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SUPPLIER SELECTION USING THE ROUGH BWM-MAIRCA MODEL: A CASE STUDY IN PHARMACEUTICAL SUPPLYING IN LIBYA

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Abstract: *The quality of health system in Libya has witnessed a considerable decline since the revolution in 2011. One of the major problems this sector is facing is the loss of control over supply medicines and pharmaceutical equipments from international suppliers for both public and private sectors. In order to take the right decision and select the best medical suppliers among the available ones, many criteria have to be considered and tested. This paper presents a multiple criteria decision-making analysis using modified BWM (Best-Worst method) and MAIRCA (Multi-Attribute Ideal-Real Comparative Analysis) methods. In the present case study five criteria and three suppliers are identified for supplier selection. The results of the study show that cost comes first, followed by quality as the second and company profile as the third relevant criterion. The model was tested and validated on a study of the optimal selection of supplier.*

Key Words: *Supplier Selection, Multi-criteria Decision-making, Rough Numbers, BWM, MAIRCA.*

1. Introduction

Selecting and managing medicines and pharmaceutical equipment supplies for primary health care services have a significant impact on the quality of patient care and represent a high proportion of health care costs. In developing countries health services need to choose appropriate supplies, equipment and drugs, in order to meet priority health needs and avoid wasting their limited resources. Items can be inappropriate because they are technically unsuitable or incompatible with existing equipment, if spare parts are not available, or, because staff have not been trained to use them (Kaur et al., 2001). Recently, supplier evaluation and selection have received more attention from various researchers in the literature (Mardani et al.,

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2016; De Boer et al., 2001; Govindan et al., 2015; Chai et al., 2013; Prakash et al., 2015; Abdulshahed et al., 2017; Badi et al., 2018; Stević et al., 2017a). Supplier selection is a multi-criteria problem which includes both quantitative and qualitative factors (Liang et al., 2013). Generally, the criterion for supplier selection is highly dependent on individual industries and companies. Therefore, different companies have different management strategies, enterprise culture and competitiveness. Furthermore, company background can make a huge difference and can impact supplier selection. Thus, the identification of supplier selection criteria is largely requiring the domain expert's assessment and judgment. To select the best supplier, it is necessary to make a trade-off between these qualitative and quantitative factors some of which may be in conflict (Ghodsypour & O'Brien, 1998). The traditional supplier selection methods are often based on the quoted price, which ignores significant direct and indirect costs associated with quality, delivery, and service cost of purchased materials; however, uncertainty is present because the future can never be exactly predicted.

The selection of the best supplier is done based on quoted price and considering all the possibilities of the analysis, but there is always uncertainty about indirect costs associated with quality, delivery time, and the like. One of the key problems in the supplier selection is to find the best supplier among several alternatives according to various criteria, such as service, cost, risk, and others. After identifying the criteria, a systematic methodology is required to integrate experts' assessments in order to find the best supplier. At present, various methods have been used for the supplier selection, such as the analytic network process (ANP) and the analytical hierarchy process (AHP) (Porras-Alvarado et al., 2017). AHP is a common multi-criteria decision-making method; it is developed by Saaty (1979, 1990) to provide a flexible and easily understood way of analyzing complex problems. The method breaks a complex problem into hierarchy or levels, and then makes comparisons among all possible pairs in a matrix to give a weight for each factor and a consistency ratio.

Libya began privatizing the pharmaceutical system in 2003. Pharmaceutical supplies were previously provided to both public and private sectors by the National Company of Pharmaceutical Industry (NCPI), but drug companies are also permitted to market and supply their products to both public and private health sectors through local agencies. In 2009, over 300 international pharmaceutical manufacturers from Europe, Asia, and the Middle East were registered as permitted drug suppliers for Libya (Alsageer, 2013).

All the drugs consumed in Libya are imported except few items, which are manufactured locally. The headquarters of the NCPI until 2003 was responsible for all drug manufacture and imports in Libya. Its branches are the channels of drugs distribution for governmental hospitals, private pharmacies, and clinics (Khalifa et al., 2017).

From 2004 till date the Libyan Secretariat of Health, by executing a public tender through Medical Supply Organization (MSO), has been responsible for purchasing and distributing drugs to public hospitals and clinics. Worth noting is that, on sporadic intervals, the budget has been allocated to the major public hospitals to locally purchase their own general drug demands. However, since 2011 (post-17th February 2011 revolution) MSO has lost its control on importing medicines due to receiving many drugs as donations from different international sources without acceptable level of coordination (Zhai et al., 2008); this has resulted in the supply of pharmaceuticals and medical equipment growing considerably in recent years. For instance, in Misrata (the third-largest city in Libya) the number of companies operating in the field of medical supply exceeded 170 companies, and more than 425 companies in Tripoli (Capital city). The items that are supplied vary but the most common drugs are capsules, injections, ointments, inhalants, solutions, etc.; these drugs and materials are supplied from several countries, including Arab (e.g. Egypt, Morocco, Algeria, UAE, and Jordan), European (e.g. Germany, Switzerland, and Britain), and Asian ones (e.g. India, China, and Malaysia) as well as America. The suppliers in each of these countries have some special characteristics distinguishing them from others. The closest Arab countries have the ability to speed supply and hence the flexibility in providing these drugs more quickly than the rest. On the other hand, products coming from European countries are of better quality, but their prices are higher compared to competitors from other countries. Thus, to make informed choices about what to buy and what to select among available suppliers, clear criteria for selection remain important, and efforts should be made to make suitable decision support tools for right decision-making.

In this paper, a Rough BWM-MAIRCA model for selection of the best supplier is proposed. The presented model is used for the analysis of the supplier selection process in pharmaceutical supplies in Libya. In this case study there are three suppliers with high medicine supplies to Libya. In order to maintain confidentiality of the supplier, we have denoted the given suppliers as A, B, and C.

2. Rough numbers

In group decision-making problems, the priorities are defined with respect to multi-expert's aggregated decision and process subjective evaluation of the expert's decisions. Rough numbers consisting of upper, lower and boundary interval, respectively, determine intervals of their evaluations without requiring additional information by relying only on original data (Zhai et al., 2008). Hence, the obtained expert decision-makers (DMs) perceptions objectively present and improve their decision-making process. According to Zhai et al. (2010), the definition of rough number is shown below.

Let's U be a universe containing all objects and X be a random object from U. Then we assume that there exists a set built with k classes representing DMs preferences, $R=(J_1,J_2,...,J_k)$ with condition $J_1<J_2<,...,<J_k$. Then, $\forall\ X\in U,\ J_q\in R,\ 1\le q\le k$ lower approximation $\underline{Apr}(J_q)$, upper approximation $\overline{Apr}(J_q)$ and boundary interval $Bnd(J_q)$ are determined, respectively, as follows:

$$\underline{Apr}(J_q)=\bigcup\left\{X\in U/R(X)\le J_q\right\} \tag{1}$$

$$\overline{Apr}(J_q)=\bigcup\left\{X\in U/R(X)\ge J_q\right\} \tag{2}$$

$$\begin{aligned} Bnd(J_q)&=\bigcup\left\{X\in U/R(X)\ne J_q\right\} \\ &=\left\{X\in U/R(X)>J_q\right\}\bigcup\left\{X\in U/R(X)<J_q\right\} \end{aligned} \tag{3}$$

The object can be presented with rough number (RN) defined with lower limit $\underline{Lim}(J_q)$ and upper limit $\overline{Lim}(J_q)$, respectively:

$$\underline{Lim}(J_q) = \frac{1}{M_L} \sum R(X) \big| X \in \underline{Apr}(J_q) \tag{4}$$

$$\overline{Lim}(J_q) = \frac{1}{M_U} \sum R(X) \big| X \in \overline{Apr}(J_q) \tag{5}$$

where M_L and M_U represent the sum of objects contained in the lower and upper object approximation of J_q, respectively. For object J_q, rough boundary interval $\left(IRBnd(J_q)\right)$ presents an interval between the lower and the upper limits as:

$$IRBnd(J_q) = \overline{Lim}(J_q) - \underline{Lim}(J_q) \tag{6}$$

The rough boundary interval presents measure of uncertainty. The bigger $IRBnd(J_q)$ value shows that variations in the experts' preferences exist, while smaller values show that the experts have harmonized opinions without major deviations.

In $IRBnd(J_q)$ are comprised all the objects between lower limit $\underline{Lim}(J_q)$ and upper limit $\overline{Lim}(J_q)$ of rough number $RN(J_q)$. That means that $RN(J_q)$ can be presented using $\underline{Lim}(J_q)$ and $\overline{Lim}(J_q)$.

$$RN(J_q) = \left[\underline{Lim}(J_q), \overline{Lim}(J_q)\right] \tag{7}$$

Since rough numbers belong to the group of interval numbers, arithmetic operations applied in interval numbers are also appropriate for rough numbers (Zhu et al., 2015).

3. Rough based Best-Worst method (R-BWM)

In order to take into account the subjectivity that appears in group decision-making more comprehensively, in this study a modification of the Best-Worst method (BWM) is carried out using rough numbers (RN). The application of RN eliminates the necessity for additional information when determining uncertain intervals of numbers. In this way, the quality of the existing data is retained in group decision-making and the perception of experts is expressed in an objective way in aggregated Best-to-Others (BO) and Others-to-Worst (OW) matrices. Since the method is very recent, the literature so far only has the traditional (crisp) BWM (Rezaei, 2015, 2016; Rezaei et al., 2015; Ren et al., 2017) and modification of the BWM carried out using fuzzy numbers (Guo & Zhao, 2017). Also, Stević et al. (2017b) used rough BWM to solve an internal transportation problem of the paper manufacturing company. The approach in this section introduces RN which enables a more objective expert evaluation of criteria in a subjective environment. The proposed modification of the BWM using RN (R-BWM) makes it possible to take into account the doubts that occur during the expert evaluation of criteria. R-BWM makes it possible to bridge the existing gap in the BWM methodology with the application of a novel approach in the treatment of uncertainty based on RN. The following section presents the algorithm for the R-BWM that includes the following steps:

Step 1. Determining a set of evaluation criteria. This starts from the assumption that the process of decision-making involves *m* experts. In this step, the experts consider a set of evaluation criteria and select the final one $C = \{c_1, c_2, \ldots c_n\}$, where *n* represents the total number of criteria.

Step 2. Determining the most significant (most influential) and worst (least significant) criteria. The experts decide on the best and the worst criteria from the set of criteria $C = \{c_1, c_2, \ldots c_n\}$. If the experts decide on two or more criteria as the best, or worst, the best and worst criteria are selected arbitrarily.

Step 3. Determining the preferences of the most significant (most influential) criteria (*B*) from set C over the remaining criteria from the defined set. Under the assumption that there are *m* experts and *n* criteria under consideration, each expert should determine the degree of influence of best criterion *B* on criteria *j* ($j = 1, 2, \ldots, n$). This is how we obtain a comparison between the best criterion and the others. The preference of criterion *B* compared to the *j*-th criterion defined by the *e*-th expert is denoted with a_{Bj}^e ($j = 1, 2, \ldots, n; 1 \le e \le m$). The value of each pair a_{Bj}^e takes a value from the predefined scale in interval $a_{Bj}^e \in [1, 9]$. As a result a Best-to-Others (BO) vector is obtained:

$$A_B^e = (a_{B1}^e,\ a_{B2}^e\ , \ldots,\ a_{Bn}^e);\ \ 1 \le e \le m \tag{8}$$

where a_{Bj}^e represents the influence (preference) of best criterion *B* over criterion *j*, whereby $a_{BB}^e = 1$. This is how we obtain BO matrices A_B^1, A_B^2, ..., A_B^m for each expert.

Step 4. Determining the preferences of the criteria from set C over the worst criterion (*W*) from the defined set. Each expert should determine the degree of influence of criterion *j* ($j = 1, 2, \ldots, n$) in relation to criterion *W*. The preference of criterion *j* in relation to criterion *W* defined by the *e*-th expert is denoted as a_{jW}^e ($j = 1, 2, \ldots, n; 1 \le e \le m$). The value of each pair a_{jW}^e takes a value from the predefined scale in interval $a_{jW}^e \in [1, 9]$. As a result an Others-to-Worst (OW) vector is obtained:

$$A_W^e = (a_{1W}^e,\ a_{2W}^e\ , \ldots,\ a_{nW}^e);\ \ 1 \le e \le m \tag{9}$$

where a_{jW}^e represents the influence (preference) of criterion *j* in relation to criterion *W*, whereby $a_{WW}^e = 1$. This is how we obtain OW matrices A_W^1, A_W^2, ..., A_W^m for each expert.

Step 5. Determining the rough BO matrix for the average answers of the experts. Based on the BO matrices of the experts' answers $A_B^e = \left[a_{Bj}^e \right]_{1 \times n}$, we form matrices of the aggregated sequences of experts A_B^{*e}

$$A_B^{*e} = \left[a_{B1}^m, a_{B1}^2, \ldots, a_{B1}^k;\quad a_{B2}^1; a_{B2}^2; \ldots; a_{B2}^m,\quad \ldots,\quad a_{Bn}^1; a_{Bn}^2, \ldots, a_{Bn}^m \right]_{1 \times n} \tag{10}$$

where $a_{Bj}^{e}=\left\{a_{Bj}^{1},a_{Bj}^{2},\ldots,a_{Bn}^{m}\right\}$ represents sequences by means of which the relative significance of criterion *B* is described in relation to criterion *j*. Using equations (1)-(7) each sequence a_{Bj}^{e} is transformed into rough sequence $RN\left(a_{Bj}^{e}\right)=\left[\underline{Lim}(a_{Bj}^{e}),\overline{Lim}(a_{Bj}^{e})\right]$, where $\underline{Lim}(a_{Bj}^{e})$ represent the lower limits, and $\overline{Lim}(a_{Bj}^{e})$ the upper limit of rough sequence $RN\left(a_{Bj}^{e}\right)$, respectively.

So for sequence $RN\left(a_{Bj}^{e}\right)$ we obtain a BO matrix A_{B}^{*1}, A_{B}^{*2}, ..., A_{B}^{*m}. By applying equation (11), we obtain the average rough sequence of the BO matrix

$$RN(\overline{a}_{Bj})=RN(a_{Bj}^{1},a_{Bj}^{2},...,a_{Bj}^{e})=\begin{cases}\overline{a}_{Bj}^{L}=\dfrac{1}{m}\sum\limits_{e=1}^{m}a_{Bj}^{eL}\\ \overline{a}_{Bj}^{U}=\dfrac{1}{m}\sum\limits_{e=1}^{m}a_{Bj}^{eU}\end{cases}\tag{11}$$

where *e* represents the *e*-th expert ($e=1,2,...,m$), while $RN\left(a_{Bj}^{e}\right)$ represents the rough sequences. We thus obtain the averaged rough BO matrix of average responses $\overline{A}_{B}$

$$\overline{A}_{B}=\left[\overline{a}_{B1},\overline{a}_{B2},...,\overline{a}_{Bn}\right]_{1\times n}\tag{12}$$

Step 6. Determining the rough OW matrix of average expert responses. Based on the WO matrices of the expert responses $A_{W}^{e}=\left[a_{jW}^{e}\right]_{1\times n}$, as with the rough BO matrices, for each element a_{jW}^{e} we form matrices of the aggregated sequences of the experts A_{W}^{*e}

$$A_{W}^{*e}=\left[a_{1W}^{1},a_{1W}^{2},\ldots,a_{1W}^{m};\quad a_{2W}^{1};a_{2W}^{2};\ldots;a_{2W}^{m},\quad\ldots,\quad a_{nW}^{1};a_{nW}^{2},\ldots,a_{nW}^{m}\right]_{1\times n}\tag{13}$$

where $a_{jW}^{e}=\left\{a_{jW}^{1},a_{jW}^{2},\ldots,a_{nW}^{m}\right\}$ represents sequence with which the relative significance of criterion *j* is described in relation to criterion *W*.

As in step 5, using (1)-(7), sequences a_{jW}^{e} are transformed into rough sequences $RN\left(a_{jW}^{e}\right)=\left[\underline{Lim}(a_{jW}^{e}),\overline{Lim}(a_{jW}^{e})\right]$. Thus for each rough sequence of expert *e* ($1\le e\le m$) a rough BO matrix is formed. Equation (14) is used to average the rough sequences of the OW matrix of the experts to obtain an averaged rough OW matrix.

$$RN(\overline{a}_{jW})=RN(a_{jW}^{1},a_{jW}^{2},...,a_{jW}^{e})=\begin{cases}\overline{a}_{jW}^{L}=\dfrac{1}{m}\sum\limits_{e=1}^{m}a_{jW}^{eL}\\ \overline{a}_{jW}^{U}=\dfrac{1}{m}\sum\limits_{e=1}^{m}a_{jW}^{eU}\end{cases}\tag{14}$$

Where *e* represents the *e*-th expert ($e=1,2,...,m$), while $RN(a_{jW})$ represents the rough sequences. Thus, we obtain the averaged rough OW matrix of average responses $\overline{A}_W$

$$\overline{A}_W = \left[\overline{a}_{1W}, \overline{a}_{2W}, ..., \overline{a}_{nW}\right]_{1\times n} \tag{15}$$

Step 7*.* Calculation of the optimal rough values of the weight coefficients of criteria $[RN(w_1), RN(w_2),...,RN(w_n)]$ from set C. The goal is to determine the optimal value of the evaluation criteria, which should satisfy the condition that the difference in the maximum absolute values (16)

$$\left|\frac{RN(w_B)}{RN(w_j)} - RN(a_{Bj})\right| \quad and \quad \left|\frac{RN(w_j)}{RN(w_W)} - RN(w_{jW})\right| \tag{16}$$

for each value of *j* is minimized. In order to meet these conditions, the solution that satisfies the maximum differences according to the absolute value $\left|\frac{RN(w_B)}{RN(w_j)} - RN(a_{Bj})\right|$ and $\left|\frac{RN(w_j)}{RN(w_W)} - RN(w_{jW})\right|$ should be minimized for all values of *j*. For all values of the interval rough weight coefficients of the criteria $RN(w_j) = \left[\underline{Lim}(w_j), \overline{Lim}(w_j)\right] = [w_j^L, w_j^U]$ the condition is met that $0 \le w_j^L \le w_j^U \le 1$ for each evaluation criterion $c_j \in C$. Weight coefficient w_j belongs to interval $[w_j^L, w_j^U]$, that is $w_j^L \le w_j^U$ for each value $j=1,2,...,n$. On this basis we can conclude that in the case of the rough of the weight coefficients of the criteria the condition is met that $\sum_{j=1}^{n} w_j^L \le 1$ and $\sum_{j=1}^{n} w_j^U \ge 1$. In this way the condition is met that the weight coefficients are found at interval $w_j \in [0,1], \quad (j=1,2,...,n)$ and that $\sum_{j=1}^{n} w_j = 1$.

The previously defined limits will be presented in the following min-max model:

$$\min \max_j \left\{\left|\frac{RN(w_B)}{RN(w_j)} - RN(a_{Bj})\right|, \left|\frac{RN(w_j)}{RN(w_W)} - RN(w_{jW})\right|\right\}$$

$$s.t. \tag{17}$$

$$\begin{cases} \sum_{j=1}^{n} w_j^L \le 1 \\ \sum_{j=1}^{n} w_j^U \ge 1; \\ w_j^L \le w_j^U, \quad \forall j=1,2,...,n \\ w_j^L, w_j^U \ge 0, \quad \forall j=1,2,...,n \end{cases}$$

Where $RN(w_j) = \left[\underline{Lim}(w_j), \overline{Lim}(w_j)\right] = [w_j^L, w_j^U]$ is the rough weight coefficient of a criterion.

Model (17) is equivalent to the following model:

$$
\begin{aligned}
&\min \xi \\
&s.t. \\
&\begin{cases}
\left|\dfrac{w_B^L}{w_j^U} - \overline{a}_{Bj}^{U}\right| \le \xi; \ \left|\dfrac{w_B^U}{w_j^L} - \overline{a}_{Bj}^{L}\right| \le \xi; \\
\left|\dfrac{w_j^L}{w_W^U} - \overline{a}_{jW}^{U}\right| \le \xi; \ \left|\dfrac{w_j^U}{w_W^L} - \overline{a}_{jW}^{L}\right| \le \xi; \\
\sum_{j=1}^{n} w_j^L \le 1; \\
\sum_{j=1}^{n} w_j^U \ge 1; \\
w_j^L \le w_j^U, \ \ \forall j = 1,2,...,n \\
w_j^L, w_j^U \ge 0, \ \ \forall j = 1,2,...,n
\end{cases}
\end{aligned}
\tag{18}
$$

where $RN(w_j) = [w_j^L, w_j^U]$ represents the optimum values of the weight coefficients, $RN(w_B) = [w_B^L, w_B^U]$ and $RN(w_W) = [w_W^L, w_W^U]$ represents the weight coefficients of the best and worst criterion, respectively, while $RN(\overline{a}_{jW}) = \left[\overline{a}_j^L, \overline{a}_j^U\right]$ and $RN(\overline{a}_{Bj}) = \left[\overline{a}_{Bj}^L, \overline{a}_{Bj}^U\right]$, respectively, represent the values from the average rough OW and rough BO matrices (see equations (12) and (15)).

By solving model (18) we obtain the optimal values of the weight coefficients of evaluation criteria $[RN(w_1), RN(w_2),..., RN(w_n)]$ and ξ^*.

The consistency ratio of the rough BWM

The consistency ratio is a very important indicator by means of which we check the consistency of the pair wise comparison of the criteria in the rough BO and rough OW matrices.

Definition 1 Comparison of the criteria is consistent when condition $RN(a_{Bj}) \times RN(a_{jW}) = RN(a_{BW})$ is fulfilled for all criteria *j*, where $RN(a_{Bj})$, $RN(a_{jW})$ and $RN(a_{BW})$, respectively, represent the preference of the best criterion over criterion *j*, the preference of criterion *j* over the worst criterion, and the preference of the best criterion over the worst criterion.

However, when comparing the criteria it can happen that some pairs of criteria *j* are not completely consistent. Therefore, the next section defines consistency ratio (*CR*), which gives us information on the consistency of the comparison between the rough BO and the rough OW matrices. In order to show how *CR* is determined we start from calculation of the minimum consistency when comparing the criteria, which is explained in the following section.

As previously indicated, the pair wise comparison of the criteria is carried out based on a predefined scale in which the highest value is 9 or any other maximum from a scale defined by the decision-maker. The consistency of the comparison decreases when $RN(a_{Bj}) \times RN(a_{jW})$ is less or greater than $RN(a_{BW})$, that is when $RN(a_{Bj}) \times RN(a_{jW}) \neq RN(a_{BW})$. It is clear that the greatest inequality occurs when $RN(a_{Bj})$ and $RN(a_{jW})$ have the maximum values that are equal to $RN(a_{BW})$, which continues to affect the value of ξ. Based on these relationships we can conclude that

$$\left[RN(w_B)/RN(w_j)\right] \times \left[RN(w_j)/RN(w_W)\right] = RN(w_B)/RN(w_W) \tag{19}$$

As the largest inequality occurs when $RN(a_{Bj})$ and $RN(a_{jW})$ have their maximum values, then we need to subtract the value ξ from $RN(a_{Bj})$ and $RN(a_{jW})$ and add $RN(a_{BW})$. Thus we obtain equation (20)

$$\left[RN(a_{Bj}) - \xi\right] \times \left[RN(a_{jW}) - \xi\right] = \left[RN(a_{BW}) + \xi\right] \tag{20}$$

Since for the minimum consistency $RN(a_{Bj}) = RN(a_{jW}) = RN(a_{BW})$ applies, we present equation (20) as

$$\left[RN(a_{BW}) - \xi\right] \times \left[RN(a_{BW}) - \xi\right] = \left[RN(a_{BW}) + \xi\right] \quad \Rightarrow$$
$$\xi^2 - \left[1 - 2RN(a_{BW})\right]\xi + \left[RN(a_{BW})^2 - RN(a_{BW})\right] = 0$$

Since we are using rough numbers, and if there is no consensus between the DM on their preferences of the best criterion over the worst criterion, then $RN(a_{BW})$ will not have a crisp value but we will use $RN(\bar{a}_{BW}) = \left[\bar{a}_{BW}^{L}, \bar{a}_{BW}^{U}\right]$. Since for RN condition $\bar{a}_{BW}^{L} \leq \bar{a}_{BW}^{U}$ applies, we can conclude that the preference of the best criterion over the worst cannot be greater than $\bar{a}_{BW}^{U}$. In this case, when we use upper limit $\bar{a}_{BW}^{U}$ for determining the value of *CI*, then all the values connected with $RN(\bar{a}_{BW})$ can use the *CI* obtained for calculating the value of *CR*. We can conclude this from the fact that the consistency index which corresponds to $\bar{a}_{BW}^{U}$ has the highest value in interval $\left[\bar{a}_{BW}^{L}, \bar{a}_{BW}^{U}\right]$. Based on this conclusion we can transform equation (21) in the following way:

$$\xi^2 - \left(1 + 2\bar{a}_{BW}^{U}\right)\xi + \left(\bar{a}_{BW}^{U\,2} - \bar{a}_{BW}^{U}\right) = 0 \tag{22}$$

By solving equation (22) for the different values of $\bar{a}_{BW}^{U}$ we can determine the maximum possible values of ξ ,which is the *CI* for the R-BW method. Since we obtain the values of $RN(\bar{a}_{BW})$, i.e. $\bar{a}_{BW}^{U}$ on the basis of the aggregated decisions of the DM, and these change the IVFRN interval, it is not possible to predefine the values of ξ. The values of ξ depend on uncertainties in the decisions, since uncertainties change the RN interval. As explained in the algorithm for the R-BW method, interval $\left[a_{BW}^{L}, a_{BW}^{U}\right]$ changes depending on uncertainties in evaluating the criteria.

If the DM agree on their preference for the best criterion over the worst then a_{BW} represents the crisp value of a_{BW} from the defined scale and then the maximum values of ξ apply for different values of $a_{BW} \in \{1,2,\ldots,9\}$, Table 1.

Table 1. Values of the consistency index (CI)

a_{BW}	1	2	3	4	5	6	7	8	9
CI ($\max\xi$)	0.00	0.44	1.00	1.63	2.30	3.00	3.73	4.47	5.23

In Table 1. values a_{BW} are taken from the scale $\{1,2,\ldots,9\}$ which is defined in Rezaei (2015). On the basis of CI (Table 1) we obtain consistency ratio (CR)

$$CR = \frac{\xi^*}{CI} \tag{23}$$

CR takes values from interval $[0,1]$, where the values closer to zero show high consistency while the values of CR closer to one show low consistency.

4. Rough MAIRCA method

The basic assumption of the MAIRCA method is to determine the gap between ideal and empirical weights. The summation of the gaps for each criterion gives the total gap for every observed alternative. Finally, alternatives will be ranked, and the best ranked alternative is the one with the smallest value of the total gap. The MAIRCA method shall be carried out in 6 steps (Pamučar et al., 2014; Gigović et al., 2016):

Step 1. Formation of the initial decision matrix (Y). The first step includes evaluation of l alternatives per n criteria. Based on response matrices $Y_k=[y^k_{ij}]_{l\times n}$by all m experts we obtain matrix Y^* of aggregated sequences of experts

$$Y^* = \begin{bmatrix} y_{11}^1, y_{11}^2, \ldots, y_{11}^m & y_{12}^1; y_{12}^2; \ldots; y_{12}^m, & \ldots, & y_{1n}^1; y_{1n}^2, \ldots, y_{1n}^m \\ y_{21}^1, y_{21}^2, \ldots, y_{21}^m & y_{22}^1; y_{22}^2; \ldots; y_{22}^m, & \ldots, & y_{2n}^1; y_{2n}^2, \ldots, y_{2n}^m \\ \ldots & \ldots & \ldots & \ldots \\ y_{n1}^1, y_{n1}^2, \ldots, y_{n1}^m & y_{n2}^1; y_{n2}^2; \ldots; y_{n2}^m, & \ldots, & y_{nn}^1; y_{nn}^2, \ldots, y_{nn}^m \end{bmatrix} \tag{24}$$

where $y_{ij} = \{y_{ij}^1, y_{ij}^2, \ldots, y_{ij}^m\}$ denote sequences for describing relative importance of criterion i in relation to alternative j. By applying equations (1) through (7), sequences y_{ij}^m are transformed into rough sequences $RN\left(y_{ij}^m\right)$. Consequently, rough matrices Y^{1L}, Y^{2L}, …,Y^{mL} will be obtained for rough sequence $RN\left(y_{ij}^m\right)$, where m denotes the number of experts. Therefore, for the group of rough matrices Y^1, Y^2, …,Y^m we obtain rough sequences

$$RN\left(y_{ij}\right) = \left\{\left[\underline{Lim}(y_{ij}^1), \overline{Lim}(y_{ij}^1)\right], \left[\underline{Lim}(y_{ij}^2), \overline{Lim}(y_{ij}^2)\right], \ldots, \left[\underline{Lim}(y_{ij}^m), \overline{Lim}(y_{ij}^m)\right]\right\}.$$

By applying equation (25), we obtain mean rough sequences

$$RN(y_{ij}) = RN(y_{ij}^1, y_{ij}^2, ..., y_{ij}^e) = \begin{cases} y_{ij}^L = \dfrac{1}{m}\sum_{e=1}^{m} y_{ij}^{eL} \\ y_{ij}^U = \dfrac{1}{m}\sum_{e=1}^{m} y_{ij}^{eU} \end{cases} \tag{25}$$

Where e denotes e-th expert ($e = 1, 2, ..., m$), $RN(y_{ij})$ denotes rough number $RN(y_{ij}) = \left[\underline{Lim}(y_{ij}), \overline{Lim}(y_{ij})\right]$.

In such a way, rough vectors $A_i = \left(RN(y_{i1}), RN(y_{i2}), ..., RN(y_{in})\right)$ of mean initial decision matrix is obtained, where $RN(y_{ij}) = \left[\underline{Lim}(y_{ij}), \overline{Lim}(y_{ij})\right] = \left[y_{ij}^L, y_{ij}^U\right]$ denotes value of i-th alternative as per j-th criterion ($i = 1, 2, ..., l;\ j = 1, 2, ..., n$).

$$Y = \begin{array}{c} \\ A_1 \\ A_2 \\ ... \\ A_l \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & ... & C_n \end{array} \\ \begin{bmatrix} RN(y_{11}) & RN(y_{12}) & ... & RN(y_{1n}) \\ RN(y_{21}) & RN(y_{22}) & & RN(y_{2n}) \\ ... & ... & ... & ... \\ RN(y_{l1}) & RN(y_{l2}) & ... & RN(y_{ln}) \end{bmatrix}_{l \times n} \end{array} \tag{26}$$

Where l denotes the number of alternatives, and n denotes total sum of criteria.

*Step 2. n*Define preferences according to selection of alternatives P_{A_i}. When selecting alternative, the decision maker (DM) is neutral, i.e. does not have preferences to any of the proposed alternatives. Since any alternative can be chosen with equal probability, preference per selection of one of l possible alternatives is as follows:

$$P_{A_i} = \frac{1}{l};\ \sum_{i=1}^{l} P_{A_i} = 1,\ i = 1, 2, ..., l \tag{27}$$

Where l denotes the number of alternatives.

Step 3. Calculate theoretical evaluation matrix elements (T_p). Theoretical evaluation matrix (T_p) is developed in $l\ x\ n$ format (l denotes the number of alternatives, n denotes the number of criteria). Theoretical evaluation matrix elements ($RN(t_{pij})$) are calculated as the multiplication of the preferences according to alternatives P_{A_i} and criteria weights ($RN(w_i),\ i = 1, 2, ..., n$) obtained by application of R-BWM.

$$T_p = \begin{array}{c} \\ P_{A_1} \\ P_{A_2} \\ ... \\ P_{A_l} \end{array} \begin{array}{c} \begin{array}{cccc} RN(w_1) & RN(w_2) & ... & RN(w_n) \end{array} \\ \begin{bmatrix} RN(t_{p11}) & RN(t_{p12}) & ... & RN(t_{p1n}) \\ RN(t_{p21}) & RN(t_{p22}) & & RN(t_{p2n}) \\ ... & ... & ... & ... \\ RN(t_{pl1}) & RN(t_{pl2}) & ... & RN(t_{pln}) \end{bmatrix}_{l \times n} \end{array} \tag{28}$$

where P_{A_i} denotes preferences per selection of alternatives, $RN(w_i)$ weight coefficients of evaluation criteria, and $RN(t_{pij})$ theoretical assessment of alternative for the analyzed evaluation criterion. Elements constituting matrix T_p will be then defined by applying equation (29)

$$t_{pij} = P_{Ai} \cdot RN(w_i) = P_{Ai} \cdot \left[w_i^L, w_i^U \right] \tag{29}$$

Since DM is neutral to the initial selection of alternatives, all preferences (P_{A_i}) are equal for all alternatives. Since preferences (P_{A_i}) are equal for all alternatives, then matrix (28) will have $1\ x\ n$ format (n denotes the number of criteria).

$$\begin{array}{cccc} & RN(w_1) & RN(w_2) & \dots & RN(w_n) \end{array}$$
$$T_p = P_{A_i} \left[\left[t_{p1}^L, t_{p1}^U \right], \quad \left[t_{p2}^L, t_{p2}^U \right] \quad \dots \quad \left[t_{pn}^L, t_{pn}^U \right] \right]_{1xn} \tag{30}$$

where n denotes the number of criteria, P_{A_i} preferences according to selection of alternatives, $RN\left(w_i\right)$ weight coefficients of evaluation criteria.

Step 4. Determination of real evaluation (T_r). Calculation of the real evaluation matrix elements (T_r) is done by multiplying real evaluation matrix elements (T_p) and elements of initial decision-making matrix (X) according to the following equation:

$$RN(t_{rij}) = RN(t_{pij}) \cdot RN(x_{nij}) = \left[t_{pij}^L, t_{pij}^U \right] \cdot \left[\overset{L}{y}_{ij}, \overset{U}{y}_{ij} \right] \tag{31}$$

where $RN(t_{pij})$ denotes elements of theoretical assessment matrix, and $RN(y_{ij})$ denotes elements of normalized matrix $Y = \left[RN(y_{ij}) \right]_{l \times n}$. Normalization of the mean initial decision matrix (25) is done by applying equation (32) and (33)

$$RN(y_{ij}) = \left[\underline{Lim}(y_{ij}), \overline{Lim}(y_{ij}) \right] = \left[\overset{L}{y}_{ij}, \overset{U}{y}_{ij} \right] = \left[\frac{y_{ij}^L - y_{ij}^-}{y_{ij}^+ - y_{ij}^-}, \frac{y_{ij}^U - y_{ij}^-}{y_{ij}^+ - y_{ij}^-} \right] \tag{32}$$

b) For the „cost“ type criteria (lower criterion value is preferable)

$$IRN(y_{ij}) = \left[\underline{Lim}(y_{ij}), \overline{Lim}(y_{ij}) \right] = \left[\overset{L}{y}_{ij}, \overset{U}{y}_{ij} \right] = \left[\frac{y_{ij}^U - y_{ij}^+}{y_{ij}^- - y_{ij}^+}, \frac{y_{ij}^L - y_{ij}^+}{y_{ij}^- - y_{ij}^+} \right] \tag{33}$$

where y_i^- and y_i^+ denote minimum and maximum values of the marked criterion by its alternatives, respectively:

$$y_{ij}^- = \min_j \left\{ y_{ij}^L \right\} \tag{34}$$

$$y_{ij}^+ = \max_j \left\{ y_{ij}^U \right\} \tag{35}$$

Step 5. Calculation of total gap matrix (G). Elements of G matrix are obtained as difference (gap) between theoretical (t_{pij}) and real evaluations (t_{rij}), or by actually subtracting the elements of theoretical evaluation matrix (T_p) with the elements of real evaluation matrix (T_r)

$$G = T_p - T_r = \begin{bmatrix} RN(g_{11}) & RN(g_{12}) & \dots & RN(g_{1n}) \\ RN(g_{21}) & RN(g_{22}) & \dots & RN(g_{2n}) \\ \dots & \dots & \dots & \dots \\ RN(g_{l1}) & RN(g_{l2}) & \dots & RN(g_{ln}) \end{bmatrix}_{l\times n}$$

where n denotes the number of criteria, l denotes the number of alternatives, and g_{ij} represents the obtained gap of alternative i as per criterion j. Gap g_{ij} takes values from the interval rough number according to equation (37)

$$RN(g_{ij}) = RN(t_{pij}) - RN(t_{r_{ij}}) = \left[t_{pij}^L, t_{pij}^U\right] - \left[t_{rij}^L, t_{rij}^U\right] \tag{37}$$

It is preferable that $RN(g_{ij})$ value goes to zero ($RN(g_{ij}) \to 0$) since the alternative with the smallest difference between theoretical ($RN(t_{pij})$) and real evaluation ($RN(t_{rij})$) shall be chosen. If alternative A_i for criterion C_i has a theoretical evaluation value equal to the real evaluation value ($RN(t_{pij}) = RN(t_{rij})$) then the gap for alternative A_i for criterion C_i is zero, i.e. alternative A_i per criterion C_i is the best (ideal) alternative.

If alternative A_i for criterion C_i has a theoretical evaluation value $RN(t_{pij})$ and the real ponder value is zero, then the gap for alternative A_i for criterion C_i is $RN(g_{ij}) \approx RN(t_{pij})$. This means that alternative A_i for criterion C_i is the worst (anti-ideal) alternative.

Step 6. Calculation of the final values of criteria functions (Q_i) per alternatives. Values of criteria functions are obtained by summing the gaps from matrix (36) for each alternative as per evaluation criteria, i.e. by summing matrix elements (G) per columns as shown in equation (38)

$$RN(Q_i) = \sum_{j=1}^{n} RN(g_{ij}),\ i = 1,2,\dots,m \tag{38}$$

Where n denotes the number of criteria, m denotes the number of the chosen alternatives.

Ranking of alternatives can be done by applying rules governing ranking of rough numbers described in (Stević et al., 2017a, 2017b).

5. Calculation part

Application of the hybrid rough BWM-MAIRCA model is shown using a case study related to the selection of an optimal supplier selection in Libya. Based on an analysis of the available literature and expert evaluation of suppliers, five criteria were used: Price and costs (C1), Quality (C2), Supplier profile (C3), Delivery (C4) and Flexibility (C5).

Four experts took part in the research. The R-BWM was used to determine the weight coefficients of the criteria. After defining the criteria for evaluation, the experts also determined the best (*B*) and worst (*W*) criteria. On this basis, the experts determined the BO and OW matrices in which the preferences of the *B* and *W* over the criteria were considered for the remaining criteria from the defined set. Evaluation of the criteria was carried out using a scale $a_{ij}^{e} \in [1,9]$ [18]. The BO and OW matrices are presented in Table 2.

Table 2. The BO and OW expert evaluation matrices

Best: C1	Expert evaluation	Worst: C5	Expert evaluation
C1	1, 1, 1, 1	C1	8, 7, 8, 7
C2	2, 2, 3, 3	C2	4, 4, 3, 4
C3	2, 3, 3, 2	C3	4, 4, 5, 5
C4	4, 5, 5, 4	C4	2, 3, 2, 3
C5	8, 8, 9, 9	C5	1, 1, 1, 1

Using equations (1)-(7) the evaluations in the BO and OW matrices were transformed into rough numbers. After transforming crisp numbers into rough numbers, equations (9)-(15) were used to transform the BO and OW of the expert matrices into aggregated rough BO and rough OW matrices, Table 3.

Table 3. Aggregating the rough BO and rough OW matrices

Best: C1	RN	Worst: C5	RN
C1	[1.00, 1.00]	C1	[7.25, 7.75]
C2	[2.25, 2.75]	C2	[3.56, 3.94]
C3	[2.25, 2.75]	C3	[4.25, 4.75]
C4	[4.25, 4.75]	C4	[2.25, 2.75]
C5	[8.25, 8.75]	C5	[1.00, 1.00]

On the basis of the rough BO and rough OW matrices for criteria, the optimal values of the rough weight coefficients of the criteria were calculated. Based on model (18) the optimal values of the weight coefficients of the criteria were calculated, Table 4.

Table 4. Optimal values of the criteria

Criterion	Weights	Rank
C1	[0.4113, 0.4286]	1
C2	[0.2035, 0.2169]	2
C3	[0.1498, 0.1576]	3
C4	[0.1062, 0.1424]	4
C5	[0.0667, 0.0748]	5

By solving the model (18) the value of ξ^* is obtained, $\xi^* = 0.8464$. The value of ξ^* is used to determine consistency ratio (*CR*=0.16), equation (23). Since we obtain the value of $\overline{a}_{BW}$ i.e. $\overline{a}_{BW}^{U}$ on the basis of the aggregated decisions of the experts, and they affect the interval of the RN, it is not possible to predefine the values of consistency index ξ. Using equation (22), the values of consistency index (ξ) is defined (CI=5.04). After calculating the weight coefficients of the criteria, expert evaluation of the alternatives was carried out with the predefined evaluation criteria. Once the evaluation process is completed by applying equations from (24) through (26) decisions were aggregated and initial decision-making matrix Y^* obtained, Table 5. Evaluation of the alternatives was carried out using a scale $y_{ij}^e \in [1,5]$.

Table 5. Aggregated initial decision-making matrix

Criteria/ Alternatives	C1	C2	C3	C4	C5
A1	[2.05, 2.39]	[2.06, 2.43]	[2.23, 2.73]	[2.25, 3.20]	[1.98, 2.86]
A2	[2.43, 3.44]	[4.58, 4.95]	[2.10, 2.77]	[4.55, 4.93]	[4.00, 4.00]
A3	[4.26, 4.76]	[4.55, 4.93]	[4.54, 4.93]	[4.46, 5.00]	[4.46, 5.00]

After aggregation of evaluated criteria (Table 5) preferences were determined as per selection of alternatives P_{Ai}=1/m=0.33, where m denotes the number of alternatives and $P_{A1}=P_{A2}=P_{A3}=0.33$. Based on preferences P_{Ai}, and by applying equation (29), theoretical evaluation matrix (T_p) rank *1xn*, will be obtained. In order to determine real evaluation matrix T_r (Table 6), elements of the theoretical evaluation matrix will be multiplied with normalized elements of the aggregated initial decision matrix.

Table 6. Real evaluation matrix T_r

Criteria/ Alternatives	C1	C2	C3	C4	C5
A1	[0.12, 0.14]	[0.00, 0.01]	[0.00, 0.01]	[0.00, 0.02]	[0.00, 0.01]
A2	[0.07, 0.12]	[0.06, 0.07]	[0.00, 0.01]	[0.03, 0.05]	[0.01, 0.02]
A3	[0.00, 0.03]	[0.06, 0.07]	[0.04, 0.05]	[0.03, 0.05]	[0.02, 0.02]

Normalization of the initial decision-making aggregated matrix will be done by applying equations (32) and (33). In next step, elements of theoretical evaluation matrix (T_p) will be deducted from the elements of real evaluation matrix (T_p) to obtain total gap matrix (G). By summing up the rows of the total gap matrix we obtain the total gap for every alternative, equation (37). Based on the obtained values of the total gap between theoretical and real evaluations, the initial evaluation of alternatives will be performed, Table 7.

Table 7. Values of the total gap of alternatives and their ranking

Alternatives	Alternative gap $RN(Q_i)$	Rank
A1	[0.13, 0.22]	3
A2	[0.04, 0.17]	1
A3	[0.09, 0.19]	2

6. Conclusion

Supplier selection is a very important step in the purchasing process; therefore, to carry out the selection process, it is first important to identify the criteria for selection. This is particularly important for a company operating in the pharmaceutical industry and working mainly with international suppliers. The study addresses the problem of medicine supply from international suppliers for both public and private sectors in Libya. Five criteria and three suppliers are identified for supplier selection in this problem. This multiple criteria decision-making analysis problem is solved using the rough BWM method. As a result of the presented calculations, it is shown that cost comes first, followed by quality as the second and company profile as the third relevant criterion.

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