Applied Mathematics and Computational Intelligence
Volume 11, No.1, Dec 2022 [412-422]

An Integrated Approach of Fuzzy TOPSIS and Graph Theory with Confidence Analysis on Personnel Selection

Mohd Halimi Ab Hamid[1*], Anas Fathul Ariffin[1]

[1]Mathematical Sciences Studies, College of Computing, Informatics and Media, Universiti Teknologi MARA, Perlis Branch, Arau Campus, 02600 Arau, Perlis, Malaysia

[*] Corresponding author: halimi@uitm.edu.my

Received: 28 September 2022; Accepted: 7 November 2022; Available online (in press): 5 December 2022

ABSTRACT

This paper proposes a methodology based on combined approach of graph theory with Fuzzy TOPSIS and equipped with confidence analysis in solving a multi-criteria decision-making problem (MCDM). The theoretical background of some graph theories is reviewed and the basic principle of fuzzy TOPSIS is presented. Graph-theoretic method is used to clearly depict a logical and systematic framework in accessing the available criteria with the relative importance. The main concept of Fuzzy TOPSIS is that the chosen alternative should be the closest to the fuzzy positive ideal solution and the furthest away from the fuzzy negative ideal solution, which may be found by computing the closeness coefficient. In this paper, the fuzzy closeness coefficient with ⟨-level set is determined. The coefficient can be represented as a fuzzy number, resulting in a more accurate fuzzy assessment of relative closeness. To show the applicability of the approach, a numerical analysis is presented to study the personnel selection based on the proposed method. It was found that the approach is able to generate a more comprehensive, systematic, and reliable result.

Keywords: Confidence analysis, fuzzy TOPSIS, graph theory, MCDM, personnel selection

1 INTRODUCTION

The process of selecting people who best meet the credentials needed to carry out a specific task is known as personnel selection. Personnel selection has always been crucial for both public and private sector companies to ensure that the proper individuals are hired for the correct positions. It is clear that by investing in its people, the company may acquire a competitive edge [1]. Besides, a suitable personnel selection, taking into account the company circumstances, will allow managers to maximise production costs and accomplish corporate objectives [2]. Due to the direct influence it will have on an organisation's success, personnel selection is important in the numerous aspects of human resource management. For instance, organising skills, creativity, personality, emotional stability, comprehension, leadership, and general aptitude are all taken into account. Prior to now, choosing the most qualified and suitable candidate from a pool of candidates has received a lot of attention in the literature.

Like many decision problems, the personnel selection problem is extremely complex in reality. Humans generally cannot make good predictions on qualitative problems, while on quantitative predictions they can make accurate guesses. In the real world, personnel suitability ratings under each of the subjective criteria as well as the importance weights of the subjective criteria are very often assessed by linguistic terms, such as, 'good', 'very low', 'poor', etc. Because fuzzy linguistic variables may more effectively convey the subjective evaluation data, a fuzzy multiple-criteria decision-making approach is employed to combine different linguistic evaluations and weights to create the fuzzy appropriateness index [3].

Multi-criteria decision making (MCDM), is a study that examines the criteria to evaluate if each one is a favourable or an unfavourable option for a certain application. In an effort to help the decision-maker choose an alternative with the fewest trade-offs and the most benefits, it also compares this criterion, depending on the chosen criteria, against every other option [4]**.** Application of multi-criteria decision-making (MCDM) theory is the use of computational methods that combine numerous criteria and order of preference in evaluating and selecting the best choice among several possibilities depending on the intended outcome. MCDM is used in a variety of disciplines to find the best solution to a problem when there are several parameters to consider that cannot be determined by the users' experiences. The criteria utilised in personnel selection evaluations might be either qualitative or quantitative in nature. As a result, the conventional MCDM cannot address cases in which the ratings' values are linguistic phrases represented by fuzzy sets. Fuzzy MCDM was created and employed to deal with such a situation. Table 1 summarized a few applications of different MCDM in personnel selection in recent years.

Table 1 : Application of MCDM in personnel selection

Author(s)	**MCDM Method**	**Case Study in Personnel Selection**
Chuang et al. [5]	PROMETHEE	Managerial position selection in food company
Kilic et al. [6]	ELECTRE	Industrial engineer selection in manufacturing company
Chen and Hung [7]	PROMETHEE, 2-tuple linguistic variables	Marketing manager selection
Petridis et al. [8]	Fuzzy AHP	Internal Auditor selection
Samalioglu et al. [9]	Fuzzy TOPSIS	IT Specialist selection
Sang et al. [10]	Fuzzy TOPSIS	Engineer selection in software company

Fuzzy Technique for Order Performance by Similarity to Ideal Solution (TOPSIS) was proposed by Hwang and Yoon [11] and this technique is based on the concept that the chosen alternative should have the shortest distance to the Positive Ideal Solution (PIS) and the farthest distance to Negative Ideal Solution (NIS). Wang et al. [12] have used Fuzzy TOPSIS in energy resources evaluation with criteria such as population, energy consumption and total renewable energy are considered. Meanwhile, Jasiulewicz et al. [13] have applied Fuzzy TOPSIS technique to study the impact of maintenance function on more sustainable manufacturing process.

The graph-theoretic method can offer a logical and systematic solution to the current difficulty of selecting personnel with different backgrounds [14]. The extensive literature review reveals that advanced graph theory, and its applications are widespread and well-documented. To depict a complicated system, a graph or digraph model may be useful in modelling and analysing many sorts of systems that are important in many different disciplines. Previously, Mumtaz [15] used digraph approach in identifying the critical factors of green supply chain management. In health sector, Prajapati et al. [16] represented the interdependence of enablers and characteristics to interpret the performances of the sustainability enablers before and during the time of Covid-19. Earlier, Qureshi et al. [17] combined the graph-theoretic approach with Fuzzy AHP to determine the best service provider. Later, Safari et al. [18] have integrated the same diagraph approach with fuzzy AHP in equipment selection.

As mentioned above, there are studies that have discussed MCDM technique with graph theory or MCDM technique with alpha confidence. However, this paper integrates those three components together, Fuzzy TOPSIS method and graph-theoretic approach based with confidence analysis in order to provide more structured, systematic and effective analysis. In the following section, some preliminaries and definitions from the graph theory and fuzzy set theory are presented. Later, the proposed methodology with numerical example is discussed in Section 3.

2 PRELIMINARIES

In this section, some preliminaries and techniques that are used throughout this paper are provided.

Definition 1 [19]. A graph G is an ordered pair of disjoint sets (V(Γ), E(Γ)) such that E is a subset of the set V of unordered pairs where V(Γ) is the set of vertices and E(Γ) is the set of edges.

Definition 2 [19]. A complete graph is a simple graph where any two vertices are adjacent and any complete graph of nn vertices is denoted as K_n.

Definition 3 [9]. A fuzzy number $\tilde{A} = (a_1, a_2, a_3)$ are called triangular fuzzy number (TFN), and is defined by its membership function,

$$\mu_{\tilde{A}}(x) = \{0\ x < a_1\ \frac{x - a_1}{a_2 - a_1}\ a_1 \leq x < a_2\ \frac{x - a_3}{a_2 - a_3}\ a_2 \leq x < a_3\ 0\ x > a_3 \tag{1}$$

and it can be expressed as $\mu_{\tilde{A}} = (a_1, a_2, a_3)$.

Definition 4 [20]. The α-cut of the fuzzy number $\tilde{A}$ is defined as $\tilde{A} = \{x \in X, \mu_{\tilde{A}}(x) \geq \alpha\}$ and $\alpha \in [0,1]$.

2.1 Fuzzy TOPSIS

Fuzzy (TOPSIS) was developed as one of the MCDM methods and the technique is based on the principle that the chosen alternative should have the shortest distance to the Positive Ideal Solution (PIS) and the farthest distance to Negative Ideal Solution (NIS). The solution was intended to minimize the cost criteria and maximize the benefit criteria. The procedure of Fuzzy TOPSIS is:

Step 1. Develop a fuzzy decision criteria matrix $\tilde{x}_{ij} = \left(a_{ij}^k, b_{ij}^k, c_{ij}^k\right)$ with a decision group of k members. The weight criterion is denoted by $\widetilde{w}_{ij} = \left(w_{ij}^k, w_{ij}^k, w_{ij}^k\right)$.

Step 2. Calculate the aggregated fuzzy ratings for criteria and aggregated fuzzy weight for criteria according to linguistic variables in Table 2 and linguistic variables for ratings in Table 3.

Table 2: Linguistic variables

Linguistic Variable	**Fuzzy Number**
Very High (VH)	(0.9, 1.0,1.0)
High (H)	(0.7, 0.9, 1.0)
Medium high (MH)	(0.5, 0.7, 0.9)
Medium (M)	(0.3, 0.5, 0.7)
Medium Low (ML)	(0.1, 0.3, 0.5)
Low (L)	(0, 0.1, 0.3)
Very Low (VL)	(0, 0, 0.1)

Table 3: Linguistic variables for the ratings

Linguistic Variable	**Fuzzy Number**
Very Good (VG)	(9, 10,10)
Good (G)	(7, 9, 10)
Medium Good (MG)	(5, 7, 9)
Fair (F)	(3, 5, 7)
Medium Poor (MP)	(1, 3, 5)
Poor (P)	(0, 1, 3)
Very Poor (VP)	(0, 0, 1)

Step 3. Normalise the fuzzy decision matrix $\tilde{R} = [\tilde{r}_{ij}]$, where

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), \qquad c_j^* = \frac{max}{i}\{c_{ij}\}$$

$$\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^-}, \frac{b_{ij}}{c_j^-}, \frac{c_{ij}}{c_j^-}\right), \qquad c_j^- = \frac{min}{i}\{c_{ij}\} \tag{2}$$

Step 4. Compute the weighted normalised decision matrix $\tilde{V} = (\tilde{v}_{ij})_{m\times n}, i = 1,2, \ldots, m, j = 1,2, \ldots, n$ where$\tilde{v}_{ij} = \tilde{r}_{ij}.\widetilde{w}_j$, $\widetilde{w}_j$ is the relative weight of the *j*th criteria and $\sum_{j=1}^{n} \quad w_j = 1$.

Step 5. Compute the Fuzzy PIS and Fuzzy NIS

$$A^* = (\tilde{v}_1^*, \tilde{v}_2^*, \ldots, \tilde{v}_n^*); \tilde{v}_j^* = \frac{max}{i}\{v_{ij}\},$$

$$A^- = (\tilde{v}_1^-, \tilde{v}_2^-, \ldots, \tilde{v}_n^-); \tilde{v}_j^- = \frac{min}{i}\{c_{ij}\}. \tag{3}$$

Step 6. Calculate the separation measure or the distance from each alternative to the FPIS and FNIS. Given $\tilde{d}_i^* \sum_{j=1}^{n} \quad d\left(\tilde{v}_{ij}, \tilde{v}_{ij}^*\right)$ and $\tilde{d}_i^- \sum_{j=1}^{n} \quad d\left(\tilde{v}_{ij}, \tilde{v}_{ij}^-\right)$ where

$$d(\widetilde{m}, \tilde{n}) = \sqrt{\frac{1}{3}\left[(m_1 - n_1)^2 + (m_2 - n_2)^2 + (m_3 - n_3)^2\right]}, \widetilde{m} = (m_1, m_2, m_3) \text{ and } \tilde{n} = (n_1, n_2, n_3) \quad (4)$$

are triangular numbers.

Step 7. Determine the relative closeness of each alternative as follows:

$$RC_i = \frac{\tilde{d}_i^-}{\tilde{d}_i^* + \tilde{d}_i^-} \quad (5)$$

Step 8. Rank the alternative with highest closeness coefficient as the best alternative.

2.1.1 Fuzzy TOPSIS with Alpha Level Set

According to Wang & Elhag [21], let the normalized decision matrix given as $\tilde{R} = \left[\tilde{r}_{ij}\right]$, where

$$\begin{aligned} \tilde{r}_{ij} &= \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right), and\ c_j^* = \frac{max}{i}\left\{c_{ij}\right\} for\ j \in B; \\ \tilde{r}_{ij} &= \left(\frac{a_j^-}{a_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{c_{ij}}\right), and\ a_j^- = \frac{min}{i}\left\{a_{ij}\right\} for\ j \in C. \end{aligned} \quad (6)$$

with B and C are the set of benefit criteria and cost criteria respectively, with normalized $\tilde{r}_{ij} = \left[\left(\tilde{r}_{ij}\right)_\alpha^L \left(\tilde{r}_{ij}\right)_\alpha^U\right]$ and $\left(w_j\right)_\alpha = \left[\left(w_j\right)_\alpha^L \left(w_j\right)_\alpha^U\right]$ be alpha level set of $\tilde{r}_{ij}$ and $\widetilde{w}_{ij}$. Then, the relative closeness in Eq. (4) can be written as in Eq. (6-7).

$$\left(RC_i\right)_\alpha^L = Min \frac{\sqrt{\sum_{j=1}^{m} \quad \left(w_j \left(r_{ij}\right)_\alpha^L\right)^2}}{\sqrt{\sum_{j=1}^{m} \quad \left(w_j \left(r_{ij}\right)_\alpha^L\right)^2} + \sqrt{\sum_{j=1}^{m} \quad \left(w_j \left(\left(r_{ij}\right)_\alpha^L - 1\right)\right)^2}} \quad (7)$$

such that $\left(w_j\right)_\alpha^L \le w_j \le \left(w_j\right)_\alpha^U, \left(r_{ij}\right)_\alpha^L \le r_{ij} \le \left(r_{ij}\right)_\alpha^U, j = 1, \ldots, m.$

$$\left(RC_i\right)_\alpha^U = Min \frac{\sqrt{\sum_{j=1}^{m} \quad \left(w_j \left(r_{ij}\right)_\alpha^U\right)^2}}{\sqrt{\sum_{j=1}^{m} \quad \left(w_j \left(r_{ij}\right)_\alpha^U\right)^2} + \sqrt{\sum_{j=1}^{m} \quad \left(w_j \left(\left(r_{ij}\right)_\alpha^U - 1\right)\right)^2}} \quad (8)$$

such that $(w_j)_\alpha^L \le w_j \le (w_j)_\alpha^U, (r_{ij})_\alpha^L \le r_{ij} \le (r_{ij})_\alpha^U, j = 1, \dots, m.$

In final step, which is to rank the alternatives, the RC_i must be defuzzified first. Oussalah [22] has suggested the application of averaging level cuts (ALC) as the defuzzification method on α -level set and the defuzzified value of RC_i for N α - level set can be determined by

$$(RC_i)^*_{ALC} = \frac{1}{N}\sum_{j=1}^{N} \left(\frac{(RC_i)^L_{\alpha_j} + (RC_i)^U_{\alpha_j}}{2}\right), \qquad i = 1, \dots, n \tag{9}$$

3 METHODOLOGY

In this section, the proposed methodology based on combined approach of graph theory with Fuzzy TOPSIS and equipped with confidence analysis is presented.

Step 1: Identifying the criteria for personnel selection.

In this step, all potential criteria alternatives are determined based on the relevant attributes available in the literature or previous study.

Step 2: Modelling the diagraph representation for a given criteria.

The arc of the graph is based on their inter relationship of the criteria, while the nodes represent the criteria considered in the study. The relative importance obtained from the decision makers are stated to justify the inter relationship of the criteria.

Step 3: Application of Fuzzy TOPSIS method.

The technique stated in preliminaries are utilised in this stage.

Step 4: Calculate the level of confidence.

The alpha-cut (〈-cut) concept is used with five levels of confidence to determine the fuzzy relative closeness of the candidates

Step 5: Defuzzification and rating the alternatives.

The relative closeness of each alternative will decide the ranking in which the best alternative with the highest relative closeness to the ideal solution.

3.1 Numerical Analysis

In this paper, study from [23] is reconsidered as numerical example. This study weighs up three candidates namely A_1, A_2, and A_3, with four decision makers namely DM_1, DM_2, DM_3, and DM_4. There are six subjective criteria considered: emotional steadiness (C_1), leadership (C_2), self-confidence (C_3), communication skill (C_4), personality (C_5), and past experience (C_6).

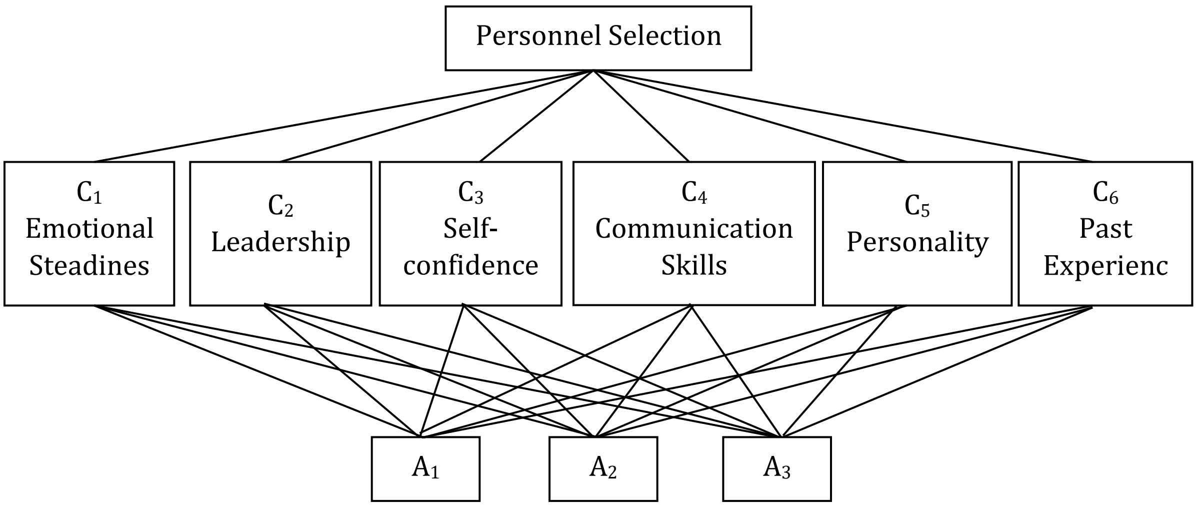

Figure 1: Hierarchical structure of the criteria and alternatives for personnel selection

Figure 1 shows hierarchical structure of the identified criteria and alternatives for personnel selection whereas, graph in Figure 2 depicts the relationships between the criteria and the decision-makers in term of the relative importance together with their respective aggregated fuzzy number

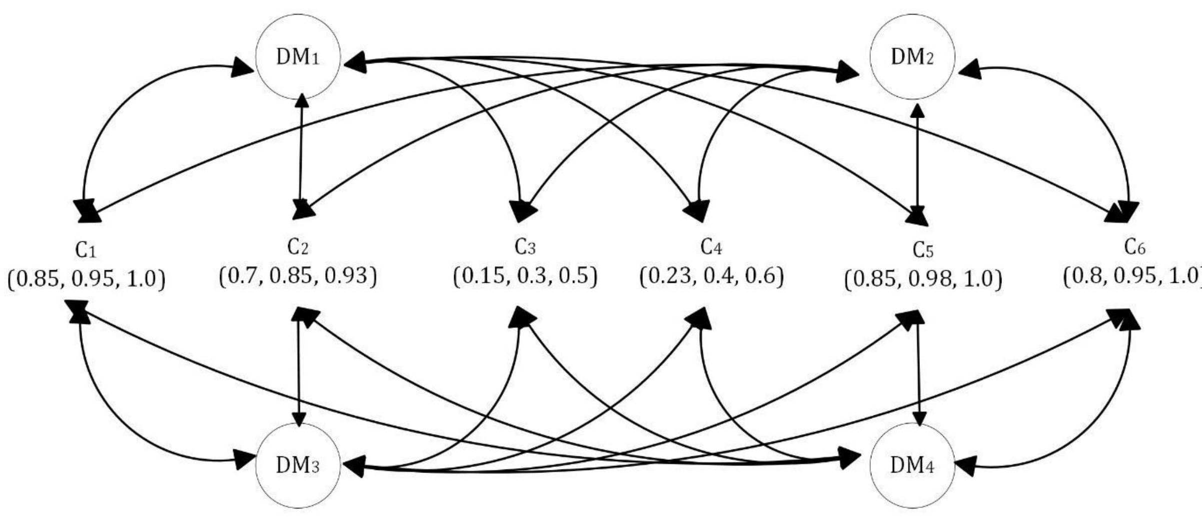

Figure 2: Relative importance and their aggregated fuzzy number by decision makers

Table 4 represents the rating of candidates by the decision makers according to the criteria. In the final column, the aggregated fuzzy number are provided.

Table 4: Ratings of the candidates

Criteria	Candidates	Decision makers				Aggregated fuzzy number
		DM_1	**DM_2**	**DM_3**	**DM_4**	
C_1	A_1	VG	G	F	F	(5.5,7.25,8.5)
	A_2	G	F	G	F	(5,7,8.5)
	A_3	G	VG	F	G	(6.5,8.25,9.25)
C_2	A_1	F	G	P	G	(4.25,6,7.5)
	A_2	F	VG	G	VG	(7,8.5,9.25)
	A_3	G	VG	F	G	(6.5,8.25,8.75)
C_3	A_1	F	G	F	F	(4,6,7.75)
	A_2	G	VG	F	G	(7.4,8.25,9.25)
	A_3	VG	G	G	G	(7.5,9.5,10)
C_4	A_1	G	VG	F	F	(5.5,7.25,8.5)
	A_2	F	G	F	F	(4,5,7.75)
	A_3	F	F	F	F	(3,5,7)
C_5	A_1	G	G	F	F	(5,7,8.5)
	A_2	F	F	G	F	(4,6,7.75)
	A_3	G	F	G	G	(6,8,9.25)
C_6	A_1	VG	VG	F	F	(6,7,5,8.5)
	A_2	G	VG	G	G	(7.5,9.25,10)
	A_3	G	G	VG	VG	(8,9.5,10)

Then, the normalised fuzzy decision matrix is calculated and shown in Table 5.

Table 5: Normalised fuzzy decision matrix

	C_1	**C_2**	**C_3**	**C_4**	**C_5**	**C_6**
A_1	(0.255,0.76,1.0)	(0,0.198,0.651)	(0.045,0.15,0.35)	(0.069,0.32,0.6)	(0.255,0.6203,1.0)	(0.24,0.6337,1.0)
A_2	(0.255,0.7287,1.0)	(0.21,0.68,0.93)	(0.045,0.24,0.5)	(0.069,0.2532,0.6)	(0.255,0.6203,1.0)	(0.56,0.9187,1.0)
A_3	(0.255,0.756,1.0)	(0.21,0.68,0.93)	(0.105,0.2799,0.5)	(0.069,0.2,0.42)	(0.255,0.7517,1.0)	(0.56,0.8864,1.0)

In the next step, the 〈-cut concept is used with five levels of confidence to determine the fuzzy relative closeness of the candidates. Also, the defuzzification is calculated based on the relative closeness and the rank is presented in Table 6.

Table 6: Fuzzy relative closeness

	Candidate		
α	**A_1**	**A_2**	**A_3**
0.1	[0.1955, 0.7545]	[0.2342,0.8283]	[0.2517,0.8701]
0.3	[0.2613, 0.6624]	[0.2568, 0.7931]	[0.2756, 0.8031]
0.5	[0.3053, 0.5964]	[0.3491, 0.6709]	[0.3712, 0.7211]

0.7	[0.3538,0.5367]	[0.3982, 0.5513]	[0.4109, 0.5832]
0.9	[0.4217, 0.4413]	[0.4604, 0.4762]	[0.4906, 0.4997]
Defuzzified value	0.4974	0.5401	0.5864
Rank	3	2	1

4 CONCLUSION

In this paper, the integration of graph theory with fuzzy TOPSIS equipped with 〈-level is discussed. The graph-theoretic method is used in the earlier stage of evaluation to clearly depict a logical and systematic framework in accessing the available criteria with the relative importance obtained from decision makers describes the inter relationship of the criteria. Furthermore, the five 〈-level of confidence are utilised in this study to ensure a higher accuracy and reliability. The final evaluation based on this proposed technique is intended to generate a more comprehensive, systematic, and reliable result.

Moreover, a numerical analysis is presented in this study to select the best personnel. The defuzzified values that are obtained after all the criteria has been considered by the decision makers are RC_1=0.4974, RC_2=0.5401, and RC_3=0.5864. This indicates that A_3 is clearly the best candidate with the highest relative closeness to the ideal solution, followed by A_2 and A_1. Also, the numerical example has shown that this technique defuzzified the imprecise value at the end of the process rather than at the beginning to justify the rationale of using fuzzy method.

Future research can improvise this proposed method by equipping it with the Z-number valuation concept or implementing a different decision-making method such as Fuzzy ELECTRE and Fuzzy Delphi to compare or promote the accuracy of the research.

ACKNOWLEDGEMENT

The authors would like to acknowledge the contributions of the reviewers for their help in improving the article.

REFERENCES

[1] D. Karabasevic, E. Kazimieras Zavadskas, D. Stanujkic, and M. Brzakovic, "An Approach to Personnel Selection in the IT Industry Based on the EDAS Method," *Transformations in Business & Economics*, vol. 17, no. 2, pp. 54–65, 2018.

[2] L. Canós and V. Liern, "Soft computing-based aggregation methods for human resource management," *Eur J Oper Res*, vol. 189, no. 3, pp. 669–681, 2008, doi: 10.1016/j.ejor.2006.01.054.

[3] G. S. Liang and M. J. J. Wang, "Personnel selection using fuzzy MCDM algorithm," *Eur J Oper Res*, vol. 78, no. 1, pp. 22–33, 1994, doi: 10.1016/0377-2217(94)90119-8.

[4] A. Jahan, K. L. Edwards, and M. Bahraminasab, *Multi-criteria Decision Analysis for Supporting the Selection of Engineering Materials in Product Design: Second Edition*. 2016. doi: 10.1016/C2014-0-03347-3.

[5] Y. C. Chuang, S. K. Hu, J. J. H. Liou, and G. H. Tzeng, "A data-driven madm model for personnel selection and improvement," *Technological and Economic Development of Economy*, vol. 26, no. 4, pp. 751–784, Jun. 2020, doi: 10.3846/tede.2020.12366.

[6] H. S. Kilic, A. E. Demirci, and D. Delen, "An integrated decision analysis methodology based on IF-DEMATEL and IF-ELECTRE for personnel selection," *Decis Support Syst*, vol. 137, no. November 2019, p. 113360, 2020, doi: 10.1016/j.dss.2020.113360.

[7] C. T. Chen and W. Z. Hung, "A two-phase model for personnel selection based on multi-type fuzzy information," *Mathematics*, vol. 8, no. 10, pp. 1–20, 2020, doi: 10.3390/math8101703.

[8] K. Petridis, G. Drogalas, and E. Zografidou, "Internal auditor selection using a TOPSIS/non-linear programming model," *Ann Oper Res*, vol. 296, no. 1–2, pp. 513–539, 2021, doi: 10.1007/s10479-019-03307-x.

[9] I. Dzitac, "The fuzzification of classical structures: A general view," *International Journal of Computers, Communications and Control*, vol. 10, no. 6, pp. 772–788, 2015, doi: 10.15837/ijccc.2015.6.2069.

[10] X. Sang, X. Liu, and J. Qin, "An analytical solution to fuzzy TOPSIS and its application in personnel selection for knowledge-intensive enterprise," *Applied Soft Computing Journal*, vol. 30, pp. 190–204, 2015, doi: 10.1016/j.asoc.2015.01.002.

[11] C.-L. Hwang and K. Yoon, *Multiple attribute decision making: Methods and applications*, vol. 1. Berlin, Heidelberg: Springer, 1981.

[12] C. N. Wang, T. T. Dang, H. Tibo, and D. H. Duong, "Assessing renewable energy production capabilities using DEA window and fuzzy topsis model," *Symmetry (Basel)*, vol. 13, no. 2, pp. 1–21, 2021, doi: 10.3390/sym13020334.

[13] M. Jasiulewicz-Kaczmarek *et al.*, "Application of micmac, fuzzy ahp, and fuzzy topsis for evaluation of the maintenance factors affecting sustainable manufacturing," *Energies (Basel)*, vol. 14, no. 5, 2021, doi: 10.3390/en14051436.

[14] N. Deo, "GRAPH THEORY WITH APPLICATIONS TO ENGINEERING AND COMPUTER SCIENCE," *Networks*, vol. 5, no. 3, 1975, doi: 10.1002/net.1975.5.3.299.

[15] U. Mumtaz, Y. Ali, A. Petrillo, and F. De Felice, "Identifying the critical factors of green supply chain management: Environmental benefits in Pakistan," *Science of the Total Environment*, vol. 640–641, pp. 144–152, 2018, doi: 10.1016/j.scitotenv.2018.05.231.

[16] D. Prajapati, S. Agarwal, and Q. Murtaza, "Impact of COVID-19 on Sustainability Enablers and Evaluation of Performance Index," *Mater Today Proc*, vol. 56, pp. 3790–3796, 2022, doi: 10.1016/j.matpr.2022.01.137.

[17] M. N. Qureshi, P. Kumar, and D. Kumar, "Selection of 3PL service providers: a combined approach of AHP and Graph theory," *International Journal of Services, Technology and Management*, vol. 12, no. 1, pp. 35–60, 2009, doi: 10.1504/IJSTM.2009.025035.

[18] H. Safari, A. Faghih, and M. R. Fathi, "Integration of graph theory and matrix approach with fuzzy AHP for equipment selection," *Journal of Industrial Engineering and Management*, vol. 6, no. 2, pp. 477–494, 2013, doi: 10.3926/jiem.403.

[19] W. D. Wallis, "Graph Theory with Applications (J. A. Bondy and U. S. R. Murty)," *SIAM Review*, vol. 21, no. 3, 1979, doi: 10.1137/1021086.

[20] G. Bohlender, A. Kaufmann, and M. M. Gupta, "Introduction to Fuzzy Arithmetic, Theory and Applications," *Math Comput*, vol. 47, no. 176, 1986, doi: 10.2307/2008199.

[21] Y. M. Wang and T. M. S. Elhag, "Fuzzy TOPSIS method based on alpha level sets with an application to bridge risk assessment," *Expert Syst Appl*, vol. 31, no. 2, pp. 309–319, 2006, doi: 10.1016/j.eswa.2005.09.040.

[22] M. Oussalah, "On the compatibility between defuzzification and fuzzy arithmetic operations," *Fuzzy Sets Syst*, vol. 128, no. 2, pp. 247–260, 2002, doi: 10.1016/S0165-0114(01)00125-7.

[23] M. Dursun and E. E. Karsak, "A fuzzy MCDM approach for personnel selection," *Expert Syst Appl*, vol. 37, no. 6, pp. 4324–4330, 2010, doi: 10.1016/j.eswa.2009.11.067.