



Paper Type: Research Paper



The Utilization of MARCOS Method for Different Engineering Applications: a Comparative Study

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Citation:



El-Araby, A. (2023). The utilization of MARCOS method for different engineering applications: a comparative study. *International journal of research in industrial engineering*, 12(2), 155-164.

Received: 20/01/2023

Reviewed: 22/02/2023

Revised: 15/04/2023

Accepted: 14/05/2023

Abstract

Multiple Criteria Decision Making (MCDM) methods are used widely by researchers to make decisions in the presence of numerous criteria. It is essential to make the right decision for the most of engineering applications which makes the decision-making process more complex and requires further analysis. A major issue of MCDM methods that they suffer from the Rank Reversal Phenomenon (RRP). Another drawback to MCDM methods that they produce different ranking when evaluating the same problem. Thus, researchers tend to develop new methods to overcome these problems. This paper explores the applicability of a new MCDM approach namely Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) by solving four different engineering problems. The results of MARCOS method are analyzed throughout a comparison with the results of other MCDM methods. The rank reversal test is explored for each problem to check the robustness of the method. The two phases of analysis indicate that the method is robust and applicable for different types of engineering applications.

Keywords: Multiple criteria decision making, Rank reversal phenomenon, Measurement alternatives and ranking according to compromise solution method, Comparative study.

1 | Introduction



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Multiple Criteria Decision Making (MCDM) is the most well-known branch of decision making, generally Operations Research (OR), which refers to making decisions under multiple, usually complex, criteria [1]. The main target of OR is to improve the decision-making process by providing mathematical tools of analysis, modelling and optimization that help in making better decisions. The MCDM science deals with mathematical theories and methods during the implementation of the decision-making process where multiple criteria are considered through the decision process. The MCDM science resulted from an interdisciplinary background, combining several branches like engineering, economics, computer science and for sure the most used branch in multiple criteria analysis, mathematics. MCDM has changed alongside OR since the early seventies becoming a very important approach in the decision-making processes.



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<https://doi.org/10.22105/riej.2023.395104.1379>

Through its evolution process, MCDM has changed from “a conceptual-theoretical enterprise of interests practiced by a limited number of disciplines and individuals to a universally embraced philosophy” [2]. Furthermore, MCDM has changed its pattern to give voice to the Decision Maker (DM), as searching for the optimal solution is not required anymore but a solution that satisfies the DM [3].

No matter where the decision-making problems appear, they usually fall under four important categories including selection, ranking, sorting and elimination problems. Since the main use of MCDM methods is to select the best from a set of alternatives or options by considering multiple criteria, the performance of alternatives is measured relative to the set of criteria chosen by the DMs to construct the decision model followed by applying a MCDM approach. The measured data either quantitative or qualitative may have some errors due to the dynamic environment. As a result, MCDM methods produces different rankings when moving from approach to another one, especially when dealing with linguistic terms. The translation of linguistic terms into numerical data is also a complex process that contains uncertainty. Voogd [4] claimed that each MCDM method produces different ranking from the other ones at least 40% of time. Another shortage to MCDM methods is the Rank Reversal Phenomenon (RRP). The RRP refers to a change in the ranking of the alternatives that are previously ranked due to the addition or removal of an alternative from the group already ranked. Most of MCDM methods are supposed to RRP. Thus, several modifications in the mathematical models are done by researchers to overcome the RRP [5]. The occurrence of RRP in a decision-making problem when adding or removing an irrelevant alternative, is clearly conflicts the principle of independence between the alternatives.

The shortages in MCDM methods were an incentive for the researchers to evolve new methods to overcome the drawbacks subjected to the classical models. The most common classical methods in the MCDM science are Analytical Hierarchical Process (AHP) [6], the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) [7], Grey Relational Analysis (GRA) [8], The Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) family [9], the Elimination And Choice Translating Reality (ELECTRE) family [10] and the Weighted Sum Model (WSM) [11]. The newly developed methods may include Combined Compromise Solution (CoCoSo) method [12], Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval (RAFSI) method [13], multi-normalization multi-distance assessment (TRUST) method [14], Logarithm Methodology of Additive Weights (LMAW) method [15] and Measurement Alternatives and Ranking according to Compromise Solution (MARCOS) method [16]. The aim of developing new methods is to improve the decision-making process by overcome the limitations of the classical approaches. However, the new methods need to be investigated for their applicability of providing efficient decision-making process.

There are several studies that investigated the applicability of the MCDM methods through different applications. The Weighted Aggregated Sum Product Assessment (WASPAS) method which is literally a combination of two methods namely WSM and Weighted Product Method (WPM), had been proved to be an efficient MCDM method by solving different engineering problems [17]. The Multi-Objective Optimization method by Ratio Analysis (MOORA) method was used to solve different problems in manufacturing environment [18]. The MOORA had been proven to be simple and robust MCDM method through the comparative study. The reliability of CoCoSo method was investigated through a comparison with different MCDM methods for solving facility location problem [19]. The newly developed methods were not used widely in the engineering applications. Moreover, the MARCOS method was frequently used to solve the supplier selection problem. Stević et al. [16] evaluated a supplier selection problem in healthcare industries and compared their results with six MCDM methods which totally agreed with MARCOS method except for TOPSIS method. The supplier selection problem in a steel industry was addressed by D-MARCOS approach [20] and grey-MARCOS approach [21]. Both hybrid approaches proved the reliability of MARCOS method to handle the uncertainty in information and deal with qualitative attributes. Furthermore, MARCOS method was used for evaluating human resources problem [22], road traffic risk analysis problem [23] and location selection for healthcare waste

[24]. Since the MARCOS method needs a method for assigning the weights for attributes, the Step-wise Weight Assessment Ratio Analysis (SWARA) method was used alongside MARCOS method for inventory classification problem [25]. The integrated AHP-MARCOS was used for the evaluation of renewable energy sources in Turkey [26]. The authors compared their results with other MCDM methods which stated that the best and worst selections were the same for the other methods. Accordingly, the MARCOS method is used in this research to solve different engineering problems due to its simple computational steps compared to the other newly developed methods. The MARCOS method has different integrations with other approaches such as fuzzy sets, grey number and rough sets theory, whereas the raw version of MARCOS method is used in this research to prove its robustness and reliability.

The remainder of this research is organized as follows: Section 2 provides the mathematical procedures of MARCOS method. Section 3 illustrates the numerical examples concerning the selection of industrial robot, gear material, layout design and side-loading forklift. The four examples are solved using MARCOS method and the RRP is explored for each example. Section 4 provides the drawn conclusions from the current research and provides suggestions for future research.

2 | MARCOS Method

The MARCOS method depends on the relation between the alternative's score and the reference values (ideal and anti-ideal solution). Based on this relation, the utility function is calculated and the compromise solution is obtained. The following are the steps of the MARCOS method:

Step 1. Construct the decision-making matrix [D] which indicates the performance of alternatives relatives to the set of chosen criteria.

$$D = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1j} & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2j} & x_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & \dots & x_{ij} & x_{in} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mj} & x_{mn} \end{bmatrix}_{m \times n} .$$

The rows stand for alternatives and the columns stand for criteria, $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$.

Step 2. Determine the ideal solution for each criterion (x_{ai}) in the decision-making matrix as follows:

$$D = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1j} & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2j} & x_{2n} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{i1} & x_{i2} & \dots & x_{ij} & x_{in} \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_{m1} & x_{m2} & \dots & x_{mj} & x_{mn} \\ x_{ai1} & x_{ai2} & \dots & x_{aij} & x_{ain} \end{bmatrix}_{m \times n} ,$$

where $x_{ai} = \{ \max_j x_{ij} ; j \in \mathcal{B} \text{ or } \min_j x_{ij} ; j \in \mathcal{C} \}$.

Step 3. Normalization of the decision-making matrix through Eqs. (1) and (2).

$$r_{ij} = \frac{x_{ij}}{x_{ai}} \tag{1}$$

$$r_{ij} = \frac{x_{ai}}{x_{ij}} \tag{2}$$

Step 4. Determination of the weighted normalized matrix using Eq. (3).

$$v_{ij} = w_j \times r_{ij} . \tag{3}$$

Step 5. Calculate the utility degrees for each alternative (K_i) using Eqs. (4) and (5).

$$K_i^+ = \frac{S_i}{S_{ai}} \tag{4}$$

$$K_i^- = \frac{S_i}{S_{aai}}, \tag{5}$$

where S_i is the sum of row elements in the weighted normalized matrix ($S_i = \sum_{j=1}^n v_{ij}$), S_{ai} is the sum of the ideal solutions in the weighted normalized matrix and S_{aai} is the sum of the anti-ideal solutions in the weighted normalized matrix.

Step 6. Calculation of the utility function in relation to the ideal solution $f(K_i^+)$ and the utility function in relation to the anti-ideal solution $f(K_i^-)$.

$$f(K_i^+) = \frac{K_i^-}{K_i^+ + K_i^-} \tag{6}$$

$$f(K_i^-) = \frac{K_i^+}{K_i^+ + K_i^-} \tag{7}$$

Step 7. Determination of the utility function of the alternatives using:

$$f(K_i) = \frac{K_i^+ + K_i^-}{1 + \frac{1 - f(K_i^+)}{f(K_i^+)} + \frac{1 - f(K_i^-)}{f(K_i^-)}} \tag{8}$$

Step 8. Ranking of the alternatives based on the utility function values. The higher the utility function the more preferred the alternative.

3 | Numerical Examples and Discussion

In this section, the applicability of MARCOS method to solve different types of engineering problems will be discussed through four different examples. The utility function and the related ranking for each alternative will be illustrated for each example. The ranking provided from MARCOS method will be compared to the ranking developed by different methods through the past researches. The rank reversal test will be discussed for each example to review the robustness of MARCOS method. The RRP will be investigated in MARCOS method by the removal of irrelevant alternatives. The lowest ranked alternative is removed at first and the ranking is observed. When the lowest ranked alternative is removed, the ranking either change if the method suffers from RRP or remains in the same order. The series continues until there is only one alternative, the ranked first alternatives. The following are the cited numerical examples in time order. The calculations for each example and the rank reversal tests are done using MATLAB software.

3.1 | Industrial Robot Selection

In this example, the selection of the best industrial robot for pick-n-place operation is discussed. Bhangale et al. [27] aimed to select the best industrial robot among seven candidate robots while five criteria are considered. The criteria are load capacity (C_1), repeatability (C_2), maximum tip speed (C_3), memory capacity (C_4) and manipulator reach (C_5). Among the five criteria, only repeatability (C_2) is non-beneficial attribute. The numerical data for this example are shown in *Table 1*. Bhangale et al. [27] employed TOPSIS method to rank the industrial robots while calculated the criteria weights from relative importance matrix. The criteria weights were found to be completely inconsistent as Rao [28] recalculated the weights of criteria as $w_1 = 0.036$, $w_2 = 0.192$, $w_3 = 0.326$, $w_4 = 0.326$ and $w_5 = 0.120$. The same example was solved by two methods namely, Graph Theory and Matrix Approach (GTMA) and AHP method [28]. The ranking from MARCOS method and the reference methods are shown in *Table 2* where $Rank_G$ and $Rank_A$ refers to the ranking from GTMA and AHP respectively. The rank reversal test for this example is shown in *Fig. 1* which indicates that the method does not suffer from RRP.

Table 1. The data set for industrial robot selection [27].

Alter.	Criteria				
	C ₁	C ₂	C ₃	C ₄	C ₅
A ₁	60	0.4	2540	500	990
A ₂	6.35	0.15	1016	3000	1041
A ₃	6.8	0.1	1727.2	1500	1676
A ₄	10	0.2	1000	2000	965
A ₅	2.5	0.1	560	500	915
A ₆	4.5	0.08	1016	350	508
A ₇	3	0.1	1778	1000	920

Table 2. The ranking of MARCOS method and ref. methods for industrial robots.

Alter.	MARCOS Method		Ref. Methods	
	f(K _i)	Rank	Rank _G	Rank _A
A ₁	0.5107	4	2	4
A ₂	0.6190	2	3	2
A ₃	0.6435	1	1	1
A ₄	0.4835	5	5	5
A ₅	0.3370	7	7	7
A ₆	0.3882	6	6	6
A ₇	0.5423	3	4	3
r _s	-	-	0.89	1.00

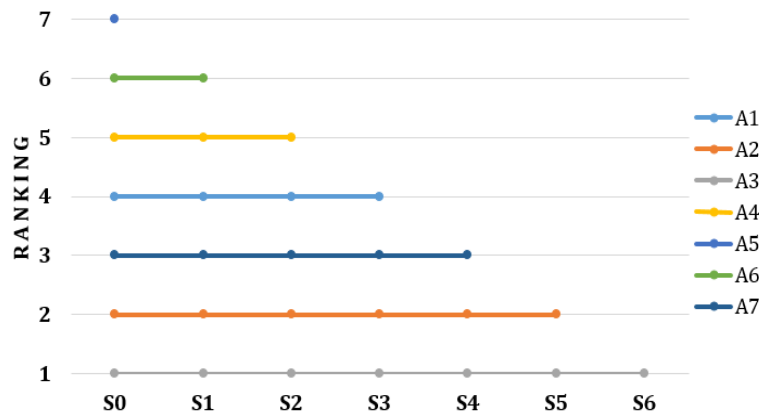


Fig. 1. The rank reversal test for robot selection problem.

3.2 | Material Selection Problem

The applicability of MARCOS method for material selection problem can be investigated by solving the problem of Milani et al. [29] who used TOPSIS method for solving a problem addressing the selection of the best gear material for a power transmission system. They picked up nine candidate materials to rank them relative to set of five criteria. The criteria are tooth surface hardness (C₁), tooth core hardness (C₂), surface fatigue (C₃), bending fatigue limit (C₄) and ultimate tensile strength (C₅). Among the five criteria, only tooth core hardness (C₂) is non-beneficial attribute. The authors used entropy method to assign the weights of criteria which is calculated as $w_1 = 0.172$, $w_2 = 0.005$, $w_3 = 0.426$, $w_4 = 0.292$ and $w_5 = 0.102$. The same problem was later solved using preferential ranking methods and the ranking was compared to both VIKOR and PROMETHEE methods [30]. The results of TOPSIS, VIKOR and PROMETHEE will be adopted in the comparison scale for MARCOS method. The data set for this example are shown in Table 3. The ranking provided from MARCOS method and reference methods are shown in Table 4 where Rank_T, Rank_V and Rank_P refers to the ranking from TOPSIS, VIKOR and PROMETHEE respectively. The removal of irrelevant alternatives in the ranking of MARCOS method is shown in Fig. 2 which does not affect the ranking. Hence, the method is stable regarding RRP.

Table 3. The data set for gear material selection [29].

Alter.	Criteria				
	C ₁	C ₂	C ₃	C ₄	C ₅
A ₁	200	200	330	100	380
A ₂	220	220	460	360	880
A ₃	240	240	550	340	845
A ₄	270	270	630	435	590
A ₅	270	270	670	540	1190
A ₆	585	240	1160	680	1580
A ₇	700	315	1500	920	2300
A ₈	750	315	1250	760	1250
A ₉	185	185	500	430	635

Table 4. The ranking of MARCOS method and ref. methods for gear materials.

Alter.	MARCOS Method f(K _i)	Rank	Ref. Methods		
			Rank _T	Rank _V	Rank _P
A ₁	0.1878	9	9	9	9
A ₂	0.3298	8	8	8	8
A ₃	0.3511	6	7	6	6
A ₄	0.3979	5	5	5	5
A ₅	0.4673	4	4	4	4
A ₆	0.7337	3	3	3	3
A ₇	0.9579	1	1	1	1
A ₈	0.8051	2	2	2	2
A ₉	0.3448	7	6	7	7
r _s	-	-	0.98	1.00	1.00

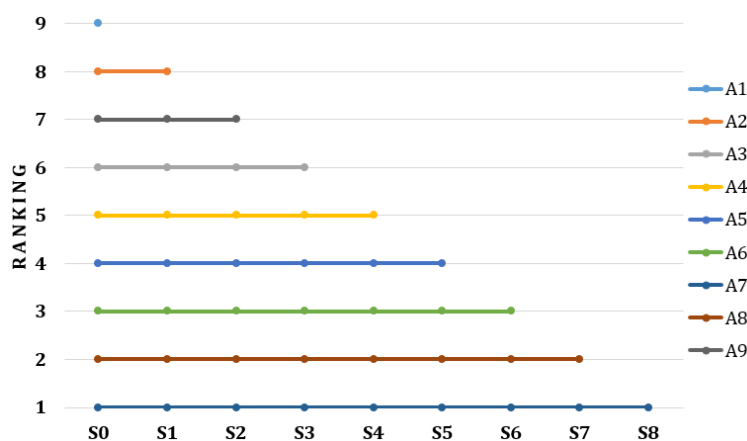


Fig. 2. The rank reversal test for material selection problem.

3.3 | Facility Layout Design Selection

The case study concerning the selection of the best facility layout design is discussed in this section. Yang et al. [31] tested the efficiency of hybrid rough set-AHP and TOPSIS method by solving the problem of selecting the best layout for a facility. They considered ten different layouts in the presence of five criteria. The criteria are space requirement (C₁), investment (C₂), transport performance (C₃), distance request (C₄) and energy saving (C₅). Among the five criteria, distance request (C₄) and energy saving (C₅) are beneficial attributes. The criteria weights are calculated using rough set-AHP method as $w_1 = 0.224$, $w_2 = 0.178$, $w_3 = 0.299$, $w_4 = 0.075$ and $w_5 = 0.224$. The data set for the layout selection problem is illustrated in Table 5. The PROMETHEE and AHP method were applied to the same problem as a comparison scale for TOPSIS method [31]. Hence, the three methods are compared with the ranking from MARCOS method as showed in Table 6 where Rank_T, Rank_A and Rank_P refers to the ranking from TOPSIS, AHP and PROMETHEE respectively. The ranking reversibility in MARCOS

method is checked as shown in Fig. 3. The method does not suffer from any rank reversals which approves the stability of MARCOS method.

Table 5. The data set for facility layout design selection problem [31].

Alter.	Criteria				
	C ₁	C ₂	C ₃	C ₄	C ₅
A ₁	1012	210	259	3872	8.412
A ₂	972	150	176	3530	8.358
A ₃	972	270	406	3322	8.887
A ₄	1217	190	208	3892	8.471
A ₅	1069	195	241	3777	8.521
A ₆	1069	200	234	3836	8.554
A ₇	1090	220	278	3666	8.578
A ₈	1139	185	199	3738	8.496
A ₉	1026	230	293	3513	8.576
A ₁₀	1071	165	189	3630	8.453

Table 6. The ranking of MARCOS method and ref. methods for facility layouts.

Alter.	MARCOS Method f(K _i)	Ref. Methods			
		Rank	Rank _T	Rank _A	Rank _P
A ₁	0.6518	7	7	7	6
A ₂	0.7674	1	1	1	1
A ₃	0.5801	10	10	9	10
A ₄	0.6744	4	4	5	7
A ₅	0.6631	6	6	4	5
A ₆	0.6671	5	5	6	4
A ₇	0.6245	8	8	10	8
A ₈	0.6941	3	3	3	3
A ₉	0.6202	9	9	8	9
A ₁₀	0.7258	2	2	2	2
r _s	-	-	1.00	0.93	0.93

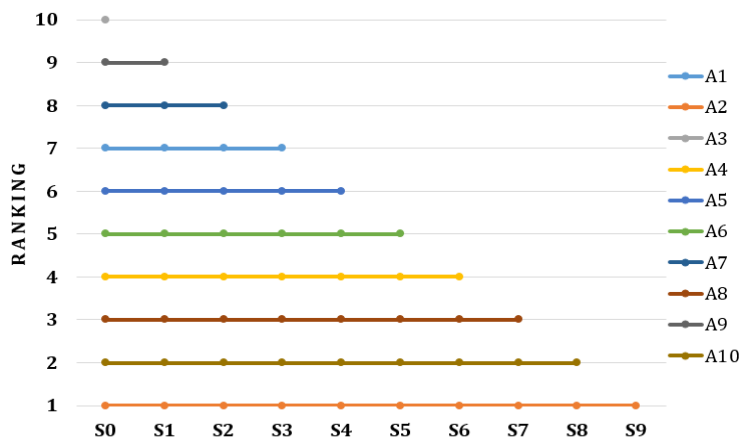


Fig. 3. The rank reversal test for material selection problem.

3.4 | Forklift Selection Problem

The selection of a side-loading forklift is discussed within this section as Fazlollahtabar et al. [32] evaluated ten forklifts to select the best forklift between them. They considered seven criteria to measure the performance of the alternative. The criteria are purchasing price (C₁), age of forklift (C₂), utilization time (C₃), maximum load capacity (C₄), maximum lift height (C₅), environmental factor (C₆) and supply of spare parts (C₇). Among the seven criteria, purchase price (C₁), age of forklift (C₂) and utilization time (C₃) are non-beneficial attributes as the lower is more preferred. The authors calculated the criteria weights using full consistency method (FUCOM) which provided the weights as $w_1 = 0.09$, $w_2 = 0.129$, $w_3 = 0.409$, $w_4 = 0.133$, $w_5 = 0.112$, $w_6 = 0.057$ and $w_7 = 0.07$. The data set for the forklift selection problem is shown in

Table 7. The WASPAS method was implemented to solve the problem and the results from WASPAS were compared to two common approaches namely, SAW and ARAS. Accordingly, the ranking from MARCOS method is compared with the ranking from the previously mentioned three MCDM methods as shown in Table 8 where $Rank_W$, $Rank_S$ and $Rank_{AR}$ refers to the ranking from WASPAS, SAW and ARAS respectively. The rank reversal test is checked for this example as shown in Fig. 4 which shows the stability of MARCOS method as the removal of irrelevant alternatives does not affect the ranking.

Table 7. The data set for forklift selection problem [32].

Alter.	Criteria						
	C ₁	C ₂	C ₃	C ₄	C ₅	C ₆	C ₇
A ₁	7.95	10	5012	4000	5400	5	7.67
A ₂	12.9	10	7140	3000	3500	7	7.67
A ₃	17.8	9	6500	5000	4500	7	5
A ₄	19.3	19	4312	3000	6000	3	3.67
A ₅	10.87	18	12000	3000	4000	5	3
A ₆	30.4	7	4800	4000	4000	7.67	9
A ₇	8.093	25	12000	4000	5900	3	5
A ₈	29.8	11	3720	3000	5100	9	9
A ₉	13.75	17	15350	4500	4800	3	5
A ₁₀	18.297	13	6122	3000	4000	5	7

Table 8. The ranking of MARCOS method and ref. methods for forklifts.

Alter.	MARCOS Method f(K _j)	Ref. Methods			
		Rank	Rank _W	Rank _S	Rank _{AR}
A ₁	0.7184	2	2	2	2
A ₂	0.5583	6	6	6	6
A ₃	0.6196	5	4	5	5
A ₄	0.6215	4	5	4	4
A ₅	0.4153	10	10	10	10
A ₆	0.7063	3	3	3	3
A ₇	0.4828	8	8	8	8
A ₈	0.7503	1	1	1	1
A ₉	0.4329	9	9	9	9
A ₁₀	0.5488	7	7	7	7
r _s	-	-	0.98	1.00	1.00

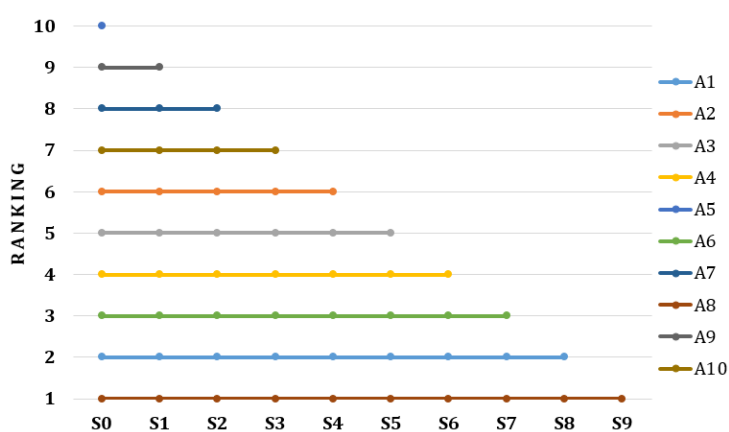


Fig. 4. The rank reversal test for forklift selection problem.

4 | Conclusions

The selection of a suitable approach to solve a decision-making problem is a complex process which consumes a lot of time from the DMs and needs to be analyzed carefully. In this study, the raw version

of MARCOS method is used to solve four engineering problems. In each of those four problems, the number of alternatives, the number of criteria and the weighting method and are not the same. Furthermore, the MCDM methods that were implemented by past researchers to solve each problem are not of the same concept of evaluation which expanded the comparison scale for MARCOS method. The results are in favor of MARCOS method as it provided almost perfect correlation coefficients with the other MCDM methods. The rank reversal test for each problem proved that MARCOS method provides stable and consistent ranking regardless the number of alternatives being evaluated.

The MARCOS method has simple computations procedures which can be implemented easily by the DMs to any multiple criteria decision-making problem. The only limitation to MARCOS method is that it cannot handle the qualitative criteria, moreover, this limitation can be easily overcome using the fuzzy sets or grey numbers. Among the newly developed methods, the MARCOS method is the simplest and the most stable method. Thus, it is recommended to use MARCOS method for critical applications such as military, aerospace and healthcare wastes.

In this research, the applicability of MARCOS method is explored by solving four different problems that considers only quantitative data. The recommendations are to explore the applicability of the MARCOS method to deal with qualitative terms through different examples and comparisons with other MCDM methods to check the robustness of the MARCOS method. The fuzzy sets fit this type of problems as a natural extension of every MCDM method. This will approve the method is able to handle any type of multiple criteria decision-making problem under different considerations.

References

- [1] Triantaphyllou, E., Shu, B., Sanchez, S. N., & Ray, T. (1998). Multi-criteria decision making: an operations research approach. *Encyclopedia of electrical and electronics engineering*, 15(1998), 175–186.
- [2] Lootsma, F. A. (1990). The French and the American school in multi-criteria decision analysis. *RAIRO-operations research*, 24(3), 263–285.
- [3] Zavadskas, E. K., & Turskis, Z. (2011). Multiple criteria decision making (MCDM) methods in economics: an overview. *Technological and economic development of economy*, 17(2), 397–427.
- [4] Voogd, H. (1982). Multicriteria evaluation with mixed qualitative and quantitative data. *Environment and planning b: planning and design*, 9(2), 221–236.
- [5] Aires, R. F. D. F., & Ferreira, L. (2018). The rank reversal problem in multi-criteria decision making: a literature review. *Pesquisa operacional*, 38, 331–362.
- [6] Saaty, T. L. (1988). What is the analytic hierarchy process? In *Mathematical models for decision support* (pp. 109–121). Springer.
- [7] Hwang, C. L., & Yoon, K. (1981). Methods for multiple attribute decision making. In *Multiple attribute decision making* (pp. 58–191). Springer.
- [8] Kuo, Y., Yang, T., & Huang, G. W. (2008). The use of grey relational analysis in solving multiple attribute decision-making problems. *Computers & industrial engineering*, 55(1), 80–93.
- [9] Brans, J. P., & De Smet, Y. (2016). PROMETHEE methods. In *Multiple criteria decision analysis* (pp. 187–219). Springer.
- [10] Tzeng, G. H., & Huang, J. J. (2011). *Multiple attribute decision making: methods and applications*. CRC Press.
- [11] Fishburn, P. C. (1967). Additive utilities with incomplete product sets: Application to priorities and assignments. *Operations research*, 15(3), 537–542.
- [12] Yazdani, M., Zarate, P., Zavadskas, E. K., & Turskis, Z. (2018). A combined compromise solution (CoCoSo) method for multi-criteria decision-making problems. *Management decision*, 57(9), 2501–2519.
- [13] Žižović, M., Pamučar, D., Albijanić, M., Chatterjee, P., & Pribičević, I. (2020). Eliminating rank reversal problem using a new multi-attribute model—The RAFSI method. *Mathematics*, 8(6), 1015. <https://doi.org/10.3390/math8061015>
- [14] Torkayesh, A. E., & Deveci, M. (2021). A multi-normalization multi-distance assessment (TRUST) approach for locating a battery swapping station for electric scooters. *Sustainable cities and society*, 74, 103243. <https://doi.org/10.1016/j.scs.2021.103243>

- [15] Pamucar, D., Žižović, M., Biswas, S., & Božanić, D. (2021). A new logarithm methodology of additive weights (LMAW) for multi-criteria decision-making: Application in logistics. *Facta universitatis, series: mechanical engineering*, 2021. <https://scidar.kg.ac.rs/handle/123456789/14033>
- [16] Stević, Ž., Pamučar, D., Puška, A., & Chatterjee, P. (2020). Sustainable supplier selection in healthcare industries using a new MCDM method: Measurement of alternatives and ranking according to COmpromise solution (MARCOS). *Computers and industrial engineering*, 140, 106231. DOI:10.1016/j.cie.2019.106231
- [17] Chakraborty, S., Zavadskas, E. K., & Antucheviciene, J. (2015). Applications of WASPAS method as a multi-criteria decision-making tool. *Economic computation and economic cybernetics studies and research*, 49(1), 5–22.
- [18] Chakraborty, S. (2011). Applications of the MOORA method for decision making in manufacturing environment. *The international journal of advanced manufacturing technology*, 54(9), 1155–1166.
- [19] El-Araby, A., Sabry, I., & El-Assal, A. (2022). A comparative study of using mcdm methods integrated with entropy weight method for evaluating facility location problem. *Operational research in engineering sciences: theory and applications*, 5(1), 121–138.
- [20] Chakraborty, S., Chattopadhyay, R., & Chakraborty, S. (2020). An integrated D-MARCOS method for supplier selection in an iron and steel industry. *Decision making: applications in management and engineering*, 3(2), 49–69.
- [21] Badi, I., & Pamucar, D. (2020). Supplier selection for steelmaking company by using combined Grey-MARCOS methods. *Decision making: applications in management and engineering*, 3(2), 37–48.
- [22] Stević, Ž., & Brković, N. (2020). A novel integrated FUCOM-MARCOS model for evaluation of human resources in a transport company. *Logistics*, 4(1), 4. <https://doi.org/10.3390/logistics4010004>
- [23] Stanković, M., Stević, Ž., Das, D. K., Subotić, M., & Pamučar, D. (2020). A new fuzzy MARCOS method for road traffic risk analysis. *Mathematics*, 8(3), 457. <https://doi.org/10.3390/math8030457>
- [24] Torkayesh, A. E., Zolfani, S. H., Kahvand, M., & Khazaelpour, P. (2021). Landfill location selection for healthcare waste of urban areas using hybrid BWM-grey MARCOS model based on GIS. *Sustainable cities and society*, 67, 102712. <https://doi.org/10.1016/j.scs.2021.102712>
- [25] Miškić, S., Stević, Ž., & Tanackov, I. (2021). A novel integrated SWARA-MARCOS model for inventory classification. *International journal of industrial engineering & production research*, 32(4), 1–17.
- [26] Karaaslan, A., Adar, T., & Delice, E. K. (2022). Regional evaluation of renewable energy sources in Turkey by new integrated AHP-MARCOS methodology: a real application. *International journal of sustainable energy*, 41(2), 103–125.
- [27] Bhangale, P. P., Agrawal, V. P., & Saha, S. K. (2004). Attribute based specification, comparison and selection of a robot. *Mechanism and machine theory*, 39(12), 1345–1366.
- [28] Rao, R. V. (2007). *Decision making in the manufacturing environment: using graph theory and fuzzy multiple attribute decision making methods* (Vol. 2). Springer.
- [29] Milani, A. S., Shanian, A., Madoliat, R., & Nemes, J. A. (2005). The effect of normalization norms in multiple attribute decision making models: a case study in gear material selection. *Structural and multidisciplinary optimization*, 29(4), 312–318.
- [30] Chatterjee, P., & Chakraborty, S. (2012). Material selection using preferential ranking methods. *Materials & design*, 35, 384–393.
- [31] Yang, L., Deuse, J., & Jiang, P. (2013). Multiple-attribute decision-making approach for an energy-efficient facility layout design. *The international journal of advanced manufacturing technology*, 66(5), 795–807.
- [32] Fazlollahabbar, H., Smailbašić, A., & Stević, Ž. (2019). FUCOM method in group decision-making: Selection of forklift in a warehouse. *Decision making: applications in management and engineering*, 2(1), 49–65.