TRANSPORT
ISSN 1648-4142 / eISSN 1648-3480
2022 Volume 37 Issue 2: 73–97
https://doi.org/10.3846/transport.2022.16645

AN EXTENSION OF THE MABAC AND OS MODEL USING LINGUISTIC NEUTROSOPHIC NUMBERS: SELECTION OF UNMANNED AIRCRAFT FOR FIGHTING FOREST FIRES

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Submitted 7 September 2019; resubmitted 1 November 2019; accepted 3 February 2020; first published online 2 May 2022

Abstract. The paper presents a new approach to the treatment of 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 LNN 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 in which the optimal unmanned aircraft were selected to combat forest fires. After defining the criteria and their attributes, they were prioritized using the LNN–OS model, in which the weights of the criteria and their attributes are a combination of the objective values obtained by the method of maximum deviation and the subjective values of the criteria obtained by expert examination using LNN. The ranking and selection of the optimal unmanned aircraft from those on offer with similar characteristics was carried out using the LNN–MABAC model. Testing of the model showed that the proposed model based on LNN provides an objective expert evaluation by eliminating subjective assessments when determining the numerical values of criteria. A sensitivity analysis of the LNN–OS–MABAC model, carried out through 54 scenarios of changes in the weight coefficients, showed a high degree of stability in the solutions obtained when the alternatives were ranked. The results were validated by comparison with LNN extensions of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) model.

Keywords: firefighting UAV, LNN, MABAC, MCDM, objective–subjective (OS) model, TOPSIS.

Notations

AHP – analytic hierarchy process;
BAA – border approximation area;
ELECTRE – elimination and choice translating reality (in French: *ELimination Et Choice Translating REality*);
IFN – intuitive fuzzy numbers;
IT – information technology;
LIFN – linguistic IFN;
LNN – linguistic neutrosophic numbers;
LNNWAA – LNN weighted arithmetic averaging;
LNNWGA – LNN weighted geometric averaging;
MABAC – multi-attributive border approximation area comparison;
MCDM – multi-criteria decision-making;
MMD – model of maximum deviation;
MULTIMOORA – multi-objective optimization by a ratio analysis;
OS – objective–subjective;
SC – Spearman's coefficient;
SD – standard deviation;
SVNLN – single-valued neutrosophic linguistic numbers;

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SVNN – single-valued neutrosophic number;
TODIM – interactive multi-criteria decision-making (in Portuguese: *TOmada de Decisão Interativa Multicritério*);
TOPSIS – technique for order of preference by similarity to ideal solution;
UAV – unmanned aerial vehicle;
VIKOR – multi-criteria optimization and compromise solution (in Serbian: *Višekriterijumska optimizacija I KOmpromisno Rešenje*);
WASPAS – weighted aggregated sum product assessment.

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 the qualitative attributes that are used to describe certain phenomena (Nikolić *et al.* 2018). Therefore, in this paper, LNN are used to show expert preferences. Since modelling 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 detecting and fighting against forest fires that is based on LNN.

The multi-criteria model is based on the modification of the traditional MABAC method (Pamučar, Ćirović 2015) using the LNN approach. In the hybrid OS–MABAC model expert preferences are represented using LNN. In this way, it is possible to present qualitative expert preferences, even in cases when they are not clear and precise. The LNN–OS model was used to determine the weight values of the evaluation criteria; in the model the weights of the criteria are a combination of the objective and subjective values of the weight coefficients of the criteria. The objective values of the criteria weights are obtained by the method of maximum deviation, while the subjective values of the weights are obtained on the basis of expert evaluation. By integrating the OS–MABAC model with LNN it was shown that it is possible to take into account the uncertainty and indeterminacy in qualitative expert assessments that arise in complex decision-making conditions. The LNN–OS–MABAC model was tested and validated using the case study of selecting optimal unmanned aircraft for fighting forest fires.

An UAV is an aircraft that, using aerodynamics and propulsion force flies a fixed path without a pilot onboard (Odido, Madara 2013). The aerodynamic surfaces that serve to create aerodynamic forces and moments that control the flight of a UAV are built in the form of fixed or rotary wings. The flight of this type of aircraft is controlled from a ground center system via a data link in 2 ways: by means of a pilot controlling the flight path using a camera and a joystick or tracking landmarks during the flight based on a programmed automatic mode of flight (Ceruti *et al.* 2013; Arola, Akhloufi 2019). A wide range of applications in many different activities have been made possible by these aircraft, including the fight against fires, due to: technological advancements in their design, the capabilities and technical performance, the absence of a person in the aircraft, relatively simple control modes, significantly smaller dimensions than manned aircrafts (easier storage and transport), and the possibility of carrying different types of payloads (Ambrosia, Zajkowski 2015). The use of unmanned aircraft in the fight against fires is a result of the fact that these aircraft together with an appropriate sensor and computer system, secure the fast, unhindered and relatively inexpensive monitoring and detection of fires on inaccessible terrain over a longer period of time (Bosch *et al.* 2013). Using unmanned aircraft for the monitoring and detection of fires is carried out from air space, which eliminates the negative effects of extinguishing and detecting fires in the form of obstacles related to the terrain, vegetation, hydrography, and the like. All of this has resulted in the increasing applicability of unmanned aircraft in the fight against forest fires in the last decade, which, according to available data, destroy millions of hectares of forests every year world wide, while hundreds of millions of dollars are spent on extinguishing them (Martinez-de-Dios *et al.* 2008). These fires, besides destroying the natural balance in the biosphere, cause priceless damage to material goods and the environment around the world. They most commonly occur in inaccessible and poorly populated areas, spread rapidly and have along combustion cycle (Lin *et al.* 2014). In order to reduce the destructive effects of such fires, early detection, monitoring and rapid neutralization are crucial, which the application of modern UAVs can provide (Zhang *et al.* 2019).

This paper has several objectives:

- the 1st objective is to improve the methodology for treating uncertainty in the field of group MCDM;
- the 2nd goal of the paper is to prioritize the criteria and form a model that will enable an objective, scientifically based approach to the selection of optimal unmanned aircraft for the detection and fight against forest fires;
- the 3rd objective of this paper is to bridge the gap that exists in the methodology for the evaluation of unmanned aircraft designed for the detection and fight against forest fires through a new approach to the treatment of uncertainty that is based on LNN.

One of the contributions of this paper is an original MCDM model in which modifications of the MABAC method were carried out using LNN. Another contribution is the LNN–OS model for determining the weight coefficients of criteria that has been developed by the authors and which improves MCDM techniques. The 3rd contribution of the paper is to improve the methodology for selecting optimal unmanned aircraft intended to detect and fight forest fires by means of a new approach to the treatment of uncertainty based on LNN. Its practical contribution can be seen in the possibility of applying the proposed criteria and model in the development of documents for the selection of unmanned aircraft for fighting forest fires. Also, bearing in mind the possibility of transferring technology (the upgrade of technologies adopted for the development of unmanned aircraft) and knowledge in this field (particularly in the IT sector), the defined criteria and proposed model can be the basis for improving the design of unmanned aircraft for the fight against forest fires.

The rest of the paper is organized in the following way. The Section 1 is a literature review, which includes the application of linguistic variables and the theory of uncertainty in the field of MCDM. The Section 2 presents the algorithm for the hybrid LNN–OS–MABAC model, which is later tested in Section 3 through the real case-study of selecting optimal unmanned aircraft for the detection and fight against forest fires in the Republic of Serbia. The Section 4 includes a discussion of the results for the LNN–OS–MABAC model. This discussion is in the form of a sensitivity analysis and comparison of the results with LNN extensions of the TOPSIS and VIKOR models. Finally, last section presents concluding considerations with a special emphasis on directions for future research.

1. Literature review

Modelling expert preferences in decision-making problems using linguistic terms (Naeini *et al.* 2019) is an interesting field of research, which has been the subject of studies by numerous authors in the last decade.

Zadeh (1975) 1st introduced the concept of linguistic variables and their application in fuzzy logic. Later, the possibility of using linguistic information in mathematical models for decision-making was presented (Herrera *et al.* 1996; Herrera, Herrera-Viedma 2000). Then, goal programming models were developed with a linguistic hybrid arithmetic averaging operator for group MCDM using linguistic information (Xu 2006). In order to keep as much linguistic information as possible in an evaluation of the attributes, a number of models have been proposed that allow the use of linguistic variables (Table 1).

Table 1 shows the most commonly used linguistic approaches from the literature for presenting the qualitative values of the attributes in MCDM. A total of 9 approaches are included that represent an evaluation of the linguistic approaches from their emergence in fuzzy theory (Zadeh 1975) to linguistic neutrosophic variables (Liang *et al.* 2017). As can be seen from Table 1, 2-dimensional uncertain linguistic sets (Liu, Teng 2016) and operators to aggregate their values are proposed, and the possibility of their application in group decision-making is demonstrated. After this, other approaches are also shown to present uncertainty using linguistic variables: intuitionistic linguistic sets (Szmidt, Kacprzyk 2003), hesitant fuzzy linguistic term sets (Rodriguez *et al.* 2012), hesitant intuitionistic fuzzy linguistic variables (Yang *et al.* 2017), probabilistic linguistic term sets (Pang *et al.* 2016), rough sets (Pamučar *et al.* 2018) and so on. By combining IFN (Atanassov 1986) and fuzzy linguistic variables (Zadeh 1975), LIFN are proposed (Meng *et al.* 2019). Then, based on that approach, improved LIFN aggregators were introduced, which are used in MCDM (Liu, Wang 2017).

Since LIFN cannot successfully cope with all types of uncertainty in different real problems (such as problems with indeterminate information) a SVNLN was introduced (Ye 2015) which is made up of SVNN (Ye 2013). With SVNLN, a linguistic variable represents the assessment of the decision maker concerning the object of the evaluation, and a SVNN expresses the reliability of the given linguistic variable (Ye 2015). In addition to the basic SVNLN model, the traditional TOPSIS method was expanded and the possibility of its application in group decision-making using SVNLN was demonstrated (Ye 2015).

However, SVNLN cannot be successfully used to represent truth, indeterminacy and falsity based on linguistic variables (Liang *et al.* 2017). In order to overcome the above-mentioned disadvantages of IFN, LIFN and SVNLN, one of the solutions is to independently represent the degree of truth, indeterminacy and falsity of the object being evaluated using 3 independent linguistic variables. On the other hand, it is necessary in human reasoning when making decisions to use linguistic information on the degree of truth, indeterminacy and falsity, since SVNN already holds this information. On the basis of these ideas, the concept of a LNN is proposed, which is a combination of SVNN and linguistic variables. LNN uses independent linguistic variables to represent the degree of truth, indeterminacy and falsity, and not crisp values like in SVNN, that is, linguistic variables and SVNN, as with SVNLN. We can present the concept of LNN using the example of selecting providers for transport services. Suppose that the decision makers evaluate unmanned aircraft using a set of linguistic expressions $s = \{s_0$ – exceedingly low, s_1 – pretty low, s_2 – low, s_3 – medium, s_4 – high, s_5 – pretty high, s_6 – exceedingly high$\}$. If expert E1 evaluates unmanned aircraft A2 according to criterion K1 with a score of s_5 for the truth membership degree, s_3 for the indeterminacy membership degree and s_3 for the falsity membership degree, then on the basis of the LNN concept, we can present the assessment in the form $e = \langle s_5, s_3, s_3 \rangle$. On the basis of this example it is obvious that LIFN and SVNLN cannot represent this kind of linguistic evaluation, while by extending the concept of SVNN and LIFN, that is, by means of the LNN concept we can represent these evaluations simply. For this reason, LNN is a very interesting concept to study since it allows the presentation of the uncertain and inconsistent linguistic information that is present in human reasoning. LNNs are very suitable for presenting linguistic information about the complex attributes of a decision, especially when it comes to qualitative attributes, since LNN simultaneously exploits the advantages of SVNN and linguistic variables.

Table 1. Linguistic approach

Uncertainty approach	Reference	Methods	Applications
Fuzzy linguistic variable	Zadeh (1975)	fuzzy linguistic variable	application fuzzy linguistic variable to approximate reasoning
	Herrera *et al.* (1996)	linguistic assessments	a consensus model in group decision-making under linguistic assessments
	Bordogna *et al.* (1997)	fuzzy linguistic ordered weighted average operators	fuzzy linguistic model for group decision-making based on ordered weighted average operators
	Herrera, Herrera-Viedma (2000)	a MCDM model based on linguistic information	steps for solving MCDM problems under linguistic information
	Chang *et al.* (2006)	fuzzy multiple attribute decision-making model	applying fuzzy linguistic quantifier to select supply chain partners
	Xu (2006)	multi-attribute group decision-making with linguistic information	linguistic hybrid arithmetic averaging operator in multiple attribute group decision-making with linguistic information
	Yan *et al.* (2013)	quality function deployment fuzzy linguistic model	prioritizing engineering design requirements in quality function deployment
	Lin *et al.* (2013)	balanced scorecard and fuzzy linguistic method	balanced scorecard and fuzzy linguistic method for evaluating operating room performance.
2-dimension uncertain linguistic variable	Liu, Teng (2016)	2-dimension linguistic TODIM method	extension of the TODIM method to 2-dimensions, uncertain linguistic information
	Liu *et al.* (2015)	2-dimension linguistic average operators	2-dimension linguistic average operators are applied to MCDM
	Liu, You (2018)	2-dimension linguistic weighted Hamy mean aggregation operator	application in group decision-making
Intuitionistic linguistic variables	Szmidt, Kacprzyk (2003)	degrees of consensus under intuitionistic fuzzy preferences	a new concept of a distance from consensus under intuitionistic fuzzy preferences is introduced
	Xu (2006)	group decision-making model based on intuitionistic preference relations	the intuitionistic fuzzy arithmetic averaging operators are used to aggregate intuitionistic preference information
	Chen *et al.* (2015)	group decision-making model based on intuitionistic linguistic aggregation operators	application and validation of proposed intuitionistic linguistic group decision-making model
	Meng *et al.* (2019)	intuitionistic linguistic ordered weighted averaging operator and consistency-based linear programming model	group decision-making with intuitionistic linguistic preference relations
	Liu, Wang (2017)	intuitionistic linguistic aggregation operators	based on proposed aggregators fuzzy intuitionistic linguistic MCDM model is developed
Hesitant fuzzy linguistic variables	Rodriguez *et al.* (2012)	a multi-criteria linguistic decision-making model	hesitant fuzzy linguistic MCDM model is presented
	Beg, Rashid (2013)	hesitant fuzzy linguistic TOPSIS method	hesitant fuzzy linguistic TOPSIS method with illustrative examples is proposed
	Gou *et al.* (2017b)	Bonferroni means with hesitant fuzzy linguistic information	2 Bonferroni means operators for hesitant fuzzy linguistic term sets are introduced
	Wang *et al.* (2016)	hesitant fuzzy linguistic TOPSIS and TODIM methods	2 hesitant fuzzy linguistic MCDM methods are proposed, which are based on the Hausdorff distance measure
	Tüysüz, Şimşek (2017)	a hesitant fuzzy linguistic term sets-based AHP method	analysing the performance evaluation factors: an application in the cargo sector
	Gou *et al.* (2017a)	hesitant fuzzy linguistic MULTIMOORA method	comparisons between the MULTIMOORA method and the hesitant fuzzy linguistic TOPSIS method
Hesitant intuitionistic fuzzy linguistic variables	Yang *et al.* (2017)	hesitant intuitionistic fuzzy linguistic TOPSIS method	application of the TOPSIS method based on the generalized linguistic hesitant intuitionistic fuzzy correlated averaging operator
	Faizi *et al.* (2017)	hesitant intuitionistic fuzzy linguistic based outranking method	an outranking method for group decision-making using hesitant intuitionistic fuzzy linguistic term sets
	Rashid *et al.* (2018)	hesitant intuitionistic fuzzy linguistic ELECTRE method	application of the hesitant intuitionistic fuzzy linguistic ELECTRE method based on directional Hausdorff distance

End of Table 1

Uncertainty approach	Reference	Methods	Applications
Probabilistic linguistic variables	Pang *et al.* (2016); Bai *et al.* (2017)	probabilistic linguistic TOPSIS method	proposed an extended TOPSIS method and an aggregation-based method for MCDM with probabilistic linguistic information
	Zhang, She (2017)	the probabilistic linguistic MCDM model	the probabilistic linguistic method is applied in the service quality in wireless sensor networks
Single-valued neutrosophic number	Zavadskas *et al.* (2015)	single-valued neutrosophic linguistic WASPAS method	sustainable assessment of waste incineration plant construction site alternatives by single-valued neutrosophic linguistic WASPAS method
	Biswas *et al.* (2016)	single-valued neutrosophic TOPSIS Method	application of single-valued neutrosophic TOPSIS method in uncertainty environment
	Ye (2013, 2014); Biswas *et al.* (2014); Deli, Şubaş (2017)	a MCDM model	application of single-valued neutrosophic MCDM method
SVNLN	Ye (2015)	single-valued neutrosophic linguistic TOPSIS method	extension of TOPSIS method based on single-valued neutrosophic linguistic approach
	Wang *et al.* (2018); Tan *et al.* (2017); Garg, Nancy (2018); Wu *et al.* (2018)	single-valued neutrosophic linguistic aggregation operators	application of proposed single-valued neutrosophic linguistic aggregation operators in group MCDM methods
LNN	Liang *et al.* (2017)	LNN–TOPSIS method	evaluating investment risks of a gold mine using the proposed TOPSIS method
	Fang, Ye (2017); Fan *et al.* (2017); Liu, You (2018)	linguistic neutrosophic aggregation operators	application of proposed linguistic neutrosophic aggregation operators in group MCDM methods
	She, Ye (2017)	a MCDM model	MCDM method based on the cosine similarity measures under an linguistic neutrosophic environment

2. A multi-criterial model based on LNN

The following section (Section 2.1) gives the basic framework of the linguistic neutrosophic concept, as well as the basic arithmetic operations with LNN (Figure 1). After this, the OS–MABAC multi-criteria model based on the concept of LNN is presented in Sections 2.2 and 2.3.

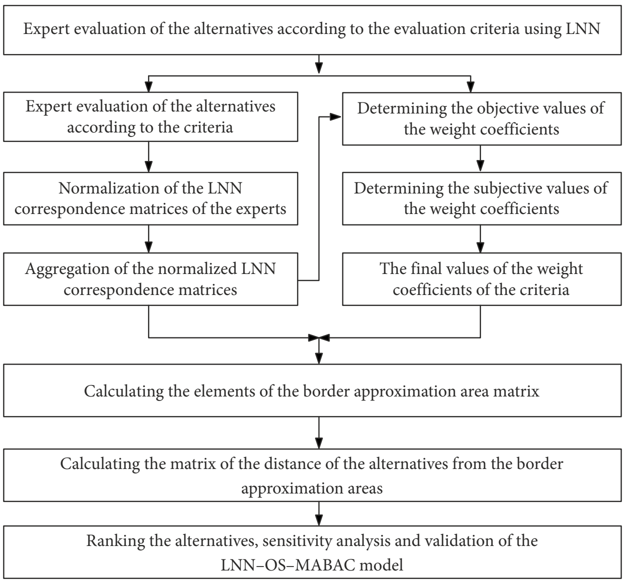

Figure 1. Framework of the proposed model

2.1. Some concepts of LNN

Definition 1. 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. 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 LNNs in S and $k>0$, then we can define the arithmetic operations for LNN (Liang *et al.* 2017):

»» addition of LNN "+":

$$e_1+e_2=\langle s_{p_1}, s_{q_1}, s_{r_1}\rangle+\langle s_{p_2}, s_{q_2}, s_{r_2}\rangle=\left\langle s_{p_1+p_2-\frac{p_1\cdot p_2}{t}}, s_{\frac{q_1\cdot q_2}{t}}, s_{\frac{r_1\cdot r_2}{t}}\right\rangle; \quad (1)$$

»» multiplication of LNN "×":

$$e_1 \times e_2 = \left\langle s_{p_1}, s_{q_1}, s_{r_1} \right\rangle \times \left\langle s_{p_2}, s_{q_2}, s_{r_2} \right\rangle =$$
$$\left\langle s_{\frac{p_1 \cdot p_2}{t}}, s_{q_1+q_2-\frac{q_1 \cdot q_2}{t}}, s_{r_1+r_2-\frac{r_1 \cdot r_2}{t}} \right\rangle; \quad (2)$$

»» multiplying LNN by a scalar, where $k > 0$:

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

»» LNN power, where $k > 0$:

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

Definition 3. Let $e = \left\langle s_p, s_q, s_r \right\rangle$ be the LNN in S, then we can define the score function and the accuracy function according to the following (Fang, Ye 2017):

$$Q(e) = \frac{2 \cdot t + p - q - r}{3 \cdot t},$$
$$\forall\ Q(e) \in [0,1]; \quad (5)$$
$$T(e) = \frac{p - r}{t}$$
$$\forall\ T(e) \in [-1,1]. \quad (6)$$

Definition 4. Let $e_1 = \left\langle s_{p_1}, s_{q_1}, s_{r_1} \right\rangle$ and $e_2 = \left\langle s_{p_2}, s_{q_2}, s_{r_2} \right\rangle$ be 2 LNNs in S, then their relations of comparison can be defined as:

»» if $Q(e_1) < Q(e_2)$, then $e_1 < e_2$;

»» if $Q(e_1) > Q(e_2)$, then $e_1 > e_2$;

»» if $Q(e_1) = Q(e_2)$ and $T(e_1) < T(e_2)$, then $e_1 < e_2$;

»» if $Q(e_1) = Q(e_2)$ and $T(e_1) > T(e_2)$, then $e_1 > e_2$;

»» if $Q(e_1) = Q(e_2)$ and $T(e_1) = T(e_2)$, then $e_1 = e_2$.

Definition 5. If with $e_j = \left\langle s_{p_j}, s_{q_j}, s_{r_j} \right\rangle$, $j = 1, 2, \ldots, n$, we denote n LNN in S, then we can define the LNNWAA operator in the following way:

$$LNNWAA(e_1, e_2, \ldots, e_n) = \sum_{j=1}^{n} w_j \cdot e_j, \quad (7)$$

where: $w_j \in [0,1]$ represents the weight coefficient of e_j, $j = 1, 2, \ldots, n$, which satisfies the condition that $\sum_{j=1}^{n} w_j = 1$.

Then on the basis of Definitions 2 and 5 we can introduce the following theorem.

Theorem 1. Let $e_j = \left\langle s_{p_j}, s_{q_j}, s_{r_j} \right\rangle$, $j = 1, 2, \ldots, n$, we denote n LNN in S, then the aggregation of the results that we obtain using Equation (7) represents the LNN. The aggregated LNN is obtained using the following equation (Liang *et al.* 2017):

$$LNNWAA(e_1, e_2, \ldots, e_n) = \sum_{j=1}^{n} w_j \cdot e_j =$$
$$\left\langle s_{t-t\cdot\prod_{j=1}^{n}\left(1-\frac{p_j}{t}\right)^{w_j}}, s_{t\cdot\prod_{j=1}^{n}\left(\frac{q_j}{t}\right)^{w_j}}, s_{t\cdot\prod_{j=1}^{n}\left(\frac{r_j}{t}\right)^{w_j}} \right\rangle, \quad (8)$$

where: $w_j \in [0,1]$ represents the weight coefficient of e_j, $j = 1, 2, \ldots, n$, which satisfies the condition that $\sum_{j=1}^{n} w_j = 1$.

Definition 6. If with $e_j = \left\langle s_{p_j}, s_{q_j}, s_{r_j} \right\rangle$, $j = 1, 2, \ldots, n$, we denote n LNN in S, then we can define the LNNWGA operator in the following way:

$$LNNWAA(e_1, e_2, \ldots, e_n) = \prod_{j=1}^{n} e_j^{w_j}, \quad (9)$$

where $w_j \in [0,1]$ is the weight coefficient of e_j, $j = 1, 2, \ldots, n$, which satisfies the condition that $\sum_{j=1}^{n} w_j = 1$.

Then on the basis of Definitions 2 and 6 we can present the following theorem.

Theorem 2. Let $e_j = \left\langle s_{p_j}, s_{q_j}, s_{r_j} \right\rangle$; $(j = 1,2,\ldots,n)$ we denote n LNN in S, then the aggregation of the results that we obtain using Equation (9) represents the LNN. The aggregated LNN is obtained using the following equation:

$$LNNWGA(e_1, e_2, \ldots, e_n) = \prod_{j=1}^{n} e_j^{w_j} =$$
$$\left\langle s_{t\cdot\prod_{j=1}^{n}\left(\frac{p_j}{t}\right)^{w_j}}, s_{t-t\cdot\prod_{j=1}^{n}\left(1-\frac{q_j}{t}\right)^{w_j}}, s_{t-t\cdot\prod_{j=1}^{n}\left(1-\frac{r_j}{t}\right)^{w_j}} \right\rangle, \quad (10)$$

where: $w_j \in [0,1]$ represents the weight coefficient of e_j, $j = 1, 2, \ldots, n$, which satisfies the condition that $\sum_{j=1}^{n} w_j = 1$.

If the condition is satisfied that $w_j = \frac{1}{n}$ for $j = 1, 2, \ldots, n$, then the LNNWGA operator is transformed into an LNN geometric averaging operator.

Definition 7. Let $e_1 = \left\langle s_{p_1}, s_{q_1}, s_{r_1} \right\rangle$ and $e_2 = \left\langle s_{p_2}, s_{q_2}, s_{r_2} \right\rangle$ be 2 cases of LNN. Let $S = \left\{ s_i \mid i \in [0, t] \right\}$ be a linguistic set and let $f(s_i) = \frac{i}{t}$ be a linguistic function. Then we can determine the distance between e_1 and e_2 using the following equation:

$$d(e_1, e_2) = \left(\frac{1}{3} \cdot \left(\left| f(s_{p_1}) - f(s_{p_2}) \right|^{\varphi} + \right.\right.$$
$$\left| f(s_{t-q_1}) - f(s_{t-q_2}) \right|^{\varphi} +$$
$$\left.\left. \left| f(s_{t-r_1}) - f(s_{t-r_2}) \right|^{\varphi} \right) \right)^{\frac{1}{\varphi}},$$
$$\varphi > 0. \quad (11)$$

By transforming Equation (11) we can easily obtain equations for determining the Hamming, Euclidean and

Hausdorff distances between 2 LNNs (Fang, Ye 2017):

- if $\varphi = 1$ we obtain the equation for the Hamming distance:

$$d_{Hm}\left(e_1, e_2\right) = \frac{1}{3}\cdot\left(\left|f\left(s_{p_1}\right) - f\left(s_{p_2}\right)\right| + \left|f\left(s_{t-q_1}\right) - f\left(s_{t-q_2}\right)\right| + \left|f\left(s_{t-r_1}\right) - f\left(s_{t-r_2}\right)\right|\right); \quad (12)$$

- if $\varphi = 2$ we obtain the equation for the Euclidean distance:

$$d_{Ed}\left(e_1, e_2\right) = \sqrt{\frac{1}{3}\cdot\left(a^2 + b^2 + c^2\right)}, \quad (13)$$

where:

$$a = \left|f\left(s_{p_1}\right) - f\left(s_{p_2}\right)\right|;$$

$$b = \left|f\left(s_{t-q_1}\right) - f\left(s_{t-q_2}\right)\right|;$$

$$c = \left|f\left(s_{t-r_1}\right) - f\left(s_{t-r_2}\right)\right|;$$

- Hausdorff distance:

$$d_{Hd}\left(e_1, e_2\right) = \max\left(\left|f\left(s_{p_1}\right) - f\left(s_{p_2}\right)\right| + \left|f\left(s_{t-q_1}\right) - f\left(s_{t-q_2}\right)\right| + \left|f\left(s_{t-r_1}\right) - f\left(s_{t-r_2}\right)\right|\right). \quad (14)$$

For any three LNNs $e = \left\langle s_p, s_q, s_r\right\rangle$, $e_1 = \left\langle s_{p_1}, s_{q_1}, s_{r_1}\right\rangle$ and $e_2 = \left\langle s_{p_2}, s_{q_2}, s_{r_2}\right\rangle$ from the linguistic set $S = \left\{s_0, s_1, \ldots, s_t\right\}$ with odd cardinality $t + 1$, where for $s_p, s_q, s_r \in S$ and $p, q, r \in \left[0, t\right]$ the following properties apply:

- $0 \le d\left(e_1, e_2\right) \le 1$;
- $d\left(e_1, e_2\right) = d\left(e_2, e_1\right)$;
- $d\left(e_1, e_2\right) = 0$, if $e_1 = e_2$;
- $d\left(e_1, e\right) = d\left(e_1, e_2\right) + d\left(e_2, e\right)$.

2.2. 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 (Zavadskas *et al.* 2015; Karabašević *et al.* 2019), 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 (Biswas *et al.* 2016; Marković *et al.*, 2020). The advantage of the OS model is that it simultaneously takes into account subjective and objective information. OS model considers 2 aspects of information, which can influence decision-making. The 1st aspect means that the model takes into account preferences by decision-makers (subjectivity information), while the 2nd aspect means including objective information based on real quantitative data. The integration of such information helps to obtain more precise criteria weights, which including all relevant information, considering both aspects. Therefore, by combining the subjective and objective weights we obtain the final values of the weight coefficients of the evaluation criteria.

The model is implemented in 2 phases: in the 1st phase the objective values of the criteria are determined using the method of maximum deviation; in the 2nd 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.

2.2.1. Phase I: determining the objective values of the weight coefficients

Determining the objective values of the weight coefficients is based on the model of maximum deviation (MMD). It begins with the assumption that the process of decision-making involves m experts who evaluate the set of alternatives $A = \left\{a_1, a_2, \ldots, a_b\right\}$ according to the criteria $C = \left\{c_1, c_2, \ldots, c_n\right\}$. The alternatives are evaluated based on a predefined set of linguistic variables $S = \left\{s_i \mid i \in \left[0, t\right]\right\}$. So for each expert, we construct an initial decision correspondence matrix $N^{(l)} = \left[\xi_{ij}^{(l)}\right]_{b\times n}$. After normalization of the expert correspondence matrix, we obtain aggregated normalized decision matrix $\hat{Y} = \left[\hat{y}_{ij}\right]_{b\times n}$. The aggregated normalized decision matrix $\hat{Y}$ is further transformed into weighted matrix $D = \left[d_{ij}\right]_{b\times n}$, $d_{ij} = w_j \cdot\left\langle \hat{s}_{p_{ij}}, \hat{s}_{q_{ij}}, \hat{s}_{r_{ij}}\right\rangle$.

In matrix D we can calculate the degree of deviation of the observed element in relation to the other elements within criterion c_j, $j = 1, 2, \ldots, n$:

$$D_{ij}\left(w_j\right) = \sum_{u=1}^{b} d\left(d_{ij}, d_{uj}\right) = \sum_{u=1}^{b} d\left(\hat{y}_{ij}, \hat{y}_{uj}\right)\cdot w_j, \quad (15)$$

where: $d\left(\hat{y}_{ij}, \hat{y}_{uj}\right)$ represents the distance between $\hat{y}_{ij}$ and $\hat{y}_{uj}$.

From Equation (15) we can clearly see that for greater values of $D_{ij}\left(w_j\right)$ alternative a_i, $i = 1, 2, \ldots, b$ is better. The MMD model is based on the following starting points: (1) if there are small deviations between the observed value ξ_{ij} and all other values within the evaluation criteria c_j, $j = 1, 2, \ldots, n$, then criterion c_j has little impact on the ranking of the alternatives (c_j has a low value of weight coefficient w_j); (2) in contrast to this, if there are significant deviations between the observed value ξ_{ij} and all other values within the evaluation criteria c_j, $j = 1, 2, \ldots, n$, then criterion c_j has a high impact on the ranking of the alternatives (c_j has a high value of weight coefficient w_j);

(3) if all the values of $\hat{y}_{ij}$ are identical within the evaluation criteria c_j, $j = 1, 2, \ldots, n$, then criterion c_j has no influence on the ranking of the alternatives (c_j has the value of the weight coefficient $w_j = 0$).

In the next step the degree of deviation is calculated between all of the elements within the framework of the observed criterion c_j, $j = 1, 2, \ldots, n$:

$$D_j\left(w_j\right)=\sum_{i=1}^{b} D_{ij}\left(w_j\right)=\sum_{i=1}^{b}\sum_{u=1}^{b} d\left(\hat{y}_{ij},\hat{y}_{uj}\right)\cdot w_j. \quad (16)$$

That is, the total deviation of all the alternatives according to the criterion:

$$D\left(w\right)=\sum_{j=1}^{n}\sum_{i=1}^{b} D_{ij}\left(w_j\right)=$$
$$\sum_{j=1}^{n}\sum_{i=1}^{b}\sum_{u=1}^{b} d\left(\hat{y}_{ij},\hat{y}_{uj}\right)\cdot w_j. \quad (17)$$

The weight coefficients w_j are obtained by solving the optimization model that is based on maximum deviation:

$$\max D\left(w\right)=\sum_{j=1}^{n}\sum_{i=1}^{b}\sum_{u=1}^{b} d\left(\hat{y}_{ij},\hat{y}_{uj}\right)\cdot w_j$$

subject to:

$$\begin{cases}\sum_{j=1}^{n} w_j^2=1; \\ 0\le w_j\le 1;\ j=1,2,\ldots,n.\end{cases} \quad (18)$$

In order to obtain a solution to the model – Equation (18) – the Lagrange function was introduced:

$$L\left(w,p\right)=\sum_{j=1}^{n}\sum_{i=1}^{b}\sum_{u=1}^{b} d\left(\hat{y}_{ij},\hat{y}_{uj}\right)\cdot w_j+$$
$$\frac{p}{2}\cdot\left(\sum_{j=1}^{n} w_j^2-1\right). \quad (19)$$

After partial deviation, 2 equations are obtained $D\left(w\right)+p\cdot w_j=0$ and $\sum_{j=1}^{n} w_j^2=1$, we obtain:

$$w_j=\frac{a_1}{a_2}, \quad (20)$$

where:

$$a_1=\sum_{i=1}^{b}\sum_{u=1}^{b}\left(\frac{1}{3}\cdot\left(\left|f\left(\hat{s}_{pij}\right)-f\left(\hat{s}_{p_{uj}}\right)\right|^{\varphi}+\right.\right.$$
$$\left|f\left(\hat{s}_{t-q_{ij}}\right)-f\left(\hat{s}_{t-q_{uj}}\right)\right|^{\varphi}+$$
$$\left.\left.\left|f\left(\hat{s}_{t-r_{ij}}\right)-f\left(\hat{s}_{t-r_{uj}}\right)\right|^{\varphi}\right)\right)^{\frac{1}{\varphi}};$$

$$a_2=\sqrt{\sum_{j=1}^{n}\left(\sum_{i=1}^{b}\sum_{u=1}^{b}\frac{1}{3}\cdot\left(a_{21}+a_{22}+a_{23}\right)\right)^2},$$

where:

$$a_{21}=\left|f\left(\hat{s}_{pij}\right)-f\left(\hat{s}_{p_{uj}}\right)\right|^{\varphi};$$

$$a_{21}=\left|f\left(\hat{s}_{pij}\right)-f\left(\hat{s}_{p_{uj}}\right)\right|^{\varphi};$$

$$a_{23}=\left|f\left(\hat{s}_{t-r_{ij}}\right)-f\left(\hat{s}_{t-r_{uj}}\right)\right|^{\varphi}.$$

By normalizing the values – Equation (20) – we obtain the final values of the objective weight coefficients:

$$w_j^*=\frac{w_j}{\sum_{j=1}^{n} w_j}. \quad (21)$$

2.2.2. Phase II: determining the subjective values of the weight coefficients

Suppose that each expert e_l from the set of experts $\left\{e_1,e_2,\ldots,e_m\right\}$, $l = 1, 2, \ldots, m$, constructs a subjective vector of the weight coefficients of the criteria $w_j^{(l)}=\left\{w_1^{(l)},w_2^{(l)},\ldots,w_n^{(l)}\right\}$, $l = 1, 2, \ldots, m$, where $\sum_{j=1}^{n} w_j^{(l)}=1$, $0\le w_j^{(l)}\le 1$. We obtain the aggregated (final) values of the subjective weight coefficients using equation:

$$w_j'=\frac{\sum_{l=1}^{m} w_j^{(l)}}{\sum_{j=1}^{n}\sum_{l=1}^{m} w_j^{(l)}}, \quad (22)$$

where: $w_j^{(l)}$, $1\le l\le m$, $j = 1, 2, \ldots, n$ represents the subjective value of the weight coefficient of criterion c_j assigned by expert l; w_j' represents the final values of the subjective weight coefficients.

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

$$w_j=\frac{w_j^*\cdot w_j'}{\sum_{j=1}^{n} w_j^*\cdot w_j'}, \quad (23)$$

where: w_j^* represents the objective and w_j' represents the 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 (23) goes beyond the restrictions of the one-sided application of subjective or objective factors. In addition, Equation (23) enables a simultaneous display of the influence of subjective and objective information on the ranking of the alternatives.

2.3. 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 (Pamučar, Ćirović 2015). 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 MCDM: material selection with incomplete weight information (Xue *et al.* 2016), investment problems (Peng, Dai 2018), manufacturing (Nunić 2018) military problems (Bojanic *et al.* 2018; Božanić *et al.* 2018), renewable energy (Gigović *et al.* 2017), website selection (Yu *et al.* 2017), logistics (Pamučar, Božanić 2019) and so on. The basic method for the MABAC model is that it defines the distance of the criterion function of each of the given alternatives from the BAA. 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 $A=\{a_1,a_2,\dots,a_b\}$ (where: b denotes the final number of alternatives) in relation to the defined set of evaluation criteria $C=\{c_1,c_2,\dots,c_n\}$ (where: n represents the total number of criteria). The experts $\{e_1,e_2,\dots,e_m\}$ are assigned weight coefficients $\{\delta_1,\delta_2,\dots,\delta_m\}$, $0\le\delta_l\le 1$, $l=1,2,\dots,m$ 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, $i=1,2,\dots,b$, from the set of alternatives A, each expert e_l, $l=1,2,\dots,m$, evaluates the alternatives according to the defined set of criteria $C=\{c_1,c_2,\dots,c_n\}$. So for each expert we construct a correspondence initial decision matrix:

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

where the basic elements of matrix $N^{(l)}\left(\xi_{ij}^{(l)}\right)$ 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 $p_{ij},q_{ij},r_{ij}\in[0,t]$. Linguistic expressions $\xi_{ij}^{(l)}=\left\langle s_{p_{ij}}^{(l)},s_{q_{ij}}^{(l)},s_{r_{ij}}^{(l)}\right\rangle$, that is $s_{p_{ij}}^{(l)}$, $s_{q_{ij}}^{(l)}$ and $s_{r_{ij}}^{(l)}$ independently provide information on the degree of truth, indeterminacy and falsity when evaluating the alternatives a_i, $i=1,2,\dots,b$, according to the defined set of criteria $C=\{c_1,c_2,\dots,c_n\}$.

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

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

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

Step 3. Calculating the elements of the aggregated normalized matrix. The final aggregated decision matrix N is obtained by averaging the elements $\hat{y}_{ij}^{(l)}=\left\langle \hat{s}_{p_{ij}}^{(l)},\hat{s}_{q_{ij}}^{(l)},\hat{s}_{r_{ij}}^{(l)}\right\rangle$ of matrix $\hat{Y}^{(l)}=\left[\hat{y}_{ij}^{(l)}\right]_{b\times n}$ using Equations (27) or (28):

$$\hat{Y}=\left[\hat{y}_{ij}\right]_{b\times n}=\begin{bmatrix}\hat{y}_{11} & \hat{y}_{12} & \cdots & \hat{y}_{1n}\\ \hat{y}_{21} & \hat{y}_{22} & \cdots & \hat{y}_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \hat{y}_{b1} & \hat{y}_{b2} & \cdots & \hat{y}_{bn}\end{bmatrix}=$$
$$\begin{bmatrix}\left\langle \hat{s}_{p_{11}},\hat{s}_{r_{11}},\hat{s}_{q_{11}}\right\rangle & \left\langle \hat{s}_{p_{12}},\hat{s}_{r_{12}},\hat{s}_{q_{12}}\right\rangle & \cdots & \left\langle \hat{s}_{p_{1n}},\hat{s}_{r_{1n}},\hat{s}_{q_{1n}}\right\rangle\\ \left\langle \hat{s}_{p_{21}},\hat{s}_{r_{21}},\hat{s}_{q_{21}}\right\rangle & \left\langle \hat{s}_{p_{22}},\hat{s}_{r_{22}},\hat{s}_{q_{22}}\right\rangle & \cdots & \left\langle \hat{s}_{p_{2n}},\hat{s}_{r_{2n}},\hat{s}_{q_{2n}}\right\rangle\\ \vdots & \vdots & \ddots & \vdots\\ \left\langle \hat{s}_{p_{b1}},\hat{s}_{r_{b1}},\hat{s}_{q_{b1}}\right\rangle & \left\langle \hat{s}_{p_{b2}},\hat{s}_{r_{b2}},\hat{s}_{q_{b2}}\right\rangle & \cdots & \left\langle \hat{s}_{p_{bn}},\hat{s}_{r_{bn}},\hat{s}_{q_{bn}}\right\rangle\end{bmatrix},\tag{26}$$

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

$$\hat{y}_{ij}=LNNWAA\left(\hat{y}_{ij}^{(1)},\hat{y}_{ij}^{(2)},\dots,\hat{y}_{ij}^{(m)}\right)=\sum_{l=1}^{m}\hat{y}_{ij}^{(l)}\cdot\delta_l=$$
$$\left\langle \hat{s}_{t-t\cdot\prod_{l=1}^{m}\left(1-\frac{p_{ij_l}}{t}\right)^{\delta_l}},\hat{s}_{t\cdot\prod_{l=1}^{m}\left(\frac{q_{ij_l}}{t}\right)^{\delta_l}},\hat{s}_{t\cdot\prod_{l=1}^{m}\left(\frac{r_{ij_l}}{t}\right)^{\delta_l}}\right\rangle,\tag{27}$$

or using an LNNWGA operator:

$$\hat{y}_{ij}=LNNWGA\left(\hat{y}_{ij}^{(1)},\hat{y}_{ij}^{(2)},\dots,\hat{y}_{ij}^{(m)}\right)=\prod_{l=1}^{m}\hat{y}_{ij}^{(l)\delta_l}=$$
$$\left\langle \hat{s}_{t\cdot\prod_{l=1}^{m}\left(\frac{p_{ij_l}}{t}\right)^{\delta_l}},\hat{s}_{t-t\cdot\prod_{l=1}^{m}\left(1-\frac{q_{ij_l}}{t}\right)^{\delta_l}},\hat{s}_{t-t\cdot\prod_{l=1}^{m}\left(1-\frac{r_{ij_l}}{t}\right)^{\delta_l}}\right\rangle,\tag{28}$$

where elements $\hat{y}_{ij}^{(l)}=\left\langle \hat{s}_{p_{ij}}^{(l)},\hat{s}_{q_{ij}}^{(l)},\hat{s}_{r_{ij}}^{(l)}\right\rangle$ are elements of the expert correspondence matrix – Equation (24).

Step 4. Calculating the elements of weighted matrix D. We obtain the elements of weighted matrix $D=\left[d_{ij}\right]_{b\times n}=\left[\left\langle s^*_{p_{ij}}, s^*_{q_{ij}}, s^*_{r_{ij}}\right\rangle\right]_{b\times n}$ using equation:

$$d_{ij}=\left\langle s^*_{p_{ij}}, s^*_{q_{ij}}, s^*_{r_{ij}}\right\rangle = w_j\cdot\left\langle \hat{s}_{p_{ij}}, \hat{s}_{q_{ij}}, \hat{s}_{r_{ij}}\right\rangle =$$

$$\left\langle s^*_{t-t\cdot\left(1-\frac{p_{ij}}{t}\right)^{w_j}}, s^*_{t\cdot\left(\frac{q}{t}\right)^{w_j}}, s^*_{t\cdot\left(\frac{r}{t}\right)^{w_j}}\right\rangle. \tag{29}$$

Step 5. Calculating the elements of the BAA 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:

$$g_j=\prod_{i=1}^{b}\left(d_{ij}\right)^{\frac{1}{b}}=$$

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

Step 6. Calculating the matrix of the distance of the alternatives from the BAA Q. We obtain the elements of matrix $S=\left[s_{ij}\right]_{b\times n}$ using equation:

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

where: g_j represents the BAA for criterion C_j; $d_{ij}=\left\langle s^*_{p_{ij}}, s^*_{q_{ij}}, s^*_{r_{ij}}\right\rangle$ represents the elements of weighted matrix D.

Alternative a_i can belong to the BAA 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 alternatives found in the lower approximation area A^- (Figure 2).

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:

$$Q_i=\sum_{j=1}^{n}s_j,$$

$$i = 1, 2, \ldots, b;\ j = 1, 2, \ldots, n. \tag{32}$$

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.

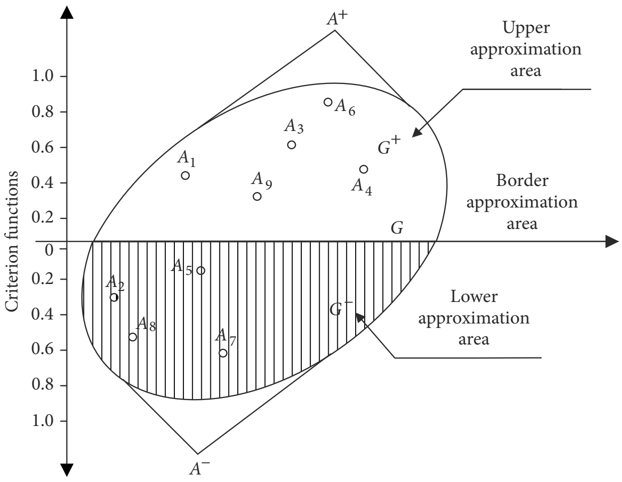

Figure 2. Upper G^+, lower G^- and border G approximation areas

3. Application of the LNN–OS–MABAC model

The application of the LNN–OS–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 10844 hectares of forest area were burned (Aleksić, Jančić 2011). There are different types of unmanned aircraft, such as: target and decoy, reconnaissance, research and development and civil and commercial UAVs (Gupta *et al.* 2013; Jalayer *et al.* 2019; Daly, Paul, 2019; Sudhakar *et al.* 2020). For the purpose of evaluating the criteria and selecting unmanned firefighting aircraft according to the established requirements and the necessary (similar) technical characteristics, the paper considers civil and commercial tactical short–medium range UAVs (Vidović, Diminić 2014). 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 firefighting equipment for the stages of firefighting that are discussed in this paper.

UAVs need to satisfy many requirements in order to fight fires effectively. For example, the requirements relating to capability are: detection, diagnosis of the type of fire and prognosis of its spread, as well as the possibility of a coordinated fight against a fire with a large number of aircraft in the affected area (Yuan *et al.* 2015).The possibility of calculating the fire front shape and other parameters of fire propagation is a very important requirement that needs to be met by UAVs in the fight against fires (Merino *et al.* 2012).The efficiency of a UAV in the detection and monitoring of fires depends on: the propulsion system, the navigation and communication system, and the systems for managing the technical and operational tasks (Vidović, Diminić 2014). There are also general requirements that UAVs need to satisfy in the fight against fire. These requirements relate to adequate: aerodynamics, mission profile flight safety, costs, operational requirements, etc. (Ceruti *et al.* 2013; Calantropio 2019). On the basis of the above, the criteria and attributes for selecting unmanned firefighting 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.

4 experts e_i, $i = 1, 2, \ldots, 4$, from the Ministry of Defence in the Republic of Serbia were involved in the research who have a minimum of 10 years' experience in the field of fire protection and who are familiar with the method of use and the capabilities of using unmanned aircraft in the fight against forest fires. The experts $\left\{e_1, e_2, \ldots, e_4\right\}$ were assigned weight coefficients $\delta_1 = 0.284$, $\delta_2 = 0.267$, $\delta_3 = 0.241$ and $\delta_3 = 0.207$.

During the evaluation of the unmanned aircraft there were no indications given as to the manufacturers of the aircraft, but rather the unmanned aircraft were assigned symbols A1 to A7. Evaluation of the alternatives according to the criteria was carried out using a set of linguistic variables $S = \left\{s_i \mid i \in \left[0, 8\right]\right\}$, in which $s = \left\{s_0 - \text{exceedingly low},\ s_1 - \text{pretty low},\ s_2 - \text{low},\ s_3 - \text{slightly low},\ s_4 - \text{medium},\ s_5 - \text{slightly high},\ s_6 - \text{high},\ s_7 - \text{pretty high},\ s_8 - \text{exceedingly high}\right\}$.

3.1. 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 2 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 2 phases.

3.1.1. 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 4 experts were involved in the research, each of them evaluated the alternatives according to the criteria (Appendix, Table A1). Equation (25) was used to calculate the elements of the normalized expert correspondence matrix $\hat{Y}^{(l)} = \left[\hat{y}_{ij}^{(l)}\right]_{b \times n}$, $l = 1, 2, \ldots, 4$; $b = 1, 2, \ldots, 7$; $n = 1, 2, \ldots, 18$. The expert correspondence matrices are presented in Table A1.

The normalized expert matrices $\hat{Y}^{(l)}$ were aggregated using LNNWGA, Equation (10). The aggregated normalized initial decision matrix is shown in Table 4.

Table 2. Explanation of the criteria

Criteria/sub-criteria	Description of the criteria/sub-criteria
Affordability – C1 (min)	
Maintenance cost – C11 (min)	includes the cost of basic and technical maintenance and general overhaul
Acquisition cost – C12 (min)	procurement costs of the UAV
Operator training – C13 (min)	includes the cost of training operators
Operation cost – C14 (min)	personnel and equipment costs during the life cycle of the UAV
Disposal cost – C15 (min)	cost of disposing of the UAV after completion of its life-cycle
Construction and general system – C2 (max)	
Wing mechanization – C21 (max)	technological solution for the parameters and shape of the wings
Vehicle external configuration – C22 (max)	materials and structure of the framework
Remote via ground central system – C23 (max)	ability to manage and control via the ground central system
Propulsion system – C24 (max)	relates to the type of (electric, fuel or gas) reliability and the engine's thrust
Aerodynamics and ability to process data– C3 (max)	
Flight performance – C31 (max)	speed, altitude, loiter time, cruise distance, manoeuvring and stability performance
Payload capacity – C32 (max)	the load capacity is in line with the other requirements
Ability of data – telemetry and processing – C33 (max)	speed and reliability of data - telemetry and processing
Ability to monitor and detect– C4 (max)	
Detection method – C41 (max)	application used for the detection of fire (fuzzy logic, support vector machine, wavelet analysis, neural network, etc.)
Camera performance – C42 (max)	spectra and resolution of cameras, adopted features of smoke – colour, motion and geometry, ability of image vibration elimination
Ability of detection object – C43 (max)	ability to detect flame – smoke
Fusion of images – C44 (max)	ability of fusion of visual and infrared images
Ability for diagnosis and prognosis – C5 (max)	
Ability to measure geometrical features of fire – C51 (max)	fire front location, fire site width and perimeter, flame length and height, inclination angle, coordinates of burnt areas and location of hotspots
Propagation prediction – C52 (max)	ability to calculate the rate of spread, fire intensity and flame front geometry

Table 3. Experts' characteristics

Age	Gender	Education	Expert's field	Experience's years on UAVs	Expert's field
47	male	PhD	mechatronics	15	UAV's construction
43	male	Engineer	mechatronics and computing	12	UAV's construction and software support
35	male	Engineer	mechatronics and computing	12	UAV's construction and software support
37	male	Engineer	electrical engineering and computing	14	UAV's construction and software support

Table 4. Aggregated normalized initial decision matrix

Criteria/ sub-criteria	Alternative						
	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_{4.92}, s_{1.99}, s_{3.00}\rangle$	$\langle s_{1.39}, s_{5.23}, s_{7.75}\rangle$	$\langle s_{6.00}, s_{2.97}, s_{3.77}\rangle$	$\langle s_{7.75}, s_{4.77}, s_{6.89}\rangle$	$\langle s_{3.00}, s_{3.90}, s_{2.68}\rangle$	$\langle s_{7.26}, s_{1.16}, s_{4.00}\rangle$	$\langle s_{1.39}, s_{6.48}, s_{3.22}\rangle$
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	$\langle s_{4.92}, s_{3.75}, s_{4.45}\rangle$	$\langle s_{0.00}, s_{1.72}, s_{1.16}\rangle$	$\langle s_{5.68}, s_{1.00}, s_{6.00}\rangle$	$\langle s_{5.19}, s_{4.45}, s_{4.45}\rangle$	$\langle s_{3.22}, s_{1.00}, s_{5.00}\rangle$	$\langle s_{7.03}, s_{1.91}, s_{5.00}\rangle$	$\langle s_{0.00}, s_{5.70}, s_{2.00}\rangle$
C21	$\langle s_{4.80}, s_{5.19}, s_{1.22}\rangle$	$\langle s_{2.21}, s_{4.70}, s_{5.09}\rangle$	$\langle s_{7.17}, s_{1.41}, s_{1.37}\rangle$	$\langle s_{4.74}, s_{5.48}, s_{6.49}\rangle$	$\langle s_{4.17}, s_{6.23}, s_{6.46}\rangle$	$\langle s_{4.10}, s_{2.72}, s_{5.00}\rangle$	$\langle s_{5.90}, s_{0.00}, s_{2.43}\rangle$
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	$\langle s_{5.49}, s_{3.95}, s_{1.74}\rangle$	$\langle s_{1.69}, s_{1.69}, s_{4.71}\rangle$	$\langle s_{5.19}, s_{2.43}, s_{3.48}\rangle$	$\langle s_{3.71}, s_{5.6}, s_{5.49}\rangle$	$\langle s_{7.72}, s_{2.86}, s_{2.25}\rangle$	$\langle s_{2.43}, s_{7.54}, s_{2.72}\rangle$	$\langle s_{5.78}, s_{7.72}, s_{1.00}\rangle$
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	$\langle s_{1.18}, s_{5.44}, s_{5.00}\rangle$	$\langle s_{2.48}, s_{1.90}, s_{7.11}\rangle$	$\langle s_{3.88}, s_{1.87}, s_{1.41}\rangle$	$\langle s_{3.26}, s_{3.58}, s_{3.89}\rangle$	$\langle s_{5.03}, s_{1.81}, s_{1.18}\rangle$	$\langle s_{7.53}, s_{2.00}, s_{6.00}\rangle$	$\langle s_{1.00}, s_{1.44}, s_{6.51}\rangle$
C42	$\langle s_{5.74}, s_{7.17}, s_{3.00}\rangle$	$\langle s_{4.74}, s_{5.70}, s_{1.22}\rangle$	$\langle s_{2.00}, s_{6.00}, s_{6.27}\rangle$	$\langle s_{1.37}, s_{1.69}, s_{6.70}\rangle$	$\langle s_{4.45}, s_{4.68}, s_{2.00}\rangle$	$\langle s_{6.00}, s_{6.16}, s_{1.18}\rangle$	$\langle s_{3.69}, s_{2.86}, s_{4.17}\rangle$
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	$\langle s_{3.26}, s_{1.91}, s_{6.04}\rangle$	$\langle s_{1.64}, s_{2.43}, s_{1.44}\rangle$	$\langle s_{7.03}, s_{6.98}, s_{1.64}\rangle$	$\langle s_{1.21}, s_{2.38}, s_{1.64}\rangle$	$\langle s_{1.74}, s_{2.25}, s_{7.51}\rangle$	$\langle s_{7.70}, s_{7.03}, s_{8.00}\rangle$	$\langle s_{3.13}, s_{6.700}, s_{1.39}\rangle$
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	$\langle s_{6.25}, s_{1.81}, s_{2.18}\rangle$	$\langle s_{1.69}, s_{1.22}, s_{6.49}\rangle$	$\langle s_{7.27}, s_{0.00}, s_{2.21}\rangle$	$\langle s_{5.50}, s_{7.11}, s_{3.77}\rangle$	$\langle s_{1.00}, s_{1.47}, s_{7.23}\rangle$	$\langle s_{4.30}, s_{6.47}, s_{4.45}\rangle$	$\langle s_{6.94}, s_{2.18}, s_{2.18}\rangle$

Using Equations (15)–(19) the deviations were calculated between the observed values $\hat{y}_{ij}$ and the remaining values from the aggregated normalized matrix (Table 3) within the framework of the evaluation criteria c_j, j = 1, 2, …, 18. Based on the deviations obtained, Equations (20) and (21) were used to obtain the final objective values of the weight coefficients $\left(w_j^*,\ j=1,2,\ldots,18\right)$:

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

3.1.2. Phase II: determining the subjective values of the weight coefficients

The subjective values of the weight coefficients were assigned by the experts as shown in Table 5. 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.

Table 5. The subjective values of the weight coefficients

Criteria/ sub-criteria	Expert 1	Expert 2	Expert 3	Expert 4	Subjective weights		Rank
					local	global	
C1	0.107	0.067	0.144	0.138	0.114	–	5
C11	0.218	0.214	0.200	0.206	0.206	0.0235	15
C12	0.233	0.286	0.215	0.235	0.238	0.0272	14
C13	0.141	0.143	0.185	0.147	0.151	0.0172	17
C14	0.288	0.357	0.231	0.324	0.295	0.0336	12
C15	0.120	0.071	0.169	0.088	0.110	0.0126	18
C2	0.128	0.133	0.184	0.154	0.150	–	4
C21	0.419	0.344	0.357	0.338	0.364	0.0546	8
C22	0.306	0.281	0.286	0.257	0.282	0.0423	11
C23	0.160	0.219	0.214	0.230	0.206	0.0308	13
C24	0.115	0.156	0.143	0.176	0.147	0.0221	16
C3	0.218	0.200	0.208	0.215	0.210	–	3
C31	0.180	0.167	0.262	0.255	0.216	0.0454	10
C32	0.236	0.333	0.333	0.333	0.309	0.0650	6
C33	0.585	0.500	0.405	0.412	0.475	0.1000	3
C4	0.292	0.333	0.240	0.261	0.282	–	1
C41	0.313	0.280	0.276	0.283	0.288	0.0812	5
C42	0.375	0.220	0.329	0.317	0.310	0.0873	4
C43	0.205	0.240	0.224	0.250	0.230	0.0647	7
C44	0.107	0.260	0.171	0.150	0.172	0.0484	9
C5	0.255	0.267	0.224	0.231	0.244	–	2
C51	0.597	0.518	0.478	0.508	0.525	0.1282	1
C52	0.403	0.482	0.522	0.492	0.475	0.1159	2

Equation (21) was used to carry out the aggregation of the subjective values of the weight coefficients of the criteria from which we obtained the local values of the weights. For criterion C11 we obtained the local value of the weight coefficient (Equation (21)):

$$w'_{C11} = \frac{\sum_{l=1}^{4} w_{C11}^{(l)}}{\sum_{j=1}^{5}\sum_{l=1}^{4} w_{C11}^{(l)}} =$$

$$\frac{0.218+0.214+0.2+0.206}{0.218+0.214+...+0.071+0.169+0.088} = 0.206.$$

After calculating the objective and subjective values of the weight coefficients of the criteria using Equation (22) we obtained the combined values of the weights that we further used in the multi-criteria model, Table 6.

On the basis of the subjective and objective values of weight coefficients, using Equation (22) we obtained the final value of the weight coefficient of criterion C11:

$$w_{C11} = \frac{w^{*}_{C11} \cdot w'_{C11}}{\sum_{j=1}^{18} w^{*}_{C11} \cdot w'_{C11}} =$$

$$\frac{0.0235 \cdot 0.0647}{0.001521+0.001439+...+0.007427} = 0.0283.$$

The remaining values of the final weights of the criteria were calculated in a similar way, as shown in Table 5.

Table 6. The final values of the weight coefficients

Criteria/ sub-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

3.2. 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. 4 experts carried out an evaluation of 7 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, $S=\left\{s_i \mid i\in\left[0,8\right]\right\}$, in which $s=\{s_0$ – 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 hight$\}$.

Step 1. Forming the expert correspondence matrix. The expert evaluations of the alternatives according to the criteria are shown in Table A1.

Step 2. Calculating the elements of the normalized expert correspondence matrix. Using Equation (25) normalization of the expert correspondence matrices was carried out. The normalized expert correspondence matrices are shown in Table A2.

Step 3. Calculating the elements of the aggregated normalized matrix. Based on the normalized expert correspondence matrices (Appendix, Table A2), using Equation (28) aggregation of the values was carried out and an aggregated normalized matrix obtained, Table 4. The element in position C11–A1 was aggregated using Equation (28):

$$\hat{y}_{11}=\prod_{l=1}^{4}\hat{y}_{11}^{(l)\delta_l}=$$

$$\left\langle \begin{array}{l}\hat{s}_{8\cdot\left((5/8)^{0.284}\cdot(5/8)^{0.267}\cdot(4/8)^{0.241}\cdot(6/8)^{0.207}\right)},\\ \hat{s}_{8-8\cdot\left((1-1/8)^{0.284}\cdot(1-3/8)^{0.267}\cdot(1-2/8)^{0.241}\cdot(1-3/8)^{0.207}\right)},\\ \hat{s}_{8-8\cdot\left((1-3/8)^{0.284}\cdot(1-3/8)^{0.267}\cdot(1-3/8)^{0.241}\cdot(1-3/8)^{0.207}\right)}\end{array}\right\rangle=$$

$$\left\langle \hat{s}_{4.923},\hat{s}_{1.993},\hat{s}_{3.003}\right\rangle,$$

where: δ_l $\left(\delta_1=0.284,\ \delta_2=0.267,\ \delta_3=0.241\text{ and }\delta_3=0.207\right)$ are the weight coefficients of the experts. Aggregation of the remaining elements of the aggregated normalized matrix was carried out in the same way (Table 4).

Step 4. Calculating the elements of the weighted matrix. The elements of the weighted matrix (Table 6) were obtained by multiplying the final values of the weight coefficients (Table 6) with the elements of the aggregated normalized matrix (Table 4). Using Equation (29) we obtained the elements of the weighted matrix (Table 7).

Table 7. The weighted matrix

Criteria/ sub-criteria	Alternative						
	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_{0.21}, s_{7.69}, s_{7.78}\rangle$	$\langle s_{0.04}, s_{7.90}, s_{7.99}\rangle$	$\langle s_{0.31}, s_{7.78}, s_{7.83}\rangle$	$\langle s_{0.74}, s_{7.88}, s_{7.97}\rangle$	$\langle s_{0.11}, s_{7.84}, s_{7.76}\rangle$	$\langle s_{0.52}, s_{7.57}, s_{7.84}\rangle$	$\langle s_{0.04}, s_{7.95}, s_{7.80}\rangle$
C12	$\langle s_{0.15}, s_{7.73}, s_{7.64}\rangle$	$\langle s_{0.14}, s_{7.82}, s_{7.90}\rangle$	$\langle s_{0.03}, s_{7.64}, s_{7.82}\rangle$	$\langle s_{0.11}, s_{7.84}, s_{7.99}\rangle$	$\langle s_{0.04}, s_{7.75}, s_{7.60}\rangle$	$\langle s_{0.04}, s_{7.74}, s_{7.94}\rangle$	$\langle s_{0.03}, s_{7.74}, s_{7.98}\rangle$
C13	$\langle s_{0.17}, s_{7.85}, s_{7.93}\rangle$	$\langle s_{0.02}, s_{7.75}, s_{7.63}\rangle$	$\langle s_{0.14}, s_{7.67}, s_{7.85}\rangle$	$\langle s_{0.15}, s_{7.99}, s_{7.79}\rangle$	$\langle s_{0.13}, s_{7.67}, s_{8.00}\rangle$	$\langle s_{0.15}, s_{7.67}, s_{7.77}\rangle$	$\langle s_{0.29}, s_{7.99}, s_{7.66}\rangle$
C14	$\langle s_{0.13}, s_{7.63}, s_{7.80}\rangle$	$\langle s_{0.16}, s_{7.54}, s_{7.87}\rangle$	$\langle s_{0.16}, s_{7.83}, s_{7.95}\rangle$	$\langle s_{0.40}, s_{7.85}, s_{7.97}\rangle$	$\langle s_{0.06}, s_{7.71}, s_{7.95}\rangle$	$\langle s_{0.04}, s_{7.83}, s_{7.89}\rangle$	$\langle s_{0.05}, s_{7.86}, s_{7.91}\rangle$
C15	$\langle s_{0.11}, s_{7.92}, s_{7.93}\rangle$	$\langle s_{0.00}, s_{7.83}, s_{7.79}\rangle$	$\langle s_{0.14}, s_{7.77}, s_{7.97}\rangle$	$\langle s_{0.12}, s_{7.93}, s_{7.93}\rangle$	$\langle s_{0.06}, s_{7.77}, s_{7.95}\rangle$	$\langle s_{0.23}, s_{7.84}, s_{7.95}\rangle$	$\langle s_{0.00}, s_{7.96}, s_{7.85}\rangle$
C21	$\langle s_{0.31}, s_{7.85}, s_{7.37}\rangle$	$\langle s_{0.11}, s_{7.82}, s_{7.84}\rangle$	$\langle s_{0.76}, s_{7.41}, s_{7.40}\rangle$	$\langle s_{0.31}, s_{7.87}, s_{7.93}\rangle$	$\langle s_{0.25}, s_{7.91}, s_{7.93}\rangle$	$\langle s_{0.25}, s_{7.63}, s_{7.84}\rangle$	$\langle s_{0.46}, s_{0.00}, s_{7.59}\rangle$
C22	$\langle s_{0.06}, s_{7.46}, s_{7.83}\rangle$	$\langle s_{1.49}, s_{7.72}, s_{7.94}\rangle$	$\langle s_{0.10}, s_{7.42}, s_{7.69}\rangle$	$\langle s_{0.11}, s_{7.91}, s_{7.97}\rangle$	$\langle s_{0.46}, s_{7.74}, s_{7.47}\rangle$	$\langle s_{0.61}, s_{7.97}, s_{7.59}\rangle$	$\langle s_{0.40}, s_{7.41}, s_{7.89}\rangle$
C23	$\langle s_{0.23}, s_{7.94}, s_{7.93}\rangle$	$\langle s_{0.47}, s_{7.99}, s_{7.85}\rangle$	$\langle s_{0.21}, s_{7.52}, s_{7.76}\rangle$	$\langle s_{0.07}, s_{7.99}, s_{7.92}\rangle$	$\langle s_{0.06}, s_{7.71}, s_{7.90}\rangle$	$\langle s_{0.30}, s_{7.51}, s_{7.95}\rangle$	$\langle s_{0.05}, s_{7.66}, s_{7.67}\rangle$
C24	$\langle s_{0.03}, s_{7.95}, s_{7.77}\rangle$	$\langle s_{0.10}, s_{7.99}, s_{7.91}\rangle$	$\langle s_{0.07}, s_{7.83}, s_{7.99}\rangle$	$\langle s_{0.12}, s_{7.84}, s_{7.89}\rangle$	$\langle s_{0.02}, s_{7.81}, s_{7.77}\rangle$	$\langle s_{0.07}, s_{7.95}, s_{7.91}\rangle$	$\langle s_{0.09}, s_{7.81}, s_{7.89}\rangle$
C31	$\langle s_{0.42}, s_{7.69}, s_{7.44}\rangle$	$\langle s_{0.09}, s_{7.44}, s_{7.80}\rangle$	$\langle s_{0.38}, s_{7.56}, s_{7.69}\rangle$	$\langle s_{0.23}, s_{7.87}, s_{7.86}\rangle$	$\langle s_{1.17}, s_{7.62}, s_{7.54}\rangle$	$\langle s_{0.13}, s_{7.98}, s_{7.60}\rangle$	$\langle s_{0.47}, s_{7.99}, s_{7.26}\rangle$
C32	$\langle s_{0.10}, s_{7.41}, s_{7.95}\rangle$	$\langle s_{0.27}, s_{7.75}, s_{7.83}\rangle$	$\langle s_{0.40}, s_{7.60}, s_{7.85}\rangle$	$\langle s_{0.89}, s_{7.39}, s_{7.68}\rangle$	$\langle s_{0.16}, s_{7.92}, s_{7.37}\rangle$	$\langle s_{0.49}, s_{7.42}, s_{7.83}\rangle$	$\langle s_{0.08}, s_{7.65}, s_{7.83}\rangle$
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	$\langle s_{0.12}, s_{7.72}, s_{7.66}\rangle$	$\langle s_{0.27}, s_{7.00}, s_{7.91}\rangle$	$\langle s_{0.48}, s_{6.99}, s_{6.81}\rangle$	$\langle s_{0.38}, s_{7.42}, s_{7.48}\rangle$	$\langle s_{0.70}, s_{6.97}, s_{6.70}\rangle$	$\langle s_{1.86}, s_{7.03}, s_{7.79}\rangle$	$\langle s_{0.10}, s_{6.82}, s_{7.85}\rangle$
C42	$\langle s_{0.75}, s_{7.93}, s_{7.41}\rangle$	$\langle s_{0.54}, s_{7.79}, s_{6.91}\rangle$	$\langle s_{0.18}, s_{7.82}, s_{7.85}\rangle$	$\langle s_{0.12}, s_{7.09}, s_{7.89}\rangle$	$\langle s_{0.49}, s_{7.67}, s_{7.18}\rangle$	$\langle s_{0.82}, s_{7.84}, s_{6.89}\rangle$	$\langle s_{0.38}, s_{7.38}, s_{7.60}\rangle$
C43	$\langle s_{0.11}, s_{7.77}, s_{7.50}\rangle$	$\langle s_{0.13}, s_{7.04}, s_{7.83}\rangle$	$\langle s_{8.00}, s_{6.92}, s_{6.90}\rangle$	$\langle s_{0.13}, s_{7.14}, s_{7.58}\rangle$	$\langle s_{1.41}, s_{7.11}, s_{7.94}\rangle$	$\langle s_{0.35}, s_{7.60}, s_{7.94}\rangle$	$\langle s_{0.41}, s_{7.29}, s_{7.00}\rangle$
C44	$\langle s_{0.24}, s_{7.35}, s_{7.87}\rangle$	$\langle s_{0.11}, s_{7.46}, s_{7.23}\rangle$	$\langle s_{0.94}, s_{7.94}, s_{7.29}\rangle$	$\langle s_{0.08}, s_{7.45}, s_{7.29}\rangle$	$\langle s_{0.11}, s_{7.42}, s_{7.97}\rangle$	$\langle s_{1.41}, s_{7.94}, s_{8.00}\rangle$	$\langle s_{0.23}, s_{7.92}, s_{7.22}\rangle$
C51	$\langle s_{0.23}, s_{7.10}, s_{7.01}\rangle$	$\langle s_{0.28}, s_{6.88}, s_{7.15}\rangle$	$\langle s_{0.87}, s_{7.78}, s_{7.84}\rangle$	$\langle s_{0.14}, s_{7.60}, s_{0.00}\rangle$	$\langle s_{0.46}, s_{7.98}, s_{7.16}\rangle$	$\langle s_{0.17}, s_{6.78}, s_{7.84}\rangle$	$\langle s_{0.51}, s_{7.39}, s_{7.78}\rangle$
C52	$\langle s_{1.52}, s_{6.52}, s_{6.68}\rangle$	$\langle s_{0.26}, s_{6.17}, s_{7.77}\rangle$	$\langle s_{2.25}, s_{0.00}, s_{6.70}\rangle$	$\langle s_{1.19}, s_{7.87}, s_{7.21}\rangle$	$\langle s_{0.15}, s_{6.33}, s_{7.89}\rangle$	$\langle s_{0.81}, s_{7.77}, s_{7.38}\rangle$	$\langle s_{1.95}, s_{6.68}, s_{6.68}\rangle$

The element in the position C11–A1 was normalized using Equation (29):

$$d_{11} = w_{C11} \cdot \left\langle \hat{s}_{p_{11}}, \hat{s}_{q_{11}}, \hat{s}_{r_{11}} \right\rangle =$$
$$\left\langle s^*_{8-8\cdot\left(1-\frac{4.923}{8}\right)^{0.0283}}, s^*_{8\cdot\left(\frac{1.993}{8}\right)^{0.0283}}, s^*_{8\cdot\left(\frac{3.003}{8}\right)^{0.0283}} \right\rangle =$$
$$\left\langle s^*_{0.21}, s^*_{7.69}, s^*_{7.78} \right\rangle,$$

where: $w_{C11} = 0.0283$ represents the weight coefficient of criterion C11; $\left\langle \hat{s}_{p_{11}}, \hat{s}_{q_{11}}, \hat{s}_{r_{11}} \right\rangle$ represents the element in position C11–A1 of the aggregated normalized matrix (Table 4).

Step 5. Calculating elements of the BAA matrix. Using equation (30) we obtained the elements of the BAA matrix, Table 8.

The element in position C11 was calculated using Equation (30):

$$g_{C11} = \prod_{i=1}^{7} \left(d_{11}\right)^{1/7} =$$
$$\left\langle s^\bullet_{8\cdot\left((0.21/8)^{0.143}\cdot(0.05/8)^{0.143}\cdot\ldots\cdot(0.04/8)^{0.143}\right)}, \right.$$
$$s^\bullet_{8-8\cdot\left((1-7.69/8)^{0.143}\cdot(1-7.9/8)^{0.143}\cdot\ldots\cdot(1-7.95/8)^{0.143}\right)},$$
$$\left. s^\bullet_{8-8\cdot\left((1-7.78/8)^{0.143}\cdot(1-7.99/8)^{0.143}\cdot\ldots\cdot(1-7.8/8)^{0.143}\right)} \right\rangle =$$
$$\left\langle s^\bullet_{0.17}, s^\bullet_{7.84}, s^\bullet_{7.91} \right\rangle.$$

Table 8. BAA matrix

Criteria/sub-criteria	BAA
C11	$\langle s_{0.17}, s_{7.84}, s_{7.91} \rangle$
C12	$\langle s_{0.06}, s_{7.76}, s_{7.92} \rangle$
C13	$\langle s_{0.12}, s_{7.89}, s_{7.88} \rangle$
C14	$\langle s_{0.10}, s_{7.77}, s_{7.92} \rangle$
C15	$\langle s_{0.00}, s_{7.88}, s_{7.93} \rangle$
C21	$\langle s_{0.30}, s_{7.66}, s_{7.79} \rangle$
C22	$\langle s_{0.27}, s_{7.76}, s_{7.85} \rangle$
C23	$\langle s_{0.15}, s_{7.90}, s_{7.88} \rangle$
C24	$\langle s_{0.06}, s_{7.92}, s_{7.91} \rangle$
C31	$\langle s_{0.30}, s_{7.86}, s_{7.65} \rangle$
C32	$\langle s_{0.25}, s_{7.66}, s_{7.82} \rangle$
C33	$\langle s_{0.17}, s_{7.58}, s_{7.49} \rangle$
C41	$\langle s_{0.36}, s_{7.21}, s_{7.60} \rangle$
C42	$\langle s_{0.38}, s_{7.74}, s_{7.55} \rangle$
C43	$\langle s_{0.44}, s_{7.35}, s_{7.73} \rangle$
C44	$\langle s_{0.25}, s_{7.77}, s_{8.00} \rangle$
C51	$\langle s_{0.32}, s_{7.59}, s_{7.39} \rangle$
C52	$\langle s_{0.81}, s_{6.95}, s_{7.40} \rangle$

Step 6. Calculating the matrix of the distance of the alternatives from the BAA. We used Equation (31) to determine the distance of the alternatives from the BAA (Table 9).

The element in position C11–A1 was obtained using Equation (31):

$$d_{Ed_{11}}\left(d_{11}, g_1\right) = \sqrt{\frac{1}{3}\cdot\left(a_1 + a_2 + a_3\right)} = -0.014,$$

where:

$$a_1 = \left|f\left(s_{p_{11}}\right) - f\left(s_{p_1}\right)\right|^2 = \left|0.027 - 0.022\right|^2;$$
$$a_2 = \left|f\left(s_{8-q_{11}}\right) - f\left(s_{8-q_1}\right)\right|^2 = \left|0.039 - 0.020\right|^2;$$
$$a_3 = \left|f\left(s_{8-r_{11}}\right) - f\left(s_{8-r_1}\right)\right|^2 = \left|0.027 - 0.012\right|^2,$$

where: we obtain the elements of equation $d_{Ed_{11}}\left(d_{11}, g_1\right)$ from the condition $f\left(s_i\right) = \frac{i}{t}$, that is:

$$f\left(s_{p_{11}}\right) = \frac{0.21}{8} = 0.027;$$
$$f\left(s_{8-q_{11}}\right) = \frac{8-7.69}{8} = 0.039;$$
$$f\left(s_{8-r_{11}}\right) = \frac{8-7.78}{8} = 0.027;$$
$$f\left(s_{p_1}\right) = \frac{0.17}{8} = 0.022;$$
$$f\left(s_{8-q_1}\right) = \frac{8-7.84}{8} = 0.020;$$
$$f\left(s_{8-r_1}\right) = \frac{8-7.91}{8} = 0.012.$$

Step 7. Ranking the alternatives. Based on the distance of the alternatives from the BAA (Table 9), using Equation (32),we obtained the final values of the criterion functions of the alternatives and the final ranking of the alternatives (Table 10).

4. Discussion of results

The research results clearly indicate that the use of the MCDM selected is justified. On one hand, the LNN–OS–MABAC model is based on a complex mathematical apparatus and as such its application can cause an aversion with its user. However, on the other hand, this model makes it possible to obtain credible results when making decisions under conditions of uncertainty and when the data on which a decision is based are only partially known. And in addition to the data on the UAV offered being based on the technical characteristics of the aircraft and intended payload, its capabilities in the fight against forest fires are evaluated on the basis of the experiments presented and the performance of the aircraft in the fight against specific fires. Each fire, particularly a forest fire, is

Table 9. Distance of the alternatives from the BAA

Criteria/sub-criteria	Alternative						
	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

Table 10. 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

an occurrence with unique characteristics that affect the way it is neutralized. Under such conditions it is difficult to say which method of detection is best applied to discover a fire, which type of camera has the optimal characteristics or which expansion estimation models are most reliable.

Based on the above, it can be concluded that besides the numerous objective indicators, the selection of optimal UAVs carries with it a certain risk based on uncertainty, which is additionally present because of the subjective assessment of the managers – decision makers. Therefore, the application of this model is significant. 1st, it helps managers to fight against their own subjectivity when prioritizing criteria and attributes. 2nd, when prioritizing, the LNN–OS model applied also reduces the uncertainty of the objective values of the weights of the criteria and attributes obtained. 3rd, the application of the LNN–MABAC approach significantly reduces uncertainty in the selection of the optimal UAV resulting from information about the characteristics of the criteria of the aircraft offered not being completely reliable. Finally, the LNN–OS–MABAC model applied makes it possible to favour specific criteria when selecting UAVs in accordance with the requirements of the managers. For example, if managers consider that the monitoring and timely detection of the source of a fire are more important than prognosis of the spread of the fire and determining its other characteristics, this model ensures that managers can choose the most suitable product – the type of UAV in line with current requirements while minimizing the risk during decision-making.

In addition, the results of the research indicate the optimal solutions required when selecting unmanned aircraft. Namely, it is evident that the expansion in the development of technology in the production of unmanned aircraft has made the product cheaper. Yet it should be emphasized that this type of aircraft is highly specialized and that modern hardware and software solutions on which the total process of monitoring, detection, forecasting and predicting forest fires are based can significantly increase the price of the aircraft (Yuan *et al.* 2015). However, based on the results, it can be concluded that the experts consider that the purchase of high-quality unmanned aircraft is far more economically acceptable than the extent of the damage caused by forest fires.

Forest fires mainly occur in inaccessible terrain because of which the following criteria are very important: the ability to monitor and detect and the ability for diagnosis and prognosis (Yuan *et al.* 2015). The usefulness of the technologically developed aircraft depends largely upon the performance of the camera, the method of detection applied and the ability to locate different types of fire (Merino *et al.* 2012; Yuan *et al.* 2017). In addition, the ability to diagnose and make a prognosis has particular significance in the development of a strategic fight against forest fires (Ghamry *et al.* 2017). The monitoring, early detection and quality diagnosis and prognosis of the spread of a fire ensure the optimum engagement of all forces in preventing its and in extinguishing it. In this way, the loss of material goods and of human lives is reduced. It is not possible to control the state of a fire or extinguish it without a valid determination of the front of the advancing fire, the fire site width and perimeter, the shape of the flames and inclination angle, and the exact coordinates of the area affected by the fire. Prognosis of the spread of forest fires significantly affects the use of all forces designed to neutralize them. At the same time, the quality of these criteria has the greatest impact on the price of unmanned aircraft of this type.

The high speed of processing and transmission of information from unmanned aircraft to the command center shortens the reaction time of the whole fire fighting system, secures better monitoring of the situation and improves the coordination of all the forces involved in firefighting (Merino *et al.* 2015).

The construction of an unmanned aircraft is essentially a platform for upgrading the firefighting system (Freeman *et al.* 2012; Aydin *et al.* 2019). For this reason the criteria Construction and general system and Aerodynamics and ability to process data were evaluated as less significant by the experts. Modern technological solutions make it relatively easy to manage unmanned aircraft with a remote via ground central system. However, it should be emphasized that the possibility of making the maximum use of the firefighting system with which the aircraft is equipped depends on the platforms and quality of the solutions for the wing mechanization, the reliability and engine's thrust, the materials from which the UAV is designed and the flight performance (Ceruti *et al.* 2013). Therefore, improving the performance of these criteria has been the subject of many studies relating to defining the criteria for selecting optimal fire fighting UAV, as discussed in the literature analysis. In addition, having an optimal relationship between the configuration, the general system and the aerodynamics of the unmanned aircraft makes it possible to have a greater payload capacity, which ensures that unmanned aircraft with firefighting systems are better equipped (Choi, Kim 2019).

The following section of the discussion of the results has 2 parts. The 1st section is a comparison of the results with the MCDM models based on an LNN approach that have already been developed. The analysis of the literature presented in Table 1 shows that there have been 2 MCDM models developed so far based on an LNN approach: (1) the LNN–TOPSIS model (Liang *et al.* 2017), which is an extension of the traditional TOPSIS model using LNN, and (2) the LNN–MCDM model (Fang, Ye 2017), which is a new MCDM model based on an LNN approach. The 2nd part of the discussion of the results is a sensitivity analysis of the LNN-OS-MABAC model through 54 scenarios. A more detailed analysis of the 1st and 2nd part of the discussion of the results is presented in the next section.

4.1. Sensitivity analysis of the LNN–OS–MABAC model to changes in the weight coefficients of the criteria

Changes in the weight coefficients can significantly affect the ranks of the alternatives, and for this reason an analysis of the weight coefficients and their influence on the ranks of the alternatives as a rule goes alongside decision-making models. This section of the paper presents a sensitivity analysis of the ranks of the alternatives to changes in the weight coefficients of the criteria through 54 scenarios, which are divided into three groups. In the 1st group there are 18 scenarios, denoted as S1 to S18. In each scenario one criterion was favoured, the value of which was increased by 1.25, while the values of the remaining criteria were reduced by 0.25. In the 2nd group of scenarios denoted with S19 to S36 the same process was repeated, and in each scenario the favoured criterion was increased by 1.45, while the remaining criteria were reduced by 0.25. In the 3rd group of scenarios (scenarios from S37 to S54) the value of the favoured criterion was increased by 1.65, while the remaining values, as with the previous 2 groups of scenarios, were reduced by 0.25. Changes in the ranks of the alternatives through the 54 scenarios are shown in Figure 3.

The results (Figure 3) show that assigning different weights to the criteria through the scenarios leads to a change in the ranks of individual alternatives, which confirms that the model is sensitive to changes in the weight coefficients. By comparing the 1st-ranked alternatives (A6 and A3) through the scenarios with the initial ranks from Table 10, we see that the initial rank is confirmed. Alternative A6 remains in 1st place in 46 of the 54 scenarios, that is, 96.3% of the scenarios. Alternative A6 is in 2nd place in 5 scenarios, while in three scenarios it is in 3rd place. This is similar to the case with alternative A3 (the 2nd-ranked alternative). In 32 scenarios alternative A3 retains 2nd rank, while in the remaining scenarios it is ranked 1st or 3rd. During changes in the weights of the criteria through the scenarios there were changes in the ranks of the remaining alternatives. However, we can conclude that these changes were not drastic, which also confirms the SD of the ranks through the scenarios, Figure 4.

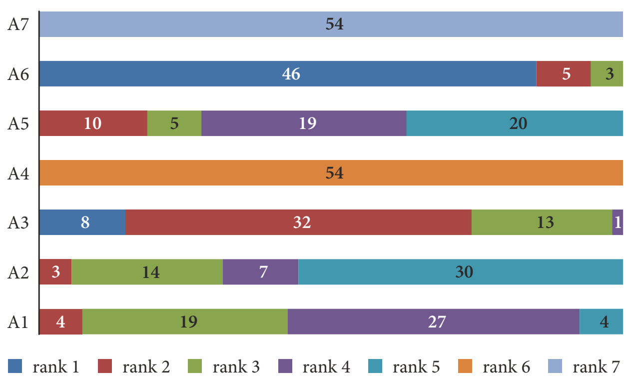

Figure 3. Analysis of the changes in the ranks of the alternatives through 54 scenarios

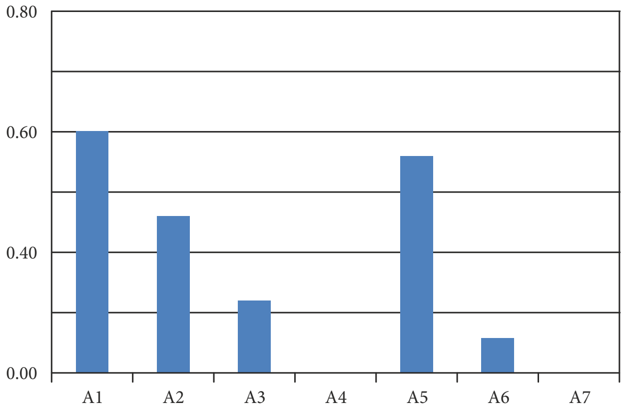

Figure 4. SD of the ranks through the scenarios

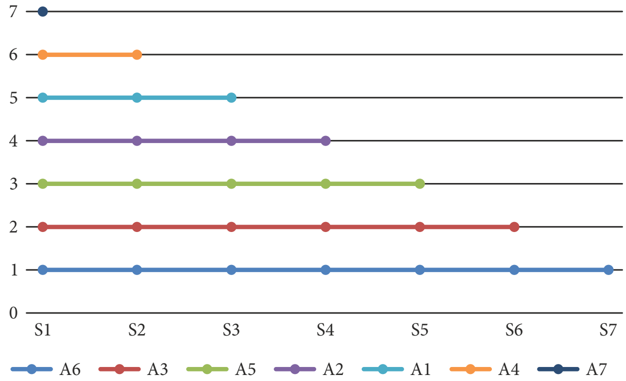

Figure 5. Effects of dynamic decision matrices in LNN–OS–MABAC method

The values of the SD of the ranks through the scenarios were obtained by comparing the initial rank from the LNN–OS–MABAC model (Table 9) with the ranks obtained through the scenarios. In Figure 3 we see that through all of the scenarios there is no deviation in the ranks for alternatives A4 and A7. For the remaining alternatives the SD values are no greater than 0.6, and for 5 of the 7 alternatives (in all 54 scenarios) the value does not exceed 0.45. The mean SD value of all alternatives is 0.25, indicating that the correlation of the ranks is very high through the scenarios. Since all SDD values are significantly less than 0.6, we can conclude that there is a very high correlation (closeness) of ranks and that the proposed ranking is confirmed and credible (Stević *et al.* 2017b).

Changing certain parameters of decision-making matrix, such as introducing a new or eliminating the existing alternative, can lead to changes in preferences. In the following part, therefore, several scenarios are formed in which the change of the elements of decision-making matrix is simulated. For each scenario, a change in the number of alternatives is made, after which in newly created conditions the LNN–OS–MABAC model is applied. The scenarios are formed in such a way that in each scenario the worst alternative is eliminated from subsequent consideration. At the same time, for each scenario the remaining alternatives are ranked according to the new initial decision-making matrix. This analysis has 2 objectives: (1) understanding the robustness of the solution obtained in uncertain conditions, and (2) the analysis of the performances of the LNN–OS–MABAC model in the conditions of a dynamic initial matrix of decision-making. The initial solution applying the LNN–OS–MABAC model is generated as A6 > A3 > A5 > A2 > A1 > A4 > A7.

Alternative A7 is identified as the worst, so in the 1st scenario alternative A7 is eliminated from the set. Thus, a new decision-making matrix is obtained with a total of 7 alternatives. A new solution is generated and the following preferences are obtained: A6 > A3 > A5 > A2 > A1 > A4. The preferences from the 1st scenario shows that A6 remains the best alternative, while A4 remains the worst alternative. The preferences throughout the remaining 5 scenarios are obtained by further implementation of the procedure and the effects are shown in Figure 5.

From Figure 5, it is observed that there are no rank reversals throughout the scenarios. In LNN–OS–MABAC model, alternative A6 remains the best-ranked in all scenarios. This establishes the robustness and stability of LNN–OS–MABAC model in a dynamic environment.

4.2. Comparing the ranks of MCDM methods

In this section, the LNN–OS–MABAC model is validated by comparing the results with those shown by LNN models in the literature so far: (1) the LNN–TOPSIS model (Liang *et al.* 2017), and (2) the LNN–MCDM model (Fang, Ye 2017). A comparison of the results for the LNN–MCDM models is presented in Figure 6.

To determine the relationship between the results obtained by different approaches, SC of the correlation of ranks was used, as one of the most reliable measures of the correlation of ranks (Stević *et al.* 2017a). The results of the comparison of ranks using SC show an exceptionally high correlation between the models applied. Correlation between the LNN–OS–MABAC and the LNN–TOPSIS models was 0.964, while the correlation between the LNN–OS–MABAC and the LNN–MCDM models was 0.961. Based on the results shown we can conclude that

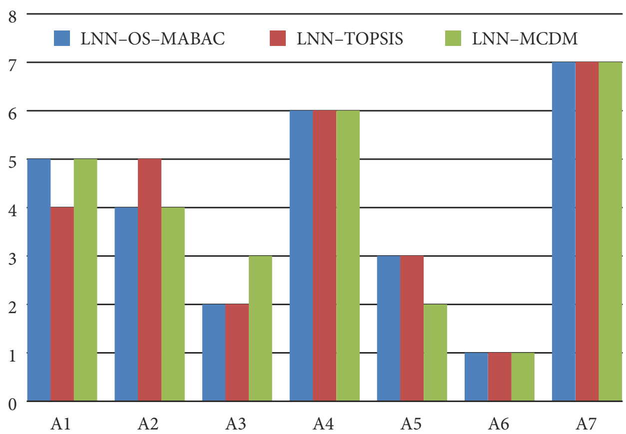

Figure 6. Comparison of the ranks of the alternatives according to different methods

the proposed ranking is confirmed and credible. Based on the presented analysis, in addition to the confirmation of the credibility of the ranking, we can conclude that an approach based on LNN successfully exploits the uncertainty that arises in group decision-making.

Conclusions

In group decision-making, experts are expected to make objective and impartial decisions while taking uncertainty into account. Therefore, the appreciation of the uncertainty that exists in the decision-making process is the prerequisite for objective decision-making. This paper presents a novel approach to the treatment of uncertainty that is based on the application of LNN. The approach based on LNN represents an integration of linguistic variables into the neutrosophic theory of decision-making. Integrating linguistic variables into neutrosophic theory eliminates the subjectivity that prevails when determining numerical values. The LNN approach eliminates these constraints, since for every rating the decision maker uses only linguistic variables from a predefined set of variables. The application of LNN in MCDM models uses exclusively linguistic variables from a predefined set of variables. This eliminates subjective assessments when determining the numerical values of the attributes.

The LNN approach was tested on a case study of the selection of unmanned aircraft for the detection and fight against forest fires. In the OS–MABAC multi-criteria model an original modification of the MABAC method was made using LNN. In addition to this modification, the paper presents an original OS model for determining the weight coefficients of the criteria. Finally, validation of the model was carried out by comparing the results with existing MCDM models based on LNN. The discussion of the results and validation showed significant stability of the results and indicated significant possibilities for applying the LNN–OS–MABAC model.

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.

Based on the above, it can be concluded that besides the numerous objective indicators, the selection of optimal UAVs carries with it a certain risk based on uncertainty, which is additionally present because of the subjective assessment of the managers – decision makers. Therefore, the application of this model is significant. 1st, it helps managers to fight against their own subjectivity when prioritizing criteria and attributes. 2nd, when prioritizing, the LNN–OS model applied also reduces the uncertainty of the objective values of the weights of the criteria and attributes obtained. 3rd, the application of the LNN–MABAC approach significantly reduces uncertainty in the selection of the optimal UAV resulting from information about the characteristics of the criteria of the aircraft offered not being completely reliable. Finally, the LNN–OS–MABAC model applied makes it possible to favour specific criteria when selecting UAVs in accordance with the requirements of the managers. For example, if managers consider that the monitoring and timely detection of the source of a fire are more important than prognosis of the spread of the fire and determining its other characteristics, this model ensures that managers can choose the most suitable product – the type of UAV in line with current requirements while minimizing the risk during decision-making.

Bearing in mind the stated advantages, one of the improvements to this model would be the development and implementation of software for real-world applications. This would make the model much more within the reach of users and enable full exploitation of all the benefits stated in the paper.

The sensitivity analysis of the LNN–OS–MABAC model to changes in the weight values of the evaluation criteria showed the robustness of the model. It was shown that the model is sensitive to changes in the weight coefficients of the criteria. In addition, the results obtained showed remarkable stability. The model was validated by comparing the results with those obtained by the LNN–MCDM models developed so far that can be found in the literature. The results showed that the LNN–OS–MABAC model gives similar results, with negligible deviation compared to the existing 2 models developed on the basis of the LNN approach.

As shown in Table 1, there are only 5 papers that consider the application of the LNN concept in MCDM. In view of this, the LNN–OS–MABAC model is an original MCDM approach that has not been considered so far in the literature and which gives promising results. The authors suggest that one of the directions for future research should be directed towards the application of LNN in other traditional MCDM models for determining the weight coefficients of the criteria and evaluation of the alternatives. 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. In addition, future research should include extension of the LNN–OS–MABAC model with a stability analysis determining the weight stability intervals. That research should include determination of the weight stability interval for each criterion. In addition, applications of the proposed hybrid MCDM method can be explored to tackle practical problems in other decision-making areas, such as project portfolio selection, inventory problems, supply chain management and location problems.

Appendix

Table A1. Expert correspondence matrices

Expert 1							
Criteria/sub-criteria	Alternative						
	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_3, s_7, s_5 \rangle$	$\langle s_7, s_1, s_0 \rangle$	$\langle s_2, s_6, s_4 \rangle$	$\langle s_0, s_2, s_2 \rangle$	$\langle s_5, s_3, s_6 \rangle$	$\langle s_1, s_7, s_4 \rangle$	$\langle s_7, s_2, s_5 \rangle$
C12	$\langle s_3, s_7, s_6 \rangle$	$\langle s_4, s_4, s_4 \rangle$	$\langle s_7, s_7, s_5 \rangle$	$\langle s_5, s_4, s_0 \rangle$	$\langle s_7, s_7, s_7 \rangle$	$\langle s_7, s_5, s_1 \rangle$	$\langle s_7, s_4, s_1 \rangle$
C13	$\langle s_3, s_5, s_2 \rangle$	$\langle s_7, s_7, s_7 \rangle$	$\langle s_4, s_6, s_5 \rangle$	$\langle s_4, s_0, s_6 \rangle$	$\langle s_4, s_7, s_0 \rangle$	$\langle s_4, s_6, s_6 \rangle$	$\langle s_2, s_0, s_7 \rangle$
C14	$\langle s_4, s_7, s_4 \rangle$	$\langle s_4, s_7, s_4 \rangle$	$\langle s_4, s_4, s_2 \rangle$	$\langle s_2, s_4, s_2 \rangle$	$\langle s_6, s_6, s_1 \rangle$	$\langle s_7, s_3, s_2 \rangle$	$\langle s_7, s_2, s_3 \rangle$
C15	$\langle s_3, s_3, s_4 \rangle$	$\langle s_8, s_5, s_7 \rangle$	$\langle s_3, s_7, s_2 \rangle$	$\langle s_3, s_4, s_4 \rangle$	$\langle s_5, s_7, s_3 \rangle$	$\langle s_1, s_6, s_3 \rangle$	$\langle s_8, s_3, s_6 \rangle$
C21	$\langle s_4, s_5, s_2 \rangle$	$\langle s_2, s_4, s_4 \rangle$	$\langle s_8, s_2, s_1 \rangle$	$\langle s_6, s_7, s_6 \rangle$	$\langle s_5, s_8, s_6 \rangle$	$\langle s_5, s_3, s_5 \rangle$	$\langle s_6, s_1, s_2 \rangle$
C22	$\langle s_1, s_2, s_5 \rangle$	$\langle s_8, s_3, s_8 \rangle$	$\langle s_1, s_2, s_4 \rangle$	$\langle s_2, s_7, s_8 \rangle$	$\langle s_5, s_3, s_2 \rangle$	$\langle s_6, s_7, s_3 \rangle$	$\langle s_5, s_4, s_6 \rangle$
C23	$\langle s_6, s_6, s_6 \rangle$	$\langle s_7, s_8, s_4 \rangle$	$\langle s_5, s_1, s_3 \rangle$	$\langle s_2, s_8, s_5 \rangle$	$\langle s_2, s_2, s_5 \rangle$	$\langle s_6, s_1, s_6 \rangle$	$\langle s_2, s_3, s_3 \rangle$
C24	$\langle s_3, s_6, s_1 \rangle$	$\langle s_5, s_6, s_4 \rangle$	$\langle s_4, s_3, s_8 \rangle$	$\langle s_6, s_1, s_4 \rangle$	$\langle s_1, s_1, s_1 \rangle$	$\langle s_4, s_5, s_4 \rangle$	$\langle s_4, s_2, s_3 \rangle$
C31	$\langle s_5, s_4, s_2 \rangle$	$\langle s_2, s_2, s_5 \rangle$	$\langle s_5, s_2, s_3 \rangle$	$\langle s_4, s_5, s_5 \rangle$	$\langle s_8, s_3, s_3 \rangle$	$\langle s_2, s_8, s_3 \rangle$	$\langle s_6, s_8, s_1 \rangle$
C32	$\langle s_1, s_7, s_7 \rangle$	$\langle s_4, s_4, s_7 \rangle$	$\langle s_4, s_3, s_6 \rangle$	$\langle s_7, s_4, s_4 \rangle$	$\langle s_3, s_7, s_2 \rangle$	$\langle s_5, s_1, s_6 \rangle$	$\langle s_1, s_4, s_6 \rangle$
C33	$\langle s_2, s_1, s_6 \rangle$	$\langle s_4, s_2, s_4 \rangle$	$\langle s_1, s_6, s_3 \rangle$	$\langle s_6, s_1, s_2 \rangle$	$\langle s_1, s_8, s_1 \rangle$	$\langle s_3, s_5, s_2 \rangle$	$\langle s_1, s_7, s_5 \rangle$
C41	$\langle s_1, s_5, s_5 \rangle$	$\langle s_3, s_1, s_6 \rangle$	$\langle s_4, s_3, s_2 \rangle$	$\langle s_4, s_6, s_3 \rangle$	$\langle s_6, s_1, s_1 \rangle$	$\langle s_8, s_2, s_6 \rangle$	$\langle s_1, s_2, s_7 \rangle$
C42	$\langle s_6, s_6, s_3 \rangle$	$\langle s_6, s_5, s_2 \rangle$	$\langle s_2, s_6, s_7 \rangle$	$\langle s_1, s_2, s_6 \rangle$	$\langle s_4, s_4, s_2 \rangle$	$\langle s_6, s_5, s_1 \rangle$	$\langle s_3, s_7, s_5 \rangle$
C43	$\langle s_1, s_6, s_4 \rangle$	$\langle s_1, s_1, s_7 \rangle$	$\langle s_8, s_2, s_2 \rangle$	$\langle s_1, s_7, s_4 \rangle$	$\langle s_8, s_2, s_8 \rangle$	$\langle s_4, s_5, s_8 \rangle$	$\langle s_4, s_2, s_3 \rangle$
C44	$\langle s_4, s_2, s_7 \rangle$	$\langle s_2, s_2, s_2 \rangle$	$\langle s_7, s_8, s_1 \rangle$	$\langle s_1, s_7, s_1 \rangle$	$\langle s_2, s_3, s_8 \rangle$	$\langle s_7, s_7, s_8 \rangle$	$\langle s_4, s_6, s_1 \rangle$
C51	$\langle s_3, s_2, s_2 \rangle$	$\langle s_3, s_1, s_3 \rangle$	$\langle s_6, s_5, s_7 \rangle$	$\langle s_1, s_4, s_2 \rangle$	$\langle s_4, s_8, s_3 \rangle$	$\langle s_1, s_1, s_6 \rangle$	$\langle s_4, s_3, s_6 \rangle$
C52	$\langle s_7, s_2, s_2 \rangle$	$\langle s_2, s_2, s_6 \rangle$	$\langle s_8, s_3, s_2 \rangle$	$\langle s_6, s_6, s_4 \rangle$	$\langle s_1, s_2, s_7 \rangle$	$\langle s_5, s_7, s_4 \rangle$	$\langle s_7, s_2, s_2 \rangle$
...							
Expert 4							
Criteria/sub-criteria	Alternative						
	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_2, s_5, s_5 \rangle$	$\langle s_6, s_4, s_0 \rangle$	$\langle s_2, s_3, s_5 \rangle$	$\langle s_0, s_4, s_0 \rangle$	$\langle s_5, s_6, s_5 \rangle$	$\langle s_1, s_6, s_4 \rangle$	$\langle s_6, s_3, s_5 \rangle$
C12	$\langle s_4, s_5, s_6 \rangle$	$\langle s_3, s_6, s_2 \rangle$	$\langle s_7, s_7, s_4 \rangle$	$\langle s_4, s_5, s_1 \rangle$	$\langle s_5, s_3, s_7 \rangle$	$\langle s_7, s_7, s_2 \rangle$	$\langle s_7, s_7, s_0 \rangle$
C13	$\langle s_3, s_5, s_3 \rangle$	$\langle s_7, s_5, s_7 \rangle$	$\langle s_3, s_7, s_4 \rangle$	$\langle s_3, s_0, s_5 \rangle$	$\langle s_4, s_7, s_1 \rangle$	$\langle s_4, s_7, s_6 \rangle$	$\langle s_2, s_0, s_6 \rangle$
C14	$\langle s_4, s_7, s_5 \rangle$	$\langle s_4, s_7, s_3 \rangle$	$\langle s_5, s_4, s_0 \rangle$	$\langle s_0, s_5, s_1 \rangle$	$\langle s_6, s_5, s_2 \rangle$	$\langle s_6, s_5, s_3 \rangle$	$\langle s_6, s_5, s_0 \rangle$
C15	$\langle s_2, s_5, s_3 \rangle$	$\langle s_7, s_5, s_6 \rangle$	$\langle s_2, s_7, s_2 \rangle$	$\langle s_2, s_1, s_3 \rangle$	$\langle s_5, s_7, s_3 \rangle$	$\langle s_2, s_7, s_3 \rangle$	$\langle s_7, s_2, s_6 \rangle$
C21	$\langle s_5, s_6, s_1 \rangle$	$\langle s_2, s_5, s_6 \rangle$	$\langle s_8, s_2, s_2 \rangle$	$\langle s_4, s_5, s_6 \rangle$	$\langle s_4, s_6, s_7 \rangle$	$\langle s_3, s_3, s_5 \rangle$	$\langle s_7, s_0, s_3 \rangle$

End of Table A1

Expert 4							
Criteria/sub-criteria	Alternative						
	A1	A2	A3	A4	A5	A6	A7
C22	s_1, s_2, s_5	$\langle s_7, s_4, s_6 \rangle$	$\langle s_2, s_1, s_4 \rangle$	$\langle s_2, s_6, s_7 \rangle$	$\langle s_6, s_6, s_3 \rangle$	$\langle s_5, s_8, s_4 \rangle$	$\langle s_5, s_1, s_6 \rangle$
C23	$\langle s_5, s_5, s_6 \rangle$	$\langle s_6, s_8, s_5 \rangle$	$\langle s_3, s_1, s_4 \rangle$	$\langle s_1, s_7, s_6 \rangle$	$\langle s_2, s_3, s_5 \rangle$	$\langle s_5, s_2, s_7 \rangle$	$\langle s_1, s_1, s_2 \rangle$
C24	$\langle s_3, s_6, s_2 \rangle$	$\langle s_5, s_8, s_4 \rangle$	$\langle s_3, s_2, s_7 \rangle$	$\langle s_4, s_4, s_3 \rangle$	$\langle s_1, s_2, s_2 \rangle$	$\langle s_3, s_7, s_4 \rangle$	$\langle s_5, s_1, s_3 \rangle$
C31	$\langle s_5, s_4, s_1 \rangle$	$\langle s_2, s_2, s_5 \rangle$	$\langle s_6, s_3, s_3 \rangle$	$\langle s_4, s_7, s_5 \rangle$	$\langle s_8, s_4, s_2 \rangle$	$\langle s_3, s_7, s_3 \rangle$	$\langle s_5, s_8, s_1 \rangle$
C32	$\langle s_2, s_2, s_7 \rangle$	$\langle s_4, s_5, s_5 \rangle$	$\langle s_5, s_5, s_5 \rangle$	$\langle s_7, s_1, s_5 \rangle$	$\langle s_1, s_8, s_2 \rangle$	$\langle s_4, s_4, s_6 \rangle$	$\langle s_1, s_4, s_6 \rangle$
C33	$\langle s_2, s_3, s_6 \rangle$	$\langle s_3, s_2, s_4 \rangle$	$\langle s_2, s_6, s_3 \rangle$	$\langle s_4, s_1, s_2 \rangle$	$\langle s_1, s_6, s_1 \rangle$	$\langle s_4, s_3, s_1 \rangle$	$\langle s_1, s_3, s_5 \rangle$
C41	$\langle s_1, s_4, s_5 \rangle$	$\langle s_2, s_4, s_8 \rangle$	$\langle s_2, s_2, s_2 \rangle$	$\langle s_3, s_3, s_4 \rangle$	$\langle s_4, s_2, s_1 \rangle$	$\langle s_6, s_2, s_6 \rangle$	$\langle s_1, s_1, s_6 \rangle$
C42	$\langle s_6, s_7, s_3 \rangle$	$\langle s_4, s_5, s_1 \rangle$	$\langle s_2, s_5, s_6 \rangle$	$\langle s_2, s_2, s_6 \rangle$	$\langle s_5, s_4, s_2 \rangle$	$\langle s_6, s_6, s_1 \rangle$	$\langle s_4, s_2, s_5 \rangle$
C43	$\langle s_1, s_5, s_4 \rangle$	$\langle s_2, s_3, s_7 \rangle$	$\langle s_8, s_1, s_2 \rangle$	$\langle s_1, s_1, s_4 \rangle$	$\langle s_8, s_2, s_7 \rangle$	$\langle s_3, s_5, s_7 \rangle$	$\langle s_4, s_3, s_2 \rangle$
C44	$\langle s_3, s_1, s_5 \rangle$	$\langle s_1, s_3, s_1 \rangle$	$\langle s_6, s_7, s_2 \rangle$	$\langle s_1, s_2, s_2 \rangle$	$\langle s_1, s_2, s_7 \rangle$	$\langle s_8, s_6, s_8 \rangle$	$\langle s_3, s_6, s_2 \rangle$
C51	$\langle s_2, s_4, s_2 \rangle$	$\langle s_2, s_2, s_2 \rangle$	$\langle s_6, s_4, s_6 \rangle$	$\langle s_2, s_4, s_2 \rangle$	$\langle s_4, s_7, s_2 \rangle$	$\langle s_2, s_1, s_7 \rangle$	$\langle s_4, s_3, s_6 \rangle$
C52	$\langle s_6, s_3, s_3 \rangle$	$\langle s_2, s_1, s_6 \rangle$	$\langle s_7, s_0, s_2 \rangle$	$\langle s_5, s_8, s_3 \rangle$	$\langle s_1, s_1, s_7 \rangle$	$\langle s_6, s_5, s_5 \rangle$	$\langle s_7, s_4, s_3 \rangle$

Table A2. Normalized expert correspondence matrices

Expert 1							
Criteria/sub-criteria	Alternative						
	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_5, s_1, s_3 \rangle$	$\langle s_1, s_7, s_8 \rangle$	$\langle s_6, s_2, s_4 \rangle$	$\langle s_8, s_6, s_6 \rangle$	$\langle s_3, s_5, s_2 \rangle$	$\langle s_7, s_1, s_4 \rangle$	$\langle s_1, s_6, s_3 \rangle$
C12	$\langle s_5, s_1, s_2 \rangle$	$\langle s_4, s_4, s_4 \rangle$	$\langle s_1, s_1, s_3 \rangle$	$\langle s_3, s_4, s_8 \rangle$	$\langle s_1, s_1, s_1 \rangle$	$\langle s_1, s_3, s_7 \rangle$	$\langle s_1, s_4, s_7 \rangle$
C13	$\langle s_5, s_3, s_6 \rangle$	$\langle s_1, s_1, s_1 \rangle$	$\langle s_4, s_2, s_3 \rangle$	$\langle s_4, s_8, s_2 \rangle$	$\langle s_4, s_1, s_8 \rangle$	$\langle s_4, s_2, s_2 \rangle$	$\langle s_6, s_8, s_1 \rangle$
C14	$\langle s_4, s_1, s_4 \rangle$	$\langle s_4, s_1, s_4 \rangle$	$\langle s_4, s_4, s_6 \rangle$	$\langle s_6, s_4, s_6 \rangle$	$\langle s_2, s_2, s_7 \rangle$	$\langle s_1, s_5, s_6 \rangle$	$\langle s_1, s_6, s_5 \rangle$
C15	$\langle s_5, s_5, s_4 \rangle$	$\langle s_0, s_3, s_1 \rangle$	$\langle s_5, s_1, s_6 \rangle$	$\langle s_5, s_4, s_4 \rangle$	$\langle s_3, s_1, s_5 \rangle$	$\langle s_7, s_2, s_5 \rangle$	$\langle s_0, s_5, s_2 \rangle$
C21	$\langle s_4, s_5, s_2 \rangle$	$\langle s_2, s_4, s_4 \rangle$	$\langle s_8, s_2, s_1 \rangle$	$\langle s_6, s_7, s_6 \rangle$	$\langle s_5, s_8, s_6 \rangle$	$\langle s_5, s_3, s_5 \rangle$	$\langle s_6, s_1, s_2 \rangle$
C22	$\langle s_1, s_2, s_5 \rangle$	$\langle s_8, s_3, s_8 \rangle$	$\langle s_1, s_2, s_4 \rangle$	$\langle s_2, s_7, s_8 \rangle$	$\langle s_5, s_3, s_2 \rangle$	$\langle s_6, s_7, s_3 \rangle$	$\langle s_5, s_4, s_6 \rangle$
C23	$\langle s_6, s_6, s_6 \rangle$	$\langle s_7, s_8, s_4 \rangle$	$\langle s_5, s_1, s_3 \rangle$	$\langle s_2, s_8, s_5 \rangle$	$\langle s_2, s_2, s_5 \rangle$	$\langle s_6, s_1, s_6 \rangle$	$\langle s_2, s_3, s_3 \rangle$
C24	$\langle s_3, s_6, s_1 \rangle$	$\langle s_5, s_6, s_4 \rangle$	$\langle s_4, s_3, s_8 \rangle$	$\langle s_6, s_1, s_4 \rangle$	$\langle s_1, s_1, s_1 \rangle$	$\langle s_4, s_5, s_4 \rangle$	$\langle s_4, s_2, s_3 \rangle$
C31	$\langle s_5, s_4, s_2 \rangle$	$\langle s_2, s_2, s_5 \rangle$	$\langle s_5, s_2, s_3 \rangle$	$\langle s_4, s_5, s_5 \rangle$	$\langle s_8, s_3, s_3 \rangle$	$\langle s_2, s_8, s_3 \rangle$	$\langle s_6, s_8, s_1 \rangle$
C32	$\langle s_1, s_7, s_7 \rangle$	$\langle s_4, s_4, s_7 \rangle$	$\langle s_4, s_3, s_6 \rangle$	$\langle s_7, s_4, s_4 \rangle$	$\langle s_3, s_7, s_2 \rangle$	$\langle s_5, s_1, s_6 \rangle$	$\langle s_1, s_4, s_6 \rangle$
C33	$\langle s_2, s_1, s_6 \rangle$	$\langle s_4, s_2, s_4 \rangle$	$\langle s_1, s_6, s_3 \rangle$	$\langle s_6, s_1, s_2 \rangle$	$\langle s_1, s_8, s_1 \rangle$	$\langle s_3, s_5, s_2 \rangle$	$\langle s_1, s_7, s_5 \rangle$
C41	$\langle s_1, s_5, s_5 \rangle$	$\langle s_3, s_1, s_6 \rangle$	$\langle s_4, s_3, s_2 \rangle$	$\langle s_4, s_6, s_3 \rangle$	$\langle s_6, s_1, s_1 \rangle$	$\langle s_8, s_2, s_6 \rangle$	$\langle s_1, s_2, s_7 \rangle$
C42	$\langle s_6, s_6, s_3 \rangle$	$\langle s_6, s_5, s_2 \rangle$	$\langle s_2, s_6, s_7 \rangle$	$\langle s_1, s_2, s_6 \rangle$	$\langle s_4, s_4, s_2 \rangle$	$\langle s_6, s_5, s_1 \rangle$	$\langle s_3, s_7, s_5 \rangle$
C43	$\langle s_1, s_6, s_4 \rangle$	$\langle s_1, s_1, s_7 \rangle$	$\langle s_8, s_2, s_2 \rangle$	$\langle s_1, s_7, s_4 \rangle$	$\langle s_8, s_2, s_8 \rangle$	$\langle s_4, s_5, s_8 \rangle$	$\langle s_4, s_2, s_3 \rangle$
C44	$\langle s_4, s_2, s_7 \rangle$	$\langle s_2, s_2, s_2 \rangle$	$\langle s_7, s_8, s_1 \rangle$	$\langle s_1, s_7, s_1 \rangle$	$\langle s_2, s_3, s_8 \rangle$	$\langle s_7, s_7, s_8 \rangle$	$\langle s_4, s_6, s_1 \rangle$
C51	$\langle s_3, s_2, s_2 \rangle$	$\langle s_3, s_1, s_3 \rangle$	$\langle s_6, s_5, s_7 \rangle$	$\langle s_1, s_4, s_2 \rangle$	$\langle s_4, s_8, s_3 \rangle$	$\langle s_1, s_1, s_6 \rangle$	$\langle s_4, s_3, s_6 \rangle$
C52	$\langle s_7, s_2, s_2 \rangle$	$\langle s_2, s_2, s_6 \rangle$	$\langle s_8, s_3, s_2 \rangle$	$\langle s_6, s_6, s_4 \rangle$	$\langle s_1, s_2, s_7 \rangle$	$\langle s_5, s_7, s_4 \rangle$	$\langle s_7, s_2, s_2 \rangle$
...							

End of Table A2

Expert 4							
Criteria/ sub-criteria	Alternative						
	A1	A2	A3	A4	A5	A6	A7
C11	$\langle s_6, s_3, s_3 \rangle$	$\langle s_2, s_4, s_8 \rangle$	$\langle s_6, s_5, s_3 \rangle$	$\langle s_8, s_4, s_8 \rangle$	$\langle s_3, s_2, s_3 \rangle$	$\langle s_7, s_2, s_4 \rangle$	$\langle s_2, s_5, s_3 \rangle$
C12	$\langle s_4, s_3, s_2 \rangle$	$\langle s_5, s_2, s_6 \rangle$	$\langle s_1, s_1, s_4 \rangle$	$\langle s_4, s_3, s_7 \rangle$	$\langle s_3, s_5, s_1 \rangle$	$\langle s_1, s_1, s_6 \rangle$	$\langle s_1, s_1, s_8 \rangle$
C13	$\langle s_5, s_3, s_5 \rangle$	$\langle s_1, s_3, s_1 \rangle$	$\langle s_5, s_1, s_4 \rangle$	$\langle s_5, s_8, s_3 \rangle$	$\langle s_4, s_1, s_7 \rangle$	$\langle s_4, s_1, s_2 \rangle$	$\langle s_6, s_8, s_2 \rangle$
C14	$\langle s_4, s_1, s_3 \rangle$	$\langle s_4, s_1, s_5 \rangle$	$\langle s_3, s_4, s_8 \rangle$	$\langle s_8, s_3, s_7 \rangle$	$\langle s_2, s_3, s_6 \rangle$	$\langle s_2, s_3, s_5 \rangle$	$\langle s_2, s_3, s_8 \rangle$
C15	$\langle s_6, s_3, s_5 \rangle$	$\langle s_1, s_3, s_2 \rangle$	$\langle s_6, s_1, s_6 \rangle$	$\langle s_6, s_7, s_5 \rangle$	$\langle s_3, s_1, s_5 \rangle$	$\langle s_6, s_1, s_5 \rangle$	$\langle s_1, s_6, s_2 \rangle$
C21	$\langle s_5, s_6, s_1 \rangle$	$\langle s_2, s_5, s_6 \rangle$	$\langle s_8, s_2, s_2 \rangle$	$\langle s_4, s_5, s_6 \rangle$	$\langle s_4, s_6, s_7 \rangle$	$\langle s_3, s_3, s_5 \rangle$	$\langle s_7, s_0, s_3 \rangle$
C22	$\langle s_1, s_2, s_5 \rangle$	$\langle s_7, s_4, s_6 \rangle$	$\langle s_2, s_1, s_4 \rangle$	$\langle s_2, s_6, s_7 \rangle$	$\langle s_6, s_6, s_3 \rangle$	$\langle s_5, s_8, s_4 \rangle$	$\langle s_5, s_1, s_6 \rangle$
C23	$\langle s_5, s_5, s_6 \rangle$	$\langle s_6, s_8, s_5 \rangle$	$\langle s_3, s_1, s_4 \rangle$	$\langle s_1, s_7, s_6 \rangle$	$\langle s_2, s_3, s_5 \rangle$	$\langle s_5, s_2, s_7 \rangle$	$\langle s_1, s_1, s_2 \rangle$
C24	$\langle s_3, s_6, s_2 \rangle$	$\langle s_5, s_8, s_4 \rangle$	$\langle s_3, s_2, s_7 \rangle$	$\langle s_4, s_4, s_3 \rangle$	$\langle s_1, s_2, s_2 \rangle$	$\langle s_3, s_7, s_4 \rangle$	$\langle s_5, s_1, s_3 \rangle$
C31	$\langle s_5, s_4, s_1 \rangle$	$\langle s_2, s_2, s_5 \rangle$	$\langle s_6, s_3, s_3 \rangle$	$\langle s_4, s_7, s_5 \rangle$	$\langle s_8, s_4, s_2 \rangle$	$\langle s_3, s_7, s_3 \rangle$	$\langle s_5, s_8, s_1 \rangle$
C32	$\langle s_2, s_2, s_7 \rangle$	$\langle s_4, s_5, s_5 \rangle$	$\langle s_5, s_5, s_5 \rangle$	$\langle s_7, s_1, s_5 \rangle$	$\langle s_1, s_8, s_2 \rangle$	$\langle s_4, s_4, s_6 \rangle$	$\langle s_1, s_4, s_6 \rangle$
C33	$\langle s_2, s_3, s_6 \rangle$	$\langle s_3, s_2, s_4 \rangle$	$\langle s_2, s_6, s_3 \rangle$	$\langle s_4, s_1, s_2 \rangle$	$\langle s_1, s_6, s_1 \rangle$	$\langle s_4, s_3, s_1 \rangle$	$\langle s_1, s_3, s_5 \rangle$
C41	$\langle s_1, s_4, s_5 \rangle$	$\langle s_2, s_4, s_8 \rangle$	$\langle s_2, s_2, s_2 \rangle$	$\langle s_3, s_3, s_4 \rangle$	$\langle s_4, s_2, s_1 \rangle$	$\langle s_6, s_2, s_6 \rangle$	$\langle s_1, s_1, s_6 \rangle$
C42	$\langle s_6, s_7, s_3 \rangle$	$\langle s_4, s_5, s_1 \rangle$	$\langle s_2, s_5, s_6 \rangle$	$\langle s_2, s_2, s_6 \rangle$	$\langle s_5, s_4, s_2 \rangle$	$\langle s_6, s_6, s_1 \rangle$	$\langle s_4, s_2, s_5 \rangle$
C43	$\langle s_1, s_5, s_4 \rangle$	$\langle s_2, s_3, s_7 \rangle$	$\langle s_8, s_1, s_2 \rangle$	$\langle s_1, s_1, s_4 \rangle$	$\langle s_8, s_2, s_7 \rangle$	$\langle s_3, s_5, s_7 \rangle$	$\langle s_4, s_3, s_2 \rangle$
C44	$\langle s_3, s_1, s_5 \rangle$	$\langle s_1, s_3, s_1 \rangle$	$\langle s_6, s_7, s_2 \rangle$	$\langle s_1, s_2, s_2 \rangle$	$\langle s_1, s_2, s_7 \rangle$	$\langle s_8, s_6, s_8 \rangle$	$\langle s_3, s_6, s_2 \rangle$
C51	$\langle s_2, s_4, s_2 \rangle$	$\langle s_2, s_2, s_2 \rangle$	$\langle s_6, s_4, s_6 \rangle$	$\langle s_2, s_4, s_2 \rangle$	$\langle s_4, s_7, s_2 \rangle$	$\langle s_2, s_1, s_7 \rangle$	$\langle s_4, s_3, s_6 \rangle$
C52	$\langle s_6, s_3, s_3 \rangle$	$\langle s_2, s_1, s_6 \rangle$	$\langle s_7, s_0, s_2 \rangle$	$\langle s_5, s_8, s_3 \rangle$	$\langle s_1, s_1, s_7 \rangle$	$\langle s_6, s_5, s_5 \rangle$	$\langle s_7, s_4, s_3 \rangle$

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