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Gülin Feryal Can, Pelin Toktas,

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Gülin Feryal Can
Department of Industrial Engineering, Başkent University, Ankara, Turkey and Faculty of Engineering, Başkent University, Bağlıca Kampüsü, Turkey, and

Pelin Toktas
Baskent University, Ankara, Turkey

Abstract

Purpose – Traditional risk assessment (RA) methodologies cannot model vagueness in risk and cannot prioritize corrective-preventive measures (CPMs) by considering effectiveness of those on risk types (RTs). These cannot combine and reflect accurately different subjective opinions and cannot be used in a linguistic manner. Risk factors (RFs) are assumed to have the same importance and interrelations between RFs are not considered. This study aims to overcome these disadvantages by combining fuzzy logic with multi-criteria decision-making in a dynamic manner.

Design/methodology/approach – This study proposes a novel three-stage fuzzy risk matrix-based RA integrating fuzzy decision-making trial and evaluation laboratory (F-DEMATEL) and fuzzy multi-attributive border approximation area comparison (F-MABAC). At the first stage, importance weights of RFs are computed by F-DEMATEL. At the second stage, risk degrees of RTs are computed via using fuzzy risk matrix. At the third stage, CPMs are ranked by F-MABAC. Finally, a numerical example for RA in a warehouse is given.

Findings – Results show that developing instructions for material loading or unloading is the most important CPM and severity is the most important RF for the warehouse.

Originality/value – This study has originality in terms of having fuzzy dynamic structure. At first, RFs are assumed to be criteria sets then, RTs are assumed to be criteria set considering their risk degrees to rank CPMs in a fuzzy manner. Risk degrees of RTs are used for weights of RTs and effectiveness of CPMs are used for performance values of CPMs.

Keywords Fuzzy logic, Risk assessment, F-DEMATEL, F-MABAC

Paper type Research paper

1. Introduction

A warehouse is large, busy area where raw materials or manufactured goods may be stored before their export or distribution for sale. Places in which to work and the conditions of work can change quickly in warehouses. In this term, warehouses include many different kinds of risk types (RTs). In warehouses, lifting, stacking, pushing, pulling, storage, equipment using, etc. are performed by workers and these tasks lead to emerge different types of work-related risks. Thus, risk assessment (RA) has a vital role for workers and work environment. Workers are protected from occupational accidents and ill health. Work environment is also protected from the various damages via using RA. In this concept, employers must perform RA regularly regarding safety and health at work, and determine corrective-protective measures (CPMs) to take.

Risk has uncertain and vague structure. The realization and consequences of risks are generally indefinite. In RA, risks should be precisely determined for worker and work place protection. Data and information for former times are important for this estimation.

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However, insufficient access to data and information for former times related to cause and effect relations of certain risks renders hard RA. In addition, RA involves subjectivity because of occupational health and safety team performing RA. This team has experts who work in different departments of the company, and have different levels of knowledge and experience. Each member of this team may not understand the causes of risks and their characteristics completely. These experts-related problems cause subjective information that provides imprecise data. For these reasons, performance of traditional RA models is insufficient for determining the risk degrees in a vague environment.

Traditional RA models use scales with crisp values in their procedure. These scales are inadequate for risk evaluation. In traditional RA procedure, risk factors (RFs) are evaluated before the risk occurs. This kind of estimation is related to the future state. Because of this, it is difficult to give a direct and correct numerical value to RFs by a crisp manner. In addition, these models use verbal expressions named as linguistic data for evaluation of risks, such as "likely, very important or high," etc. more than it uses numerical values. The linguistic variable has values as words or sentences in a natural or artificial language. Fuzzy logic is a powerful tool to model linguistic data. Linguistic terms are converted to numerical ones by using fuzzy operators (Ross, 2010; Zadeh, 1965). In this way, fuzzy logic can reflect the human thinking system. Reasons given above show that using fuzzy models is a hot topic to understand and to assess occupational risks.

RA process has a multi-criteria decision-making (MCDM) structure because of involving different experts as a decision-maker group, different RTs as criteria and different CPMs as alternatives. It is aimed to select the best alternative in MCDM process. MCDM process can be implemented easily with quantitative criteria by using traditional MCDM methodologies. However, these tools are insufficient for qualitative criteria because these criteria involve subjectivity and these are mainly vague and ill-defined (Samantra *et al.*, 2017). Experts evaluate the alternatives according to subjective criteria via using linguistic variables in fuzzy environment to select the best alternative. For RA, expert team is formed from people who recognize the work done and the working environment. Thanks to this feature, fuzzy logic and MCDM structure can be used in RA and disadvantages of traditional RA models are overcome. In addition, traditional RA models assume that RFs have the same importance levels for all RTs, but in real case, these factors have relatively different importance levels. In addition, assessment aggregation of different experts cannot be realized accurately with traditional RA. MCDM structure can also solve this problem with its mathematical aggregation procedure. Differentiation between experts for RA can be modeled by this procedure.

In this concept, this study proposes a three-stage fuzzy risk matrix based MCDM approach for RA. At the first stage, fuzzy decision-making trial and evaluation laboratory (F-DEMATEL) method, which is one of the MCDM methods, is used for determining importance weights of the RFs considering interactions between the RFs. DEMATEL developed by Fontela and Gabus (1974) can represent strengths of influence between the RFs (Tzeng *et al.*, 2010; Kumar *et al.*, 2017a, 2017b, 2017c). DEMATEL can present the cause–effect relations between the RFs by dividing them into cause and effect groups (Kumar *et al.*, 2017c). DEMATEL could improve understanding of the complex decision problems by the clustering of intertwined problems by determining the interdependence among the elements of a system through a causal diagram (Kumar and Dash, 2016). DEMATEL has the potential not only to present visual relationships among the criteria but also to show the direction of the relationships (Kumar *et al.*, 2017a). To aggregate and to demystify experts' evaluations for RA in DEMATEL, consisting of vague and ambiguous verbal expressions F-DEMATEL is performed (Shahi *et al.*, 2018; Ocampo *et al.*, 2018).

F-DEMATEL allows the construction and analysis of a structural decision model in a vague environment (Kazancoglu *et al.*, 2018). At the second stage, fuzzy risk degrees of RTs are computed considering the importance weights of RFs. For this aim, fuzzy risk matrix is used. This matrix is established via using fuzzy scales of the RFs. The fuzzy scores in these scales are multiplied together and fuzzy risk degree combinations are obtained. These combinations form the fuzzy risk matrix. Fuzzy risk degrees of RTs are computed by multiplying fuzzy importance weights of RFs with the fuzzy risk degree combinations and in this way, weighted fuzzy risk degrees are obtained. In this part, fuzzy importance weights of RFs have an important role to determine the effect of each RF on fuzzy risk degree of each RT. At the third stage, after determining CPMs for each RT, these are ranked by using fuzzy multi-attributive border approximation area comparison (F-MABAC) advanced by the research center at the University of Defense in Belgrade according to weighted fuzzy risk degrees of RTs (Pamučar and Ćirović, 2015). MABAC is a reliable and powerful tool for giving logical decisions (Pamučar and Ćirović, 2015; Chatterjee *et al.*, 2017). It uses the distance function to aggregate the differences between the opinions of experts in RA in an accurate manner. MABAC has a simple mathematical computation, a systematic procedure that represents the rationale of human decision-making (Pamučar and Ćirović, 2015, Biswas and Das, 2018; Pamučar *et al.*, 2018). The proposed approach is used in the warehouse acceptance process of the tractor production firm.

The rest of the paper is organized as follows: in the second part, the literature review for RA, DEMATEL and MABAC is given. In the third part, fuzzy algebra, MBAC and the proposed approach are explained. In the fourth part, application of the proposed RA approach in a warehouse is presented.

2. Literature review

There are various studies related to RA implementation in the literature. Karwowski and Mital (1986) mentioned the benefits of the application of fuzzy set theory in industrial safety engineering. They stated that RA has fuzzy aspects because of covering linguistic parameters. McCauley-Bell and Badiru (1992) defined the risk levels for the different workers and different tasks by developing an expert system based on fuzzy logic. McCauley-Bell and Crumpton (1997) investigated the relation of personal and organizational factors concerning working conditions for carpal tunnel syndrome with a fuzzy model. Maiti and Bhattacherjee (1999) tried to assess injury risk of coal miners using binary logit model and multinomial logit model. Sii *et al.* (2001) used fuzzy IF–THEN rules to identify the risk degrees of danger sources in work environment. Pokoradi (2002) mentioned the contribution and importance of fuzzy logic in RA. Markowski and Mannan (2008) proposed a fuzzy risk matrix including accident types and frequencies in work environment as inputs for RA. Gürcanlı and Müngen (2009) assessed the risks in tunnel construction by using fuzzy logic-based RA method. Jeong *et al.* (2010) suggested a risk matrix based on fuzzy inference logic to analyze nuclear and nonnuclear risks that could be encountered employees in a nuclear facility. Nieto-Morote and Ruz-Vila (2011) used fuzzy inference algorithm in RA. Beriha *et al.* (2010) implemented fuzzy logic to estimate different kinds of accidents having less fatal natures. Samantra *et al.* (2017) developed a fuzzy MCDM method, which has a unique hierarchical structure to assess occupational health hazards in an underground coal mine. Özceylan *et al.* (2017) proposed a geographic information system (GIS)-based approach to quantify the factors on each link in the transportation network that contribute to a possible route that minimizes the transport distance, the population exposure, the probability of an incident and the emergency response. Ilbahar *et al.* (2018) suggested Pythagorean Fuzzy Proportional Risk Assessment, including Fine Kinney, Pythagorean fuzzy analytic hierarchy process (AHP) and a fuzzy inference system for RA. Demir *et al.* (2018) examined occupational health and safety activities in five dimensions as tangibility, reliability, responsiveness, assurance and empathy using the SERVQUAL scale. Gul and Celik (2018) proposed a combination of Fine–Kinney method and a fuzzy rule-based expert system to make RA in rail transportation system. Tremblay and Badri (2018) proposed a novel occupational health and safety tool for small- and medium-sized enterprises to overcome overloading of experts in accident prevention. Oliveira *et al.* (2018) used MACBETH-Choquet integration to model interdependent impacts, and a system of rules to risk probability assessment.

In addition, there are limited studies that implement MABAC. Pamučar and Ćirović (2015) applied DEMATEL–MABAC integration to determine the best forklift alternative. Xue *et al.* (2016) used interval-valued intuitionistic fuzzy MABAC to determine the best material for production. Peng and Yang (2016) performed Choquet integral operator for Pythagorean fuzzy aggregation operators, such as Pythagorean fuzzy Choquet integral average operator and Pythagorean fuzzy Choquet integral geometric operator with MABAC method. Yu *et al.* (2017) used MABAC based on the likelihood of interval type-2 fuzzy numbers for hotel selection from a tourism website. Roy *et al.* (2016) represented a type-2 fuzzy multi-attribute decision-making methodology-integrated trapezoidal interval type-2 fuzzy numbers and MABAC to select the suitable software company. Roy *et al.* (2016) proposed rough number-based AHP and rough number-based MABAC integration to select the most appropriate cities in India for medical tourism. Božanić *et al.* (2016) used fuzzy AHP (F-AHP) and MABAC to determine locations for the preparation of laying-up positions. Liu *et al.* (2017) performed an integrated risk prioritization approach based on FMEA by using interval-valued intuitionistic fuzzy sets and MABAC. They used a linear programming model to obtain the optimal weights of RFs when the weight information is incompletely known. Chatterjee *et al.* (2017) advanced the analytical network process (ANP) with D numbers to model ambiguous evaluations and to determine the weight of RFs. In addition, an extended MABAC method in D number is proposed to select the best risk response strategy. Gigović *et al.* (2017) developed a new model by integrating GIS and DEMATEL, the ANP and MABAC to determine locations for the installation of wind farms Serbia. Sun *et al.* (2017) developed a projection-based MABAC with hesitant fuzzy linguistic term sets to make prioritization of patients easier for hospital management. Pamučar *et al.* (2018) suggested a new MCDM approach consisting of interval-valued fuzzy-rough numbers (IVFRN), best-worst method (BWM) and MABAC. In addition, they tested IVFRN BWM-MABAC model to show the stability of the ranking results. Peng *et al.* (2017) proposed a new axiomatic definition of interval-valued fuzzy distance measure and similarity measure in the form of interval-valued fuzzy number and the objective weights of parameters are computed via grey system theory by developing the combined weights consisting of both the subjective information and the objective information. Then, they used three algorithms as MABAC, evaluation based on distance from average solution (EDAS) and new similarity measure to solve interval-valued fuzzy soft decision-making problems. Peng and Dai (2017b) developed a new axiomatic definition of interval neutrosophic similarity measure based on interval neutrosophic number. The combined weight of attributes includes subjective and objective informations are determined using Shannon entropy theory. They advanced three approaches to obtain solution for interval neutrosophic decision-making problems as MABAC, EDAS and similarity measure. Biswas and Das (2018) used entropy-based MABAC to select hybrid vehicle for green environment. Sennaroglu and Celebi (2018) aimed to select the best location for a military airport via using AHP, PROMETHEE and VIKOR methods. The results produced from PROMETHEE and VIKOR methods are compared with the results of complex proportional assessment (COPRAS), multi-attributive ideal-real comparative analysis (MAIRCA) and MABAC for sensitivity analysis.

There are many studies that implement F-DEMATEL for different decision problems (Büyüközkan and Çifçi, 2012; Lin, 2013; Yeh and Huang, 2014; Patil and Kant, 2014; Liu *et al.*, 2015; Abdullah and Zulkifli, 2015; Luthra *et al.*, 2016; Sangaiah *et al.*, 2017). Additionally, Chang and Cheng (2010) proposed an intuitionistic fuzzy DEMATEL (IF-DEMATEL) to improve the performance of failure modes and effects analysis. Nikjoo and Saeedpoor (2014) combined IF-DEMATEL with strengths, weaknesses, opportunities and threats (SWOT) analysis to determine the most important components of the SWOT matrix. Keshavarzfard and Makui (2015) used intuitionistic fuzzy AHP (IF-AHP) and IF-DEMATEL to choose managers in the automobile industry in Iran. Wu *et al.* (2017) integrated big data and F-DEMATEL to determine the critical factors for employee engagement for hospitality industry. Vinodh *et al.* (2016) applied a hybrid MCDM approach based on F-DEMATEL, fuzzy ANP (F-ANP) and fuzzy technique for order preference by similarity to ideal solution (F-TOPSIS) to select agile concept. Gölcük and Baykasoğlu (2016) used ANP to analyze criteria interaction in DEMATEL. Tooranloo *et al.* (2017) performed a hybrid approach on the basis of F-AHP and Type-2 F-DEMATEL to identify the factors that affect success of sustainable human resource management implementation. Toosi and Samani (2017) prioritized watersheds by implementing a novel hybrid approach including F-DEMATEL, F-ANP and Fuzzy VIseKriterijumska Optimizacija I Kompromisno Resenje (F-VIKOR). Baykasoğlu and Gölcük (2017) proposed a hierarchical multi-attribute decision-making model by integrating interval Type-2 fuzzy sets with DEMATEL and TOPSIS combination. Pandey and Kumar (2017) used F-AHP and F-DEMATEL integration to evaluate criteria for human resource for science and technology. Peng and Dai (2017a) proposed three novel hesitant fuzzy soft set-based methods such as MABAC, weighted aggregated sum product assessment (WASPAS) and COPRAS. Shannon entropy theory is implemented to compute the objective weights of parameters. Lin *et al.* (2018) advanced the approximate fuzzy DEMATEL (AFDEMATEL) to analyze uncertain influential factors in supply chain management. Shahi *et al.* (2018) modified F-DEMATEL and GIS by spatial combination process to build a nuclear power plant to present both the cause and effect relationship among effective criteria in the decision-making process and the importance weight for each criterion. Abdullah and Zulkifli (2018) performed a new F-DEMATEL based on interval type-2 fuzzy sets. Kazancoglu *et al.* (2018) implemented F-DEMATEL to assess performance of green supply chain management. Ocampo *et al.* (2018) performed F-DEMATEL to identify the antecedents of organizational citizenship behavior in the hospitality industry and to identify their causal relationships. Wang *et al.* (2018a) aimed to present a novel group multi-attribute decision analysis approach for prioritizing the municipal solid waste treatment alternatives based on integration of DEMATEL and the interval-valued fuzzy set theory. Wang *et al.* (2018b) combined DEMATEL and interpretative structural modeling to obtain the influencing degree, influenced degree, centrality and causality of various influencing factors of mining safety in China.

As seen from the literature, fuzzy form of MABAC has not been implemented by the researchers and it has not been also performed for RA. F-DEMATEL and F-MABAC can provide many advantages for RA process. DEMATEL can classify and handle individual subjective perceptions, brief and impressionistic human outlook into problem complexity (Tzeng *et al.*, 2010). It can represent power of influence between the RFs (Tzeng *et al.*, 2010; Kumar *et al.*, 2017a, 2017b, 2017c; Suo *et al.*, 2012). MABAC can model the assessment differentiations between experts in terms of CPMs ranking by using distance function.

3. Methods

3.1 Fuzzy logic and algebra

Fuzzy logic was first developed by Dr Lotfi Zadeh in the 1960s. Fuzzy logic not only consists 0 and 1 as extreme cases of truth (or "the state of matters" or "fact") but also includes the various states of truth in between (Nguyen and Elbert, 2005; Ross, 2016). Therefore, fuzzy logic works closer to the way of human brains working. Human aggregate data and form a number of partial truths which we aggregate further into higher truths which in turn, when certain thresholds are exceeded, cause certain further results such as motor reaction. Actually, fuzzy logic may be viewed as an approach to compute with words rather than numbers. Even though, words are naturally less precise than numbers, their use is closer to human intuition. Fuzzy logic emerged in the context of the theory of fuzzy sets (Zadeh, 1965). A fuzzy set assigns a degree of membership, typically a real number from the interval [0, 1] to elements of a universe.

A fuzzy set $\tilde{A}$ in universe of discourse, X; $X = \{x_1, x_2, \ldots x_n\}$, is defined by a membership function $\mu_{\tilde{A}}(x)$. $\mu_{\tilde{A}}(x)$ is called as the grade of membership x in $\tilde{A}$. x has a membership degree in the interval [0, 1] as an element in X. A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse. Membership functions allow to graphically representing a fuzzy set.

A fuzzy number is a quantity whose value is imprecise, rather than exact as is the case with "ordinary" (single-valued) numbers. There are various types of fuzzy numbers, such as triangular and trapezoidal. A fuzzy number is a fuzzy subset of X (Huang *et al.*, 2001). From many perspectives, fuzzy numbers depict the physical world more realistically than single-valued numbers.

3.2 Triangular fuzzy number

There are three parameters to denote a triangular fuzzy number (TFN) as (a_1, a_2, a_3). a_1 represents the smallest possible value, a_2 indicates the most promising value, a_3 denotes the largest possible value of $\tilde{A}$ providing that $a_1 \leq a_2 \leq a_3$. In this study, all fuzzy numbers are formed as TFNs. Membership function of a TFN $\tilde{A}$ is defined as in equation (1) and is given in Figure 1:

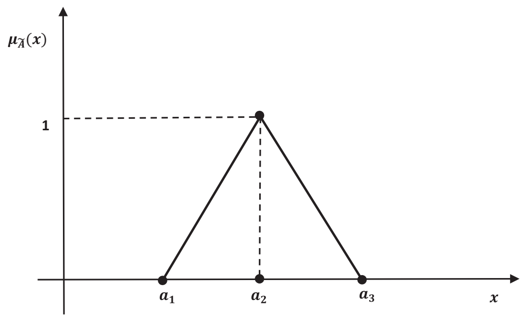

Figure 1. Triangular fuzzy number

$$\mu_{\tilde{A}}(x) = \begin{cases} 0, & x < a_1 \\ \dfrac{x - a_1}{a_1 - a_2}, & a_1 \leq x \leq a_2 \\ \dfrac{a_3 - x}{a_3 - a_2}, & a_2 \leq x \leq a_3 \\ 0, & x > a_3 \end{cases} \tag{1}$$

Let $\tilde{A} = (a_1, a_2, a_3)$ and $\tilde{B} = (b_1, b_2, b_3)$ be two positive TFNs and r be a positive real number, then the basic arithmetic operations of TFNs can be defined as in equation (2-6):

$$\tilde{A} + \tilde{B} = (a_1 + b_1, a_2 + b_2, a_3 + b_3) \tag{2}$$

$$\tilde{A} - \tilde{B} = (a_1 - b_3, a_2 - b_2, a_3 - b_1) \tag{3}$$

$$\tilde{A} \times \tilde{B} \cong (a_1 b_1, a_2 b_2, a_3 b_3) \tag{4}$$

$$r \times \tilde{A} = (ra_1, ra_2, ra_3) \tag{5}$$

$$\tilde{A} \div \tilde{B} \cong \left(\frac{a_1}{b_3}, \frac{a_2}{b_2}, \frac{a_3}{b_1}\right) \tag{6}$$

The scales used in this study are in the form of TFNs and these are linguistic scales that include set of words. These words can be prioritized by their degree of informativeness. There are various linguistic scales applied in different studies. Fuzzy scales should be selected according to available knowledge domain, simplicity of membership function and calibration of membership function (Samantra *et al.*, 2017). In this study, triangular membership function is selected and used scales are chosen due to this membership function features. The reason for selecting triangular membership function in this study is the form of TFN. The form of TFN is the most generic category of fuzzy numbers with linear membership function (Dubois and Prade, 2016). TFNs are commonly used to structure linear uncertainty rather than the other types of fuzzy numbers, such as trapezoidal. In addition, the fuzzy mathematical operations can be performed easily with TFNs.

3.3 Multi-attributive border approximation area comparison method

In this study, MABAC, which is a novel MCDM method, is selected to rank RTs. It has a simple mathematical computation, a systematic procedure that represents the rationale of human decision-making (Pamučar and Ćirović, 2015). The logic of MABAC method is based on the definition of the distance of the criterion functions of each alternative from the border approximation area (BAA). The implementation step of MABAC is given below:

Step 1. Determine the alternatives and criteria for decision problem.

m alternatives $A_i (i = 1, \ldots, m)$ and n criteria, $C_j (j = 1, \ldots, z, \ldots, n)$ related to decision problem are determined.

Step 2. Formulate the initial decision matrix.

m alternatives are evaluated according to n criteria and x_{ij} is obtained. x_{ij} is the performance value of the *ith* alternative for the *jth* criterion ($i = 1, 2, \ldots, m; j = 1, 2, \ldots, n$). x_{ij} forms initial decision matrix $[X]$ as in equation (7):

$$[X] = \begin{bmatrix} x_{11} & x_{12} & \ldots & x_{1n} \\ x_{21} & x_{22} & \ldots & x_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \ldots & x_{mn} \end{bmatrix} \tag{7}$$

Step 3. Normalize the initial decision matrix.

$[X]$ is normalized for cost- and benefit-type criteria separately and normalized initial decision matrix $[N]$ is formed. Higher values of the criteria are preferable for benefit type criteria and lower values are preferable for cost type criteria. Normalization processes are given in equations (8) and (9) for cost- and benefit-type criteria, respectively:

$$n_{ij} = \frac{x_{ij} - x_i^{-}}{x_i^{+} - x_i^{-}} \tag{8}$$

$$n_{ij} = \frac{x_{ij} - x_i^{+}}{x_i^{+} - x_i^{-}} \tag{9}$$

where, x_i^{+} is the criterion in $[X]$ that has the maximum value among the observed criteria according to the alternatives:

$$x_i^{+} = max(x_1,\ x_2, \ldots,\ x_m),$$

x_i^{-} is the criterion in $[X]$ that has the minimum value among the observed criteria according to the alternatives:

$$x_i^{-} = min(x_1,\ x_2, \ldots,\ x_m),$$

n_{ij} is the normalized performance value of *ith* alternative according to *jth* criterion in $[N]$.

Step 4. Formulate the weighted decision matrix.

Weighted decision matrix $[V]$ given in equation (11) is formed by using equation (10). The element of $[V]$ is denoted as v_{ij}. v_{ij} is the weighted performance values of *ith* alternative according to *jth* criterion:

$$v_{ij} = w_j \times \left(n_{ij} + 1\right) \tag{10}$$

where w_j is the importance weight of *jth* criterion:

$$[V] = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix}$$

$$= \begin{bmatrix} w_1 \times (n_{11}+1) & w_2 \times (n_{12}+1) & \dots & w_n \times (n_{1n}+1) \\ w_1 \times (n_{21}+1) & w_2 \times (n_{22}+1) & \dots & w_n \times (n_{2n}+1) \\ \vdots & \vdots & \vdots & \vdots \\ w_1 \times (n_{11}+1) & w_2 \times (n_{11}+1) & \dots & w_n \times (n_{11}+1) \end{bmatrix} \quad (11)$$

Step 5. Determine the BAA.

BAA is determined for each criterion as in equation (12):

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{\frac{1}{m}} \quad (12)$$

After calculating the value g_i for each criterion, BAA matrix $[G]$ is formed as in equation (13) in the format of $n \times 1$ (n is the total number of criteria):

$$\begin{array}{cc} & \begin{matrix} C_1 & C_2 & \dots & C_n \end{matrix} \\ [G] = & [\begin{matrix} g_1 & g_2 & \dots & g_n \end{matrix}] \end{array} \quad (13)$$

Step 6. Formulate the distance matrix.

The distance of each alternative from the BAA is calculated and distance matrix $[Q]$ is formed as in equation (14). The element of $[Q]$ is denoted as q_{ij}:

$$[Q] = [V] - [G] = \begin{bmatrix} v_{11} & v_{12} & \dots & v_{1n} \\ v_{21} & v_{22} & \dots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \dots & v_{mn} \end{bmatrix} - \begin{bmatrix} g_1 & g_2 & \dots & g_n \\ g_1 & g_2 & \dots & g_n \\ \vdots & \vdots & \vdots & \vdots \\ g_1 & g_2 & \dots & g_n \end{bmatrix} \quad (14)$$

Alternative A_i could belong to the BAA (G), upper approximation area (G^+) or lower approximation area (G^-), that is, $A_i \in (G \vee G^+ \vee G^-)$. The upper approximation area (G^+) is the area that contains the ideal alternatives (A^+), whereas the lower approximation area (G^-) is the area that contains the anti-ideal alternatives (A^-). These conditions are given in equation (15):

$$A_i = \begin{cases} G^+ \ if & q_{ij} > 0 \\ G \ if & q_{ij} = 0 \\ G^- \ if & q_{ij} < 0 \end{cases} \quad (15)$$

If the value $q_{ij} > 0$, that is $q_{ij} \in G^+$, then alternative A_i is near or equal to the ideal alternative. If the value $q_{ij} < 0$, that is $q_{ij} \in G^-$, it shows that alternative A_i is near or equal to the anti-ideal alternative. If A_i is selected as the best among all alternatives, it has to have many criteria as possible belonging to (G^+).

3.4 The proposed risk assessment approach

The proposed approach has three stages as *determining importance weights of RFs, determining risk degrees of RTs and determining the ranking of CPMs*. The steps of the proposed approach are given in Figure 2.

3.4.1 First stage: determining importance weights of risk factors.

Step 1. Form the expert team and determine the potential RTs and RFs.

l experts $E_k;(k = 1,\ldots, m)$ form the expert team. This team is responsible for assessment of RFs' importance weights, determining fuzzy risk degrees of RTs and ranking CPMs. m RTs $RT_i(i = 1,\ldots, m)$ related to work place are identified and these RTs are assessed due to n RFs, $RF_j(j = 1,\ldots z,\ldots, n)$.

Step 2. Assign relative importance values to each expert.

The fuzzy relative assessment importance of each expert is denoted as $\tilde{\beta}_k$ according to their experience level via using the fuzzy assessment importance scale given in Table I. Here, it is ensured that the opinion of the expert with more experience has more influence on the RA.

$\tilde{\beta}_k$ is converted into crisp value β_{kdef} as in equation (16). Then, crisp weight of each expert, C_k is computed as in equation (17).

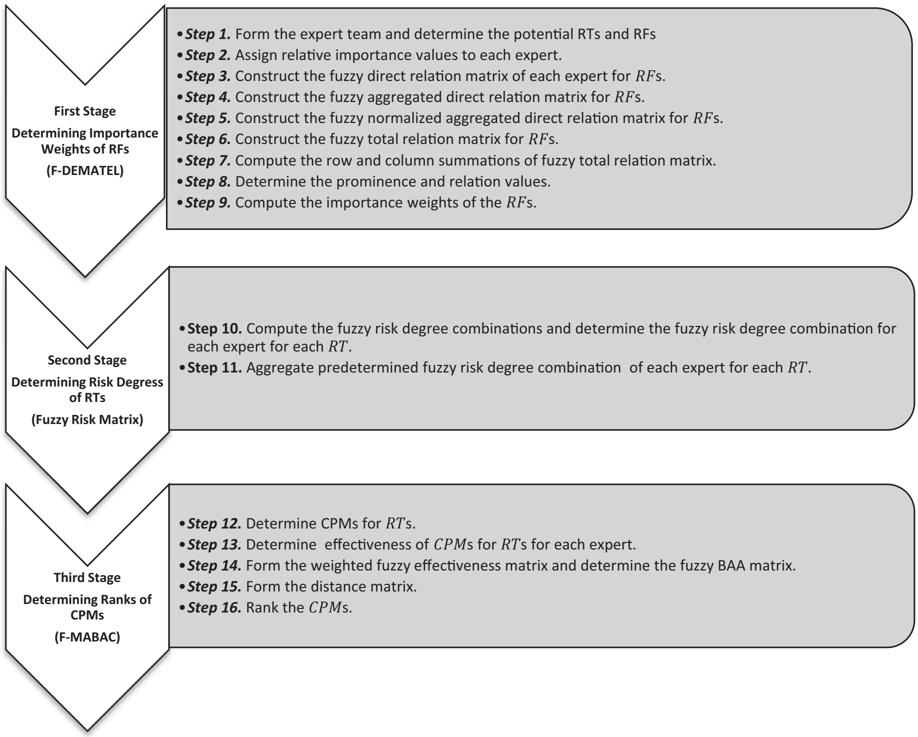

Figure 2.
The steps of the proposed approach

$$\beta_{kdef} = \frac{1}{4}(a_1 + 2a_2 + a_3) \tag{16}$$

$$C_k = \frac{\beta_{kdef}}{\sum_{k=1}^{l} \beta_{kdef}} \tag{17}$$

Step 3. Construct the fuzzy direct relation matrix of each expert for RFs.

Fuzzy direct relation matrix of each expert $[\tilde{P}]_k$ is constructed as in equation (18) by using fuzzy effect scale depicted in Table II. $\tilde{p}_{jzk} = (p_{jz1\ k},\ p_{jz2\ k}, p_{jz3\ k})$ is an element of $[\tilde{P}]_k$ denoting the effect level of *ith* RF on *zth* RF for *kth* expert:

$$[\tilde{P}]_k = \begin{bmatrix} (p_{111k}, p_{112k}, p_{113k}) & (p_{121k}, p_{122k}, p_{123k}) & \cdots & (p_{1v1k}, p_{1v2k}, p_{1v3k}) \\ (p_{211k}, p_{212k}, p_{213k}) & (p_{221k}, p_{222k}, p_{223k}) & \cdots & (p_{2v1k}, p_{2v2k}, p_{2v3k}) \\ \vdots & \vdots & \vdots & \vdots \\ (p_{m11k}, p_{m12k}, p_{m13k}) & (p_{m21k}, p_{m22k}, p_{m23k}) & \cdots & (p_{mv1k}, p_{mv2k}, p_{mv3k}) \end{bmatrix} \tag{18}$$

Step 4. Construct the fuzzy aggregated direct relation matrix for RFs.

Fuzzy aggregated direct relation matrix is denoted as $[\tilde{P}]$. $\tilde{p}_{jz} = (p_{jz1}, p_{jz2}, p_{jz3})$ is the element of $[\tilde{P}]$. Fuzzy weighted geometric mean operator is used for aggregation as in equation (19):

$$\tilde{p}_{jz} = \prod_{i=1}^{n} \tilde{p}_{jzk}^{\,C_k / \sum_{j=1}^{n} C_k} \tag{19}$$

Step 5. Construct the fuzzy normalized aggregated direct relation matrix for RFs.

Definition	a_2	$\tilde{\beta}_k$ a_2	a_3
Inexperienced	1	1	2
Nearly 5 years	1	2	3
Nearly 10 years	2	3	4
Nearly 15 years	3	4	5
More than 15 years	4	5	5

Table I.
Fuzzy assessment importance scale

Definition	Triangular fuzzy no. p_{jz1k}	p_{jz2k}	p_{jz3k}
Ineffective	1	1	2
Low effective	1	2	3
Moderately effective	2	3	4
Highly effective	3	4	5
Very effective	4	5	5

Table II.
Fuzzy effect scale

Fuzzy normalized aggregated direct relation matrix is denoted as $[\tilde{N}]$. $\tilde{n}_{jz} = (n_{jz1}, n_{jz2}, n_{zj3})$ is the element of $[\tilde{N}]$. Columns of $[\tilde{P}]$ are summed as in equation (20). Then, the maximum value of column summation is selected as r. All elements of $[\tilde{P}]$ are divided by r as in equation (21) and $[\tilde{N}]$ is constructed:

$$r = \max_{1 \leq z \leq n} \sum\nolimits_{j=1}^{n} p_{jz3} \tag{20}$$

$$\tilde{n}_{jz} = \frac{\tilde{p}_{jz}}{r} = \left(\frac{p_{jz1}}{r}, \frac{p_{jz2}}{r}, \frac{p_{jz3}}{r}\right) \tag{21}$$

Step 6. Construct the fuzzy total relation matrix for RFs.

Total relation matrix $[\tilde{T}] = \left[\tilde{t}_{jz}\right]_{n \times n}$ is constructed by using equation (22):

$$\tilde{T} = \tilde{N}^1 + \tilde{N}^2 + \ . \ . \ . \ = \sum\nolimits_{i=1}^{\infty} \tilde{N}^i = \tilde{N}(I - \tilde{N})^{-1} \tag{22}$$

Step 7. Compute the row and column summations of fuzzy total relation matrix.

The row summation of $[\tilde{T}]$ is denoted as $\tilde{D} = (d_1, d_2, d_3)$ and the column summation is indicated as $\tilde{R} = (r_1, r_2, r_3)$ computed as in equations (23) and (24), respectively:

$$\tilde{D} = \sum\nolimits_{z=1}^{n} \tilde{t}_{jz} \tag{23}$$

$$\tilde{R} = \sum\nolimits_{z=1}^{n} \tilde{t}_{jz} \tag{24}$$

Step 8. Determine the prominence and relation values.

$\tilde{D} - \tilde{R} = (s_1, s_2, s_3)$ and $\tilde{D} + \tilde{R} = (u_1, u_2, u_3)$ values are computed for each RF by using equations (2) and (3). $\tilde{D} + \tilde{R}$ value is called as prominence, $\tilde{D} - \tilde{R}$ value is named as relation. Then, these values are defuzzified as in equations (25) and (26):

$$(\tilde{D} - \tilde{R})_{def} = \frac{1}{4}(s_1 + 2s_2 + s_3) \tag{25}$$

$$(\tilde{D} + \tilde{R})_{def} = \frac{1}{4}(u_1 + 2u_2 + u_3) \tag{26}$$

RFs with positive $(\tilde{D} - \tilde{R})_{def}$ values have higher effect on the other RFs and these types of RFs have higher priority than the others. RFs with negative $(\tilde{D} - \tilde{R})_{def}$ values are affected more than the other RFs. In addition, $(\tilde{D} + \tilde{R})_{def}$ values show the relation with the other RFs and RFs with high $(\tilde{D} + \tilde{R})_{def}$ values have more relation with the other RFs. RFs with low $(\tilde{D} + \tilde{R})_{def}$ values have less relation between the other RFs (Fontela and Gabus, 1974).

Step 9. Compute the importance weights of the RFs.

Importance weights of RFs, w_j; ($j = 1, 2, 3, \ldots, n$) are computed as in equations (27) and (28):

$$w_j = \sqrt{\left(\tilde{D}+\tilde{R}\right)_{def}{}^2 + \left(\tilde{D}-\tilde{R}\right)_{def}{}^2} \tag{27}$$

$$w_j = \frac{W_j}{\sum_{j=1}^{n} W_j} \tag{28}$$

3.4.2 Second stage: determining risk degrees of risk types.
Step 10. Compute the fuzzy risk degree combinations and determine the fuzzy risk degree combination for each expert for each RT.

Fuzzy risk score, FRS_b, $b = 1,\ldots, d$ are computed by using fuzzy evaluation scales of each RF depicted in Table V. Scores in the scales are multiplied and FRS_b are obtained. Then, FRS_b are multiplied with the w_j as in equation (29) and weighted fuzzy risk degree combinations $\widetilde{FRDC}_b = (x_1, x_2, x_3)$ are computed. In this way, it is ensured that the most important RF more affects the $\widetilde{FRDC}_b$ than the other RFs:

$$\widetilde{FRDC}_b = \mathrm{w_j} \times FRS_b \tag{29}$$

Each expert evaluates each RT for each RF and identifies $FRDC_b$ as $FRDC_{bk}$; $\tilde{x}_k = (x_{1k}, x_{2k}, x_{3k})$ for each RT.
Step 11. Aggregate predetermined fuzzy risk degree combination of each expert for each RT.

$FRDC_{bk}$ is aggregated as in equation (30) and it is denoted as $FRDC_i$; $\tilde{\mathrm{y}} = (y_{i1}, y_{i2}, y_{i3})$:

$$\tilde{\mathrm{y}} = \prod_{\mathrm{i}=1}^{\mathrm{n}} FRDC_{bk}{}^{\mathrm{c_k}/\sum_{\mathrm{j}=1}^{\mathrm{n}} \mathrm{c_k}} \tag{30}$$

3.4.3 Third stage: determining the ranks of CPMs according to weighted fuzzy risk degrees of RTs by using fuzzy multi-attributive border approximation area comparison.
Step 12. Determine CPMs for RTs.

Occupational health and safety expert team determines CPMs for RTs.
Step 13. Determine effectiveness of CPMs for RTs for each expert.

Each occupational health and safety expert determines the effectiveness of CPMs for each RTs by using fuzzy effectiveness scale given in Table III and fuzzy effectiveness matrix for

Score	Definition	Triangular fuzzy no. f_{ti1k}	f_{ti2k}	f_{ti3k}
1	Ineffective (IE)	1	1	2
2	Low effective (LE)	1	2	3
3	Moderately effective (ME)	2	3	4
4	Effective (E)	3	4	5
5	Highly effective (HE)	4	5	5

Table III. Fuzzy effectiveness scale each expert $[\tilde{F}]_k$ given in equation (31) is formed. The effectiveness shows which CPM can more effectively prevent which one of the RTs.

The element of $[\tilde{F}]_k$ is denoted as $f_{tik} = (f_{ti1k}, f_{ti2k}, f_{ti3k})$ indicating fuzzy effectiveness degree of tth measure (CPM_t, $t = 1, 2,\ldots, p$) for ith RT (RT_i, $i = 1, 2,\ldots, m$) for expert k (E_k, $k = 1, 2,\ldots, l$):

$$[\tilde{F}]_k = \begin{array}{c} \\ M_1 \\ M_2 \\ \vdots \\ M_p \end{array} \begin{array}{c} \begin{array}{cccc} RT_1 & RT_2 & \cdots & RT_m \end{array} \\ \begin{bmatrix} (f_{111}, f_{112}, f_{113})_k & (f_{121}, f_{122}, f_{123})_k & \cdots & (f_{1m1}, f_{1m2}, f_{1m3})_k \\ (f_{211}, f_{212}, f_{213})_k & (f_{221}, f_{222}, f_{223})_k & & (f_{2m1}, f_{2m2}, f_{2m3})_k \\ \vdots & \vdots & \ddots & \vdots \\ (f_{p11}, f_{p12}, f_{p13})_k & (f_{p21}, f_{p22}, f_{p23})_k & \cdots & (f_{pm1}, f_{pm2}, f_{pm3})_k \end{bmatrix} \end{array} \tag{31}$$

Then, $[\tilde{F}]_k$ is multiplied with the assessment importance of each expert (C_k, $k = 1, 2,\ldots l$) as in equation (32) and aggregated fuzzy relationship matrix $[\tilde{F}]$ is obtained:

$$[\tilde{F}] = \sum_{k=1}^{l} C_k (f_{ti})_k \tag{32}$$

Step 14. Form the weighted fuzzy effectiveness matrix and determine the fuzzy BAA matrix.

To form the weighted fuzzy effectiveness matrix $[\tilde{V}]$, $\tilde{y}$ values calculated in *Step 11* is multiplied by the aggregated fuzzy effectiveness matrix $[\tilde{F}]$ as in equation (33):

$$[\tilde{V}] = \tilde{y}[\tilde{F}] \tag{33}$$

The element of $[\tilde{V}]$ is indicated as $v_{ti} = (v_{ti1}, v_{ti2}, v_{ti3})$ denoting the weighted fuzzy effectiveness degree of tth measure (CPM_t, $t = 1, 2\ldots, p$) for ith RT (RT_i, $i = 1, 2,\ldots, m$). For each RT, the fuzzy BAA matrix $[\tilde{G}]$ given in equation (35) is formed by $\tilde{g}_i = (g_{i1}, g_{i2}, g_{i3})$, $i = 1, 2, \ldots, m$ as in equation (34):

$$\tilde{g}_i = \left[\left(\prod_{t=1}^{p} v_{ti1} \right)^{1/p}, \left(\prod_{t=1}^{p} v_{ti2} \right)^{1/p}, \left(\prod_{t=1}^{p} v_{ti3} \right)^{1/p} \right], \quad i = 1, 2, \ldots, m \tag{34}$$

$$[\tilde{G}] = \begin{array}{c} \begin{array}{cccc} RT_1 & RT_2 & \ldots & RT_m \end{array} \\ [\begin{array}{cccc} \tilde{g}_1 & \tilde{g}_2 & \ldots & \tilde{g}_m \end{array}] \end{array} \tag{35}$$

Step 15. Form the distance matrix.

Distance matrix $[\tilde{Q}]$ given in equation (36) is obtained by equation (37):

$$[\tilde{Q}] = \begin{bmatrix} \tilde{q}_{11} & \tilde{q}_{12} & \cdots & \tilde{q}_{1m} \\ \tilde{q}_{21} & \tilde{q}_{22} & & \tilde{q}_{2m} \\ \vdots & & \ddots & \vdots \\ \tilde{q}_{p1} & \tilde{q}_{p2} & \cdots & \tilde{q}_{pm} \end{bmatrix} = \begin{bmatrix} (q_{111}, q_{112}, q_{113}) & (q_{121}, q_{122}, q_{123}) & \cdots & (q_{1m1}, q_{1m2}, q_{1m3}) \\ (q_{211}, q_{212}, q_{213}) & (q_{221}, q_{222}, q_{223}) & & (q_{2m1}, q_{2m2}, q_{2m3}) \\ & \vdots & \ddots & \vdots \\ (q_{p11}, q_{p12}, q_{113}) & (q_{p21}, q_{p22}, q_{p23}) & \cdots & (q_{pm1}, q_{pm2}, q_{pm3}) \end{bmatrix} \tag{36}$$

where $\tilde{q}_{ti}$, $t = 1, 2, \ldots, p; i = 1, 2, \ldots, m$ is the distance of CPMs from the BAA:

$$[\tilde{Q}] = [\tilde{V}] - [\tilde{G}] \tag{37}$$

$[\tilde{G}]$ is formed as in equation (38):

$$[\tilde{G}] = \begin{bmatrix} (g_{11}, g_{12}, g_{13}) & (g_{21}, g_{22}, g_{23}) & \cdots & (g_{m1}, g_{m2}, g_{m3}) \\ (g_{11}, g_{12}, g_{13}) & (g_{21}, g_{22}, g_{23}) & & (g_{m1}, g_{m2}, g_{m3}) \\ & \vdots & \ddots & \vdots \\ (g_{11}, g_{12}, g_{13}) & (g_{21}, g_{22}, g_{23}) & \cdots & (g_{m1}, g_{m2}, g_{m3}) \end{bmatrix} \tag{38}$$

Step 16. Rank the CPMs.

Sum of the distance from the BAA of each CPM, $\tilde{S}_t$ for each RTs is computed as in equation (39):

$$\tilde{S}_t = \left(S_{t1} = \sum\nolimits_{i=1}^{m} q_{ti1},\ S_{t2} = \sum\nolimits_{i=1}^{m} q_{ti2},\ \ S_{t3} = \sum\nolimits_{i=1}^{m} q_{ti3}\right), \quad t = 1, 2, \ldots, p \tag{39}$$

$\tilde{S}_t$ is converted into crisp value; $\tilde{S}_{tdef}$ as in equation (16). Then, crisp distance value of each CPM is computed as in equation (40):

$$S_t = \frac{S_{tdef}}{\sum_{t=1}^{p} S_{tdef}} \tag{40}$$

According to equation (41), the belonging of a CPM_t to the approximation area (G, G^+ or G^-) is determined:

$$CPM_t \in \begin{cases} G^+ & \text{if crisp value of } \tilde{q}_{tj} > 0 \\ G & \text{if crisp value of } \tilde{q}_{tj} = 0 \\ G^- & \text{if crisp value of } \tilde{q}_{tj} < 0 \end{cases} \tag{41}$$

If a CPM_t is selected as the best in the set of corrective-preventive measures (CPM_t, t = 1, 2,. . ., m), it must have as many RTs (RT_i, i = 1, 2,. . ., p) as possible belonging to the upper approximate area (G^+). For example, CPM_t has six RTs (out of a total of seven RTs) belonging to the upper approximate area, and one RT belonging to the lower approximate area (G^-); it means that according to the six RTs, the CPM_t is near or equal to the ideal CPM, whereas for one RT, it is near or equal to the anti-ideal CPM.

If the crisp value of $\tilde{q}_{ij} > 0$, that is $\tilde{q}_{ij} \in G^+$, then CPM_t is near or equal to the ideal CPM. If the crisp value $\tilde{q}_{ij} < 0$, that is $\tilde{q}_{ij} \in G^-$, it shows that CPM_t is near or equal to the anti-ideal CPM.

4. Application of the proposed risk assessment approach in a warehouse

The proposed approach is performed for dispatching and delivery areas in the warehouse of a tractor manufacturing factory in Turkey. The proposed approach is used step by step as follows.

4.1 First stage: determining importance weights of risk factors

Step 1. Form the expert team and determine the potential RTs and potential RFs.

Three experts (E_k, k = 1, 2, 3) form the expert team. One of them has an A class, the others have B class occupational safety expert certificate. Expert who has A class certificate has nearly 15 years' working experiences in tractor manufacturing. He is a mechanical engineer and he has a special expertise on handling equipment. Expert who has B class certificate has more than 15 years' working experiences in tractor manufacturing and he is an industrial engineer. He has an expertise on ergonomic working conditions. In addition, he has Occupational Safety and Health Administration ergonomics certificate. The other expert has nearly 10 years' working experiences in automotive sector. He is a mechanical engineer and he has an expertise on lifting equipment. These three experts are working in occupational health and safety directorate of the company.

According to 12th item of the directive on the duties, authorities, responsibilities and training of occupational safety experts issued in accordance with Law No. 6331 on occupational health and safety in Turkey, companies with 500 or more employees who are involved in the dangerous class must employ at least one occupational safety expert who will work full time for every 500 employees. There are 1,700 people working in this company and four occupational safety experts are employed. In the study, only three of the four experts were taken into consideration because the fourth expert has just started to work and does not have enough knowledge about tractor manufacturing. In addition, he has C class occupational safety expert certificate and he has worked for five years in a firm that produced dishwasher previously. In this study, the most experienced experts working at this company were selected for RA.

In this company, RA is performed every year, periodically. RA is carried out separately for each department within the company. RA is implemented in accordance with a procedure prepared by the company. According to this procedure, all occupational safety experts observe the related department for a month. Each expert prepares his own RT list than a meeting is held to discuss the RTs in the prepared lists. The final RT list is prepared by combining the RT list of each expert. After that, each expert determines the risk degrees of RTs considering probability, frequency and severity RFs. Then, risk degree assessments of each expert are aggregated. Ranking of RTs is obtained in this way. Finally, CPMs are identified and prioritized according to this ranking by expert group. In this study, this RA procedure was performed by using proposed algorithm after the final list-preparing phase.

After this phase, each expert determined the impact of each of the RFs on each other via using Table II. These impact values are used for computing importance weights of RFs. Then, each expert identified fuzzy risk scores of each RT using Table V. Finally, each expert specifies the effectiveness level of each CPM on each RT by using fuzzy effect scale depicted in Table III.

18 RTs $RT_i(i = 1,\ldots,18)$ for two areas given in Table IV are identified by experts. Expert team assessed these RTs according to three RFs, $RF_j(j = 1,2,3)$ as probability (RF_1), frequency (RF_2) and severity (RF_3). Probability of risk defines the chance of something happening that damages workers, work places or machines. Frequency of risk explains how often the danger occurs. Severity of risk represents which bad results related to the risk may emerge.

The fuzzy evaluation scales of these three RFs are given in Table V.

Step 2. Assign relative assessment importance to each expert.

$\tilde{\beta}_k$ is assigned by using Table I. β_{kdef} and C_k ($k = 1,2,3$) are computed as in equations (16) and (17), respectively. $\tilde{\beta}_k$ and C_k values are depicted in Tables VI and VII.

Step 3. Construct the fuzzy direct relation matrix of each expert for RFs.

Dispatching area	RT_i
Entry of vehicles such as waste tractor, car, etc. to the area	RT_1
Entry of pedestrians to the area	RT_2
Entry of non-authorized truck drivers to the area	RT_3
Not to use of the PPEs given to truck drivers at the factory entrance	RT_4
More than one forklift work in the area at the same time	RT_5
Hitting of equipment to trucks or baskets	RT_6
Hitting of out-of-control equipment to workers/drivers	RT_7
Dispatching of parts to production environment	
Hitting of forklifts to baskets or equipment	RT_8
Crashing of forklifts with each other	RT_9
Overflow of forklifts to pedestrian paths	RT_{10}
Hitting of forklifts to operators or workers in the area	RT_{11}
Hitting of forklifts to workers or equipment during maneuvering	RT_{12}
Extension of the stopping distance of the vehicle	RT_{13}
Connecting more cars than needed to tow car	RT_{14}
Pulling out of KIT cars from tow car without a full stop	RT_{15}
Getting off tow car without a full stop	RT_{16}
Getting off idea without a full stop	RT_{17}
Carriage of box materials on the palette by idea fork	RT_{18}

Table IV. RTs in dispatching and delivery areas of warehouse

Probability/Frequency/Severity	a_1	a_2	a_3
Not expected/Very rare/No impact	1	1	2
Unlikely/Rare/Small Damage	1	2	3
Possible/Sometimes/Significant damage	2	3	4
High possibility/Often/Permanent damage	3	4	5
Exact/Continuous/Lethal damage	4	5	5

Table V. Fuzzy evaluation scales of RFs

$[\tilde{P}]_k$ is constructed as in equation (18) by using fuzzy effect scale depicted in Table II. $[\tilde{P}]_1$ for E_1 is given in Table VIII as an example.

Step 4. Construct the fuzzy aggregated direct relation matrix for RFs.

$[\tilde{P}]$ depicted in Table IX is constructed by using equation (19).

Step 5. Construct the fuzzy normalized aggregated direct relation matrix for RFs.

r = (6.70, 8.72, 10.00) is computed as in equation (20). Then, $[\tilde{N}]$ as shown in Table X is established by using equation (21).

Step 6. Construct the fuzzy total relation matrix.

$[\tilde{T}]$ shown in Table XI is constructed as in equation (22).

Step 7. Compute the row and column summations of fuzzy total relation matrix.

$\tilde{D}$ and $\tilde{R}$ values given in Table XII are computed as in equations (23) and (24).

Table VI.
$\tilde{\beta}_k$ Values

		$\tilde{\beta}_k$		
E_k	Experience level	a_1	a_2	a_3
E_1	Nearly 15 years	3	4	5
E_2	More than 15 years	4	5	5
E_3	Nearly 10 years	2	3	4

Table VII.
C_k values

E_k	Experience level	C_k
E_1	Nearly 15 years	0.34
E_2	More than 15 years	0.40
E_3	Nearly 10 years	0.26

Table VIII.
Fuzzy direct relation matrix of E_1, $[\tilde{P}]_1$

	$\tilde{p}_{jzk}$								
	RF_1			RF_2			RF_3		
	p_{jz11}	p_{jz21}	p_{jz31}	p_{jz11}	p_{jz21}	p_{jz31}	p_{jz11}	p_{jz21}	p_{jz31}
RF_1	0	0	0	4	5	5	4	5	5
RF_2	3	4	5	0	0	0	3	4	5
RF_3	4	5	5	4	5	5	0	0	0

Table IX.
Fuzzy aggregated direct relation matrix, $[\tilde{P}]$

	$\tilde{p}_{jz}$								
	RF_1			RF_2			RF_3		
	p_{jz1}	p_{jz2}	p_{jz3}	p_{jz1}	p_{jz2}	p_{jz3}	p_{jz1}	p_{jz2}	p_{jz3}
RF_1	0.00	0.00	0.00	3.31	4.32	5.00	3.56	4.57	5.00
RF_2	2.70	3.72	4.72	0.00	0.00	0.00	3.00	4.00	5.00
RF_3	4.00	5.00	5.00	3.31	4.32	5.00	0.00	0.00	0.00
Total	6.70	8.72	9.72	6.62	8.63	10.00	6.56	8.57	10.00

Step 8. Determine the prominence and relation values.

$\tilde{D}-\tilde{R}$ and $\tilde{D}+\tilde{R}$ values are computed as in Table XIII. Then, these values are defuzzified by using equation (25) and (26).

As seen from Table XIII, frequency (RF_2) has higher priority than the other *RF*s for RA in these delivery and dispatching areas. Severity (RF_3) has higher effect on the other *RF*s than the others for the same areas.

Step 9. Compute the importance weights of the RFs.

w_j; ($j = 1, 2, 3, \ldots, n$) given in Table XIV are computed as in equations (27) and (28).

As seen from Table XIV, severity (RF_3) is the most important RF for DMs for the warehouse.

Table X. Fuzzy normalized aggregated direct relation matrix, $[\tilde{N}]$

	RF_1			$\tilde{n}_{jz}$ RF_2			RF_3		
	n_{jz1}	n_{jz2}	n_{jz3}	n_{jz1}	n_{jz2}	n_{jz3}	n_{jz1}	n_{jz2}	n_{jz3}
RF_1	0.00	0.00	0.00	0.49	0.50	0.50	0.53	0.52	0.50
RF_2	0.40	0.43	0.47	0.00	0.00	0.00	0.45	0.46	0.50
RF_3	0.60	0.57	0.50	0.49	0.50	0.50	0.00	0.00	0.00

Table XI. Fuzzy total relation matrix, $[\tilde{T}]$

	RF_1			$\tilde{t}_{jz}$ RF_2			RF_3		
	$\tilde{t}_{jz1}$	$\tilde{t}_{jz2}$	$\tilde{t}_{jz3}$	$\tilde{t}_{jz1}$	$\tilde{t}_{jz2}$	$\tilde{t}_{jz3}$	$\tilde{t}_{jz1}$	$\tilde{t}_{jz2}$	$\tilde{t}_{jz3}$
RF_1	0.00	0.00	0.00	14.42	18.61	18.06	15.44	19.61	18.06
RF_2	10.46	14.65	16.43	0.00	0.00	0.00	11.45	15.60	17.72
RF_3	18.35	22.42	17.72	15.03	19.21	18.06	0.00	0.00	0.00

Table XII. $\tilde{D}$ and $\tilde{R}$ Values

		$\tilde{D}$			$\tilde{R}$	
RF_j	d_1	d_2	d_3	r_1	r_2	r_3
RF_1	29.85	38.22	36.11	28.81	37.07	34.15
RF_2	21.90	30.24	34.15	29.45	37.82	36.11
RF_3	33.39	41.63	35.78	26.89	35.21	35.78

Table XIII. $\tilde{D}-\tilde{R}$, $\tilde{D}+\tilde{R}$, $(\tilde{D}+\tilde{R})_{def}$ and $(\tilde{D}-\tilde{R})_{def}$ values

		$(\tilde{D}+\tilde{R})$			$(\tilde{D}-\tilde{R})$			
RF_j	s_1	s_2	s_3	u_1	u_2	u_3	$(\tilde{D}+\tilde{R})_{def}$	$(\tilde{D}-\tilde{R})_{def}$
RF_1	29.85	38.22	36.11	28.81	37.07	34.15	35.60	34.28
RF_2	21.90	30.24	34.15	29.45	37.82	36.11	29.13	35.30
RF_3	33.39	41.63	35.78	26.89	35.21	35.78	38.11	33.27

4.2 Second stage: determining risk degrees of risk types

Step 10. Compute the fuzzy risk degree combinations and determine the fuzzy risk degree combinations for each expert for each RT.

$\widetilde{FRDC}_b$ presented in Table XV is computed by using equation (29).

$\widetilde{FRDC}_{b1}$ is given for E_1 in Table XVI as an example.

Step 11. Aggregate the predetermined fuzzy risk degree combination of each expert for each RT.

$\widetilde{FRDC}_{bk}$ is aggregated as in equation (30) and $\widetilde{FRDC}_i$ values are shown in Table XVII.

4.3 Third stage: determining the ranks of corrective-preventive measures according to the weighted fuzzy risk degrees of risk types by using F-MABAC

Step 12. Determine CPMs for RTs.

Three experts determined 12 preventive corrective measures (CPM_t $t = 1,2,\ldots,12$) given in Table XVIII for the RTs for delivery and dispatching areas.

Step 13. Determine the effectiveness of CPMs for RTs for each expert.

Each expert determines the effectiveness of each CPM on each RT. Fuzzy effectiveness matrix for E_1, $[\tilde{F}]_1$ is given in Table XIX. In addition, a part of $[\tilde{F}]$ given in Table XX is established as in equation (32).

Step 14. Form the weighted fuzzy effectiveness matrix and determine the fuzzy BAA.

Table XIV. Importance weights of the RFs, w_j

RF_j	RF_1	RF_2	RF_3
w_j	0.33	0.24	0.42

Table XV. Fuzzy risk degree combinations, $\widetilde{FRDC}_b$

	Fuzzy risk degree combinations $\widetilde{FRDC}$		
$\widetilde{FRDC}_b$	x_1	x_2	x_3
$\widetilde{FRDC}_1$	0.03	0.03	0.27
$\widetilde{FRDC}_2$	0.03	0.07	0.41
$\widetilde{FRDC}_3$	0.03	0.07	0.41
$\widetilde{FRDC}_4$	0.07	0.10	0.55
$\widetilde{FRDC}_5$	0.03	0.07	0.41
$\widetilde{FRDC}_6$	0.10	0.14	0.69
$\widetilde{FRDC}_7$	0.07	0.10	0.55
$\widetilde{FRDC}_8$	0.07	0.10	0.55
⋮	⋮	⋮	⋮
$\widetilde{FRDC}_{121}$	1.24	2.75	4.30
$\widetilde{FRDC}_{122}$	1.65	3.44	4.30
$\widetilde{FRDC}_{123}$	1.65	3.44	4.30
$\widetilde{FRDC}_{124}$	1.65	3.44	4.30
$\widetilde{FRDC}_{125}$	2.20	4.30	4.30

RT_i	FRS_{b1} x_{11}	x_{21}	x_{31}
RT_1	0.03	0.14	0.62
RT_2	0.41	1.24	2.75
RT_3	0.27	1.03	2.06
RT_4	0.62	1.65	3.44
RT_5	0.55	1.72	2.58
RT_6	0.27	1.03	2.06
RT_7	0.41	1.24	2.75
RT_8	0.55	1.55	2.75
RT_9	0.41	1.37	2.58
RT_{310}	0.93	2.20	4.30
RT_{11}	1.65	3.44	4.30
RT_{12}	0.55	0.86	1.72
RT_{13}	0.14	0.62	1.65
RT_{14}	0.82	2.06	3.44
RT_{15}	0.07	0.41	1.24
RT_{16}	1.65	3.44	4.30
RT_{17}	0.41	1.24	2.75
RT_{18}	0.41	1.37	2.58

Table XVI. Fuzzy risk degree combination for E_1

RT_i	$FRDC_i$ y_{i1}	y_{i2}	y_{i3}
RT_1	0.16	0.37	1.15
RT_2	0.35	1.15	2.45
RT_3	0.26	0.99	2.09
RT_4	0.47	1.46	2.84
RT_5	0.71	1.91	3.30
RT_6	0.46	1.44	2.72
RT_7	0.26	1.00	2.14
RT_8	0.72	1.87	3.18
RT_9	0.51	1.58	2.78
RT_{10}	0.50	1.52	3.07
RT_{11}	0.62	1.75	3.02
RT_{12}	0.61	1.36	2.48
RT_{13}	0.34	1.16	2.38
RT_{14}	1.11	2.57	3.64
RT_{15}	0.26	0.98	2.16
RT_{16}	0.71	1.90	3.15
RT_{17}	0.38	1.25	2.41
RT_{18}	0.55	1.26	2.35

Table XVII. $FRDC_i$; $i = 1,\ldots,18$ values

A part of $[\tilde{V}]$ given in Table XXI is constructed as in equation (33).

For each RT (RT_i, $i = 1, 2,\ldots, 18$), the fuzzy BAA is determined by using equation (34). $[\tilde{G}]$ formed as in equation (34) and (35) is given in Table XXII. As an example, the fuzzy BAA for RT_1 is computed by using equation (34) as seen below.

Table XVIII.
CPMs for RTs

CPMs	CPM_t
Revision of pedestrian paths	CPM_1
Developing waiting areas for truck drivers	CPM_2
Developing instructions for material loading or unloading	CPM_3
Determining extra unloading region outside	CPM_4
Launching the blue light project	CPM_5
Placing extra warning signs in the work area	CPM_6
Keeping empty of forklift paths	CPM_7
Developing instructions for using the equipment	CPM_8
Weight reduction in the manual carrying operations	CPM_9
Staff training and preparation of training documents	CPM_{10}
Developing instructions for pallet carriage	CPM_{11}
Making periodic checks of equipment	CPM_{12}

$$\tilde{g}_1 = \left[(0.53 \cdot 0.57 \ldots \cdot 0.16)^{\frac{1}{12}},\ (1.75 \cdot 1.70 \ldots \cdot 0.74)^{1/12}, (5.73 \cdot 5.73 \ldots \cdot 3.43)^{1/12}\right]$$
$$= [0.23,\ 0.75,\ 3.50]$$

Step 15. Form the distance matrix.

A part of $[\tilde{Q}]$ calculated as in equation (37) is formed as in equation (38). A part of $[\tilde{Q}]$ is given in Table XXIII. As an example, $\tilde{q}_{11}$ is calculated as follow:

$$\tilde{q}_{11} = \tilde{v}_{11} - \tilde{g}_{11} = [053,\ 1.75,\ 5.73] - [0.23,\ 0.75,\ 3.50] = [0.23,\ 0.75,\ 3.50]$$

Step 16. Rank the CPMs.

The criterion function value of RT_i for the alternatives (CPM_t) is obtained by the sum of each row of elements from the fuzzy matrix $[\tilde{Q}]$ as given in equation (39). Then, values of $\tilde{S}_t$ are defuzzified by using equation (16) and S_t is calculated as in equation (40). The criterion function of the first alternative CPM_1 is calculated using equation (39) as below:

$$\tilde{S}_1 = \left(S_{11} = \sum_{i=1}^{18} q_{1i1},\ \ S_{12} = \sum_{i=1}^{18} q_{1i2}, S_{13} = \sum_{i=1}^{18} q_{1i3}\right)$$
$$= \left[(0.30 + 0.66 + \ldots + (-0.33)),\ (1.00 + 2.94 + (-1.46)),\right.$$
$$\left.(2.33 + 3.99 + \ldots + (-2.68)\right] = (-2.08,\ \ -8.84,\ \ -15.93)$$

Table XXIV shows $\tilde{S}_t$, $S_{t_{def}}$ and the rank of the CPMs. Distribution of CPMs in lower, upper and BAAs is given in Figure 3.

As seen from Table XXIV, developing instructions for material loading or unloading (CPM_3) should be implemented first in the warehouse.

5. Discussion

The main objective of the study is to enable experts to prioritize the CPMs considering effectiveness level of CPMs on RTs and to determine interrelations between RFs. Proposed RA approach is used in warehouse acceptance process of a tractor manufacturing company.

	RT_1	RT_2	RT_3	RT_4	RT_5	RT_6	RT_7	RT_8	$RT9$	RT_{10}	RT_{11}	RT_{12}	RT_{13}	RT_{14}	RT_{15}	RT_{16}	RT_{17}	RT_{18}
CPM_1	(4,5,5)	(4,5,5)	(2,3,4)	(1,1,2)	(2,3,4)	(1,1,2)	(3,4,5)	(1,1,2)	(1,1,2)	(4,5,5)	(1,1,2)	(3,4,5)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)
CPM_2	(4,5,5)	(1,1,2)	(4,5,5)	(3,4,5)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)
CPM_3	(2,3,4)	(3,4,5)	(3,4,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(1,2,3)	(4,5,5)	(4,5,5)	(4,5,5)
CPM_4	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(3,4,5)	(4,5,5)	(4,5,5)	(4,5,5)	(3,4,5)	(4,5,5)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)
CPM_5	(1,2,3)	(4,5,5)	(4,5,5)	(1,2,3)	(4,5,5)	(1,2,3)	(3,4,5)	(1,2,3)	(4,5,5)	(1,2,3)	(4,5,5)	(3,4,5)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)
CPM_6	(1,1,2)	(4,5,5)	(4,5,5)	(4,5,5)	(2,3,4)	(1,1,2)	(1,1,2)	(1,1,2)	(4,5,5)	(3,4,5)	(2,3,4)	(4,5,5)	(1,1,2)	(3,4,5)	(4,5,5)	(4,5,5)	(4,5,5)	(1,1,2)
CPM_7	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(4,5,5)	(2,3,4)	(1,2,3)	(4,5,5)	(1,2,3)	(1,2,3)	(4,5,5)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)
CPM_8	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(3,4,5)	(3,4,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)
CPM_9	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)
CPM_{10}	(4,5,5)	(4,5,5)	(1,2,3)	(1,2,3)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(3,4,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(3,4,5)
CPM_{11}	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,2,3)	(1,2,3)	(3,4,5)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(1,1,2)	(4,5,5)	(1,1,2)	(1,1,2)	(1,1,2)	(4,5,5)
CPM_{12}	(1,2,3)	(1,2,3)	(1,2,3)	(1,2,3)	(3,4,5)	(4,5,5)	(4,5,5)	(4,5,5)	(4,5,5)	(3,4,5)	(4,5,5)	(3,4,5)	(4,5,5)	(3,4,5)	(4,5,5)	(1,2,3)	(1,2,3)	(1,2,3)

Table XIX. Fuzzy effectiveness matrix for Expert 1

As seen from prominence and relation results (Table XIII), severity (RF_3) has the highest relation among the other RFs. This means that severity (RF_3) has higher effect on the other RFs. In addition, frequency (RF_2) has the highest priority among the other RFs. This is an expectable result because it is not desirable to expose to risks frequently in a company that is in dangerous class.

Table XX. A Part of weighted fuzzy relationship matrix $[\widetilde{F}]$

	RT_1	RT_2	RT_3	. . .	RT_{18}
CPM_1	(3.34, 4.74, 5.00)	(3.60, 5.00, 5.00)	(2.26, 3.26, 4.26)	. . .	(1.00, 1.00, 2.00)
CPM_2	(3.60, 4.60, 5.00)	(1.00, 1.26, 2.26)	(3.74, 4.74, 5.00)	. . .	(1.00, 1.00, 2.00)
CPM_3	(2.00, 3.00, 4.00)	(3.00, 4.00, 5.00)	(3.00, 4.00, 5.00)	. . .	(4.00, 5.00, 5.00)
⋮	⋮	⋮	⋮		⋮
CPM_{12}	(1.00, 2.00, 3.00)	(1.00, 2.00, 3.00)	(1.00, 2.00, 3.00)	. . .	(1.26, 2.26, 3.26)

Table XXI. A Part of fuzzy weighted relationship matrix $[\widetilde{V}]$

	RT_1	RT_2	RT_3	. . .	RT_{18}
CPM_1	(0.53,1.75, 5.73)	(1.26, 5.75, 12.24)	(0.58, 3.21, 8.90)	. . .	(0.56, 1.26, 4.71)
CPM_2	(0.57, 1.70, 5.73)	(0.35, 1.44, 5.52)	(0.96, 4.68, 10.46)	. . .	(0.56, 1.26, 4.71)
CPM_3	(0.32, 1.11, 4.58)	(1.05, 4.6, 12.24)	(0.77, 3.95, 10.46)	. . .	(2.21, 6.3, 11.77)
⋮	⋮	⋮	⋮		⋮
CPM_{12}	(0.16, 0.74, 3.44)	(0.35, 2.30, 7.34)	(0.26, 1.97, 6.27)	. . .	(0.78, 3.03, 8.01)

Table XXII. Elements of border approximation area matrix

RT_i	$\widetilde{g}_i$	RT_i	$\widetilde{g}_i$	RT_i	$\widetilde{g}_i$
RT_1	(0.23, 0.75, 3.50)	RT_7	(0.55, 2.87, 8.15)	RT_{13}	(0.53, 2.22, 6.92)
RT_2	(0.60, 2.80, 8.24)	RT_8	(1.55, 5.29, 11.75)	RT_{14}	(2.17, 6.51, 12.69)
RT_3	(0.42, 2.43, 7.16)	RT_9	(1.14, 4.45, 10.21)	RT_{15}	(0.40, 2.05, 6.66)
RT_4	(0.69, 3.13, 8.94)	RT_{10}	(1.09, 4.47, 11.71)	RT_{16}	(1.20, 4.26, 10.07)
RT_5	(1.37, 4.92, 11.54)	RT_{11}	(1.49, 5.52, 11.81)	RT_{17}	(0.59, 2.54, 7.30)
RT_6	(0.43, 2.38, 7.06)	RT_{12}	(1.47, 4.35, 10.03)	RT_{18}	(0.89, 2.72,7.39)

Table XXIII. A part of distance of the CPM from the BAA matrix

	RT_1	RT_2	RT_3	...	RT_{18}
CPM_1	(0.30, 1.00, 2.23)	(0.66, 2.94, 3.99)	(0.15, 0.78, 1.74)	...	(−0.33, −1.46, −2.68)
CPM_2	(0.34, 0.94, 2.24)	(−0.25, −1.36, −2.72)	(0.54, 2.25, 3.30)	...	(−0.33, −1.46, −2.68)
CPM_3	(0.09, 0.35, 1.09)	(0.45, 1.79, 3.99)	(0.35, 1.52, 3.30)	...	(1.33, 3.59, 4.38)
⋮	⋮	⋮	⋮		⋮
CPM_{12}	(−0.07, −0.02, −0.06)	(−0.25, −0.51, −0.90)	(−0.16, −0.46, −0.88)		(−0.11, 0.31, 0.62)

CPM_i	CPMs	S_{t1}	$\widetilde{S}_t$ S_{t2}	S_{t3}	S_{tdef}	S_t	Ranking
CPM_1	Revision of pedestrian paths	−2.08	−8.84	−15.93	−0.5209	−0.0532	10
CPM_2	Developing waiting areas for truck drivers	−5.87	−26.61	−45.44	−1.4683	−0.1499	11
CPM_3	Developing instructions for material unloading	15.77	52.81	66.79	3.9433	0.4027	1
CPM_4	Determining extra unloading region outside	0.57	−2.70	−12.48	0.1423	0.0145	7
CPM_5	Launching the blue light project	1.68	6.94	2.30	0.4212	0.0430	6
CPM_6	Placing extra warning signs in the work area	7.69	25.42	30.67	1.9226	0.1963	4
CPM_7	Keeping empty of forklift paths	−1.89	2.18	−0.11	−0.4713	−0.0481	9
CPM_8	Developing instructions for using the equipment	10.36	36.72	45.64	2.5911	0.2646	3
CPM_9	Weight reduction in the manual carrying operations	−7.04	−11.63	−17.76	−1.7595	−0.1797	12
CPM_{10}	Staff training and preparation of training documents	14.34	50.07	62.39	3.5846	0.3660	2
CPM_{11}	Developing instructions for pallet carriage	−1.64	−15.22	−35.02	−0.4110	−0.0420	8
CPM_{12}	Making periodic checks of equipment	7.28	30.50	42.22	1.8189	0.1857	5
				TOTAL	9.7931		

Table XXIV. CPMs' ranking

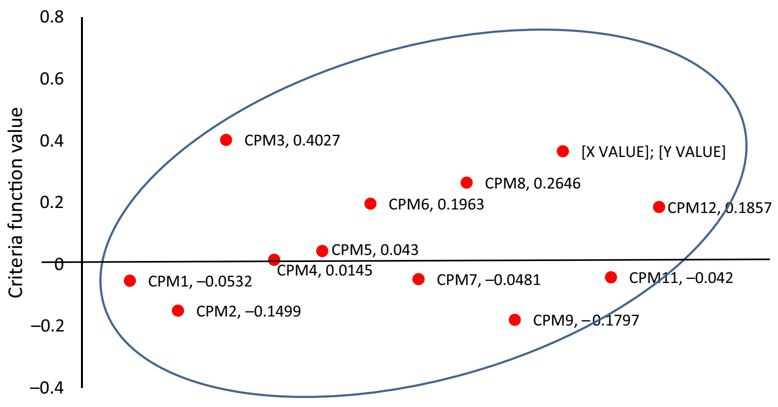

Figure 3. Distribution of CPMs in lower, upper and border approximation area

Importance weights results (Table XIV) showed that severity (RF_3) has higher importance than the other two RFs according to DMs. Actually this result is also appropriate because company where the application is performed is in dangerous class for occupational safety and health conditions. RTs occurring in this company may cause serious injuries and deaths.

According to CPMs ranking results, developing instructions for material loading or unloading (CPM_3) is the most important CPM for delivery and dispatching areas of the warehouse. Workers should know the potential hazards associated with the task at hand

and how to control their workplaces to minimize the danger because numerous injuries can result from improperly moving, handling, and storing materials. Workers must be aware of both manual handling safety concerns and safe equipment operating techniques. Thus, CPM_3 is a vital action to prevent injury because there are various materials that have different size and weights in tractor manufacturing especially heavy ones. These materials are sometimes loaded or unloaded with equipment, sometimes manually. In addition, CPM_3 can prevent all dispatching and delivery areas-related RTs mentioned in this study. Due to this, it is reasonable to determine CPM_3 as the most important one. The mean of "the most important one" is that CPM_3 should be implemented in warehouse first.

According to importance weights of RFs results, severity (RF_3) is the most important RF for RA in warehouse. The severity of risk is the extent of the damage to the institution, workers and goals of institution resulting from a risk event occurring. Severity may change from discomfort, slight bruising, small cut, abrasion, basic first aid need strain, sprain, incapacitation for several days, fracture, hospitalization, incapacitation to death. In this concept, it affects the risk degree of a RT mostly. In the proposed approach, the most effective RF on risk degree of RTs is considered as severity because warehouse includes various types of task, some of them performed with equipment such as crane, truck, forklift, some of them are performed by workers. This leads to various RTs in warehouses so there are different risks that cause different severity levels.

6. Conclusion

In this study, an integrated fuzzy approach based on fuzzy risk matrix combining F-DEMATEL and F-MABAC is proposed for RA. The proposed approach is used for delivery and dispatching areas of a warehouse as a generic one. The proposed approach support to reflectively handle the vagueness and uncertainty included subjective human judgment in a logical way. The differentiations between experts' opinions can be combined more accurately and a systematic categorization of RTs is proposed by considering importance weights of RFs, interrelations between them and risk degrees of RTs. This approach serves as a powerful tool for health and safety managers to plan CPMs effectively by implementing fuzzy MCDM structure.

Generally, only RTs are prioritized according to their risk degrees. Bu in this study, 125 different risk degree combinations were created and these risk degrees are considered as importance of RTs. Then via taking into consideration these importance CPMs are prioritized. In this way, a work plan for occupational safety experts or managers could be obtained.

RA in work places consists of danger identification, risk determination, risk prioritization and CPM determination. An occupational safety expert as a DM is responsible for RA procedure. One of the most difficult tasks in RA is that which CPM is implemented first. In this study, the proposed approach helps occupational safety experts to prioritize CPMs considering effectiveness of CPMs for RTs. Sometimes one CPM may prevent one more than RTs, sometimes one more than CPMs may prevent one RT. For this reason, effectiveness relations should be taken into consideration for prioritization of CPMs. In addition, in the proposed approach, importance weights of RFs are computed considering causal relations between them. Occupational safety experts can see these relations in RA process and recognize that which RF has the most effect on the other RFs.

In traditional RA approaches, three or sometimes two RFs are considered and these RFs are multiplied to obtain risk degree of RTs. It is a well-known fact that multiplication operation is sensitive to changes in scale values of RFs and the same risk degrees may be obtained in different conditions. For example, it is assumed that severity, probability and frequency have the values 1, 2 and 4, respectively; in this condition, the risk degree is computed as 8. At the same time, it is assumed that severity, probability and frequency have the values 2, 2 and 2, respectively for another RT. At this time, the risk degree is computed as 8 again. However, both of these two RTs have not the same characteristic and negative results. The proposed approach can overcome this limitation because of its mathematical MCDM procedure.

This study has a limitation as in every research because small numbers of experts are considered for RA because of legal requirements in Turkey, so expert group was not selected randomly. This may lead to nonoccurrence of unbiased evaluations. Different experts may report different ideas. However, the results obtained are trusted because DMs who are expert in their fields and the tractor manufacturing were selected for RA.

For the future researches, different RFs may be used for RA in warehouses. In addition, this approach can be implemented in an intuitionistic fuzzy, grey or stochastic manner and different MCDM approaches can be integrated for RA.

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Corresponding author
Gülin Feryal Can can be contacted at: gfcan@baskent.edu.tr