Comparative analysis of fuzzy multi-criteria decision-making methods for quality of service-based web service selection

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ABSTRACT

This research aims to compare and analyze the effectiveness of four popular fuzzy multi-criteria decision-making methods (FMCDMMs) for quality of service (QoS)-based web service selection. These methods are fuzzy DEMATEL (FD), fuzzy TOPSIS (FT), fuzzy VIKOR (FV), and fuzzy PROMETHEE (FP), including three ranking versions of FV. We assess the ranking similarities among these methods using Spearman's relationship figure. We describe the algorithms of these six FMCDMs in the methods section. In a case study, we collected primary data from five experts who rated nine QoS factors of nine web services. We used modified online software for analysis. The results showed that S6 ranked first in all FMCDMs, except for FD and FP, where it was ranked 2nd and 8th, respectively. The highest association coefficient (Rs) was found between FT and FV ranking in S techniques (0.983), FV ranking in S and FV ranking in Q (0.883), and FT and FV ranking Q (0.833) when comparing the similarity measure of the FMCDMMs. This analysis helps decision-makers and researchers choose the most suitable methods for integrated FMCDMs studies and real-world problem-solving.

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1. INTRODUCTION

The choice of high-quality online services is essential for businesses to succeed in the modern digital era and obtain a competitive advantage. With the variety of available web services, it becomes increasingly tough to identify the most appropriate ones that fulfill the needed quality of service (QoS) standar. Comparative analysis of decision-making techniques like fuzzy decision-making trial and evaluation laboratory (DEMATEL), fuzzy technique for order of preference by similarities to ideal solution (TOPSIS), fuzzy vlsekriterijumska optimizacija i kompromisno resenje (VIKOR), and fuzzy preference ranking organization method for enrichment evaluation (PROMETHEE) can be a useful strategy in this situation for choosing the best online services that adhere to the necessary QoS criteria. A web service is any service that is available through the internet, uses a standardized extensible markup language (XML) communications system, and is not limited to a particular operating system or programming language [1], [2]. Web service selection research

is now quite common [3]. The popularity of services and the uniformity of their functions result in nonfunctional attributes that are comparable [4]. The features and quality of the candidate service are the two criteria for web service selection. Input, output, preconditions, and effects (IOPE) are the candidate service features and are referred to as functional requirements or web service attributes. The quality of a potential online service, often known as QoS, relates to non-functional needs or features [5].

It is critical that web service selection research address both functional and non-functional criteria. A web service user's functional requirement is insufficient; web service users want rapid, dependable, available, and standard services (i.e., quality factors). Web service consumers, for example, will not hesitate to reject a service even if it satisfies all expected functional criteria but fails to offer the requisite quality results (non-functional requirements). There is an efficient and equitable obligation to ensuring that the functional and non-functional web service requirements satisfy both the service provider and the service client. Non-functional requirements, in particular, because web service ranking and selection are dependent on QoS variables.

Petrović *et al.* [6] examined the suitability of fuzzy analytical hierarchy process (AHP), fuzzy TOPSIS (FT) and fuzzy VIKOR (FV) methods in the context of supplier selection, which was a complex decision-making problem with multiple criteria and alternatives. The paper provided a comprehensive review of the existing literature on the topic and presented a case study to illustrate the practical application of the methods. The results of the study indicated that all three methods could be used effectively for supplier selection, but each method had its advantages and disadvantages. The paper concluded that the choice of method depended on the decision-maker's preferences and the characteristics of the decision problem.

Suartini *et al.* [7] provided a comparative study of AHP-simple additive weighting (SAW), AHP-weighted product (WP), AHP-TOPSIS on a private tutor selection. They study aimed to identify the most effective and efficient method to select a private tutor based on the decision-makers' criteria and preferences. The paper highlighted the importance of the private tutor selection process and the need for a reliable and objective decision-making method. It analyzed the key features, assumptions, and steps involved in each method and compared their performance based on different evaluation criteria such as accuracy, consistency, and sensitivity. Bhaskar and Khan [8] aimed to demonstrate the capability of five distinct hybrid multi criteria decision making (HMCDM) methods in identifying the best polymer-based biomaterial used in dentistry. Initially, the weights of the identified criteria were determined using the AHP, followed by the use of AHP-VIKOR, AHP-TOPSIS, AHP-multi-objective optimization based on ratio analysis (MOORA), AHP-elimination et choix traduisant la realitè (ELECTRE), and AHP-PROMTHEE methods to rank the materials. Bhaskar and Khan [8] found that the comparison of the methods indicated that AHP-VIKOR, AHP-TOPSIS, and AHP-PROMETHEE exhibit a stronger correlation than AHP-MOORA and AHP-ELECTRE.

Kizielewicz and Baczkiewicz [9] compared the performance of four fuzzy multi-criteria decision-making methods (FMCDMM), namely FT, FV, fuzzy weighted aggregated sum product assessment (FWASPAS), and fuzzy MMOORA (FM), in the context of a housing selection problem. The study utilized a comprehensive set of criteria related to different aspects of housing selection, such as location, price, and facilities, and analyzed the ranking results obtained from each method. In Table 1, very few studies only 3 studies compared fuzzy multi-criteria decision methods. Only one study compared multi-criteria decision making (MCDMs) applied on web service selection problem. Bagga *et al.* [10] which addressed the web service selection problem did not deplore fuzzy systems with the MCDMs. VIKOR and FV have been used in varies applications areas as showed in the Table 1. However, to the best knowledge of the authors, no study has explored the three versions of the FV in a comparative analysis before. The motivation for this problem is to provide a comprehensive analysis of multiple FMCDM methods for QoS-based web service selection. This is important because QoS-based web service selection is a complex decision-making problem with multiple criteria and alternatives. Therefore, having a reliable and objective decision-making method is crucial for selecting the most suitable web service.

The comparison and evaluation of different methods will help decision-makers to select the most appropriate method for their specific problem and improve the overall efficiency and effectiveness of the web service selection process. The main objective of this research is to compare and evaluate the performance of six different FMCDM methods–fuzzy DEMATEL (FD), FT, FV version R, FV version S, FV version Q, and fuzzy PROMETHEE (FP)-for selecting web services based on quality-of-service factors for real world applications. The salient contributions of this study are: providing a comparative analysis of now six popular FMCDMMs for QoS-based web service selection, which helps researchers and practitioners to choose the greatest appropriate technique for their specific problem. Evaluating the performance of the four methods based on different criteria such as response time, availability, security among others, which provides insights into selecting the ideal web service. Presenting a comprehensive review of the existing literature on QoS based web service selection using fuzzy MCDMs, which helps to identify the research gaps and future research directions in this field. Conducting a case study to illustrate the practical application of the methods, which helps to validate the effectiveness and usefulness of the methods in real-world scenarios. To establish their linkages, the current study provides a spearman's correlation coefficient of the presently six FMCDMMs.

The paper is organized as follows: section 2 handles fuzzy set (FS) theory cum multi-criteria decision-making approaches applied; section 3 presents the similarity co-efficient rankings; section 4 presents an experimental case analysis on the web service selection problem; section 5 provides an alternative ranking the factors examined comparatively. The final portion discusses the findings and potential research directions.

Table 1. Comparative table of key literature

Author	Year	Applied on	Techniques compared	Similarity measure performed
[6]	2019	Supplier selection	Fuzzy analytic hierarchy process (FAHP), FT, and FV	No
[9]	2021	House selection problem	FT, FV, FWASPAS, and fuzzy measure (FM)	Yes
[8]	2022	Dentistry biomaterial selection	AHP, followed by the use of AHP-VIKOR, AHP-TOPSIS, AHP-MOORA, AHP-ELECTRE, and AHP-PROMTHEE	Yes
[11]	2022	Supplier selection	TOPSIS, VIKOR, COMET, SPOTIS, and MARCOS	Yes
[7]	2023	Private tutor selection	AHP-SAW, AHP-WP, and AHP-TOPSIS	No
[10]	2019	Web service selection	SAW, AHP, TOPSIS VIKOR, and COPRAS	Yes
[12]	2023	Cloud service provider selection	Hesitant intuitionistic FD-TOPSIS model	No
[13]	2021	Cloud environment	AHP, PROMETHEE, TOPSIS, and VIKOR	No
[14]	2022	Clean energy evaluation	SAW, TOPSIS, ELECTRE, VIKOR and COPRAS	No
[15]	2020	Web applications security design assessment	Fuzzy AHP and FT	No

2. MATERIAL AND METHODS

2.1. Fuzzy set theory

- Definition 1: denote $\widetilde{A}$ a plotting from area X to [0,1], that is: $\widetilde{A}: X \rightarrow [0,1]$, $x \mapsto \widetilde{A}(x)$ where $\widetilde{A}$ is named FS on X, and $\widetilde{A}(x)$ is christened The FS membership function (MP) $\widetilde{A}$.
- Definition 2: triangular fuzzy number (TFN). A TFN is articulated as a triplet (e, f, g). The involvement of $\widetilde{A}(x)$ of a TFN is defined as (1).

$$\widetilde{A}(x) = \begin{cases} 0 & x < e, x > f \\ \frac{x-e}{f-e}, & e \leq x \leq f \\ \frac{g-x}{g-f}, & f \leq x \leq g \end{cases} \tag{1}$$

2.2. Fuzzy decision-making trial and evaluation laboratory

Recently, Khatun *et al.* [16] employed DEMATEL and FD techniques to assess the interplay between safety management systems and cybersecurity. See in (2)-(17) for the algorithms used in this study.

- Step 1: direct-influence matrix cum fuzzy created.

$$Z = \begin{matrix} & C_1 & C_2 & C_3 \dots C_n \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{matrix} \begin{bmatrix} \tilde{\alpha}_1^1 & \tilde{\alpha}_1^2 & \tilde{\alpha}_1^3 & \dots & \tilde{\alpha}_1^n \\ \tilde{\alpha}_2^1 & \tilde{\alpha}_2^2 & \tilde{\alpha}_2^3 & \dots & \tilde{\alpha}_2^n \\ \tilde{\alpha}_3^1 & \tilde{\alpha}_3^2 & \tilde{\alpha}_3^3 & \dots & \tilde{\alpha}_3^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{\alpha}_m^1 & \tilde{\alpha}_m^2 & \tilde{\alpha}_m^3 & \dots & \tilde{\alpha}_m^n \end{bmatrix}, i = 1,2,\dots,m; j = 1,2,\dots,n \tag{2}$$

- Step 2: the direct-influence matrix cum fuzzy normalized.

$$\tilde{x}_{ij} = \frac{\tilde{z}_{ij}}{r} = \left(\frac{l_{ij}}{r}, \frac{m_{ij}}{r}, \frac{u_{ij}}{r} \right) \tag{3}$$

Wherever

$$r = \max_{i,j} \left\{ \max_i \sum_{j=1}^n u_{ij}, \max_j \sum_{i=1}^n u_{ij} \right\} \ i,j \in \{1,2,3,\dots,n\} \tag{4}$$

- Step 3: compute the fuzzy total-influence matrix (FTIM)
Using the (5), the FTIM could be calculated in three stages.

$$\tilde{T} = \lim_{k \to +\infty} (\tilde{x}^1 \oplus \tilde{x}^2 \oplus \dots \oplus \tilde{x}^k) \tag{5}$$

If each member of FTIM is written as: $\tilde{t}_{ij} = (l''_{ij}, m''_{ij}, u''_{ij})$, the calculation is possible to compute as follows.

$$[l''_{ij}] = x_l \times (I - x_l)^{-1} \tag{6}$$

$$\left[m''_{ij}\right] = x_m \times (I - x_m)^{-1} \tag{7}$$

$$[u''_{ij}] = x_u \times (I - x_u)^{-1} \tag{8}$$

- Step 4: crisp values obtained via defuzzification. CFCS technique was proposed by Opricovic and Tzeng for getting total-influence matrix figures with the steps in (9-15).

$$l^n_{ij} = \frac{(l^t_{ij} - \min l^t_{ij})}{\Delta^{max}_{min}} \tag{9}$$

$$m^n_{ij} = \frac{(m^t_{ij} - \min l^t_{ij})}{\Delta^{max}_{min}} \tag{10}$$

$$u^n_{ij} = \frac{(u^t_{ij} - \min l^t_{ij})}{\Delta^{max}_{min}} \tag{11}$$

So that,

$$\Delta^{max}_{min} = \max - \min l^t_{ij} \tag{12}$$

The top and lower boundaries of normalized values are calculated as (13) and (14).

$$l^s_{ij} = m^n_{ij} \big/ (1 + m^n_{ij} - l^n_{ij}) \tag{13}$$

$$u^s_{ij} = u^n_{ij} \big/ (1 + u^n_{ij} - l^n_{ij}) \tag{14}$$

Crisp values are produced using the CFCS algorithm. Total normalized crisp values are calculated as (15).

$$x_{ij} = \frac{\left[l^s_{ij}\left(1 - l^s_{ij}\right) + u^s_{ij} \times u^s_{ij}\right]}{\left[1 - l^s_{ij} + u^s_{ij}\right]} \tag{15}$$

- Step 5: establish the benchmark value: benchark value is 0.2280
- Step 6: causal-effect diagram cum final result created: the following step is to compute the sum of each row and column of T (in step 4). The total of the rows (D) and columns (R) is as (16) and (17).

$$D = \sum_{j=1}^{n} T_{ij} \tag{16}$$

$$R = \sum_{i=1}^{n} T_{ij} \tag{17}$$

Then, D and R may be used to derive the values of D+R and D-R, where D+R characterizes the degree of significance of factor I in the overall system and D-R signifies the net impacts that factor I brings to the system.

2.3. Fuzzy technique for order preference by similarity to ideal solution

The FT approach is a strategy for choosing a solution that is distant from the fuzzy negative ideal solution (FNIS) yet close to the fuzzy positive ideal solution (FPIS). A FPIS shows the best performance values for each choice, whereas a FNIS shows the worst performance values [17]. To rank options, the FT technique is employed. Recently, many researchers [18], [19] used FT to rank alternatives in various application areas such as IT risk analysis, stealth fighter aircraft selection. The FT algorithms is given in (18)-(27).

- Step 1: create a decision matrix.

$$
Z = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array}
\begin{array}{cccccc}
C_1 & C_2 & C_3 & \dots C_n & \\
\left[\begin{array}{ccccc}
\tilde{\alpha}_1^1 & \tilde{\alpha}_1^2 & \tilde{\alpha}_1^3 & \dots & \tilde{\alpha}_1^n \\
\tilde{\alpha}_2^1 & \tilde{\alpha}_2^2 & \tilde{\alpha}_2^3 & \dots & \tilde{\alpha}_2^n \\
\tilde{\alpha}_3^1 & \tilde{\alpha}_3^2 & \tilde{\alpha}_3^3 & \dots & \tilde{\alpha}_3^n \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\tilde{\alpha}_m^1 & \tilde{\alpha}_m^2 & \tilde{\alpha}_m^3 & \dots & \tilde{\alpha}_m^n
\end{array}\right]
\end{array}, i = 1,2,\dots,m; j = 1,2,\dots,n \tag{18}
$$

- Step 2: construct the normalized choice matrix. A normalized decision matrix may be created using the following relation based on the positive and negative ideal solutions:

$$
\tilde{r}_{ij} = \left(\frac{a_{ij}}{c_j^*}, \frac{b_{ij}}{c_j^*}, \frac{c_{ij}}{c_j^*}\right); c_j^* = max_i\, c_{ij}; \text{PIS} \tag{19}
$$

$$
\tilde{r}_{ij} = \left(\frac{a_j^-}{c_{ij}}, \frac{a_j^-}{b_{ij}}, \frac{a_j^-}{a_{ij}}\right); a_j^- = min_i\, a_{ij}; \text{NIS} \tag{20}
$$

- Step 3: produce the weighted standardized choice matrix.

$$
\tilde{v}_{ij} = \tilde{r}_{ij}.\widetilde{w}_{ij}) \tag{21}
$$

where $\widetilde{w}_{ij}$ exemplifies weight of criterion c_j.
- Step 4: regulate the FPIS, A* and $FNIS, A^-$. The FPIS and FNIS of the alternatives can be defined as (22) and (23).

$$
A^* = \{\tilde{v}_1^*, \tilde{v}_2^*, \dots, \tilde{v}_n^*\} = \left\{\left(\max_j v_{ij}\, |i \in B\right), \left(\min_j v_{ij}\, |i \in C\right)\right\} \tag{22}
$$

$$
A^- = \{\tilde{v}_1^-, \tilde{v}_2^-, \dots, \tilde{v}_n^-\} = \left\{\left(\min_j v_{ij}\, |i \in B\right), \left(\max_j v_{ij}\, |i \in C\right)\right\} \tag{23}
$$

- Step 5: determine the distance between each alternative and the FPIS, A*, as well as the distance between each alternative and the FNIS.

$$
S_i^* = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^*)\, i = 1,2,\dots m \tag{24}
$$

$$
S_i^- = \sum_{j=1}^n d(\tilde{v}_{ij}, \tilde{v}_j^-) i = 1,2,\dots m \tag{25}
$$

d is the remoteness amid two fuzzy numbers, when given two TFN (a_1, b_1, c_1) and (a_2, b_2, c_2), the distance between the two can be calculated as (26):

$$
d_v(\widetilde{M}_1, \widetilde{M}_2) = \sqrt{\frac{1}{3}[(a_1 - a_2)^2 + (b_1 - b_2)^2 + (c_1 - c_2)^2]} \tag{26}
$$

Note that $d(\tilde{v}_{ij}, \tilde{v}_j^*)$ and $d(\tilde{v}_{ij}, \tilde{v}_j^-)$ are crisp numbers.
- Step 6: closeness coefficient cum alternative rank computed. The intimacy coefficient of each alternative can be calculated as (27).

$$
CC_i = \frac{s_i^-}{s_i^+ + s_i^-} \tag{27}
$$

The optimal option is closest to the FPIS and farthest away from the FNIS. The ranking order and the closeness coefficient of each alternative.

2.4. Fuzzy vlsekriterijumska optimizacija i kompromisno resenje

Recently, many existing literature [20], [21] have applied FV in siting electric vehicle charging station, evaluation of influenza strategies, selecting marine type air compressor, assessing energy concentration, and evaluating satisfaction level of people. FV is compared to various FMCDMMs in this study to rank a QoS-based online service selection dilemma. See steps in (28)-(39).

- Step 1: create a decision matrix.

$$Z = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \begin{array}{cccccc} C_1 & C_2 & C_3 \dots C_n \\ \left[\begin{array}{ccccc} \tilde{\alpha}_1^1 & \tilde{\alpha}_1^2 & \tilde{\alpha}_1^3 & \dots & \tilde{\alpha}_1^n \\ \tilde{\alpha}_2^1 & \tilde{\alpha}_2^2 & \tilde{\alpha}_2^3 & \dots & \tilde{\alpha}_2^n \\ \tilde{\alpha}_3^1 & \tilde{\alpha}_3^2 & \tilde{\alpha}_3^3 & \dots & \tilde{\alpha}_3^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{\alpha}_m^1 & \tilde{\alpha}_m^2 & \tilde{\alpha}_m^3 & \dots & \tilde{\alpha}_m^n \end{array} \right] \end{array}, i = 1,2,\dots,m; j = 1,2,\dots,n \tag{28}$$

- Step 2: PIS and NIS defined. Following the steps in (29)-(32) the PIS and NIS can be attained. The PIS$(\widetilde{f^*})$ is calculated as (33) when the criterion is positive.

$$\tilde{f}_j^* = \underset{i}{Max}\, \tilde{f}_{ij} \quad i = 1,2,\dots,n \tag{29}$$

The NIS $(\widetilde{f^\circ})$ is computed as in (30) when the criterion is positive.

$$\tilde{f}_j^\circ = \underset{i}{Min}\, \tilde{f}_{ij} \quad i = 1,2,\dots\dots,n \tag{30}$$

The PIS$(\widetilde{f^*})$ is computed as in (31) when the criterion is negative.

$$\tilde{f}_j^* = \underset{i}{Min}\, \tilde{f}_{ij} \quad i = 1,2,\dots\dots,n \tag{31}$$

The NIS$(\widetilde{f^*})$ is computed as in (32) when the criterion is negative.

$$\tilde{f}_j^\circ = \underset{i}{Max}\, \tilde{f}_{ij} \quad i = 1,2,\dots\dots,n \tag{32}$$

- Step 3: create a normalized choice matrix. Following the PIS and NIS, a normalized choice matrix could be computed as (33) and (34).

$$\tilde{d}_{ij} = \frac{\tilde{f}_j^* \ominus \tilde{f}_{ij}}{r_j^* - l_j^\circ} \quad PIS \tag{33}$$

$$\tilde{d}_{ij} = \frac{\tilde{f}_{ij} \ominus \tilde{f}_j^*}{r_j^\circ - l_j^*} \quad NIS \tag{34}$$

Where:

$$\tilde{f}_j^* = (l_j^*, m_j^*, r_j^*)$$

$$\tilde{f}_j^\circ = (l_j^\circ, m_j^\circ, r_j^\circ)$$

- Step 4: compute the values $\tilde{S}_i$ and $\tilde{R}_i$.

If $\tilde{R}_i = (R_i^l, R_i^m, R_i^r)$ and $\tilde{s}_i = (s_i^l, s_i^m, s_i^r)$

$$\tilde{S}_i = \sum_{j=1}^J \left(\tilde{w}_j \otimes \tilde{d}_{ij} \right) \tag{35}$$

$$\tilde{R}_i = \underset{j}{max}\left(\tilde{w}_j \otimes \tilde{d}_{ij} \right) \tag{36}$$

- Step 5: the FV index(Q) is computed. Q's value may be computed as (38).

$$\text{If } \tilde{Q}_i = (Q_i^l, Q_i^m, Q_i^r)$$

$$\tilde{Q}_i = v \frac{(\tilde{s}_i \ominus \tilde{s}^*)}{s^{\circ r} - s^{*l}} \oplus (1 - v) \frac{(\tilde{R}_i \ominus \tilde{R}^*)}{R^{\circ r} - R^{*l}} \tag{37}$$

Where
$$\tilde{s}^* = \min_i \tilde{s}_i$$
$$s^{\circ r} = \max_i s_i^r$$
$$\tilde{R}^* = \min_i \tilde{R}_i$$
$$R^{\circ r} = \max_i R_i^r$$

$$Crisp(\tilde{A}) = \frac{2m + l + r}{4} \tag{38}$$

2.5. Fuzzy preference ranking organization method for enrichment evaluation

The FP method have been used recently for transport mode analysis [22], ranking startups [23], and for ensemble feature selection [24]. See the steps in (40)-(49) for the FP application in the present comparative study.

- Step 1: create a decision matrix.

$$Z = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \vdots \\ A_m \end{array} \overset{\displaystyle C_1 \quad C_2 \quad C_3 \ldots . C_n}{\begin{bmatrix} \tilde{\alpha}_1^1 & \tilde{\alpha}_1^2 & \tilde{\alpha}_1^3 & \cdots & \tilde{\alpha}_1^n \\ \tilde{\alpha}_2^1 & \tilde{\alpha}_2^2 & \tilde{\alpha}_2^3 & \cdots & \tilde{\alpha}_2^n \\ \tilde{\alpha}_3^1 & \tilde{\alpha}_3^2 & \tilde{\alpha}_3^3 & \cdots & \tilde{\alpha}_3^n \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ \tilde{\alpha}_m^1 & \tilde{\alpha}_m^2 & \tilde{\alpha}_m^3 & \cdots & \tilde{\alpha}_m^n \end{bmatrix}}, i = 1,2,\ldots,m; j = 1,2,\ldots,n \tag{39}$$

- Step 2: aggregations of decisions. This stage combines the fuzzy weights of the criteria with the ratings of the alternatives. This is accomplished by using the interval valued approach, as shown in (41) and (42).

$$\widetilde{w}_j = \frac{1}{n} [\widetilde{w}_j^1 + \widetilde{w}_j^2 + \cdots \ldots \ldots \ldots \ldots \widetilde{w}_j^n] \tag{40}$$

$$\tilde{x}_{ij} = \frac{1}{n} [\widetilde{X}_{ij}^1 + \widetilde{X}_{ij}^2 + \cdots \ldots \ldots \ldots \ldots \widetilde{X}_{ij}^n] \tag{41}$$

- Step 3: the choice matrix has been normalized. In this phase, the combined fuzzy decision matrix produced in step 2 is standardized. In (42) defines the standardized fuzzy choice matrix, which may be obtained using (43). The outcome of the normalized matrix is still a TFN.

$$\tilde{S} = [\tilde{S}_{ij}] \text{mxn } i = 1,2,3,\ldots,m; \; j = 1,2,3,\ldots\ldots,n \tag{42}$$

$$\tilde{S}_{ij} = \left(\frac{\tilde{r}_{ij}}{v_j^+}, \frac{\tilde{u}_{ij}}{v_j^+}, \frac{\tilde{v}_{ij}}{v_j^+}\right) v_j^+ = \max_i v_{ij} \tag{43}$$

- Step 4: building of the fuzzy favorite function.

$$\tilde{P}_j(m,n) \text{ is}$$

$$\tilde{P}_j(m,n) = \begin{cases} 0, & \tilde{S}_{mj} \leq \tilde{s}_{nj} \\ 1 & \tilde{S}_{mj} > \tilde{s}_{nj} \end{cases} j = 1,2,3,\ldots\ldots,k \tag{44}$$

- Step 5: determine the weighted aggregated preference function.

$$\tilde{\pi}(m,l) = \sum_{j=1}^{i} \tilde{P}_j(m,n)\tilde{w}_j \tag{45}$$

- Step 6: calculate the outgoing, incoming, and net flows.

$$\text{Leaving flows: } \tilde{\phi}^+(m) = \frac{1}{n-1}\sum_{m\neq 1}\tilde{\pi}(m,l), \forall m,l \in A, \tag{46}$$

$$\text{Entering flows: } \tilde{\phi}^-(m) = \frac{1}{n-1}\sum_{m\neq 1}\tilde{\pi}(l,m), \forall m,l \in A, \tag{47}$$

The number of options is presented by n.
- Step 7: inaugurating position. this stage uses PROMETHEE II to rank based on net flow, as illustrated in (48).

$$\tilde{\phi} = \tilde{\phi}^+(m) - \tilde{\phi}^-(m), \forall m,l \in A, \tag{48}$$

3. SIMILARITY MEASURE

According to Kizielewicz and Baczkiewicz [9] the resemblance rank number is a coefficient based on the method in which the highest spots in the rankings have a substantial similarity influence. The Spearman's rank correlation coefficient approach aids in determining the similarity of two sets of rankings derived by two separate FMCDMM. In (49) is represents its formal form. Spearman's association figure (Rs).

$$\frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \tag{49}$$

Wherever n is the number of web services and di is the difference in rank between two FMCDM techniques. A higher absolute value shows strong agreement between one MCDM approach and another.

4. DATA SOURCE FOR THE EXPERIMENTAL CASE

This article addresses the subject of online service ranking decision making. The data was gathered using the ratings of five experts based on a linguistic term scale [25] given in Table 2. There were nine criteria (QoS factors) discovered, with min and max types related to cost and profit. Response time, and latency are the cost QoS factors that require minimization. Availability, throughput, success ability, reliability, compliance, best practices, and documentation are the profit/benefit QoS factors that require maximization/optimization. Table 3 provides a snapshot of the expert's qualifications, experience, job titles, and ages. This information is important for understanding the background and expertise of the experts involved in the study, which can influence the reliability and credibility of the data they provided.

Table 2. Code, linguistic terms, and triangular numbers

Code	Linguistic terms	L	M	U
1	NI	0	0	0.25
2	VLI	0	0.25	0.5
3	LI	0.25	0.5	0.75
4	HI	0.5	0.75	1
5	VHI	0.75	1	1

Table 3. Experts, qualification, experience, job title, and age

Experts	Qualification	Experience	Job title	Age
EXPERT1	Ph.D. computer science	17	Professor of service-oriented computing	63
EXPERT2	Ph.D. information technology	15	Senior lecturer	45
EXPERT3	Ph.D. information systems	20	Professor	43
EXPERT4	MB.A. management information systems	25	Director technology services	58
EXPERT5	M.Sc. computer science	12	Senior IT administrator (service computing)	48

4.1. Determining the weights of quality of service factors

By utilizing the linguistic scale presented in Table 2 and the FD algorithms described in the methodology section of this paper, the weights of the 9 QoS factors were calculated. Following this, the FD, FT, FV ranking S, FV ranking Q, FV ranking R, and FP techniques utilized the experts' rating data along with their own algorithms to generate the ranking and similarity measure results, as detailed in the methodology section of this paper.

5.　RESULTS AND DISCUSSION

Table 4 compares the rankings of nine choices investigated using the now-six FMCDM techniques. Alternative S6 ranked first in the FV ranking R, FV ranking S, and FV ranking Q procedures. However, using the FD and FP approaches, this alternative was ranked second (2nd) and eighth (8th), respectively. Alternative S7, which ranked first using the FP method, was placed eighth in the FT, FV ranking S, and FV ranking Q rankings. The given alternative was ranked seventh and second in the FD and FV ranking R rankings, respectively. Alternative S2 was ranked first in the FD method. Both FV ranking R and FV ranking Q rated the discussion alternative sixth. FP ranked alternative S1 second, whereas the other FMCDM approaches placed it eighth and ninth. None of the prepared ranks had total consistency for any option. However, alternative S6 had the maximum conformance of 4 out of 6 (i.e., S6 (position 1)). Alternatives S1 and S4 recorded the second-highest conformity with 3 out of 6. Surprisingly, all nine alternatives had at least two out of six conformities. The FD and FT methodology, the FD and FV ranking S method, and the FD and FV ranking Q method provide fundamentally different results. The results of the FD technique were the oddest. Figure 1 shows the positions of all evaluated alternatives in the rankings obtained with the now six MCDM approaches engaged in this study using a column chart. The given graph shows that for six of the nine options studied (S2, S3, S4, S5, S6, S7), FD is the strategy that produces the most outlier findings.

Table 4. FMCDMMs rankings

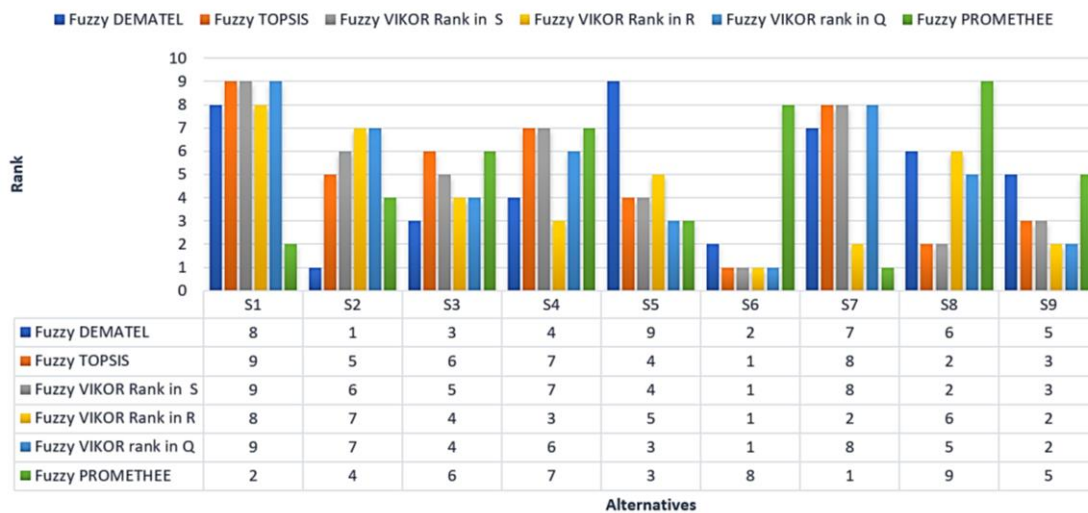| Alternatives	FD	FT	FV ranking R	FV ranking S	FV ranking Q	FP
S1	8	9	8	9	9	2
S2	1	5	7	6	7	4
S3	3	6	4	5	4	6
S4	4	7	3	7	6	7
S5	9	4	5	4	3	3
S6	2	1	1	1	1	8
S7	7	8	2	8	8	1
S8	6	2	6	2	5	9
S9	5	3	2	3	2	5

Figure 1. FD, FT, FV ranking S, FV ranking R, FV ranking Q, and FP comparisons

Figure 2 displays the rankings generated by six FMCDM methods: FD, FT, FV ranking S, FV ranking in R, FV ranking Q, and FP. The analysis of the rankings presented in the graphs indicates that there is a significant similarity between the rankings obtained by FT and FV ranking S methods, with seven options having identical ranks. Moreover, two options with the same positions were observed when comparing the rankings generated using FV ranking S and FV ranking R methods, FT and FV ranking Q methods, FT and FP methods, FV ranking Q and FT methods, and FV R Q and FV ranking S methods. When comparing the FT and FV ranking Q techniques and the FV ranking Q and FV ranking R methods, three options with the same positions were identified. The remaining FMCDMMs compared had either one option or no similarities.
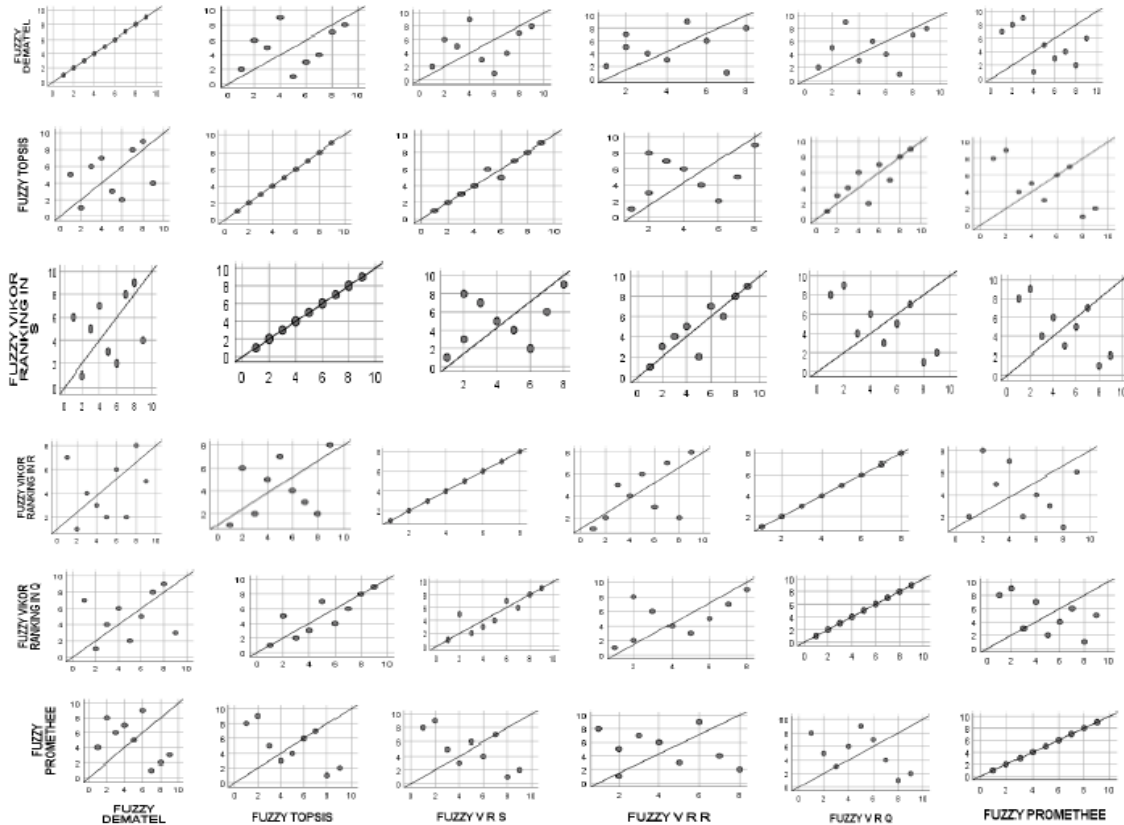
Figure 2. The now six comparatives FMCDMMs used in this study

Table 5 presents a comparison of the rankings produced by the six FMCDM techniques, along with their corresponding Spearman's correlation coefficient (Rs) values. The highest correlation was observed between the ranks generated by FT and FV ranking in S techniques (0.983), FV ranking in S and FV ranking in Q (0.883), and FT and FV ranking Q (0.833). However, weaker correlations were found between the FV ranking S and FP (0.717), FT and FP (0.683), and FV ranking Q and FV ranking R (0.58). Additionally, FP and FV ranking in Q had a moderate correlation of ranks (0.550), while FD and FP had a lower correlation (0.500). The study's results indicate that the estimated similarity values when comparing the rankings obtained from FV ranking in S, FT, and FV ranking Q are higher than those obtained from the Fuzzy V FD method. This study's findings is similar to [8]–[11] findings where the similarity measured performed on the method compared is not a 100% conformant.

Table 5. Spearman's correlation coefficient of the now six fuzzy MCDM method

Methods	FD	FT	FV ranking in S	FV ranking in R	FV ranking in Q	FP
FD	1	.317	.283	.225	.225	.500
FT		1	.983	.318	.833	.683
FV ranking in S			1	.374	.883	.717
FV ranking in R				1	.580	.225
FV ranking in Q					1	.550
FP						1

6.   CONCLUSION

The study contributes to the field of QoS-based web service selection by providing a comparative analysis of different FMCDMMs. This work provides a technique for analyzing the decision issue of selecting the best online service alternative based on comparing six FMCDM methods: FD, FT, FV ranking in S, FV ranking in R, FV ranking Q, and FP. In a case study, a technique was employed to assess nine distinct online service options. The problem involved identifying nine essential criteria from the decision maker's perspective, which were then employed to evaluate the options. The analysis of the results obtained, which included ranking comparison and calculation of ranking similarity coefficients, demonstrated that the FMCDM method used

significantly influenced the effectiveness of solving the problem described in the study. Additionally, there were variations in the similarities and differences in the outcomes produced by the various methodologies used. The FT and FV ranking in S had the highest similarity, whereas the most significant differences were observed when comparing the results generated by the FD approach. The study highlighted the importance of employing multiple fuzzy MCDM approaches for comparison analysis and carefully selecting the appropriate methods to address the challenge of selecting the best online service alternative based on criteria values in TFN. The rankings resulting from the use of the six FMCDM techniques in this study indicate a clear top choice for the best online service alternative, with S6 being the preferred option. It received first place in four rankings and second and eighth place in the remaining two. The second and third best options were S8 and S9, respectively. However, the research is limited because the data used were collected from only five experts from a developing country, Ghana. The main goal of this study was to compare the six FMCDMs using the FV three versions and determine their relationship using a similarity measure. In future studies, other FMCDMs could be compared using secondary open access datasets of QoS factors. The findings of this study encourage the extension of the approach utilized to additional FMCDM methods, such as types-3 fuzzy with other MCDMs. The next step could be to eliminate the methods that produce the most extreme results from the applied methodology, resulting in a model that incorporates various MCDM techniques that produce rankings with greater convergence.

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