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Sara SALEHI [0000-0003-1463-7304]*

FUZZY MULTIPLE CRITERIA GROUP DECISION-MAKING IN PERFORMANCE EVALUATION OF MANUFACTURING COMPANIES

Abstract

In today's competitive industry landscape, it is crucial to assess manufacturing processes to enhance efficiency. However, identifying the critical factors that impact productivity can be a daunting task due to their intricate nature. To tackle this challenge, we propose a novel approach that combines fuzzy logic with TOPSIS to comprehensively evaluate manufacturing company efficiency. The method presented by the author treats this as a complex MCDM problem and accommodates diverse factors with distinct weights, which are crucial for a thorough efficiency analysis. This approach was applied to evaluate potential manufacturing entities in Cyprus through a three-step process. Firstly, relevant criteria were curated using literature and expert insights, endowing them with linguistic terms that were then translated into fuzzy values. Next, fuzzy TOPSIS evaluated efficiency, and sensitivity analysis gauged the criteria weight impact on decisions. This article introduces a new methodology for holistic manufacturing company evaluation. The synergy of fuzzy-set theory and TOPSIS proves effective amidst the ambiguity inherent in performance measurement. By uniting these methodologies, this study advances manufacturing performance evaluation, aiding informed decision-making. The research contributes a pioneering method to enhance manufacturing efficiency assessment while accommodating uncertainty through fuzzy logic integration.

1. INTRODUCTION

Performance measurement is one of the most effective tools for identifying areas in manufacturing companies that lead to optimized improvement. Measuring the performance of manufacturing companies is essential to provide a financial view to the stakeholders. Manufacturing performance evaluation is not new, however, it has changed considerably. Some companies consider efficiency metrics that only capture a small part of the actual/true productivity (Ahmad & Dhafr, 2002).

Conventional methods in performance measurement cannot help managers to continuously and effectively monitor, control, and improve industrial operations (Pourjavad & Mayorga 2019). Manufacturing performance evaluation was primarily

* Rauf Denktas Universit, Faculty of Architecture and Engineering, Department of Software Engineering, Northern Cyprus, sara.salehi@rdu.edu.tr

focused on only one or two criteria at a time, such as cost and labor efficiency (Norman & Bahiri, 1972), total productivity (Barlev & Callen, 1986; National Research Council, 1979), quality and output volume (Leachman, Pegels & Kyoon Shin, 2005), infrastructure (Sakakibara, Flynn, Schroeder & Morris, 1997).

The other drawback is that studies have usually analyze performance against individual indicators and have reported them separately (Leachman et al., 2005). However, taking this approach rather than in a consolidated manner through an aggregate index of performance cannot illustrate a thorough picture of a firm’s performance to the senior managers (Leachman et al., 2005). Focusing on only one or two dimensions can lead to more harm than good. Making decisions based on incomplete metrics can cause improper actions. Therefore, considering multiple factors was required instead of examining manufacturing efficiency based on a particular dimension (Eccles, 1991; Kaplan, Norton, 2005).

To solve a problem involving multiple factors, researchers and scholars use multicriteria decision-making (MCDM) methods (Chowdhury & Paul, 2020; Emovon & Oghenenyerovwho, 2020; Stojčić, Zavadskas, Pamučar, Stević & Mardani, 2019). Making decisions while there are multiple criteria and usually conflicting ones refers to MCDM (Kahraman, Onar & Oztaysi, 2015). Multicriteria decision-making methods have been used to select the best alternative out of a group of possibilities as well as to find a solution for the problems regarding sorting or ranking the potential alternatives (Palczewski & Sałabun, 2019). Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), introduced by Hwang and Yoon (Hwang & Yoon, 1981a), is one of the effective MCDM methods. TOPSIS has been widely used in many challenges and real-world issues due to its comprehensive mathematical concept, simplicity, and computational efficiency (Palczewski & Sałabun, 2019).

Since the output of MCDM methods is highly dependent on its weight value, the method itself is unable to conclusively process imprecise and uncertain data within decision criteria (Liu, Kwong, Zhang & Li, 2019). Combining with fuzzy set theory, the methods of MCDM are successfully modified and improved (Bashir et al., 2018; Karczmarczyk, Jankowski & Wątróbski, 2018; Sotoudeh-Anvari, 2022). When holding comprehensive knowledge is impossible, fuzzy set theory is applied to describe complexity, uncertainty, and ambiguity valid to decision-making processes (Zadeh, 1996). The TOPSIS method improves by the combination with fuzzy set theory to solve imprecise and uncertain issues (Sotoudeh-Anvari, 2022). Fuzzy TOPSIS differentiates between two kinds of criteria and then selects solutions that are close to positive ideal solutions and far from negative ones (Rouyendegh, Yildizbasi, and & Üstünyer, 2020a).

Fuzzy TOPSIS has been successfully applied in different areas such as privacy measurement (Guo, Yao, Lin & Xu, 2023), risk assessment (Awodi, Liu, AyoImoru & Ayodeji, 2023), selection of location (Hooshangi, Gharakhanlou & Razin, 2023), analyzing smart manufacturing technologies (Abdullah, Al-Ahmari & Anwar, 2023), sustainability (Regragui, Sefiani, Azzouzi & Cheikhrouhou, 2023; Solangi, Tan, Mirjat & Ali, 2019), retail industries (Rouyendegh, Yildizbasi & Yilmaz, 2020b), green suppliers performance evaluation (Dos Santos, Godoy & Campos, 2019; Hajiaghaei-Keshteli, Cenk, Erdebilli, Ozdemir & Gholian-Jouybari, 2023), suppliers performance evaluation (Chatterjee & Stević, 2019; Hosseinzadeh Lotfi, Allahviranloo, Shafiee & Saleh, 2023).

As a first attempt in the literature, this study thus proposes a hybrid method that combines fuzzy logic with TOPSIS to assess the efficiency of manufacturing companies in addressing the criteria respected by managers and stakeholders. In other words, considering the number of factors involved, this study formulates the performance of manufacturing companies as an MCDM problem. The main focus of this article is to find a novel method to evaluate the performance of manufacturing companies in a consolidated manner through an aggregate index of performance rather than for each indicator. The approach presented in this study may interest senior managers and decision-making authorities in the industry.

2. PRELIMINARIES

Definition 1. Let $U = \{u_1, u_2, \ldots, u_n\}$ be the universal discourse. A fuzzy set $\tilde{F}$ in U is defined as follows:

$$\begin{gathered} \tilde{F} = \{(u, \mu_{\tilde{F}(u)}) | u \in U\} \\ \mu_{\tilde{F}(u)}: \mathrm{U} \to [0,1] \end{gathered} \tag{1}$$

where $\mu_{\tilde{F}(u)}$ is the membership function.

Definition 2. The membership function of a triangular fuzzy number (TFN), $\tilde{f} = (f_1, f_2, f_3)$ is given by

$$\mu_{\tilde{f}(u)} = \begin{cases} 0, & u \le f_1, \\ \dfrac{u - f_1}{f_2 - f_1}, & f_1 \le u \le f_2, \\ \dfrac{f_3 - u}{f_3 - f_2}, & f_2 \le u \le f_3, \\ 0, & u > f_3 \end{cases} \tag{2}$$

Fig. 1 shows the triangular fuzzy number $\tilde{f}$.

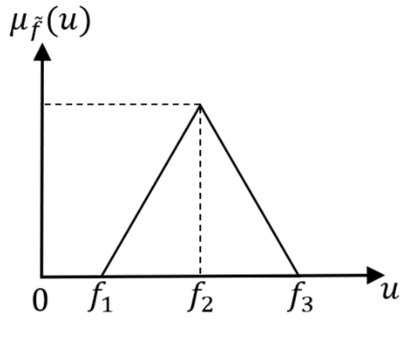

Fig. 1. Triangular fuzzy number $\tilde{f}$

Definition 3. Let $\tilde{f} = (f_1, f_2, f_3)$ and $\tilde{e} = (e_1, e_2, e_3)$ be two TFNs and $k \ge 0$ be any real number. We can have the following operations:

1. Multiplication:

$$\tilde{f} \times \tilde{e} = (f_1 \times e_1, f_2 \times e_2, f_3 \times e_3)$$

$$k\tilde{f} = (kf_1, kf_2, kf_3)$$

2. Addition:

$$\tilde{f} + \tilde{e} = (f_1 + e_1, f_2 + e_2, f_3 + e_3)$$

3. Subtraction:

$$\tilde{f} - \tilde{e} = (f_1 - e_1, f_2 - e_2, f_3 - e_3)$$

4. Division:

$$\tilde{f}/\tilde{e} = (f_1/e_1, f_2/e_2, f_3/e_3)$$

$$\tilde{f}/k = (f_1/k, f_2/k, f_3/k)$$

$$k/\tilde{f} = (k/f_1, k/f_2, k/f_3)$$

Definition 4. The distance between $\tilde{f} = (f_1, f_2, f_3)$ and $\tilde{e} = (e_1, e_2, e_3)$:

$$d(\tilde{f}, \tilde{e}) = \sqrt{\frac{1}{3}[(f_1 - e_1)^2 + (f_2 - e_2)^2 + (f_3 - e_3)^2]}$$

Definition 5. A matrix with at least one fuzzy number element is a fuzzy matrix.

Definition 6. A variable whose values are linguistic terms is called a linguistic variable. The linguistic variables and the corresponding fuzzy ratings used for the alternatives and criteria are listed in Tab. 1 and 2, respectively, with a scale of 1–9. The representation of rating scales for the alternatives and criteria are presented in Fig. 2 and 3, correspondingly.
The review of more than 200 publications that focus on fuzzy MCDM, shows that more articles extended TOPSIS into a fuzzy environment by using triangular membership rather than trapezoidal membership (Salih, Zaidan, Zaidan & Ahmed, 2019; Sotoudeh-Anvari, 2022). The triangular fuzzy membership was used since it is the largest, easiest, and most used membership function applied by scholars. They are simple to interpret and computationally easy to use in a fuzzy environment (Nila & Roy, 2023). By this means, in this article triangular fuzzy membership was employed.

Tab. 1. Linguistic variables for alternatives

Linguistic variables	Abbreviation	TFN
Very Poor	VP	(1,1,3)
Poor	P	(1,3,5)
Fair	F	(3,5,7)
Good	G	(5,7,9)
Very Good	VG	(7,9,9)

Tab. 2. **Linguistic variables for criteria**

Linguistic variables	Abbreviation	TFN
Very Low	VL	(1,1,3)
Low	L	(1,3,5)
Medium	M	(3,5,7)
High	H	(5,7,9)
Very High	VH	(7,9,9)

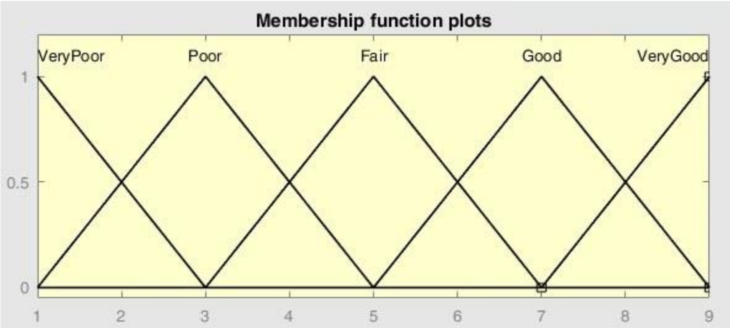

Fig. 2. Rating scale for alternatives

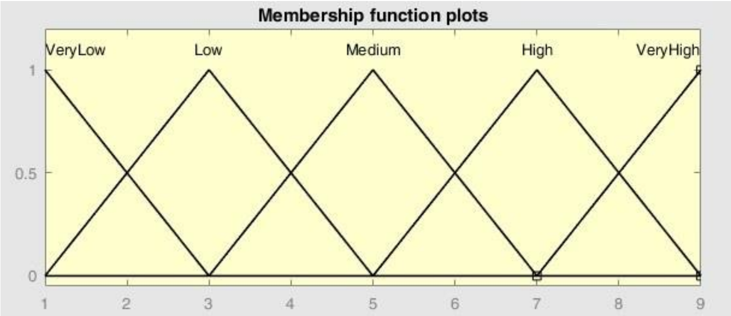

Fig. 3. Rating scale for criteria

3. PROPOSED METHOD

The fuzzy TOPSIS approach uses fuzzy evaluations of criteria and alternatives in TOPSIS. The method selects the alternative with the maximum similarity to the positive-ideal solution (Hwang & Yoon, 1981b). Considering the difficulty of measuring an alternative's performance precisely, employing a fuzzy approach provides the chance to assign relative importance to attributes for real-world situations (Kuo, Tzeng & Huang, 2007; Yang & Hung, 2007). The fuzzy TOPSIS method is proposed as a suitable approach for solving MCDM issues under uncertainty (Chen, 2000).

Employing the fuzzy TOPSIS, this study proposes a novel systematic hybrid approach that can be used to evaluate the efficiency of manufacturing companies. In the following, the proposed method is described.

3.1. Selection of criteria

The first step is selecting criteria for measuring the performance of manufacturing companies. Since the criteria have a significant impact on evaluating the performance of manufacturing companies, decision-makers and managers need to consider different criteria. Asking the opinion of experts and with reference to the literature (Alqahtani, Gupta & Nakashima, 2019; Anderl, Haag, Schützer & Zancul, 2018; Attaran, 2017; Bartosik-Purgat & Ratajczak-Mrożek, 2018; Büchi, Cugno & Castagnoli, 2020; Choi, 2018; Coxon, Kelly & Page, 2016; Druehl, Carrillo & Hsuan, 2018; Khorram Niaki & Nonino, 2017; Lee, Bagheri, & Jin, 2016; Lu, 2017; Markopoulos & Hosanagar, 2018; Pourjavad & Mayorga, 2019; Rezk, Singh Srai & Williamson, 2016; Xu, Xu & Li, 2018), eleven criteria have been chosen which are derived from five main categories. The list of criteria is shown in Tab. 3.

Then, each criterion is classified into Benefits (+) and Costs (-). Benefit means the higher the value, the more preferable the alternative is, while Cost means the lower the value, the more preferable the alternative is.

Tab. 3. List of criteria

Category	K_a: Productivity	K_b: Production Rate	K_c: Production Cost			K_d: Sale Amount			K_e: Quality Cost		
Criteria	K_1	K_2	K_3	K_4	K_5	K_6	K_7	K_8	K_9	K_{10}	K_{11}
	Average ratio (monthly)	Production rate	Direct material cost	Direct labor cost	Factory burden	Internal sale (detail)	Internal sales (general)	External sale	Failure cost (internal)	Failure cost (external)	Prevention cost
Class	+	+	-	-	-	+	+	+	-	-	-

3.2. Numerical Example

In this study, the author proposes using the fuzzy TOPSIS technique to measure the efficiency of manufacturing companies, with a focus on the textile industry in Cyprus. This is important because textiles make up a significant portion of the country's exports, and their success in producing and exporting high-quality products is crucial for the nation's economy. Three potential manufacturing companies were evaluated using a list of decision criteria and linguistic terms provided by expert decision-makers. These experts were directors of manufacturing and production line inspectors with at least 15 years of industry experience.

The proposed fuzzy multicriteria approach for evaluating the efficiency of manufacturers consists of the following steps.

Step 1: Alternatives and criteria are rated.

Suppose $M = \{M_1, M_2, \ldots, M_j\}$ is a set of J possible alternatives which are to be evaluated against *n* criteria, $K = \{K_1, K_2, \ldots, K_i\}$. In this article, three potential textile manufacturing companies in Cyprus were selected to be evaluated and compared against the selected list of criteria.

Three decision-makers (D_1, D_2, D_3), using the linguistic terms presented in Tab. 1, assessed the ratings of alternatives against each criterion. The ratings of three alternatives (M_1, M_2, and M_3) under eleven criteria ($K_1, K_2, K_3, \ldots, K_{11}$) are shown in Tab. 4. Using the linguistic terms in Tab. 2, the decision-makers assessed the significance of the criterion. The assessment results are shown in Tab. 5.

Tab. 4. Linguistic evaluation for alternatives

Criteria	Alternatives								
	M_1			M_2			M_3		
	D_1	D_2	D_3	D_1	D_2	D_3	D_1	D_2	D_3
K_1	VG	VG	VG	VG	VG	G	G	G	VG
K_2	VG	VG	G	G	G	VG	G	G	G
K_3	VG	G	VG	G	VG	VG	F	G	F
K_4	VG	VG	VG	G	VG	G	VG	VG	VG
K_5	G	VG	G	G	VG	G	F	G	G
K_6	VG	VG	VG	F	G	F	F	G	G
K_7	G	G	VG	F	G	F	P	G	P
K_8	VG	VG	G	P	G	P	VP	F	VP
K_9	VP	VP	P	VP	P	VP	VG	VG	VG
K_{10}	P	P	F	P	F	VP	VG	VG	VG
K_{11}	G	VG	VG	G	VG	G	VP	P	VP

Step 2: Aggregate the weight of criteria.
Fuzzy triangular numbers $\tilde{R}_k = (l_k, m_k, u_k)$, $k = 1, 2, \ldots, K$, is the fuzzy ratings given by all decision-makers. The aggregated fuzzy rating is determined by $\tilde{R}_k = (l, m, u)$. Here,

$$l = \min_k \{l_k\}, \;\; m = \frac{1}{K}\sum_{k=1}^{K} m_k, \qquad u = \max_k \{u_k\} \tag{3}$$

The fuzzy rating and importance weight of the kth decision-maker is indicated as $\tilde{x}_{ijk} = (l_{ijk}, m_{ijk}, u_{ijk})$ and $\tilde{y}_{ijk} = (y_{jk1}, y_{jk2}, y_{jk3})$, correspondingly, where $i = 1, 2, \ldots, m$, $j = 1, 2, \ldots, n$, then the aggregated fuzzy ratings of alternatives with respect to each criterion is defined as $\tilde{x}_{ij} = (l_{ij}, m_{ij}, u_{ij})$. Here,

$$l_{ij} = \min_k \{l_{ijk}\}, \;\; m_{ij} = \frac{1}{K}\sum_{k=1}^{K} m_{ijk}, \;\; u_{ij} = \max_k \{u_{ijk}\} \tag{4}$$

The aggregated fuzzy weights of each criterion are defined as $\tilde{y}_j = (y_{j1}, y_{j2}, y_{j3})$, where

$$y_{j1} = \min_k \{y_{jk1}\}, \;\; y_{j2} = \frac{1}{K}\sum_{k=1}^{K} y_{jk2}, \;\; y_{j3} = \max_k \{y_{jk3}\} \tag{5}$$

Tab. 5. Linguistic evaluation for criteria

Criteria	Decision-makers		
	D_1	D_2	D_3
K_1	H	VH	H
K_2	VH	H	VH
K_3	H	M	M
K_4	M	M	M
K_5	H	M	H
K_6	M	H	M
K_7	VH	VH	H
K_8	M	L	L
K_9	H	H	VH
K_{10}	H	H	M
K_{11}	H	M	H

For instance, for the first criterion (K_1), the aggregated fuzzy weight was denoted by $\tilde{y}_j = (y_{j1}, y_{j2}, y_{j3})$, where

$$y_{j1} = \min_k(5,7,5), \quad y_{j2} = \frac{1}{3}\sum_{k=1}^{3}(7+9+7), \quad y_{j3} = \max_k(9,9,9)$$
$$\tilde{y}_j = (5,7.667,9)$$

Tab. 6 shows the calculated $\tilde{y}_j$ for all criteria.

Step 3: Construct the fuzzy decision matrix.

The construction of the fuzzy decision matrix ($\widetilde{D}$) for the alternatives and the criteria is as follows:

$$\widetilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} & \cdots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} & \cdots & \tilde{x}_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \cdots & \tilde{x}_{mn} \end{bmatrix}, i = 1,2,\ldots,m; \; j = 1,2,\ldots,n \tag{6}$$

$$\widetilde{W} = (\tilde{y}_1, \tilde{y}_2, \tilde{y}_3) \tag{7}$$

Then, by using Eqn. 3 the aggregate fuzzy weights of the alternatives were calculated. For instance, to calculate the aggregate rating for the first manufacturing company (M_1) against criterion (K_1), based on the rating given by the decision-makers, the following calculation was done:

$$l_{ij} = \min_k(7,7,7), \; m_{ij} = \frac{1}{3}\sum_{k=1}^{3}(9+9+9), \; u_{ij} = \max_k(9,9,9)$$
$$\tilde{x}_{ij} = (7,9,9)$$

Tab. 6. Aggregated fuzzy criteria weights

Criteria	Decision-makers			Aggregated weights ($\tilde{y}_j$)
	***D*1**	***D*2**	***D*3**	
K1	(5,7,9)	(7,9,9)	(5,7,9)	(5,7.667,9)
K2	(7,9,9)	(5,7,9)	(7,9,9)	(5,8.333,9)
***K*3**	(5,7,9)	(3,5,7)	(3,5,7)	(3,5.667,9)
***K*4**	(3,5,7)	(3,5,7)	(3,5,7)	(3,5,7)
***K*5**	(5,7,9)	(3,5,7)	(5,7,9)	(3,6.333,9)
K6	(3,5,7)	(5,7,9)	(3,5,7)	(3,5.667,9)
K7	(7,9,9)	(7,9,9)	(5,7,9)	(5,8.333,9)
K8	(3,5,7)	(1,3,5)	(1,3,5)	(1,3.667,7)
K9	(5,7,9)	(5,7,9)	(7,9,9)	(5,7.667,9)
K10	(5,7,9)	(5,7,9)	(3,5,7)	(3,6.333,9)
K11	(5,7,9)	(3,5,7)	(5,7,9)	(3,6.333,9)

Tab. 7 shows the value of $\tilde{x}_{ij}$ for all alternatives (M_j) with respect to all criteria (K_i).

Tab. 7. Aggerate fuzzy decision matrix for alternatives

Criteria	Alternatives		
	***M*1**	***M*2**	***M*3**
K1	(7,9,9)	(5,8.333,9)	(5,7.667,9)
K2	(5,8.333,9)	(5,7.667,9)	(5,7,9)
***K*3**	(5,8.333,9)	(5,8.333,9)	(3,5.667,9)
***K*4**	(7,9,9)	(5,7.667,9)	(7,9,9)
***K*5**	(5,7.667,9)	(5,7.667,9)	(3,6.33,9)
K6	(7,9,9)	(3,5.667,9)	(3,6.33,9)
K7	(5,7.667,9)	(3,5.667,9)	(1,4.333,9)
K8	(5,8.333,9)	(1,4.333,9)	(1,2.333,7)
K9	(1,1.667,5)	(1.1.667,5)	(7,9,9)
K10	(1,3.667,7)	(1,3,7)	(7,9,9)
K11	(5,8.333,9)	(5,7.667,9)	(1,1.667,5)

Step 4: Normalize the fuzzy decision matrix.
The normalized fuzzy decision matrix $\tilde{R}$ is defined as follows:

$$\tilde{R} = [\tilde{r}_{ij}]_{m\times n}, i = 1,2,\dots,m;\ j = 1,2,\dots,n; \tag{8}$$

where,

$$\tilde{r}_{ij} = \left(\frac{l_{ij}}{u_j^*}, \frac{m_{ij}}{u_j^*}, \frac{u_{ij}}{u_j^*}\right),\quad u_j^* = \max_i(u_{ij})\quad (\text{Benefit criteria}, +) \tag{9}$$

$$\tilde{r}_{ij} = \left(\frac{l_j^-}{u_{ij}}, \frac{l_j^-}{m_{ij}}, \frac{l_j^-}{l_{ij}}\right),\quad l_j^- = \min_i(l_{ij})\quad (\text{Cost criteria}, -) \tag{11}$$

For instance, the calculation of the normalized rating for the first alternative (M_1) against criterion (K_1) was:

$$l_j^- = \min_i(7,5,5) = 5$$
$$u_j^* = \max_i(9,9,9) = 9$$

The category of (K_1) was a Benefit (+), so

$$\tilde{r}_{ij} = \left(\frac{7}{9},\frac{9}{9},\frac{9}{9}\right) = (0.778,1,1)$$

Tab. 8 shows the normalized fuzzy decision matrix.

Tab. 8. Normalized fuzzy decision matrix

Criteria	Alternatives		
	M_1	M_2	M_3
K_1	(0.778,1,1)	(0.556,0.926,1)	(0.556,0.926,1)
K_2	(0.556,0.926,1)	(0.556,0.852,1)	(0.556,0.852,1)
K_3	(0.333,0.36,0.6)	(0.333,0.36,0.6)	(0.333,0.529,1)
K_4	(0.556,0.556,0.714)	(0.556,0.652,1)	(0.556,0.556,0.714)
K_5	(0.333,0.391,0.6)	(0.333,0.391,0.6)	(0.333,0.474,1)
K_6	(0.778,1,1)	(0.333,0.629,1)	(0.333,0.629,1)
K_7	(0.556,0.852,1)	(0.333,0.629,1)	(0.111,0.629,1)
K_8	(0.556,0.926,1)	(0.111,0.481,1)	(0.111,0.481,1)
K_9	(0.2,0.6,1)	(0.2,0.6,1)	(0.111,0.111,0.143)
K_{10}	(0.143,0.273,1)	(0.143,0.333,1)	(0.111,0.111,0.143)
K_{11}	(0.111,0.12,0.2)	(0.111,0.130,0.2)	(0.2,0.6,1)

Step 5: Construct the weighted normalize matrix.

The matrix $\widetilde{H}$ is defined as follows:

$$\widetilde{H} = [\tilde{h}_{ij}]_{m\times n} \text{ where } \tilde{h}_{ij} = \tilde{r}_{ij}(.)\tilde{y}_j, \qquad i = 1,2,\ldots,m;\ j = 1,2,\ldots,n; \tag{11}$$

where $\tilde{y}_j$ is the weights of evaluation criteria.

To construct $\widetilde{H}$, for the alternatives, the $\tilde{y}_j$ values from the last column of Tab. 6 and $\tilde{r}_{ij}$ values from Tab. 8 were used. For instance, for alternative (M_1) and criterion (K_1) we have the following:

$$\tilde{h}_{ij} = (5,7.667,9)(.)(0.778,1,1) = (3.889,7.667,9)$$

Tab. 9 shows the weighted normalized fuzzy decision matrix for alternatives.

Step 6: Calculate the fuzzy positive (FPIS, M^*) and negative (FNIS, M^-) ideal solutions.

(FPIS, M^*) is founded as:

$$(\text{FPIS}, M^*) = \left(\tilde{h}_1^*, \tilde{h}_2^*, \ldots, h_n^*\right)$$
$$\tilde{h}_j^* = \max_i\{h_{ij3}\},\ i = 1,2,\ldots,m;\ j = 1,2,\ldots,n; \tag{12}$$

(FNIS, M^{-}) is founded as:

$$(\text{FNIS}, M^{-}) = \left(\tilde{h}_1^{-}, \tilde{h}_2^{-}, \dots, h_n^{-}\right)$$
$$\tilde{h}_j^{-} = \min_i \{h_{ij1}\},\ i = 1,2,\dots,m;\ j = 1,2,\dots,n; \tag{13}$$

For instance, (FPIS, M^*)=(9, 9, 9) and (FNIS, M^{-})=(2.778, 2.778, 2.778), for criterion (K_1). The last two columns of Tab. 9 shows (FPIS, M^*) and (FNIS, M^{-}) for all criteria.

Tab. 9. Weighted normalized matrix, (FPIS, M^*) and (FNIS, M^{-})

Criteria	Alternatives				
	M_1	M_2	M_3	(FPIS, M^*)	(FNIS, M^{-})
K_1	(3.889,7.667,9)	(2.778,7.099,9)	(2.778,7.099,9)	(9,9,9)	(2.778,2.778,2.778)
K_2	(2.778,7.716,9)	(2.778,7.099,9)	(2.778,7.099,9)	(9,9,9)	(2.778,2.778,2.778)
K_3	(1,2.04,5.4)	(1,2.04,5.4)	(1,3,9)	(9,9,9)	(1,1,1)
K_4	(1.667,2.778,5)	(1.667,3.261,7)	1.667,2.778,5)	(7,7,7)	(1.667,1.667,1.667)
K_5	(1,2.478,5.4)	(1,2.478,5.4)	(1,3,9)	(9,9,9)	(1,1,1)
K_6	(2.333,5.667,9)	(1,3.3.568,9)	(1,3.568,9)	(9,9,9)	(1,1,1)
K_7	(2.778,7.098,9)	(1.667,5.247,9)	(0.556,5.247,9)	(9,9,9)	(0.556,0.556,0.556)
K_8	(0.556,3.395,7)	(0.111,1.765,7)	(0.111,1.765,7)	(7,7,7)	(0.111,0.111,0.111)
K_9	(1,4.6,9)	(1,4.6,9)	(0.556,0.852,1.286)	(9,9,9)	(0.556,0.556,0.556)
K_{10}	(0.428,1.727,9)	(0.492,2.111,9)	(0.333,0.704,1.286)	(9,9,9)	(0.333,0.333,0.333)
K_{11}	(0.333,0.76,1.8)	(0.333,0.826,1.8)	(0.6,3.8,9)	(9,9,9)	(0.333,0.333,0.333)

Step 7: Calculate the distance of each alternative from (FPIS, M^*) and (FNIS, M^{-}).
q_i^* is computed as:

$$q_i^* = \sum_{j=1}^{n} q_h(\tilde{h}_{ij}, \tilde{h}_j^*),\ \ i = 1,2,\dots,m \tag{14}$$

q_i^{-} is computed as:

$$q_i^{-} = \sum_{j=1}^{n} q_h(\tilde{h}_{ij}, \tilde{h}_j^{-}),\ \ i = 1,2,\dots,m \tag{15}$$

For instance, for alternative (M_1) and the criterion (K_1), the distances were given by

$$q_h(M_1, M^*) = \sqrt{\frac{1}{3}[(3.889-9)^2 + (7.667-9)^2 + (9-9)^2]} = 3.050$$

$$q_h(M_1, M^{-}) = \sqrt{\frac{1}{3}[(3.889-2.778)^2 + (7.667-2.778)^2 + (9-2.778)^2]} = 4.613$$

In the same way, the distances for the other criteria for all alternatives were calculated as shown in Tab. 10.
Then, the distances q_i^* and q_i^{-} were calculated using Eqns. 14 and 15. For instance, for alternative (M_1), the distances q_1^* and q_1^{-} were calculated as:

$$
\begin{aligned}
q_1^* = & \sqrt{\frac{1}{3}[(3.889-9)^2+(7.667-9)^2+(9-9)^2]} \\
& + \sqrt{\frac{1}{3}[(2.778-9)^2+(7.716-9)^2+(9-9)^2]} \\
& + \sqrt{\frac{1}{3}[(1-9)^2+(2.04-9)^2+(5.4-9)^2]+\ \dots} \\
& + \sqrt{\frac{1}{3}[(0.333-9)^2+(0.76-9)^2+(1.8-9)^2]} = 55.731
\end{aligned}
$$

$$
\begin{aligned}
q_1^- = & \sqrt{\frac{1}{3}[(3.889-2.778)^2+(7.667-2.778)^2+(9-2.778)^2]} \\
& + \sqrt{\frac{1}{3}[(2.778-2.778)^2+(7.716-2.778)^2+(9-2.778)^2]} \\
& + \sqrt{\frac{1}{3}[(1-1)^2+(2.04-1)^2+(5.4-1)^2]+\ \dots} \\
& + \sqrt{\frac{1}{3}[(0.333-0.333)^2+(0.76-0.333)^2+(1.8-0.333)^2]} \\
& = 43.996
\end{aligned}
$$

In the same way, the distances q_i^* and q_i^- were calculated for the rest of the alternatives as shown in the last row of Tab. 10.

Step 8: Calculate a closeness coefficient (CC_i) of each alternative.

The CC_i is calculated as follows:

$$CC_i = \frac{q_i^-}{q_i^* + q_i^-},\ \ i\ =\ 1, 2, \dots, m \tag{16}$$

The value of (CC_i) shows the distances to the (FPIS, M^*) and (FNIS, M^-). For instance, for alternative (M_1) we have:

$$CC_1 = \frac{q_1^-}{q_1^* + q_1^-} = \frac{43.996}{55.731\ +\ 43.996} = 0.441$$

In the same way, CC_i were calculated for the remaining alternatives, and the results are shown in Tab. 11.

Tab. 10. Distance $q_h(M_j, M^*)$ and $q_h(M_j, M^-)$

Criteria	$q_h(M_j, M^*)$			$q_h(M_j, M^-)$		
	M_1	M_2	M_3	M_1	M_2	M_3
K_1	3.050	3.756	3.756	4.613	4.374	4.374
K_2	3.668	3.756	3.756	4.586	4.374	4.374
K_3	6.465	6.465	5.774	2.610	2.610	4.761
K_4	4.094	3.761	4.094	2.029	3.214	2.029
K_5	6.311	6.311	5.774	2.680	2.680	4.761
K_6	4.303	5.583	5.583	5.402	4.851	4.851
K_7	3.756	4.756	5.335	6.300	5.614	5.577
K_8	4.263	4.995	4.995	4.414	4.090	4.090
K_9	5.271	5.271	8.108	5.412	5.412	0.455
K_{10}	6.490	6.349	8.235	5.068	5.108	0.590
K_{11}	8.059	8.037	5.704	0.882	0.893	5.391
Sum	55.731	59.041	61.113	43.996	43.220	41.253

Tab. 11. The value of CC_i for each alternative

	Alternatives		
	M_1	M_2	M_3
q_i^-	43.996	43.220	41.253
q_i^*	55.731	59.041	61.113
CC_i	0.441	0.423	0.403

Step 9: Rank the alternatives.
In the final step, according to the value of CC_i in Tab. 11, the alternatives were ranked. Then the alternative with the highest CC_i was selected. The best alternative is the one that is the closest to the FPIS and the farthest from the FNIS.

According to the values of CC_i for the alternatives in Tab. 11, the ranking order of the alternatives was found as $M_1 > M_2 > M_3$. Therefore, it can be concluded that manufacture (M_1) has the best performance (efficiency).

3.3. Sensitivity analysis

To investigate the impact of criteria weights on evaluating the performance of manufacturing companies, a sensitivity analysis was conducted. The criteria weights are represented by W_{K_i} for criteria K_i where $i = 1, \dots, n$. In total, twenty experiments were performed, as shown in Tab. 12. The criteria weights W_{K_i} in the experiment E.1 to E.5 are set to equal $W_{K_1-K_{11}} = (1,1,3)$, $W_{K_1-K_{11}} = (1,3,5)$, $W_{K_1-K_{11}} = (3,5,7)$, $W_{K_1-K_{11}} = (5,7,9)$, $W_{K_1-K_{11}} = (7,9,9)$, respectively. In the experiment E6. the weights of all Cost criteria, $W_{K_3-K_5,K_9-K_{11}}$, have the highest weights while the remaining criteria are set to the lowest value. In the experiment E7. the weights of all Benefit criteria, $W_{K_1-K_2,K_6-K_8}$, have the highest weights while the remaining criteria are set to the lowest value. In the experiment E.8 to E.18, the W_{K_i} of one criterion is set to (7,9,9) which is the highest weight, while the weights of other criteria are set to $(1,1,3)$ which are the lowest weights. In experiment E.19, the weight of the Cost category (K_c):$W_{K_3-K_5} = (7,7,9)$ is the highest, and the remaining W_{K_i} is the lowest. In the last experiment, the weight of the Cost category (K_e): $W_{K_9-K_{11}} = (7,7,9)$ is set to the highest value, and the remaining W_{K_i} is the lowest. The main objective of the sensitivity analysis is to determine which criteria have the most significant impact on the decision-making process. Fig. 4 displays the findings of the sensitivity analysis. According to the result of the sensitivity tests in Tab.12 and Fig.4, alternative M_1 has the highest CC_i value in fourteen out of twenty experiments. Therefore, manufacture M_1, compared to other alternatives, showed the best performance in meeting the decision criteria.

Tab. 12. Experiment results for sensitivity analysis

E. no.	Definition	Closeness coefficient (CC_i)			Ranking
		M_1	M_2	M_3	
E.1	$W_{K_1-K_{11}} = (1,1,3)$	0.385	0.380	0.364	$M_1 > M_2 > M_3$
E.2	$W_{K_1-K_{11}} = (1,3,5)$	0.424	0.415	0.399	$M_1 > M_2 > M_3$
E.3	$W_{K_1-K_{11}} = (3,5,7)$	0.436	0.416	0.398	$M_1 > M_2 > M_3$
E.4	$W_{K_1-K_{11}} = (5,7,9)$	0.444	0.417	0.397	$M_1 > M_2 > M_3$
E.5	$W_{K_1-K_{11}} = (7,9,9)$	0.481	0.434	0.411	$M_1 > M_2 > M_3$
E.6	$W_{K_3-K_5,K_9-K_{11}} = (7,9,9)$, $W_{K_1-K_2,K_6-K_8} = (1,1,3)$	0.363	0.375	0.347	$M_2 > M_1 > M_3$
E.7	$W_{K_3-K_5,K_9-K_{11}} = (1,1,3)$, $W_{K_1-K_2,K_6-K_8} = (7,9,9)$	0.554	0.466	0.451	$M_1 > M_2 > M_3$
E.8	$W_{K_1} = (7,9,9)$, $W_{K_2-K_{11}} = (1,1,3)$	0.425	0.407	0.392	$M_1 > M_2 > M_3$
E.9	$W_{K_2} = (7,9,9)$, $W_{K_1,K_3-K_{11}} = (1,1,3)$	0.412	0.403	0.389	$M_1 > M_2 > M_3$
E.10	$W_{K_3} = (7,9,9)$, $W_{K_1-K_2,K_4-K_{11}} = (1,1,3)$	0.369	0.366	0.381	$M_3 > M_1 > M_2$
E.11	$W_{K_4} = (7,9,9)$, $W_{K_1-K_3,K_5-K_{11}} = (1,1,3)$	0.376	0.393	0.357	$M_2 > M_1 > M_3$
E.12	$W_{K_5} = (7,9,9)$, $W_{K_1-K_4,K_6-K_{11}} = (1,1,3)$	0.371	0.368	0.379	$M_3 > M_1 > M_2$
E.13	$W_{K_6} = (7,9,9)$, $W_{K_1-K_5,K_7-K_{11}} = (1,1,3)$	0.443	0.400	0.386	$M_1 > M_2 > M_3$
E.14	$W_{K_7} = (7,9,9)$, $W_{K_1-K_6,K_8-K_{11}} = (1,1,3)$	0.442	0.416	0.395	$M_1 > M_2 > M_3$
E.15	$W_{K_8} = (7,9,9)$, $W_{K_1-K_2,K_4-K_{11}} = (1,1,3)$	0.445	0.401	0.388	$M_1 > M_2 > M_3$
E.16	$W_{K_9} = (7,9,9)$, $W_{K_1-K_8,K_9-K_{11}} = (1,1,3)$	0.414	0.409	0.323	$M_1 > M_2 > M_3$
E.17	$W_{K_{10}} = (7,9,9)$, $W_{K_1-K_9,K_{11}} = (1,1,3)$	0.397	0.395	0.323	$M_1 > M_2 > M_3$
E.18	$W_{K_{11}} = (7,9,9)$, $W_{K_1-K_{10}} = (1,1,3)$	0.343	0.341	0.396	$M_3 > M_1 > M_2$
E.19	$W_{K_1-K_2,K_6-K_{11}} = (1,1,3), W_{K_3-K_5} = (7,7,9)$	0.353	0.368	0.385	$M_3 > M_2 > M_1$
E.20	$W_{K_1-K_8} = (1,1,3), W_{K_9-K_{11}} = (7,7,9)$	0.386	0.385	0.324	$M_1 > M_2 > M_3$

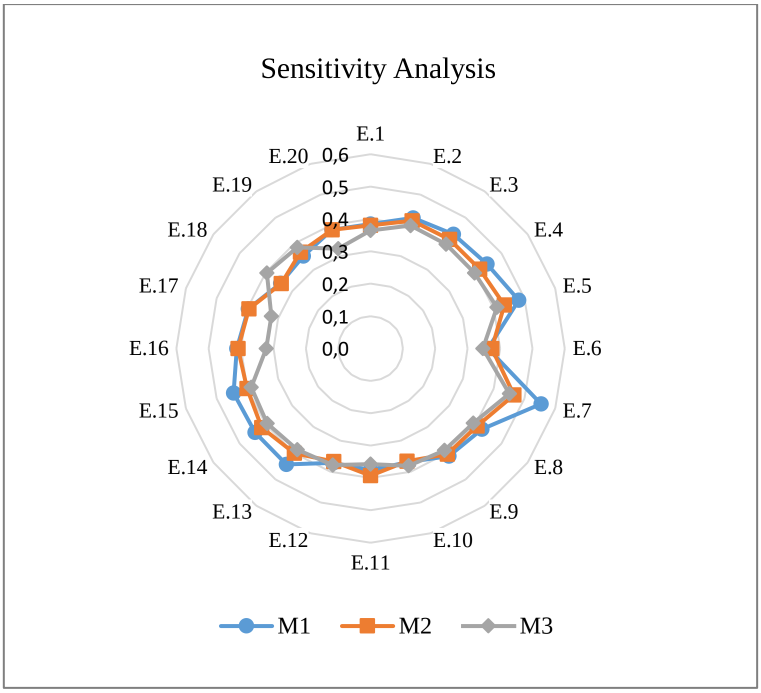

Fig. 4. Results of sensitivity analysis

4. CONCLUSION AND DISCUSSION

The conventional techniques for assessing performance fall short due to their limited scope, failing to capture the full complexity of the issue at hand. To address this, a more comprehensive approach is proposed in this article, treating the problem as one with multiple criteria. Given that performance measurement often involves incomplete or uncertain data, fuzzy-set theory is introduced to tackle this challenge. Specifically, this study examines fuzzy-set theory in conjunction with the TOPSIS technique, which considers the imprecision and ambiguity inherent in decision-making when evaluating different alternatives.

In decision-making, linguistic variables are highly beneficial when numerical values cannot indicate performance values. In other words, in assessing manufacturing companies concerning criteria and importance weights, it is appropriate to use linguistic variables instead of numerical values. The proposed approach copes effectively with problems of uncertain, imprecise, and ambiguous information because the evaluations of the alternatives are fuzzified. Additionally, fuzzy numbers have orientations, which allow us to distinguish the types of criteria (benefit or cost). The case study demonstrates that the Fuzzy TOPSIS method proposed here can be applied successfully in practical application.

After consulting with industry experts and conducting thorough literature research, we developed a list of eleven criteria. These criteria were assigned linguistic variables and converted into fuzzy numbers. We then utilized the fuzzy TOPSIS approach to evaluate the performance of three manufacturing companies in meeting these criteria. Finally, a sensitivity analysis was conducted to determine the impact of criteria weights on decision-making.

Based on the closeness coefficient values and observations from the sensitivity analysis, we concluded that alternative M_1 performed the best in meeting the decision criteria compared to the other alternatives. This approach not only allows for performance evaluation but also the ability to rank the alternatives, showcasing the flexibility of the approach.

This method is especially useful when dealing with a lack of quantitative information. It can provide a more objective evaluation of manufacturing companies. Findings have indicated that implementing a systematic hybrid TOPSIS approach can equip senior management and other decision-makers within the manufacturing industry with a more comprehensive and impartial comprehension of their organization's effectiveness. By conducting a thorough analysis, this holistic approach can facilitate more informed decision-making and policy formulation by authorized stakeholders, ultimately resulting in better financial investments. Ultimately, this methodology can enable stakeholders to optimize their policies and utilize their financial resources more efficiently.

5. LIMITATIONS AND RECOMMENDATIONS

The proposed method boasts a crucial advantage in its adaptability, making it suitable for application in other manufacturing companies. This is possible because the criteria provided are broad, enabling successful evaluation of other industries. The study also emphasizes the need for thorough research into potential areas of improvement for a company, taking into account its unique characteristics.

Further research into the comparison of various MCDM techniques would be highly beneficial. To overcome data vagueness and uncertainty, it is recommended to use fuzzy numbers combined with MCDM, as real numbers can make it challenging to determine subjective opinions. TOPSIS has faced several problems that researchers intend to address in future studies. The weight of criteria can significantly impact the final selection and aggregation techniques, which can be resolved using normalization and distance measuring approaches. These issues provide a valid reason for academics to pursue further research in this field.

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