# Comparison of Monolithic and Structural Decision Models Using the Hamming Distance

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Abstract: This study shows a simple yet effective approach to comparing decision models built using the Characteristic Objects Method (COMET). The proposed approach is based on the Hamming Distance and its adaptation for complex decision problems that involve structural division of the model. We demonstrate the simulation-based proof-of-concept and then demonstrate the proposed approach to the case study of evaluating ten hydrogen cars based on the information provided by the manufacturers. We compared six decision models created based on the preferences of three decision makers expressed using Expected Solution Point (ESP) and Triad Support algorithm. The results obtained provide, on the one hand, some useful insights into customers' preferences and expectations for hydrogen cars and, on the other hand, show the utilization of the proposed comparison methodology.

## 1 INTRODUCTION

Multi-Criteria Decision Making (MCDM) is the domain of operational research that investigates complex decision problems, which usually involve many different criteria (Zavadskas and Turskis, 2011). In case of complex problems, the decision maker can turn to a vast choice of decision support methods, from simple ones such as Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) (Li et al., 2023) or Stable Preference Ordering Towards Ideal Solution (SPOTIS) (Dezert et al., 2020), to complex methods, such as Characteristic Objects METhod (COMET) (Sałabun et al., 2019), which can identify even complex decision maker's preferences in the complete domain of the decision problem.

The motivation for this study comes from the fact that the COMET method and other pairwise comparison methods lack a clear way to measure or compare the results of different decision models. For example, it may be necessary to include the opinions of multiple experts or to build several decision models and use methods to combine their results (Dehe and Bamford, 2015). In these cases, correlation measures can help identify and understand differences between the results of different methods or models (Yelmikheiev and Norek, 2021). However, there is no simple way to compare COMET models or predict how much their results might differ, creating a gap in the tools available for decision-making analysis.

In this paper, we present a simple yet effective approach to measuring the differences between COMET decision models, demonstrated by using the example of hydrogen cars. In such a case study was chosen, the use of MCDM methods has become essential with the increasing number of hydrogen-powered alternatives available not only in the transportation field. Recently, there has been interest in research in the MCDM field in hydrogen technologies, such as covering production, infrastructure, and transportation systems.

The main contribution of this paper is to show an approach on how to compare decision models based on the COMET model using the Hamming distance and how to adapt this approach to the structural models. To demonstrate our proposed approach, we present a simulation that shows that it is possible to predict the outcome of the ranking comparisons based on the Hamming distance between Matrices of Expert Judgements for different models. We also present this

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approach in a real-life case study on the evaluation of hydrogen cars.

The rest of the paper is structured as follows. In Section 3, we briefly present the methods and algorithms used for this research. Next, in Section 4.1, we present the proof of concept of the comparison of COMET models using the Hamming distance, then in Sections 4.2 and 4.3, we present the case study of hydrogen cars and a proposition for the comparison of structural COMET models. Finally, in Section 5, we summarize our findings and discuss the directions for future works.

## 2 RELATED WORKS

The field of MCDM has seen extensive research, providing a wide array of methods to assist decision-makers in addressing complex multi-criteria problems. Well-established techniques such as TOPSIS and the Analytic Hierarchy Process (AHP), along with their various modifications, offer clear and efficient ranking mechanisms. However, more advanced methods such as COMET are specifically designed to capture and model intricate decision-maker preferences. Despite the widespread application of these methods, a significant research gap persists in the comparison of decision models, particularly in the case of approaches such as COMET or AHP, which are being increasingly used in emerging areas. In this section, we provide an overview of selected related works and the usage of the AHP and COMET methods in practical applications.

Panchal et al. applied the AHP to address the critical issue of slope failure along highways in hilly regions (Panchal and Shrivastava, 2022). In their study, they developed a landslide hazard map for a section of National Highway 5, using various causative factors. Each of these factors was further divided into subfactors, with weights assigned according to the AHP methodology. It shows the need to investigate how to effectively compare MCDM models, especially when different model structures can lead to varying results. To facilitate such comparisons, additional tools and methodologies are needed to ensure robust evaluations of model effectiveness across different scenarios.

Several other studies emphasize the importance of the AHP method in various domains, demonstrating its utility while avoiding the issue of model structure sensitivity and the need for tools to compare MCDM models effectively. Awad and Jung applied AHP to prioritize sustainable urban regeneration factors in Dubai, identifying the urban environment, economic, and social / cultural sectors as key elements. Although their findings were insightful, they did not address how the structure of their model could have influenced the results, leaving this challenge unaddressed (Awad and Jung, 2022). Similarly, Ekmekcioğlu et al. used fuzzy AHP to create a district-based flood risk map for Istanbul, classifying land use and storm return periods as the most significant factors, but also did not explore how different model structures could impact the results (Ekmekcioğlu et al., 2021). Yariyan et al. combined FAHP-ANN for earthquake vulnerability mapping in Iran, achieving superior accuracy compared to traditional AHP, but again without investigating how varying structures could affect their findings (Yariyan et al., 2020). These examples highlight the widespread use of AHP in decision making, but also show that none of these studies addresses the critical issue of comparing models with different structures, underscoring the need for more advanced tools to fill this gap.

In current practice, the common approach to comparing MCDM methods typically involves analyzing the results obtained from different methods and, in some cases, applying distance metrics to assess the similarities or differences between these results. For example, Yelmikheiev and Norek compared the COMET and TOPSIS methods for selecting optimal vacuum cleaner robots based on criteria such as price, engine power, and noise level. After ranking the alternatives using both methods, they evaluated the results based on distance to the reference objects, showing that the COMET method provided more accurate results in their case (Yelmikheiev and Norek, 2021). This highlights the utility of comparing results, but also points to the limitations of relying solely on final rankings, because it does not offer a true model comparison, which should focus on comparing the entire structure of the models rather than discrete points or outputs.

Shekhovtsov et al. tackled a similar problem by using three different MCDM methods to evaluate preferences across a set of alternatives. They tested the impact of varying the number of alternatives and criteria on the final rankings and then compared the results using correlation coefficients (Shekhovtsov et al., 2021). Their findings indicated that the rankings were very similar and that an increase in alternatives and criteria improved this similarity. Więckowski and Dobryakova also explored this comparative approach, applying the COMET method to evaluate swimming athletes for sprint events (Więckowski and Dobryakova, 2021). They reduced the complexity of the problem by dividing the initial structure and later compared the COMET results with other

MCDM methods using correlation metrics such as Pearson and WS similarity coefficients. A more comprehensive approach was presented by Sałabun et al., who conducted a broad simulation study to benchmark multiple MCDA methods (Sałabun et al., 2020). Their research compared a variety of MCDA techniques, including TOPSIS, VIKOR, COPRAS, and PROMETHEE II, by evaluating their performance using different criteria, parameters, and ranking similarity coefficients such as Weighted Spearman correlation and WS coefficients. Through extensive simulations, the study revealed how factors like the number of attributes, decision variants, and normalization techniques influenced the final rankings.

However, the current study builds on these efforts by focusing on a more effective approach to comparing decision models identified through different structures of the COMET method. Unlike previous works that primarily evaluate ranking outcomes, this study delves into the comparison of the entire structure of decision models. By shifting the focus from merely comparing results to analyzing the underlying model architectures within the COMET framework, this research offers a deeper and more comprehensive understanding of the differences and similarities between decision models identified using various COMET structures.

# 3 PRELIMINARIES

In this section, we briefly describe the methods and algorithms used in this study. Each subsection contains a short description of the method and related references.

## 3.1 Characteristic Objects Method (COMET)

The Characteristic Objects Method (COMET) distinguishes itself from other Multiple Criteria Decision Analysis (MCDA) methods by being completely immune to the ranking reversal phenomenon (Sałabun et al., 2019). It makes it possible to develop a Multi-Criteria Decision Analysis (MCDA) model that always provides unambiguous results, no matter how much the alternative set changed (Kizielewicz et al., 2021). The key points of the algorithm of the COMET method are as follows:

**Step 1.** Define the Problem Space – Identify the criteria for the decision problem and assign fuzzy numbers to represent each criterion.

**Step 2.** Generate Characteristic Objects – Use the Cartesian product of fuzzy numbers to create a set of Characteristic Objects representing all possible combinations.

**Step 3.** Rank the Characteristic Objects – Perform pairwise comparisons of the Characteristic Objects to rank them based on expert judgment. Summarize the judgments and calculate the preference values.

**Step 4.** Build the Rule Base – Convert each characteristic object and its preference value into a fuzzy rule.

**Step 5.** Inference and Final Ranking – Use the fuzzy rule base and Mamdani's inference method to evaluate and rank alternatives. Alternatives with a higher preference value are better.

In **Step 3.** of the COMET method, the identified pairwise comparison matrix contains only the values $\{0, 0.5, 1\}$ and defines the decision model. The research gap lies in the fact that there are no studies showing how to compare such models without calculating the final results.

## 3.2 COMET Extensions

The main limitation of the COMET method is the curse of dimensionality, which becomes a significant challenge when the method is applied to decision problems involving a large number of criteria. This issue arises because the number of pairwise comparisons required grows exponentially with the number of criteria, making it impractical for large problems. However, recent advancements in research have addressed these limitations, making the COMET method more applicable even when larger sets of criteria are involved in the decision-making process.

One such advancement is the Expected Solution Point (ESP) in COMET, which automates the pairwise comparison step. This automation is achieved by allowing the decision maker to provide an ESP, from which the Matrix of Expert Judgements (MEJ) is automatically generated. This innovation significantly reduces the decision maker's workload and enhances the efficiency of the model identification process, as shown in recent studies (Shekhovtsov et al., 2023).

Another approach to mitigating the complexity of the COMET method is the Triad Support Algorithm, which minimizes the number of pairwise comparisons required. The algorithm assumes that if the expert judgments are consistent and free from errors, the evaluations of characteristic objects should form a transitive relationship. Using this property, the algorithm reduces the need for redundant comparisons, thereby streamlining the process of identifying the MEJ matrix (Shekhovtsov and Sałabun, 2023).

Finally, the Structural COMET approach offers a solution by breaking down a complex decision problem into several smaller submodels, which are then aggregated to form the final decision model. This method significantly reduces the size of the MEJ matrices, which in turn reduces the number of pairwise comparisons needed to build the model. This structural model approach makes COMET more manageable for larger decision problems and has proven to be an effective way to handle the curse of dimensionality (Shekhovtsov et al., 2020).

These advancements collectively represent substantial progress in overcoming the limitations of the COMET method, making it more suitable for decision problems with a larger number of criteria, while preserving the method's strengths in capturing complex preferences.

### 3.3 Weighted Spearman's Coefficient

The Weighted Spearman's correlation coefficient is often used in the MCDM domain because of its useful properties for the decision-making process. This approach places a larger weight on the comparison in the head of the rankings, which is usually more important to the decision maker. This is the main difference from the Spearman rank correlation coefficient, which has equal weights for all positions (Pinto da Costa and Soares, 2005). Weighted Spearman's correlation coefficient $r_w$ is defined for two samples with rank values $x_i$ and $y_i$ of size $N$ as (1).

$$r_w = 1 - \frac{6\sum_{i=1}^{N}(x_i - y_i)^2((N - x_i + 1) + (N - y_i + 1))}{N^4 + N^3 - N^2 - N} \quad (1)$$

## 4 CASE STUDY

In this section, we first show the proof of concept of measuring the differences in MEJ matrices with normalized Hamming distance using a simulation study, and then we try to adapt the same approach to complex structural models built for the evaluation of hydrogen cars.

### 4.1 Simulation Proof of Concept

The Hamming distance can be easily adapted to measure the differences between two different COMET models expressed as MEJ matrices. Suppose that we have two MEJ matrices of size $N \times N$ with elements $\alpha_{ij}^{(1)}$ and $\alpha_{ij}^{(2)}$, respectively. In this notation, the general formula for the Hamming distance will take the form of (2):

$$d_H = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N}\delta(\alpha_{ij}^{(1)}, \alpha_{ij}^{(2)})}{N^2}, \quad (2)$$

where $\delta(\alpha_{ij}^{(1)}, \alpha_{ij}^{(2)})$ is a special function equal to 1 only and only if $x_i$ and $y_i$ are different. In this way, the Hamming distance provides a simple way to quantify the differences between two MEJ matrices (Norouzi et al., 2012).

We designed a simple simulation experiment to check if there is any correlation between the Hamming distance, which allows us to measure the differences between models, and Weighted Spearman's correlation, which allows us to measure differences in the resulting rankings. The single run of the simulation can be described as follows:

1. Define the decision matrix $X$ of a specific size.
2. Calculate two random ESP points $esp1$ and $esp2$ in the problem domain.
3. Identify two COMET models using generated ESPs.
4. Calculate the Hamming distance between identified models and save it for further analysis.
5. Calculate two rankings, one using the COMET model defined by $esp1$ and the other using COMET defined by $esp2$.
6. Calculate the correlation $r_w$ between these rankings and save it for further analysis.

Notice that both the decision matrix values and the ESP points values were generated from the uniform random distribution in the range $[0, 1)$.

We ran the simulation 1000 times for all combinations of a number of criteria $m \in \{3, 4, 5, 6, 7\}$ and a number of alternatives $m \in \{10, 15, 20\}$ to include results for different decision matrix sizes. However, all those results turn out to be very similar, and therefore, in Fig. 1, we present 15000 simulation runs total. The upper and right parts of this figure present the distribution of the normalized Hamming distance and the $r_w$ values, respectively. The middle part of the figure presents the joint distribution of simulation results. The black line determines the sigmoid function fitted to the data. As can be seen, there is a certain dependency of $r_w$ value and Hamming distance for monolithic models (e.g., the model with no submodels). It can be observed that we got lower similarity in the results for those models for larger values of the Hamming distance. To be sure that we will get similar results, we need to have models that are different for no more than 0.1-0.15 Hamming distance. Besides the fact that it is possible to get similar rankings with models with a 0.4 distance value, it is much more possible to obtain results that are uncorrelated or even inverted. On the other side of the visualization, there are a small number of examples when generated

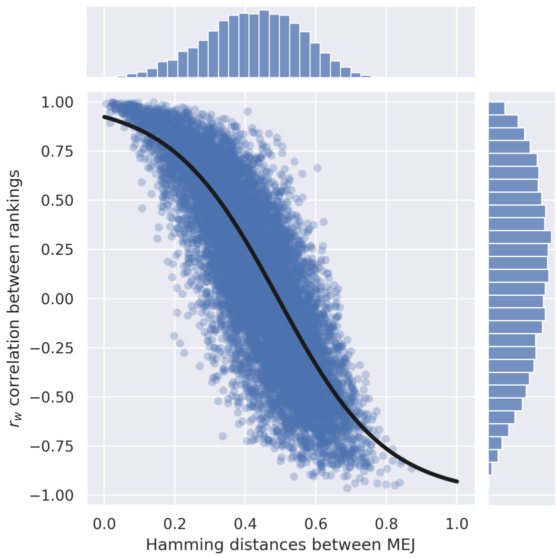


Figure 1: Simulation results.

Table 1: Criteria description.

| $C_i$ | Criteria names | Units | $CV_1$ | $CV_2$ | $CV_3$ |
|---|---|---|---|---|---|
| $C_1$ | Year | – | 2015 | 2022 | 2024 |
| $C_2$ | Estimated price | $K | 30 | 60 | 100 |
| $C_3$ | Range | km | 400 | 600 | 800 |
| $C_4$ | Power output | KW | 100 | 150 | 400 |
| $C_5$ | Hydrogen tank capacity | kg | 4.4 | 5.5 | 6 |
| $C_6$ | Horse power | – | 130 | 180 | 550 |
| $C_7$ | Max torque | Nm | 260 | 350 | 410 |
| $C_8$ | 0 to 100 acceleration time | s | 4.5 | 8 | 12.5 |
| $C_9$ | Max speed | km/h | 130 | 170 | 250 |

COMET models have almost inverted MEJ (normalized Hamming distance close to 1), and it is expected that the resulted rankings for those models are almost reversed ($r_w$ value close to -1). The Pearson $r$ correlation between those two vectors is approximately $-0.85$, implying a negative correlation between those variables.

## 4.2 Example of Hydrogen Cars Evaluation

We present a case study of the evaluation of hydrogen cars based on the following criteria: year of the start of the production, approximated or estimated price, range of the car, technical parameters of the engine, tank capacity, acceleration and maximum speed. All criteria are presented in Table 1 along with the measurement units and characteristic values required to create and identify the COMET model.

The data of the alternatives were manually collected from the manufacturer's websites during the preliminary stage of the study, and the characteristic values were selected based on the minimum, maximum, and median values of the collected alternatives. The alternatives and the respective values of the criteria are presented in Table 2.

Table 2: Alternatives' data.

| $A_i$ | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ | $C_9$ |
|---|---|---|---|---|---|---|---|---|---|
| $A_1$ | 2023 | 50.00 | 646 | 128 | 5.60 | 182 | 406 | 9.20 | 161 |
| $A_2$ | 2023 | 60.00 | 612 | 135 | 6.33 | 161 | 394 | 9.20 | 179 |
| $A_3$ | 2021 | 59.00 | 579 | 103 | 5.46 | 174 | 299 | 9.00 | 165 |
| $A_4$ | 2019 | 45.00 | 437 | 155 | 4.40 | 211 | 364 | 5.80 | 160 |
| $A_5$ | 2022 | 30.00 | 400 | 150 | 4.40 | 134 | 260 | 7.80 | 130 |
| $A_6$ | 2015 | 66.50 | 594 | 100 | 5.64 | 136 | 406 | 12.50 | 160 |
| $A_7$ | 2024 | 90.00 | 504 | 295 | 6.00 | 401 | 347 | 6.00 | 180 |
| $A_8$ | 2023 | 45.00 | 590 | 134 | 5.60 | 182 | 300 | 7.80 | 170 |
| $A_9$ | 2022 | 68.00 | 800 | 220 | 5.43 | 300 | 347 | 6.50 | 200 |
| $A_{10}$ | 2022 | 100.00 | 800 | 400 | 5.43 | 550 | 347 | 4.50 | 250 |

Each decision maker has their own preferences, and therefore we need to identify personalized decision models using the COMET method. However, if we try a straightforward approach to solving this problem using this decision problem, we will fail because of the dimensionality problem. The decision maker will need to compare $t = 3^9 = 19683$ characteristic objects, which will result in $\frac{t(t-1)}{2} = 193,700,403$ pairwise comparisons. However, as we showed in Section 3, there are several methods to drastically reduce the number of pairwise comparisons, namely the ESP-COMET approach, the Triad Support algorithm, and the structural model approach.

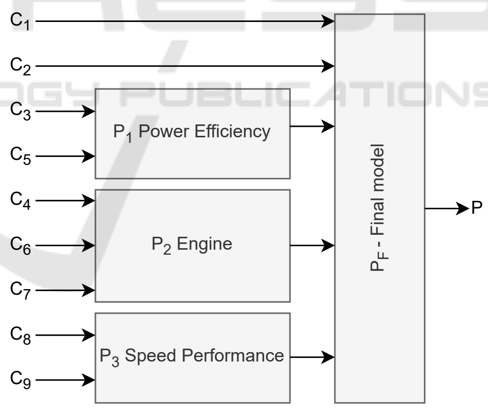


Figure 2: Structural division of the problem.

Taking this into account, we first divide our decision problem into four submodels, as shown in Fig. 2. This structure logically aggregates the criteria that determine the power efficiency of the vehicle, engine power, speed performance, and price and production year in the final model. Next, we asked three decision makers $E1$, $E2$, and $E3$ for input to identify six decision models with this structure: Each decision maker identifies two models, one using the ESP-COMET approach and the other using the Triad Support algorithm. Exemplary results of the identification process can be seen in Fig. 3, where three MEJ matrices identified using the Triad Support algorithm are presented. The final model for each decision maker was automatically calculated based on the importance weights of the criteria provided by each of them. Using the ESP-COMET approach does not require pairwise comparison and manual identification. Usage of the structural approach requires only 423 pairwise comparisons instead of 193 million, which is more than 450 thousand times less. However, the Triad Support algorithm provides an additional reduction, which depends on the decision maker and, in the case of $E1$ (Fig. 3), results in only 182 comparisons.

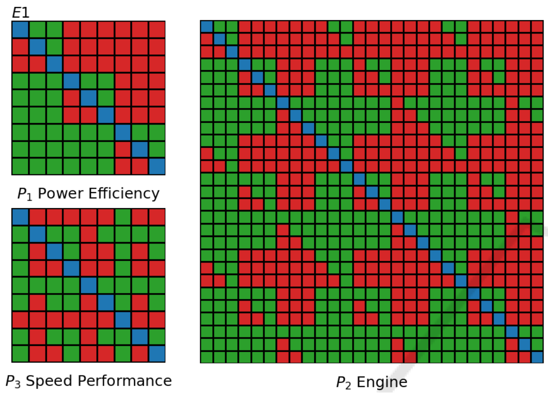


Figure 3: The MEJ matrices for submodels identified by the first expert with the help of Triad Support algorithm. Green, blue and red values represent values 1, 0.5 and 0 respectively.

For the sake of shortness, we do not demonstrate the rest of the models but present the resulting rankings $R_i$ in Table 3 for the six identified models: $E1$, $ESP^{(E1)}$, $E2$, $ESP^{(E2)}$, $E3$, $ESP^{(E3)}$, where $Ej$ is a model built using the Triad Support algorithm by j$-th$ decision maker and $ESP^{(Ej)}$ is the model built using the ESP-COMET approach using input from j$-th$ decision maker.

Table 3: Rankings obtained using all six models.

| $A_i$ | $R_i$ $E1$ | $R_i$ $ESP^{(E1)}$ | $R_i$ $E2$ | $R_i$ $ESP^{(E2)}$ | $R_i$ $E3$ | $R_i$ $ESP^{(E3)}$ |
|---|---|---|---|---|---|---|
| $A_1$ | 1 | 1 | 3 | 5 | 2 | 2 |
| $A_2$ | 7 | 8 | 9 | 9 | 7 | 7 |
| $A_3$ | 6 | 4 | 7 | 7 | 6 | 6 |
| $A_4$ | 5 | 6 | 5 | 3 | 4 | 4 |
| $A_5$ | 3 | 5 | 10 | 10 | 1 | 1 |
| $A_6$ | 8 | 7 | 8 | 8 | 10 | 9 |
| $A_7$ | 10 | 10 | 4 | 4 | 9 | 10 |
| $A_8$ | 2 | 2 | 6 | 6 | 3 | 3 |
| $A_9$ | 4 | 3 | 2 | 2 | 5 | 5 |
| $A_{10}$ | 9 | 9 | 1 | 1 | 8 | 8 |

Table 3 contains the ranking for all identified models. As we can see, there are little differences between $R_i$ $Ej$ and $R_i$ $ESP^{(Ej)}$ rankings which are expected behavior. For the $E1$, the most preferred alternative is $A_1$, and the least preferred is $A_7$. Notice that the differences in rankings between the models identified manually and automatically for $E1$ begin at the second position of the ranking. The most preferred alternative for a second expert is $A_1$0, which landed ninth and eighth in other rankings. The second most preferred alternative for $E2$ is $A_9$, and the differences in these rankings can be visible only at the 3rd and 5th positions. The rankings $R_i$ $E3$ and $R_i$ $ESP^{(E3)}$ are almost the same, with only two last alternatives swapped. In further investigation, we can see that the rankings created using models from $E1$ and $E3$ are generally similar, but the rankings provided by the $E2$ models differ significantly.

The conclusions about the similarity of the rankings are clearly visible in Fig. 4 where the heatmap of Weighted Spearman's $r_w$ correlation values is presented. As expected, we can see that the rankings provided by the models identified by the input of $Ej$ expert (e.g. $Ej$ and $ESP^{(Ej)}$) are similar. Between models of the expert $E1$ Weighted Spearman's correlation value is 0.92. This correlation is equal to 0.94 for $E2$ and 0.997 for $E3$. It proves the point that automatic identification using ESP can provide results that are very similar to the manually identified models. The rankings of the $E1$ models are generally similar to the ranks obtained with $E3$ due to the similar preferences of both experts. However, the correlation values of the models $E1$ and $E3$ with models of $E2$ are close to zero, which implies that these rankings have really low correlation or are not correlated at all. This shows that $E2$ has very different preferences from the other two experts.

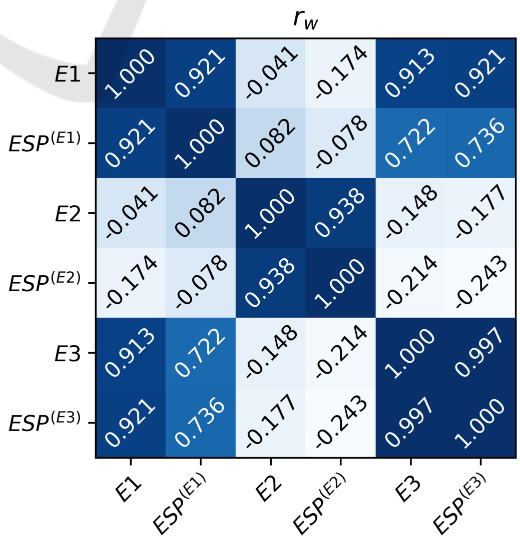


Figure 4: Weighted Spearman's $r_w$ correlation values between all rankings (rounded up to 3 positions).

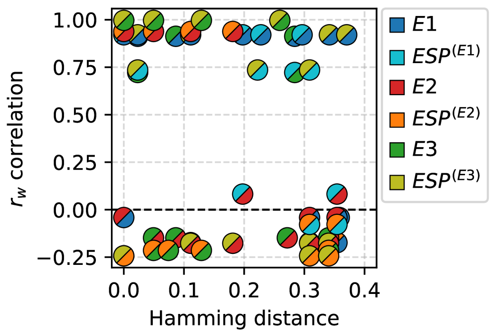


Figure 5: Relations between hamming distances between MEJ and $r_w$ correlation between final rankings for each submodels.

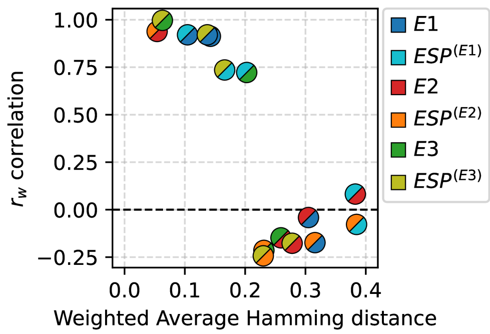


Figure 6: Relations between Weighted Average normalized Hamming distance between MEJ and $r_w$ correlation between results in different models.

However, is it possible to predict the similarity of the results on the basis of the similarity of the models? To investigate this, we prepare the visualization in Figure 5 in which each dot represents a comparison between submodels for two different experts. For example, one of the dots is created by calculating the Hamming distance between the $P_1$ submodel of $E1$ and the respective submodel of $E3$ and Weighted Spearman's correlation between final rankings of those two models (e.g., $E1$ and $E3$ models). In this visualization, we can see that there is no easy way to tell if we get high or low similarity in the results based on the Hamming distances between different submodels.

### 4.3 Weighted Average Hamming Distance

The simulation designed showed that there is a correlation between the Hamming distance between two different MEJ matrices and the $r_w$ correlation between the final ranking obtained using these two models in the case of the monolithic model. However, the problem is less trivial if we need to compare structural models. Therefore, we propose to use the Weighted Average Normalized Hamming Distance $d_{\mathbf{w},H}$, which allows us to get a value that will aggregate all submodels. The weights should be determined based on how many criteria are included in the specific submodel, and then the final results should be divided by the sum of weights to obtain the normalized values (3).

$$d_{\mathbf{w},H} = \frac{w_i \cdot d_H(MEJ_i^{(1)}, MEJ_i^{(2)})}{\sum_{i=1}^{n} w_i}, \qquad (3)$$

where $w_i$ is a weight for the $i$-th submodel, $d_H(MEJ_i^{(1)}, MEJ_i^{(2)})$ is the normalized Hamming distance between MEJ for the $i$-th submodels for two different experts calculated according to (2).

Based on the structure of the problem 2, we can assign the following weight vector: $\mathbf{w} = \{\mathbf{2}, \mathbf{3}, \mathbf{2}, \mathbf{9}\}$ for the set of submodels $\{P_1, P_2, P_3, P_F\}$, based on the number of criteria aggregated using the model.

Next, we visualize the relation between the Weighted Average Normalized Hamming distances and the respective $r_w$ correlations in Figure 6. It can be clearly seen that we can distinguish two clusters with a Weighted Average Hamming distance lower than or higher than 0.2. It can be seen that we obtain a smaller distance and a higher similarity of results for models identified toward similar preferences (that is, rankings $E1$, $E3$, and $ESP$ rankings for them, as well as manual and $ESP$ ranking for $E2$). However, if we move to the combinations of other rankings with the ranks identified based on the preferences of the expert $E3$. Those models are more different, which can be seen in the Weighted Average Normalized Hamming distance values, and the final rankings are slightly reversed or uncorrelated (based on the respective values $r_w$. It shows that we can predict to a certain point if or not we will get similar results in terms of rankings even for the structural model, even if there are no alternatives or we don't want to evaluate them.

## 5 CONCLUSIONS

In this paper, we propose a simple but effective solution to approximate the differences in the results of the identified COMET models. We also show how to adapt this approach to a more complex structural model and show its efficiency in the practical case study of choosing a hydrogen car. In addition to that, we show that the ESP-COMET approach can provide results that can be obtained using the manual or triad-supported identification of the MEJ. This underlines its usefulness in solving practical decision-making problems, as this approach eliminated the pairwise comparison step of model identification, but allowed us to achieve a similar level of accuracy.

However, the work has some limitations that should be addressed in future research. In addition to the fact that the normalized Hamming distance and the average normalized Hamming distance provide satisfactory results in predicting $r_w$ values for both monolithic and structural models, the precision of this method can be higher and this fact should be investigated in future work. This approach should also be investigated in depth in other study cases to show its practical applicability, as well as extended to a larger sample of people, to better investigate differences in models and preferences. There is also a possibility to generalize the approach for other methods such as AHP or Ranking Comparison (RANCOM) methods.

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