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A NEW OBJECTIVE METHOD FOR DETERMINING CRITERIA WEIGHTS IN MCDM MODELS – LOGSTA

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Abstract

Determining criteria weights is the crucial part of the MCDM process as the weights significantly affect the ranking results of alternatives. Therefore, various techniques have been created to determine the weights of criteria, which are grouped into subjective, objective, and hybrid techniques. In this study, a new method based on LOGarithmic normalization and STAndard deviation (LOGSTA) is developed to determine objective criteria weights. The method has been described through two examples, one with square matrix (six alternatives and six criteria) and the second with seven alternatives and five criteria. The outcomes of the LOGSTA technique are compared with the Entropy, CRITIC, MEREC techniques to present the validity of results. LOGSTA shows various ranks although in some cases, it is fully correlated, which has been provided with *SCC* and *WS* correlation coefficients. The comparative analysis shows that the LOGSTA is efficient to determine objective weights of criteria. This method allows consideration of both types of criteria, a separate normalization process for benefit and cost criteria, and a different normalization procedure compared to other methods.

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Key Words: LOGSTA, MCDM, Criteria Weights, Objective Method

1. INTRODUCTION

During the decision-making process, several alternatives are ranked based on determined criteria to identify the best alternative. Nowadays, decision-making has become more complex and dynamic. Individuals must handle various objectives, criteria, and alternatives in a rapidly changing environment [1]. Therefore, multi-criteria decision-making (MCDM) techniques are commonly used in solving decision problems as they provide a systematic approach to handle complex decision problems with several conflicting criteria and alternatives. MCDM techniques present a comprehensive framework to assure the coherence of findings. Typically, four stages are followed during the assessment of alternatives with MCDM techniques. First, the criteria and alternatives are determined. Second, the criteria weights are found. Third, the scores of alternatives based on each criterion are calculated. Fourth, the cumulative performance of all alternatives is determined. There are numerous MCDM techniques in literature. They are categorized into two groups: MCDM techniques, (1) which determine alternative rankings and (2) which determine criteria weights. The focus of this study is on determining the criteria weights in the second step. Determining criteria weights is one of the most significant and complex parts of the MCDM process, as criteria weights present the significance of each criterion, which eventually affects ranking of alternatives. Thus, incorrect weights can result in wrong ranking results. There are different ways to find the weights. One of the earliest approaches in determining the criteria weights is giving equal weights to each criterion, such as in [2]. It ignores the differences in the criteria, therefore presents an easy way for weight calculation. This approach is helpful if there is an insufficient amount of knowledge and if there is no possibility to gather the decision maker's opinion about the significance of the criteria. Although it has been one of the commonly used approaches, there is a significant loss of information as the equal weights approach does not consider the relative importance of criteria, thus, it is not commonly used nowadays. To deal with the loss of information, it is important to rank the criteria.

There are three groups of weight determination techniques to rank the criteria and therefore to assign weights to the criteria. The first group is subjective weighting techniques, which identifies the weights based on the opinions of decision makers. Techniques such as Analytic Hierarchy Process (AHP) [3-5], Step-Wise Weight Assessment Ratio Analysis (SWARA) [6], and Decision Making Trial and Evaluation Laboratory (DEMATEL) [7] provide an analytical framework to assess criteria weights using subjective judgment of experts. The process of decision making is improved as decision makers are significantly involved in the process therefore decisions are made as adapted to the given conditions [8]. On the other hand, the reliability of weights determined based on decision maker opinions decreases if the number of criteria increases because of the mental capacity of decision makers [9]. The second group is the objective weighting techniques, which do not include decision maker opinions, but determine weights by applying mathematical approaches such as Entropy method [10], Criteria Importance Through Intercriteria Correlation (CRITIC) [11-13], Mean Entropy-based Relative Criteria Weighting (MEREC) [14], Criterion Impact Loss (CILOS) [15], Integrated Determination of Objective Criteria Weights (IDOCRIW). Compared to subjective techniques, the objective techniques present flexibility in weight determination [16]. The third group is integrated techniques which combine both subjective and objective weighting techniques.

This study aims to develop a novel criteria weighting technique using objective data, called LOGSTA (LOGarithmic normalization and STAndard deviation). The contributions of this study are: A new approach has been developed for calculating criteria weights, the LOGSTA can solve the inconsistency issue, two numerical examples are solved with the LOGSTA technique, and findings are found to be consistent, the LOGSTA technique is compared with the CRITIC, Entropy, and MEREC methods to determine validity.

2. LITERATURE REVIEW

Several recent studies offering novel objective weight techniques and applying them to specific decision problems are summarized in this section.

2.1 Entropy

The entropy technique determines weight using real data. Chodha et al. [17] evaluated industrial robots using the Entropy and TOPSIS methods. They found that average energy consumption is the most significant criterion. Wang et al. [18] used the Entropy and Combined Compromise Solution (CoCoSo) techniques to assess the road sustainability of OECD countries. It was found that energy use is the most important criterion, and Japan is the first country in terms of road sustainability. Yadav et al. [19] examined five dental composites with 11 criteria based on the Entropy and Vlsekriterijumska Optimizacija I KOmpromisno Resenje (VIKOR) techniques. Polymerization shrinkage indicator was found to be the most significant criterion. Yucenur and Maden [20] applied the Entropy and Additive Ratio Assessment (ARAS) techniques to select the most optimal city to establish a hydroponic greenhouse in Turkiye using geothermal energy. Geothermal water flow was determined to be the most important criterion and Denizli was found to be the best location. Wang et al. [21] examined international 3PL suppliers with the Entropy and Measurement of Alternatives and Ranking According to Compromise Solution (MARCOS) methods. Jameel et al. [22] examined the sustainability of alternative energy systems in Turkiye with the circular intuitionistic fuzzy sets (CIFS), Entropy, SWARA, and CoCoSo. System efficiency factor was presented as the most important criterion, and geothermal energy was determined as the most optimal option.

2.2 Criteria Importance Through Intercriteria Correlation (CRITIC)

CRITIC technique calculates weights by taking the contrast intensity and correlations among criteria into account [11]. Yu et al. [23] used the CRITIC and TOPSIS techniques for selecting the best methodology for the detection of transmission line component. Among all criteria, the performance criterion was found to have the most significance. Ranjan et al. [24] utilized the CRITIC and MARCOS techniques to solve material selection decision problem in automobile industry. Cost criterion was revealed as the most important criterion and sintered hardened steel is the best material. Dhara et al. [25] used the CRITIC and TOPSIS techniques for business plane selection. The results suggested that the Cessna Citation jet M2 is the best alternative. Ali et al. [26] examined the financial sustainability of banks in Iraq with the CRITIC and Ranking of Alternatives through Functional Mapping of Criterion Sub-intervals into a Single Interval (RAFSI) method. It was presented that BTRI has the highest score.

2.3 Mean Entropy-based Relative Criteria Weighting (MEREC)

MEREC enhances the consistency in distribution of weights by decreasing the surplus of information entropy [14]. Mastilo et al. [27] evaluated the financial performance of banks in Bosnia and Herzegovina using the MEREC and MARCOS techniques. Return on assets was determined to be the most significant and Raiffeisen Bank has the best performance. Wang et al. [28] utilized the MEREC and CoCoSo methods to choose the best optimal sensor alternative. The study indicated that Ease of Installation is the most crucial factor and proximity sensor is the best alternative. Popović et al. [29] developed an MCDM model with the MEREC and Comprehensive Distance Based Ranking (COBRA) methods to choose the best strategy for developing e-commerce. Compliance with mission and vision of the company is the most crucial criterion. It was also found that the social e-commerce adoption model is the best strategy for e-commerce development. Ivanović et al. [30] used the MEREC and double normalized MARCOS techniques to choose the most optimal pump for concrete mixer vehicles. The findings presented that drum feeding speed is the most critical criterion and Magnum MK 24.4Z-80/115 RH is the best alternative pump to use in concrete mixers. Ulutaş et al. [31] solved insulation material selection problem in construction sector using the Preference Selection Index (PSI), MEREC, Logarithmic Percentage Change-Driven Objective Weighting (LOPCOW), and Multiple Criteria Ranking by Alternative Trace (MCRAT) methods. Energy consumption was determined as the most significant criterion and sheep wool was identified as the best insulation material to be used in the construction of buildings.

2.4 Criterion Impact Loss (CILOS)

The CILOS technique evaluates criterion loss against the alternative with the optimal (maximal or minimal) value [15]. Naz et al. [32] examined the beauty companies with CILOS and WASPAS. Şahin Macit [33] ranked European and Central Asian nations based on the macroeconomic performance between 2019 and 2021 with CILOS and AROMAN. The results identified that Germany is ranked first in 2019, Turkiye in 2020, and Armenia in 2021. Nebati [34] used the CILOS and COPRAS to determine the most efficient LED screen. Price criterion was identified as the most important factor, and LG was selected as the best LED screed alternative.

2.5 Integrated Determination of Objective Criteria Weights (IDOCRIW)

The IDOCRIW technique integrates both Entropy and CILOS methods. With IDOCRIW, the disadvantages of Entropy method are alleviated using the CILOS method [15]. Ozdemir [35] ranked EU-27 nations based on the environmental resilience using IDOCRIW and CoCoSo. Fossil fuel subsidies factor was determined as the most critical factor in the analysis of environmental resilience. The results suggested that Switzerland is the most resilient country. Chatterjee et al. [36] selected the most optimal oil used in electrical discharge machining with the IDOCRIW and Double Normalization-Based Multiple Aggregation (DNMA). The results showed that Spark SPO-A EDM oil is the best alternative.

2.6 Standard Deviation (SD)

SD Technique determines the weights with the fluctuation of data. Standard deviation of criteria defines the weights. The higher deviation means the higher weight. Camlibel [37] ranked the performance pension firms with the SD and MARCOS techniques. The results show that the total debts criterion is the most significant criterion. Vavrek [38] evaluated financial performance of state organizations with the SD and TOPSIS methods. The SD results indicated that the most efficient criterion is the total debt. Topal and Ulutaş [39] ranked G8 states based on the logistics performance using the SD and Alternative Ranking Order Method Accounting for Two-Step Normalization (AROMAN). It was found that timeliness is the most crucial indicator, and Germany has the best performance.

3. A NEW LOGSTA METHOD

This method represents a new objective method for determining criteria weights based on quantitative data and consists of the following procedure (Fig. 1).

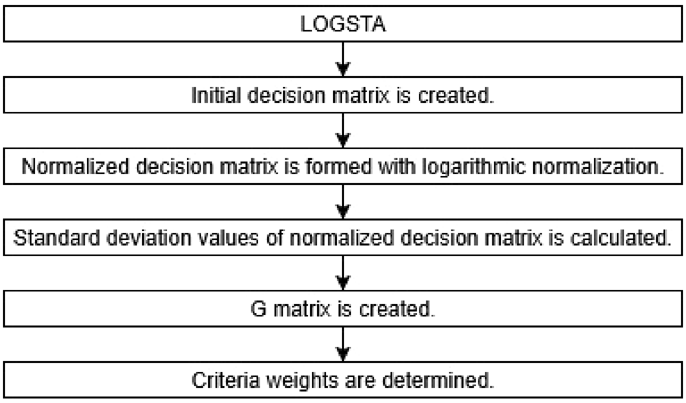

Figure 1: The flowchart of LOGSTA method.

Step 1: The initial decision matrix Z is organized for n alternatives and m criteria.

$$Z = \left[z_{ij} \right]_{n \times m} \tag{1}$$

where z_{ij} denotes the value of alternative i per criterion j.

Step 2: The initial decision-making matrix is normalized using logarithmic normalization depending on the criterion type. Compared to Entropy, for instance, this method considers the type of criterion, which results in various criterion weights. Eq. (3) is applied if the criterion belongs to the benefit group, while Eq. (4) is used if the criterion belongs to the cost group.

$$N = \left[n_{ij} \right]_{n \times m} \tag{2}$$

$$n_{ij} = \left| \frac{\ln z_{ij}}{\left| \ln\left(\prod_{i=1}^{n} z_{ij} \right) \right|} \right|, \quad j \in B \tag{3}$$

$$n_{ij} = \left| \frac{1 - \dfrac{\ln z_{ij}}{\ln\left(\prod_{i=1}^{n} z_{ij} \right)}}{n-1} \right|, \quad j \in C \tag{4}$$

Step 3: Computation of matrix G that represents product of the standard deviation σ_j of normalized values and the inverse value of ln of sum n_{ij}.

$$G = \left[g_j \right]_{1\times m} \tag{5}$$

$$g_j = \sigma_j \times \left(\left| \sum_{i=1}^{n} \left(\ln\left(n_{ij} \right) \right) \right| \right)^{-1} \tag{6}$$

Step 4: The final value of each criterion w_j is obtained using Eq. (7), as follows:

$$w_j = \frac{g_j}{\sum_{j=1}^{n} g_j} \tag{7}$$

4. ILLUSTRATIVE EXAMPLES

This section provides illustrative examples created with Monte Carlo simulation to prove the validity of the proposed new objective method for determining the weights of criteria named LOGSTA. The method is tested on two examples with matrices of sizes 7×5 and 6×6. It is important to note that the proposed objective LOGSTA method is tested considering various scenarios from the criteria type aspect (cost, benefit, and combination of cost and benefit criteria).

4.1 Example 1: matrix 7×5

The initial matrix (7×5) is shown in Table I.

Table I: Simulated initial decision-making matrix of size 7×5.

	C1	C2	C3	C4	C5
A1	368	262	495	198	618
A2	988	336	780	31	860
A3	38	680	716	745	806
A4	886	137	904	501	577
A5	914	722	891	480	183
A6	797	107	335	905	240
A7	99	654	699	610	887

To understand the procedure of the LOGSTA method we have provided an example of calculation for the data shown in Table I. So, after creating initial decision matrix, next step representing the normalisation process using Eq. (3) manifested through logarithmic normalization and benefit group of criteria.

$$n_{11} = \left| \frac{\ln z_{11}}{\ln\left(\prod_{i=1}^{7} z_{ij}\right)} \right| = \left| \frac{\ln(368)}{\ln\left(368\times 988\times 38\times 886\times 914\times 797\times 99\right)} \right| = \left| \frac{5.9081}{41.32187} \right| = 0.1430$$

The remaining normalized values are calculated using the same equation because all criteria are benefit and Table II gives the completed normalized matrix with standard deviation.

Table II: Normalized matrix of size 7×5 (benefit criteria).

	C1	C2	C3	C4	C5
A1	0.1430	0.1373	0.1367	0.1291	0.1470
A2	0.1669	0.1434	0.1467	0.0839	0.1546
A3	0.0880	0.1608	0.1448	0.1615	0.1531
A4	0.1642	0.1213	0.1499	0.1518	0.1455
A5	0.1650	0.1623	0.1496	0.1508	0.1192
A6	0.1617	0.1152	0.1281	0.1663	0.1254
A7	0.1112	0.1598	0.1443	0.1566	0.1553
σ_j	**0.0313**	**0.0194**	**0.0079**	**0.0286**	**0.0146**

In the next step, the coefficients of matrix G are calculated as follows:

$$g_1 = \sigma_1 \times \left(\left| \sum_{i=1}^{n} \left(\ln\left(n_{ij}\right) \right) \right| \right)^{-1}, g_1 = 0.0313 \times \left(\left| \ln(0.1430) + \ln(0.1669) ... + \ln(0.112) \right| \right)^{-1} = 0.0023$$

and the final weight for the first criterion has been obtained using Eq. (7) as $w_1 = 0.3064$, while Table III gives the weights for other criteria, g_j and rank of criteria.

Table III: Final values of criteria for matrix of size 7×5 (benefit criteria).

	C1	C2	C3	C4	C5
g_j	0.0023	0.0014	0.0006	0.0021	0.0011
w_j	0.3064	0.1909	0.0781	0.2799	0.1447
rank	**1**	**3**	**5**	**2**	**4**

In the next part of the paper, we will represent the situation when all criteria belong to the cost group, so we are using data from Table I and Eq. (4) for the normalisation process because all criteria are within the cost group of criteria. The normalised matrix size of 7×5 with all cost criteria is presented in Table IV.

Table IV: Normalized matrix of size 7×5 (cost criteria).

	C1	C2	C3	C4	C5
A1	0.1428	0.1438	0.1439	0.1451	0.1422
A2	0.1389	0.1428	0.1422	0.1527	0.1409
A3	0.1520	0.1399	0.1425	0.1397	0.1412
A4	0.1393	0.1465	0.1417	0.1414	0.1424
A5	0.1392	0.1396	0.1417	0.1415	0.1468
A6	0.1397	0.1475	0.1453	0.1390	0.1458
A7	0.1481	0.1400	0.1426	0.1406	0.1408

Applying the same methodology, we have obtained final results for matrix with all cost criteria and for matrix with combined type of criteria (1st, 3rd, and 5th are cost, while 2nd and 4th are benefit). These results are shown in Table V.

$$n_{21} = \left| \frac{1 - \dfrac{\ln z_{21}}{\ln\left(\prod_{i=1}^{7} z_{ij}\right)}}{7-1} \right| = \left| \frac{1 - \dfrac{\ln(988)}{\ln(368 \times 988 \times 38 \times 886 \times 914 \times 797 \times 99)}}{6} \right| = \left| \frac{1 - 0.1669}{6} \right| = 0.1389$$

Table V: Final values of criteria for matrix of size 7×5 (cost criteria and combination of B and C).

	C1	C2	C3	C4	C5		C1	C2	C3	C4	C5
Cost criteria						**1st, 3rd, 5th (C); 2nd, 4th (B)**					
g_j	0.0004	0.0002	0.0001	0.0003	0.0002	g_j	0.0004	0.0014	0.0001	0.0021	0.0002
w_j	0.3078	0.1902	0.0775	0.2807	0.1439	w_j	0.0924	0.3411	0.0233	0.5000	0.0432
rank	**1**	**3**	**5**	**2**	**4**	rank	**3**	**2**	**5**	**1**	**4**

4.2 Example 2: matrix 6×6

To show applicability of our proposed objective method for determining criteria weights, we have performed calculation for matrix with equal number of alternatives and criteria, in this case matrix 6×6 with initial data shown in Table VI.

Table VI: Simulated initial decision-making matrix of size 6×6.

	C1	C2	C3	C4	C5	C6
A1	29	472	97	519	826	804
A2	490	60	819	973	84	61
A3	168	682	818	649	134	400
A4	979	43	723	801	174	527
A5	713	72	150	454	391	417
A6	501	522	660	433	832	657

After applying the LOGSTA method results for simulated matrix 6×6 in cases where all criteria are benefit, all criteria are cost, and when there is combination of both types of criteria have been shown in Table VII.

Table VII: Final values of criteria for matrix of size 6×6 for all cases.

	C1	C2	C3	C4	C5	C6
Benefit criteria						
g_j	0.0035	0.0037	0.0025	0.0008	0.0026	0.0024
w_j	0.2241	0.2401	0.1586	0.0507	0.1705	0.156
rank	**2**	**1**	**4**	**6**	**3**	**5**
Cost criteria						
g_j	0.0007	0.0008	0.0005	0.0002	0.0005	0.0005
w_j	0.2251	0.2412	0.1581	0.0502	0.1699	0.1555
rank	**2**	**1**	**4**	**6**	**3**	**5**
1st, 3rd, and 5th are cost, while 2nd and 4th are benefit						
g_j	0.0007	0.0037	0.0005	0.0008	0.0005	0.0024
w_j	0.0814	0.4299	0.0572	0.0907	0.0614	0.2794
rank	**4**	**1**	**6**	**3**	**5**	**2**

5. COMPARATIVE ANALYSIS

In the papers on the proposal of new MCDM methods, it is mandatory to verify the results obtained with the existing MCDM methods through comparison analysis (CA). In our case, we compared the proposed LOGSTA method with other objective methods to determine the weight of the criteria: CRITIC [11, 40], Entropy [10], and MEREC [41]. Figs. 2 and 3 show the results of the CA with the above methods for the 7×5 and 6×6 respectively. Fig. 2 shows that the LOGSTA method gives good results in comparison to other MCDM methods. In case when all criteria are simulated as beneficial, the most significant criterion is identical with CRITIC and Entropy methods, while in comparison with MEREC method the most important and second important criteria changed places. Considering only beneficial criteria for matrix 7×5 it can be concluded that the results provided with the LOGSTA method are less correlated with CRITIC, while the Entropy and MEREC have high correlation. The same conclusion can be derived in case that all criteria are simulated as cost criteria, with note that the most important criterion is C1 in the whole comparative analysis. In third case where considered criteria are both type LOGSTA method gives same results as MEREC method, while Entropy and CRITIC showed some differences.

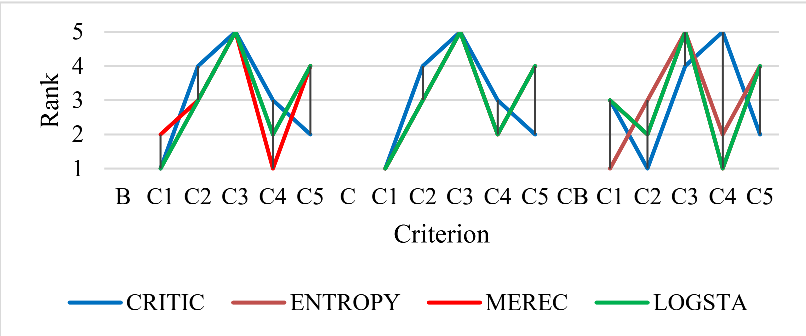

Figure 2: Results of the comparative analysis for the 7×5 matrix.

Fig. 3 shows that the LOGSTA method gives good results in comparison to other MCDM methods, but with a higher difference in comparison to the 7×5 matrix. In case when all criteria are simulated as beneficial, the most significant criterion is identical with the Entropy method, while in comparison with MEREC and CRITIC methods, there is a variety in three positions. The LOGSTA method provides results closer to other methods where all criteria belong to the cost group, so C2 is the most important criterion in all comparative analyses except the CRITIC method. In case where we have a combination of both types of criteria, results are very different so next should be calculated correlation coefficients to check exact correlations.

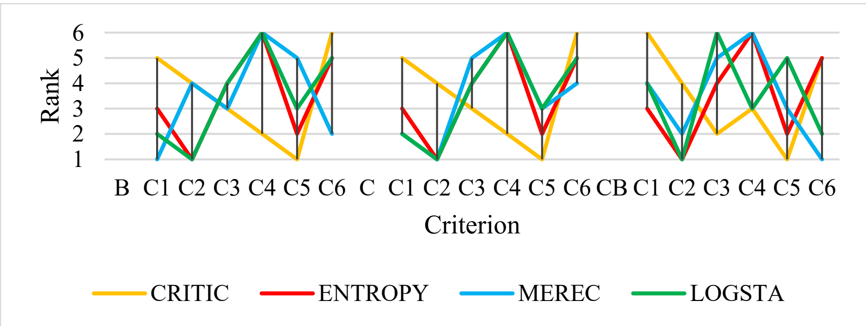

Figure 3: Results of the comparative analysis for the 6×6 matrix.

Fig. 4 shows the deviation in the ranks of different methods in relation to LOGSTA with different criterion orientation structures for matrix 7×5 (left) and for matrix 6×6 (right).

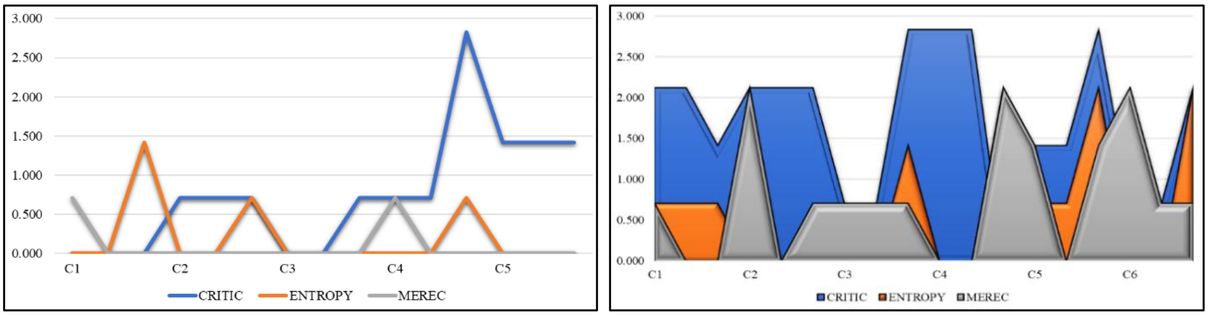

Figure 4: Stdev in ranking criteria of LOGSTA and three other MCDM methods for matrix 7×5 (left) and for matrix 6×6 (right).

Depending on the structure of the orientation of the criteria, it can be concluded that the smallest deviation when modelling the MCDM problem exists in the case where there are only cost criteria, while in the structure of the combination of cost and benefit criteria, the largest deviation occurs, which reaches the maximum compared to the CRITIC method (2.828). To prove the stability of the proposed LOGSTA method, we have calculated the correlation coefficients *WS* [42, 43] and *SCC* [44, 45] which are shown in Fig. 5.

The average values for the group of benefit-cost criteria (*SCC* = 0.650 and *WS* = 0.744) of the calculated correlation coefficients show differences in the mutual comparison of LOGSTA and other methods. An extreme difference is obtained in comparison to the CRITIC method. The average values in the situation when the criteria in model are only beneficial (*SCC* = 0.900 and *WS*=0.901) or only cost (*SCC*=0.925 and *WS*=0.953) show high correlation in total. In the square matrix in which the initial matrices are also simulated, it can be seen that the LOGSTA method, compared to other methods and the previous analysis with the 7×5 matrix, has larger deviations, that is, smaller matches in the ranks. The highest value of the deviation is also 2.828, which appears more than once in the analysis, and in general, the average value of the standard deviation is quite higher compared to the non-square matrix. In the case of a square matrix, the ranks obtained with the LOGSTA method have small correlation in the comparative analysis with other methods (Fig. 6), which is a consequence of a different normalisation process and the fact that the LOGSTA method uses the natural logarithm twice in its procedure.

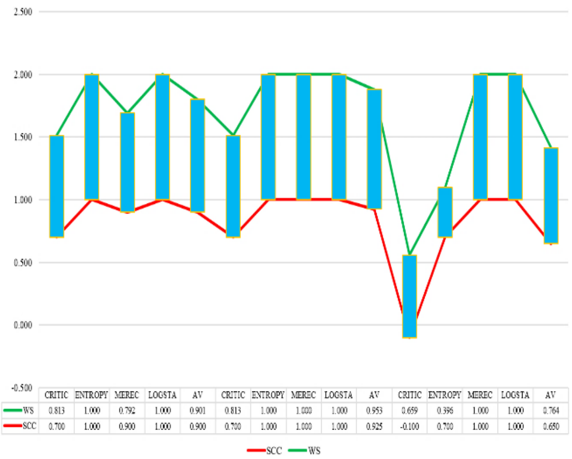

Figure 5: *SCC* and *WS* correlation coefficients in comparative analysis for matrix 7×5.

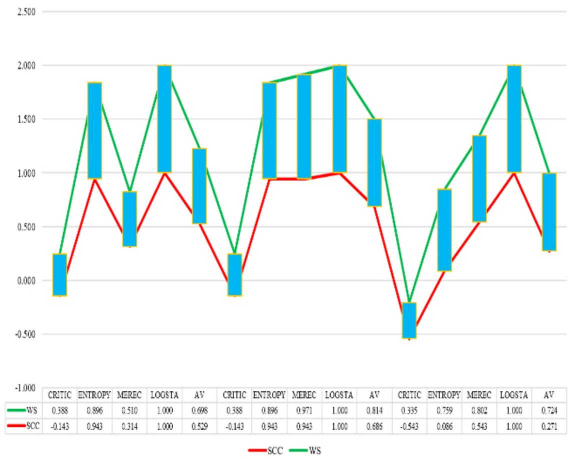

Figure 6: *SCC* and *WS* correlation coefficients in comparative analysis for matrix 6×6.

6. CONCLUSION

In this paper, we have developed a new method based on LOGarithmic normalisation and STAndard deviation (LOGSTA) to determine objective criteria weights. This method allows simple and easy computation in cases where quantitative data are available, and it is needed to consider both types of criteria. We have demonstrated the application of the LOGSTA method on a square matrix and a non-square matrix, sized 6×6 and 7×5, respectively. The results obtained have been checked and compared with the three main methods used for calculating the criteria weights: CRITIC, Entropy, and MEREC. It is important to note that this method in comparison with Entropy considers type of criteria and due to that criteria weights are various, which should be in each method for determining the criteria weights. In comparison to different methods, LOGSTA shows various ranks. However, in some cases, it is fully correlated, which has been provided with *SCC* and *WS* correlation coefficients. Our proposed method provides consideration of both types of criteria, a separate normalization process for benefit and cost criteria, a different normalization procedure compared to CRITIC, Entropy, and MEREC methods, the application of natural logarithm twice, and a combination with standard deviation. Future research related to developed methods should be manifested with application of real case studies, extension of various forms of uncertainties, and combination with methods for ranking potential variants potentially also as a part of hybrid approaches [46]. Future research related to the developed method should be manifested with the application of real case studies, the extension of various forms of uncertainties, and the combination with methods to classify potential variants.

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