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Comparing best-worst method and full consistency method in a fuzzy environment

Arash Haqbina*

^aShiraz University, Iran

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ABSTRACT

Multicriteria Decision Making (MCDM) is one the most important branches of decision theory. Due to the fact that MCDM methods have the utmost significance in management, scholars try to develop more MCDM methods. Since calculating the weights of criteria is an important step in any MCDM method, increasing the accuracy of weight calculating methods can highly affect these methods. This accuracy can be improved by less pairwise comparison between criteria. To this end, the present study seeks to make a comparison between two new weight calculating techniques, namely BWM and FUCOM in a fuzzy environment using a real-world case study Results of this study shows that FUCOM-F provides more reliable results compared to FBWM since its consistency is less than FBWM by a great amount.

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1. Introduction

Being an inseparable and one of the most fundamental aspects of management, decision-making can highly affect the success of any system. Decision-making can be defined as choosing the most ideal alternative from a set of alternatives (Plous, 1993; Janis & Mann, 1977). Due to the significance of decision-making, researchers and scholars in the field of management studies tried to develop various quantitative methodologies throughout time in order to facilitate the decisionmaking process while increasing the reliability and accuracy of the decisions simultaneously. Needless to say, all the decisions in the real world are made based on more than one criteria. According to Triantaphyllou (2000), when several criteria are considered the decision-making will be known as Multicriteria Decision Making (MCDM). In a classic MCDM problem, a set of alternatives will be prioritized with respect to several criteria. MCDM gained momentum over the last decades, resulting in the development of numerous quantitative techniques such as AHP (Saaty, 1980), ANP (Saaty, 1999), TOPSIS (Hwang & Yoon, 1981), VIKOR (Opricovic & Tzeng, 2004), And PROMETHEE (Olson, 2001). There are also more recently developed techniques including SWARA (Keršuliene et al., 2010), WASPAS (Chakraborty & Zavadskas, 2014), CoCoSo (Yazdani et al., 2019), and MARCOS (Stević et al., 2020). Moreover, in any MCDM problem, the researcher must determine the weight coefficient of all the criteria regardless of utilized techniques. To this end, various mathematical approaches based on pairwise comparison were proposed. Popular amongst them are the Best-Worst Method (BWM), which is developed by Rezaei (2015), and the Full Consistency Method (FUCOM), proposed by Pamučar et al. (2018). The two mentioned techniques are different in the number required pairwise. The required pairwise comparisons for BWM are 2n-3 whereas it is n-1 for FUCOM. Noteworthy to mention that the weight coefficients highly influence the results of the decision-making and special attention must be paid to the methods for calculating the weights of each criterion (Pamučar & Ecer, 2020). Furthermore, According to Pamučar & Ecer (2020), the accuracy of methods for determining the

E-mail address: haqbin.arash@gmail.com (A. Haqbin)

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^{*} Corresponding author.

weight coefficients is extremely dependent on the number of pairwise comparisons. Consequently, FUCOM must have more accurate and reliable results compare to BWM.

Accordingly, the primary purpose of the present paper is to compare the two above-mentioned techniques in a fuzzy environment through a real-world case study selecting the most ideal recovery measures for tourism small and medium-sized enterprises (SMEs). By providing a comparison, the present paper helps those interested in adopting MCDM methods in choosing more efficient weight calculating methods. Also, the case study provides empirical findings regarding recovery measures of SMEs active in the field of tourism.

The rest of this paper is structured as follows. In the next section, the techniques employed for the analysis are explained. Section 3 provides a real-world case study as well as the results. Then, in section 4 a discussion is provided, and finally, the conclusions are drawn in section 5.

2. Material and Methods

2.1. Fuzzy Set Theory

Fuzzy set theory is initially proposed by Zadeh (1965) as an extension to classic set theory. fuzzy set theory is a membership function that plots elements to degrees of membership within a specific interval (Commonly [0, 1]). Fuzzy set theory can be extremely practical in uncertain decision-making environments and can eliminate the vagueness, ambiguity, and subjectiveness of the decision-makers (DMs). In the following, the fuzzy set theory and triangular fuzzy numbers (TFNs) are further described:

Definition 1. Assume that $\widetilde{\omega} \in F(R)$ is a fuzzy number if two conditions are met. First, there is $x_0 \in R$ such that $\mu_{\widetilde{\omega}}(x_0) = 1$. Second, for any $\alpha \in [0,1]$, $\widetilde{\omega}_{\alpha} = [x, \mu_{\widetilde{\omega}_{\alpha}}(x) \ge \alpha]$ is a closed interval. It should be noted that R is the set of real numbers and F(R) shows the fuzzy set.

Definition 2. A fuzzy number $\widetilde{\omega}$ on R is a triangular fuzzy number (TFN) if its member function $\mu_{\widetilde{\omega}_{\alpha}}(x): R \to [0, 1]$ is:

$$\mu_{\widetilde{\omega}_{\alpha}}(x) = \begin{cases} 0, & x < 1 \\ \frac{x-1}{m-1}, & 1 \le x < m \\ \frac{u-x}{u-m}, & m \le x \le u \\ 0, & x > u \end{cases}$$
 (1)

where l, m, and u denote the lower, modal, and upper value of the $\widetilde{\omega}$ in crisp form, respectively. A TFN always is shown as (l, m, u). Also, refer to Carlsson & Fullér (2001) for basic operations between two TFNs.

Definition 3. The graded mean integration representation (GMIR) of a TFN $\tilde{\omega}$ shows the ranking of that triangular fuzzy number and can be computed as:

$$R(\widetilde{\omega}_i) = \frac{l_i + 4m_i + u_i}{6} \tag{2}$$

2.2. Fuzzy Best-Worst Method (FBWM)

Fuzzy BWM was first proposed by Guo and Zhao (2017) and successfully applied in various contexts including supplier selection (Gupta & Barua, 2017; Ecer & Pamučar, 2020), healthcare management (Rowshan et al., 2020; Amiri et al., 2020), organizations performance evaluation (Gupta, 2018), and supply chain risk assessment (Khan et al., 2020). According to Guo and Zhao (2017), the steps of Fuzzy BWM are as follows:

Step 1. First, a set of decision criteria will be determined, which are depicted as $\{C_1, C_2, ..., C_n\}$. Then, the best (most important and most desirable) and worst (least important or least desirable) criteria will be identified. The best criterion is C_B whereas the worst criterion is C_W .

Step 2. Next, the preference of the best criterion in comparison to other criteria will be determined according to the scale shown in Table 1. The Best-to-Others vector is depicted by:

$$\tilde{A}_{B}=(a_{B1}, a_{2}, ..., a_{Bn})$$
 (3)

where a_{Bj} indicates the preference of the best criterion B over criterion j, and: $a_{BB} = (1,1,1)$. Similarly, the preference of the worst criterion compared to other criteria will be determined, and The Others-to-Worst vector is as follows:

$$\widetilde{A}_{W} = (a_{1W}, a_{2W}, ..., a_{nW})$$
 (4)

where a_{jW} indicates the preference of the criterion j over the worst criterion W. Needless to say that: $a_{ww} = (1,1,1)$

 Table 1

 Fuzzy Linguistic Terms for Decision-makers

| Linguistic Terms | Membership Function | Consistency Index (FBWM) |
|---------------------------|---------------------|--------------------------|
| Equally Important (EI) | (1, 1, 1) | 3.00 |
| Weakly Important (WI) | (2/,3,13/2) | 3.80 |
| Fairly Important (FI) | (3/,2 ,2 5/2) | 5.29 |
| Very Important (VI) | (5/,2 ,3 7/2) | 6.69 |
| Absolutely Important (AI) | (7/,2 ,4 9/2) | 8.04 |

(Source: Guo & Zhao, 2017; Pamučar & Ecer, 2020)

Step 3. Then, the optimal weights $(\widetilde{w}_1^*, \widetilde{w}_2^*, ..., \widetilde{w}_n^*)$ will be found. To calculate the optimal weights of each criterion, the following model must be solved.

$$\min \max_{j} \left\{ \left| \frac{\widetilde{w}_{B}}{\widetilde{w}_{j}} - \widetilde{a}_{B_{j}} \right|, \left| \frac{\widetilde{w}_{j}}{\widetilde{w}_{W}} - \widetilde{a}_{j_{W}} \right| \right\}$$

$$s.t. \begin{cases} \sum_{j=1}^{n} R(\widetilde{W}_{j}) = 1 \\ l_{j}^{w} \leq m_{j}^{w} \leq u_{j}^{w} \\ l_{j}^{w} \geq 0 \\ i = 1, 2, \dots, n \end{cases}$$
(5)

To solve the above-mentioned model, it can be transformed to the following nonlinearly constrained optimization model, where $\tilde{\epsilon}$ is also a TFN.

$$\min \tilde{\varepsilon}$$

$$\left\{ \begin{array}{l} \left| \frac{\widetilde{W}_{B}}{\widetilde{W}_{j}} - \tilde{a}_{B_{j}} \right| \leq \tilde{\varepsilon} \\ \left| \frac{\widetilde{W}_{j}}{\widetilde{W}_{W}} - \tilde{a}_{j_{W}} \right| \leq \tilde{\varepsilon} \end{array} \right.$$

$$\text{s.t.} \left\{ \begin{array}{l} \sum_{j=1}^{n} R(\widetilde{W}_{j}) = 1 \\ l_{j}^{w} \leq m_{j}^{w} \leq u_{j}^{w} \\ l_{j}^{w} \geq 0 \\ j = 1, 2, ..., n \end{array} \right.$$

$$(6)$$

Since $l^\epsilon \le m^\epsilon \le u^\epsilon$, it can be assumed that $\tilde{\epsilon}^* = (k^*, k^*, k^*)$ and $k^* \le l^\epsilon$. Thus, the model can also be transformed to:

$$\begin{cases}
\left| \frac{(l_{B}^{w}, m_{B}^{w}, u_{B}^{w})}{(l_{J}^{w}, m_{J}^{w}, u_{J}^{w})} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^{*}, k^{*}, k^{*}) \\
\left| \frac{(l_{J}^{w}, l_{J}^{w}, u_{J}^{w})}{(l_{W}^{w}, m_{W}^{w}, u_{W}^{w})} - (l_{JW}, m_{JW}, u_{JW}) \right| \leq (k^{*}, k^{*}, k^{*}) \\
\sum_{j=1}^{n} R(\widetilde{W}_{j}) = 1 \\
l_{J}^{w} \leq m_{J}^{w} \leq u_{J}^{w} \\
l_{J}^{w} \geq 0 \\
j = 1, 2, ..., n
\end{cases} (7)$$

By solving the model in Eq. (7), the optimal weights $(\widetilde{w}_1^*, \widetilde{w}_2^*, ..., \widetilde{w}_n^*)$ will be determined.

Step 4. Finally, the consistency of the model must be calculated. Consistency ratio (CR) is a significant index to evaluate the consistency degree of the pairwise comparison using Eq. (8). According to Rezaei (2015), models with a consistency ratio (CR) less than 0.1 are considered consistent.

$$CR = \frac{\tilde{\epsilon}^*}{c_I} \tag{8}$$

2.3. Fuzzy Full Consistency Method (FUCOM-F)

Pamučar and Ecer (2020) combined the Full Consistency Method with fuzzy set theory to develop FUCOM-F. This recently developed technique is used in several contexts such as transportation management (Pamučar et al., 2020; Mitrović Simić et al., 2020; Pamučar et al., 2021) and healthcare management (Khan et al., 2021). In the following, steps of FUCOM-F are explained:

Step 1. Similar to BWM, a set of decision criteria will be identified, which are represented by $\{C_1, C_2, ..., C_n\}$. Then, the decision-maker arrange the identified criteria based on their significance in a way that the first criterion is expected to be the most important whereas the last criterion is expected to be the least important

$$C_1 \ge C_2 \ge \cdots \ge C_n \tag{9}$$

Step 2. Afterward, a pairwise comparison will be done. All the criteria are mutually compared to the most significant criteria using a fuzzy linguistic scale similar to fuzzy BWM (Table 1) to obtain the fuzzy criterion significance $(\widetilde{\omega}_{C_n})$. Also, because the first-ranked criterion is compared with itself its membership function is (1, 1, 1). Using the fuzzy criterion significance $(\widetilde{\omega}_{C_n})$, fuzzy comparative significance $(\varphi_{k/(k+1)})$ is computed as follows:

$$\varphi_{k/(k+1)} = \frac{\widetilde{\omega}_{C_{(k+1)}}}{\widetilde{\omega}_{C_{(k)}}} = \frac{(\omega^{l}_{C_{(k+1)}}, \omega^{m}_{C_{(k+1)}}, \omega^{u}_{C_{(k+1)}})}{(\omega^{l}_{C_{(k)}}, \omega^{m}_{C_{(k)}}, \omega^{u}_{C_{(k)}})}$$
(10)

Note that $\varphi_{k/(k+1)}$ shows the importance that the criterion of $C_{(k)}$ rank has with respect to the criterion of $C_{(k+1)}$ rank. Finally, a fuzzy vector of the comparative significance of the evaluation criteria is determined as follows:

$$\vartheta = (\varphi_{1/2}, \varphi_{2/3}, \dots \varphi_{k/k+1}) \tag{11}$$

Step 3. Next, the fuzzy optimal weights are computed. The final weight values must satisfy two conditions mentioned below:

Condition 1: The ratio of weight coefficients of the criteria should be tantamount to their comparative significance:

$$\varphi_{k/(k+1)} = \frac{W_k}{W_{k+1}} \tag{12}$$

Condition 2: the final weight values should satisfy transitivity regulation as follows:

$$\varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} = \frac{w_k}{w_{k+2}}$$
 (13)

According to the two conditions mentioned above, the final nonlinear model for calculating the optimal fuzzy values of the weight coefficients for all criteria is developed as follows:

$$\min \tilde{\varepsilon}$$

$$\left\{ \begin{array}{l} \frac{w_{k}}{|w_{k+1}|} - \varphi_{k/(k+1)}| \leq \tilde{\varepsilon} \\ \left| \frac{w_{k}}{|w_{k+2}|} - \varphi_{k/(k+1)} \otimes \varphi_{(k+1)/(k+2)} \right| \leq \tilde{\varepsilon} \\ \sum_{j=1}^{n} R(\widetilde{W}_{j}) = 1 \\ l_{j}^{w} \leq m_{j}^{w} \leq u_{j}^{w} \\ l_{j}^{w} \geq 0 \\ j = 1, 2, ..., n \end{array} \right. \tag{14}$$

Similar to fuzzy BWM, the model mentioned in Eq. (14) can be transformed into the model mention in Eq. (7). By solving this model, the optimal weights $(\widetilde{w}_1^*, \widetilde{w}_2^*, ..., \widetilde{w}_n^*)$ will be computed.

3. Real World Case Study

FBWM and FUCOM-F are compared in a real-world problem of selecting the most ideal market-based recovery measure for small and medium-sized enterprises (SMEs) active in the field of tourism. Due to the COVID-19 pandemic started in 2019 (World Health Organization, 2020), the tourism industry has been experiencing tragic years, and, as a result, tourism SMEs had faced severe losses. Obviously, SMEs have encountered major challenges due to the coronavirus, but they still have an alternative to prioritize necessary measures to be able to bounce back as fast as possible. Amongst different measures to help tourism SMEs recover from this pandemic, marketing solutions are considered as one the most significant type of measures (Haqbin et al., 2021). Accordingly, the related literature was reviewed to identify the marketing measures that tourism SMEs can adopt to recover faster from COVID-19. Table 2 shows these possible measures.

Table 4
Marketing Measures for Tourism SMEs recovery from COVID-19

| Code | Marketing Measure | References |
|------|------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------------------------------|
| M1 | Digital marketing development | Pavlatos et al. (2020), Liu et al. (2015), Rodríguez-Antón et al. (2020), Čorak et al. (2020) |
| M2 | Brand image Recovery | Leung & Lam (2004), Kim et al. (2005), Gu & Wall (2006), Beirman (2006), Johnson Tew et al. (2008), Mao et al. (2010), Fung et al. (2020), Pavlatos et al. (2020) |
| M3 | Marketing campaigns development | Avraham & Ketter (2017a), Avraham & Ketter (2017b), Avraham (2020), Čorak et al. (2020) |
| M4 | Market development strategies | Gu & Wall (2006), Johnson Tew et al. (2008), Pavlatos et al. (2020), Rodríguez-Antón et al. (2020) |
| M5 | Guest satisfaction management | Fung et al. (2020), Pavlatos et al. (2020) |
| M6 | Personalized marketing development | Mao et al. (2010) |

There are different SMEs with various functions in the tourism industry (Zehrer, 2009) including tourism and travel agencies (TTAs), accommodation service providers, food suppliers, tour operator firms, handicraft suppliers, and car hire agencies. However, according to Imani Khoshkhoo Mohammad & Nadalipour (2016) TTAs are more important since they manage many tasks, such as selling tickets, offering tour guide services, and advising clients about different traveling-related issues (e.g. making hotel reservations, applying for a visa based on passport information, and registering information for travel insurance. Hence, the identified measures were tested in TTAs. To this end, pairwise comparisons are obtained in a consensus by 5 decision-makers (DMs), who were all experienced senior managers of TTAs in Shiraz, Iran. The data were then analyzed according to FBWM and FUCOM-F. Finally, the weights coefficients of the measures calculated with the techniques are compared with each other.

3.1. Results: FBWM

The DMs selected digital marketing development (M1) as the Best criterion and personalized marketing development (M6) as the Worst one. The DMs, then, determined the preference of the best and worst criteria compared to other criteria according to the fuzzy scale mentioned in Table 1, which are represented in Table 3 and Table 4.

Linguistic Terms for the Preference of the Best Criterion over all the Criteria

| Criteria | M1 | M2 | M3 | M4 | M5 | M6 |
|-----------|----|----|----|----|----|----|
| Best = C1 | EI | WI | WI | VI | VI | AI |

Table 4Linguistic Terms for the Preference of all the Criteria over the Worst Criterion

| Criteria | Worst = C6 |
|----------|------------|
| M1 | AI |
| M2 | VI |
| M3 | FI |
| M4 | WI |
| M5 | WI |
| M6 | EI |

According to the fuzzy preferences, the Best-to-Others vector and the Others-to-Worst vector are as follows:

$$\widetilde{A}_{B}$$
= ((1, 1, 1), (2/3, 1, 3/2), (2/3, 1, 3/2), (5/2, 3, 7/2), (5/2, 3, 7/2), (7/2, 4, 9/2))

$$\widetilde{A}_{W}$$
= ((7/2, 4, 9/2), (5/2, 3, 7/2), (3/2, 2, 5/2), (2/3, 1, 3/2), (2/3, 1, 3/2), (1, 1, 1))

Then, the optimization model can be constructed using the Best-to-Others and the Others-to-Worst vectors according to Eqs. (5) – (7). The optimization model is represented in Appendix. By solving the model in LINGO 18.0 software the fuzzy weights are determined and transformed into crisp weights using the graded mean integration representation (GMIR) mentioned in Eq. (2). Table 5 shows the fuzzy and crisp weights.

Table 5
Fuzzy and Crisp Weights of Measures According to FBWM

| 7 1 8 8 | | | | | |
|--------------------|--------------------------|---------------|--|--|--|
| Marketing Measures | Fuzzy Weights | Crisp Weights | | | |
| M1 | (0.3073, 0.3405, 0.3587) | 0.3380 | | | |
| M2 | (0.1616, 0.1981, 0.2212) | 0.1959 | | | |
| M3 | (0.1616, 0.1981, 0.2212) | 0.1959 | | | |
| M4 | (0.0850, 0.0915, 0.0955) | 0.0911 | | | |
| M5 | (0.0850, 0.1012, 0.1525) | 0.1070 | | | |
| M6 | (0.0687, 0.0728, 0.0728) | 0.0722 | | | |

Ultimately, the consistency of the optimization model is determined. Since $\tilde{a}_{BW} = AI$; therefore, CI has a value of 8.04. Also, $\tilde{\epsilon}^* = 0.7191$. According to Eq. (8), the optimization model has a consistency ratio (CR) of 0.0894. According to Rezaei (2015). CR values less than 0.1 are acceptable and considered consistent.

3.2. Results: FUCOM-F

According to the steps of FUCOM-F, DMs also selected digital marketing development (M1) as the most significant recovery measure. DMs put the rest of the marketing measures in the following order:

Afterward, the fuzzy criterion significance $(\widetilde{\omega}_{c_n})$ determined by DMs using the fuzzy scale in Table 1. Table 6 fuzzy criterion significance is denoted for all the measures.

Table 6Fuzzy Criterion Significance for the Measures

| Marketing Measures | M11 | M12 | M13 | M15 | M14 | M16 |
|---------------------------|-----------|---------------|---------------|---------------|---------------|---------------|
| Linguistic term | EI | WI | WI | VI | VI | AI |
| TFN | (1, 1, 1) | (2/3, 1, 3/2) | (2/3, 1, 3/2) | (5/2, 3, 7/2) | (5/2, 3, 7/2) | (7/2, 4, 9/2) |

Then, fuzzy comparative significance $(\varphi_{k/(k+1)})$ is computed for all the measures as represented in Table 7.

Table 7Fuzzy Comparative Significance

| Fuzzy Comparative Significance | | | | |
|---------------------------------------------|--------------------|--|--|--|
| ${arphi_1}_{\!\!/_2}$ | (0.67, 1.00, 1.50) | | | |
| ${\left. {{{arphi }_{2}}_{/_{3}}} \right.}$ | (0.45, 1.00, 2.24) | | | |
| ${\left. arphi_3 ight _5}$ | (1.67, 3.00, 5.22) | | | |
| ${\varphi_5}_{\!/_4}$ | (0.71, 1.00, 1.40) | | | |
| $\varphi_{4/_{6}}$ | (1.00, 1.33, 1.80) | | | |
| ${arphi_1}_{\!\!/_3}$ | (0.67, 1.00, 1.50) | | | |
| ${\left. arphi_2 ight _5}$ | (1.67, 3.00, 5.22) | | | |
| $\left. arphi_{3} ight _{4}$ | (1.67, 3.00, 5.22) | | | |
| ${\left. {{{arphi }_{{5}}}} \right _{6}}$ | (1.00, 1.33, 1.80) | | | |

According to Table 7, and, by taking into consideration the two conditions mentioned in Eqs. (12) - (13), an optimization model is developed and solved using LINGO 18.0 software. The model is shown in Appendix (A). Table 8 shows the fuzzy and crisp weights computed by the FUCOM-F technique.

Table 8Fuzzy and Crisp Weights of Measures According to FUCOM-F

| Marketing Measures | Fuzzy Weights | Crisp Weights |
|--------------------|--------------------------|---------------|
| M1 | (0.1677, 0.2521, 0.3733) | 0.2582 |
| M2 | (0.2512, 0.2521, 0.2521) | 0.2519 |
| M3 | (0.1677, 0.2513, 0.3733) | 0.2577 |
| M4 | (0.0715, 0.0837, 0.1003) | 0.0844 |
| M5 | (0.0715, 0.0839, 0.1003) | 0.0846 |
| M6 | (0.0556, 0.0630, 0.0713) | 0.0631 |

Also, by solving the optimization model, it is determined that $\tilde{\epsilon}^*$ = 0.0028, which indicates the deviation from the full consistency.

4. Discussion

The present study tried to make a comparison between FBWM and FUCOM-F thorough out a case study. Being a fundamental part of the MCDM problems, calculating the weight coefficients of the criteria can be highly affected by the number of pairwise comparisons made by the DMs. Therefore, researchers tried to propose mathematical approaches to reduce the number of these comparisons. In accordance with this issue, the two most novel weight calculating methods namely, BWM and FUCOM were selected to be compared in a fuzzy environment. As mentioned earlier, BWM has 2n-3 pairwise comparisons while FUCOM has only n-1. Furthermore, a real-world problem of choosing the best market recovery measure for tourism SMEs were proposed to achieve the goal of this study. According to secondary materials obtained from the literature review, 6 main marketing measures were identified that can help tourism SMEs recover faster from the COVID-19 pandemic. These measures include digital marketing development (M1), brand image recovery (M2), marketing campaigns development (M3), market development strategies (M4), guest satisfaction management (M5), and personalized marketing development (M6). 5 DMs expressed their judgments using fuzzy linguistic terms. Noteworthy to mention that fuzzy set theory was adopted in this study to overcome the vagueness and uncertainty of DMs' opinions. Figure 1 illustrates the importance of each measure according to FBWM and FUCOM-F.

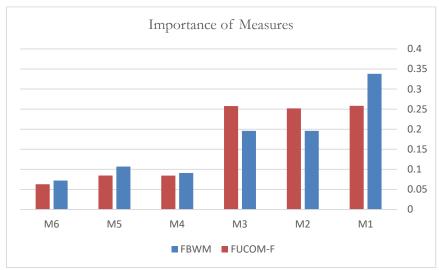


Fig. 1. Weight of each Measure According to FBWM and FUCOM-F

According to Fig. 1, digital marketing development (M1) is considered the most important recovery measure for tourism SMEs based on the two adopted techniques. On the other hand, personalized marketing development (M6) is the least significant according to the techniques as well. Moreover, it should be noted that the disparity amongst the weight coefficients of measures calculated by FBWM is much higher compared to FUCOM-F. After digital marketing development, brand image recovery (M2) and marketing campaigns development (M3) are the most important marketing measures; however, by only a negligible amount according to FUCOM-F. Fig. 2 also represents the comparison of the weight coefficients of measures computed by the two techniques.

The other important factor in comparing FBWM and FUCOM-F is their consistency. Due to the fact that FUCOM-F has fewer pairwise comparisons, its consistency is higher than FBWM. Of course, the findings of both methods are consistent (less than 0.1); the consistency of FBWM is 0.0894 whereas FUCOM-F deviates from the maximum consistency by only 0.0028. Nevertheless, FUCOM-F provides more reliable results.

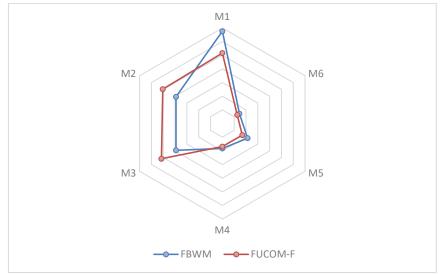


Fig. 2. Weight Values Comparison between FBWM and FUCOM-F

5. Conclusion

Multicriteria Decision Making (MCDM) is an integral part of decision-making methods in management since almost all real-world decision-making processes are based on more than one criteria. Because of the importance of MCDM in management, scholars in the field of management sciences seek more reliable and more accurate MCDM methods. Also, calculating the weights of criteria is an important stage in any MCDM method. Hence, increasing the accuracy of weight calculating methods can highly influence the MCDM methods. This accuracy can be achieved by less pairwise comparison between criteria. To this end, the present study tried to make a comparison between the two most novel weight calculating techniques, namely BWM and FUCOM using a case study of selecting the most ideal recovery measure for tourism SMEs in Shiraz, Iran. Moreover, these methods integrated fuzzy set theory to deal with the uncertainty of the judgments, resulting in FBWM and FUCOM-F. The findings of this study show that FUCOM-F provides more reliable results compared to FBWM since its consistency is less than FBWM by a great amount.

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Appendix

In the following, the optimization models for FBWM and FUCOM-F in LINGO 18.0 software are presented, respectively:

```
FBWM:
model:
min=k;
11-0.67*u2 \le k*u2; 11-0.67*u2 \ge k*u2;
m1-1*m2 \le k*m2; m1-1*m2 \ge k*m2;
u1-1.5*12 \le k*12; u1-1.5*12 \ge k*12;
11-0.67*u3 \le k*u3; 11-0.67*u3 \ge k*u3;
m1-1*m3 \le k*m3; m1-1*m3 \ge k*m3;
u1-1.5*l3<=k*l3; u1-1.5*l3>=k*l3;
11-2.5*u4 \le k*u4; 11-2.5*u4 \ge k*u4;
m1-3*m4 \le k*m4; m1-3*m4 \ge k*m4;
u1-3.5*14 \le k*14; u1-3.5*14 \ge k*14;
11-2.5*u5<=k*u5; 11-2.5*u5>=k*u5;
m1-3*m5 \le k*m5; m1-3*m5 \ge k*m5;
u1-3.5*15 \le k*15; u1-3.5*15 \ge k*15;
11-3.5*u6<=k*u6; 11-3.5*u6>=k*u6;
m1-4*m6 \le k*m6; m1-4*m6 \ge k*m6;
u1-4.5*16 \le k*16; u1-4.5*16 \ge k*16;
12-2.5*u6<=k*u6; 12-2.5*u6>=k*u6;
m2-3*m6 \le k*m6; m2-3*m6 \ge k*m6;
u2-3.5*l6<=k*l6; u2-3.5*l6>=k*l6;
13-1.5*u6<=k*u6; 13-1.5*u6>=k*u6;
m3-2*m6 \le k*m6; m3-2*m6 \ge k*m6;
u3-2.5*16 \le k*16; u3-2.5*16 \ge k*16;
14-0.67*u6<=k*u6; 14-1*u6>=k*u6;
m4-1*m6 \le k*m6; m4-0.67*m6 \ge k*m6;
u4-1.5*l6<=k*l6; u4-1.5*l6>=k*l6;
15-0.67*u6<=k*u6; 15-1*u6>=k*u6;
m5-1*m6<=k*m6; m5-0.67*m6>=k*m6;
u5-1.5*16<=k*16; u5-1.5*16>=k*16;
1/6*(11+4*m1+u1+12+4*m2+u2+13+4*m3+u3+14+4*m4+u4+15+4*m5+u5+16+4*m6+u6)=1;
11 \le m1; m1 \le u1;
12<=m2; m2<=u2;
13<=m3; m3<=u3;
14<=m4; m4<=u4;
15<=m5; m5<=u5;
16<=m6: m6<=u6:
11>0; 12>0; 13>0; 14>0; 15>0; 16>0;
```

k>=0; end model

FUCOM-F

```
model:
min=k;
11\hbox{-}0.67*u2 <= k*u2; 11\hbox{-}0.67*u2 >= k*u2;
m1-1*m2 \le k*m2; m1-1*m2 \ge k*m2;
u1-1.5*12 \le k*12; u1-1.5*12 \ge k*12;
12-0.45*u3<=k*u3; 12-0.45*u3>=k*u3;
m2-1*m3 \le k*m3; m2-1*m3 \ge k*m3;
u2-2.24*13 \le k*13; u2-2.24*13 \ge k*13;
13-1.67*u5<=k*u5; 13-1.67*u5>=k*u5;
m3-3*m5 \le k*m5; m3-3*m5 \ge k*m5;
u3-5.22*15 \le k*15; u3-5.22*15 \ge k*15;
15-0.71*u4<=k*u4; 15-0.71*u4>=k*u4;
m5-1*m4<=k*m4; m5-1*m4>=k*m4;
u5-1.40*14 \le k*14; u5-1.40*14 \ge k*14;
14-1*u6<=k*u4; 14-1*u6>=k*u6;
m4-1.33*m6<=k*m4; m4-1.33*m6>=k*m6;
u4-1.80*16<=k*14; u4-1.80*16>=k*16;
11-0.67*u3<=k*u3; 11-0.67*u3>=k*u3;
m1-1*m3 \le k*m3; m1-1*m3 \ge k*m3;
u1-1.50*13<=k*13; u1-1.50*13>=k*13;
12-1.67*u5<=k*u5; 12-1.67*u5>=k*u5;
m2-3*m5 \le k*m5; m2-3*m5 \ge k*m5;
u2-5.22*l5<=k*l5; u2-5.22*l5>=k*l5;
13-1.67*u4 \le k*u4; 13-1.67*u4 \ge k*u4;
m3-3*m4 \le k*m4; m3-3*m4 \ge k*m4;
u3-5.22*14 \le k*14; u3-5.22*14 \ge k*14;
15-1*u6<=k*u6; 15-1*u6>=k*u6;
m5-1.33*m6<=k*m6; m5-1.33*m6>=k*m6;
u5-1.80*l6<=k*l6; u5-1.80*l6>=k*l6;
1/6*(11+4*m1+u1+12+4*m2+u2+13+4*m3+u3+14+4*m4+u4+15+4*m5+u5+16+4*m6+u6) = 1;\\
11 \le m1; m1 \le u1;
12<=m2; m2<=u2;
13<=m3; m3<=u3;
14<=m4; m4<=u4;
15<=m5; m5<=u5;
16<=m6; m6<=u6;
11>0; 12>0; 13>0; 14>0; 15>0; 16>0;
k > = 0;
end model
```



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