Comparing Global and Local Weights in Multi-Criteria Decision-Making: A COMET-Based Approach

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Abstract: In the multi-criteria decision-making (MCDM) domain, decision-makers encounter the challenge of considering multiple criteria with varying importance. While numerous methods exist to determine global weights, less attention has been given to identifying local weights for individual alternatives. Unlike global weights, local weights indicate the relevance of individual criteria in the context of a specific alternative. Global weights assume a constant linear dependence of substitutability throughout the domain, where local weights indicate a local dependence, depending on the value of all attributes of a given alternative.

This paper demonstrates the usage of Characteristic Objects METhod (COMET) to determine local criteria weights and provides simulation results to show the differences in those weights. By understanding the significance of criteria for specific alternatives and their impact on the overall evaluation, local weights contribute to a more comprehensive and reliable ranking. This paper presents the necessary methodologies, describes the pseudocode algorithm, and showcases two examples of two COMET models and a simulation that utilizes the ESP-COMET approach. The simulation results highlight generalized results showing the importance of identifying local weights.

1 INTRODUCTION

In every decision problem, one or more different criteria are included. Decisions are usually made based on these criteria, which can be more or less obvious to the decision-maker. In complex decision-making problems, the decision-maker can be forced to handle multiple opposing criteria, which can be difficult to do. In this case, the expert can use the methodologies and approaches utilized in the Multi-Criteria Decision Analysis (MCDA) domain, where the decision maker should identify a set of alternatives and criteria. However, further use of MCDA methods requires the definition of the criteria weights (Mahmoody Vanolya and Jelokhani-Niaraki, 2021). Many different methods allow one to identify global weights in decision problems, such as Analytic Hierarchy Process (AHP) (Saaty, 2004), RANking COMparison (RANCOM) (Więckowski et al., 2023b), and others (Biswas et al., 2022; Lipka and Szwed, 2021). However, little attention is paid to identifying local weights for individual alternatives (Choo et al., 1999; Ullah et al., 2018).

Local weights play a vital role in the conduct of a thorough analysis of decision problems, criteria, and alternatives, as evidenced by previous studies (Elanchezhian et al., 2010; Więckowski et al., 2023a). They address the critical question of the relative importance of specific criteria for particular alternatives and how much they influence the overall evaluation of the considered alternatives. The determination of local criteria not only aids in gaining a deeper understanding of the decision problem but also clarifies the prerequisites that the alternatives must meet. For example, they allow one to adjust the importance of specific attributes within the context of a given alternative. In contrast, global weights maintain uniform importance for each criterion. To illustrate, consider the body temperature problem of a patient with COVID-19, where temperature is one of the basis of diagnosis. The relevance of body temperature in the context of COVID-19 patients is meaningful only in specific circumstances, as excessively high temperatures can potentially harm proteins. This means that normal temperature levels have no significant impact on the severity of COVID-19, whereas high tempera-

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tures become very important and are more important when they increase (Yombi et al., 2020).

The Characteristic Objects METhod is an MCDA method utilizing the fuzzy theory and rule-based system to provide reliable and accurate rankings of the alternatives based on the expert's knowledge (Sałabun, 2015). It has many extensions (Faizi et al., 2018; Faizi et al., 2017) and has proven its robustness in many application fields, such as energetic (Kizielewicz et al., 2020), agriculture (Habeeb et al., 2022), sport (Więckowski and Dobryakova, 2021) and other (Kozlov and Norek, 2021).

The novelty and main contribution of the paper is to demonstrate the algorithm for the identification of local and global weights on the simple examples and provide a simulation based on the ESP-COMET approach, which shows how significant and useful the knowledge about local weights can be in the case of personalized decision-making when dealing with complex nonlinear expert preferences. The simulation based on the ESP-COMET approach clearly emphasizes the significance of knowledge about local weights when making personalized decisions when dealing with complex nonlinear expert preferences. This is important because it highlights that in a nonlinear model, the importance of individual criteria changes.

The rest of the paper is structured as follows: In Section 2, we describe all the necessary methodologies required to understand the described Study Case. In the next part of the paper, we present two examples that utilize the COMET method to determine the local weights of the criteria: the example with a linear expert function is shown in Section 3.1, and the example with a nonlinear expert function is shown in Section 3.2. To simulate nonlinear expert preferences, we utilize the recently proposed ESP-COMET approach. Next, we present a simulation that repeats the experiment described in Section 3.2 to obtain generalized differences between local and global weights. The simulation results are presented in Section 3.3. Finally, in Section 4, we conclude our work and propose future research directions.

2 PRELIMINARIES

This section provides the information necessary to understand the presented methodology. In Section 2.1, we briefly describe the Characteristic Objects METhod, which will be used as the main instrument to identify the local weights of the alternatives. Next, we explain the ESP-COMET procedure and how it can be used to simulate non-linear expert preferences. We also describe the recently introduced Weighted Similarity Coefficient WSC_2, allowing us to measure the distance between different weights efficiently. The description of the WSC_2 coefficient can be found in Section 2.3.

2.1 The Characteristic Objects Method

The Characteristic Objects Method (COMET) is the MCDA method that was initially proposed by (Sałabun, 2015) as a more reliable and robust substitution of classical MCDA methods. It allows the model expert preferences with different levels of complexity utilizing the Matrix of Experts Judgements (Kizielewicz et al., 2021). The algorithm of the COMET method is completely free of rank reversal paradox because of the independent evaluation of every alternative. The implementation of the COMET method can be found in the easy-to-use Python library of the MCDA methods called pymcdm (Kizielewicz et al., 2023). The algorithm is fully explained in the other publications, such as (Sałabun, 2015), therefore we will provide only a short version.

Step 1. Define the Space of the Problem – the expert determines the dimensionality of the problem by selecting the number r of criteria, $C_1, C_2, ..., C_r$. Then, the set of fuzzy numbers for each criterion C_i should be selected.

Step 2. Generate Characteristic Objects – The characteristic objects (CO) are obtained by using the Cartesian Product of fuzzy numbers cores for each criteria as follows.

Step 3. Rank the Characteristic Objects – the expert determines the Matrix of Expert Judgment (MEJ). The MEJ matrix contains results of comparing characteristic objects by the expert, where α_{ij} is the result of comparing CO_i and CO_j by the expert. The function f_{exp} denotes the mental function of the expert represented as (1). Afterward, the vertical vector of the Summed Judgments (SJ) is obtained as follows (2).

$$\alpha_{ij} = \begin{cases} 0.0, & f_{exp}(CO_i) < f_{exp}(CO_j) \\ 0.5, & f_{exp}(CO_i) = f_{exp}(CO_j) \\ 1.0, & f_{exp}(CO_i) > f_{exp}(CO_j) \end{cases} \tag{1}$$

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \tag{2}$$

Finally, values of preference are approximated for each characteristic object. As a result, the vertical vector P is obtained, where $i-th$ row contains the approximate value of preference for CO_i.

Step 4. The Rule Base – each characteristic object and value of preference is converted to a fuzzy rule as follows (3):

$$IF\ C(\tilde{C}_{1i})\ AND\ C(\tilde{C}_{2i})\ AND\ ...\ THEN\ P_i \quad (3)$$

In this way, the complete fuzzy rule base is obtained.

Step 5. Inference and Final Ranking – each alternative is presented as a set of crisp numbers (e.g., $A_i = \{a_{1i}, a_{2i}, ..., a_{ri}\}$). This set corresponds to criteria $\{C_1, C_2, ..., C_r\}$. Mamdani's fuzzy inference method is used to compute the preference of $i-th$ alternative. The better alternatives have higher preference values.

2.2 Expected Solution Point - COMET

The Matrix of Expert Judgements should be identified in the third step of the described COMET method. It is an easy task if the number of characteristic objects and criteria is small. However, if we increase the number of criteria we consider, the number of required comparisons grows rapidly. A number of comparisons depend on the number of characteristic objects t and are calculated as $\frac{t(t-1)}{2}$.

The ESP-COMET method introduced by Shekhovtsov et al. addresses this problem by utilizing the concept of the Expected Solution Point (ESP), which is inspired by the works of (Jahan and Edwards, 2013) and (Dezert et al., 2020). This approach allows us to identify the Matrix of Expert Judgements automatically, based on ESPs provided by an expert.

The procedure of ESP-COMET changes the **Step 3** of the COMET method's algorithm. The expert should choose n vectors of length r, which will be used as expected solutions. The selection should be based on the expert's domain knowledge. Here and in the following equations, we denote the number of criteria in the problem as r and the number of chosen ESP as n (4).

$$ESP = \left\{esp_{ij}\right\}_{n\times r} \quad (4)$$

In the original procedure, an expert function f_{exp} was utilized to determine values in the MEJ matrix. However, the ESP-COMET uses Equation (5), which utilizes a different function denoted f_{ESP}. This function will be defined later, and its purpose is to calculate the aggregated normalized distance between selected ESPs and considered characteristic object. The smaller the resulting distance, the better the Characteristic Object.

$$\alpha_{ij} = \begin{cases} 1.0, & f_{ESP}(CO_i) < f_{ESP}(CO_j) \\ 0.5, & f_{ESP}(CO_i) = f_{ESP}(CO_j) \\ 0.0, & f_{ESP}(CO_i) > f_{ESP}(CO_j) \end{cases}, \quad (5)$$

The function $f_{ESP}(CO_i)$ defined as (6).

$$f_{ESP}(X) = min_i \sqrt{\sum_{j=1}^{r} (x'_j - esp'_{ij})^2} \quad (6)$$

In (6), X stands for the abstract Characteristic Object that is represented by values x_j, $j \in \{1, 2, \ldots, r\}$, and esp_{ij} is an expected value i for the criterion j. Values x'_j and esp'_{ij} are normalized values of x_j and esp_{ij} calculated according to equation (7). The values $c_j^{(min)}, c_j^{(max)}$ refer to the smallest and largest characteristic values for the criterion j and are used to normalize the criterion and expected values in the domain of the decision problem. The same normalization procedure shown in (7) applies to each ESP.

$$x'_j = \frac{x_j - c_j^{(min)}}{c_j^{(max)} - c_j^{(min)}} \quad (7)$$

2.3 Weights Similarity Coefficient

The Weights Similarity Coefficient was proposed as the robust measure of differences between identified criteria weight sets (Shekhovtsov, 2023). It uses the Manhattan distance to determine the distance between weights, and the normalization allows the comparison of results for the different weight sets. The formula of the WSC_2 is as follows (8):

$$WSC_2 = 1 - \frac{d_1(\mathbf{w}, \mathbf{v})}{2} = 1 - \frac{\sum_{i=1}^{N} |w_i - v_i|}{2}, \quad (8)$$

where $\mathbf{w} = \{w_1, w_2, \ldots, w_n\}$ and $\mathbf{v} = \{v_1, v_2, \ldots, v_n\}$ are two sets of the criteria weights.

2.4 Nonlinearity Index

In this paper, we use a nonlinearity index to measure the difference of the identified COMET model from a simple linear model. The nonlinearity index is defined as (9):

$$I = \frac{\sum_{i=1}^{t} |p_i - p'_i|}{0.5 \cdot t}, \quad (9)$$

where t denotes the number of characteristic objects, p_i means the identified preferences of those characteristic objects and p'_i are preference values obtained using linear regression fitted to p_i. That way, we can measure the difference between linear approximation and identified models.

2.5 Identification of the Local Weights

In this paper, we utilize the algorithm for the identification of the local weights proposed by (Więckowski et al., 2023a). The procedure is conducted for the single alternative A_j. It requires an identified COMET model, e.g., the expert should define characteristic values and fill the MEJ matrix. The algorithm's following argument defines minimum and maximum values of the criteria *min* and *max* derived from the characteristic values, as well as the step in percentage α.

When all the required variables are provided, we can apply the procedure described in the pseudocode 1. First, on line `1`, we prepare an empty array that will contain the ranges of the preference values. Next, using the loop on lines `2-11`, we calculate ranges of the preference values for every criterion for the chosen alternative A_j. In lines `3-4`, we calculate the step for the values s based on provided α, min_i, and max_i and then prepare an empty array to collect all the preference values obtained in the next steps. On lines `5-9`, we utilize the for loop in order to substitute the value of the criteria C_i in the A_j on the new values $v \in \{min_i, min_i + s, min_i + 2s, \dots, max_i\}$. Each alternative obtained this way is evaluated using the COMET method, and the obtained preference values are memorized in the array p. In the and, in line `10`, we calculate the possible range of the preferences as a difference between the largest and the smallest values in p. Once again, the procedure is repeated for each criterion C_i, and then in line `12`, we normalize the obtained ranges to get the local weights W_{A_j}.

Data: Alternative A_j
Data: Identified COMET model $comet(\cdot)$
Data: *min* and *max* values for each C_i
Data: Step value change in percents α

1 $ranges \leftarrow$ empty array;
2 **for** i *in* $\{1, 2, \dots, N\}$ **do**
3 $\quad s \leftarrow (max_i - min_i) \cdot \alpha$;
4 $\quad p \leftarrow$ empty array;
5 $\quad$ **for** v *in* $\{min_i, min_i + s, min_i + 2s, \dots, max_i\}$ **do**
6 $\quad\quad A_j^{(copy)} \leftarrow$ Copy of A_j;
7 $\quad\quad$ Change value for C_i in alternative $A_j^{(copy)}$ to v;
8 $\quad\quad p_v \leftarrow comet(A_j^{(copy)})$;
9 $\quad$ **end**
10 $\quad ranges_i \leftarrow maximum(p_v) - minimum(p_v)$;
11 **end**
12 $W_{A_j} \leftarrow ranges / \sum_{i=1}^{N} ranges$;

Algorithm 1: Local weights identification algorithm.

The local weights identified this way can answer in a simple way how important a specific criterion is in the final evaluation of the specific alternative. Such knowledge can be useful in deeper decision analysis to guarantee reliable results in the decision-making process.

3 STUDY CASE

In this paper, we demonstrate the described approach for local weight identification on two simple study cases and a simulation study case. We use a randomly generated decision matrix presented in Table 1 to demonstrate the approach. The generated example consists of 5 alternatives $A_1 - A_5$ and four criteria $C_1 - C_4$. All values are generated from uniform distribution in range $[0, 1]$, therefore characteristic values for each criteria are determined as $\{0, 0.5, 1\}$. Synthetic examples are proven efficient in works like (Manolitzas et al., 2020; Yang and Qian, 2023). In the following sections, we will evaluate those five alternatives using two different COMET models: linear and non-linear.

Table 1: Randomly generated decision matrix.

	C_1	C_2	C_3	C_4
A_1	0.3745	0.9507	0.7320	0.5987
A_2	0.1560	0.1560	0.0581	0.8662
A_3	0.6011	0.7081	0.0206	0.9699
A_4	0.8324	0.2123	0.1818	0.1834
A_5	0.3042	0.5248	0.4319	0.2912

3.1 Example with the Linear Model

In this Section, we show the identification of the local weights using the linear COMET model. In this example, 81 characteristic objects identified were evaluated using some linear function instead of expert knowledge to simulate simple expert preferences. Identified MEJ is presented in Figure 1. There are few ties, but the general triangle pattern suggests that the model is linear.

If we evaluate the generated alternatives using this COMET model, we will obtain the following preference vector:

$$P^{(linear)} = \{0.7201, 0.3029, 0.6661, 0.3403, 0.4135\},$$

where value P_i shows the preference value for the alternative A_i, the alternatives with higher preference values are better. Therefore, this preference vector implies that the order of the alternatives in ranking is as follows: $A_1 > A_3 > A_5 > A_4 > A_2$. However, with this information, we cannot determine which criterion plays the biggest role in the evaluation of those alternatives because the COMET method does not use explicit criteria weights.

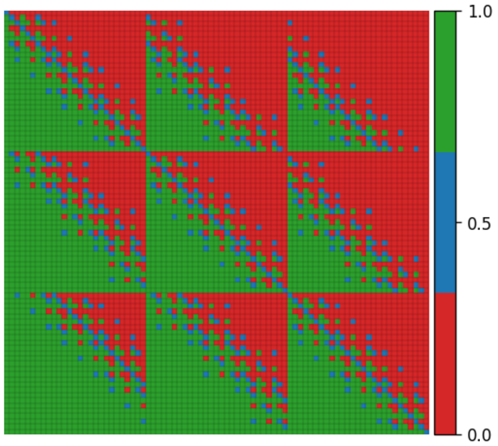

Figure 1: Identified MEJ matrix.

There is, however, a way to determine global weights based on the characteristic objects (Więckowski et al., 2023a). With the information about characteristic objects and their preferences calculated based on the MEJ, we can fit the linear regression in order to obtain the global criteria weights from the model.

Identified global weights W_{LR} are presented in Figure 2. Other bars present local weights for each alternative identified using the algorithm described previously in Section 2.5. Local weights are trying to answer the question of how specific criteria influence the evaluation of the specific alternative. In the case of the linear model, the global weights are identified using linear regression, and the local weights are equal. The criterion that influences the preference values most is the C_2. Then criteria C_1 and C_4 have the same weights and, therefore, are in a tie, and criterion C_3 has a smaller influence on the final preference value. The equality of the global and local weights suggests that the preference values of the alternatives change linearly if we linearly change the criteria values.

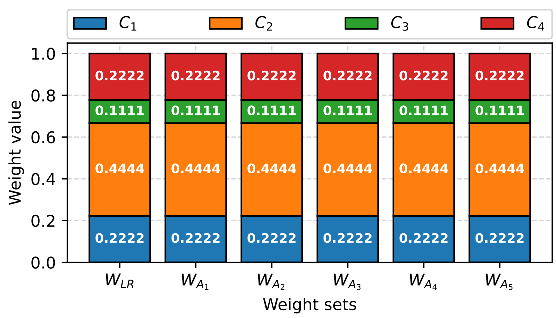

Figure 2: Visualization of the identified weights.

3.2 Example with the ESP-COMET Model

In this example, to simulate non-linear expert preferences, we use a recently proposed ESP-COMET algorithm (Shekhovtsov et al., 2023) described fully in Section 2.2. For the same characteristic values as presented in the linear example, we randomly choose the ESP value:

$$ESP = \{0.3371, 0.5218, 0.9290, 0.5265\},$$

and identified the model according to it.

Figure 3 presents the resulting MEJ matrix. As we can see, there are more ties in this matrix, and the pattern is less repeatable than in the MEJ presented in Figure 1. This implies that the identified model is non-linear in this case.

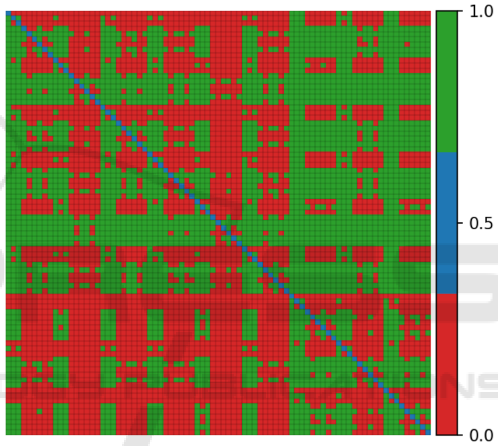

Figure 3: MEJ matrix identified using ESP-COMET algorithm.

We calculate the preferences of the characteristic objects based on the identified MEJ matrix and evaluate alternatives presented in Table 1 using the COMET method. The preference vector for this example is defined as:

$$P^{(ESP)} = \{0.7614, 0.2488, 0.1996, 0.1890, 0.6230\},$$

The bigger value P_i indicates that alternative A_i is better. Following this rule, we can determine the ranking of the alternatives, which differs from the order obtained with linear expert function: $A_1 > A_5 > A_2 > A_3 > A_4$. Next, we process the obtained COMET model as well as the alternatives using the algorithm of identification of the global weights using the linear regression, as well as the described in Section 2.5 algorithm for the local weights identification.

The results of the weights identification are visualized in Figure 4. As we can see, the weight vectors are quite different. In the case of the complex non-linear decision function, the final preference value may be changed differently for different alternatives, creating differences in the local weights for investigated alternatives.

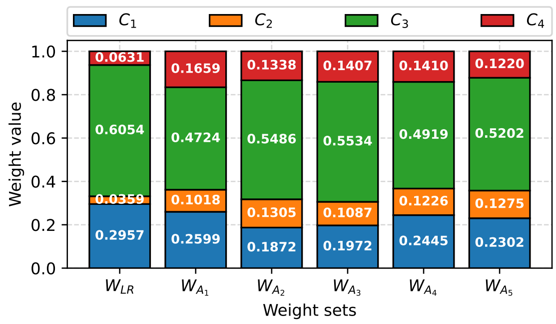

Figure 4: Visualization of the identified weights.

Analyzing Figure 4 we can see that the identified weights vary significantly. The identified global weight for the criterion C_1 is 0.2957; however, the importance of this criterion in the different alternatives' evaluation changes from 0.1872 for the alternative A_2 to 0.2599 for the alternative A_1. The global weight for the C_2 is 0.0359, but for alternatives, it varies from 0.1018 to 0.1305, which is significantly bigger. Next, the local weights for the criterion C_3 change from 0.4724 to 0.5534. However, the identified global weight is 0.6054. For the last criterion C_4, the global weight is 0.0631, and the local weights are changed from 0.1220 to 0.1659. Those differences show that the global weights are not necessarily the same as local weights for the alternatives in the specific decision problem.

Next, we calculate the WSC_2 coefficient between every pair of the identified weights and present it in the form of a heatmap in Figure 5. The range of the WSC_2 values is $[0,1]$, where 1 means equal weights and 0 most different weights. As we can see, the values in the heatmap suggest that the identified weights are rather similar. The lower WSC_2 value calculated between local weights for alternatives A_2 and A_4 is equal to 0.65. The most similar pair of the weights is local weights for alternatives A_1 and A_5, and the WSC_2 coefficient value is equal to 0.94 for this comparison. The identified global weights are most similar to the local weights identified for the alternatives A_1 (0.93) and A_5 (0.92).

3.3 Simulation on Local Weights

In this section, we describe the simulation designed to investigate the differences between global weights computed based on a COMET model identified based on random ESP and local weights identified with the

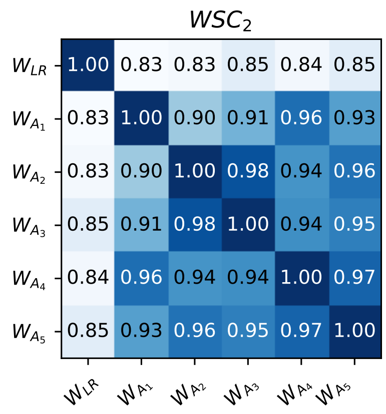

Figure 5: Similarities between weights calculated using WSC_2.

algorithm described in Section 2. To help understand the simulation, we illustrate it with the use of Algorithm 2. This algorithm describes the single simulation run. At first, we should define the number of alternatives and the number of criteria to generate. Next, the procedure creates a random matrix A with size $n \times r$ and a random ESP vector based on the number of criteria r. Random values are drawn from the uniform distribution with range $[0,1)$. The COMET method is designed in such a way that it does not require a normalization, therefore these simulation results can also be generalized for other ranges of the data. Next, we need to define the ESP Expert object based on ESP. We will evaluate characteristic objects based on them. We also need to create a $cvalues$ structure which defines a grid of the characteristic objects based on ESP, as it was described in (Shekhovtsov et al., 2023). Next, we determine local weights lw_i for each alternative A_i and global weights gl utilizing a linear regression model as described in (Więckowski et al., 2023a). These results returned from the simulation procedure and were processed later.

Data: Number of alternatives n
Data: Number of criteria r
$A \leftarrow$ random_matrix(n, r);
$ESP \leftarrow$ random_esp(r);
$expert \leftarrow$ ESPExpert(ESP);
$cvalues \leftarrow$ expert.make_cvalues();
$comet \leftarrow$ COMET(cvalues, expert);
$lw \leftarrow$ empty_array();
for i *in* $\{1,2,\ldots,n\}$ **do**
  $lw_i \leftarrow$ get_local_weights(comet, A_i);
end
$gl \leftarrow$ get_global_weights(comet);
return gl, lw

Algorithm 2: Single iteration of the simulation.

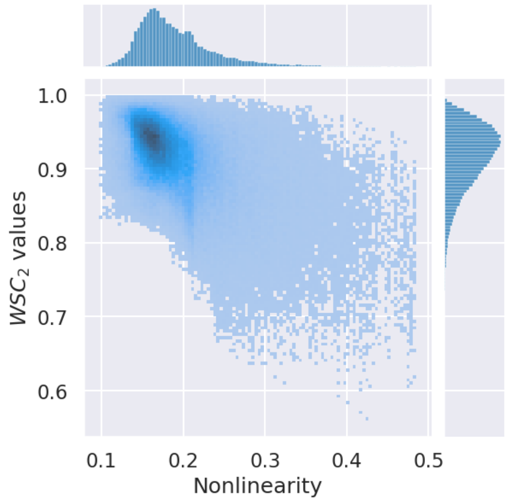

Figure 6: Results of the simulations computed based on 50,000 runs.

We ran the simulation procedure 50,000 times for the number of criteria $r = 4$ and the number of alternatives $n = 5$. Such numbers were chosen because it is more realistic to be able to identify the MEJ matrix for this size of the decision problem. However, we also ran the simulations for other values r and n and got very similar results. Based on gl and lw vectors collected during the simulation, we compute nonlinearity index values as well as WSC_2 values to get a numerical representation of the differences in the local and global weights. Notice that because one gl vector is related to $n = 5$ lw vectors, nonlinearity index values were duplicated to correspond to each WSC_2 value calculated between gl and each lw_i vector from one simulation run.

Figure 6 contains the visualization of the joint distribution of both the nonlinearity index and WSC_2 variables. On the side parts of the visualization, we can also see the respective distributions of these two variables. The mean WSC_2 value is 0.91, and the average nonlinearity index value is 0.19. It can be seen as the darkest point in the visualization. Also, it can be seen that the resulting WSC_2 values are laid in the range $[0.5, 1.0]$, and nonlinearity index values lie in the range $[0.1, 0.5]$. The Pearson r correlation value computed on both variables equals -0.52, which implies that there is a small level of reversed correlation between these variables. It also can be observed in the visualization, where smaller values of the nonlinearity index frequently correspond to higher values of WSC_2. For the higher value of the nonlinearity index, it is almost impossible for global and local weights to match, and in those cases, most of the WSC_2 values are below 0.9.

The observations drawn from the simulation and its results demonstrate how important local weights can be for deeper analysis of the decision problems, especially when it was solved with the help of expert knowledge. If the model identified by an expert is nonlinear, we cannot simply draw the global weights and use them to evaluate alternatives further. The local weights computed for the identified decision model can be crucial in further analysis, as they can answer the question of what should be improved on the existing alternatives to be evaluated higher in the decision problem. This information can also be used when looking for better decision alternatives than the ones included in the consideration.

4 CONCLUSION

In this paper, we demonstrate two simple examples of local weights identification for the alternatives in decision-making problems. Additionally, we design the simulation experiment based on the second example, which demonstrates the importance of the local weights in an in-depth analysis of the decision problem. The utilized approach is based on the Characteristic Objects Method and demonstrates its efficiency in the identification of the local weights in both linear and nonlinear decision problems. To simulate the artificial expert in the simulation, we used the ESP-COMET model, which can simulate the identification of the MEJ matrix based on a randomly chosen ESP. The presented experiments show that in the case of the linear problem, the global criteria weights identified from the evaluated characteristic objects using linear regression are equal to the local weights. However, in the case of complex nonlinear problems, the WSC_2 similarity value between local and global weights can fall below 0.6.

This demonstrates the importance of identifying local weights for the deeper decision problem analysis. For example, identified local weights can answer how much different criteria influence the final evaluation of the specific alternatives. It can also be helpful to have an idea of how the alternatives in the considered set can be improved to score higher preference values.

Future research may include further investigation of the properties of local weights in the context of the practical decision-making problem. We also want to improve the conception of the local weights and look for ways to determine them more precisely.

REFERENCES

Biswas, S., Bandyopadhyay, G., Pamucar, D., and Sanyal, A. (2022). A decision making framework for comparing sales and operational performance of firms in emerging market. *International Journal of Knowledge-based and Intelligent Engineering Systems*, 26(3):229–248.

Choo, E. U., Schoner, B., and Wedley, W. C. (1999). Interpretation of criteria weights in multicriteria decision making. *Computers & Industrial Engineering*, 37(3):527–541.

Dezert, J., Tchamova, A., Han, D., and Tacnet, J.-M. (2020). The spotis rank reversal free method for multi-criteria decision-making support. In *2020 IEEE 23rd International Conference on Information Fusion (FUSION)*, pages 1–8. IEEE.

Elanchezhian, C., Ramnath, B. V., and Kesavan, R. (2010). Vendor evaluation using multi criteria decision making. *International Journal of Computer Applications*, 5(9):4–9.

Faizi, S., Rashid, T., Sałabun, W., Zafar, S., and Wątróbski, J. (2018). Decision making with uncertainty using hesitant fuzzy sets. *International Journal of Fuzzy Systems*, 20:93–103.

Faizi, S., Sałabun, W., Rashid, T., Wątróbski, J., and Zafar, S. (2017). Group decision-making for hesitant fuzzy sets based on characteristic objects method. *Symmetry*, 9(8):136.

Habeeb, R., Hussain, I., Al-Ansari, N., and Sammen, S. S. (2022). A proposed comparative algorithm for regional crop yield assessment: An application of characteristic objects method. *Mathematical Problems in Engineering*, 2022.

Jahan, A. and Edwards, K. (2013). Vikor method for material selection problems with interval numbers and target-based criteria. *Materials & Design*, 47:759–765.

Kizielewicz, B., Shekhovtsov, A., and Sałabun, W. (2021). A new approach to eliminate rank reversal in the mcda problems. In *Computational Science–ICCS 2021: 21st International Conference, Krakow, Poland, June 16–18, 2021, Proceedings, Part I*, pages 338–351. Springer.

Kizielewicz, B., Shekhovtsov, A., and Sałabun, W. (2023). pymcdm—the universal library for solving multi-criteria decision-making problems. *SoftwareX*, 22:101368.

Kizielewicz, B., Wątróbski, J., and Sałabun, W. (2020). Identification of relevant criteria set in the mcda process—wind farm location case study. *Energies*, 13(24):6548.

Kozlov, V. and Norek, T. (2021). Towards objective multi-criteria drone evaluation based on vikor and comet methods. *Procedia Computer Science*, 192:4522–4531.

Lipka, W. and Szwed, C. (2021). Multi-attribute rating method for selecting a clean coal energy generation technology. *Energies*, 14(21):7228.

Mahmoody Vanolya, N. and Jelokhani-Niaraki, M. (2021). The use of subjective–objective weights in gis-based multi-criteria decision analysis for flood hazard assessment: A case study in mazandaran, iran. *GeoJournal*, 86:379–398.

Manolitzas, P., Grigoroudis, E., Christodoulou, J., and Matsatsinis, N. (2020). S-meduta: Combining balanced scorecard with simulation and mcda techniques for the evaluation of the strategic performance of an emergency department. In *GeNeDis 2018: Computational Biology and Bioinformatics*, pages 1–22. Springer.

Saaty, T. L. (2004). Decision making—the analytic hierarchy and network processes (ahp/anp). *Journal of systems science and systems engineering*, 13:1–35.

Sałabun, W. (2015). The characteristic objects method: a new distance-based approach to multicriteria decision-making problems. *Journal of Multi-Criteria Decision Analysis*, 22(1-2):37–50.

Shekhovtsov, A. (2023). Evaluating the performance of subjective weighting methods for multi-criteria decision-making using a novel weights similarity coefficient. *Procedia Computer Science*, 225:4785–4794.

Shekhovtsov, A., Kizielewicz, B., and Sałabun, W. (2023). Advancing individual decision-making: An extension of the characteristic objects method using expected solution point. *Information Sciences*, 647:119456.

Ullah, K., Hamid, S., Mirza, F. M., and Shakoor, U. (2018). Prioritizing the gaseous alternatives for the road transport sector of pakistan: A multi criteria decision making analysis. *Energy*, 165:1072–1084.

Więckowski, J. and Dobryakova, L. (2021). A fuzzy assessment model for freestyle swimmers-a comparative analysis of the mcda methods. *Procedia Computer Science*, 192:4148–4157.

Więckowski, J., Kizielewicz, B., Paradowski, B., Shekhovtsov, A., and Sałabun, W. (2023a). Application of multi-criteria decision analysis to identify global and local importance weights of decision criteria. *International Journal of Information Technology & Decision Making*, 22(06):1867–1892.

Więckowski, J., Kizielewicz, B., Shekhovtsov, A., and Sałabun, W. (2023b). Rancom: A novel approach to identifying criteria relevance based on inaccuracy expert judgments. *Engineering Applications of Artificial Intelligence*, 122:106114.

Yang, C. and Qian, Z. (2023). Street network or functional attractors? capturing pedestrian movement patterns and urban form with the integration of space syntax and mcda. *URBAN DESIGN International*, 28(1):3–18.

Yombi, J. C., De Greef, J., Marsin, A.-S., Simon, A., Rodriguez-Villalobos, H., Penaloza, A., and Belkhir, L. (2020). Symptom-based screening for covid-19 in healthcare workers: the importance of fever. *The Journal of hospital infection*, 105(3):428.