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MULTI-CRITERIA MODEL BASED ON LINGUISTIC NEUTROSOPHIC NUMBERS: THE SELECTION OF UNMANNED AIRCRAFT

Abstract:

The paper presents a new approach in treating uncertainty and subjectivity in the decision making process based on the modification of Multi Attributive Border Approximation area Comparison (MABAC) and an Objective-Subjective (OS) model by applying linguistic neutrosophic numbers (LNN) instead of traditional numerical values. By integrating these models with linguistic neutrosophic numbers it was shown that it is possible to a significant extent to eliminate subjective qualitative assessments and assumptions by decision makers in complex decision-making conditions. On this basis, a new hybrid LNN OS-MABAC model was formed. This model was tested and validated on a case-study of the selection of optimal unmanned aircraft intended to combat forest fires.

Keywords: Linguistic Neutrosophic Numbers, MABAC, Multicriteria Decision Making

ВИШЕКРИТЕРИЈУМСКИ МОДЕЛ БАЗИРАН НА ПРИМЕНИ ЛИНГВИСТИЧКИХ NEUTROSOPHIC БРОЈЕВА: ИЗБОР БЕСПИЛОТНЕ ЛЕТЕЛИЦЕ

Сажетак:

У раду је приказан нови приступ у третирању неизвесности и субјективности у процесу доношења одлука који је заснован на модификацији MABAC и OS модела применом лингуистиц неутрософхиц бројева (LNN), уместо традиционалних нумеричких вредности. Интеграцијом наведених модела са лингуистиц неутрософхиц бројевима показано је да је могуће у значајној мери отклонити субјективне квалитативне процене и претпоставке експерата у сложеним условима одлучивања. На бази наведених поставки формиран је нови, хибридни LNN OS-MABAC модел у VKO. Наведени модел је тестиран и валидиран на примеру избора оптималне беспилотне летелице намењене за борбу против шумских пожара.

Кључне ријечи: лингвистички неутрософхиц бројеви, MABAC, вишекритеријумско одлучивање

1. INTRODUCTION

Because of the ambiguity of human thinking in complex decision-making conditions, it is difficult to represent the reasoning of experts and their preferences using numerical values. It is much more convenient and realistic to make it possible to present the preferences of experts using linguistic terms, particularly when it comes to qualitative attributes that are used to describe certain phenomena. Therefore, in this paper, linguistic neutrosophic numbers are used to show expert preferences. Since modeling expert preferences in decision-making problems using linguistic terms is an interesting field of research, the authors of this paper present an original multi-criteria model for the evaluation and selection of optimal unmanned aircraft intended for the detection and fight against forest fires which is based on LNN.

The multi-criteria model is based on the modification of the traditional MABAC method [1] by applying the LNN approach. An LNN OS model was used to determine the weights of the evaluation criteria, in which the weights of the criteria are a combination of objective and subjective values of the weighting coefficients of the criteria. The objective values of the criteria weights were obtained by the maximum deviation method, while the subjective values of the weights were obtained based on expert estimates. By integrating the OS-MABAC model with the LNN, it has been demonstrated that uncertainties and uncertainties can be taken into account in qualitative expert judgments that occur in complex decision conditions. The LNN OS-MABAC model has been tested and validated by selecting the optimal unmanned aerial vehicle designed to fight forest fires

2. A MULTI-CRITERIAL MODEL BASED ON LINGUISTIC NEUTROSOPHIC NUMBERS

The following section (Section 3.2) gives the basic framework of the linguistic neutrosophic concept, as well as the basic arithmetic operations with LNN. After this, the OS-MABAC multi-criteria model based on the concept of LNN is presented in sections 3.2 and 3.3.

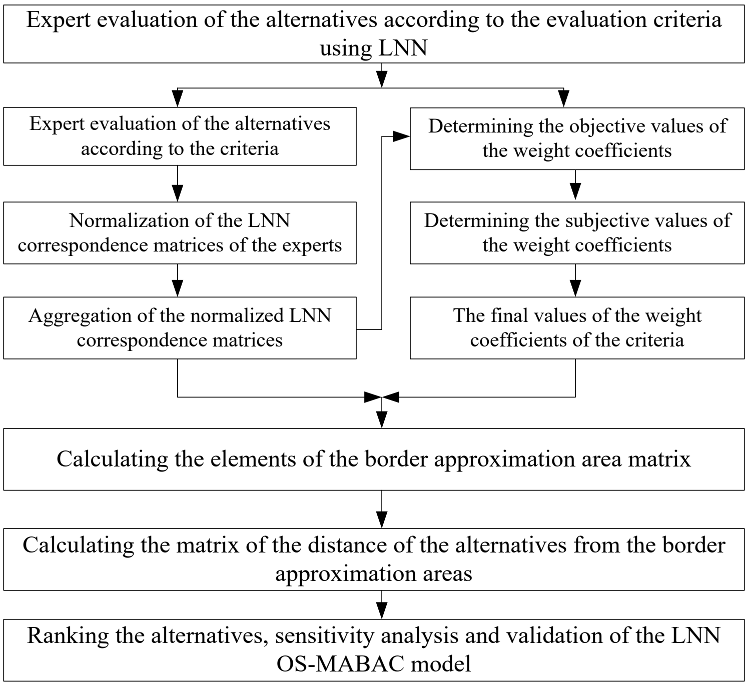

Figure 1. *Framework of the proposed model*

2.2. Some concepts of LNN

Definition 1 [2]. Assume that $S = \{s_0, s_1, ..., s_t\}$ is a linguistic set with odd cardinality $t+1$. If $e = \langle s_p, s_q, s_r \rangle$ is defined for $s_p, s_q, s_r \in S$ and $p, q, r \in [0, t]$, where s_p, s_q and s_r represent linguistic expressions which independently express the degree of truth, indeterminacy and falsity, then e is called the LNN.

Definition 2 [3]. Let $e = \langle s_p, s_q, s_r \rangle$, $e_1 = \langle s_{p_1}, s_{q_1}, s_{r_1} \rangle$ and $e_2 = \langle s_{p_2}, s_{q_2}, s_{r_2} \rangle$ be three LNN in S and $k > 0$, then we can define the arithmetic operations for LNN (Liang & Zhao, 2017):

(1) Addition of LNN "+"

$$e_1 + e_2 = \langle s_{p_1}, s_{q_1}, s_{r_1} \rangle + \langle s_{p_2}, s_{q_2}, s_{r_2} \rangle = \left\langle s_{p_1+p_2-\frac{p_1p_2}{t}}, s_{\frac{q_1q_2}{t}}, s_{\frac{r_1r_2}{t}} \right\rangle \tag{1}$$

(2) Multiplication of LNN "×"

$$e_1 \times e_2 = \langle s_{p_1}, s_{q_1}, s_{r_1} \rangle \times \langle s_{p_2}, s_{q_2}, s_{r_2} \rangle = \left\langle s_{\frac{p_1p_2}{t}}, s_{q_1+q_2-\frac{q_1q_2}{t}}, s_{r_1+r_2-\frac{r_1r_2}{t}} \right\rangle \tag{2}$$

(3) Multiplying LNN by a scalar, where $k > 0$

$$k \times e = k \langle s_p, s_q, s_r \rangle = \left\langle s_{t-t\left(1-\frac{p}{t}\right)^k}, s_{t\left(\frac{q}{t}\right)^k}, s_{t\left(\frac{r}{t}\right)^k} \right\rangle \tag{3}$$

(4) LNN power, where $k > 0$

$$e^k = \langle s_p, s_q, s_r \rangle^k = \left\langle s_{t\left(\frac{p}{t}\right)^k}, s_{t-t\left(1-\frac{q}{t}\right)^k}, s_{t-t\left(1-\frac{r}{t}\right)^k} \right\rangle \tag{4}$$

2.3. The LNN OS model for determining the weight coefficients of the criteria

In this paper, a new approach for obtaining the weights of the criteria was used when determining the weight coefficients of the evaluation criteria, which includes a combination of subjective and objective elements. Methods that subjectively determine the weight coefficients of the criteria focus on information obtained based on the preferences of the decision makers [4,5] while ignoring objective information. Methods of objectively determining the weight coefficients do not take into account the preferences of the decision makers, namely, these methods do not take into account the subjective attitudes of the decision makers [4]. The advantage of the OS model is that it simultaneously takes into account subjective and objective information. Thus, by combining subjective and objective weights we obtain the final values of the eight coefficients of the evaluation criteria.

The model is implemented through two phases: in the first phase the objective values of the criteria are determined using the method of maximum deviation; (2) in the second phase, experts evaluate the criteria and determine the subjective values of the weight coefficients. After calculating the objective and subjective values of the weight coefficients of the criteria we obtain combined values of the weights that are further used in the multi-criteria model.

Finally, on the basis of the objective and subjective values of the weight coefficients, we obtain the combined values of the weight coefficients

$$w_j = \frac{w_j^* w_j^{'}}{\sum_{j=1}^{n} w_j^* w_j^{'}} \tag{5-23}$$

where w_j^* and $w_j^{'}$ respectively represent the objective and subjective values of the weight coefficients of the criteria. The objective and subjective weights are aggregated by means of a non-linear model in which higher values of the subjective and objective weights give a higher combined value of the weight coefficient and vice versa. The use of equation (5) goes beyond the restrictions of the one-sided application of subjective or objective factors. In addition, equation (5) enables a simultaneous display of the influence of subjective and objective information on the ranking of the alternatives.

2.4. The LNN MABAC model

The MABAC method falls into the category of more recent MCDM methods. It was developed at the Center for Research in the field of Logistics Defence at the University of Defence in Belgrade [1]. Due to its robustness and stability, its results have so far found wide application and modifications, with the purpose of solving numerous problems from the field of multi-criteria decision making: material selection with incomplete weight information, investment problems, manufacturing, military problems; renewable energy, website selection, logistics and so on. In the following section, the algorithm of the modified LNN-MABAC method is presented, which consists of 7 steps:

Step 1. Forming the expert correspondence matrices ($N^{(l)}$). Starting from the assumption that in the process of decision making m experts are involved who evaluate the set of alternatives $A=\{a_1,a_2,...,a_b\}$ (where b denotes the final number of alternatives) in relation to the defined set of evaluation criteria $C=\{c_1,c_2,...c_n\}$ (where n represents the total number of criteria). The experts $\{e_1,e_2,...,e_m\}$ are assigned weight coefficients $\{\delta_1,\delta_2,...,\delta_m\}$, $0\le\delta_l\le 1,\ (l=1,2,...,m)$ and $\sum_{l=1}^{m}\delta_l=1$. The alternatives are evaluated based on a predefined set of linguistic variables $S=\{s_i\mid i\in[0,t]\}$.

In order to achieve the final ranking of the alternatives a_i ($i=1,2,..,b$) from the set of alternatives A, each expert e_l ($l=1,2,...,m$) evaluates the alternatives according to the defined set of criteria $C=\{c_1,c_2,...c_n\}$. So for each expert we construct a correspondence initial decision matrix

$$N^{(l)}=\left[\xi_{ij}^{(l)}\right]_{b\times n}=\begin{bmatrix}\xi_{11}^{(l)} & \xi_{12}^{(l)} & \dots & \xi_{1n}^{(l)}\\ \xi_{21}^{(l)} & \xi_{22}^{(l)} & \dots & \xi_{2n}^{(l)}\\ \vdots & \vdots & \ddots & \vdots\\ \xi_{b1}^{(l)} & \xi_{b2}^{(l)} & \dots & \xi_{bn}^{(l)}\end{bmatrix}=\begin{bmatrix}\left\langle s_{p_{11}}^{(l)},s_{r_{11}}^{(l)},s_{q_{11}}^{(l)}\right\rangle & \left\langle s_{p_{12}}^{(l)},s_{r_{12}}^{(l)},s_{q_{12}}^{(l)}\right\rangle & \dots & \left\langle s_{p_{1n}}^{(l)},s_{r_{1n}}^{(l)},s_{q_{1n}}^{(l)}\right\rangle\\ \left\langle s_{p_{21}}^{(l)},s_{r_{21}}^{(l)},s_{q_{21}}^{(l)}\right\rangle & \left\langle s_{p_{22}}^{(l)},s_{r_{22}}^{(l)},s_{q_{22}}^{(l)}\right\rangle & \dots & \left\langle s_{p_{2n}}^{(l)},s_{r_{2n}}^{(l)},s_{q_{2n}}^{(l)}\right\rangle\\ \vdots & \vdots & \ddots & \vdots\\ \left\langle s_{p_{b1}}^{(l)},s_{r_{b1}}^{(l)},s_{q_{b1}}^{(l)}\right\rangle & \left\langle s_{p_{b2}}^{(l)},s_{r_{b2}}^{(l)},s_{q_{b2}}^{(l)}\right\rangle & \dots & \left\langle s_{p_{bn}}^{(l)},s_{r_{bn}}^{(l)},s_{q_{bn}}^{(l)}\right\rangle\end{bmatrix}\tag{6-24}$$

where the basic elements of matrix $N^{(l)}$ ($\xi_{ij}^{(l)}$) represent the linguistic variables from the sets $S=\{s_i\mid i\in[0,t]\}$, $s_{p_{ij}}^{(l)},s_{q_{ij}}^{(l)},s_{r_{ij}}^{(l)}\in S$ and $p_{ij},q_{ij},r_{ij}\in[0,t]$.

Step 2. Calculating the elements of the normalized expert correspondence matrix ($\tilde{N}^{(l)}$). The elements of normalized matrix $\tilde{N}^{(l)}=\left[\tilde{\xi}_{ij}^{(l)}\right]_{b\times n}$ are calculated using equation (7)

$$\tilde{\xi}_{ij}^{(l)}=\left\langle\tilde{s}_{p_{ij}}^{(l)},\tilde{s}_{q_{ij}}^{(l)},\tilde{s}_{r_{ij}}^{(l)}\right\rangle=\begin{cases}\tilde{s}_{p_{ij}}^{(l)}=s_{t-p_{ij}}^{(l)};\ \tilde{s}_{q_{ij}}^{(l)}=s_{t-q_{ij}}^{(l)};\ \tilde{s}_{r_{ij}}^{(l)}=s_{t-r_{ij}}^{(l)} & if\ \ \tilde{\xi}_{ij}^{(l)}\in C;\\ \tilde{s}_{p_{ij}}^{(l)}=s_{p_{ij}}^{(l)};\ \tilde{s}_{q_{ij}}^{(l)}=s_{q_{ij}}^{(l)};\ \tilde{s}_{r_{ij}}^{(l)}=s_{r_{ij}}^{(l)} & if\ \ \tilde{\xi}_{ij}^{(l)}\in B.\end{cases}\tag{7-25}$$

where B and C respectively represent sets of criteria of the benefit and cost type, and $\tilde{\xi}_{ij}^{(l)}=\left\langle\tilde{s}_{p_{ij}}^{(l)},\tilde{s}_{q_{ij}}^{(l)},\tilde{s}_{r_{ij}}^{(l)}\right\rangle$ represents the elements of the normalized matrix $\tilde{N}^{(l)}$.

Step 3. Calculating the elements of the aggregated normalized matrix. The final aggregated decision matrix N is obtained by averaging the elements $\tilde{\xi}_{ij}^{(l)}=\left\langle\tilde{s}_{p_{ij}}^{(l)},\tilde{s}_{q_{ij}}^{(l)},\tilde{s}_{r_{ij}}^{(l)}\right\rangle$ of matrix $\tilde{N}^{(l)}=\left[\tilde{\xi}_{ij}^{(l)}\right]_{b\times n}$ using equations (9) or (10)

$$\tilde{N}=\left[\tilde{\xi}_{ij}\right]_{b\times n}=\begin{bmatrix}\tilde{\xi}_{11} & \tilde{\xi}_{12} & \dots & \tilde{\xi}_{1n}\\ \tilde{\xi}_{21} & \tilde{\xi}_{22} & \dots & \tilde{\xi}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \tilde{\xi}_{b1} & \tilde{\xi}_{b2} & \dots & \tilde{\xi}_{bn}\end{bmatrix}=\begin{bmatrix}\left\langle\tilde{s}_{p_{11}},\tilde{s}_{r_{11}},\tilde{s}_{q_{11}}\right\rangle & \left\langle\tilde{s}_{p_{12}},\tilde{s}_{r_{12}},\tilde{s}_{q_{12}}\right\rangle & \dots & \left\langle\tilde{s}_{p_{1n}},\tilde{s}_{r_{1n}},\tilde{s}_{q_{1n}}\right\rangle\\ \left\langle\tilde{s}_{p_{21}},\tilde{s}_{r_{21}},\tilde{s}_{q_{21}}\right\rangle & \left\langle\tilde{s}_{p_{22}},\tilde{s}_{r_{22}},\tilde{s}_{q_{22}}\right\rangle & \dots & \left\langle\tilde{s}_{p_{2n}},\tilde{s}_{r_{2n}},\tilde{s}_{q_{2n}}\right\rangle\\ \vdots & \vdots & \ddots & \vdots\\ \left\langle\tilde{s}_{p_{b1}},\tilde{s}_{r_{b1}},\tilde{s}_{q_{b1}}\right\rangle & \left\langle\tilde{s}_{p_{b2}},\tilde{s}_{r_{b2}},\tilde{s}_{q_{b2}}\right\rangle & \dots & \left\langle\tilde{s}_{p_{bn}},\tilde{s}_{r_{bn}},\tilde{s}_{q_{bn}}\right\rangle\end{bmatrix}\tag{8-26}$$

where we obtain elements $\tilde{\xi}_{ij}=\left\langle\tilde{s}_{p_{ij}},\tilde{s}_{q_{ij}},\tilde{s}_{r_{ij}}\right\rangle$ using the LNNWAA operator

$$\tilde{\xi}_{ij}=LNNWAA(\tilde{\xi}_{ij}^{(1)},\tilde{\xi}_{ij}^{(2)},...,\tilde{\xi}_{ij}^{(m)})=\sum_{l=1}^{m}\tilde{\xi}_{ij}^{(l)}\delta_l=\left\langle\tilde{s}_{t-t\prod_{l=1}^{m}\left(1-\frac{p_{ij,l}}{t}\right)^{\delta_l}},\tilde{s}_{t\prod_{l=1}^{m}\left(\frac{q_{ij,l}}{t}\right)^{\delta_l}},\tilde{s}_{t\prod_{l=1}^{m}\left(\frac{r_{ij,l}}{t}\right)^{\delta_l}}\right\rangle\tag{9-27}$$

Or using an LNNWGA operator

$$\tilde{s}_{ij} = LNNWGA(\tilde{s}_{ij}^{(1)}, \tilde{s}_{ij}^{(2)}, ..., \tilde{s}_{ij}^{(m)}) = \prod_{l=1}^{m} \tilde{s}_{ij}^{(l)\delta_l} = \left\langle \tilde{s}_{t\prod_{l=1}^{m}\left(\frac{p_{ij\,l}}{t}\right)^{\delta_l}}, \tilde{s}_{t-t\prod_{l=1}^{m}\left(1-\frac{q_{ij\,l}}{t}\right)^{\delta_l}}, \tilde{s}_{t-t\prod_{l=1}^{m}\left(1-\frac{r_{ij\,l}}{t}\right)^{\delta_l}} \right\rangle \tag{10-28}$$

where elements $\tilde{s}_{ij}^{(l)} = \left\langle \tilde{s}_{p_{ij}}^{(l)}, \tilde{s}_{q_{ij}}^{(l)}, \tilde{s}_{r_{ij}}^{(l)} \right\rangle$ are elements of the expert correspondence matrix (6).

Step4. Calculating the elements of weighted matrix (*D*). We obtain the elements of the weighted matrix $D = \left[d_{ij}\right]_{b\times n} = \left[\left\langle \overset{*}{s}_{p_{ij}}, \overset{*}{s}_{q_{ij}}, \overset{*}{s}_{r_{ij}} \right\rangle\right]_{b\times n}$ using equation (11)

$$d_{ij} = \left\langle s^*_{p_{ij}}, s^*_{q_{ij}}, s^*_{r_{ij}} \right\rangle = w_j \cdot \left\langle \tilde{s}_{p_{ij}}, \tilde{s}_{q_{ij}}, \tilde{s}_{r_{ij}} \right\rangle = \left\langle s^*_{t-t\left(1-\frac{p_{ij}}{t}\right)^{w_j}}, s^*_{t\left(\frac{q}{t}\right)^{w_j}}, s^*_{t\left(\frac{r}{t}\right)^{w_j}} \right\rangle \tag{11-29}$$

Step5. Calculating the elements of the border approximation area matrix (*G*). We obtain the elements of matrix $G = \left[g_j\right]_{1\times n} = \left[\left\langle s^\bullet_{p_{ij}}, s^\bullet_{q_{ij}}, s^\bullet_{r_{ij}} \right\rangle\right]_{1\times n}$ using equation (12)

$$g_j = \prod_{i=1}^{b}\left(d_{ij}\right)^{1/b} = \left\langle s^\bullet_{t\prod_{i=1}^{b}\left(\frac{p_{ij}}{t}\right)^{1/b}}, s^\bullet_{t-t\prod_{i=1}^{b}\left(1-\frac{q_{ij}}{t}\right)^{1/b}}, s^\bullet_{t-t\prod_{i=1}^{b}\left(1-\frac{r_{ij}}{t}\right)^{1/b}} \right\rangle \tag{12-30}$$

Step 6. Calculating the matrix of the distance of the alternatives from the border approximation area (*Q*). We obtain the elements of matrix $S = \left[s_{ij}\right]_{b\times n}$ using equation (13)

$$s_{ij} = \begin{cases} d_{Ed}(d_{ij}, g_j), & if \;\; d_{ij} > g_j; \\ 0, & if \;\; d_{ij} = g_j; \\ -d_{Ed}(d_{ij}, g_j), & if \;\; d_{ij} < g_j. \end{cases} \tag{13-31}$$

where g_j represents the border approximation area for criterion C_j, $d_{ij} = \left\langle \overset{*}{s}_{p_{ij}}, \overset{*}{s}_{q_{ij}}, \overset{*}{s}_{r_{ij}} \right\rangle$ represents the elements of weighted matrix (*D*).

Alternative a_i can belong to the border approximation area (G), to the upper approximation area (G^+) or to the lower approximation area (G^-), that is $a_i \in \left\{G \vee G^+ \vee G^-\right\}$. The upper approximation area (G^+) is the area in which the ideal alternative is located (A^+), while the anti-ideal alternative is found in the lower approximation area (A^-) (Figure 1).

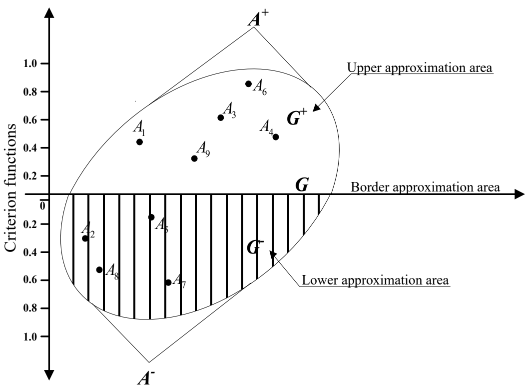

Figure 2. *Figure 1. Upper (G^+), lower (G^-) and border (G) approximation areas*

If the value of $s_{ij} > 0$, that is $s_{ij} \in G^+$, then alternative a_i is close to or equal to the ideal alternative. The value $s_{ij} < 0$, that is $s_{ij} \in G^-$, shows that alternative a_i is close to or equal to the anti-ideal alternative. In order for alternative a_i to be selected as the best from the set it is necessary for as many criteria as possible to belong to the upper approximation area (G^+).

Step 7. Ranking the alternatives. Based on the criterion functions of the alternatives Q_i ($i=1,2,...,b$) the alternatives are ranked. The criterion functions are obtained using equation (14)

$$Q_i=\sum_{j=1}^{n}s_j,\quad i=1,2,...,b;\ j=1,2,...,n. \tag{14-32}$$

Ranking of the alternatives is determined based on the value of Q_i, whereby it is preferable for an alternative to have as high a value as possible of criterion function Q_i.

3. APPLICATION OF THE LNN-OSM-MABAC MODEL

The application of the LNN-OSM-MABAC model was demonstrated on the case-study of selecting unmanned aircraft for the fight against forest fires in Serbia. In the period 2010-2014 in the territory of the Republic of Serbia 428 fires were registered, during which 10 844 hectares of forest area were burned [6]. For the purpose of evaluating the criteria and selecting unmanned fire-fighting aircraft according to the established requirements and the necessary (similar) technical characteristics, the paper considers civil and commercial tactical – short – medium range UAVs [7]. The unmanned aircraft under consideration have the following technical characteristics: short range (to 100 km), maximum take-off weight 200 kg, maximum flight altitude 5000 m, endurance of 6-10 hours, data link range of 30-100 km. The payload of these aircraft allows the installation of fire-fighting equipment for the stages of fire-fighting that are discussed in this paper. On the basis of the above, the criteria and attributes for selecting unmanned fire-fighting aircraft were introduced. The selected criteria are as follows (Table 2): Affordability (C1), Construction and general system (C2), Aerodynamics and ability to process data (C3), Ability to monitor and detect (C4) Ability for diagnosis and Prognosis (C5).

Table 1. *Explanation of the criteria*

Criteria/sub-criteria
Affordability – C1 (*min*)
Maintenance Cost – C11 (*min*)
Acquisition Cost – C12 (*min*)
Operator Training – C13 (*min*)
Operation Cost – C14 (*min*)
Disposal Cost – C15 (*min*)
Construction and General System – C2 (*max*)
Wing Mechanization – C21 (*max*)
Vehicle External Configuration – C22 (*max*)
Remote via Ground Central System – C23 (*max*)
Propulsion system – C24 (*max*)
Aerodynamics and Ability to Process data– C3 (*max*)
Flight Performance – C31 (*max*)
Payload Capacity – C32 (*max*)
Ability of Data – Telemetry and Processing – C33 (*max*)
Ability to Monitor and Detect– C4 (*max*)
Detection Method – C41 (*max*)
Camera Performance – C42 (*max*)

Ability of Detection Object – C43 (*max*)
Fusion of images – C44 (*max*)
Ability for Diagnosis and Prognosis – C5 (*max*)
Ability to Measure Geometrical Features of Fire – C51 (*max*)
Propagation Prediction – C52 (*max*)

3.2. Determining the weight coefficients of the criteria– the LNN OS model

The OS model involves determining the objective values of the criteria using the maximum deviation method and combining the obtained values with the subjective values of the weight coefficients defined by the experts. Since the OS model is carried out in two phases (phase *I* – determining the objective values and phase *II* – determining the subjective values) the following section presents the application of the OS model through the two phases.

Phase I: Determining the objective values of the weight coefficients.

The objective values of the weight coefficients are determined based on the initial decision matrix. Since four experts were involved in the research, each of them evaluated the alternatives according to the criteria (Appendix A, Table A1). Equation (25) was used to calculate the elements of the normalized expert correspondence matrix $\tilde{N}^{(l)}=\left[\tilde{\varsigma}_{ij}^{(l)}\right]_{b\times n}$ ($l=1,2,..,4$; $b=1,2,...,7$; $n=1,2,...,18$).

The normalized expert matrices $\tilde{N}^{(l)}$ were aggregated using LNNWGA. The aggregated normalized initial decision matrix is shown in Table 2.

Table 2. *Aggregated normalized initial decision matrix*

Crit.	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_{4.92},s_{1.99},s_{3.00}\rangle$	$\langle s_{1.39},s_{5.23},s_{7.75}\rangle$	$\langle s_{6.00},s_{2.97},s_{3.77}\rangle$	$\langle s_{7.75},s_{4.77},s_{6.89}\rangle$	$\langle s_{3.00},s_{3.9},s_{2.68}\rangle$	$\langle s_{7.26},s_{1.16},s_{4.00}\rangle$	$\langle s_{1.39},s_{6.48},s_{3.22}\rangle$
C12	$\langle s_{3.98},s_{2.20},s_{1.41}\rangle$	$\langle s_{3.91},s_{3.39},s_{5.09}\rangle$	$\langle s_{1.21},s_{1.43},s_{3.44}\rangle$	$\langle s_{3.19},s_{3.77},s_{7.78}\rangle$	$\langle s_{1.51},s_{2.44},s_{1.18}\rangle$	$\langle s_{1.34},s_{2.30},s_{6.00}\rangle$	$\langle s_{1.00},s_{2.33},s_{7.43}\rangle$
C13	$\langle s_{4.98},s_{3.48},s_{5.53}\rangle$	$\langle s_{1.00},s_{1.97},s_{1.00}\rangle$	$\langle s_{4.42},s_{1.22},s_{3.44}\rangle$	$\langle s_{4.45},s_{7.46},s_{2.43}\rangle$	$\langle s_{4.16},s_{1.21},s_{7.78}\rangle$	$\langle s_{4.46},s_{1.22},s_{2.23}\rangle$	$\langle s_{6.48},s_{7.48},s_{1.16}\rangle$
C14	$\langle s_{3.39},s_{1.57},s_{3.20}\rangle$	$\langle s_{4.00},s_{1.00},s_{4.45}\rangle$	$\langle s_{4.00},s_{3.71},s_{6.37}\rangle$	$\langle s_{6.64},s_{4.16},s_{6.92}\rangle$	$\langle s_{1.84},s_{2.18},s_{6.53}\rangle$	$\langle s_{1.16},s_{3.72},s_{4.99}\rangle$	$\langle s_{1.64},s_{4.23},s_{5.51}\rangle$
C15	$\langle s_{4.92},s_{3.75},s_{4.45}\rangle$	$\langle s_{0.00},s_{1.72},s_{1.16}\rangle$	$\langle s_{5.68},s_{1.00},s_{6.00}\rangle$	$\langle s_{5.19},s_{4.45},s_{4.45}\rangle$	$\langle s_{3.22},s_{1.00},s_{5.00}\rangle$	$\langle s_{7.03},s_{1.91},s_{5.00}\rangle$	$\langle s_{0.00},s_{5.7},s_{2}\rangle$
C21	$\langle s_{4.80},s_{5.19},s_{1.22}\rangle$	$\langle s_{2.21},s_{4.70},s_{5.09}\rangle$	$\langle s_{7.17},s_{1.41},s_{1.37}\rangle$	$\langle s_{4.74},s_{5.48},s_{6.49}\rangle$	$\langle s_{4.17},s_{6.23},s_{6.46}\rangle$	$\langle s_{4.1},s_{2.72},s_{5.00}\rangle$	$\langle s_{5.90},s_{0.00},s_{2.43}\rangle$
C22	$\langle s_{1.00},s_{2.37},s_{5.49}\rangle$	$\langle s_{7.78},s_{4.32},s_{7.04}\rangle$	$\langle s_{1.64},s_{2.13},s_{4.00}\rangle$	$\langle s_{1.66},s_{6.51},s_{7.51}\rangle$	$\langle s_{5.19},s_{4.49},s_{2.40}\rangle$	$\langle s_{6.02},s_{7.43},s_{3.19}\rangle$	$\langle s_{4.74},s_{2.11},s_{6.23}\rangle$
C23	$\langle s_{4.66},s_{6.25},s_{6.23}\rangle$	$\langle s_{6.72},s_{7.72},s_{4.45}\rangle$	$\langle s_{4.50},s_{1.21},s_{3.19}\rangle$	$\langle s_{1.91},s_{7.78},s_{5.91}\rangle$	$\langle s_{1.66},s_{2.62},s_{5.49}\rangle$	$\langle s_{5.53},s_{1.16},s_{6.70}\rangle$	$\langle s_{1.44},s_{2.15},s_{2.25}\rangle$
C24	$\langle s_{2.03},s_{5.18},s_{1.16}\rangle$	$\langle s_{4.71},s_{7.40},s_{3.73}\rangle$	$\langle s_{3.52},s_{1.90},s_{7.51}\rangle$	$\langle s_{5.03},s_{2.12},s_{3.26}\rangle$	$\langle s_{1.43},s_{1.51},s_{1.16}\rangle$	$\langle s_{3.77},s_{5.34},s_{3.73}\rangle$	$\langle s_{4.19},s_{1.59},s_{3.00}\rangle$
C31	$\langle s_{5.49},s_{3.946},s_{1.74}\rangle$	$\langle s_{1.69},s_{1.69},s_{4.71}\rangle$	$\langle s_{5.19},s_{2.43},s_{3.48}\rangle$	$\langle s_{3.71},s_{5.6},s_{5.49}\rangle$	$\langle s_{7.72},s_{2.86},s_{2.25}\rangle$	$\langle s_{2.43},s_{7.54},s_{2.72}\rangle$	$\langle s_{5.78},s_{7.72},s_{1.00}\rangle$
C32	$\langle s_{1.37},s_{2.42},s_{7.23}\rangle$	$\langle s_{3.33},s_{4.91},s_{5.78}\rangle$	$\langle s_{4.42},s_{3.60},s_{6.00}\rangle$	$\langle s_{6.72},s_{2.33},s_{4.19}\rangle$	$\langle s_{2.17},s_{6.91},s_{2.21}\rangle$	$\langle s_{5.01},s_{2.50},s_{5.72}\rangle$	$\langle s_{1.18},s_{4.00},s_{5.74}\rangle$
C33	$\langle s_{1.84},s_{1.97},s_{5.72}\rangle$	$\langle s_{3.52},s_{1.41},s_{4.22}\rangle$	$\langle s_{1.64},s_{5.93},s_{2.44}\rangle$	$\langle s_{5.03},s_{1.75},s_{1.66}\rangle$	$\langle s_{1.00},s_{6.79},s_{1.00}\rangle$	$\langle s_{2.55},s_{3.47},s_{1.91}\rangle$	$\langle s_{1.21},s_{2.85},s_{4.74}\rangle$
C41	$\langle s_{1.18},s_{5.44},s_{5.00}\rangle$	$\langle s_{2.48},s_{1.9},s_{7.11}\rangle$	$\langle s_{3.88},s_{1.87},s_{1.41}\rangle$	$\langle s_{3.26},s_{3.58},s_{3.89}\rangle$	$\langle s_{5.03},s_{1.81},s_{1.18}\rangle$	$\langle s_{7.53},s_{2.00},s_{6.00}\rangle$	$\langle s_{1.00},s_{1.44},s_{6.51}\rangle$
C42	$\langle s_{5.74},s_{7.17},s_{3.00}\rangle$	$\langle s_{4.74},s_{5.70},s_{1.22}\rangle$	$\langle s_{2.00},s_{6.00},s_{6.27}\rangle$	$\langle s_{1.37},s_{1.69},s_{6.7}\rangle$	$\langle s_{4.45},s_{4.68},s_{2.00}\rangle$	$\langle s_{6.00},s_{6.16},s_{1.18}\rangle$	$\langle s_{3.69},s_{2.86},s_{4.17}\rangle$
C43	$\langle s_{1.18},s_{5.71},s_{3.73}\rangle$	$\langle s_{1.39},s_{1.79},s_{6.20}\rangle$	$\langle s_{8.00},s_{1.47},s_{1.41}\rangle$	$\langle s_{1.43},s_{2.10},s_{4.22}\rangle$	$\langle s_{7.17},s_{2.00},s_{7.27}\rangle$	$\langle s_{3.26},s_{4.36},s_{7.27}\rangle$	$\langle s_{3.71},s_{2.68},s_{2.96}\rangle$
C44	$\langle s_{3.26},s_{1.91},s_{6.04}\rangle$	$\langle s_{1.64},s_{2.43},s_{1.44}\rangle$	$\langle s_{7.03},s_{6.98},s_{1.64}\rangle$	$\langle s_{1.21},s_{2.38},s_{1.64}\rangle$	$\langle s_{1.74},s_{2.25},s_{7.51}\rangle$	$\langle s_{7.7},s_{7.03},s_{8.00}\rangle$	$\langle s_{3.13},s_{6.7},s_{1.39}\rangle$
C51	$\langle s_{2.12},s_{2.31},s_{2.00}\rangle$	$\langle s_{2.48},s_{1.64},s_{2.48}\rangle$	$\langle s_{5.59},s_{5.44},s_{6.51}\rangle$	$\langle s_{1.37},s_{4.71},s_{0.00}\rangle$	$\langle s_{3.71},s_{7.78},s_{2.50}\rangle$	$\langle s_{1.64},s_{1.43},s_{6.46}\rangle$	$\langle s_{4.00},s_{3.48},s_{6.00}\rangle$
C52	$\langle s_{6.25},s_{1.81},s_{2.18}\rangle$	$\langle s_{1.69},s_{1.22},s_{6.49}\rangle$	$\langle s_{7.27},s_{0.00},s_{2.21}\rangle$	$\langle s_{5.50},s_{7.11},s_{3.77}\rangle$	$\langle s_{1.00},s_{1.47},s_{7.23}\rangle$	$\langle s_{4.30},s_{6.47},s_{4.45}\rangle$	$\langle s_{6.94},s_{2.18},s_{2.18}\rangle$

Based on the deviations obtained, the final objective values of the weight coefficients (w_j^*, $j = 1,2,...,18$):

$$w_{C11}^* = 0.0647; w_{C12}^* = 0.0529; w_{C13}^* = 0.0704; w_{C14}^* = 0.0459; w_{C15}^* = 0.0600; w_{C21}^* = 0.0431;$$
$$w_{C22}^* = 0.0725; w_{C23}^* = 0.0575; w_{C24}^* = 0.0359; w_{C31}^* = 0.0557; w_{C32}^* = 0.0530; w_{C33}^* = 0.0380;$$
$$w_{C41}^* = 0.0616; w_{C42}^* = 0.0479 w_{C43}^* = 0.0710; w_{C44}^* = 0.0655; w_{C51}^* = 0.0401; w_{C52}^* = 0.0641.$$

Phase II: Determining the subjective values of the weight coefficients.

The subjective values of the weight coefficients were assigned by the experts. The local values of the weight coefficients were obtained from the subjective assessment of the experts. The global weights of the criteria were obtained by multiplying the weight coefficient of the clusters (C1, C2, C3, C4 and C5) with the weight coefficients of the sub-criteria.

After calculating the objective and subjective values of the weight coefficients of the criteria we obtained the combined values of the weights that we further used in the multi-criteria model, Table 3.

Table 3. *The final values of the weight coefficients*

Criteria	Subjective (w_j)	Objective (w_j)	Final (w_j)	Rank
C11	0.0235	0.0647	0.0283	14
C12	0.0272	0.0529	0.0268	15
C13	0.0172	0.0704	0.0225	16
C14	0.0336	0.0459	0.0287	13
C15	0.0126	0.0600	0.0141	18
C21	0.0546	0.0431	0.0438	11
C22	0.0423	0.0725	0.0571	9
C23	0.0308	0.0575	0.0329	12
C24	0.0221	0.0359	0.0148	17
C31	0.0454	0.0557	0.0470	10
C32	0.0650	0.0530	0.0641	7
C33	0.1000	0.0380	0.0708	6
C41	0.0812	0.0616	0.0930	3
C42	0.0873	0.0479	0.0778	5
C43	0.0647	0.0710	0.0854	4
C44	0.0484	0.0655	0.0590	8
C51	0.1282	0.0401	0.0957	2
C52	0.1159	0.0641	0.1382	1

3.3. Application of the LNN MABAC model

After determining the final values of the weight coefficients of the criteria, the alternatives were evaluated using the LNN-MABAC model. Four experts carried out an evaluation of seven unmanned aircraft denoted as A1 to A7. As with the OS model, the experts evaluated the alternatives by assigning a certain value from a set of linguistic variables, $S = \{s_i \mid i \in [0,8]\}$, where $s = \{$*s_0 – exceedingly low, s_1– pretty low, s_2– low, s_3– slightly low, s_4 – medium, s_5– slightly high, s_6– high, s_7– pretty high, s_8– exceedingly high*$\}$.

Step 1. Forming the expert correspondence matrix.

Step 2. Calculating the elements of the normalized expert correspondence matrix. Using equation (7) normalization of the expert correspondence matrices was carried out.

Step 3. Calculating the elements of the aggregated normalized matrix. Based on the normalized expert correspondence matrices, using expression (9) aggregation of the values was carried out and an aggregated normalized matrix obtained, Table 2.

Step 4. Calculating the elements of the weighted matrix. The elements of the weighted matrix were obtained by multiplying the final values of the weight coefficients with the elements of the aggregated normalized matrix (Table 2).Using expression (10) we obtained the elements of the weighted matrix, Table 4.

Table 4. *The weighted matrix*

Crit.	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_{0.21},s_{7.69},s_{7.78}\rangle$	$\langle s_{0.04},s_{7.9},s_{7.99}\rangle$	$\langle s_{0.31},s_{7.78},s_{7.83}\rangle$	$\langle s_{0.74},s_{7.88},s_{7.97}\rangle$	$\langle s_{0.11},s_{7.84},s_{7.76}\rangle$	$\langle s_{0.52},s_{7.57},s_{7.84}\rangle$	$\langle s_{0.04},s_{7.95},s_{7.8}\rangle$
C12	$\langle s_{0.15},s_{7.73},s_{7.64}\rangle$	$\langle s_{0.14},s_{7.82},s_{7.9}\rangle$	$\langle s_{0.03},s_{7.64},s_{7.82}\rangle$	$\langle s_{0.11},s_{7.84},s_{7.99}\rangle$	$\langle s_{0.04},s_{7.75},s_{7.6}\rangle$	$\langle s_{0.04},s_{7.74},s_{7.94}\rangle$	$\langle s_{0.03},s_{7.74},s_{7.98}\rangle$
C13	$\langle s_{0.17},s_{7.85},s_{7.93}\rangle$	$\langle s_{0.02},s_{7.75},s_{7.63}\rangle$	$\langle s_{0.14},s_{7.67},s_{7.85}\rangle$	$\langle s_{0.15},s_{7.99},s_{7.79}\rangle$	$\langle s_{0.13},s_{7.67},s_{8}\rangle$	$\langle s_{0.15},s_{7.67},s_{7.77}\rangle$	$\langle s_{0.29},s_{7.99},s_{7.66}\rangle$
C14	$\langle s_{0.13},s_{7.63},s_{7.8}\rangle$	$\langle s_{0.16},s_{7.54},s_{7.87}\rangle$	$\langle s_{0.16},s_{7.83},s_{7.95}\rangle$	$\langle s_{0.4},s_{7.85},s_{7.97}\rangle$	$\langle s_{0.06},s_{7.71},s_{7.95}\rangle$	$\langle s_{0.04},s_{7.83},s_{7.89}\rangle$	$\langle s_{0.05},s_{7.86},s_{7.91}\rangle$
C15	$\langle s_{0.11},s_{7.92},s_{7.93}\rangle$	$\langle s_{0},s_{7.83},s_{7.79}\rangle$	$\langle s_{0.14},s_{7.77},s_{7.97}\rangle$	$\langle s_{0.12},s_{7.93},s_{7.93}\rangle$	$\langle s_{0.06},s_{7.77},s_{7.95}\rangle$	$\langle s_{0.23},s_{7.84},s_{7.95}\rangle$	$\langle s_{0},s_{7.96},s_{7.85}\rangle$
C21	$\langle s_{0.31},s_{7.85},s_{7.37}\rangle$	$\langle s_{0.11},s_{7.82},s_{7.84}\rangle$	$\langle s_{0.76},s_{7.41},s_{7.4}\rangle$	$\langle s_{0.31},s_{7.87},s_{7.93}\rangle$	$\langle s_{0.25},s_{7.91},s_{7.93}\rangle$	$\langle s_{0.25},s_{7.63},s_{7.84}\rangle$	$\langle s_{0.46},s_{0},s_{7.59}\rangle$
C22	$\langle s_{0.06},s_{7.46},s_{7.83}\rangle$	$\langle s_{1.49},s_{7.72},s_{7.94}\rangle$	$\langle s_{0.1},s_{7.42},s_{7.69}\rangle$	$\langle s_{0.11},s_{7.91},s_{7.97}\rangle$	$\langle s_{0.46},s_{7.74},s_{7.47}\rangle$	$\langle s_{0.61},s_{7.97},s_{7.59}\rangle$	$\langle s_{0.4},s_{7.41},s_{7.89}\rangle$
C23	$\langle s_{0.23},s_{7.94},s_{7.93}\rangle$	$\langle s_{0.47},s_{7.99},s_{7.85}\rangle$	$\langle s_{0.21},s_{7.52},s_{7.76}\rangle$	$\langle s_{0.07},s_{7.99},s_{7.92}\rangle$	$\langle s_{0.06},s_{7.71},s_{7.9}\rangle$	$\langle s_{0.3},s_{7.51},s_{7.95}\rangle$	$\langle s_{0.05},s_{7.66},s_{7.67}\rangle$
C24	$\langle s_{0.03},s_{7.95},s_{7.77}\rangle$	$\langle s_{0.1},s_{7.99},s_{7.91}\rangle$	$\langle s_{0.07},s_{7.83},s_{7.99}\rangle$	$\langle s_{0.12},s_{7.84},s_{7.89}\rangle$	$\langle s_{0.02},s_{7.81},s_{7.77}\rangle$	$\langle s_{0.07},s_{7.95},s_{7.91}\rangle$	$\langle s_{0.09},s_{7.81},s_{7.89}\rangle$
C31	$\langle s_{0.42},s_{7.69},s_{7.44}\rangle$	$\langle s_{0.09},s_{7.44},s_{7.8}\rangle$	$\langle s_{0.38},s_{7.56},s_{7.69}\rangle$	$\langle s_{0.23},s_{7.87},s_{7.86}\rangle$	$\langle s_{1.17},s_{7.62},s_{7.54}\rangle$	$\langle s_{0.13},s_{7.98},s_{7.6}\rangle$	$\langle s_{0.47},s_{7.99},s_{7.26}\rangle$
C32	$\langle s_{0.1},s_{7.41},s_{7.95}\rangle$	$\langle s_{0.27},s_{7.75},s_{7.83}\rangle$	$\langle s_{0.4},s_{7.6},s_{7.85}\rangle$	$\langle s_{0.89},s_{7.39},s_{7.68}\rangle$	$\langle s_{0.16},s_{7.92},s_{7.37}\rangle$	$\langle s_{0.49},s_{7.42},s_{7.83}\rangle$	$\langle s_{0.08},s_{7.65},s_{7.83}\rangle$
C33	$\langle s_{0.15},s_{7.25},s_{7.81}\rangle$	$\langle s_{0.32},s_{7.07},s_{7.65}\rangle$	$\langle s_{0.13},s_{7.83},s_{7.36}\rangle$	$\langle s_{0.54},s_{7.18},s_{7.16}\rangle$	$\langle s_{0.08},s_{7.91},s_{6.91}\rangle$	$\langle s_{0.21},s_{7.54},s_{7.23}\rangle$	$\langle s_{0.09},s_{7.44},s_{7.71}\rangle$
C41	$\langle s_{0.12},s_{7.72},s_{7.66}\rangle$	$\langle s_{0.27},s_{7},s_{7.91}\rangle$	$\langle s_{0.48},s_{6.99},s_{6.81}\rangle$	$\langle s_{0.38},s_{7.42},s_{7.48}\rangle$	$\langle s_{0.7},s_{6.97},s_{6.7}\rangle$	$\langle s_{1.86},s_{7.03},s_{7.79}\rangle$	$\langle s_{0.1},s_{6.82},s_{7.85}\rangle$
C42	$\langle s_{0.75},s_{7.93},s_{7.41}\rangle$	$\langle s_{0.54},s_{7.79},s_{6.91}\rangle$	$\langle s_{0.18},s_{7.82},s_{7.85}\rangle$	$\langle s_{0.12},s_{7.09},s_{7.89}\rangle$	$\langle s_{0.49},s_{7.67},s_{7.18}\rangle$	$\langle s_{0.82},s_{7.84},s_{6.89}\rangle$	$\langle s_{0.38},s_{7.38},s_{7.6}\rangle$
C43	$\langle s_{0.11},s_{7.77},s_{7.5}\rangle$	$\langle s_{0.13},s_{7.04},s_{7.83}\rangle$	$\langle s_{8},s_{6.92},s_{6.9}\rangle$	$\langle s_{0.13},s_{7.14},s_{7.58}\rangle$	$\langle s_{1.41},s_{7.11},s_{7.94}\rangle$	$\langle s_{0.35},s_{7.6},s_{7.94}\rangle$	$\langle s_{0.41},s_{7.29},s_{7.35}\rangle$
C44	$\langle s_{0.24},s_{7.35},s_{7.87}\rangle$	$\langle s_{0.11},s_{7.46},s_{7.23}\rangle$	$\langle s_{0.94},s_{7.94},s_{7.29}\rangle$	$\langle s_{0.08},s_{7.45},s_{7.29}\rangle$	$\langle s_{0.11},s_{7.42},s_{7.97}\rangle$	$\langle s_{1.41},s_{7.94},s_{8}\rangle$	$\langle s_{0.23},s_{7.92},s_{7.22}\rangle$
C51	$\langle s_{0.23},s_{7.1},s_{7.01}\rangle$	$\langle s_{0.28},s_{6.88},s_{7.15}\rangle$	$\langle s_{0.87},s_{7.78},s_{7.84}\rangle$	$\langle s_{0.14},s_{7.6},s_{0}\rangle$	$\langle s_{0.46},s_{7.98},s_{7.16}\rangle$	$\langle s_{0.17},s_{6.78},s_{7.84}\rangle$	$\langle s_{0.51},s_{7.39},s_{7.78}\rangle$
C52	$\langle s_{1.52},s_{6.52},s_{6.68}\rangle$	$\langle s_{0.26},s_{6.17},s_{7.77}\rangle$	$\langle s_{2.25},s_{0},s_{6.7}\rangle$	$\langle s_{1.19},s_{7.87},s_{7.21}\rangle$	$\langle s_{0.15},s_{6.33},s_{7.89}\rangle$	$\langle s_{0.81},s_{7.77},s_{7.38}\rangle$	$\langle s_{1.95},s_{6.68},s_{6.68}\rangle$

Step 5. Calculating elements of the border approximation area matrix (BAA). Using equation (11) we obtained the elements of the border approximation area matrix.

Step 6. Calculating the matrix of the distance of the alternatives from the border approximation area. We used equation (12) to determine the distance of the alternatives from the BAA, Table 5.

Table 5. *Distance of the alternatives from the border approximation area*

Crit.	A1	A2	A3	A4	A5	A6	A7
C11	-0.014	0.012	-0.012	0.041	-0.012	0.032	-0.015
C12	-0.022	0.007	-0.012	0.008	-0.023	-0.003	0.005
C13	0.006	-0.022	-0.016	0.010	-0.018	-0.018	0.021
C14	-0.013	-0.018	0.006	0.022	-0.006	-0.007	0.007
C15	0.008	-0.011	0.013	0.009	-0.009	0.017	-0.008
C21	-0.033	0.018	-0.046	0.018	0.021	-0.006	-0.553
C22	-0.027	0.088	-0.030	0.018	-0.031	0.034	-0.027
C23	0.007	0.024	-0.029	0.009	-0.015	-0.031	-0.024
C24	-0.011	0.006	-0.008	-0.007	-0.013	0.003	-0.008
C31	-0.021	-0.036	-0.022	0.016	0.065	-0.015	-0.032
C32	-0.023	0.007	0.012	0.051	-0.038	0.024	-0.012
C33	-0.034	-0.040	0.021	-0.046	-0.049	-0.019	-0.020
C41	0.040	-0.026	-0.063	0.019	-0.075	0.109	-0.037
C42	0.031	-0.048	0.027	-0.057	-0.028	-0.057	-0.026
C43	-0.042	-0.032	0.550	-0.029	0.074	0.024	-0.028
C44	-0.032	-0.061	0.072	-0.058	-0.027	0.084	-0.058
C51	-0.045	-0.055	0.052	-0.534	0.034	-0.068	0.035
C52	-0.079	-0.074	-0.515	0.073	-0.075	0.059	0.099

Step 7. Ranking the alternatives. Based on the distance of the alternatives from the BAA, using equation (13),we obtained the final values of the criterion functions of the alternatives and the final ranking of the alternatives, Table 6.

Table 6. *Criterion functions and ranking of the alternatives*

Alternative	Q_i	Rank
A1	-0.303	5
A2	-0.258	4
A3	-0.001	2
A4	-0.433	6
A5	-0.225	3
A6	0.164	1
A7	-0.680	7

4. CONCLUSION

Research has shown that the selection of the optimal UAV, in addition to being influenced by predictable indicators, is also influenced by numerous unknown and partially known indicators. The LNN OS-MABAC model takes all parameters into consideration that affect the final decision, regardless of the degree and nature of their uncertainty. This model makes it possible to process qualitative subjective expert preferences, even when decisions are made on the basis of data that are partially known or even not very well known at all. In this way, it makes it easier for decision makers to express their own preferences, while taking into account subjectivity and the lack of information about certain occurrences. In addition, the LNN OS model for determining the weight coefficients of the criteria introduces objective values of weight coefficients, which reduces the subjective impact of the expert preferences on the final values of the weights of the criteria. Bearing in mind the given advantages, one of the improvements of this model will be the creation and implementation of software for real-world applications, which now can be one of the limitations and managerial implications. This will make the model much closer to users and will enable full exploitation of all the benefits stated in the paper.

Further integration of the LNN approach in traditional MCDM models, such as in the Best-Worst and AHP methods, would make it possible to determine the degree of consistency of the expert comparisons. This would indirectly be able to determine the degree of reliability of the results obtained, which would significantly contribute to the validation of the model.

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