

CHAPTER 11

A NOVEL OCCUPATIONAL HEALTH AND SAFETY RISK ASSESSMENT APPROACH USING DF-BASED MCDM MODEL

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Introduction

Occupational health and safety (OHS) risk assessment is a fundamental study subject in ergonomics, providing hazard control, accident prevention, loss reduction, and employee protection. There are many risk assessment methods available in the literature (Tixier, et al., 2002; Marhavidas & Koulouriotis, 2012). The traditional L-type matrix is widely used across industries, including furniture manufacturing, due to its simplicity, although its limitations may receive insufficient consideration.

The L-type matrix assigns rates from 1 to 5 to the parameters of likelihood and severity, then multiplies these rates to obtain the level of risk related to each hazard. Using accident records to determine these parameters correctly requires more time and effort. On the other hand, literature has highlighted the shortcomings of the L-type matrix (Gul & Guneri, 2016).

In literature, multi-criteria decision-making (MCDM) techniques are commonly integrated to decision problems (Khodadadi-Karimvand & Shirouyehzad, 2021; Shadkam & Cheraghchi, 2022); however, classical formulations require precise inputs that are not available in real practice. In addition, fuzzy set theories have been incorporated into assessment methods to handle uncertain information (Toptanci et al., 2025; Jatwa & Sukhwani, 2022; Yılmaz & Şenol, 2017).

OHS risk assessment recently relies on classical fuzzy sets and Type-1 fuzzy numbers. However, several fuzzy set theories exist in the literature with different characteristics and restrictions (Toptanci et al., 2025). Therefore, this issue encourages further developments in fuzzy sets and systems (Gündoğdu

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et al., 2023). Decomposed fuzzy (DF) theory is recently developed as an extension of Atanassov's intuitionistic fuzzy set theory, representing assessments using DF numbers (Cebi et al., 2022). Its mathematical framework gives a more detailed representation of uncertain judgments (Moslem et al., 2024).

In addition, hybrid decision-making models have attracted increasing interest for improving decision processes in the literature. Accordingly, this study proposes an integrated risk assessment model that considers uncertainty, the weights of decision-makers' opinions and risk criteria. This study addresses traditional limitations of L-type matrix by integrating DF set with the Simple Weight Calculation (SIWEC) and Root Assessment Method (RAM). Although many risk assessment methods have been presented, to the author's knowledge, this study is the first to extend both SIWEC and RAM to a DF setting.

The remaining sections describe the proposed methodology, introduce its application and comparative assessment, and present the conclusions.

Methodology

Decomposed fuzzy (DF) sets

The decision-making process has uncertain information in real-world applications. To handle this issue, various fuzzy set theories have been introduced by researchers. DF set is one of them. DF set takes into account both optimistic (O) and pessimistic (P) perspectives to decrease inconsistencies in decision-makers (DMs) opinions. Responses to functional and dysfunctional questions are evaluated. It assesses the reliability of DMs' judgements to estimate the ambiguity level in the decision environment (Moslem, et al., 2024).

Definition 1. Let X be a universe of discourse. A DF set $\tilde{A}$ on a X is,

$$\tilde{A} = \left\{ \langle x, (O(\mu_A^O(x), v_A^O(x)), P(\mu_A^P(x), v_A^P(x))) \mid x \in X \rangle \right\} \quad (1)$$

where the function $\mu_A^O(x)$ and $v_A^O(x)$ indicates the membership and non-membership degrees of x in the functional (optimistic) set, while $\mu_A^P(x)$ and $v_A^P(x)$ correspond to those in the dysfunctional (pessimistic) set. These values

satisfy the conditions $0 \leq \mu_A^O(x) + v_A^O(x) \leq 1$ and $0 \leq \mu_A^P(x) + v_A^P(x) \leq 1$.

Definition 2. Let $\tilde{a} = \{O(a, b), P(c, d)\}$, $\tilde{a}_1 = \{O(a_1, b_1), P(c_1, d_1)\}$ and $\tilde{a}_2 = \{O(a_2, b_2), P(c_2, d_2)\}$ be DF numbers and basic mathematical operations are defined as follows:

$$\tilde{a}_1 + \tilde{a}_2 = \left\{ O\left(\frac{a_1 + a_2 - 2a_1a_2}{1 - a_1a_2}, \frac{b_1b_2}{b_1 + b_2 - b_1b_2}\right), P\left(c_1 + c_2 - c_1c_2, d_1d_2\right) \right\} \quad (2)$$

$$\tilde{a}_1 \times \tilde{a}_2 = \left\{ O\left(a_1a_2, b_1 + b_2 - b_1b_2\right), P\left(\frac{c_1c_2}{c_1 + c_2 - c_1c_2}, \frac{d_1 + d_2 - 2d_1d_2}{1 - d_1d_2}\right) \right\} \quad (3)$$

$$\gamma \times \tilde{a} = \left\{ O\left(\frac{\gamma a}{(\gamma - 1)a + 1}, \frac{b}{\gamma - (\gamma - 1)b}\right), P\left((1 - (1 - c)^\gamma), d^\gamma\right) \right\} \text{ for } \gamma > 0 \quad (4)$$

$$\tilde{a}^\gamma = \left\{ O\left(a^\gamma, (1 - (1 - b)^\gamma)\right), P\left(\frac{c}{\gamma - (\gamma - 1)c}, \frac{\gamma d}{(\gamma - 1)d + 1}\right) \right\} \text{ for } \gamma > 0 \quad (5)$$

Definition 3. Let $\tilde{a}_i = \{O(a_i, b_i), P(c_i, d_i)\}$ be a collection of DF numbers. Let $\lambda = (\lambda_1, \lambda_2, \dots, \lambda_n)$ be the associated weight vector, where $\lambda_i \in [0, 1]$ and $\sum_{i=1}^n \lambda_i = 1$. The Modified Decomposed Weighted Geometric Mean (MDWGM) operator is introduced as follows (Aslantas et al., 2025).

$$MDWGM = \tilde{a}_1^{\lambda_1} \times \dots \times \tilde{a}_n^{\lambda_n} = \left\{ O\left(\prod_{i=1}^n a_i^{\lambda_i}, (1 - \prod_{i=1}^n (1 - b_i)^{\lambda_i})\right), P\left(\frac{\prod_{i=1}^n c_i}{\sum_{i=1}^n c_i^{n-1} \lambda_i (1 - c_i) + \sum_{i=1}^n \frac{c_i^n}{n}}, \frac{\sum_{i=1}^n \lambda_i d_i}{1 + \sum_{i=1}^n (\lambda_i d_i - \frac{d_i}{n})}\right) \right\} \quad (6)$$

Definition 4. The consistency index (CI) of DF number $\tilde{a} = \{O(a, b), P(c, d)\}$ is introduced as follows (Moslem, et al. 2024):

$$CI(\tilde{a}) = 1 - \left(\frac{\sqrt{(a-d)^2 + (b-c)^2 + (1-a-b)^2 + (1-c-d)^2}}{2} \right); \quad (7)$$

$$0 \leq CI(\tilde{a}) \leq 1$$

Definition 5. The score function (SF) of DF number $\tilde{a} = \{O(a, b), P(c, d)\}$ is proposed as follows (Moslem, et al. 2024):

$$SF(\tilde{a}) = \begin{cases} \frac{(a+b-c+d).CI(\tilde{a})}{2.k}, SF(\tilde{a}) > 0 \\ 0, SF(\tilde{a}) \leq 0 \end{cases} \quad (8)$$

where k indicated the linguistic scale multiplier. It is calculated based on the maximum value of the proposed linguistic scale.

Proposed Integrated DF-SIWEC-RAM Approach

SIWEC, introduced by Puška et al. (2024) and RAM, developed by Sotoudeh-Anvari (2023) cannot address uncertainties in decision-making processes in their classical forms. Therefore, they are extended below to the DF environment.

The steps of *DF-SIWEC method* are explained as follows:

Step 1: Construct the linguistic decision table and convert the terms to DFNs using Table 1 to form the initial decision-making matrix $[\tilde{X}]$.

$$\tilde{X} = \begin{pmatrix} \tilde{x}_{11} & \cdots & \tilde{x}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{x}_{m1} & \cdots & \tilde{x}_{mn} \end{pmatrix} \quad (9)$$

whose columns shows the criteria and rows shows the DMs. In this matrix $\tilde{x}_{ij}$ ($i = 1, 2, \dots, m; j = 1, 2, \dots, n$) present the evaluations of each DMs of certain criteria as DFNs.

Table 1. Linguistic scale of DF model

Linguistic terms	DF numbers
Very low (VL)	$\langle(0.20,0.80), (0.80,0.20)\rangle$
Low (L)	$\langle(0.35,0.65), (0.65,0.35)\rangle$
Medium (M)	$\langle(0.50,0.50), (0.50,0.50)\rangle$
High (H)	$\langle(0.65,0.35), (0.35,0.65)\rangle$
Very high (VH)	$\langle(0.80,0.20), (0.20,0.80)\rangle$

Step 2: Multiply initial decision-making matrix by the DMs' weights to obtain weighted decision matrix $(\lambda\tilde{x}_{ij})$ using Equation 4.

Step 3: Normalize weighted decision matrix with the help of Equation 10.

$$\tilde{n}_{ij} = \frac{1}{\max score (\lambda\tilde{x}_{ij})} \times \lambda\tilde{x}_{ij} \quad (10)$$

where $\max score (\lambda\tilde{x}_{ij})$ is a scalar number.

Step 4: Obtain a normalized weighted crisp decision matrix $[n_{ij}]$ using Equation 8.

Step 5: Multiply the values in the $[n_{ij}]$ with the standard deviation values of each DMs.

$$v_{ij} = n_{ij} \times st.dev_j \quad (11)$$

Step 6: Compute the sum of the weights of the criteria.

$$s_{ij} = \sum_{i=1}^m v_{ij} \quad (12)$$

Step 7: Compute the final weight values of selected criteria.

$$w_j = \frac{s_{ij}}{\sum_{j=1}^n s_{ij}} ; \sum_{j=1}^n w_j = 1 \quad (13)$$

The steps of *DF-RAM method* are explained as follows:

Step 1: Obtain the linguistic decision matrices from each DMs and convert the assessment terms to DFNs using Table 1 to construct the initial decision-making matrices $[\tilde{D}_k]$.

$$\begin{matrix} & C_1 & \cdots & C_n \\ \tilde{D}_k = & A_1 & \begin{pmatrix} \tilde{d}_{11} & \cdots & \tilde{d}_{1n} \\ \vdots & \ddots & \vdots \\ A_m & \tilde{d}_{m1} & \cdots & \tilde{d}_{mn} \end{pmatrix} \end{matrix} \quad (14)$$

Step 2: Aggregate the decision matrices using Equation 6 and construct an aggregated crisp decision matrix using the score function provided in Equation 8.

Step 3: Normalize the aggregated decision matrix by Equation 15.

$$n_{agg,ij} = \frac{d_{agg,ij}}{\sum_{i=1}^m d_{agg,ij}} \quad (i = 1, 2, \dots, m; j = 1, 2, \dots, n) \quad (15)$$

Here, $d_{agg,ij}$ shows the aggregated crisp decision matrix values.

Step 4: Compute the weighted normalized decision matrix.

$$f_{ij} = n_{agg,ij} \times w_j \quad (16)$$

where w_j represents the weight value of the j th criteria.

Step 5: Compute the sums of weighted normalized values of i th alternative corresponding to the criteria type.

$$s_{B,i}^{+} = \sum_{j \in B}^n f_{ij} ; s_{NB,i}^{-} = \sum_{j \in NB}^n f_{ij} \quad (17)$$

where B and NB denote the beneficial and non-beneficial criteria, respectively.

Step 6: Obtain the total scores using Equation 18 and normalize the scores through min-max normalization approach.

$$RI_i = (2 + s_{B,i}^{+})^{\frac{1}{2+s_{NB,i}^{-}}} \quad (18)$$

The constant 2 maintains computational stability and accommodates cases where $s_{B,i}^{+}$ or $s_{NB,i}^{-}$ is zero.

Step 7: Rank the alternatives using the normalized scores.

Application of the Proposed Model

This study aims to demonstrate the applicability and effectiveness of the proposed risk assessment model through its application in a furniture manufacturing workshop in İstanbul, Türkiye. In this study, likelihood (C1) and severity (C2) were used as criteria in accordance with the L-type risk matrix approach, and a total of 17 alternatives (hazards) were identified in the workshop's production area based on the DMs' field observations. The identified hazards are presented in Table 2.

The necessary data were collected through a questionnaire administered to three DMs responsible for risk assessment at the workshop. The importance weights of the DMs' opinions were assumed to be equal in this study ($\lambda_i = 1/3$). The hazards were assessed using the proposed model.

Table 2. Hazards identified in the study

Hazard Code	Hazards
H1	Lack of guards at machine operating points
H2	Failure to inspect machinery and machine tools
H3	Defective or worn electrical hand tools and sockets
H4	Improper use of hand tools
H5	Hazards associated with chemical materials
H6	Inadequate ventilation
H7	Hazards associated with failure to use personal protective equipment
H8	Inadequate lighting
H9	Noise
H10	Vibration
H11	Lack of knowledge of safe manual handling, loading, and unloading practices, heavy lifting
H12	Improperly stacked materials
H13	Uneven or slippery surfaces
H14	Lack of tetanus immunity among workers in the production area
H15	Absence of a first aid cabinet
H16	Poor hygiene
H17	Unauthorized access to and exit from the production area

In the first phase, the DF-SIWEC method was used to determine the importance weights of the selected criteria. Table 3 presents the DMs' linguistic evaluations and their corresponding DF values. The resulting weighted decision matrix, normalized weighted decision matrix, and criterion weights are presented in Tables 4 and 5. The linguistic scale multiplier k was set to 0.80, and the maximum score of the weighted DF decision matrix was calculated as 0.746.

Table 3. Initial decision-making matrix

DM	C1	C2	C1	C2
DM ₁	M	H	$\langle(0.50,0.50), (0.50,0.50)\rangle$	$\langle(0.65,0.35), (0.35,0.65)\rangle$
DM ₂	L	VH	$\langle(0.35,0.65), (0.65,0.35)\rangle$	$\langle(0.80,0.20), (0.20,0.80)\rangle$
DM ₃	H	VH	$\langle(0.65,0.35), (0.35,0.65)\rangle$	$\langle(0.80,0.20), (0.20,0.80)\rangle$

Table 4. Weighted decision matrix

DM	C1	C2
DM ₁	$\langle(0.250,0.750), (0.206,0.794)\rangle$	$\langle(0.382,0.618), (0.134,0.866)\rangle$
DM ₂	$\langle(0.152,0.848), (0.295,0.705)\rangle$	$\langle(0.571,0.429), (0.072,0.928)\rangle$
DM ₃	$\langle(0.382,0.618), (0.134,0.866)\rangle$	$\langle(0.571,0.429), (0.072,0.928)\rangle$

Table 5. Normalized crisp weighted decision matrix and criteria weight values

DM	C1	C2	st. dev _j
DM ₁	0.527	0.648	0.085
DM ₂	0.444	0.833	0.275
DM ₃	0.648	0.833	0.131
s _{ij}	0.252	0.393	
w _{ij}	0.391	0.609	

According to the result, the final weights of criteria C1 and C2 were determined as 0.391 and 0.609, respectively. This result indicates that severity parameter has greater importance than likelihood in the risk assessment.

After determining the criterion weights, the identified hazards are evaluated against these criteria using DF-RAM. The linguistic assessments of hazards are presented in Table 6.

Table 6. The linguistic decision matrix

Criteria	C1			C2		
Alternatives						
DMs	DM ₁	DM ₂	DM ₃	DM ₁	DM ₂	DM ₃
H1	VH	VH	H	VH	VH	H
H2	L	M	M	H	VH	M
H3	L	M	L	VH	H	M
H4	VL	L	L	M	H	L
H5	VL	M	L	VH	H	H
H6	VH	H	VH	VH	H	H
H7	H	M	VH	VH	H	H
H8	M	L	L	M	L	L
H9	H	H	VH	M	M	L
H10	L	VL	L	M	M	L
H11	H	VH	VH	H	M	M
H12	VL	L	L	L	L	L
H13	M	L	L	L	L	VL
H14	M	L	VL	VH	M	H

H15	L	VL	VL	L	VL	VL
H16	L	L	M	VL	VL	VL
H17	L	M	L	VL	L	L

The matrix values obtained by applying the DF-RAM are presented in Table 7, while the ranking results are provided in Table 8.

Table 7. Aggregated, normalized and weighted normalized decision matrices

Hazar d	C1 (+)	C2 (+)	Normalize d C1 (+)	Normalize d C2 (+)	Weighted Normalize d C1 (+)	Weighted Normalize d C2 (+)
	0.92	0.92				
H1	1	1	0.094	0.087	0.037	0.053
	0.56	0.78				
H2	1	3	0.057	0.074	0.022	0.045
	0.50	0.78				
H3	1	3	0.051	0.074	0.020	0.045
	0.37	0.61				
H4	7	6	0.038	0.058	0.015	0.036
	0.43	0.86				
H5	9	2	0.045	0.082	0.018	0.050
	0.92	0.86				
H6	1	2	0.094	0.082	0.037	0.050
	0.78	0.86				
H7	3	2	0.080	0.082	0.031	0.050
	0.50	0.50				
H8	1	1	0.051	0.048	0.020	0.029
	0.86	0.56				
H9	2	1	0.088	0.053	0.034	0.032
	0.37	0.56				
H10	7	1	0.038	0.053	0.015	0.032
	0.92	0.68				
H11	1	4	0.094	0.065	0.037	0.040
	0.37	0.43				
H12	7	8	0.038	0.042	0.015	0.025
	0.50	0.37				
H13	1	7	0.051	0.036	0.020	0.022
	0.43	0.78				
H14	9	3	0.045	0.074	0.018	0.045
	0.31	0.31				
H15	6	6	0.032	0.030	0.013	0.018

	0.50	0.25				
H16	1	0	0.051	0.024	0.020	0.014
	0.50	0.37				
H17	1	7	0.051	0.036	0.020	0.022

Table 8. Ranking results

Hazard	s_B^+	s_{NB}^-	RI	Normalized RI	Rank
H1	0.090	0.000	1.4457	1.000	1
H2	0.068	0.000	1.4379	0.624	5
H3	0.065	0.000	1.4371	0.583	8
H4	0.051	0.000	1.4320	0.336	10
H5	0.067	0.000	1.4378	0.618	6
H6	0.087	0.000	1.4445	0.942	2
H7	0.081	0.000	1.4426	0.850	3
H8	0.049	0.000	1.4314	0.307	11
H9	0.067	0.000	1.4377	0.610	7
H10	0.047	0.000	1.4309	0.283	12
H11	0.076	0.000	1.4409	0.769	4
H12	0.040	0.000	1.4284	0.161	14
H13	0.042	0.000	1.4289	0.185	13
H14	0.063	0.000	1.4362	0.542	9
H15	0.031	0.000	1.4251	0.000	16
H16	0.034	0.000	1.4263	0.061	15
H17	0.042	0.000	1.4289	0.185	13

The risk levels of hazards were prioritized as $H1 > H6 > H7 > H11 > H2 > H5 > H9 > H3 > H14 > H4 > H8 > H10 > H13 = H17 > H12 > H16 > H15$. According to result, the importance of the H1: Lack of guards at machine operating points is higher than the others. On the other

hand, H15: Absence of a first aid cabinet is found to be minor hazard for furniture manufacturing work.

The validity of the proposed integrated risk assessment model was further tested through comparison analysis between the proposed DF- MCDM model and classical L-type matrix. The result of this comparison is shown in Figure 1.

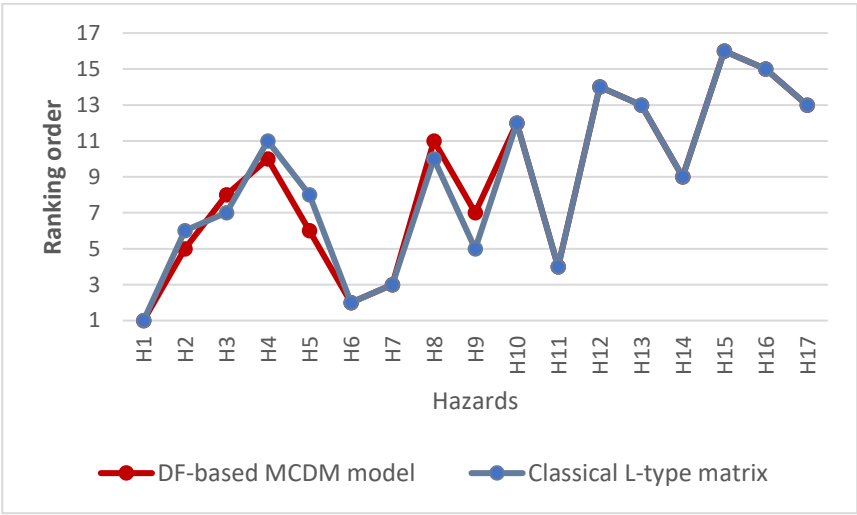


Figure 1. Ranking comparison of hazards

The comparison revealed a strong and statistically significant association between the hazard rankings obtained using the proposed model and the classical L-type matrix (Spearman’s rank correlation coefficient: 0.985, $p < 0.001$). Despite this close agreement, minor differences in prioritization may have important implications in areas such as ergonomics. These differences highlight the need for careful evaluation of assessment methods and their ability to support reliable decisions.

Conclusion

Risk assessment is important to prevent ergonomic problems and to provide safer working conditions. Methodological improvements can help address the shortcomings of traditional approaches. This study introduced an integrated risk assessment model that extends the classical L-type matrix using DF settings and two MCDM techniques, namely DF-SIWEK and DF-RAM.

DF-SIWEC is used to determine the the weights of the likelihood and severity criteria, while DF-RAM is used to prioritized the identified hazards. The model was applied in a furniture manufacturing workshop, and its ranking consistency was examined by conducting a comparison test with the result of classical L-type matrix. This study presents the DF-SIWEC and DF-RAM as a novel contribution to both the literature and methodology. The proposed approach may also be used to solve different decision problems.

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