Assessing the Impact of Criterion Significance on Ranking Stability - Offshore Wind Farm Case Study

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Abstract. The assessment of offshore wind farm (OWF) projects typically relies on multi-criteria decision analysis (MCDA), which often involves a large number of evaluation criteria reflecting technical, economic, environmental, and social aspects. While comprehensive, high-dimensional decision models may suffer from reduced transparency and increased sensitivity of results. This paper proposes a data-driven framework for criterion significance assessment and controlled reduction of MCDA models. The framework combines objective significance measures, namely the coefficient of variation (CV) and entropy, with a structured sensitivity analysis based on percentile-based exclusion thresholds. Using the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method, the framework is applied to the evaluation of seven OWFs described by 32 criteria. The results demonstrate that even criteria classified as weakly significant can substantially influence ranking outcomes, including changes in the ranking leader. At the same time, the proposed sensitivity-based reduction procedure enables the identification of stable and robust alternatives and reveals the degree of ranking dependence on the criterion set. The framework improves the transparency and interpretability of multi-criteria assessments and provides practical support for decision-makers by explicitly quantifying the risks associated with model simplification.

Keywords: Offshore wind energy · Multi-criteria decision analysis · TOPSIS method · Criterion significance · Sensitivity analysis · Multi-criteria model reduction.

1 Introduction

Offshore wind energy is a strategic component of the energy transition, contributing to energy security, independence, and economic development. As a

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domestic renewable energy source, it supports the diversification of the energy mix while reducing dependence on energy imports and geopolitical risk [10]. Offshore wind has high potential to provide stable and predictable energy resources [13]. Due to their technological complexity, high capital intensity, and significant economic, environmental, and social impacts, offshore wind farm (OWF) projects are commonly evaluated using multi-criteria decision analysis (MCDA) [22]. Multi-criteria models provide a basis for justifying the selection of projects in which investors and financial institutions decide to invest capital [8]. On the other hand, when preparing concessions and regulations, the state administration needs tools to assess the impact of investments on the economy and the environment [21]. Multi-criteria assessment enables a holistic, transparent, and objective analysis of investments of strategic importance that impact the economy, the environment, energy security, and society [15]. Such assessments require the simultaneous consideration of numerous criteria and dimensions to adequately capture investment value and risk [1].

In fields where MCDA methods are applied, such as investments or renewable energy systems, decision-making models often comprise extensive sets of criteria that describe technical, economic, environmental, and social aspects. However, a wide range of criteria can increase computational complexity, lead to information redundancy, and reduce the transparency and interpretability of results, which consequently hinders the decision-making process [7]. Consequently, the literature increasingly emphasizes the need to simplify models by identifying and eliminating less relevant criteria, while maintaining the resilience of decision outcomes [12].

The literature presents various approaches to selecting criteria for reducing model complexity in MCDA. Habibollahi et al. proposed an approach integrating Principal Component Analysis (PCA) with Multi-Criteria Decision-Making (MCDM), specifically the MOORA (Multi-Objective Optimization on the Basis of Ratio Analysis Method) method. PCA identifies dominant components and reduces dimensionality, while MOORA ranks the original features based on their compliance with these components [5]. The indicated approach incorporates multiple decision-making indicators into a unified structure. It improves the accuracy of variable reduction in high-dimensional data, providing a robust and generalized strategy for unsupervised feature selection across various fields. In turn, Jokar et al. proposed a hybrid model that integrates MCDM and a machine learning (ML) method called Random Forest regression to identify relationships between criteria and eliminate redundant criteria [6]. The proposed model accounts for interval-based fuzzy uncertainty when evaluating renewable energy projects. In another research paper, Li et al. presented a multi-criteria optimization classifier (MCOC) based on the LASSO (Least Absolute Shrinkage and Selection Operator) method (LASSO-MCOC) for simultaneous classification and feature selection [14]. The application of the proposed method was demonstrated on the problem of credit risk assessment. In another study, ridge regression, LASSO, and Elastic-Net methods were applied to reduce dimension-

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ality in various simulated datasets with different characteristics, as well as in real-world datasets [11].

A review of the literature on MCDM highlights the growing importance of model dimensionality reduction methods in relation to the number of criteria. The methods presented include both statistical approaches, such as PCA, and hybrid techniques that combine ML and MCDM. To address the challenge of high-dimensional decision models in OWF assessment, this paper proposes an alternative approach in the form of a fully transparent procedure based on a combination of the coefficient of variation (CV) and entropy as measures of criterion significance. The presented approach is extended to include an iterative sensitivity analysis used directly for their selection. Proposed data-driven framework for criterion significance analysis and controlled model reduction integrates classical MCDM methods with objective significance measures and a structured sensitivity analysis [4], enabling the systematic identification of weakly informative criteria and the evaluation of their impact on ranking stability. By transforming criterion reduction from an arbitrary preprocessing step into a transparent and risk-aware procedure, the proposed approach supports reliable decision-making while maintaining robustness of the evaluation results. Such an approach not only allows for an objective assessment of the significance of the criteria but also enables a controlled reduction in their number while preserving the interpretability of the decision-making model, which represents a significant addition to existing approaches in the literature.

The rest of the paper is organized as follows. Section 2 explains applied methodology and describes considered dataset, in section 3 research results are presented and section 4 provides conclusions and future works.

2 Methodology

The aim of this paper is to present the data-driven framework developed for criterion significance assessment and controlled model reduction in MCDM problems. Its purpose is to reduce the complexity of decision models by excluding criteria of lowest significance. The flow of the mentioned framework is demonstrated in Figure 1. The structuring process incorporates building a decision model, including selected evaluation criteria (C), alternatives (A), and efficiency values (E) collected for considered alternatives in relation to criteria. The proposed framework involves determining the significance of a complete set of criteria using two measures of significance: the coefficient of variation (CV) [20] and entropy [17]. The choice of CV and entropy is justified by the objective, data-driven nature of these measures, as well as their interpretive complementarity and the ability to cross-validate results, which enhances the reliability of the procedure. CV reflects the diversity of alternatives relative to the criteria, while entropy measures the amount of information contained in the criterion [9, 16]. Subsequently, in order to determine the thresholds for including criteria according to CV, the lower quartile is determined, while for entropy, the upper quartile is determined. This is because high entropy means low diversity, unlike CV, whose high values indi-

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cate good diversity. After eliminating the criteria from the model separately for CV and entropy, the alternatives are evaluated using a multi-criteria method, and then rankings are determined. The rankings obtained are compared with the initial ranking constructed for the full set of criteria using Spearman's correlation measure [21]. If, after excluding the criteria, there are no differences between the compared rankings or they are insignificant (e.g., single shifts of small range in the lower positions of the ranking), it means that the previously identified criteria of low significance do not have a significant impact on the assessment result, so they can be safely removed from the model without the risk of oversimplification and decision mistakes. If the changes are significant, occur in high positions, especially if they concern the leader or have a significant scope, it means that the excluded criteria, despite their low significance, nevertheless contribute significant informational value to the model, differentiating between alternatives, and their elimination is inadvisable as it risks erroneous decisions.

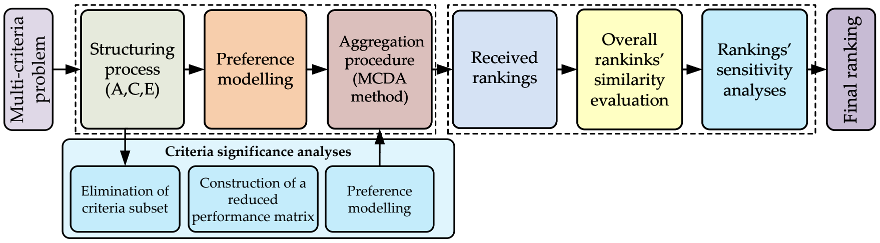

Fig. 1: The flow of the proposed framework for reducing the least significant criteria for multi-criteria decision-making.

The following stage in the proposed framework is sensitivity analysis. This procedure involves considering a given range of elimination thresholds for criteria according to their significance for both CV and entropy, so that these thresholds increase. We adopt successive percentiles for CV and entropy values as thresholds. In subsequent steps of the analysis, the groups of criteria removed from the model increase as the significance threshold for the criteria to be excluded increases. At each step, we determine which criteria are excluded, their number, the percentage they represent of the total number of criteria, the number of changes in the compared rankings before and after the elimination of criteria, the Euclidean distance between the values of the aggregated measure of the multi-criteria method, and the correlation value of the compared rankings. Sensitivity analysis allows us to establish a safe threshold for excluding the least important criteria, thus enabling us to simplify the model without losing important information. In addition, it provides additional information about the stability of the evaluated alternatives, their similarity, the stability of decisions, and identifies critical criteria. The dataset is described below in subsection 2.1, followed by

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the methods used in the research, including the TOPSIS (Technique for Order Preference by Similarity to Ideal Solution) method provided in subsection 2.2 and significance measures: CV explained in subsection 2.3 and entropy given in subsection 2.4.

2.1 The dataset

This research covers seven OWFs planned for construction in Poland's exclusive economic zone in the Baltic Sea, in the Słupsk Shoal (Ławica Słupska) area, as part of the first stage of offshore wind energy development, which constitutes the first phase of the support system. These OWFs are A_1 - OWF Bałtyk II, A_2 - OWF Bałtyk III, A_3 - Baltica 2, A_4 - Baltica 3, A_5 - F.E.W. Baltic II, A_6 - Baltic Power, and A_7 - B-C Wind. Due to its size, the dataset containing performance values for the considered OWFs in relation to 32 model criteria listed below is available in an open repository `https://github.com/energyinpython/Offshore-wind-farms-assessment`. The data sources used to develop the multi-criteria assessment model for OWFs included publicly available online reports, news websites, market and energy information centers, OWF project websites, technical and non-technical project documentation, and government websites.

C_1 Power [MW]
C_2 Total area [km^2]
C_3 Distance from shore [km]
C_4 Length of submarine export cable [km]
C_5 Average depth [m]
C_6 Maximum depth [km]
C_7 Average wind speed [m/s]
C_8 Planned launch year [number]
C_9 Efficiency of water basin utilization [MW/km^2]
C_{10} Estimated annual production [MWh/year]
C_{11} Covering household energy demand [number of households/year]
C_{12} New direct jobs [full-time equivalent jobs in the OWF life cycle]
C_{13} New indirect jobs [full-time equivalent jobs in the OWF life cycle]
C_{14} CO$_2$ reduction in the OWF life cycle [million tons]
C_{15} SO$_2$ reduction in the OWF life cycle [tons]
C_{16} NO$_2$ reduction in the OWF life cycle [tons]
C_{17} Dust reduction in the OWF life cycle [tons]
C_{18} Support for education [rating 1-5]
C_{19} Support for local communities [rating 1-5]
C_{20} Raw material savings – hard coal in the OWF life cycle [million tons]
C_{21} Raw material savings – hard coal in the OWF life cycle [PLN billion]
C_{22} Savings on the purchase of CO$_2$ emission permits in the OWF life cycle [PLN billion]
C_{23} Budget revenue from concession fees [PLN million]
C_{24} Budget revenue from location permit fees [PLN million]
C_{25} Share of local content in the development phase [PLN million]
C_{26} Share of local content in the operational phase [PLN million per year]
C_{27} Investment in installation port [1/0]
C_{28} Support for entrepreneurship [rating 1-5]
C_{29} Support for innovation [rating 1-5]

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C_{30}	CAPEX investment costs [PLN million]
C_{31}	Operating costs (OPEX) [PLN million per year]
C_{32}	Liquidation costs (DECEX) [PLN million]

The research work involved the application of the developed framework for reducing the number of criteria in the model. This framework assumes the exclusion of low-variability criteria from the evaluation process, which, due to their low informational significance, are presumably the least important for the decision-making process. CV and entropy were used as measures of criterion significance. In the first stage of the study, criteria with a CV value below the lower quartile were excluded from the assessment. In the case of entropy, because a high value of this measure means low relevance, criteria with a value above the upper quartile were excluded. In order to compare the rankings obtained from the reduced dataset, their correlation with the ranking of the full dataset was measured.

In the second part of the study, a sensitivity analysis [18] was performed by modifying the criterion exclusion threshold to examine the stability of the results when removing the least significant criteria and the dependence of decisions on criteria of little informational value. Consecutive percentile values were used as criterion exclusion thresholds. The TOPSIS method [2] was applied to rank the OWFs. TOPSIS evaluates alternatives based on their distance to the ideal and anti-ideal solutions, assigning higher rankings to alternatives closer to the ideal point. Due to its simplicity, intuitive interpretation, and widespread use in MCDM problems, TOPSIS is a suitable choice for comparing alternatives under a large set of criteria [19].

2.2 The TOPSIS Method

Step 1. Normalize the decision matrix $X = [x_{ij}]_{m \times n}$ including performance values x_{ij} collected for considered alternatives in relation to criteria assessment. For the normalization procedure, the Minimum-Maximum or another normalization method can be utilized. In Minimum-Maximum normalization r_{ij} normalized values are received by using Equation (1) for profit (r^{+}_{ij}) and cost (r^{-}_{ij}) criteria.

$$r^{+}_{ij} = \frac{x_{ij} - min_j(x_{ij})}{max_j(x_{ij}) - min_j(x_{ij})},\ r^{-}_{ij} = \frac{max_j(x_{ij}) - x_{ij}}{max_j(x_{ij}) - min_j(x_{ij})} \tag{1}$$

Step 2. Calculate the weighted normalized decision matrix with Equation (2). This paper applies equal weights due to multiple simulations that exclude criteria based on their significance.

$$v_{ij} = w_j r_{ij} \tag{2}$$

Step 3. Determine the Positive and Negative Ideal Solution (PIS and NIS) using Equation (3). PIS incorporates the maximums of the weighted normalized decision matrix. On the other hand, NIS includes its minimums.

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$$v_j^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} = \{max_j(v_{ij})\},\; v_j^- = \{v_1^-, v_2^-, \ldots, v_n^-\} = \{min_j(v_{ij})\} \tag{3}$$

Step 4. Calculate the distance from PIS and NIS for each alternative employing (4). The default distance metric in the TOPSIS method is Euclidean distance.

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2},\; D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \tag{4}$$

Step 5. Calculate the closeness coefficient for each alternative under consideration as Equation (5) shows. The alternative with the highest C_i is the ranking leader.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{5}$$

2.3 Coefficient of Variation (CV)

CV is applied as a measure of significance based on data variability (data-driven) [3]. Low CV values indicate slight variation between alternatives in terms of the criterion under consideration, which means they are of minor importance in the decision-making process. High CV values, on the other hand, indicate significant variation between alternatives in terms of the criteria, which implies that they are of high importance in the decision-making process. CV is calculated as Equation (6) presents.

$$CV_j = \frac{\sigma_j}{\overline{x}_j} \tag{6}$$

CV threshold below which criteria are excluded may, for example, be determined based on the lower quartile. Percentiles may also be employed to remove a defined percentage of criteria with the lowest informative value.

2.4 Entropy measure

Entropy may be an alternative or validation technique for CV, as it measures the amount of information in a criterion. A high entropy value indicates low diversity and, consequently, low decision relevance. The threshold for entropy above which criteria are excluded can be determined based on the upper quartile. It is also possible to use percentiles to remove a given percentage of the least informationally relevant criteria. To calculate entropy, first, normalization of the decision matrix performed in accordance with Equation (7) is necessary.

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{7}$$

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This allows to get normalized decision matrix $P = [p_{ij}]_{m \times n}$ where m defines alternatives number, n represents criteria number, $i = 1, 2, \dots, m$, and $j = 1, 2, \dots, n$, . Then calculate the entropy E_j for each j-th criterion according to Equation (8).

$$E_j = -\frac{\sum_{i=1}^{m} p_{ij} ln(p_{ij})}{ln(m)} \tag{8}$$

3 Results

In the first stage of the analysis, criterion significance was established using two data-driven measures: CV and entropy. The lower quartile (q_1) for CV and the upper quartile (q_3) for entropy were adopted as exclusion thresholds to identify the least significant criteria. In both approaches, the resulting reduction led to the elimination of the same eight criteria (C_2, C_3, C_5, C_6, C_7, C_8, C_9, and C_{19}), corresponding to 25% of the total number of criteria. The consistency of the eliminated criteria across both significance measures indicates a high level of agreement between CV and entropy in identifying weakly informative criteria. Subsequently, the TOPSIS closeness coefficients were calculated for two scenarios: the full model, including all criteria, and the reduced model excluding the identified least significant criteria. The comparative results for OWFs are presented in Table 1.

Table 1: Comparison of TOPSIS closeness coefficients and rankings before and after criterion reduction for criteria significance measured with CV and entropy.

	TOPSIS closeness coefficient			TOPSIS ranking		
A_i	Full dataset	CV q_1	Entropy q_3	Full dataset	CV q_1	Entropy q_3
A_1	0.5181	0.4623	0.4623	5	4	4
A_2	0.5297	0.4605	0.4605	3	5	5
A_3	0.6173	0.6144	0.6144	1	2	2
A_4	0.5287	0.5020	0.5020	4	3	3
A_5	0.3525	0.3058	0.3058	6	7	7
A_6	0.6053	0.6211	0.6211	2	1	1
A_7	0.3292	0.3304	0.3304	7	6	6

It can be observed that the rankings obtained after excluding the 25% least significant criteria differ from the ranking created for the full dataset, and the differences appear in all positions of the ranking. In the case of OWF A_2, the difference is as much as 2 positions, and for the other OWFs, 1 position. It is also important to note that after excluding the 25% least significant criteria, the leader of the ranking changes from A_3 to A_6. The total number of shifts between the rankings was 8. This means that there were quite a lot of them, considering the small number of alternatives considered. The Spearman correlation of the

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ranking for the reduced dataset with the ranking of the full dataset is 0.8214, and the Euclidean distance between them is 0.1051.

The results of the first part of the study showed that the least significant 25% of the criteria have a significant impact on the ranking obtained. This means that decisions and recommendations in the case of the OWFs under consideration are sensitive and strongly dependent on the least significant 25% of the criteria. Although these criteria were classified as the least significant according to CV and entropy, their joint exclusion leads to significant changes in the ranking, indicating that low individual variability does not necessarily mean little collective impact on the final ranking. It turns out that they strongly differentiate OWFs, and simplifying the model by excluding them cannot be recommended.

3.1 Sensitivity analysis

In the second part of the study, a sensitivity analysis was performed for CV and entropy to reveal the threshold for excluding criteria for which the ranking begins to change and to identify the least significant criteria that are irrelevant to the final ranking, which would allow the model to be simplified by excluding the least significant criteria without affecting the results. During the stepwise analysis, the criteria were excluded according to a stepwise change in the percentile value representing the significance threshold.

The results are presented in Tables 2 and 3, displaying the excluded criteria, their number, what percentage of the full dataset they represent, the number of shifts in the ranking in relation to the full dataset, and the Euclidean distance from the full dataset ranking. The charts display the TOPSIS closeness coefficient (C_i) values obtained during sensitivity analysis for CV (Figure 2) and entropy (Figure 4), as well as the rankings for CV (Figure 3) and entropy (Figure 5).

Table 2: Percentile-based exclusion thresholds used in the sensitivity analysis of criterion reduction for criteria significance measured with CV.

Exclusion percentile	Criteria excluded	Number of criteria excluded	% of criteria excluded	Shifts in rankings	Euclidean distance	Correlation
5	C_7, C_8	2	6.25	4	0.028	0.9286
10	C_5, C_6, C_7, C_8	4	12.5	6	0.0631	0.8929
15	C_5, C_6, C_7, C_8, C_{19}	5	15.625	6	0.0931	0.8929
20	C_2, C_5, C_6, C_7, C_8, C_9, C_{19}	7	21.875	6	0.0975	0.8929
25	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}	8	25	8	0.1051	0.8214
30	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}, C_{28}, C_{29}	10	31.25	8	0.1621	0.8214
35	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{13}, C_{19}, C_{28}, C_{29}	11	34.375	8	0.1569	0.8214
40	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{13}, C_{19}, C_{28}, C_{29}	11	34.375	8	0.1569	0.8214
45	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{13}, C_{19}, C_{28}, C_{29}	11	34.375	8	0.1569	0.8214
50	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{13}, C_{19}, C_{28}, C_{29}	11	34.375	8	0.1569	0.8214

In the case of sensitivity analysis for CV, it can be seen that already for the 5th percentile and the exclusion of 2 criteria from the decision-making process, there were 4 shifts in the ranking. At this point, there was also a change in the ranking leader from A_3 to A_6. The change in the leader, despite a slight reduction

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in the number of the least important criteria, means that they have a significant impact on the outcome of the decision-making process, as the stability of the leader is important in the multi-criteria assessment of OWFs.

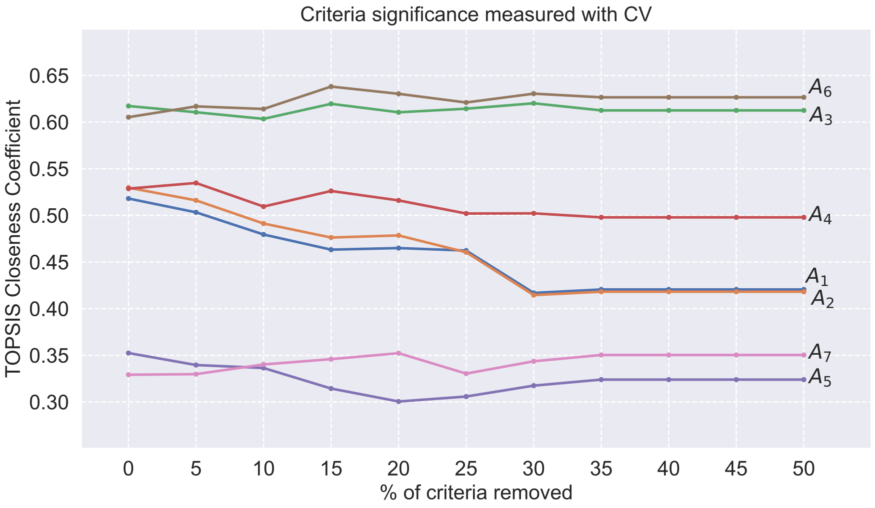

Fig. 2: Changes in TOPSIS C_i in sensitivity analysis for the criteria significance measured with CV.

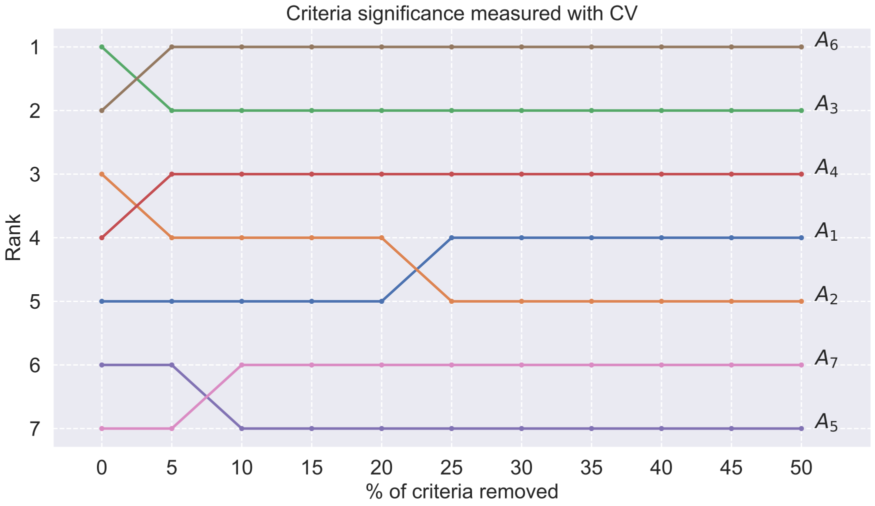

Fig. 3: Changes in TOPSIS rankings in sensitivity analysis for the criteria significance measured with CV.

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The increase in the reduction of criteria determined by the rising percentile value, indicating the reduction threshold according to their significance, shows that the new leader remains stable, and most OWFs, with the exception of A_2, do not change their position in the ranking by more than 1. The analysis carried out in the studied scope allows us to conclude that the alternatives with the best parameters enabling them to achieve top positions in the ranking are undoubtedly A_6 and A_3. The result obtained confirms their stability and resistance to changes such as the exclusion of certain criteria from the dataset.

Table 3: Percentile-based exclusion thresholds used in the sensitivity analysis of criterion reduction for criteria significance measured with Entropy.

Exclusion percentile	Criteria excluded	Number of criteria excluded	% of criteria excluded	Shifts in rankings	Euclidean distance	Correlation
95	C_7, C_8	2	6.25	4	0.028	0.9286
90	C_5, C_6, C_7, C_8	4	12.5	6	0.0631	0.8929
85	C_5, C_6, C_7, C_8, C_{19}	5	15.625	6	0.0931	0.8929
80	C_3, C_5, C_6, C_7, C_8, C_9, C_{19}	7	21.875	6	0.1039	0.8571
75	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}	8	25	8	0.1051	0.8214
70	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}, C_{28}, C_{29}	10	31.25	8	0.1621	0.8214
65	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}, C_{28}, C_{29}	10	31.25	8	0.1621	0.8214
60	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}, C_{28}, C_{29}	10	31.25	8	0.1621	0.8214
55	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}, C_{28}, C_{29}	10	31.25	8	0.1621	0.8214
50	C_2, C_3, C_5, C_6, C_7, C_8, C_9, C_{19}, C_{28}, C_{29}	10	31.25	8	0.1621	0.8214

The graph showing the closeness coefficient in the sensitivity analysis for CV additionally shows that the distance between the results obtained by A_3 and A_6 is small, which makes them almost equivalent for consideration. A_4 in third place is stable. A high degree of closeness was also found between A_1 and A_2, which indicates their similarity.

In the sensitivity analysis performed for entropy, the results are similar. More fluctuations were observed between the best OWFs, A_3 and A_6, which is due to a slightly different set of criteria excluded at this stage compared to CV. For CV, A_2 maintains its 4th position for longer, while for entropy, A_1 moves up to 4th place earlier. In terms of ranking positions, A_4 performs identically in the sensitivity analysis for both CV and entropy, which confirms the high stability of this OWF to changes in the set of evaluation criteria taken into account. On the other hand, A_5 and A_7 are OWFs that consistently perform the worst throughout the analysis. The Spearman correlation between the ranking for the full dataset and the rankings received for reduced datasets decreases as the percentage of excluded criteria increases. The closeness coefficient analysis for both significance measures shows the similarity and best performance of A_3 and A_6, and the stability of A_4 in third place. Next in the assessment are A_1 and A_2, which show great similarity and the greatest sensitivity to changes in the set of criteria. Finally, A_5 and A_7 close the ranking.

The proposed framework enables decision-makers to control the trade-off between model simplicity and decision reliability by explicitly quantifying the impact of criterion reduction on ranking stability. The results confirm that wind

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farms A_3 and A_6 have the potential to become projects recommended to stakeholders and investors. The indicated OWF alternatives are the most advanced projects among those considered in the study.

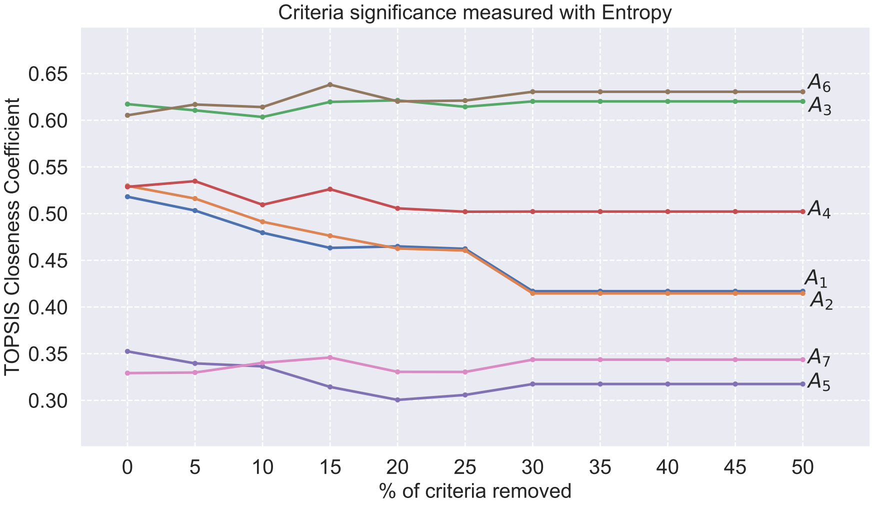

Fig. 4: Changes in TOPSIS C_i in sensitivity analysis for the criteria significance measured with entropy.

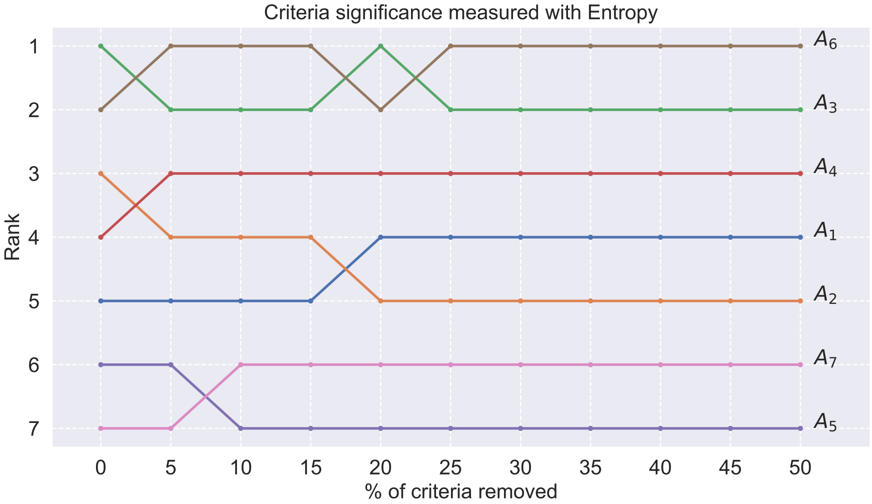

Fig. 5: Changes in TOPSIS rankings in sensitivity analysis for the criteria significance measured with entropy.

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Baltic Power (A_6) is the only project among those considered that plans to invest in an installation port in Świnoujście. In addition, it is characterized by high declared performance. Baltica 2 (A_3), on the other hand, stands out for its high declared performance and large area, which results in high productivity.

The proposed framework provides a systematic procedure for simplifying the decision-making model. From a practical perspective, it allows decision-makers to simplify the model while controlling the impact on the stability of results, which is particularly important in complex investment problems such as the evaluation of OWFs.

4 Conclusions

This paper proposed a data-driven framework for criterion significance assessment and controlled model reduction in MCDM problems. The approach combines classical MCDM methods with objective significance measures and a structured sensitivity analysis, allowing the influence of weakly informative criteria on decision outcomes to be systematically evaluated.

The results demonstrate that the framework effectively identifies both critical and redundant criteria, reveals the limits of acceptable model simplification, and supports the assessment of ranking robustness under varying reduction levels. Importantly, the proposed procedure enhances decision transparency and reduces the risk of unreliable recommendations caused by uncontrolled criterion elimination. Due to its simplicity, flexibility, and independence from expert judgment, the framework can be directly applied to complex decision problems with a large number of criteria, such as OWF assessment, and easily adapted to other multi-criteria evaluation contexts.

The proposed approach has limitations, including testing on a limited dataset for OWFs and a fixed number of criteria. Another limitation is the use of two measures of criterion importance - CV and entropy, which do not cover the broader range of possible preferences. Additionally, the proposed approach does not account for data uncertainty and preferences. Another shortcoming is the lack of consideration of other MCDA methods, which might yield slightly different rankings. Finally, to simplify the model, a single sensitivity analysis approach was used, which does not account for other variable selection methods.

Future work will focus on extending the proposed framework to other MCDM methods and alternative objective significance measures. Furthermore, future research should include a comparison of the proposed approach with other methods of criteria reduction, as well as an examination of how changes in weights affect the rankings after model reduction. Further research may include the integration of expert-based weighting schemes and the application of the framework to larger sets of alternatives and criteria to assess its scalability and generalizability.

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