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# DEVELOPMENT OF THE MCDM FUZZY LMAW-GREY MARCOS MODEL FOR SELECTION OF A DUMP TRUCK

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**ABSTRACT**

This study presents the MCDM model created for the selection of a dump truck for the needs of the army engineering units, based primarily on the truck's construction features and purchasing and maintenance costs. In this study was used the Methodology of Additive Weights (LMAW) in Fuzzy surrounding for determination of weight coefficients of criteria, while for the selection of the optimal alternative (for a dump truck) it was used the Measurement of Alternatives and Ranking according to Compromise Solution (MARCOS) method, modified by interval grey numbers. Input data for this methodology were obtained by engaging experts. Finally, the analysis was made of the sensitivity of output results of the proposed MCDM methodology to the change of weight coefficients of criteria, as well as the comparison of the obtained results with the results of other methodologies. In the conclusion, the proposed model showed stability but it was sensitive to weight coefficients change which should be taken into account by defining the same by experts.



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## 1. Introduction

During any type of construction works, dump trucks are used for the transport of materials by roads. A dump truck is a truck equipped with the movable cargo compartment which can be lifted for unloading. The cargo can be unloaded backwards or to one of each side (left or right). Dump trucks have wide-range usability. With their use, transportation time is reduced, and loading/unloading time saved, which highly increases efficiency and profitability. This type of transportation vehicle belongs to the class of machines with cyclic performance, meaning these conduct their work in cycles (Hristov, 1978). The prototype of such transportation vehicle was presented for the first time by the Canadian inventor Robert T. Mawhinney, in 1920, when he registered the patent no. CA 203004, titled "Raising and Lowering and Spreading Device for Truck Bodies" (Canadian Patents Database. Raising and lowering and spreading device for truck bodies, 2022).

Modern dump trucks consist of a truck chassis, a hydraulic lifting mechanism, a power take-off device and a cargo box. The principle of work of a movable cargo compartment is based on a hydraulic mechanism where a piston rod extends and retracts from a cylinder by hydraulic oil pressured with a hydraulic pump driven by a truck engine and other hydraulic equipment like distribution valves *etc*. The engine and the cabin of a dump truck are the same as in any other trucks but the body is additionally straightened due to heavy cargo weights, and modified for the movable hydraulic cargo compartment.

Dump trucks are mostly used for transportation of bulk materials, but can be used for transportation of any other materials suitable for unloading. During construction works, these are commonly used as a part of the working groups together with other construction machines (loaders, excavators, graders *etc*.) Differences between the dump trucks types are mostly reflected in the load weight and capacity.

For conduction of construction works in all armies over the world, engineering units are used with appropriate construction machines and transportation means assigned. Because of their characteristics, dump trucks are used for the transportation of bulk materials in this scope of works in both, military and civil engineering. Unlike in the civil engineering use, in the army these trucks must be able to handle rugged terrains, and be capable of operating in environments with austere conditions, with armored capabilities.

For the purpose of equipping engineering units with these means, commercial dump trucks are mainly used which can be found on the market but modified with certain adjustments to meet specific conditions of use during combat operations.

Considering that the procurement of dump trucks for military usage requires decision making based on various number of criteria, this study presents subject selection by implementing the MCDM model of Fuzzy LMAW (Logarithm Methodology of Additive Weights) – Grey MARCOS (Measurement of Alternatives and Ranking according to COmpromise Solution). The problem of selection of dump trucks by using the MCDM model has been subject of many researches. By using the fuzzy DEMATEL and fuzzy hierarchical TOPSIS methods Baykasoğlu et al. (2013) resolve a truck selection problem of a land transportation company. For the selection of open pit truck Yavuz (2016) uses fuzzy TOPSIS method. Chakraborty and Prasad (2016) use system based on quality function deployment (QFD) methodology for industrial truck selection in manufacturing organizations. A systematic review of decision-making support for truck selection is conducted in (dos Santos Jesus et al., 2020). For the selection of the appropriate tanker vehicle, Gorcun et al. (2021) use Fuzzy SWARA and Fuzzy CODAS methods, while for resolving of the same problem Milosavljević et al. (2018) apply AHP, MABAC,TOPSIS, EDAS, ARAS, COPRAS MOORA methods. For resolving of the problem of a truck selection in transportation systems of open pit mines Malli et al. (2021) use the AHP method for determination of weight coefficients of criteria, while by using Fuzzy WSM method perform alternatives ranking. In MCDM model which integrated the PIPRECIA and COPRAS Method under Fuzzy Environment, Özdağoğlu et al. (2021a) resolve the problem of the selection of a truck tractor. Ulutaş et al. (2022) make Pallet Truck Selection with MEREC and WISP-S methods.

In the following text it is provided the description of the proposed MCDM model and used models, the criteria which condition the selection are determined, the alternatives are defined (different dump truck models available on the market), it is conducted the application of the proposed model and consistency of output results checked, as well as the results analysis and the comparison with other MCDM methods. At the end, the conclusions are made based on the research, limitations for the proposed model are set, and further investigation directions are defined.

## 2. Methodology

For the purpose of problem solving, respectively, the selection of a dump truck for military engineering units, it is formed the MCDM model as shown in the Figure 1.

The MCDM model consists of three phases. In the first phase it is planned the definition of the selection criteria and determination of their weight coefficients by using Fuzzy LMAW method. In the next phase, the selection of the optimal alternative (dump truck) is made from the group offered by using Grey MARCOS method. Third phase includes testing of stability of the proposed methodology through sensitivity analysis and by comparison with other MCDM methods. In the following text it is provided the description of the applied method.

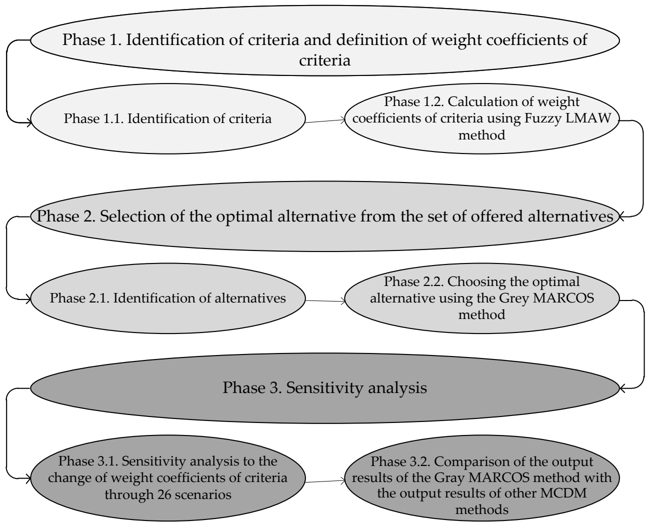


**Figure 1.** MCDM model

### 2.1. Fuzzy Logarithm Methodology of Additive Weights (LMAW)

The LMAW method presents a relatively young method which can be applied both for determining weight coefficients of criteria, as well as for the selection of optimal alternatives from the set of offered ones. It has been applied in many areas for resolving various research problems with certain modifications, and the analysis of literature in which the method is used is given in the Table 1 with indications of the problem and the methods combined trough the MCDM model.

**Table 1.** Analysis of literature related to the application of the LMAW method

| Application and reference | Used methods |
|---|---|
| To solving the problem of the location selection for a landing operations point (LOP) in combat operations of the army (Božanić et al., 2022). | Fuzzy LMAW |
| New Risk Assessment Methodology for Light Goods Vehicles on Two-Lane Road Sections (Subotić et al., 2021). | Rough Dombi Bonferroni MARCOS, Rough Dombi LMAW |
| Application in logistics (Pamučar et al., 2021a). | LMAW |
| Evaluation of Metaverse integration of freight fluidity measurement alternatives (Deveci et al., 2022). | Dombi LMAW, Dombi EDAS |
| Defining risks on road sections during the transport of dangerous goods in the Serbian army (Planić, 2022). | LMAW, DEA |
| Evaluation of the Global Multidimensional Poverty Index (Demir, 2022). | Fuzzy LMAW |
| Green Supplier Selection in an Uncertain Environment in Agriculture (Puška et al., 2022) . | Z-Numbers, Fuzzy LMAW, Fuzzy CRADIS |
| Evaluation of the Transitions Potential to Cyber-Physical Production System of Heavy Industries in Turkey (Görçün & Küçükönder, 2022). | LMAW |
| Selecting a loader (Bozanic et al., 2021). | Neuro-Fuzzy System (ANFIS), LMAW |
| Material Selection Problems (Zakeri et al., 2022). | MUltiple-TRIangles ScenarioS (MUTRISS), LMAW |

In this study, the LMAW method is modified by triangular fuzzy numbers (Božanić et al., 2022) used for determination of weight coefficient of criteria by engaging the experts $E=\{E_1,E_2,...,E_k\}$. Basics of Fuzzy theory fuzzy sets were introduced by Lotfi Zadeh in the sixties of the 20th century (Zadeh, 1965a, 1965b, 1968). Due to Fuzzy set feature according to which one element can more or less belong to a particular set, its usage is suitable for quantifying qualitative input data. (Pamučar et al., 2011, 2012, 2022; Božanić et al., 2015, 2016; Švadlenka et al., 2020; Stanković et al., 2020; Simić et al., 2021; Milovanović et al., 2021; Mustafa et al., 2022; Gayen et al., 2021). Fuzzy LMAW method steps for determination of weight coefficient of the criteria are shown as follows (Božanić et al., 2022).

*Step 1. Criteria prioritization.* First of all, the experts $e=\{e_1,e_2,...,e_k\}$ prioritize the criteria $C=\{C_1,C_2,\dots,C_n\}$, based on the values from priorly defined fuzzy linguistic, by which priority vectors are defined $\tilde{P}^e=\left(\tilde{\upsilon}_{C_1}^e,\tilde{\upsilon}_{C_2}^e,..,\tilde{\upsilon}_{C_n}^e\right)$, for every expert, where $\tilde{\upsilon}_{C_n}^e$ presents the value from fuzzy linguistic scale which was assigned to the criterion *n* by the expert *(e)*

*Step 2. Determination of the absolute fuzzy anti-ideal point ($\tilde{\upsilon}_{AIP}$).* The value of absolute fuzzy anti-ideal point is determined by a decision maker, and it presents the fuzzy number which is smaller than the smallest value from the set $\tilde{P}^e=\left(\tilde{\upsilon}_{C_1}^e,\tilde{\upsilon}_{C_2}^e,..,\tilde{\upsilon}_{C_n}^e\right)$.

*Step 3. Determination of fuzzy relation vector ($\tilde{R}^e$).* The relation between the elements of the priority vectors and absolute fuzzy anti-ideal point by the experts $e=\{e_1,e_2,...,e_k\}$ is obtained by applying the following expression (1)

$$\tilde{\rho}_{C_n}^e=\left(\frac{\tilde{\upsilon}_{C_n}^e}{\tilde{\upsilon}_{AIP}}\right)=\left(\frac{\upsilon_{C_n}^{(l)e}}{\upsilon_{AIP}^{(r)}},\frac{\upsilon_{C_n}^{(m)e}}{\upsilon_{AIP}^{(m)}},\frac{\upsilon_{C_n}^{(r)e}}{\upsilon_{AIP}^{(l)}}\right) \tag{1}$$

where *l* presents left, and *r* presents right distribution of a fuzzy number, while *m* presents the value in which the value of the membership function (μ) is the highest, and after which a vector of experts relations is obtained $R^e=\left(\tilde{\upsilon}_{C1}^e,\tilde{\upsilon}_{C2}^e,..,\tilde{\upsilon}_{Cn}^e\right)$.

*Step 4. Determination of weight coefficients vector* $w_j^e=\left(\tilde{w}_1^e,\tilde{w}_2^e,...,\tilde{w}_n^e\right)^T$, *for every expert* $e=\{e_1,e_2,...,e_k\}$ is obtained by applying the following expression (2):

$$\tilde{w}_j^e=\left(\frac{ln\left(\tilde{\upsilon}_{Cn}^e\right)}{ln\left(\prod_{j=1}^n\tilde{\upsilon}_{Cn}^e\right)}\right)=\left(\frac{ln\left(\upsilon_{Cn}^{(l)e}\right)}{ln\left(\prod_{j=1}^n\upsilon_{Cn}^{(r)e}\right)},\frac{ln\left(\upsilon_{Cn}^{(m)e}\right)}{ln\left(\prod_{j=1}^n\upsilon_{Cn}^{(m)e}\right)},\frac{ln\left(\upsilon_{Cn}^{(r)e}\right)}{ln\left(\prod_{j=1}^n\upsilon_{Cn}^{(l)e}\right)}\right) \tag{2}$$

where $\upsilon_{C_n}^{(l)e}$ presents the left distribution of fuzzy priority vector, $\upsilon_{C_n}^{(r)e}$ presents the right distribution, and

$\upsilon_{Cn}^{(m)e}$ *m* presents the value where the membership function of fuzzy priority vector equals one.

*Step 5. Calculation of aggregated fuzzy weight coefficient vectors* $w_j=\left(\tilde{w}_1,\tilde{w}_2,...,\tilde{w}_n\right)^T$. These are obtained by applying Bonferroni aggregators, by the expressions (3):

$$\tilde{w}_j=\left(\frac{1}{k(k-1)}\sum_{\substack{i,j=1\\i\neq j}}^k\tilde{w}_i^{(e)p}\tilde{w}_j^{(e)q}\right)^{\frac{1}{p+q}}=$$
$$\left\{\left(\frac{1}{k(k-1)}\sum_{\substack{i,j=1\\i\neq j}}^k w_i^{(l_e)p}w_j^{(l_e)q}\right)^{\frac{1}{p+q}},\left(\frac{1}{k(k-1)}\sum_{\substack{i,j=1\\i\neq j}}^k w_i^{(m_e)p}w_j^{(m_e)q}\right)^{\frac{1}{p+q}},\left(\frac{1}{k(k-1)}\sum_{\substack{i,j=1\\i\neq j}}^k w_i^{(r_e)p}w_j^{(r_e)q}\right)^{\frac{1}{p+q}}\right\} \tag{3}$$

where $p,q\geq 0$ present stabilization parameters of Bonferroni aggregators, $\tilde{w}_j^e$ presents the weight coefficients given by expert evaluation $e=\{e_1,e_2,...,e_k\}$, $w_j^{(l_e)}$ presents the left distribution of fuzzy weight coefficient, $\tilde{w}_j^e$, $w_j^{(r_e)}$ presents the right distribution, while $w_j^{(m_e)}$ presents the right value in which the function of fuzzy weight coefficient $\tilde{w}_j^e$ equals one.

*Step 6. Calculation of final values for weight coefficients* $w_j = \left(w_1, w_2, ..., w_n\right)^T$. Final value for weight coefficient of the criteria is obtained by defuzzification, respectively, by applying the following equation (4):

$$w_j = \frac{l + 4m + r}{6} \tag{4}$$

### 2.2. Grey MARCOS method

The MARCOS method (Measurement of Alternatives and Ranking according to COmpromise Solution) (Stević et al., 2020), presents a young MCDM method, which is based on alternatives ranking in relation to a compromise solution. In this study, the MARCOS method is modified by Grey theory, respectively, interval grey numbers, which treat well uncertainty areas. Basic settings of Grey theory were given by Deng (1982). Grey theory presents a model for the treatment of partially known and partially unknown information (Deng, 1982). According to Deng (1982), all information is classified into three categories (Figure 2).

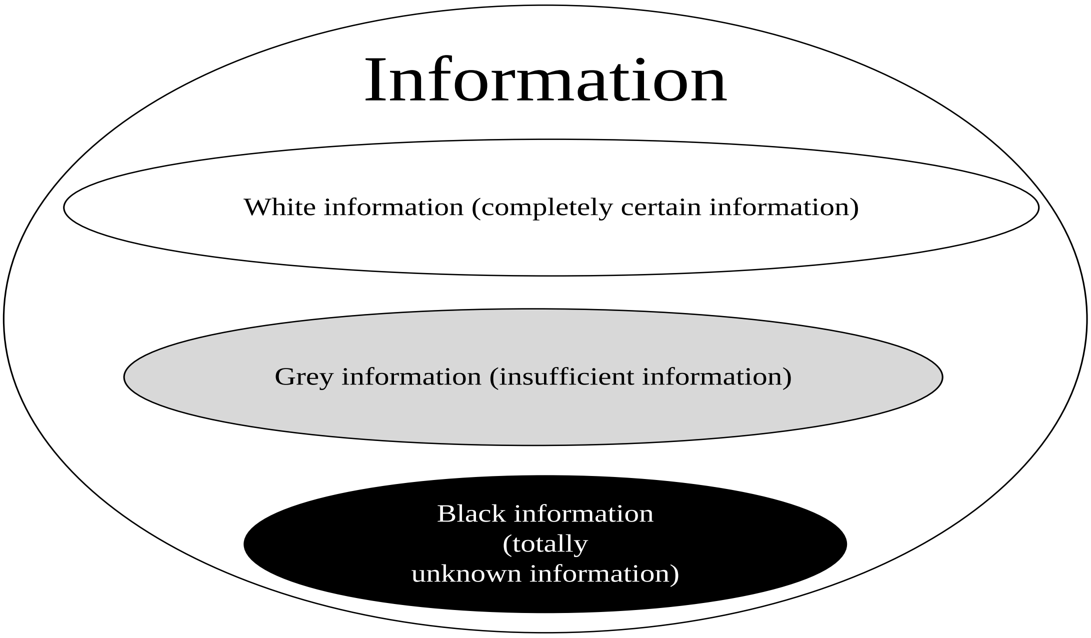


**Figure 2.** Classification of information

In further text it is provided a short description of interval grey numbers used in the study (Liu et al., 2012; Badi et al., 2019; Badi & Pamucar, 2020):

If the set U presents universal set, then Grey set (G) of the set U is defined with its two copies: $\bar{\mu}_G(U)$ and $\underline{\mu}_G(U)$ where is $\bar{\mu}_G(U): U \rightarrow [0,1]$ *and* $\underline{\mu}_G(U): U \rightarrow [0,1]$ as well as $\bar{\mu}_G(U) \geq \underline{\mu}_G(U), u \in U$. Interval Grey number ($\otimes G$) is defined as $\otimes G = \left[\underline{G}, \bar{G}\right]$, where $\underline{G}$ presents bottom limit of the grey number $\otimes G$, and $\bar{G}$ presents upper limit, and where $\underline{G} > \bar{G}$. If $\underline{G} = \bar{G}$, then grey number $\otimes G$ becomes white number, respectively, it has crisp known and precisely determined value. Basic computational operations with Grey numbers were described in many publications (Liu et al., 2012; Abdulshahed et al., 2017; Badi & Pamucar, 2020).

Different authors used Grey MARCOS method for resolution of various problems (Table 2).

**Table 2.** Analysis of literature related to the application of Grey MARCOS method

| Application and reference | Used methods |
|---|---|
| Supplier selection for steelmaking company (Badi & Pamucar, 2020). | Grey MARCOS |
| Landfill location selection (Torkayesh et al., 2021). | BWM, Grey MARCOS |
| Performance evaluation of ground operations agents (Özdağoğlu et al., 2021b). | Grey PIPRECIA, Grey MARCOS |
| Robust service quality measurement (Pamucar et al., 2021b). | Grey SWARA, Grey MARCOS |
| Supply Chain Management Contract Selection in the Oil and Gas Industry (Karbassi Yazdi, 2022). | Grey BWM, Grey MARCOS |

The steps of the Grey MARCOS method are given in the following text (Pamucar et al., 2021b).

*Step 1. Forming of aggregated initial decision-making matrix ( $\Delta$ ).* First, the experts $e=\{e_1,e_2,...,e_k\}$ evaluate all alternatives by every criterion, by which they obtain Grey initial decision-making matrices for every expert $\Delta^{(e)}=\left[\otimes x_{ij}^{(e)}\right]_{m\,x\,n}$, where $\otimes x_{ij}^{(e)}=\left[\underline{x}_{ij}^{(e)},\overline{x}_{ij}^{(e)}\right]$ , $1\le i\le m$ and $1\le j\le n$. By using the expression (5) aggregating of every part of decision-making matrices by all experts is done, resulting in initial aggregated decision-making matrix, as in the expression (6).

$$\otimes x_{ij}=\left[\underline{x}_{ij},\overline{x}_{ij}\right]=\begin{cases}\underline{x}_{ij}=\left\{\dfrac{1}{k(k-1)}\sum_{i,j=1}^{k}\underline{x}_i^{\,p}\,\underline{x}_i^{\,q}\right\}^{\frac{1}{p+q}} \\ \overline{x}_{ij}=\left\{\dfrac{1}{k(k-1)}\sum_{i,j=1}^{k}\overline{x}_i^{\,p}\,\overline{x}_i^{\,q}\right\}^{\frac{1}{p+q}}\end{cases} i\neq j \tag{5}$$

$$\Delta=\left[\otimes x_{ij}\right]_{m\,x\,n}=\begin{bmatrix}\left[\underline{x}_{11},\overline{x}_{11}\right] & \left[\underline{x}_{12},\overline{x}_{12}\right] & \cdots & \left[\underline{x}_{1n},\overline{x}_{1n}\right]\\ \left[\underline{x}_{21},\overline{x}_{21}\right] & \left[\underline{x}_{22},\overline{x}_{22}\right] & \cdots & \left[\underline{x}_{2n},\overline{x}_{2n}\right]\\ \vdots & \vdots & \ddots & \vdots\\ \left[\underline{x}_{m1},\overline{x}_{m1}\right] & \left[\underline{x}_{m2},\overline{x}_{m2}\right] & \cdots & \left[\underline{x}_{mn},\overline{x}_{mn}\right]\end{bmatrix}_{m\,x\,n} \tag{6}$$

*Step 2. Forming of extended initial decision-making matrix (X).*
Extending of initial decision-making matrix is done by definition of anty-ideal (*AAI)* and ideal (*AI*) solutions (7).

$$X=\begin{array}{c} \\ AAI\\ A_1\\ A_2\\ \dots\\ A_m\\ AI\end{array}\begin{array}{c}\begin{array}{cccc}C_1 & C_2 & \dots & C_n\end{array}\\ \begin{bmatrix}\otimes x_{aa1} & \otimes x_{aa2} & \dots & \otimes x_{aan}\\ \otimes x_{11} & \otimes x_{12} & \dots & \otimes x_{1n}\\ \otimes x_{21} & \otimes x_{22} & \dots & \otimes x_{2n}\\ \dots & \dots & \dots & \dots\\ \otimes x_{m1} & \otimes x_{22} & \dots & \otimes x_{mn}\\ \otimes x_{ai1} & \otimes x_{ai2} & \dots & \otimes x_{ain}\end{bmatrix}\end{array} \tag{7}$$

The AAI and AI are obtained by using the expressions (8) and (9):

$$AAI=\min_j \underline{x}_{ij} \quad if \;\; j\in B \quad and \quad \max_j \overline{x}_{ij} \quad if \;\; j\in C \tag{8}$$

$$AI=\max_j \overline{x}_{ij} \quad if \;\; j\in B \quad and \quad \min_j \underline{x}_{ij} \quad if \;\; j\in C \tag{9}$$

Where B refers to the benefit-type criteria, while C refers to the cost-type criteria.

*Step 3. Normalization of extended initial matrix ( $X$ ).*
Normalized matrix $\widehat{Z}=\left[\widehat{z}_{ij}\right]_{m\times n}$ , respectively, its elements are obtained by applying the expressions (10) and (11):

$$\otimes\hat{z}_{ij} = \frac{\otimes x_{ij}}{\max\limits_{1\le i\le m}\left\{\overline{x}_{ij}\right\}} = \left(\frac{\underline{x}_{ij}}{\max\limits_{1\le i\le m}\left\{\overline{x}_{ij}\right\}}, \frac{\overline{x}_{ij}}{\max\limits_{1\le i\le m}\left\{\overline{x}_{ij}\right\}}\right) \quad if \;\; j \in B \tag{10}$$

$$\otimes\hat{z}_{ij} = \frac{\min\limits_{1\le i\le m}\left\{\underline{x}_{ij}\right\}}{\otimes x_{ai}} = \left(\frac{\min\limits_{1\le i\le m}\left\{\underline{x}_{ij}\right\}}{\overline{x}_{ij}}, \frac{\min\limits_{1\le i\le m}\left\{\underline{x}_{ij}\right\}}{\underline{x}_{ij}}\right) \quad if \;\; j \in C \tag{11}$$

*Step 4. Determination of weighted matrix* $V = \left[\otimes v_{ij}\right]_{m\times n}$.

The weighted matrix V is obtained by multiplying normalized matrix $\hat{Z}$ with weight coefficients of the criteria.

*Step 5. Determination of degree of usefulness of the alternatives.* By using the expressions (12) and (13) can be obtained the degree of utility for the alternatives in relation to the anti-ideal and the ideal solution.

$$\otimes K_i^- = \frac{\otimes S_i}{\otimes S_{AAI}} = \left(\frac{\underline{S}_i}{\overline{S}_{AAI}}, \frac{\overline{S}_i}{\underline{S}_{AAI}}\right) \tag{12}$$

$$\otimes K_i^+ = \frac{\otimes S_i}{\otimes S_{AI}} = \left(\frac{\underline{S}_i}{\overline{S}_{AI}}, \frac{\overline{S}_i}{\underline{S}_{AI}}\right) \tag{13}$$

Where $\otimes S_i = \sum_{i=1}^{n} \otimes v_{ij} = \left(\sum_{i=1}^{n} \underline{v}_{ij}, \sum_{i=1}^{n} \overline{v}_{ij}\right)$ (14)

*Step 6. Determination of utility function of the alternatives* $\otimes f\left(K_i\right)$.

The alternatives utility function is obtained by applying the expression (15)

$$f\left(K_i\right) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f\left(K_i^+\right)}{f\left(K_i^+\right)} + \frac{1 - f\left(K_i^-\right)}{f\left(K_i^-\right)}}; \tag{15}$$

where $f\left(K_i^-\right)$ presents function of utility in relation to the anti-ideal solution, while $f\left(K_i^+\right)$ presents utility function in relation to the ideal solution, and are obtained by applying the expressions (16) and (17).

$$\otimes f\left(K_i^-\right) = \frac{\otimes K_i^+}{\max\limits_{1\le i\le m}\left\{\otimes K_i^+ + \otimes K_i^-\right\}} \tag{16}$$

$$\otimes f\left(K_i^+\right) = \frac{\otimes K_i^-}{\max\limits_{1\le i\le m}\left\{\otimes K_i^+ + \otimes K_i^-\right\}} \tag{17}$$

Considering that all the values within the expression (15) are crisp, it is necessary to make conversions of the grey values from the expressions (16) and (17) to crisp values, by using the following expression (18):

$g_\lambda = (1-\lambda)\cdot \underline{g} + \lambda \cdot \overline{g}$ (18)

where $\lambda$ presents whitening coefficient and $\lambda \in [0,1]$.

*Step 7. Ranking of alternatives.*

The ranking is done by ranking of utility functions values ( $f\left(K_i\right)$ ), respectively, the greater the value, the better alternative ranking.

## 3. Application of MCDM model and results discussion

In the further text it is shown the application of the presented model (Figure 1). First, the description of defined criteria is given, then weight coefficients of the criteria are determined by Fuzzy LMAW method, and at the end the alternatives are ranked by using Grey MARCOS method.

### 3.1. Criteria description

After completed analysis of competent literature, and reviewing characteristics of a dump truck that should meet the demand for the selection of equipping engineering army units, and on the basis of the opinions from five Experts, we came to the following criteria which determine the selection, as shown in the Table 3.

**Table 3.** Criteria for a dump truck selection

| Criteria | Description of criteria |
|---|---|
| **Criteria 1 (C1)** | Dump truck price – presents money value of the truck on the market (€) (Bozanic et al., 2021). |
| **Criteria 2 (C2)** | Maintenance and repair costs – presents a dump truck maintenance and repair costs during its exploiting time. Values by this criterion are shown as percentage (%) of the truck price cost, by years of usage. |
| **Criteria 3 (C3)** | Cargo compartment volume –the bigger the volume, the higher efficiency, respectively, the truck can perform transportation of greater volume of load by time unit ($m^3$). |
| **Criteria 4 (C4)** | Warranty period – warranty period that covers all vehicle mechanical and electronic parts given in years. |
| **Criteria 5 (C5)** | Guaranteed time period for vehicle spare parts supply – presents number of years, starting from the warranty expiration date, in which spare parts for the vehicle are available. |
| **Criteria 6 (C6)** | Dump truck construction features – includes basic construction characteristics, as: engine power, quality of hydraulics, drive configuration, gearbox, unloading time, movement autonomy *etc*. The criterion is of linguistic type and it is defined by seven linguistic descriptors: Very Poor (VP) – [0.0, 0.1], Poor (P) – [0.1, 0.2], Medium Poor (MP) – [0.3, 0.4], Fair (F) – [0.4, 0.5], Medium Good (MG) – [0.5, 0.6], Good (G) – [0.6, 0.9], Very Good (VG) – [0.9, 1.0] (Badi and Pamucar, 2020). |

The criteria C1 and C2 are cost-type criteria, while the criteria C3, C4, C5 and C6 are benefit-type criteria.

### 3.2. Determination of weight coefficient of the criteria by Fuzzy LMAW method

Following all the phases and steps of the presented MCDM model, the determination of weight coefficients of the criteria is done by application of Fuzzy LMAW method and engaging five experts as follows:

First, the linguistic scale is defined (Absolutely low (AL) - (1, 1, 1), Very low (VL) - (1, 1.5, 2), Low (L) - (1.5, 2, 2.5), Medium low (ML) - (2, 2.5, 3), Equal (E) - (2.5, 3, 3.5), Medium high (MH) - (3, 3.5, 4), High (H) - (3.5, 4, 4.5), Very high (EH) - (4, 4.5, 5), Absolutely high (AH) - (4.5, 5, 5)), according to which the experts completed criteria prioritization as shown in the Table 4.

**Table 4.** Priority vectors $\tilde{P}^e = \left(\tilde{\upsilon}^e_{C_1}, \tilde{\upsilon}^e_{C_2}, ..., \tilde{\upsilon}^e_{C_n}\right)$

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| **Expert 1** | AH | H | H | E | AL | L |
| **Expert 2** | H | AH | MH | E | L | AL |
| **Expert 3** | AH | H | MH | E | AL | L |
| **Expert 4** | AH | H | E | L | AL | AL |
| **Expert 5** | AH | MH | H | E | L | AL |

Next it is defined the value of the absolute fuzzy anti-ideal point which is (0.1, 0.1, 0.1) and set fuzzy vectors ratio ( $\tilde{R}^e$ ) by the expression (1), as shown in Table 5.

**Table 5.** Fuzzy relation vectors ( $\tilde{R}^e$ )

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| **Expert 1** | (45,50,50) | (35,40,45) | (35,40,45) | (25,30,35) | (10,10,10) | (25,20,25) |
| **Expert 2** | (35,40,45) | (45,50,50) | (30,35,40) | (25,30,35) | (40,20,25) | (10,10,10) |
| **Expert 3** | (45,50,50) | (35,40,45) | (30,35,40) | (25,30,35) | (40,10,10) | (25,20,25) |
| **Expert 4** | (45,50,50) | (35,40,45) | (25,30,35) | (15,20,25) | (35,10,10) | (10,10,10) |
| **Expert 5** | (45,50,50) | (30,35,40) | (35,40,45) | (25,30,35) | (45,20,25) | (10,10,10) |

In the next step the vectors of weight coefficients $w_j^e = \left(\tilde{w}_1^e, \tilde{w}_2^e, ..., \tilde{w}_n^e\right)^T$ are determined by using the expression (2) for every expert (Table 6).

**Table 6.** Weight coefficients vectors for every expert

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| **Expert 1** | (0 ,18,0.2,0.2) | (0.17,0.18,0.19) | (0.17,0.18,0.19) | (0.16,0.17,0.18) | (0.11,0.12,0.12) | (0.16,0.15,0.16) |
| **Expert 2** | (0.17,0.19,0.19) | (0.19,0.2,0.2) | (0.17,0.18,0.18) | (0.16,0.17,0.18) | (0.18,0.15,0.16) | (0.11,0.12,0.12) |
| **Expert 3** | (0.19,0.2,0.19) | (0.17,0.19,0.18) | (0.17,0.18,0.18) | (0.16,0.17,0.17) | (0.18,0.12,0.11) | (0.16,0.15,0.15) |
| **Expert 4** | (0.2,0.21,0.2) | (0.19,0.2,0.2) | (0.17,0.18,0.19) | (0.14,0.16,0.17) | (0.19,0.12,0.12) | (0.12,0.12,0.12) |
| **Expert 5** | (0.19,0.2,0.19) | (0.17,0.18,0.18) | (0.17,0.19,0.19) | (0.16,0.17,0.18) | (0.19,0.15,0.16) | (0.11,0.12,0.11) |

Applying the Bonferroni aggregators, by the expression (3), the aggregated fuzzy weight coefficients vectors are obtained (Table 7).

**Table 7.** Aggregated fuzzy vectors of the weight coefficients of criteria

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| $w_j$ | (0 ,18,0.2,0.2) | (0.17,0.18,0.19) | (0.17,0.18,0.19) | (0.16,0.17,0.18) | (0.11,0.12,0.12) | (0.16,0.15,0.16) |

Final crisp values of the weight coefficients of criteria, derived by defuzzification of fuzzy values, are obtained by using the expression (4) and shown in the Table 8.

**Table 8.** Final crisp values of the weight coefficients of criteria

| $w_1$ | $w_2$ | $w_3$ | $w_4$ | $w_5$ | $w_6$ |
|---|---|---|---|---|---|
| 0.195 | 0.187 | 0.181 | 0.168 | 0.138 | 0.131 |

### 3.2. Selection of optimal alternatives by using Grey MARCOS method

Alternatives present possibilities for resolving the problem and achieving the projected goal. During the structuring of the problem, a set of alternatives is generated with the aim of bridging the gap between the current and the desired condition. The set of alternatives in this case presents dump trucks available on the market, from proven manufacturers, which are already widely used in construction companies or other armies of the world, and which meet the minimum requirements of military engineering units' needs. After defining the alternatives, proposed MCDM methodology is applied for the selection of the optimal one.

The first step in the application of the Gray MARCOS method is the formation of the aggregated initial decision-making matrix ( $\otimes$ ), which was obtained on the basis of expert evaluations and available data on alternatives, using the expressions (5) and (6), given in the Table 9.

**Table 9.** Aggregated initial decision-making matrix ( $\Delta$ )

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| **A1** | [94800,125000] | [0.03,0.03] | [18,18] | [5,6] | [8,8] | [18,5] |
| **A2** | [202000,279800] | [0.025,0.03] | [25,25] | [6,7] | [10,10] | [25,6] |
| **A3** | [129900,132000] | [0.02,0.03] | [20,20] | [5,5] | [8,8] | [20,5] |
| **A4** | [229000,234000] | [0.03,0.035] | [22,22] | [6,8] | [10,10] | [22,6] |
| **A5** | [205000,215000] | [0.03,0.03] | [30,30] | [5,6] | [8,10] | [30,5] |

After aggregated matrix is obtained, initial decision-making matrix is extended by defining the anti-ideal (AAI) and ideal (AI) solutions, using the expressions (8) and (9), and the extended initial decision-making matrix (X) is given in the Table 10.

**Table 10.** Extended initial decision-making matrix (X)

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| **A1** | [94800,125000] | [0.03,0.03] | [18,18] | [5,6] | [8,8] | [18,5] |
| **A2** | [202000,279800] | [0.025,0.03] | [25,25] | [6,7] | [10,10] | [25,6] |
| **A3** | [129900,132000] | [0.02,0.03] | [20,20] | [5,5] | [8,8] | [20,5] |
| **A4** | [229000,234000] | [0.03,0.035] | [22,22] | [6,8] | [10,10] | [22,6] |
| **A5** | [205000,215000] | [0.03,0.03] | [30,30] | [5,6] | [8,10] | [30,5] |
| **AAI** | [244000,300000] | [0.03,0.035] | [18,18] | [5,5] | [8,8] | [18,5] |
| **AID** | [94800,125000] | [0.02,0.03] | [30,30] | [6,8] | [10,10] | [30,6] |

With the use of the expressions (10) and (11) the elements of extended initial decision-making matrix (X) are normalized, resulting with normalized matrix $\widehat{Z}$ (Table 11).

**Table 11.** Normalized matrix ( $\widehat{Z}$ )

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| **A1** | [0.758,1] | [0.667,0.667] | [0.6,0.6] | [0.625,0.75] | [0.8,0.8] | [0.111,0.222] |
| **A2** | [0.339,0.469] | [0.667,0.8] | [0.833,0.833] | [0.75,0.875] | [1,1] | [0.556,0.667] |
| **A3** | [0.718,0.73] | [0.667,1] | [0.667,0.667] | [0.625,0.625] | [0.8,0.8] | [0.444,0.556] |
| **A4** | [0.405,0.414] | [0.571,0.667] | [0.733,0.733] | [0.75,1] | [1,1] | [0.667,1] |
| **A5** | [0.441,0.462] | [0.667,0.667] | [1,1] | [0.625,0.75] | [0.8,1] | [0.556,0.667] |
| **AAI** | [0.316,0.389] | [0.571,0.667] | [1,1] | [0.75,0.875] | [0.9,1] | [0.556,0.667] |
| **AID** | [0.316,0.389] | [0.571,0.667] | [0.6,0.6] | [0.625,0.625] | [0.8,0.8] | [0.111,0.222] |

Definition of the weighted matrix $V = \left[ \otimes v_{ij} \right]_{m \times n}$ (Table 12) is done by multiplying normalized matrix $\widehat{Z}$ with weight coefficient of the criteria obtained by the application of Fuzzy LMAW method (Table 8).

**Table 12.** Weighted matrix (V)

| | C1 | C2 | C3 | C4 | C5 | C6 |
|---|---|---|---|---|---|---|
| **A1** | [0.148,0.195] | [0.125,0.125] | [0.109,0.109] | [0.105,0.126] | [0.11,0.11] | [0.015,0.029] |
| **A2** | [0.066,0.092] | [0.125,0.15] | [0.151,0.151] | [0.126,0.147] | [0.138,0.138] | [0.073,0.087] |
| **A3** | [0.14,0.142] | [0.125,0.187] | [0.121,0.121] | [0.105,0.105] | [0.11,0.11] | [0.058,0.073] |
| **A4** | [0.079,0.081] | [0.107,0.125] | [0.133,0.133] | [0.126,0.168] | [0.138,0.138] | [0.087,0.131] |
| **A5** | [0.086,0.09] | [0.125,0.125] | [0.181,0.181] | [0.105,0.126] | [0.11,0.138] | [0.073,0.087] |
| **AAI** | [0.062,0.076] | [0.107,0.125] | [0.181,0.181] | [0.126,0.147] | [0.124,0.138] | [0.073,0.087] |
| **AID** | [0.062,0.076] | [0.107,0.125] | [0.109,0.109] | [0.105,0.105] | [0.11,0.11] | [0.015,0.029] |

The next step in this study methodology is determination of the weighed matrix sum ($S_i$, Table 13) and alternatives utility degree, by using the expressions (12) and (13), what is shown in the Table 14.

**Table 13.** The sum of weighted matrix ($S_i$)

| | $S_i$ |
|---|---|
| **A1** | [0.611,0.694] |
| **A2** | [0.678,0.764] |
| **A3** | [0.659,0.738] |
| **A4** | [0.67,0.775] |
| **A5** | [0.68,0.747] |
| **A6** | [0.672,0.754] |
| **AAI** | [0.507,0.554] |
| **AID** | [0.805,1] |

**Table 14.** Alternative’s utility degree (K+ i K-)

| | Grey $K_i$- | Grey $K_i$+ | Grey f($K_i$-) | Grey f($K_i$+) |
|---|---|---|---|---|
| **A1** | [1.104,1.368] | [0.611,0.611] | [0.299,0.299] | [0.54,0.669] |
| **A2** | [1.225,1.507] | [0.678,0.678] | [0.332,0.332] | [0.599,0.737] |
| **A3** | [1.191,1.456] | [0.659,0.659] | [0.322,0.322] | [0.582,0.712] |
| **A4** | [1.21,1.529] | [0.67,0.67] | [0.328,0.328] | [0.592,0.748] |
| **A5** | [1.228,1.474] | [0.68,0.68] | [0.332,0.332] | [0.601,0.721] |
| **A6** | [1.215,1.487] | [0.672,0.672] | [0.329,0.329] | [0.594,0.727] |

The last step of the Grey MARCOS method is determination of alternatives utility functions by using the expressions (15)-(18) and their ranking (Table 15).

**Table 15.** Utility function and alternatives ranking

| | f($K_i$) | Rank |
|---|---|---|
| **A1** | 0.462 | **6** |
| **A2** | 0.582 | **1** |
| **A3** | 0.543 | **5** |
| **A4** | 0.575 | **3** |
| **A5** | 0.577 | **2** |
| A6 | 0.569 | 4 |

Using MCDM model Fuzzy LMAW-Grey MARCOS leads us to optimal alternative $A_2$ out of the set of the proposed ones, respectively, the first-ranked one. Regarding utility function values of the alternatives $A_5$ and $A_4$, it can be concluded that listed alternatives also can be included as a possible solution, while the alternatives A1 and $A_3$ shall not be taken into account in this case within this step of the proposed methodology

## 4. Sensitivity analysis

Stability of the results of the proposed methodology must be checked in one of the following ways (Durmić et al., 2020; Biswas, 2020; Jovčić et al., 2020; Gorcun et al., 2021; Badi & Abdulshahed, 2021; Arvanitis et al., 2021; Biswas et al., 2022; Tešić et al., 2022; Stević, et al., 2022; Đukić et al, 2022; Chakraborty et al., 2022). Results consistency checking is done by analyzing sensitivity with Grey MARCOS method to the weight coefficients change by using 26 different scenarios as shown in the Figure 3.

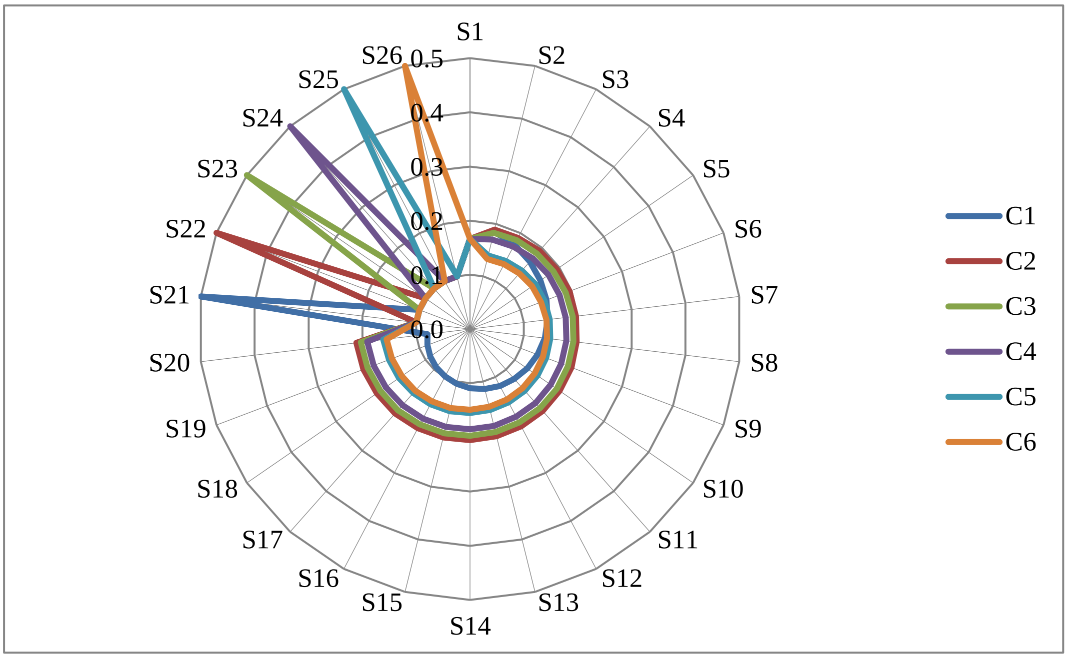


**Figure 3.** Scenarios of weight coefficient of the criteria change

In the scenario S1 all weight coefficients for all criteria have the same value. The scenarios S2-S20 present different weight coefficients for every criterion, obtained by subtracting particular percentage of the value from the most influential criteria C1, and adding it equally to other criteria. In the scenarios S21-S26, every criterion was prioritized, while the values of the other weight coefficients criteria were the same.

After applying the mentioned scenarios, respectively, the weight coefficients of the criteria in the Grey MARCOS method, the following ranks of alternatives are reached (Figure 4).

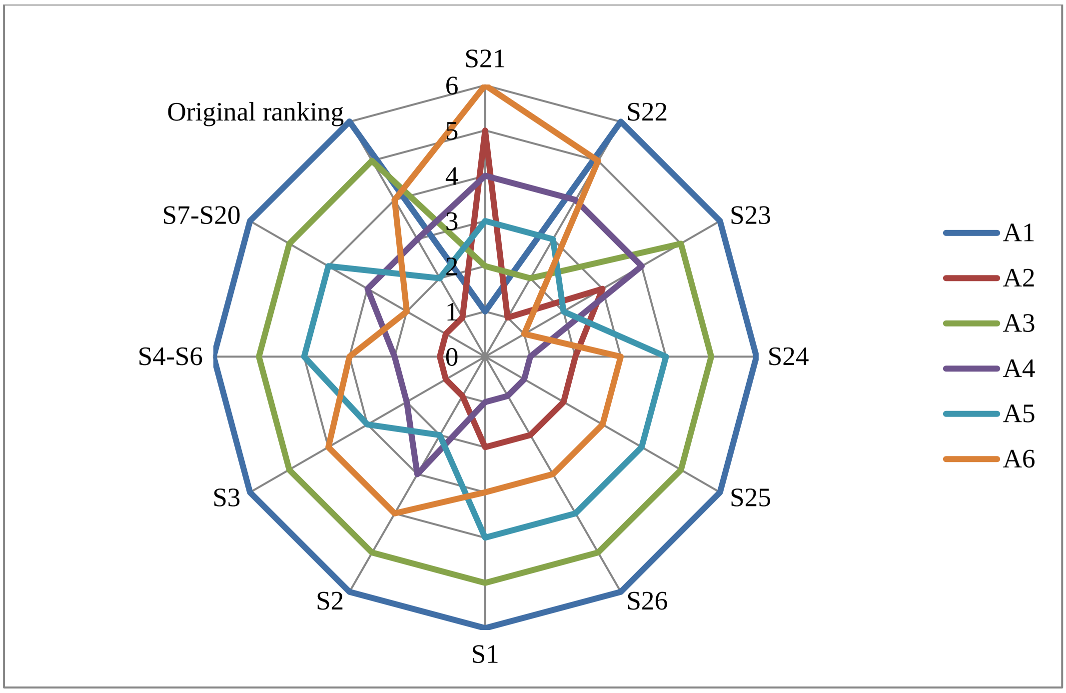


**Figure 4.** Ranks of alternatives after defined scenarios application

It can be seen from the previous figure that the alternatives ranking is identical to the first one only in the scenario S2, what is expected considering that the weight coefficient values in this scenario were approximately equal to the weight coefficient values derived from the Fuzzy LMAW method. In all other scenarios, the ranks of alternatives are different in respect to the first one, which indicates directly that the Grey MARCOS method is sensitive to the change of weight coefficients of the criteria, respectively, a special attention should be paid to determination of the same by engaging experts in the scope of the problems research.

Also, for the purpose of consistency of the method checking, it is conducted the comparison of the alternative's rankings obtained by Grey MARCOS method with the rankings obtained by ARAS, MARCOS, MABAC, MAIRCA, WASPAS, WPM and CoCoSo (Figure 5).

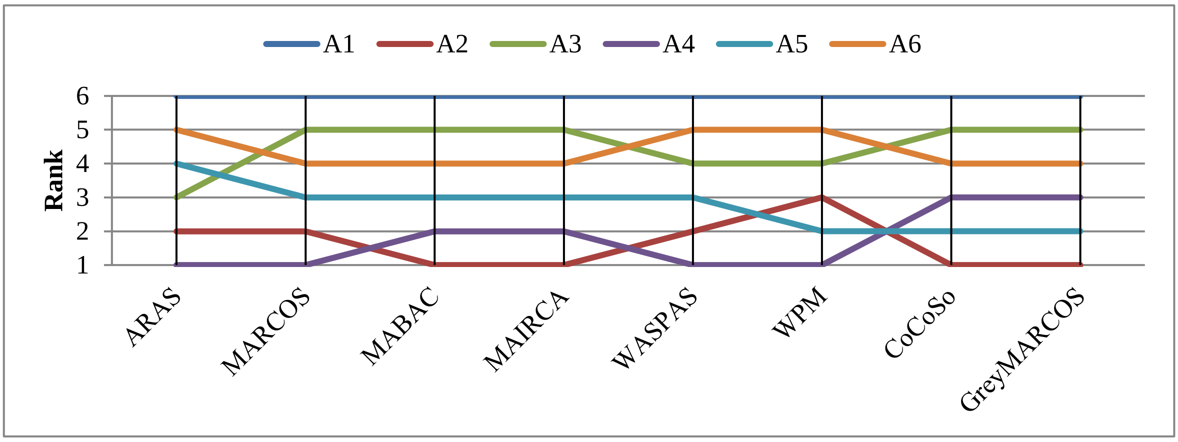


**Figure 5.** Comparison of results obtained by Grey MARCOS vs. by other MCDM methods

It is clearly visible that the results of the Grey MARCOS method are closest to the MABAC, MAIRCA and CoCoSo methods results. It can be concluded that the alternatives $A_1$, $A_3$ and $A_6$ in neither case can be selected as the optimal ones from the set of the proposed ones, and the alternatives $A_2$, $A_5$ and $A_4$ can be taken into consideration as possible solution, which is also proven by the results of the methodology Fuzzy LMAW – Grey MARCOS.

## 5. Conclusion

Selecting the assets for use in every army of the world is essential for its capabilities. In order to make a quality selection, the problem must be considered through several criteria which determine such selection. To make the best possible selection of a dump truck for military engineering unit, in this study is presented the MCDM model Fuzzy LMAW – Grey MARCOS.

The mentioned model is based on experts' evaluations, and positive characteristics of Fuzzy Grey theory for uncertainty handling. Fuzzy LMAW method was used for determination of weight coefficients of the criteria, primarily based on a dump truck construction features and costs, both purchasing and maintenance and repair costs as well. After experts had evaluated the criteria, as part of the method, the experts' opinions were aggregated by using Bonferroni aggregator. When weight coefficients for the criteria were obtained, ranking of alternatives (dump trucks) was done by MARCOS method modified with interval grey numbers (Grey MARCOS). At the end, sensitivity analysis of the outcome results of the proposed MCDM methodology was done and comparative analysis with the results obtained with other MCDM methods. It can be concluded, on the basis of the performed analysis that the model is sensitive to weight coefficients of criteria change, which must be carefully taken into account during its definition, and the output results are similar to the results of the other methods, which indicates directly the consistency of the methodology.

Further improvements of the proposed modal are possible, through more detailed criteria definitions, respectively, the elaboration of the proposed models, which is also a basic limitation of this study, and by applying more MDCM methods. Presented methodology also helps decision makers during the selection, considering higher number of criteria involved in decision making.

Further studies will be focused on the selection of various means for the needs of engineering and other military units. In the future it is also planned the application of other theories that treat uncertainty well and application of other methods for determination of weight coefficients of the criteria and selection of optimal alternative out of set of proposed ones.

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