP,MG	G,MG,MP
FM_9	F,F,MP	MG,MG,F	VP,MP,VP
FM_{10}	MG,F,MG	F,MP,MG	P,VP,MP

Table 5. Fuzzy numerical evaluations of experts for risk factors with respect to each potential failure modes

Risk factors	Severity			Occurrence			Detection		
Failure modes	Expert1	Expert2	Expert3	Expert1	Expert2	Expert3	Expert1	Expert2	Expert3
FM_1	(1,3,5)	(3,5,7)	(0,1,3)	(9,10,10)	(5,7,9)	(3,5,7)	(0,0,1)	(1,3,5)	(0,1,3)
FM_2	(3,5,7)	(1,3,5)	(0,1,3)	(7,9,10)	(9,10,10)	(3,5,7)	(5,7,9)	(1,3,5)	(0,0,1)
FM_3	(3,5,7)	(3,5,7)	(1,3,5)	(3,5,7)	(5,7,9)	(1,3,5)	(7,9,10)	(5,7,9)	(7,9,10)
FM_4	(0,1,3)	(1,3,5)	(3,5,7)	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(1,3,5)	(1,3,5)
FM_5	(5,7,9)	(1,3,5)	(0,0,1)	(9,10,10)	(9,10,10)	(9,10,10)	(0,0,1)	(1,3,5)	(0,1,3)
FM_6	(3,5,7)	(0,1,3)	(7,9,10)	(0,0,1)	(1,3,5)	(3,5,7)	(7,9,10)	(9,10,10)	(9,10,10)
FM_7	(0,0,1)	(0,1,3)	(1,3,5)	(0,0,1)	(0,0,1)	(0,0,1)	(0,1,3)	(1,3,5)	(5,7,9)
FM_8	(0,1,3)	(0,0,1)	(0,0,1)	(3,5,7)	(1,3,5)	(5,7,9)	(7,9,10)	(5,7,9)	(1,3,5)
FM_9	(3,5,7)	(3,5,7)	(1,3,5)	(5,7,9)	(5,7,9)	(3,5,7)	(0,0,1)	(1,3,5)	(0,0,1)
FM_{10}	(5,7,9)	(3,5,7)	(5,7,9)	(3,5,7)	(1,3,5)	(5,7,9)	(0,1,3)	(0,0,1)	(1,3,5)

Table 6. Aggregated fuzzy decision matrix for risk factors with respect to each failure modes

Failure modes	Severity (S)	Occurrence (O)	Detection (D)
FM_1	(1.33,3.00,5.00)	(5.67,7.33,8.67)	(0.33,1.33,3.00)
FM_2	(1.33,3.00,5.00)	(6.33,8.00,9.00)	(2.00,3.33,5.00)
FM_3	(2.33,4.33,6.33)	(3.00,5.00,7.00)	(6.33,8.33,9.67)
FM_4	(1.33,3.00,5.00)	(4.33,6.33,8.33)	(1.67,3.67,5.67)
FM_5	(2.00,3.33,5.00)	(9.00,10.0,10.0)	(0.33,1.33,3.00)
FM_6	(3.33,5.00,6.67)	(1.33,2.67,4.33)	(8.33,9.67,9.67)
FM_7	(0.33,1.33,3.00)	(0.00,0.00,1.00)	(2.00,3.67,5.67)
FM_8	(0.00,0.33,1.67)	(3.00,5.00,7.00)	(4.33,6.33,8.00)
FM_9	(2.33,4.33,6.33)	(4.33,6.33,8.33)	(0.33,1.00,2.33)
FM_{10}	(4.33,6.33,8.33)	(3.00,5.00,7.00)	(0.33,1.33,3.00)

Table 7. Normalized fuzzy decision matrix of risk factors with respect to each potential failure modes

Failure modes	Severity (S)	Occurrence (O)	Detection (D)
FM_1	(0.13,0.30,0.50)	(0.57,0.73,0.87)	(0.03,0.13,0.30)
FM_2	(0.13,0.30,0.50)	(0.63,0.80,0.90)	(0.20,0.33,0.50)
FM_3	(0.23,0.43,0.63)	(0.30,0.50,0.70)	(0.63,0.83,0.97)
FM_4	(0.13,0.30,0.50)	(0.43,0.63,0.83)	(0.17,0.37,0.37)
FM_5	(0.20,0.33,0.50)	(0.90,1.00,1.00)	(0.03,0.13,0.30)
FM_6	(0.33,0.50,0.67)	(0.13,0.27,0.43)	(0.83,0.97,0.97)
FM_7	(0.03,0.13,0.30)	(0.00,0.00,0.10)	(0.20,0.37,0.57)
FM_8	(0.00,0.03,0.17)	(0.30,0.50,0.70)	(0.43,0.63,0.80)
FM_9	(0.23,0.43,0.63)	(0.43,0.63,0.83)	(0.03,0.10,0.23)
FM_{10}	(0.43,0.63,0.83)	(0.30,0.50,0.70)	(0.03,0.13,0.30)
Weight	(0.393)	(0.294)	(0.313)

Table 8. Weighted normalized fuzzy decision matrix of risk factors with respect to each potential failure modes

Failure modes	Severity (S)	Occurrence (O)	Detection (D)
FM_1	(0.052,0.118,0.197)	(0.167,0.216,0.255)	(0.010,0.042,0.094)
FM_2	(0.052,0.118,0.197)	(0.186,0.235,0.265)	(0.063,0.104,0.157)
FM_3	(0.092,0.170,0.249)	(0.088,0.147,0.206)	(0.198,0.261,0.303)
FM_4	(0.052,0.118,0.197)	(0.127,0.186,0.245)	(0.052,0.115,0.177)
FM_5	(0.079,0.131,0.197)	(0.265,0.294,0.294)	(0.010,0.042,0.094)
FM_6	(0.131,0.197,0.262)	(0.039,0.078,0.127)	(0.261,0.303,0.303)
FM_7	(0.013,0.052,0.118)	(0.000,0.000,0.029)	(0.063,0.115,0.177)
FM_8	(0.000,0.013,0.066)	(0.088,0.147,0.206)	(0.136,0.150,0.198)
FM_9	(0.092,0.170,0.249)	(0.127,0.186,0.245)	(0.010,0.031,0.073)
FM_{10}	(0.170,0.249,0.327)	(0.088,0.147,0.206)	(0.010,0.042,0.094)

Table 9. Fuzzy TOPSIS results and final ranking of failure modes

Failure modes	d_i^+	d_i^-	$d_i^+ + d_i^-$	CC_i	Ranking
FM_1	2.6202	0.4107	3.0309	0.1355	8
FM_2	2.5449	0.4810	3.0259	0.1590	4
FM_3	2.4341	0.5940	3.0280	0.1962	1
FM_4	2.5817	0.4536	3.0353	0.1495	6
FM_5	2.5340	0.4878	3.0218	0.1614	3
FM_6	2.4359	0.5823	3.0182	0.1929	2
FM_7	2.8132	0.2191	3.0323	0.0723	10
FM_8	2.6352	0.3935	3.0288	0.1299	9
FM_9	2.6098	0.4203	3.0301	0.1387	7
FM_{10}	2.5603	0.4712	3.0315	0.1554	5

Table 10. Sensitivity analysis by changing weight of risk factors with respect to considered cases

Risk factors	Case 0	Case 1	Case 2	Case 3	Case 4
Severity Ws	0.393	0.5	0.4	0.6	0.3
Occurrence Wo	0.294	0.3	0.3	0.2	0.4
Detection W_D	0.313	0.2	0.3	0.2	0.3

Table 11. Final score and ranking of failure modes with respect to the considered cases

	Failure modes	FM_1	FM_2	FM_3	FM_4	FM_5	FM_6	FM_7	FM_8	FM_9	FM_{10}
Case 0	Score	0.1355	0.1590	0.1962	0.1495	0.1614	0.1929	0.0723	0.1299	0.1387	0.1554
	Ranking	8	4	1	6	3	2	10	9	7	5
Case 1	Score	0.1420	0.1590	0.1827	0.1479	0.1692	0.1771	0.0639	0.1105	0.1507	0.1724
	Ranking	8	5	1	7	4	2	10	9	6	3
Case 2	Score	0.1369	0.1598	0.1947	0.1498	0.1634	0.1907	0.0711	0.1285	0.1404	0.1572
	Ranking	8	4	1	6	3	2	10	9	7	5
Case 3	Score	0.1291	0.1443	0.1805	0.1377	0.1491	0.1842	0.0683	0.0964	0.1443	0.1766
	Ranking	8	6	2	7	4	1	10	9	5	3
Case 4	Score	0.1498	0.1745	0.1968	0.1600	0.1835	0.1836	0.0667	0.1425	0.1468	0.1529
	Ranking	7	4	1	5	3	2	10	9	8	6

This step is conducted to perform normalization by using Eq. (16) and presented in Table 7. Further, for the construction of fuzzy weighted evaluation matrix the weight vector obtained by fuzzy AHP is utilized as illustrated in Table 8. According to Eq. (22-27), we calculate each alternative's FPIS* and FNIS. According to Eq. (28) calculate the closeness coefficient (CC_i) and determine the most serious alternative.

Case Analysis

In this section we analyze the effectiveness of the proposed methodology in a warehouse of a food distribution company and comment on the results as shown in Table 9 and sketched in Figure 4. Based on the above description and data, it is hard to say sure which solution of risk minimization in supply chain to overcome its failures is more important, but the ranking process by using hybrid fuzzy AHP-TOPSIS approach made it more comprehensive and systematic. This hybrid approach used in a food retail organization was intended to improve the success rate of risk minimization in supply chain by evaluating the supply failures one by one. This will be achieved by implementing the solutions of risk minimization in supply chain by stepwise manner to overcome its risks. As the results from Table 9, the order of rating among those alternatives is $FM_3 > FM_6 > FM_5 > FM_2 > FM_{10} > FM_4 > FM_9 > FM_1 > FM_8 > FM_7$. The most serious alternative would be $FM_3$and FM_6. Finally, as shown in Table 9, the scores are ranked and results show that the most important failure mode is pick-up errors FM_3 and theft risk FM_6.In brief, this study recommends the case company to take the serious failures value into account to avoid the breakdown problems. Therefore, the pick-up and theft errors should be considered seriously as well as the fire risks in warehouse operations.

Sensitivity Analysis

A sensitivity analysis is conducted in order to monitor the robustness of failure modes ranking to changes in risk factors weights.

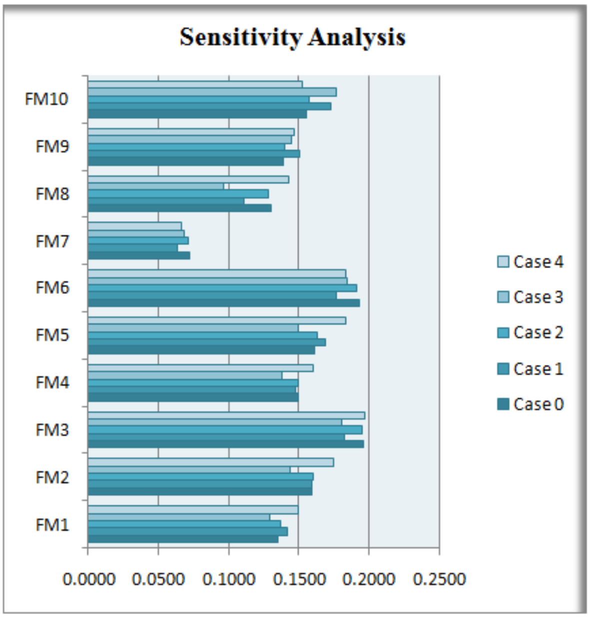

Figure 4. Sensitivity analysis for warehouse supply chain failure

Therefore, a sensitivity analysis by changing the weight of risk factors is conducted according to case wise information given in Table 10. For example in the original Case 0 shows the original risk factor weight values while the other cases represent slightly different weight values for possible outcomes. The results for ranking the supply chain failures for different cases are represented in Table 11 and Fig. 4. The sensitivity analysis results in Fig. 4 and Table 11 depict that in four of five cases the most important failure mode is pick-up errors and theft risk. In Case 3, as the weight of severity is the highest, pick-up errors failure mode is the second most important failure mode. In Case 0, Case 1, Case 2 and Case 4 theft risk is the second most important failure mode. It is also ranked the first in Case 3. In all five cases, Fire risk FM8 is in ranked the ninth and obsolescence risk FM7 is ranked the eighth. Hence, ranking the supply chain failures in warehouse operations is relatively sensitive to the risk factors weights.

Conclusions

In this study, a fuzzy multi-criteria group decision-making model by using fuzzy FMEA analysis integrated with fuzzy AHP-TOPSIS approaches is developed for managing the risks in warehouse operations problem in the food distributor company. Due to rapid changes and pressure of global competition, warehouse processes in supply chain operations contain risks which lead to a poor supply chain performance. In this context, risk analysis in warehouse operations is a critical issue which has been discussed to increase the supply chain performance. To solve this kind of problem, we used a modified fuzzy FMEA approach instead of typical FMEA for risk management in the supply chain process of warehouse operations. In this research study, fuzzy TOPSIS based FAHP is utilized to obtain the scores of potential supply chain failures, which are ranked to prioritize the failure modes. The results are used to find out the most significant and risky potential failure modes that would be tackled at first glance. Here the sensitivity analysis also performed by changing the risk factors weights to discuss and explain the results. In the literature most of the research works consider fuzzy rule based systems for fuzzy FMEA whereas this research applied a model of fuzzy TOPSIS combined with FAHP.

In addition to allowing experts to evaluate the risk factors of each supply failure mode in linguistic variables, the benefit of using this model considers the importance of the risk factors. As a managerial implication our proposed model can be applied to any case for providing information for risk management decision-making in industrial and service organizations. According to the results, the pick-up errors and theft risk have critical risk values. In addition to this, transaction type risk should also be considered as a critical risky problem in failure modes of warehouse operations. Our proposed framework, gives a new systematic and valid approach for prioritizing the high risk supply chain failures.

For further studies, the proposed model can be applied in different processes in supply chains. In this paper, a new fuzzy FMEA based on fuzzy set theory and fuzzy AHP-TOPSIS method is proposed to deal with the risk evaluation of a food retail distributor. Moreover, different quantitative or qualitative methods can be developed for evaluating the risks in supply chains. In the future, the results of our study can be compared with that of other fuzzy multi-criteria techniques like fuzzy ELECTRE, fuzzy PROMETHEE, or fuzzy VIKOR.

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