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Modification of the DIBR and MABAC Methods by Applying Rough Numbers and Its Application in Making Decisions

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Abstract: This study considers the problem of selecting an anti-tank missile system (ATMS). The mentioned problem is solved by applying a hybrid multi-criteria decision-making model (MCDM) based on two methods: the DIBR (Defining Interrelationships Between Ranked criteria) and the MABAC (Multi-Attributive Border Approximation area Comparison) methods. The methods are modified by applying rough numbers, which present a very suitable area for considering uncertainty following decision-making processes. The DIBR method is a young method with a simple mathematical apparatus which is based on defining the relation between ranked criteria, that is, adjacent criteria, reducing the number of comparisons. This method defines weight coefficients of criteria, based on the opinion of experts. The MABAC method is used to select the best alternative from the set of the offered ones, based on the distance of the criteria function of every observed alternative from the border approximate area. The paper has two main innovations. With the presented decision-making support model, the ATMS selection problem is raised to a higher level, which is based on a proven mathematical apparatus. In terms of methodology, the main innovation is successful application of the rough DIBR method, which has not been treated in this way in the literature so far. Additionally, an analysis of the literature related to the research problem as well as to the methods used is carried out. After the application of the model, the sensitivity analysis of the output results of the presented model to the change of the weight coefficients of criteria is performed, as well as the comparison of the results of the presented model with other methods. Finally, the proposed model is concluded to be stable and multi-criteria decision-making methods can be a reliable tool to help decision makers in the selection process. The presented model has the potential of being applied in other case studies as it has proven to be a good means for considering uncertainty.

Keywords: rough numbers; Defining Interrelationships Between Ranked criteria (DIBR); Multi-Attributive Border Approximation area Comparison (MABAC); anti-tank missile system; decision-making

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1. Introduction

Every day people are faced with the need to make decisions and among the possibilities offered, they choose the one that satisfies their interests more completely, in other words, targets set goals. Decision-making is present in all areas of life and work, and the circumstances of decision-making depend on the reliability with which the expected result can be assessed. Currently, a large number of quantitative methods have been developed that help us solve various problems, even in the preparation for making certain business decisions. These are primarily the methods of mathematical programming, i.e., optimization, which aim to select the optimal solution from the set of available ones, using mathematical modeling of real problems and a set of mathematical tools to solve decision-making problems, and especially multicriteria methods which are used to solve problems when it is observed from several aspects—criteria on the basis of which the decision is made [1–4].These are especially used in the problem of deciding between several alternatives. A large number of methods for multicriteria decision-making have been developed, and some of the best known are the following: ELimination Et Choice Translating Reality (ELECTRE) [5], Simple Additive Weighting (SAW) [6], Analytic Hierarchy Process (AHP) [7], Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [8], Preference Ranking Organization METHod for Enrichment of Evaluations (PROMETHEE) [9], COmpressed PRoportional ASsessment (COPRAS) [10], Višekriterijumsko KOmpromisno Rangiranje (VIKOR) [11], Multi-Objective Optimization method by Ratio Analysis (MOORA) [12], Additive Ratio ASsessment (ARAS) [13], Evaluation based on Distance from Average Solution (EDAS) [14], COmbinative Distance-based ASsessment (CODAS) [15], Weighted Aggregates Sum Product ASsessment (WASPAS) [16], MultiAtributive Ideal-Real Comparative Analysis (MAIRCA) [17], Multi-Attributive Border Approximation area Comparison (MABAC) [18], Full Consistency Method (FUCOM) [19], Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) [20], etc.

One of the young methods that provides good output results, has a small number of comparisons, and is primarily intended for determining the weight coefficients of criteria is the DIBR (Defining Interrelationships Between Ranked criteria) method [21], which is used in the paper. Given that this is a young method, so far it has been applied only to solve the problem of the circular economy concept [21], in the selection of a location for a heavy launched bridge [22], and in the prioritization of sustainable mobility sharing systems [23].

The main goal of the research was to reach a model that solves the problem of ATMS selection. The following are the predicted contributions of the paper: development of a model on the basis of which the best anti-tank missile system would be determined in accordance with the requirements of the armed forces; modification of the DIBR method using rough numbers, which has not been shown in the existing literature so far; development of a new hybrid decision-making model based on multi-attribute decision-making methods; and introduction of scientific methods in the process of equipping with weapons.

In addition to the Introduction, the paper consists of five additional sections. In the second part of the paper, an overview of the theoretical background of the researched problem is given through an analysis of the literature related to the problem. In the third part, the MCDM model is described, including the Rough DIBR and Rough MABAC methods that were used in the paper for the selection of ATMS. The fourth part of the paper shows the application of the defined model, based on the defined criteria, as well as the results obtained by applying the mentioned methodology. The sensitivity analysis of the output results of the MCDM model is presented in the fifth section, where the model is tested for the change of the weight coefficients of the criteria through twenty scenarios. In this part of the paper, the obtained results are also compared with the results of other MCDM methods. Finally, the sixth section presents the conclusions reached in this research, as well as the directions for future research.

2. Theoretical Background

The modern way of conducting combat operations has conditioned accelerated development of weapons and military equipment. Whether combat operations are conducted on maneuvering land (land combat) or in urban space, one of the main weapons that contributes to the success of both offensive and defensive operations is an anti-armor missile system with an anti-tank guided missile system (ATGM). The development of modern armored vehicles (tanks [24], armored personnel carriers, Mine-Resistant Ambush Protected (MRAP), wheeled armored vehicles, etc.) with varying degrees of ballistic and mine protection has had a direct impact on the development and improvement of anti-tank weapons. Tactics of conducting modern combat operations require successful anti-tank operations in all conditions and at all (small, medium and large) distances, in order to maximize the effects on the target.

Modern anti-tank missile systems must be able to neutralize a number of targets while achieving a high level of launch flexibility—including launches from mobile shooting ranges, wheeled or tracked infantry fighting vehicles, trucks, armored personnel carriers, tanks, helicopters, and drones (UAV—unmanned aerial vehicle and UGV—unmanned ground vehicle) [25], and it is desirable for them to have the ability to connect to the C4ISR (command, control, communications, computers, intelligence, surveillance and reconnaissance) system [26].

The paper analyzes mobile anti-tank missile systems as a part of anti-tank means. Anti-tank missile systems (ATMS) most often realize fire tasks by direct shooting, while some modern ATMS have the possibility of realizing fire tasks by direct and semi-direct shooting using the OTA (Overfly Tank Attack) missiles. This type of weapon is most often found in infantry and artillery anti-tank units [27]. The paper presents a model for decision-making support to decision makers when selecting an adequate anti-tank missile system that provides the best opportunities for anti-tank combat in a limited environment (urban environment) and in the open.

In the second half of the 20th century, along with the development of armored vehicles, anti-tank missile systems also developed, and today, the development of five generations of anti-tank systems has been recorded.

The first-generation anti-tank system "MCLOS" (Manual Command to Line of Sight) is a system of anti-tank guided missiles with manual guidance. In these systems, the operator and devices at the launch site participate in the shooting throughout the flight of the rocket. The operator, with the naked eye or through the sight, follows both the target and the rocket [28]. In accordance with the observed deviation of the rocket trajectory from the target line aimed at the target, by the method of three-point matching, the operator-missile-target moves the control stick of the guidance device in order to cancel the mentioned deviation.

The second-generation anti-tank system "SACLOS" (Semi-Automatic Command toLine Of Sight) is an anti-tank guided missile system with semi-automatic guidance. Similar to the first-generation system, the operator and devices at the launch site are engaged throughout the flight of the rocket, but a qualitative leap has been made in the way the operator is engaged. His task is only to keep the reticle aimed at the target, not following the flight of the rocket [29]. Everything else is done by the guiding system.

The third-generation anti-tank system is an anti-tank guided missile system that works according to the "Fire and Forget" principle. After launching the rocket, there is no engagement of either the operator or the device outside the rocket [30]. Cameras, thermal detectors, infrared rays, laser beams, and numerous receivers and emitters of signals are installed in the missile warhead, which enable extremely accurate and precise guidance of the rocket, where the human factor is completely excluded. These systems are more susceptible to electronic interference than the 1st and 2nd generation systems.

The fourth-generation anti-tank missile systems with anti-tank guided missiles work according to the principles Fire and Forget, Fire, Observe and Update, and Predicted Line Of Sight (PLOS)/inertial guidance, and rely on a combination of guidance trackers. These use dual seeker configuration of electro-optical thermal imager (EO/IR) and millimeter-wave active radar homing for control and guidance with lock-on before launch and lock-on after launch capabilities. They present technologically advanced means, where the operator is enabled to change the flight parameters even after the rocket is fired, as well as to shoot at targets that are hidden and which he is not able to observe.

The fifth-generation anti-tank missile systems with fifth-generation anti-tank guided missiles (ATGM5) are the most sophisticated devices with features such as: LOBL mode (Lock On Before Launch), Beyond Line Of Sight (BLOS) mode where the target is locked after launch, Lock-on after launch (LOAL) for non-line-of-sight (NLOS), and using third party target designation mode where the target is locked during the flight using GPS coordinates and the target is not visible from the launch position, Predicted Line of Sight (PLOS)/inertial guidance, fire and forget, man in the loop mode, re-assignment in flight, and even seeker lock-on after launch. It has a new infrared seeker with a smart target tracker and artificial intelligence features. It is designed to overcome active protection systems. This missile can attack targets from the top. It can be launched in fire-and-forget mode, as well as fire-observe-and-update mode. Alternatively, it can be launched in no line of sight and use the third-party target designation by the wireless datalink [31].

The application of multicriteria decision-making methods in the field of security, and specifically in military issues, is described in many papers, for example: in the selection of weapons in the model AHP-TOPSIS [32], in the selection of fire system using Adaptive Neuro-Fuzzy Inference System Based Model [33], in the risk assessment in overcoming water obstacles using fuzzy logic [34], in the position selection for military video surveillance using the AHP method [35], in the selection of military police units base by FITradeoff method in multi-criteria decision support system [36], in the selection of helicopters using PROMETHEE method [37], in the selection of a location for armored vehicle repair workshop using Multi-Expert Interval-Valued Intuitionistic Fuzzy model [38], in the selection of a fighter aircraft with the ARAS-FUCOM approach [39], in the selection of war ships using the AHP method [40], etc.

The selection of anti-armor systems using a multi-criteria approach has been slightly elaborated in domestic and foreign literature. Radovanovic et al. [29] show the selection of the 2nd and the 3rd generation anti-tank missile system using the AHP method. David [41] in his work compares the ATACMS (Army Tactical Missile System) and Javelin in order to equip units. Ramakrishna et al. [42] compare anti-tank missile guidance systems depending on which generation of anti-tank systems they belong to. Gordon et al. [43] realize a comparative analysis of weapons and military equipment of the US Army and other armies of the world by comparing the basic combat characteristics. Iyer [44] analyzes the development of the 3rd-generation anti-tank missile systems. Radovanović et al. [28] analyze anti-armor missile systems using the hybrid AHP–VIKOR method of multi-criteria decision making. Pamučar and Dimitrijević [45] select the most favorable alternative (anti-tank guided missiles) using the TOPSIS and MABAC methods of multi-criteria decision-making.

Equipping with this type of weapon is an imperative for the armed forces of any country. Most of the armed forces in the world have several different models of anti-tank missile systems in their wide range of weapons, due to their different characteristics, which expands the range of their possible use. The requirements of the characteristics that armies place before ATMS manufacturers are different. Adequate assessment and selection of effective anti-tank missile systems is a significant factor influencing the operational capabilities of the army. The complexity of the problem is conditioned by the different tactical and technical characteristics of anti-tank missile systems and the specific conditions of their application, which conditions the application of the multi-criteria decision-making model.

3. Materials and Methods

3.1. Description of the Model and the Methods Used

The proposed model of multi-criteria decision-making consists of 3 phases (Figure 1).

In the first phase, the Rough DIBR method is used for the purpose of determining the weight coefficients. The second phase includes the ranking of alternatives using the Rough MABAC method, while the third phase is the analysis of the output results of the model.

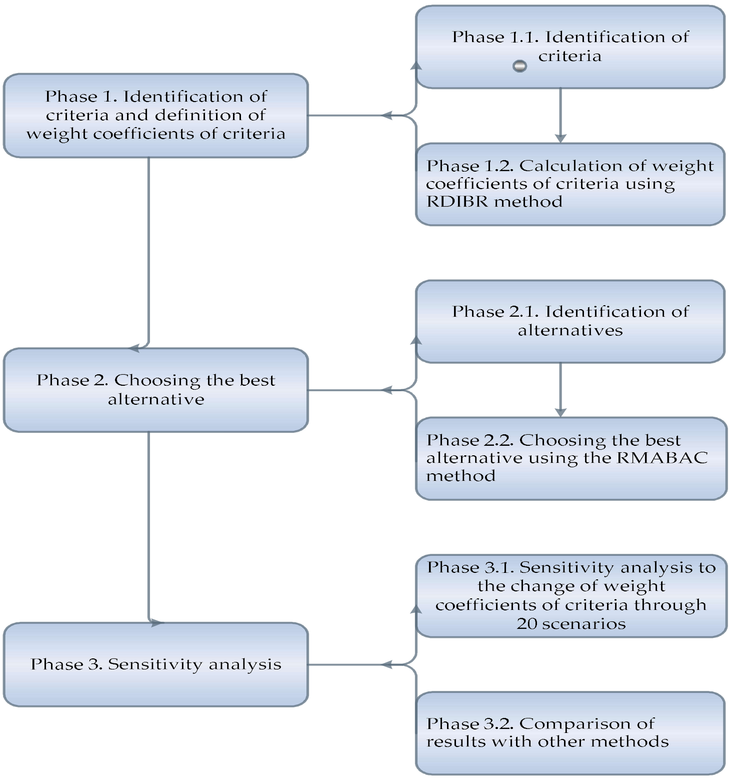

Figure 1. Rough DIBR—Rough MABAC model.

3.1.1. Rough Numbers

Theoretical settings of rough numbers were given by the Polish scientist Zdzislaw I. Pawlak [46,47]. The basic feature of rough numbers is reflected in the good treatment of inaccuracy and uncertainty in decision-making. Inaccuracy is expressed by left and right approximations, which present the core of rough numbers [46,48].

Rough numbers are used in solving a large number of problems in many areas, implemented in different MCDM models (Table 1).

Table 1. Rough numbers—literature analysis.

Application and Reference	Methods
Supplier Selection in Biofuel Companies based on Green criteria [26]	R-BWM
Supplier Selection in a Company Manufacturing PVC Carpentry Products [49]	R-AHP, R-WASPAS
Sustainable supplier selection [50]	FUCOM, R-SAW
Selection of railway wagons for the needs of internal transport [51]	R-SWARA
The risk assessment problem in a gas processing industry in Sfax (Tunisia) [52]	IR-CODAS
Evaluation of companies engaged in the transport of dangerous goods [53]	IMF-SWARA, R-MARCOS
Evaluation and ranking of insurance companies [54]	IVFRNs-TOPSIS
Offshore wind farm site selection [55]	IRNs-BWM, MARCOS
Selection of sustainable hydrogen production technology [56]	rough-fuzzy BWM, DEA
Sustainable supplier selection [57]	intuitionistic linguistic rough MULTIMOORA
Assessing sustainable production under circular economy context, a case of the forestry industry in the Eastern Black Sea region [58]	Rough PIPRECIA, Fuzzy MARCOS

Further, the description of rough numbers is provided according to [48,59].

Supposing that U is the universe containing all the objects, that Y is the limiting object of the universe U, and R is the set containing the elements $(D_1, D_2, D_3, \ldots, D_t)$ which present all the objects in the universe U. If these elements are set in a row according to $D_1 < D_2 < D_3 < \ldots < D_t$ then $\forall Y \in U$, $D_q \in R$, $1 \leq q \leq t$, based on which are defined the lower ($\underline{Apr}(D_q)$) and upper approximations ($\overline{Apr}(D_q)$) and boundary interval ($Bnd(D_q)$) of the element D_q according to:

$$\underline{Apr}(D_q) = \cup\{Y \in U/R(Y) \leq D_q\} \tag{1}$$

$$\overline{Apr}(D_q) = \cup\{Y \in U/R(Y) \geq D_q\} \tag{2}$$

$$Bnd(D_q) = \cup\{Y \in U/R(Y) \neq D_q\} = \{Y \in U/R(Y) > D_q\} \cup \{Y \in U/R(Y) < D_q\} \tag{3}$$

Further, the element G_q can be presented as the rough number ($RN(D_q)$) which is defined by its lower limit ($\underline{Lim}(D_q)$) and upper limit ($\overline{Lim}(D_q)$), where

$$\underline{Lim}(D_q) = \frac{1}{N_L} \sum R(Y)|Y \in \underline{Apr}(D_q) \tag{4}$$

$$\overline{Lim}(D_q) = \frac{1}{N_U} \sum R(Y)|Y \in \overline{Apr}(D_q) \tag{5}$$

$$RN(D_q) = \left[\underline{Lim}(D_q), \overline{Lim}(D_q)\right] \tag{6}$$

where N_L and N_U present the number of objects contained in the $\underline{Apr}(D_q)$ and $\overline{Apr}(D_q)$ in sequence. Lower and upper limits mark middle value of the elements included in the lower and upper approximations, in sequence. The difference between them presents the boundary interval ($IRBnd(D_q)$):

$$IRBnd(D_q) = \overline{Lim}(D_q) - \underline{Lim}(D_q) \tag{7}$$

The boundary interval presents non determination of the element D_q, where the larger number presents larger imprecision, while the smaller number presents better precision, based on which subjective information only now can be marked with a rough number.

In order to convert a rough number $RN(D_i) = \left[\underline{Lim}(D_i), \overline{Lim}(D_i)\right]$ into the crisp value, Equations (8)–(10) are used [39]:

$$RN(D_i) = \left[\underline{Lim}(D_i), \overline{Lim}(D_i)\right] = \left\{ \begin{array}{l} \underline{Lim}(D_i) = \frac{\underline{Lim}(D_i) - \min_i\{\underline{Lim}(D_i)\}}{\max_i\{\overline{Lim}(D_i)\} - \min_i\{\underline{Lim}(D_i)\}} \\ \overline{Lim}(D_i) = \frac{\overline{Lim}(D_i) - \min_i\{\underline{Lim}(D_i)\}}{\max_i\{\overline{Lim}(D_i)\} - \min_i\{\underline{Lim}(D_i)\}} \end{array} \right\} \tag{8}$$

where $\underline{Lim}(D_i)$ and $\overline{Lim}(D_i)$ present lower and upper limit of a rough number $RN(D_i)$, in sequence.

After the normalization, total normalized crisp value is obtained, according to the Equation (9):

$$D_i{}^N = \frac{\underline{Lim}(D_i)\, x\, \{1 - \underline{Lim}(D_i)\} + \overline{Lim}(D_i)\, x\, \overline{Lim}(D_i)}{1 - \underline{Lim}(D_i) + \overline{Lim}(D_i)} \tag{9}$$

Final crisp value $D_i{}^{crisp}$ for the rough number $RN(D)$ is obtained by applying Equation (10):

$$D_i{}^{crisp} = \min_i\{\underline{Lim}(D_i)\} + D_i{}^N x \left[\max_i\{\overline{Lim}(D_i)\} - \min_i\{\underline{Lim}(D_i)\}\right] \tag{10}$$

3.1.2. Rough DIBR

The DIBR method is based on defining the relations between ranked criteria, that is, the relations between the adjacent criteria.

The method consists of five steps, presented further [21,22].

Step 1. Ranking criteria by importance.

Based on previously defined set of n criteria $C = \{C_1, C_2, C_3, \ldots, C_n\}$, performed the ranking of criteria by importance is $C_1 > C_2 > C_3 > \ldots > C_n$, where n presents total number of criteria in the set C.

Step 2. Comparison of criteria and defining its relations.

During the comparison of criteria, we obtain the values $RN(\lambda_{12})$, $RN(\lambda_{13})$, …, $RN(\lambda_{n-1,n})$, and $RN(\lambda_{1n})$, respectively, when comparing the criterion C_3 with C_4 we obtain the value (λ_{34}), etc., where it is necessary that the obtained values meet the following condition $RN(\lambda_{n-1,n})$, $RN(\lambda_{1n}) \in [0,1]$. Based on previously defined conditions, the following relations between the criteria are obtained:

$$RN(w_1) : RN(w_2) = (1 - RN(\lambda_{12})) : RN(\lambda_{12}) \tag{11}$$

$$RN(w_2) : RN(w_3) = (1 - RN(\lambda_{23})) : RN(\lambda_{23}) \tag{12}$$

$$RN(w_{n-1}) : RN(w_n) = (1 - RN(\lambda_{n-1,n})) : RN(\lambda_{n-1,n}) \tag{13}$$

$$RN(w_1 : w_n) = (1 - RN(\lambda_{1,n})) : RN(\lambda_{1,n}) \tag{14}$$

where $RN(w_i)$, $i = 1, 2, \ldots, n$ presents the weight coefficient of the i-th criterion.

The relations (11)–(14) and the value $RN(\lambda_{n-1,n})$ are observed as the relations in which the decision maker divides total interval of importance of the criteria of 100% by two observed criteria; that is, if the decision maker presented the relation between the criterion C_3 and C_4 as $RN(\lambda_{34}) = [0.47, 0.49]$, that is interpreted so that out of the total interval of importance of 100%, criterion C_3 represents [0.51, 0.53]%, while criterion C_4 represents [0.47, 0.49]%.

Step 3. Defining the relations for the calculation of weight coefficients. Based on the defined relations are derived the expressions for determining the weight coefficients of criteria $RN(w_2)$, $RN(w_3)$, …, $RN(w_n)$:

$$RN(w_2) = \frac{RN(\lambda_{12})}{(1 - RN(\lambda_{12}))} RN(w_1) \tag{15}$$

$$RN(w_3) = \frac{RN(\lambda_{23})}{(1 - RN(\lambda_{23}))} RN(w_2) = \frac{RN(\lambda_{12}) \cdot RN(\lambda_{23})}{(1 - RN(\lambda_{12})) \cdot (1 - RN(\lambda_{23}))} RN(w_1) \tag{16}$$

$$RN(w_n) = \frac{RN(\lambda_{n-1,n})}{(1 - RN(\lambda_{n-1,n}))} RN(w_{n-1}) = \frac{RN(\lambda_{12}) \cdot RN(\lambda_{23}) \cdot \ldots \cdot RN(\lambda_{n-1,n})}{(1 - RN(\lambda_{12}))(1 - RN(\lambda_{23})) \cdot \ldots \cdot (1 - RN(\lambda_{n-1,n}))} RN(w_1) = \frac{\prod_{i=1}^{n-1} RN(\lambda_{i,i+1})}{\prod_{i=1}^{n-1} (1 - RN(\lambda_{i,i+1}))} RN(w_1) \tag{17}$$

Step 4. Calculation of the weight coefficient of the most influential criterion. Based on Equations (15)–(17), including the condition where $\sum_{j=1}^{n} RN(w_j) = 1$, the following relation is derived:

$$RN(w_1) \left(1 + \frac{RN(\lambda_{12})}{(1 - RN(\lambda_{12}))} + \frac{RN(\lambda_{12}) \cdot RN(\lambda_{23})}{(1 - RN(\lambda_{12}))(1 - RN(\lambda_{23}))} + \ldots + \frac{\prod_{i=1}^{n-1} RN(\lambda_{i,i+1})}{\prod_{i=1}^{n-1} (1 - RN(\lambda_{i,i+1}))} \right) = 1 \tag{18}$$

Based on Equation (18), the expression for the calculation of the weight coefficient of the most influential criterion:

$$RN(w_1) = \frac{1}{1 + \frac{RN(\lambda_{12})}{(1 - RN(\lambda_{12}))} + \frac{RN(\lambda_{12}) \cdot RN(\lambda_{23})}{(1 - RN(\lambda_{12}))(1 - RN(\lambda_{23}))} + \ldots + \frac{\prod_{i=1}^{n-1} RN(\lambda_{i,i+1})}{\prod_{i=1}^{n-1} \left(1 - RN(\lambda_{i,i+1})\right)}} \tag{19}$$

Based on the value of the weigh coefficient of the most influential criterion, as in Equation (19), applying the defined Equations (15)–(17), are obtained the weight coefficients of other criteria $RN(w_2)$, $RN(w_3)$, …, $RN(w_n)$.

Step 5. Defining the degree of satisfaction of subjective relations between the criteria.

The value of the weight coefficient of the criterion w_n, is defined based on Equation (14):

$$RN(w_n) = \frac{RN(\lambda_{1n})}{(1 - RN(\lambda_{1n}))} RN(w_1) \tag{20}$$

where $RN(w_n)$ represents the value of the weight coefficient of the least significant criterion.

Applying Equations (8) to (10), the obtained values of the weight coefficients, expressed by rough numbers, are converted into the crisp values.

Equation (14) presents the relation for the control of the expression (17), that is, for testing meeting the preferences of the decision maker, out of which is derived the value $\lambda'_{1,n}$, as in Equation (21):

$$\lambda'_{1,n} = \frac{w_n}{w_1 + w_n} \tag{21}$$

If the values λ_{1n} and $\lambda'_{1,n}$ are approximately equal, the required subjective relations between the criteria are met, and if they differ, it is necessary first to check the relation for λ_{1n}. If the decision maker considers the relation λ_{1n} well-defined, redefining of the relations between the criteria should be made and recalculation of the weight coefficients of the criteria. If he considers that the relation λ_{1n} is not well-defined, it is necessary to redefine it. The maximum recommended deviation of the values λ_{1n} and $\lambda'_{1,n}$ is up to 10%.

3.1.3. Rough MABAC

The MABAC (Multi-Attributive Border Approximation area Comparison) method was developed in 2015 [18]. Basic setting of the MABAC method is reflected in defining the distance of the criteria function of each observed alternative from the border approximate area. The application of the MABAC method in different areas is presented in the Table 2.

Table 2. MABAC method—analysis of the literature.

Application and Reference	Methods
Green supplier selection [60]	Gray DANP, MABAC
Public transportation pricing system selection [61]	T2NN-CRITIC, T2NN-MABAC
The selection of a location for potential roundabout construction in Doboj [62]	BWM, MABAC
Selecting a location for a brigade command post during combat operations [63]	FUCOM, Z-numbers, MABAC
Optimal Anti Tank Ground missile weapon system procurement [45]	TOPSIS, MABAC
Evaluation and selection of Manufacturer PVC carpentry [64]	FUCOM, MABAC
Selection of fire position of mortar units [65]	LBWA, Fuzzy MABAC

The improvement of the MABAC method with rough numbers is presented in the following publications (Table 3).

Table 3. Rough MABAC method—analysis of the literature.

Application and Reference	Methods
Solve the impact of major infrastructure projects on various social vulnerability factors [66]	q-ROFRBWM, q-ROFRMABAC
Selection of an arc welding robot [67]	RMABAC
Assessing and prioritizing medical tourism destinations in uncertain environment [68]	AHP, RMABAC
Supplier Selection in an Iron and Steel Industry [69]	RMABAC-design of experiments (DoE)-based metamodel

The Rough MABAC method consists of 6 steps [67,68].

Step 1. Forming initial decison-making matrix (X). The first step presents defining of the value of m alternatives by n criteria.

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ A_3 \\ \ldots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \ldots & C_n \end{array} \\ \begin{pmatrix} RN(x_{11}) & RN(x_{12}) & \ldots & RN(x_{1n}) \\ RN(x_{21}) & RN(x_{22}) & \ldots & RN(x_{2n}) \\ RN(x_{31}) & RN(x_{32}) & \ldots & RN(x_{3n}) \\ \ldots & \ldots & \ldots & \ldots \\ RN(x_{m1}) & RN(x_{m2}) & \ldots & RN(x_{mn}) \end{pmatrix} \end{array} \quad (22)$$

Step 2. Normalization of the elements of the initial decision-making matrix (X), where normalized matrix is defined as:

$$N = \left[\underline{t_{ij}}, \overline{t_{ij}}\right]_{m\,x\,n} \quad (23)$$

where $\underline{t_{ij}}$, $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ presents lower approximations of the normalized value of the initial decision-making matrix, and $\overline{t_{ij}}$, $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ presents upper approximations of the initial decision-making matrix.

The elements of the matrix (N) are defined by applying the following equations [32]:

(a) Benefit-type criteria

$$\underline{t_{ij}} = \frac{\underline{x_{ij}} - x_j^{-}}{x_j^{+} - x_j^{-}}, \quad \overline{t_{ij}} = \frac{\overline{x_{ij}} - x_j^{-}}{x_j^{+} - x_j^{-}} \quad (24)$$

(b) Cost-type criteria

$$\underline{t_{ij}} = \frac{\underline{x_{ij}} - x_j^{+}}{x_j^{-} - x_j^{+}}, \quad \overline{t_{ij}} = \frac{\overline{x_{ij}} - x_j^{-}}{x_j^{-} - x_j^{+}} \quad (25)$$

where:

$$x_j^{+} = \left\{ \max_{1 \le i \le m} \left(\overline{x_{ij}}\right), \ for\, benefit\, type\, criteria, \ \min_{1 \le i \le m} \left(\underline{x_{ij}}\right), \ for \ \cos t\, type\, criteria \right. \quad (26)$$

$$x_j^{+} = \left\{ \min_{1 \le i \le m} \left(\underline{x_{ij}}\right), \ for\, benefit\, type\, criteria, \ \max_{1 \le i \le m} \left(\overline{x_{ij}}\right), \ for \ \cos t\, type\, criteria \right. \quad (27)$$

Step 3. Calculation of the elements of weighted matrix (V), where normalized matrix is defined as:

$$V = \left[\underline{v_{ij}}, \overline{v_{ij}}\right]_{m\,x\,n} \quad (28)$$

where $\underline{v_{ij}}$, $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ presents lower approximations values in the weighted matrix, and $\overline{v_{ij}}$, $(i = 1, 2, \ldots, n; j = 1, 2, \ldots, m)$ presents upper approximations values in the weighted matrix.

The elements of the matrix (V) are obtained by applying the expressions:

$$\underline{v_{ij}} = \underline{w_i}\, x \left(\underline{t_{ij}} + 1\right), \ \overline{v_{ij}} = \overline{w_i}\, x \left(\overline{t_{ij}} + 1\right) \quad (29)$$

where $\left[\underline{w_i}, \overline{w_i}\right]$ present the weight coefficients of the criteria.

Step 4. Determining the matrix of border approximate areas—BAA (G). The matrix of border approximate areas is formed as $n \times 1$, as in:

$$G = [g_1, g_2, \ldots, g_n] \ where\, g_i = \left[\underline{g_i}, \vec{g_i}\right] \quad (30)$$

where $\underline{g_i}$, $(i = 1, 2, \ldots, n)$ presents lower approximations values of BAA for the i-th criterion, and $\overline{g_i}$, $(i = 1, 2, \ldots, n)$ presents upper approximations values of BAA for the i-th criterion.

A border approximate area by each criterion is obtained by applying the expressions in (31):

$$\underline{g_i} = \left(\prod_{j=1}^{m} \underline{v_{ij}}\right)^{1/m}, \ \overline{g_i} = \left(\prod_{j=1}^{m} \overline{v_{ij}}\right)^{1/m} \tag{31}$$

Step 5. Calculation of the elements of the distance matrix of alternatives from border approximate area (Q), where the new matrix is obtained in the form:

$$Q = \left(\left[\underline{q_{ij}}, \overline{q_{ij}}\right]\right)_{m\ x\ n} \tag{32}$$

where:

$$q_{ij} = \left\{ \begin{array}{c} d_E(v_{ij}, g_i),\ if\ RN(v_{ij}) > RN(g_i) \\ -d_E(v_{ij}, g_i),\ if\ RN(v_{ij}) < RN(g_i) \end{array} \right\} for\ benefit\ type\ criteria \tag{33}$$

$$q_{ij} = \left\{ \begin{array}{c} -d_E(v_{ij}, g_i),\ if\ RN(v_{ij}) > RN(g_i) \\ d_E(v_{ij}, g_i),\ if\ RN(v_{ij}) < RN(g_i) \end{array} \right\} for\ \cos t\ type\ criteria \tag{34}$$

$$d_E(v_{ij}, g_i) = \left\{ \begin{array}{ll} \sqrt{\left(\underline{v_{ij}} - \overline{g_i}\right)^2 + \left(\overline{v_{ij}} - \underline{g_i}\right)^2}, & for\ benefit\ type\ criteria \\ \sqrt{\left(\underline{v_{ij}} - \underline{g_i}\right)^2 + \left(\overline{v_{ij}} - \overline{g_i}\right)^2}, & for\ \cos t\ type\ criteria \end{array} \right\} \tag{35}$$

where $\left[\underline{g_i}, \overline{g_i}\right]$ presents the border of the approximate area for the criterion C_i $(i = 1, 2, \ldots, n)$, and $\left[\underline{q_{ij}}, \overline{q_{ij}}\right]$ distance of alternatives from the BAA.

The membership of the alternative A_j to certain approximate area (G, G^+ *ili* G^-) is determined as follows:

$$A_i = \left\{ \begin{array}{cc} G^+ & if\ q_{ij} > 0 \\ G & if\ q_{ij} = 0 \\ G^- & if\ q_{ij} < 0 \end{array} \right\} \tag{36}$$

In order for the alternative A_j to be selected as the optimum from the set, it is necessary that it belongs by as many criteria as possible to the lower approximate area (G^+).

Step 6. Ranking alternatives. Final values of the criteria functions of the alternatives are obtained by summing the elements of the matrix Q by rows:

$$\underline{s_j} = \sum_{i=1}^{n} \underline{q_{ij}},\ \overline{s_j} = \sum_{i=1}^{n} \overline{g_{ij}},\ i = 1, 2, \ldots, n,\ j = 1, 2, \ldots, m. \tag{37}$$

where $\underline{s_j}$, $(j = 1, 2, \ldots, m)$ presents total lower approximations distance from the BAA, and $\overline{s_j}$, $(j = 1, 2, \ldots, m)$ total upper approximations distance from the BAA.

Applying Equations (8) to (10), the values obtained by rough numbers are converted into the crisp values.

4. Application of the RDIBR-RMABAC Model

Eleven criteria are defined for the selection of ATMS. The criteria are divided into three groups: with combat, economical, and construction characteristics. The stated criteria are provided in the Table 4.

Table 4. Criteria for the selection of ATMS.

Criterion	Name of the Criterion
C1	The penetration
C2	The effective range
C3	The design characteristics of anti-tank missile systems
C4	The reliability
C5	The price of an anti-tank missile
C6	The guidance system
C7	The price of an anti-tank missile system
C8	The probability of hitting
C9	The minimum firing range
C10	Training difficulty
C11	The number of operators

The criteria C1, C2, C4, C8, C9, C10, and C11 belong to the group of combat criteria and these are described below.

The penetration (C1) is a combat property that has a significant impact on the performance of anti-tank actions [28]. Higher penetration enables successful penetration and neutralization of the target. Modern missiles for anti-tank missile systems mostly have tandem-cumulative warheads that enable the penetration of armor with active and active-reactive protection, which is an advantage over classic missiles with cumulative action. It is expressed in millimeters (mm) and in its ability to penetrate explosive reactive armor (ERA). The higher penetration of the anti-tank missile system, the higher fire and combat capabilities. The criterion is of the benefit type.

The effective range (C2) presents horizontal firing distance (in meters) at which target hitting is expected under normal ballistic conditions [28]. Effective range depends on the design of the anti-tank system, the shape, mass, and mass distribution of the projectile, and the mass of rocket fuel. Greater effective range provides the ability to conduct anti-tank actions at medium and long distances, which provides greater security and protection for the operator. In order to be able to carry out combat operations as successfully as possible, it is necessary for an anti-tank missile system to have the ability to shoot at long distances. Greater effective range increases the efficiency of an anti-tank missile system. The criterion is of the benefit type.

The reliability (C4) is one of the most important operational characteristics of an anti-tank missile system, which is expressed in the number of successful launches in relation to the number of launched missiles (number of successful launches per 100 launched missiles). Reliability is the ability of an anti-tank system to assure the required functions in certain conditions of use and during a given period of time, providing the values of the basic characteristics within defined limits [70]. Reliability is ensured by construction and exploitation measures that are developed and implemented during design, construction and construction tests in different conditions, efficient quality control of parts and assemblies of the system, selection of appropriate materials, protection from atmospheric influences, etc. The most common causes that lead to delays or failures in shooting are wear of parts, malfunction of the rocket, poor maintenance, and careless and unprofessional handling. Delays result in cessation of shooting. The criterion is of the benefit type.

The probability of hitting (C8) presents the possibility of accomplishing a fire task in accordance with the type of target being fired at and the number of projectiles fired. Based on the results of the probability of hitting, it is possible to determine the required consumption of the projectile and the mathematical expectation of the number of direct hits, which with the consumption of time for shooting, determines the degree of efficiency of direct shooting. The probability of hitting, for different types of targets, can be determined when firing one or more projectiles. The probability of hitting when firing one projectile depends on:

- medium trajectory/shot position (Sp) towards the center of the target (Cc). The larger the distance of the medium trajectory from the center of the target, the lower the probability of hitting,
- dimensions of the target, the probability of hitting goals is higher if the target is larger,
- the range of the scattering ellipse, the lower the scattering ellipse, the higher the probability of hitting because the anti-tank system is more accurate, and
- direction of shooting, the probability of hitting is higher when the longer half-axes of the scattering ellipse and the dimensions of the target coincide.

The probability of hitting increases by bringing (maintaining) the medium trajectory in the center of the target. It is expressed in percentages, and the stated criterion is of the benefit type [28].

The minimum firing range (C9) is a combat characteristic that directly affects the efficiency of the anti-tank system and the implementation of anti-tank actions in the urban environment at short distances. The modern way of conducting combat operations requires that anti-tank missile systems also have the ability to shoot at short distances, a smaller minimum range allows more efficient solving of fire tasks in urban environment, which is characterized by limited space [71]. The criterion is of the cost type and it is expressed in meters (m).

Training difficulty (C10) is an important criterion for the decision maker because it is reflected in the time, simplicity, economy, and effectiveness of conducting operator training. Simpler training allows the operator a higher probability of shooting. The duration of the training is also an important feature during the conduct of combat operations. Qualitative assessments were converted into quantitative ones by hiring experts who assessed ATMS means using a scale: 0.167—extremely difficult, 0.333—very difficult, 0.5—difficult, 0.666—simple, 0.833—very simple, and 1—extremely simple. The criterion is of the benefit type.

The number of operators (C11) is a criterion that is directly related to the possibility of resistance and protection. The smaller the number of operators, the greater the protection of powers. The criterion is of the cost type and it is expressed in numerical value in the number of operators.

The second group of criteria consists of the criteria related to economic characteristics (C5, C7).

The price of an anti-tank missile (C5) is an economic characteristic expressed in dollars ($). It is necessary to provide the required characteristics of the rocket with the minimum price of the rocket. The price of an anti-tank missile, as well as the price of the ATMS has a significant impact on the decision maker because most often the funds for procurement, both systems and missiles, are limited, and it is necessary to choose the most favorable ratio of price and efficiency of the missile [28]. The specified criterion belongs to the cost type.

The price of an anti-tank missile system (C7) is an economic characteristic expressed in dollars ($). By designing anti-tank missile systems, it is necessary to ensure the realization of the required combat requirements with minimal costs, but this must not be achieved at the expense of combat and operational characteristics. The price of an anti-tank system has a significant impact on the decision-maker because the funds for the procurement of the system are usually limited, and it is necessary to choose the most efficient system with the least possible expenditure of funds [71]. The specified criterion is the cost type.

The last group of criteria consists of criteria related to construction characteristics, namely criteria C3 and C6.

The design characteristics of anti-tank missile systems (C3) present a criterion expressed by qualitative assessments that are later translated into quantitative ones using a scale: 1—absolutely weak, 2—very weak, 3—weak, 4—medium, 5—excellent, 6—exceptional, and 7—perfect. Construction characteristics include caliber of anti-tank missile system, mass of ATMS and anti-tank missiles, type and number of missiles for different purposes, explosive charge mass, initial projectile speed and maximum projectile speed, and field of action by direction and height [28]. The criterion is of the benefit type.

The guidance system (C6) is a characteristic of the anti-tank missile system that determines the membership to the generation of anti-tank systems. The values of alternatives according to this criterion are assigned on the basis of the scale: ATMS I generation (0.2), ATMS II generation (0.4), ATMS III generation (0.6), ATMS IV generation (0.8), and ATMS V generation (1.0). The criterion is of the benefit type.

The complexity of selecting the most favorable alternative (anti-tank missile system) has conditioned the use of the RDIBR-RMABAC multi-criteria decision-making model.

Respecting the defined MCDM model (Figure 1), the calculation of the weight coefficients of the criteria is performed first using the DIBR method.

Based on the defined criteria, a set of 11 criteria is determined $C_1, C_2, \ldots, C_{11}$, which rank by importance as follows $C_1 > C_2 > C_3 > C_4 > C_5 > C_6 > C_7 > C_8 > C_9 > C_{10} > C_{11}$. Based on the range of criteria, 6 experts defined the comparison values $RN(\lambda_{1,2}), RN(\lambda_{1,3}), \ldots, RN(\lambda_{10,11})$ i $RN(\lambda_{1,11})$, the aggregation of experts' opinions was performed and the values are obtained as follows: $RN(\lambda_{1,2}) = [0.46, 0.5]$, $RN(\lambda_{2,3}) = [0.43, 0.47]$, $RN(\lambda_{3,4}) = [0.46, 0.48]$, $RN(\lambda_{4,5}) = [0.43, 0.49]$, $RN(\lambda_{5,6}) = [0.37, 0.41]$, $RN(\lambda_{6,7}) = [0.34, 0.44]$, $RN(\lambda_{7,8}) = [0.43, 0.49]$, $RN(\lambda_{8,9}) = [0.43, 0.45]$, $RN(\lambda_{9,10}) = [0.43, 0.47]$, $RN(\lambda_{10,11}) = [0.45, 0.49]$, and $RN(\lambda_{1,11}) = [0.07, 0.09]$. Based on the defined values $\lambda_{n-1,n}$ by applying Equations (11)–(14), the next relations between the criteria are defined:

$$w_1 : w_2 = [0.5,\ 0.54] : [0.46,\ 0.5]$$

$$w_2 : w_3 = [0.53,\ 0.57] : [0.43,\ 0.47]$$

$$w_3 : w_4 = [0.52,\ 0.54] : [0.46,\ 0.48]$$

$$w_4 : w_5 = [0.51,\ 0.57] : [0.43,\ 0.49]$$

$$w_5 : w_6 = [0.59,\ 0.63] : [0.37,\ 0.41]$$

$$w_6 : w_7 = [0.56,\ 0.66] : [0.34,\ 0.44]$$

$$w_7 : w_8 = [0.51,\ 0.57] : [0.43,\ 0.49]$$

$$w_8 : w_9 = [0.55,\ 0.57] : [0.43,\ 0.45]$$

$$w_9 : w_{10} = [0.53,\ 0.57] : [0.43,\ 0.47]$$

$$w_{10} : w_{11} = [0.51,\ 0.55] : [0.45,\ 0.49]$$

$$w_1 : w_{11} = [0.07,\ 0.09] : [0.91,\ 0.93]$$

Based on the previous relations, applying the Equations (15)–(17), (19), and (8)–(10), the weight coefficients of the criteria are calculated (Table 5).

Table 5. The values of the weight coefficients of the criteria.

Criterion	Value of the Weight Coefficient
C1	0.200
C2	0.192
C3	0.150
C4	0.130
C5	0.110
C6	0.071
C7	0.043
C8	0.036
C9	0.027
C10	0.022
C11	0.019

Applying Equation (21), the control value $\lambda'_{1,11}$ is calculated.

$$\lambda'_{1,11} = \frac{w_{11}}{w_1 + w_{11}} = \frac{0.019}{0.200 + 0.019} = 0.0867$$

Considering that $\lambda'_{1,11} = 0.0867 \approx \lambda_{1,11} = 0.0869$, it can be concluded that expert preferences are well-defined.

After the weight coefficients of all criteria are obtained, the ranking of 13 alternatives is performed, presenting 13 different types of ATMS available at the market, by applying the Rough MABAC method.

Forming initial decision-making matrix, the first step is made in applying this method (Table 6). The matrix is formed based on the market investigation (range of declared values).

Step 1. Forming initail decision-making matrix (X).

Table 6. Initial decision-making matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	[800, 1000]	[3000, 4000]	[1, 1]	[0.9, 0.95]	[2160, 2300]	[0.6, 0.6]	[12,100, 15,000]	[0.89, 0.94]	[60, 66]	[0.33, 0.5]	[2, 3]
A2	[500, 550]	[2000, 2200]	[6, 6]	[0.84, 0.88]	[63,000, 63,500]	[0.4, 0.4]	[112,000, 114,000]	[0.86, 0.91]	[150, 165]	[0.5, 0.5]	[2, 2]
A3	[800, 900]	[3500, 4500]	[3, 3]	[0.87, 0.92]	[52,700, 53,000]	[0.4, 0.4]	[93,000, 100,000]	[0.86, 0.9]	[200, 220]	[0.33, 0.5]	[3, 3]
A4	[1000, 1200]	[4000, 5500]	[3, 3]	[0.91, 0.96]	[15,000, 15,300]	[0.6, 0.6]	[154,000, 160,000]	[0.92, 0.97]	[100, 110]	[0.33, 0.5]	[2, 2]
A5	[800, 900]	[1500, 2000]	[7, 7]	[0.89, 0.94]	[15,000, 15,350]	[0.4, 0.4]	[150,000, 162,000]	[0.86, 0.9]	[80, 88]	[0.33, 0.5]	[2, 3]
A6	[750, 900]	[500, 600]	[4, 4]	[0.71, 0.75]	[10,000, 10,200]	[0.4, 0.4]	[60,000, 71,000]	[0.9, 0.95]	[25, 27.5]	[0.33, 0.5]	[1, 1]
A7	[600, 750]	[4000, 4750]	[6, 6]	[0.89, 0.94]	[112,000, 112,500]	[0.6, 0.6]	[175,000, 180,000]	[0.89, 0.94]	[65, 71.5]	[0.33, 0.33]	[1, 2]
A8	[800, 1000]	[5000, 5500]	[6, 6]	[0.9, 0.95]	[100,000, 101,200]	[0.8, 0.8]	[210,000, 217,000]	[0.93, 0.98]	[200, 220]	[0.5, 0.67]	[2, 2]
A9	[800, 900]	[3500, 4000]	[3, 3]	[0.9, 0.95]	[100,000, 100,700]	[0.6, 0.6]	[130,000, 143,000]	[0.86, 0.9]	[500, 550]	[0.5, 0.5]	[2, 2]
A10	[500, 600]	[3500, 4000]	[6, 6]	[0.79, 0.83]	[80,000, 81,000]	[0.6, 0.6]	[260,000, 266,000]	[0.81, 0.85]	[200, 220]	[0.33, 0.5]	[1, 1]
A11	[300, 400]	[500, 600]	[3, 3]	[0.9, 0.95]	[20,000, 20,900]	[0.8, 0.8]	[30,000, 32,000]	[0.9, 0.95]	[20, 22]	[0.17, 0.33]	[1, 1]
A12	[900, 1000]	[3500, 4000]	[2, 2]	[0.86, 0.9]	[32,000, 32,700]	[0.8, 0.8]	[90,000, 96,000]	[0.86, 0.91]	[200, 220]	[0.33, 0.33]	[2, 2]
A13	[850, 1000]	[3000, 4000]	[3, 3]	[0.89, 0.94]	[120,000, 120,900]	[1, 1]	[230,000, 244,000]	[0.89, 0.94]	[100, 110]	[0.17, 0.33]	[1, 2]

Step 2. Normalization of the elements of the initial matrix. Applying the expressions (24) and (27), the normalized matrix (N) is obtained (Table 7):

Table 7. Normalized matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	[0.56, 0.78]	[0.5, 0.7]	[0, 0]	[0.77, 0.96]	[0, 0]	[0.33, 0.33]	[0, 0.01]	[0.5, 0.77]	[0.08, 0.09]	[0.33, 0.67]	[0.5, 1]
A2	[0.22, 0.28]	[0.3, 0.34]	[0.83, 0.83]	[0.5, 0.68]	[0.51, 0.52]	[0, 0]	[0.39, 0.4]	[0.33, 0.59]	[0.25, 0.27]	[0.67, 0.67]	[0.5, 0.5]
A3	[0.56, 0.67]	[0.6, 0.8]	[0.33, 0.33]	[0.65, 0.84]	[0.43, 0.43]	[0, 0]	[0.32, 0.35]	[0.28, 0.54]	[0.34, 0.38]	[0.33, 0.67]	[1, 1]
A4	[0.78, 1]	[0.7, 1]	[0.33, 0.33]	[0.81, 1]	[0.11, 0.11]	[0.33, 0.33]	[0.56, 0.58]	[0.66, 0.94]	[0.15, 0.17]	[0.33, 0.67]	[0.5, 0.5]
A5	[0.56, 0.67]	[0.2, 0.3]	[1, 1]	[0.73, 0.92]	[0.11, 0.11]	[0, 0]	[0.54, 0.59]	[0.28, 0.54]	[0.11, 0.13]	[0.33, 0.67]	[0.5, 1]
A6	[0.5, 0.67]	[0, 0.02]	[0.5, 0.5]	[0, 0.15]	[0.07, 0.07]	[0, 0]	[0.19, 0.23]	[0.55, 0.83]	[0.01, 0.01]	[0.33, 0.67]	[0, 0]
A7	[0.33, 0.5]	[0.7, 0.85]	[0.83, 0.83]	[0.73, 0.92]	[0.93, 0.93]	[0.33, 0.33]	[0.64, 0.66]	[0.5, 0.77]	[0.08, 0.1]	[0.33, 0.33]	[0, 0.5]
A8	[0.56, 0.78]	[0.9, 1]	[0.83, 0.83]	[0.77, 0.96]	[0.82, 0.83]	[0.67, 0.67]	[0.78, 0.81]	[0.72, 1]	[0.34, 0.38]	[0.67, 1]	[0.5, 0.5]
A9	[0.56, 0.67]	[0.6, 0.7]	[0.33, 0.33]	[0.77, 0.96]	[0.82, 0.83]	[0.33, 0.33]	[0.46, 0.52]	[0.28, 0.54]	[0.91, 1]	[0.67, 0.67]	[0.5, 0.5]
A10	[0.22, 0.33]	[0.6, 0.7]	[0.83, 0.83]	[0.31, 0.47]	[0.66, 0.66]	[0.33, 0.33]	[0.98, 1]	[0, 0.25]	[0.34, 0.38]	[0.33, 0.67]	[0, 0]
A11	[0, 0.11]	[0, 0.02]	[0.33, 0.33]	[0.77, 0.96]	[0.15, 0.16]	[0.67, 0.67]	[0.07, 0.08]	[0.55, 0.83]	[0, 0]	[0, 0.33]	[0, 0]
A12	[0.67, 0.78]	[0.6, 0.7]	[0.17, 0.17]	[0.58, 0.76]	[0.25, 0.26]	[0.67, 0.67]	[0.31, 0.33]	[0.33, 0.59]	[0.34, 0.38]	[0.33, 0.33]	[0.5, 0.5]
A13	[0.61, 0.78]	[0.5, 0.7]	[0.33, 0.33]	[0.73, 0.92]	[0.99, 1]	[1, 1]	[0.86, 0.91]	[0.5, 0.77]	[0.15, 0.17]	[0, 0.33]	[0, 0.5]

Step 3. Calculation of the elements of weighted matrix (V). Applying the expression (29) gives the elements of weighted matrix (V) (Table 8):

Table 8. Weighted matrix.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	[0.31, 0.36]	[0.29, 0.33]	[0.15, 0.15]	[0.23, 0.25]	[0.11, 0.11]	[0.09, 0.09]	[0.04, 0.04]	[0.05, 0.06]	[0.03, 0.03]	[0.03, 0.04]	[0.03, 0.04]
A2	[0.24, 0.26]	[0.25, 0.26]	[0.28, 0.28]	[0.19, 0.22]	[0.17, 0.17]	[0.07, 0.07]	[0.06, 0.06]	[0.05, 0.06]	[0.03, 0.03]	[0.04, 0.04]	[0.03, 0.03]
A3	[0.31, 0.33]	[0.31, 0.35]	[0.2, 0.2]	[0.21, 0.24]	[0.16, 0.16]	[0.07, 0.07]	[0.06, 0.06]	[0.05, 0.06]	[0.04, 0.04]	[0.03, 0.04]	[0.04, 0.04]
A4	[0.36, 0.4]	[0.33, 0.38]	[0.2, 0.2]	[0.23, 0.26]	[0.12, 0.12]	[0.09, 0.09]	[0.07, 0.07]	[0.06, 0.07]	[0.03, 0.03]	[0.03, 0.04]	[0.03, 0.03]
A5	[0.31, 0.33]	[0.23, 0.25]	[0.3, 0.3]	[0.22, 0.25]	[0.12, 0.12]	[0.07, 0.07]	[0.07, 0.07]	[0.05, 0.06]	[0.03, 0.03]	[0.03, 0.04]	[0.03, 0.04]
A6	[0.3, 0.33]	[0.19, 0.2]	[0.23, 0.23]	[0.13, 0.15]	[0.12, 0.12]	[0.07, 0.07]	[0.05, 0.05]	[0.06, 0.07]	[0.03, 0.03]	[0.03, 0.04]	[0.02, 0.02]
A7	[0.27, 0.3]	[0.33, 0.36]	[0.28, 0.28]	[0.22, 0.25]	[0.21, 0.21]	[0.09, 0.09]	[0.07, 0.07]	[0.05, 0.06]	[0.03, 0.03]	[0.03, 0.03]	[0.02, 0.03]
A8	[0.31, 0.36]	[0.36, 0.38]	[0.28, 0.28]	[0.23, 0.25]	[0.2, 0.2]	[0.12, 0.12]	[0.08, 0.08]	[0.06, 0.07]	[0.04, 0.04]	[0.04, 0.04]	[0.03, 0.03]
A9	[0.31, 0.33]	[0.31, 0.33]	[0.2, 0.2]	[0.23, 0.25]	[0.2, 0.2]	[0.09, 0.09]	[0.06, 0.07]	[0.05, 0.06]	[0.05, 0.05]	[0.04, 0.04]	[0.03, 0.03]
A10	[0.24, 0.27]	[0.31, 0.33]	[0.28, 0.28]	[0.17, 0.19]	[0.18, 0.18]	[0.09, 0.09]	[0.08, 0.09]	[0.04, 0.04]	[0.04, 0.04]	[0.03, 0.04]	[0.02, 0.02]
A11	[0.2, 0.22]	[0.19, 0.2]	[0.2, 0.2]	[0.23, 0.25]	[0.13, 0.13]	[0.12, 0.12]	[0.05, 0.05]	[0.06, 0.07]	[0.03, 0.03]	[0.02, 0.03]	[0.02, 0.02]
A12	[0.33, 0.36]	[0.31, 0.33]	[0.18, 0.18]	[0.2, 0.23]	[0.14, 0.14]	[0.12, 0.12]	[0.06, 0.06]	[0.05, 0.06]	[0.04, 0.04]	[0.03, 0.03]	[0.03, 0.03]
A13	[0.32, 0.36]	[0.29, 0.33]	[0.2, 0.2]	[0.22, 0.25]	[0.22, 0.22]	[0.14, 0.14]	[0.08, 0.08]	[0.05, 0.06]	[0.03, 0.03]	[0.02, 0.03]	[0.02, 0.03]

Step 4. Determining border approximate area (G). Border approximate area g_i for every criterion is determined by applying Equation (31), after which is formed the matrix G in the form 11 x 1 (where 11 is the final number of criteria) (Table 9).

Table 9. Border approximate area.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
BAA	[0.29, 0.32]	[0.28, 0.3]	[0.22, 0.22]	[0.21, 0.23]	[0.15, 0.16]	[0.09, 0.09]	[0.06, 0.06]	[0.05, 0.06]	[0.03, 0.03]	[0.03, 0.03]	[0.02, 0.03]

Step 5. Calculation of the elements of the distance matrix of alternatives from border approximate area (Q). The distance of alternatives from border approximate area is determined by applying Equations (32)–(35) (Table 10).

Table 10. Distance matrix of alternatives from border approximate area.

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11
A1	[0.02, 0.04]	[0.01, 0.03]	[−0.07, −0.07]	[0.02, 0.02]	[−0.04, −0.05]	[0, 0]	[−0.02, −0.02]	[0, 0]	[0, 0]	[0, 0]	[0, 0.01]
A2	[−0.05, −0.06]	[−0.03, −0.04]	[0.05, 0.05]	[−0.01, −0.01]	[0.01, 0.01]	[−0.02, −0.02]	[0, 0]	[0, 0]	[0, 0]	[0.01, 0]	[0, 0]
A3	[0.02, 0.01]	[0.03, 0.04]	[−0.02, −0.02]	[0.01, 0.01]	[0, 0]	[−0.02, −0.02]	[−0.01, −0.01]	[0, −0.01]	[0, 0]	[0, 0]	[0.01, 0.01]
A4	[0.06, 0.08]	[0.05, 0.08]	[−0.02, −0.02]	[0.03, 0.03]	[−0.03, −0.03]	[0, 0]	[0.01, 0]	[0.01, 0.01]	[0, 0]	[0, 0]	[0, 0]
A5	[0.02, 0.01]	[−0.05, −0.05]	[0.08, 0.08]	[0.02, 0.02]	[−0.03, −0.03]	[−0.02, −0.02]	[0, 0.01]	[0, −0.01]	[0, 0]	[0, 0]	[0, 0.01]
A6	[0.01, 0.01]	[−0.09, −0.1]	[0, 0]	[−0.08, −0.08]	[−0.04, −0.04]	[−0.02, −0.02]	[−0.01, −0.01]	[0.01, 0.01]	[−0.01, −0.01]	[0, 0]	[−0.01, −0.01]
A7	[−0.02, −0.02]	[0.05, 0.05]	[0.05, 0.05]	[0.02, 0.02]	[0.06, 0.06]	[0, 0]	[0.01, 0.01]	[0, 0]	[0, 0]	[0, −0.01]	[−0.01, 0]
A8	[0.02, 0.04]	[0.09, 0.08]	[0.05, 0.05]	[0.02, 0.02]	[0.05, 0.05]	[0.02, 0.02]	[0.01, 0.01]	[0.01, 0.01]	[0, 0]	[0.01, 0.01]	[0, 0]
A9	[0.02, 0.01]	[0.03, 0.03]	[−0.02, −0.02]	[0.02, 0.02]	[0.05, 0.05]	[0, 0]	[0, 0]	[0, −0.01]	[0.02, 0.02]	[0.01, 0]	[0, 0]
A10	[−0.05, −0.05]	[0.03, 0.03]	[0.05, 0.05]	[−0.04, −0.04]	[0.03, 0.03]	[0, 0]	[0.02, 0.02]	[−0.01, −0.02]	[0, 0]	[0, 0]	[−0.01, −0.01]
A11	[−0.09, −0.1]	[−0.09, −0.1]	[−0.02, −0.02]	[0.02, 0.02]	[−0.03, −0.03]	[0.02, 0.02]	[−0.02, −0.02]	[0.01, 0.01]	[−0.01, −0.01]	[−0.01, −0.01]	[−0.01, −0.01]
A12	[0.04, 0.04]	[0.03, 0.03]	[−0.05, −0.05]	[0, 0]	[−0.02, −0.02]	[0.02, 0.02]	[−0.01, −0.01]	[0, 0]	[0, 0]	[0, −0.01]	[0, 0]
A13	[0.03, 0.04]	[0.01, 0.03]	[−0.02, −0.02]	[0.02, 0.02]	[0.06, 0.06]	[0.05, 0.05]	[0.02, 0.02]	[0, 0]	[0, 0]	[−0.01, −0.01]	[−0.01, 0]

Step 6. Ranking alternatives. Calculation of the values of criteria functions by alternatives is obtained by applying Equation (37). Table 11 presents the values of criteria functions of alternatives.

Table 11. Values of criteria functions of alternatives.

	Si
A1	[0.279, 0.355]
A2	[0.355, 0.277]
A3	[0.465, 0.482]
A4	[0.618, 0.714]
A5	[0.451, 0.451]
A6	[0, −0.034]
A7	[0.715, 0.74]
A8	[0.973, 1]
A9	[0.655, 0.629]
A10	[0.487, 0.464]
A11	[0.035, −0.012]
A12	[0.479, 0.446]
A13	[0.717, 0.776]

Applying Equations (8)–(10), the values of criteria functions are converted into the crisp values and the ranking of alternatives is performed (Table 12).

Based on the results from Table 12, we can conclude that the alternative A8 presents the best ranked alternative, while the alternatives A11 and A6 in no case can be selected as the solution in the selection of ATMS.

Table 12. Crisp values of criteria functions of alterntives and their rank.

	Si Crisp	Rank of Alternatives
A1	−0.069	11
A2	−0.054	10
A3	0.022	7
A4	0.133	4
A5	0.010	9
A6	−0.231	13
A7	0.161	3
A8	0.304	1
A9	0.111	5
A10	0.024	6
A11	−0.212	12
A12	0.017	8
A13	0.176	2

5. Sensitivity Analysis

In every decision-making process, an error can happen, and especially in such a complex model. Therefore, it is necessary to perform sensitivity analysis in one of the following ways presented in [72–75]. In the paper, the analysis of the sensitivity of the Rough MABAC method to the changes in weight coefficients [72] is first performed, through 20 scenarios (Figure 2).

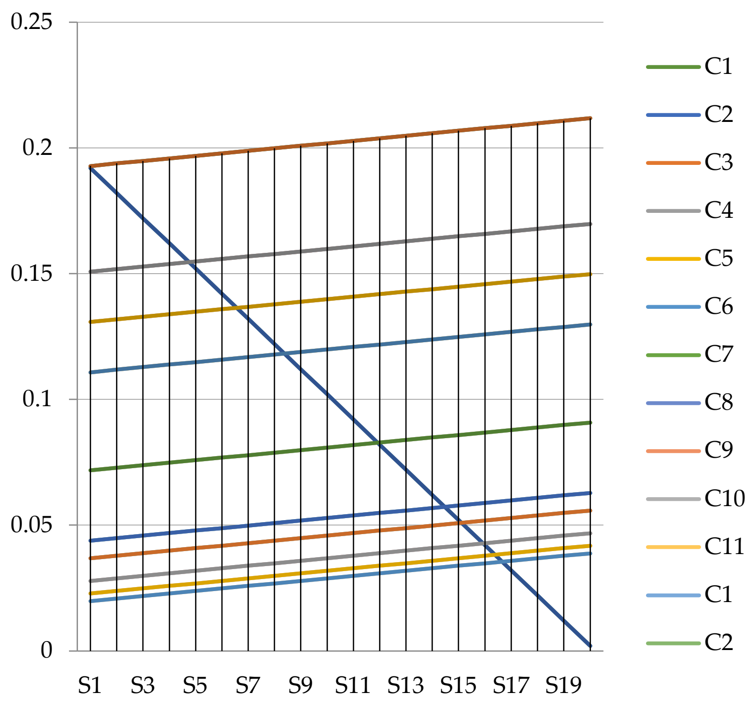

Figure 2. Scenarios with different weight coefficients of criteria.

The rank of alternatives after the application of the previously defined scenarios is provided in the Figure 3.

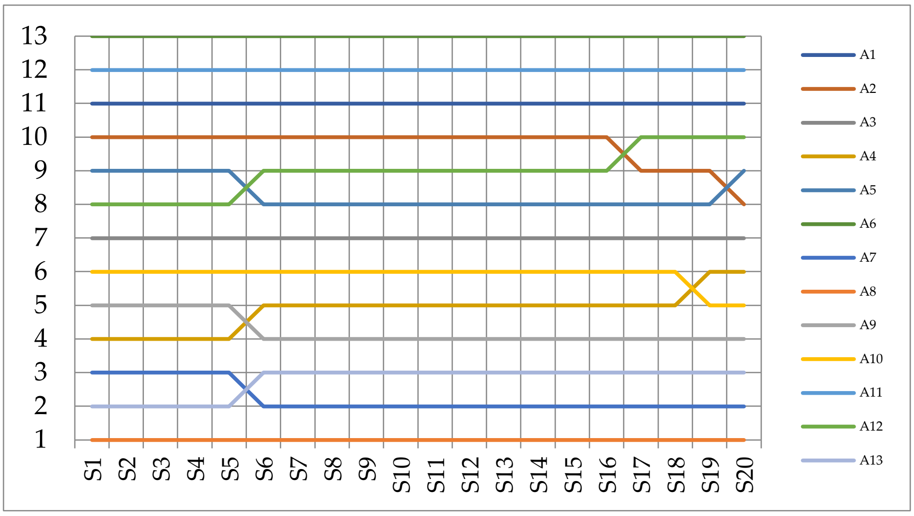

Figure 3. Rank of alternatives by scenarios.

By analyzing the obtained results, the following can be concluded:

- the rank of the alternatives in the scenarios S1–S4 is identical to the initial rank;
- the first changes occur in scenario S5: the second-ranked and the third-ranked alternatives changed places (the alternatives A13 and A7); the fourth-ranked and the fifth-ranked alternatives changed places (the alternatives A4 and A9); the eighth-ranked and the ninth-ranked alternatives changed places (the alternatives A12 and A5). This ranking is maintained until scenario S15;
- in scenarios S16 and S17, there was a rank change between the ninth-ranked and the tenth-ranked alternatives (the alternatives A12 and A2);
- in scenario S18, there is a new change, the rank is changed in the alternatives in the fifth and the sixth place (the alternatives A4 and A10);
- in scenarios S19 and S20, there was a rank change between the eighth-ranked and the ninth-ranked alternatives (the alternatives A5 and A2).

It should be noted that the alternative A8 is ranked first in all scenarios, while on the other hand, the alternatives A1, A11, and A6 retained the last positions of the ranking. In addition, the alternative A3 does not change its rank. Changes in rankings in different scenarios most often occur with middle-ranked alternatives, which does not significantly affect the final decision.

From the previous analysis, it can be concluded that the Rough MABAC method is sensitive to changes in the weights of the criteria. Furthermore, it is observed that the presented model can tolerate smaller errors in defining the weight coefficients of the criteria.

After the previous analysis, the results of the Rough MABAC method were compared with 6 other methods. The results of the comparison are presented in the Figure 4.

From Figure 4, it can be observed that when applying different methods, there are certain changes in the ranking of alternatives. However, rank changes only occur at certain intervals, for example:

- The alternative A8, which by applying the rough MABAC method retains the first rank, is the second in rank when other methods are applied;
- The alternative A13, which is ranked as the second using the rough MABAC method, retained its ranking in four cases, while in two cases it was ranked fifth;
- The alternative A4, which was ranked fourth using the rough MABAC method, changes its ranking and becomes the first ranked in two cases;
- The alternatives A11 and A6 keep the last ranks regardless of the methods;
- There are changes in the ranks of the other alternatives also, but they move in relatively small rank intervals: A1 is ranked from seventh to eleventh place, A2 from tenth to

twelfth, A3 from sixth to tenth, A5 from fourth to ninth, A7 from third to sixth, A9 from fourth to ninth, A10 from sixth to eleventh, and A12 from third to eighth place.

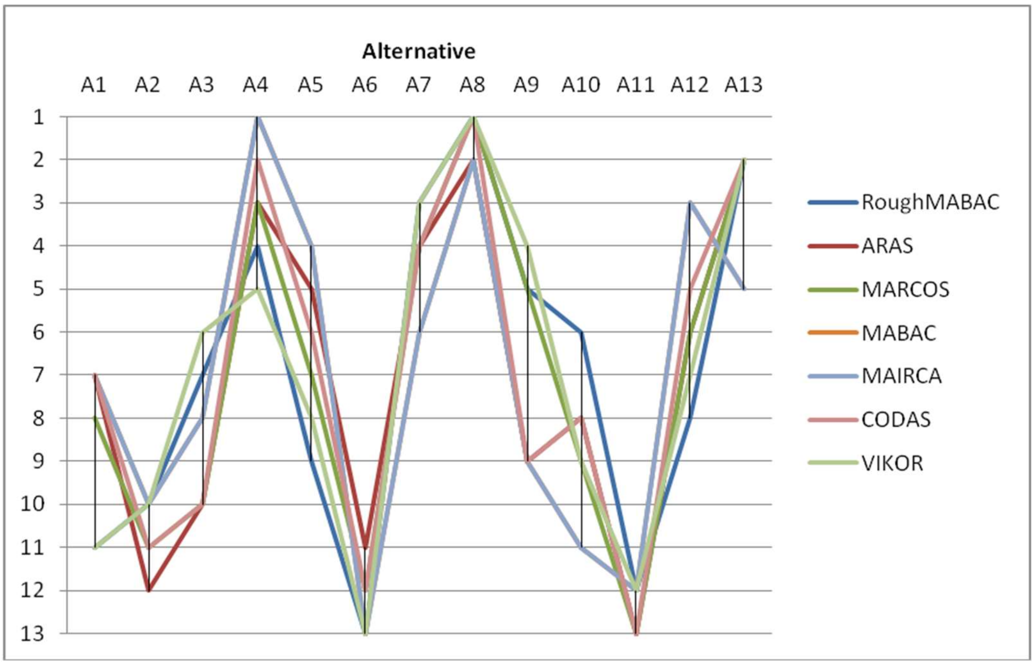

Figure 4. Rank of alternatives by applying other MCDM methods.

The consistency of the results of the MCDM method can be checked by determining the Spearman's coefficient of rank correlation (S) [76], which is obtained by applying the following expression:

$$S = 1 - \frac{6\sum_{i=1}^{n} D_i^2}{n(n^2 - 1)} \tag{38}$$

where D_i presents the difference in the rank of the observed element in the vector w and the rank of the correspondent element in the reference vector, while n presents total number of ranked elements.

The values of the Spearman's coefficient are in the range $[-1, 1]$. When the ranks of the elements are identical, the Spearman's coefficient is 1, while the Spearman's coefficient is -1 when the ranks are completely opposite. When the value of the Spearman's coefficient is equal to 0, the ranks are uncorrelated.

Applying Equation (38), we obtained the value of the Spearman's coefficient (S) (Figure 4). The correlation of the ranks obtained by changing the weight coefficients is made in relation to the initial rank, in accordance with the defined scenarios (Figure 5). Moreover, the calculation of Spearman's rank correlation coefficient is performed by comparing the ranks obtained using the Rough MABAC method with the ranks obtained using the methods ARAS [13], VIKOR [11], CODAS [15,77], MAIRCA [17], MABAC [18], and MARCOS [20,78] (Figure 6).

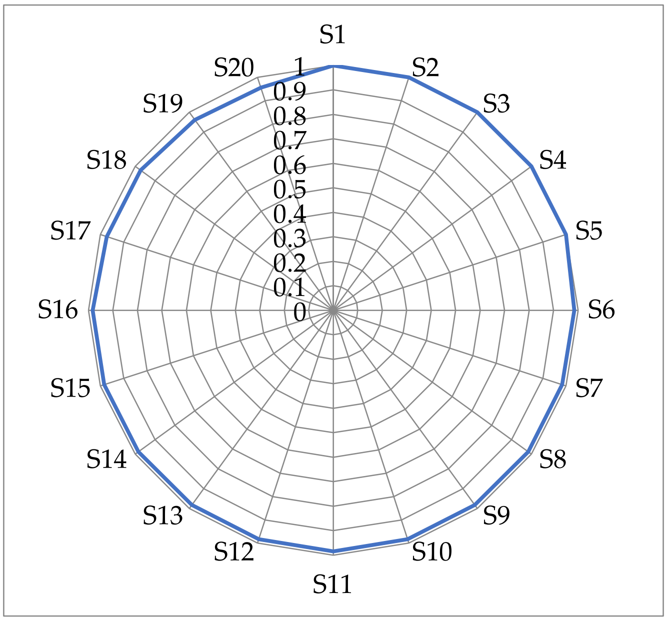

Figure 5. The values of the Spearman's coefficient of the rank correlations for 20 scenarios with the changes in weight coefficients of the criteria in relation to the initial rank of alternatives.

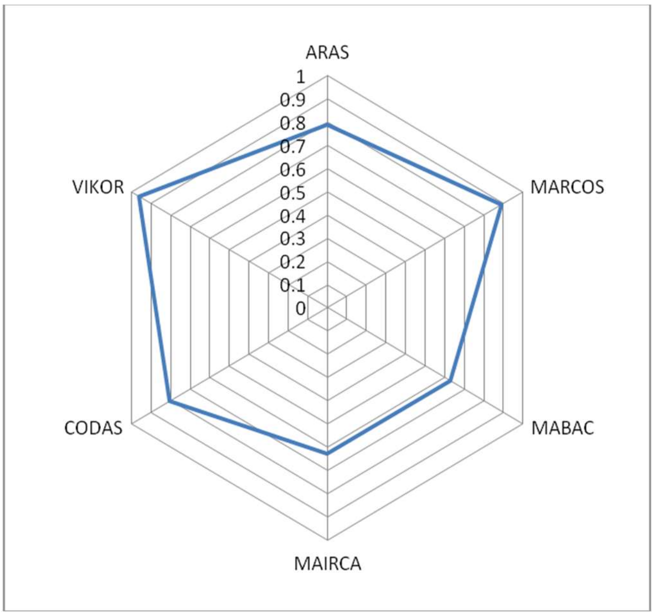

Figure 6. The values of the Spearman's coefficient of the rank correlations for 6 methods in relation to the initial rank of alternatives.

From the previous figures (Figures 5 and 6), it is concluded that the correlation coefficients in the 20 scenarios given in Figure 2 tend towards ideal positive correlation, while the correlation coefficients of 6 methods in relation to the range of alternatives using the Rough MABAC method have different values, in the range of [0.63,0.96], and mostly tend to correlate; the results obtained are most similar to the results obtained by the VIKOR method.

6. Conclusions

The DIBR and MABAC methods with rough numbers are successfully modified in this paper, which is presented on the problem of selecting anti-tank missile systems that are available on the market for equipping military units. The DIBR method was improved by rough numbers, and in the presented MCDM model, it was used to determine the weight coefficients of the criteria previously defined by the analysis of the available literature. The comparison was made by six experts in this field, and the aggregation of their opinions led to the formulation of rough numbers in the subject comparison. After the values of the weight coefficients of the criteria were obtained in the form of rough numbers, they were converted into the crisp values which were used later in the calculation. Using the Rough MABAC method, the best alternative was selected from the set offered, i.e., from the set of 13 different ATMS available on the world market. The evaluation of alternatives was also performed by six experts.

In order to validate the presented model, the sensitivity analysis of the output results to the change of the weight coefficients of the criteria was performed and the results of the proposed method were compared with the results of other methods. The above analysis and calculation of the Spearman's rank correlation coefficient led to the conclusion that the defined model was stable. It can also be concluded that the application of multi-criteria decision-making methods can be a reliable tool to help in decision-making, especially in situations where there are a number of criteria and alternatives that condition the selection.

Although the model proved to be very stable, and the research was carried out very carefully, like most multi-criteria decision-making models, this model also has its limitations. Rough numbers proved to be very good in dealing with uncertainty, but nonetheless, it cannot be said that the problem of uncertainty is completely eliminated, only significantly reduced to a rational measure. Despite the comprehensive approach in defining the criteria and their weight coefficients, it was not possible to incorporate into the model all the specifics that would be adapted to the requirements of decision-makers, because it is possible that these requirements change from one case to another.

Further research should be focused on redefining the existing criteria by engaging more experts in the field, as well as on the application of other methods for defining weight coefficients of criteria, as well as on the selection of the optimal alternative, in the same or a similar problem.

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