Comparative Analysis of Solar Panels with Determination of Local Significance Levels of Criteria Using the MCDM Methods Resistant to the Rank Reversal Phenomenon

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Abstract: This paper aims to present an innovative approach based on two newly developed Multi-Criteria Decision-Making (MCDM) methods: COMET combined with TOPSIS and SPOTIS, which could be the basis for a decision support system (DSS) in the problem of selecting solar panels. Solar energy is one of the most promising and environmentally friendly energy sources because of the enormous potential of directly converting available solar radiation everywhere into electricity. Furthermore, ever-lower prices for photovoltaic systems make solar electricity more competitive with power from conventional energy sources, increasing interest in solar panels among companies and households. This fact generates the need for a user-friendly, objective, fully automated DSS to support the multi-criteria selection of solar panels. Both MCDM methods chosen for this purpose are rank-reversal-free and precise. First, the objective entropy weighting method was applied for determining criteria weights. Final rankings were compared by two ranking correlation coefficients: symmetrical r_w and asymmetrical WS. Then the sensitivity analysis providing local weights of alternatives for decision criteria was performed. The obtained results prove the adequacy and practical usefulness of the presented approach in solving the problem of solar panels selection.

Keywords: photovoltaic technology; renewable energy; solar energy; solar panels selection; decision support system; DSS; MCDM; multi-criteria decision-making; COMET; SPOTIS

1. Introduction

The necessity to reduce greenhouse gas emissions requires the development of energy systems with lower emissions than traditional fossil-fuel-based systems [1]. Sustainable energy systems are designed to have zero or low emissions of pollutants, carbon dioxide, and greenhouse gases into the atmosphere. Thus, their use contributes to the sustainable development of countries and regions. Sustainable development can be defined as integrated economic, social, environmental, and technological development with the consumption of natural resources that considers regeneration possibilities. Renewable energy sources include hydro, wind, solar, biomass, geothermal, wave, and tidal. Solar energy is considered a significant sector to support sustainable development due to its high availability, environmental harmlessness, and non-exhaustibility [2].

Photovoltaics are the future of renewable energy technology due to the unlimited availability of solar radiation and the ability of photovoltaic cells to convert it directly into electricity [3]. Solar PV systems produce clean energy that is not harmful to the environment and human health and allows reduction of CO_2 emissions, and its dynamic expansion in recent years in developing countries provides new jobs, contributing to the improvement of welfare. Moreover, renewable energy generation supports countries' independence from foreign energy imports, is characterized by high social acceptability, and is one of the factors of sustainable development. Photovoltaics acquire energy in a decentralized way, which contributes to building a sustainable energy management system. Solar energy is an effective way to ensure clean energy in industrialized and developing countries without the risk of pollution and volatility of supply. Due to several advantages of PV, policy makers are introducing encouragement programs to increase interest in this technology also within householders [4]. In this way, increasing individual participation in electricity generation from solar energy contributes to the expected decentralization of renewable energy generation [5]. Currently, there are two main generations of photovoltaic panels available in the world market: monocrystalline solar PV panels and polycrystalline PV panels. Monocrystalline solar PV panels have the highest efficiency and longest lifespan. They can be recognized by the presence of a black frame and are usually the most expensive. Polycrystalline PV panels, in comparison with monocrystalline solar PV panels, have a larger size and lower efficiency due to the presence of only one crystal. Their lifespan is usually shorter, and their price is lower. They are characterized by blue color. Photovoltaic systems provide an increase in energy potential by providing maximum efficiency with minimum losses.

Increasing the use of renewable energy sources is becoming a necessity in view of the exhaustion of fossil fuels due to industrial growth. PV can act as an environmentally friendly alternative to the mix of fossil fuels. The main component of a photovoltaic system is the solar panel. Solar panels consist of photovoltaic modules that create the photovoltaic array of the system, which generates and delivers electricity from sunlight. The cost of energy provided by PV systems is currently less than the cost of energy from fossil fuels [6]. Solar panels used alone generate electricity on a smaller scale, such as for individual businesses and homes. Solar panels consist of several individual solar cells composed of layers of silicon, phosphorus to provide a negative charge, and boron to provide a positive charge [2].

The solar panel's price depends on many factors such as size, brand, durability, and efficiency, for example. The presence of many attributes of solar panels makes their selection for a PV system a complex multi-criteria decision problem [7]. One of the most important decisions in designing a photovoltaic system is selecting the most suitable solar panel. Due to the increasing popularity of photovoltaic technology, more and more producers are offering solar panels with different parameters, which causes difficulties in choosing the most appropriate type. The aim of this paper is to propose a decision support system for the evaluation of solar panels used in photovoltaic installations.

The problem of renewable energy sources requires consideration of many different criteria that are often conflicting, uncertain data, and possible inaccuracies [8]. MCDM methods provide an opportunity to take into account the multidimensional nature of the considered problem. It enables comparative analysis of the evaluated alternatives according to the regarded quantitative and qualitative criteria. The MCDM approach supports rational decision making that takes into account the priorities of the decision-maker, which results in an optimal solution that combines all objectives of the decision-maker [9]. MCDM increases the compatibility of the decision-making process with the decision-maker's goals [10]. MCDM methods are suitable for evaluating available alternatives considering multiple attributes, prioritizing them, and selecting the most favorable one [11,12]. The goal of using MCDM methods is to correctly determine the values of the preference functions for the alternatives under consideration and to rank them appropriately [13,14]. One of the challenges that occur in the field of decision problems solved with MCDM is a phenomenon known as the rank reversal paradox. This problem involves the appear-

ance of changes in ranking when alternatives are added or removed from their set under consideration. In this situation, the order of priority for alternatives changes, which is incompatible with the concept of independence from alternatives. In order to eliminate this negative phenomenon, MCDM methods that are completely rank-reversal-free have been proposed in recent years, among which Characteristic Objects Method (COMET) [15], Stable Preference Ordering Towards Ideal Solution (SPOTIS) [16], and Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval (RAFSI) [17] can be mentioned. A method that is not susceptible to rank reversal is also the Sequential Interactive Model of Urban Systems (SIMUS) [18], R-TOPSIS [19,20], and R-VIKOR [21].

The purpose of this article is to present an innovative approach based on two newly developed MCDM methods, COMET combined with TOPSIS and SPOTIS, which could be applied in decision support systems to evaluate solar panels for photovoltaic systems. Criteria weights were determined using the objective entropy weighting method. The similarity of the obtained rankings was compared using two ranking correlation coefficients, symmetrical r_w and asymmetrical WS. A sensitivity analysis of the weights for COMET and SPOTIS was also performed to determine local weights for each alternative to investigate the dependence of the rankings on local criterion weights. The results indicate the high suitability of the methods considered in the study in DSSs to evaluate solar panels. Furthermore, both methods show adequacy for the considered problem. Furthermore, a strong influence of global and local criteria weights on the final preference value for both MCDM methods is visible.

The rest of the paper is organized as follows. Section 2 presents a literature review accounting for the recent application of MCDM methods to renewable energy problems focusing on solar energy. In Section 3.1 the background, assumptions, and steps of the methods and techniques used in this article are explained, while in Section 3.2, an illustrative case study for demonstrating the performance of the MCDM approach is presented.

Section 4 provides results, including comparative analysis of both rankings and sensitivity analysis of criteria weights. In Section 5, the proposed approach and obtained results are discussed. Finally, in Section 6, the summary and conclusions are presented and further work directions are drawn.

2. Literature Review

The effectiveness and usefulness of MCDM methods have been demonstrated through a comprehensive presentation of its applications to solve decision-making problems related to renewable solar energy. MCDM methods are used for solar farm site selection. The article [22] presents the use of Fuzzy AHP and Fuzzy ANP to select the most advantageous solar farm location in Iran. AHP, ELECTRE, TOPSIS, and VIKOR methods were used for comparative analysis in the solar farm site selection problem in Turkey [23]. To find the best location for a solar farm in Vietnam, FAHP was used to determine the criteria weights and TOPSIS to rank the alternatives considered [24]. Multi-criteria performance analysis of photovoltaic systems for India was performed using AHP [5]. The AHP method has also been applied to the site selection of the solar farm in Northern Ireland [25] and to select a site for a photovoltaic solar power plant in Northern Chile [26]. In another work, an integrated approach combining AHP with TOPSIS was used to solve the same problem in India [27]. AHP was used for the decision problem involving the selection of a photovoltaic system in a Caribbean Country [28]. The COMET method is also applied in solving decision problems related to renewable energy sources. The use of this method in selecting offshore wind farm locations is presented in the paper [29] and in [8], where a comparative analysis of the COMET method with TOPSIS and VIKOR is provided. The COMET method was also applied to the multi-criteria problem of selecting a hydropower plant infrastructure system [30]. In the problems of renewable energy sources, such as site selection for a wind farm, the PROMETHEE method was also applied, whose results were compared with AHP [31] and PROSA, which, similarly to PROMETHEE, is based on outranking relations and has similar mathematical foundations [32]. The solution to the multi-criteria problem

of identifying the most advantageous locations for wind farm installation for the province of Vojvodina in Serbia, using a model incorporating Decision Making Trial and Evaluation Laboratory (DEMATEL), Analytic Network Process (ANP), and Multi-Attributive Border Approximation area Comparison (MABAC) is presented in [33]. The DEMATEL-ANP method was used to determine the weights, and MABAC was applied to rank the alternatives by preference. Another model for selecting wind farm sites is based on the Best-Worst Method (BWM) to determine the weights of criteria and the Multi Attributive Ideal–Real Comparative Analysis (MAIRCA) method to determine the order of available sites according to preferences [34]. To assess regions' energy consumption and potential to implement sustainable energy policies with renewable energy sources in regions in Iran's Caspian Sea coastline, a model combining Level-Based Weight Assessment (LBWA) for weighting and Weighted Aggregated Sum Product Assessment (WASPAS) was used [35].

The above literature review confirms the usefulness of MCDM methods in both the RES problem and the solar energy problem addressed in this paper and justifies the choice of this approach for solving the multi-criteria decision problem of solar panel selection. However, using methods based on fuzzy numbers is advisable due to the risk of uncertainty and imprecision in the RES problem. An example is the use of the COPRAS-Z method for renewable energy selection [36], Fuzzy TOPSIS and Fuzzy VIKOR [37], and Fuzzy AHP [22,24] used in decision problems considering RES. Therefore, COMET, founded on fuzzy set theory, was chosen as the first method used as a DSS engine for selecting solar panels. The COMET method is an efficient approach that is completely rank-reversal-free because it is based on pairwise comparisons of characteristic objects that are not dependent on the alternatives under consideration. An additional advantage resulting from this is that the algorithm's complexity is independent of the number of alternatives being evaluated [15,29,38–40]. However, when the decision problem considers multiple criteria with more than two characteristic values, the number of COs pairwise comparisons increases exponentially. Most decision-making problems related to renewable energy sources require considering multiple criteria, so it was decided that it is appropriate to use a modification of the COMET method consisting of replacing the COs pairwise comparison step by an expert with automatic and objective evaluation using the TOPSIS method. In this modification, the SJ vector is not created from the MEJ matrix but is returned by the TOPSIS method integrated with the COMET method. The described approach was successfully applied, where the laborious step of pairwise comparison of COs by an expert was replaced using TOPSIS and PROMETHEE II, and the two strategies were then compared [41]. In many papers focused on RES issues mentioned in the literature review, the authors were not limited to one MCDM method, but a comparative analysis with other methods was performed. Comparison of results is essential because various MCDM methods may provide divergent results for the same decision problem. This happens because various methods use different algorithms [42]. The authors of this paper chose the SPOTIS method to perform a comparative analysis. This method has a simple algorithm and, like many other MCDM methods, requires a decision matrix with alternatives in rows and criteria in columns, a vector of weights for the criteria and information on whether they are profit or cost. The main assumptions of this method include the need to determine the absolute bounds of the values of each criterion in order to define the decision problem correctly. In this way, all values for each criterion are within the range defined by the set bounds. The SPOTIS method is based on calculating the normalized distance of each alternative with respect to the ideal solution point [16]. SPOTIS, similar to COMET, uses reference objects in the process of determining preferences of alternatives [43]. SPOTIS is thus a distance-based method, like COMET, in which preference values for alternatives are derived from the distance to the nearest characteristic objects and their values [40]. Besides being rank-reversal-free, this is another feature that SPOTIS has in common with COMET, which justifies the suitability of the SPOTIS method to perform a comparative analysis with the hybrid approach, which is COMET joined with TOPSIS. A commonly used approach for determining criteria weights for MCDM methods in decision problems

involving RES is applying objective weighting methods. Entropy objective weighting is based on Shannon entropy, which measures information uncertainty in the context of probability. Entropy provides intrinsic information about the relative intensity of the criteria. Its use for determining criteria weights is found in many works that are focused on RES problems [36,44–50]. The widespread use of entropy weighting became the motivation for applying this method to determine the vector of criteria weights in this study.

3. Materials and Methods

The approach based on COMET and SPOTIS methods, which is considered to be applied in a decision support system for selecting solar panels for PV systems, is presented as an illustrative example of a multi-criteria problem for selecting solar panels from among thirty available alternatives, considering six selection criteria.

3.1. Preliminaries

This section provides basic notions, concepts, fundamental assumptions and stages of MCDM methods and other techniques applied in this paper.

3.1.1. The COMET Method

The COMET is an innovative approach that solves decision-making problems by identifying with the participation of an expert decision-making model including many criteria [51]. The significant advantage of the newly developed method described here involves its complete robustness to the rank reversal paradox [15,41,43]. A description of the five stages of this method is presented below, based on [40]:

Step 1. Definition of the problem dimension with the expert involves choosing criteria number r: $C_1, C_2, \ldots, C_r$. Further, the collection of fuzzy numbers for every criterion C_i considered is chosen, i.e., $\tilde{C}_{i1}, \tilde{C}_{i2}, \ldots, \tilde{C}_{ic_i}$. Every fuzzy number establishes the value representing the membership for a given linguistic concept for concrete crisp values [52,53]. Accordingly, it is even suitable for non-continuous variables. Thus, the following result is received (1):

$$
\begin{aligned}
C_1 &= \left\{ \tilde{C}_{11}, \tilde{C}_{12}, \ldots, \tilde{C}_{1c_1} \right\} \\
C_2 &= \left\{ \tilde{C}_{21}, \tilde{C}_{22}, \ldots, \tilde{C}_{2c_2} \right\} \\
&\quad \ldots \\
C_r &= \left\{ \tilde{C}_{r1}, \tilde{C}_{r2}, \ldots, \tilde{C}_{rc_r} \right\}
\end{aligned}
\tag{1}
$$

where $C_1, C_2, \ldots, C_r$ are ordinates with fuzzy numbers for considered criteria.

Step 2. Generating characteristic objects that represent reference points in n-dimensional space. These objects can exist in reality, or they may be ideal and do not exist in the real world [54]. The characteristic objects (*COs*) are received with the Cartesian product of fuzzy numbers cores produced for every criterion [55]. It results in obtaining the ordered set of all *COs* (2): required here.

$$
\begin{aligned}
CO_1 &= \langle C(\tilde{C}_{11}), C(\tilde{C}_{21}), \ldots, C(\tilde{C}_{r1}) \rangle \\
CO_2 &= \langle C(\tilde{C}_{11}), C(\tilde{C}_{21}), \ldots, C(\tilde{C}_{r2}) \rangle \\
&\quad \ldots \\
CO_t &= \langle C(\tilde{C}_{1c_1}), C(\tilde{C}_{2c_2}), \ldots, C(\tilde{C}_{rc_r}) \rangle
\end{aligned}
\tag{2}
$$

where t expresses the number of *COs* (3):

$$
t = \prod_{i=1}^{r} c_i
\tag{3}
$$

Step 3. This step aims to determine the Matrix of Expert Judgement (*MEJ*) involving the expert. This procedure is performed by comparing pairwise the characteristic objects.

The result of this step is entirely dependent on the opinion of the expert [56]. The *MEJ* structure is displayed in Equation (4):

$$MEJ = \begin{pmatrix} \alpha_{11} & \alpha_{12} & \dots & \alpha_{1t} \\ \alpha_{21} & \alpha_{22} & \dots & \alpha_{2t} \\ \dots & \dots & \dots & \dots \\ \alpha_{t1} & \alpha_{t2} & \dots & \alpha_{tt} \end{pmatrix} \tag{4}$$

where α_{ij} is the effect of comparing CO_i and CO_j. The preferable CO receives a score equal to 1, and the less preferred object receives a score equal to 0. If there is no difference between compared objects, both of them obtain a score equal to 0.5 [57]. This process is totally dependent on the expert's statement and is shown by Equation (5):

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

where f_{exp} means an expert mental judgement function. In this study, however, the TOPSIS method was used instead of an expert function. This approach is presented in [41].

Subsequently, the vertical vector containing the Summed Judgements (SJ) is received according to Equation (6):

$$SJ_i = \sum_{j=1}^{t} \alpha_{ij} \tag{6}$$

The number of required comparisons is expressed by $p = \frac{t(t-1)}{2}$. It is due to the fact that for every considered element, $\alpha_{ij}\,\alpha_{ji} = 1 - \alpha_{ij}$ can be observed. The vector named P is generated as an outcome, where i-th row includes the estimated value of preference identified for CO_i.

In this paper, the expert's evaluation of characteristic objects by pairwise comparison is replaced by evaluating a matrix containing the set of possible COs by the TOPSIS method. The vector of preference values returned by the TOPSIS method acts as a vertical vector SJ. Based on SJ, a vector P is constructed in a further step according to the classical principles of the COMET method. The subsequent stages are no longer different from the classical version of COMET.

Step 4. Every characteristic object is transformed into a fuzzy rule, in which the grade of membership to specific criteria is a reason for activating inference in P_i as presented with details in (7). In such a manner, the whole fuzzy rule base is achieved, which estimates the mental judgment function of the expert and is represented by $f_{exp}(CO_i)$ [58].

$$IF\ C(\tilde{C}_{1i})\ AND\ C(\tilde{C}_{2i})\ AND\ \dots\ THEN\ P_i \tag{7}$$

Step 5. Every considered alternative A_i represents a collection of crisp numbers a_{ri} related to criteria $C_1, C_2, \dots, C_r$. It can be demonstrated as follows (8):

$$A_i = \{a_{1i}, a_{2i}, \dots, a_{ri}\} \tag{8}$$

3.1.2. The TOPSIS Method

TOPSIS (Technique of Order Preference Similarity) is a popular and widely used MCDM method for decision problems in many fields due to its uncomplicated algorithm and ease of use. The algorithm of this method is based on determining the distance from reference points to the considered alternatives that are represented by positive and negative ideal solutions [59]. Therefore, the best alternative is the option that is closest to the Positive Ideal Solution (PIS) and is the furthest away from the Negative Ideal Solution (NIS) [60].

Step 1. This step involves determining the normalized decision matrix. In minimum–maximum method normalization, which authors of this paper used, the normalized values

of r_{ij} are calculated for the profit criteria applying equation (9), while for the cost criteria, Equation (10) is applied.

$$r_{ij} = \frac{x_{ij} - min_j(x_{ij})}{max_j(x_{ij}) - min_j(x_{ij})} \tag{9}$$

$$r_{ij} = \frac{max_j(x_{ij}) - x_{ij}}{max_j(x_{ij}) - min_j(x_{ij})} \tag{10}$$

Step 2. The weighted values contained in the normalized decision matrix v_{ij} are calculated using Equation (11).

$$v_{ij} = w_i r_{ij} \tag{11}$$

Step 3. This step aims to calculate the values in vectors named positive ideal solution (PIS) values and negative ideal solution (NIS). The PIS (12) represents the maximum values determined for every criterion considered in the problem, and the NIS (13) represents minimum values. There is no necessity to split the criteria into cost and profit types here since the cost criteria were converted to profit criteria in the step, including the normalization procedure.

$$v_j^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} = \{max_j(v_{ij})\} \tag{12}$$

$$v_j^- = \{v_1^-, v_2^-, \ldots, v_n^-\} = \{min_j(v_{ij})\} \tag{13}$$

Step 4. Distance from PIS is calculated as Equation (14) shows and from NIS, according to Equation (15) for every alternative taken into account [42].

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2} \tag{14}$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \tag{15}$$

Step 5. The result for every alternative is computed as given in Equation (16). The values of this result, named preference values, are between 0 and 1. Thus, the best alternative has a preference value closest to 1.

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \tag{16}$$

3.1.3. The SPOTIS Method

Stable Preference Ordering Towards Ideal Solution, for which the acronym is SPOTIS, is a newly developed method dedicated to multi-criteria decision making [16]. The authors' main objective of the technique described was to introduce a new method that is rank-reversal-free (free of the phenomenon of reversing the ranking when changing the number of alternatives in the provided data). The detailed method applies the idea of reference objects and is based on distance measurement. In contrast to other MCDM techniques, for instance, TOPSIS and VIKOR, where reference objects are created from a decision matrix, the SPOTIS method needs the specification of data boundaries. Application of data borders to determine the Ideal Solution Point for a linear distribution of variants between ISP prevents ranking reversals.

To apply this method, a definition of data boundaries is required. For every criterion C_j, the maximum S_j^{max} and minimum S_j^{min} borders are chosen. The Ideal Positive Solution S_j^* is represented by $S_j^* = S_j^{max}$ for benefit criteria and by $S_j^* = S_j^{min}$ for cost criteria. The

decision matrix is expressed by $X = (x_{ij})_{m \times n}$, where x_{ij} represents the value of the attribute of the *i*-th variant for *j*-th criterion.

Step 1. The first stage of SPOTIS involves the determination of the normalized distances calculated for Ideal Positive Solution (17).

$$d_{ij}(A_i, S_j^*) = \frac{|S_{ij} - S_j^*|}{|S_j^{max} - S_j^{min}|} \tag{17}$$

Step 2. The second step of the SPOTIS procedure includes computation of weighted normalized distances $d(A_i, S^*) \in [0, 1]$ in accordance with (18).

$$d(A_i, S^*) = \sum_{j=1}^{N} w_j d_{ij}(A_i, S_j^*) \tag{18}$$

Completed ranking is established on the basis of $d(A_i, S^*)$ values. More preferred alternatives have lower values of $d(A_i, S^*)$.

The technique demonstrated here can be described by an alternative algorithm, which is presented in reference [16]. The authors of this paper described and applied this version since it is clear and understandable and since both versions provide the same results.

3.1.4. Entropy Weighting Method

In this weighting technique, the weights of the criteria are calculated by applying the measure of uncertainty included in a given piece of information [61].

Step 1. The procedure of normalization of input data is realized with the sum normalization method (19).

$$p_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \quad i = 1, \ldots, m; \ j = 1, \ldots, n \tag{19}$$

Step 2. The purpose of this step is to calculate the entropy value of *j*th criterion as Equation (20) presents.

$$E_j = -\frac{\sum_{i=1}^{m} p_{ij} ln(p_{ij})}{ln(m)} \quad j = 1, \ldots, n \tag{20}$$

Step 3. The last stage aims to compute the objective weight for *j*th by Equation (21).

$$w_j = \frac{1 - E_j}{\sum_{i=1}^{n}(1 - E_j)} \quad j = 1, \ldots, n \tag{21}$$

3.1.5. Weighted Spearman's Rank Correlation Coefficient

The calculation of the weighted Spearman correlation coefficient r_w is performed as shown in Equation (22), where N is ranking size and x_i, and y_i are the values in the compared rankings.

$$r_w = 1 - \frac{6 \sum_{i=1}^{N} (x_i - y_i)^2 ((N - x_i + 1) + (N - y_i + 1))}{N^4 + N^3 - N^2 - N} \tag{22}$$

For this coefficient, the top-ranked items are more significant. The importance weight is calculated for each comparison [42,57,62].

3.1.6. Rank Similarity Coefficient

The *WS* similarity coefficient of the ranking is calculated by Equation (23). N is ranking size, and x_i and y_i represent values in the compared rankings.

$$WS = 1 - \sum_{i=1}^{N} 2^{-x_i} \frac{|x_i - y_i|}{max(|x_i - 1|, |x_i - N|)} \tag{23}$$

It is an asymmetrical coefficient that is sensitive to significant changes in ranking. The value of this coefficient is closely related to the part of the rankings where differences occur. Thus, the differences appearing at the top of the rankings are more significant than those found at the bottom [42,57,62,63].

3.2. An Illustrative Case Study of a Multi-Criteria Solar Panel Selection Problem

Table 1 provides data for the six selected evaluation criteria after conversion to the units in the form of a decision matrix.

Table 1. Decision matrix including values of criteria for evaluated alternatives.

A_i	C_1	C_2	C_3	C_4	C_5	C_6
A_1	42.8000	10.8200	21.4000	213.8728	358.9595	10.1156
A_2	40.9300	9.8200	19.3600	193.2515	105.1288	11.0429
A_3	40.2000	9.9800	19.3600	193.2515	139.2638	11.0429
A_4	40.6000	10.4000	19.6000	196.4286	100.5952	10.7143
A_5	41.2000	10.3500	19.7000	196.5318	230.0578	10.4046
A_6	43.3000	10.5000	20.8000	208.0925	344.7399	10.4046
A_7	41.6700	10.0800	19.4800	188.6228	107.7844	11.1377
A_8	40.5600	9.9400	19.0000	189.3491	167.7515	11.0651
A_9	40.6000	10.0000	19.3000	192.7711	124.6988	11.3253
A_{10}	40.5000	10.2000	19.2100	191.6168	153.2934	11.3772
A_{11}	43.3000	9.5100	19.5700	189.3491	133.8757	11.3609
A_{12}	45.0400	10.5000	20.1000	200.0000	156.8421	10.2632
A_{13}	44.0000	10.3700	20.6000	205.7143	228.0000	11.1429
A_{14}	44.3000	10.2600	20.9000	208.5714	170.8571	11.1429
A_{15}	44.2000	10.5800	21.4000	214.2857	194.2857	11.1429
A_{16}	40.6600	10.5200	19.0000	189.9441	135.3352	11.1173
A_{17}	45.4000	10.2000	19.7000	196.7213	133.8798	10.9290
A_{18}	41.0000	10.9200	18.7000	187.5000	135.0978	11.0326
A_{19}	48.0000	10.8300	21.0000	211.0553	248.7437	10.3015
A_{20}	49.8600	10.3900	20.2000	201.4925	101.9900	10.2985
A_{21}	48.3000	9.6000	20.5000	204.4199	218.2320	11.6022
A_{22}	47.6200	9.6600	18.6000	186.5285	133.1606	11.2953
A_{23}	49.6000	10.6600	20.4000	206.4677	101.9900	10.9453
A_{24}	46.8000	9.5900	17.8900	179.2929	81.3990	11.3636
A_{25}	51.2000	10.2900	20.2000	201.9704	111.8227	11.2315
A_{26}	48.9100	10.2200	20.2000	202.0202	143.8889	11.6162
A_{27}	48.9100	10.7900	20.3800	203.9801	137.3134	11.4428
A_{28}	49.1400	11.0500	19.1000	190.9091	131.5636	10.6364
A_{29}	49.0000	10.2400	19.9000	198.0198	176.2376	11.6337
A_{30}	49.3300	10.8300	20.1000	200.9346	111.3178	11.6822

Data on the selected alternatives used in this study, including the values of their evaluation criteria, which are displayed in Table 2, were obtained from various websites. Evaluation criteria are listed in Table 3. Three criteria are profit types (C_2, C_3, C_4), and their direction is maximization, while the other three criteria are cost types (C_1, C_5, C_6), and their direction is minimization. The weights, reflecting the significance of the criteria in the decision-making process, were determined with the objective entropy weighting technique. As can be observed, noticeably, the highest weight value was assigned to cost criterion C_5, which is the cost per m^2. The second most important decision criterion is C_1, the open circuit voltage, which is similar to C_5 cost type. The least important criteria are C_2, profit type, and C_6, cost type.

Table 2. Data on the evaluated alternatives obtained from websites.

A_i	Name	Open Circuit Voltage (*V*)	Short Circuit Current (*A*)	Peak Power (*W*)	Cost ($)	Module Efficiency (%)	Weight (kg)	Area (m^2)
A_1	LG LG370Q1C-V5	42.80	10.82	370	621.00	21.40	17.5	1.73
A_2	Peimar SG315M	40.93	9.82	315	171.36	19.36	18.0	1.63
A_3	Phono Solar PS315M-20/U	40.20	9.98	315	227.00	19.36	18.0	1.63
A_4	Trina TSM-DD06M.05-330BK	40.60	10.40	330	169.00	19.60	18.0	1.68
A_5	LG LG340N1K-L5	41.20	10.35	340	398.00	19.70	18.0	1.73
A_6	LG LG360N1K-V5	43.30	10.50	360	596.40	20.80	18.0	1.73
A_7	Peimar SM325M	41.67	10.08	315	180.00	19.48	18.6	1.67
A_8	Q CELLS BLK-G5 320	40.56	9.94	320	283.50	19.00	18.7	1.69
A_9	Trina TSM-DD05H.05(II)	40.60	10.00	320	207.00	19.30	18.8	1.66
A_{10}	Heliene 320 Black Mono PERC Solar Panel	40.50	10.20	320	256.00	19.21	19.0	1.67
A_{11}	Canadian Solar CS1H-320MS	43.30	9.51	320	226.25	19.57	19.2	1.69
A_{12}	Q.Peak Duo BLK ML-G9+ 380	45.04	10.50	380	298.00	20.10	19.5	1.90
A_{13}	Panasonic EVPV360	44.00	10.37	360	399.00	20.60	19.5	1.75
A_{14}	REC Solar REC365AA	44.30	10.26	365	299.00	20.90	19.5	1.75
A_{15}	REC Solar REC375AA	44.20	10.58	375	340.00	21.40	19.5	1.75
A_{16}	Q CELLS DUO BLK-G6-340	40.66	10.52	340	242.25	19.00	19.9	1.79
A_{17}	Silfab SIL-360-NX	45.40	10.20	360	245.00	19.70	20.0	1.83
A_{18}	MIssion Solar Energy MSE345SX5T	41.00	10.92	345	248.58	18.70	20.3	1.84
A_{19}	LG420QAK-A6	48.00	10.83	420	495.00	21.00	20.5	1.99
A_{20}	JA Solar JAM72-S10-405MR	49.86	10.39	405	205.00	20.20	20.7	2.01
A_{21}	Solaria PowerXT-370R-PD	48.30	9.60	370	395.00	20.50	21.0	1.81
A_{22}	Astronergy CHSM6612M-370-HV Silver Mono Solar Panel	47.62	9.66	360	257.00	18.60	21.8	1.93
A_{23}	Trina TSM-DE15M-415	49.60	10.66	415	205.00	20.40	22.0	2.01
A_{24}	Canadian Solar CS3U-355P-35MM	46.80	9.59	355	161.17	17.89	22.5	1.98
A_{25}	Trina TSM-DE15H(II)	51.20	10.29	410	227.00	20.20	22.8	2.03
A_{26}	URE/NSP D7M400H8A	48.91	10.22	400	284.90	20.20	23.0	1.98
A_{27}	Phono Solar PS410M1-24/TH	48.91	10.79	410	276.00	20.38	23.0	2.01
A_{28}	MIssion Solar Energy MSE420SX6W	49.14	11.05	420	289.44	19.10	23.4	2.20
A_{29}	Q CELLS DUO L-G5.2	49.00	10.24	400	356.00	19.90	23.5	2.02
A_{30}	Q CELLS DUO L-G8.2-430	49.33	10.83	430	238.22	20.10	25.0	2.14

Table 3. Criteria selected for evaluation alternatives.

C_i	Criterion Name	Unit	Characteristic Values	Direction	Weight
C_1	Open Circuit Voltage	$[V]$	{39.798, 44.8977, 51.712}	min	0.0401
C_2	Short Circuit Current	$[A]$	{9.4149, 10.3033, 11.1605}	max	0.0100
C_3	Module Efficiency	$[\%]$	{17.7111, 19.855, 21.614}	max	0.0109
C_4	Peak Power per m^2	$[W/m^2]$	{177.5, 198.0988, 216.4286}	max	0.0119
C_5	Cost per m^2	$[\$/m^2]$	{80.585, 160.6035, 362.5491}	min	0.9171
C_6	Weight per m^2	$[kg/m^2]$	{10.0145, 11.027, 11.7991}	min	0.0100

4. Results

Preference function values and rankings of the evaluated alternatives obtained using COMET and SPOTIS are contained in Table 4.

Table 4. Preference values and rankings obtained for evaluated alternatives with COMET and SPOTIS.

A_i	COMET *P*	SPOTIS *P*	COMET *R*	SPOTIS *R*
A_1	0.2687	0.9194	29	30
A_2	0.8111	0.1104	2	3
A_3	0.6875	0.2181	9	15
A_4	0.8690	0.0878	1	2
A_5	0.4797	0.5091	24	26
A_6	0.2621	0.8818	30	29
A_7	0.7824	0.1217	3	6
A_8	0.5640	0.3145	16	21
A_9	0.7311	0.1739	5	9
A_{10}	0.6136	0.2663	15	19
A_{11}	0.6178	0.2161	14	13
A_{12}	0.5503	0.2801	19	20
A_{13}	0.4296	0.5106	25	27
A_{14}	0.5276	0.3246	21	22
A_{15}	0.5021	0.3955	23	24
A_{16}	0.6925	0.2062	8	11
A_{17}	0.6205	0.2142	13	12
A_{18}	0.6837	0.2054	10	10
A_{19}	0.3501	0.5814	27	28
A_{20}	0.7041	0.1180	7	5
A_{21}	0.3401	0.5009	28	25
A_{22}	0.5340	0.2306	20	16
A_{23}	0.7072	0.1171	6	4
A_{24}	0.7491	0.0645	4	1
A_{25}	0.6245	0.1602	12	8
A_{26}	0.5114	0.2593	22	18
A_{27}	0.5559	0.2326	18	17
A_{28}	0.5636	0.2162	17	14
A_{29}	0.4047	0.3669	26	23
A_{30}	0.6471	0.1523	11	7

From the results obtained, differences can be observed between the rankings obtained using the two methods. The COMET method identified alternative A_4 (Trina TSM-DD06M.05-330BK) as the ranking leader. This alternative has an attractive low value for cost criterion C_5, which is the cost per m^2. Only alternative A_{24} (Canadian Solar CS3U-355P-35MM), which was indicated as the ranking leader of the SPOTIS method, has a lower value for this criterion. A_4 came second in the SPOTIS ranking, and A_{24} was fourth in the COMET ranking. For A_4, although its value of cost criterion C_5 with the highest weight was not the lowest, it took first place in the COMET ranking because the other criteria were also taken into account, which, despite their lower weight, also influence the final results. Furthermore, A_4 has an attractive low value of the second most important cost criterion C_1, whose value for A_{24} is higher. Alternative A_2 (Peimar SG315M) was ranked second by COMET and third by SPOTIS. This option has attractive, low values for relevant cost criteria C_5 and C_1 compared to most other variants considered. A_2 was ranked third in the SPOTIS ranking. Third place in the COMET ranking was taken by A_7 (Peimar SM325M), which was sixth in the SPOTIS ranking. In the form of a difference of six ranks, the most significant discrepancy

in outcomes was noted for the A_3 alternative (Phono Solar PS315M-20/U), which ranked ninth in the COMET ranking and fifteenth in the SPOTIS ranking.

Despite the observed differences in the rankings provided by the two methods investigated, the convergence of the two received rankings is high. The value of the symmetrical r_w coefficient was 0.9427. The asymmetrical *WS* coefficient has a value of 0.9445 for comparing COMET ranking with SPOTIS and 0.9229 for comparing SPOTIS ranking with COMET. Because it is asymmetrical, the *WS* coefficient takes on different values depending on the order of the compared rankings. The differences when the rankings compared are reordered illustrate graphs displayed in Figure 1. The asymmetrical *WS* coefficient accounts for these differences, while the r_w value is the same regardless of the order of the rankings compared to each other. The value of the *WS* coefficient depends on which positions in the compared rankings are different. Discrepancies occurring at the top of the ranking more significantly impact its value than discrepancies at lower positions [63].
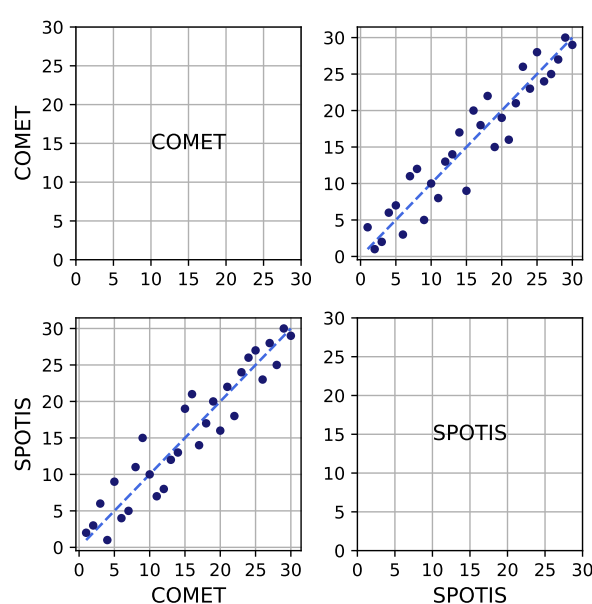

Figure 1. Comparison of rankings similarity obtained with COMET and SPOTIS.

Sensitivity Analysis

The next step in this study was to perform a sensitivity analysis to determine the significance of the impact of each decision criteria on the preference values of the alternatives. Sensitivity analysis was repeated separately for both MCDM methods. The procedure involves increasing criteria values of alternatives evaluated by 1% and calculating the preference value changed in each direction and percentage. Then, local weights are determined for each alternative based on the values obtained in the previous step by dividing by the sum of their absolute values. Results of sensitivity analysis including changes of preference values for COMET are contained in Table 5 and obtained local weights are included in Table 6. For SPOTIS results of sensitivity analysis are displayed in Table 7 and received local weights are presented in Table 8. Based on the obtained local weights, a more detailed analysis of the obtained rankings and differences for the two methods can be performed.

Table 5. Sensitivity analysis for COMET.

A_i	C_1	C_2	C_3	C_4	C_5	C_6
A_1	−3.4752	0.2144	0.4735	0.6344	−2.2234	−0.3486
A_2	−1.0926	0.4009	0.3647	0.4424	−0.5479	−0.4087
A_3	−1.2723	0.4358	0.4071	0.5008	−0.8588	−0.4523
A_4	−1.0049	0.0982	0.3910	0.4175	−0.4936	−0.1307
A_5	−1.8741	0.3844	0.4856	0.5928	−0.8700	−0.4607
A_6	−3.6035	0.6460	0.9587	1.1316	−2.2602	−0.8220
A_7	−1.1517	0.3953	0.3625	0.4620	−0.5830	−0.4372
A_8	−1.5688	0.4280	0.4039	0.5144	−0.5243	−0.4252
A_9	−1.2012	0.3905	0.3719	0.4570	−0.7177	−0.4560
A_{10}	−1.4375	0.4119	0.4089	0.5162	−1.0518	−0.5049
A_{11}	−1.5076	0.4040	0.3119	0.4471	−0.9063	−0.4094
A_{12}	−1.3402	0.1737	0.1876	0.2477	−1.2221	−0.2371
A_{13}	−2.2344	0.3964	0.5162	0.5982	−0.9451	−0.5365
A_{14}	−1.8318	0.3390	0.2925	0.3459	−0.5657	−0.5414
A_{15}	−1.9163	0.1836	0.2980	0.3754	−0.6490	−0.4229
A_{16}	−1.2767	0.1650	0.4056	0.5051	−0.8252	−0.4666
A_{17}	−1.1991	0.5384	0.4514	0.5133	−0.9268	−0.2768
A_{18}	−1.3050	0.1636	0.4111	0.5202	−0.8281	−0.4435
A_{19}	−2.2482	0.2583	0.3357	0.4728	−1.1954	−0.3038
A_{20}	−1.1963	0.1051	0.1243	0.1525	−0.6143	−0.1526
A_{21}	−2.3291	0.7116	0.6190	0.7729	−1.0798	−0.8258
A_{22}	−1.4581	0.3578	0.3239	0.4101	−1.0454	−0.3312
A_{23}	−1.1861	0.1100	0.1237	0.1520	−0.6092	−0.2347
A_{24}	−1.0201	0.1383	0.1450	0.2055	−0.4537	−0.0931
A_{25}	−1.3546	0.2014	0.1795	0.2206	−0.7614	−0.6144
A_{26}	−1.5733	0.5492	0.3073	0.3722	−1.1878	−0.7166
A_{27}	−1.4526	0.2194	0.2365	0.3006	−1.0407	−0.6048
A_{28}	−1.4330	0.2174	0.5110	0.6615	−0.9800	−0.2434
A_{29}	−1.9947	0.5815	0.4518	0.5443	−0.7885	−0.8377
A_{30}	−1.2590	0.2035	0.2154	0.2717	−0.7250	−0.5886

Table 6. Local weights for COMET.

A_i	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.4716	0.0291	0.0643	0.0861	0.3017	0.0473
A_2	0.3354	0.1231	0.1120	0.1358	0.1682	0.1255
A_3	0.3240	0.1110	0.1037	0.1275	0.2187	0.1152
A_4	0.3962	0.0387	0.1542	0.1646	0.1947	0.0515
A_5	0.4015	0.0824	0.1040	0.1270	0.1864	0.0987
A_6	0.3825	0.0686	0.1017	0.1201	0.2399	0.0872
A_7	0.3396	0.1166	0.1069	0.1362	0.1719	0.1289
A_8	0.4060	0.1107	0.1045	0.1331	0.1357	0.1100
A_9	0.3342	0.1087	0.1035	0.1272	0.1997	0.1269
A_{10}	0.3319	0.0951	0.0944	0.1192	0.2428	0.1166
A_{11}	0.3782	0.1013	0.0782	0.1122	0.2274	0.1027
A_{12}	0.3932	0.0510	0.0550	0.0727	0.3586	0.0696
A_{13}	0.4275	0.0758	0.0988	0.1144	0.1808	0.1026
A_{14}	0.4677	0.0866	0.0747	0.0883	0.1444	0.1382
A_{15}	0.4983	0.0477	0.0775	0.0976	0.1688	0.1100
A_{16}	0.3503	0.0453	0.1113	0.1386	0.2264	0.1280
A_{17}	0.3070	0.1378	0.1156	0.1314	0.2373	0.0709
A_{18}	0.3554	0.0446	0.1120	0.1417	0.2256	0.1208
A_{19}	0.4670	0.0536	0.0697	0.0982	0.2483	0.0631
A_{20}	0.5101	0.0448	0.0530	0.0650	0.2619	0.0651
A_{21}	0.3675	0.1123	0.0977	0.1219	0.1704	0.1303
A_{22}	0.3714	0.0911	0.0825	0.1044	0.2662	0.0844
A_{23}	0.4910	0.0456	0.0512	0.0629	0.2522	0.0971
A_{24}	0.4962	0.0673	0.0705	0.1000	0.2207	0.0453
A_{25}	0.4066	0.0604	0.0539	0.0662	0.2285	0.1844
A_{26}	0.3343	0.1167	0.0653	0.0791	0.2524	0.1523
A_{27}	0.3768	0.0569	0.0614	0.0780	0.2700	0.1569
A_{28}	0.3541	0.0537	0.1263	0.1635	0.2422	0.0602
A_{29}	0.3837	0.1119	0.0869	0.1047	0.1517	0.1611
A_{30}	0.3858	0.0624	0.0660	0.0833	0.2222	0.1804

Table 7. Sensitivity analysis for SPOTIS.

A_i	C_1	C_2	C_3	C_4	C_5	C_6
A_1	−0.1567	0.0673	0.0649	0.0711	−1.2699	−0.0618
A_2	−1.2473	0.5081	0.4887	0.5348	−3.0960	−0.5615
A_3	−0.6203	0.2615	0.2475	0.2708	−2.0769	−0.2843
A_4	−1.5565	0.6771	0.6225	0.6839	−3.7271	−0.6854
A_5	−0.2724	0.1162	0.1079	0.1180	−1.4697	−0.1148
A_6	−0.1653	0.0681	0.0658	0.0721	−1.2717	−0.0663
A_7	−1.1524	0.4734	0.4463	0.4737	−2.8807	−0.5139
A_8	−0.4340	0.1806	0.1684	0.1840	−1.7348	−0.1976
A_9	−0.7860	0.3287	0.3095	0.3389	−2.3329	−0.3658
A_{10}	−0.5119	0.2189	0.2011	0.2199	−1.8725	−0.2399
A_{11}	−0.6744	0.2515	0.2525	0.2678	−2.0151	−0.2952
A_{12}	−0.5412	0.2142	0.2001	0.2182	−1.8214	−0.2058
A_{13}	−0.2900	0.1161	0.1125	0.1231	−1.4525	−0.1226
A_{14}	−0.4593	0.1806	0.1795	0.1964	−1.7118	−0.1927
A_{15}	−0.3761	0.1529	0.1508	0.1656	−1.5976	−0.1582
A_{16}	−0.6636	0.2916	0.2569	0.2815	−2.1346	−0.3027
A_{17}	−0.7134	0.2722	0.2564	0.2807	−2.0331	−0.2865
A_{18}	−0.6718	0.3038	0.2538	0.2790	−2.1392	−0.3016
A_{19}	−0.2779	0.1065	0.1007	0.1109	−1.3915	−0.0995
A_{20}	−1.4222	0.5033	0.4773	0.5219	−2.8115	−0.4901
A_{21}	−0.3245	0.1095	0.1141	0.1247	−1.4170	−0.1301
A_{22}	−0.6949	0.2394	0.2248	0.2472	−1.8779	−0.2750
A_{23}	−1.4252	0.5201	0.4856	0.5388	−2.8322	−0.5247
A_{24}	−2.4421	0.8498	0.7733	0.8496	−4.1049	−0.9894
A_{25}	−1.0760	0.3672	0.3517	0.3854	−2.2711	−0.3938
A_{26}	−0.6349	0.2253	0.2172	0.2381	−1.8050	−0.2516
A_{27}	−0.7078	0.2652	0.2443	0.2681	−1.9204	−0.2763
A_{28}	−0.7650	0.2921	0.2463	0.2699	−1.9794	−0.2763
A_{29}	−0.4495	0.1595	0.1512	0.1650	−1.5626	−0.1781
A_{30}	−1.0905	0.4065	0.3681	0.4034	−2.3781	−0.4309

Table 8. Local weights for SPOTIS.

A_i	C_1	C_2	C_3	C_4	C_5	C_6
A_1	0.0926	0.0398	0.0384	0.0420	0.7507	0.0365
A_2	0.1938	0.0789	0.0759	0.0831	0.4810	0.0872
A_3	0.1649	0.0695	0.0658	0.0720	0.5522	0.0756
A_4	0.1957	0.0851	0.0783	0.0860	0.4687	0.0862
A_5	0.1239	0.0528	0.0491	0.0537	0.6684	0.0522
A_6	0.0967	0.0398	0.0385	0.0422	0.7440	0.0388
A_7	0.1940	0.0797	0.0751	0.0797	0.4849	0.0865
A_8	0.1497	0.0623	0.0581	0.0635	0.5983	0.0681
A_9	0.1762	0.0737	0.0694	0.0760	0.5229	0.0820
A_{10}	0.1568	0.0671	0.0616	0.0674	0.5736	0.0735
A_{11}	0.1795	0.0670	0.0672	0.0713	0.5364	0.0786
A_{12}	0.1691	0.0669	0.0625	0.0682	0.5690	0.0643
A_{13}	0.1308	0.0524	0.0507	0.0555	0.6552	0.0553
A_{14}	0.1573	0.0619	0.0615	0.0672	0.5862	0.0660
A_{15}	0.1446	0.0588	0.0580	0.0637	0.6142	0.0608
A_{16}	0.1688	0.0742	0.0653	0.0716	0.5430	0.0770
A_{17}	0.1857	0.0708	0.0667	0.0731	0.5291	0.0746
A_{18}	0.1701	0.0769	0.0643	0.0706	0.5417	0.0764
A_{19}	0.1331	0.0510	0.0483	0.0532	0.6668	0.0477
A_{20}	0.2284	0.0808	0.0767	0.0838	0.4515	0.0787
A_{21}	0.1462	0.0493	0.0514	0.0562	0.6383	0.0586
A_{22}	0.1952	0.0673	0.0632	0.0694	0.5276	0.0773
A_{23}	0.2253	0.0822	0.0768	0.0852	0.4477	0.0829
A_{24}	0.2440	0.0849	0.0773	0.0849	0.4101	0.0988
A_{25}	0.2221	0.0758	0.0726	0.0796	0.4687	0.0813
A_{26}	0.1883	0.0668	0.0644	0.0706	0.5353	0.0746
A_{27}	0.1922	0.0720	0.0664	0.0728	0.5216	0.0750
A_{28}	0.1998	0.0763	0.0643	0.0705	0.5169	0.0722
A_{29}	0.1686	0.0598	0.0567	0.0619	0.5861	0.0668
A_{30}	0.2148	0.0801	0.0725	0.0794	0.4684	0.0849

In the case of the leader of the COMET ranking, which is A_4, it can be observed that the highest local importance affecting the preference value is criterion C_1 (0.3962), and the second criterion in terms of local importance is C_5 (0.1947). Therefore, it explains why A_4 got first place in the COMET ranking, although it had a less attractive value of the globally most relevant criterion C_5 than A_{24}. The value of C_1, which is the most locally relevant criterion for A_4, is more advantageous in its case than in A_{24}. For the SPOTIS method, the local weights determined for A_4 have different values than for COMET. The highest local significance for A_4 is criterion C_5 (0.4687), while the second-highest local significance is criterion C_1 (0.1957). It explains why A_4 is preferred in the COMET ranking but no longer preferred in the SPOTIS ranking. For SPOTIS, C_5 (0.4101) proved to be the most locally relevant criterion for the leader of its ranking, A_{24}, followed by C_1 (0.2440), so in the SPOTIS ranking, alternative A_{24} appeared to be the most preferred.

For alternative A_2, which ranked second in COMET, the local significance for the COMET method is highest for criterion C_1 (0.3354), and the second most relevant criterion is C_5 (0.1682). For SPOTIS, it is otherwise, as the most locally significant criterion for A_2 is (0.4810) and the second most important criterion is C_1 (0.1938).

The local weights for each alternative determined by the sensitivity analysis procedure are visualized as a cumulative column chart in Figure 2. The highest contribution of criterion C_1 for all alternatives can be observed, which means it is the most locally relevant criterion in the COMET method. The second most locally relevant criterion is C_5.
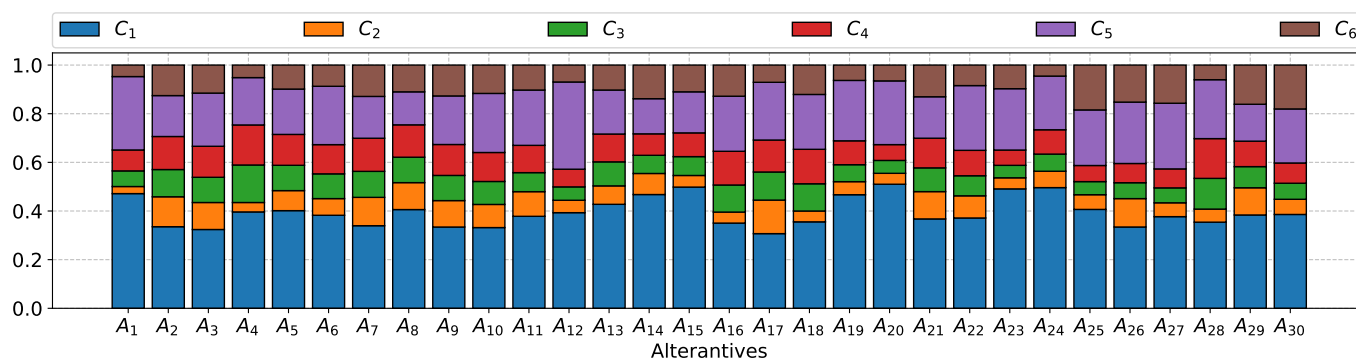
Figure 2. Local weights for individual alternatives for the COMET method.

Figure 3 displays a cumulative column chart representing the share of criteria in terms of their local relevance to the alternatives analyzed for the SPOTIS method. In this case, the highest local importance is shown by criterion C_5, followed by C_1.
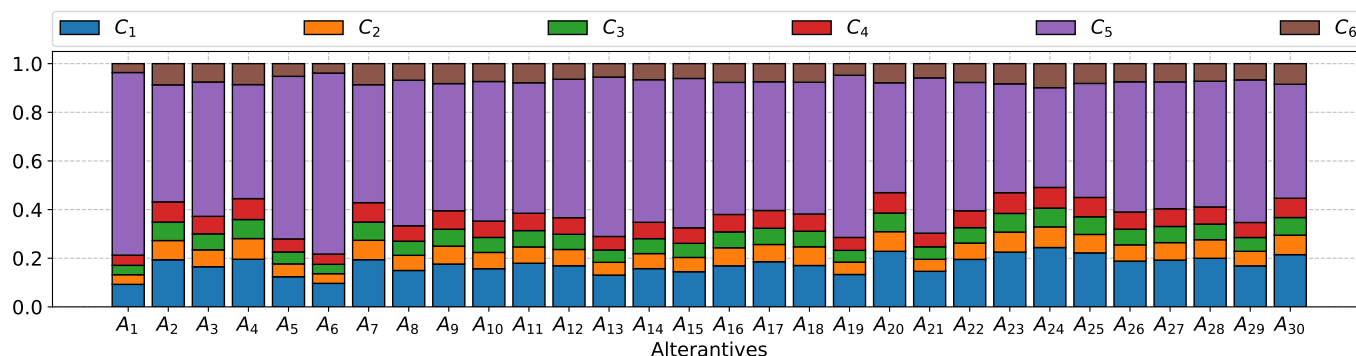

Figure 3. Local weights for individual alternatives for SPOTIS method.

For all alternatives analyzed, criterion C_1 has the highest local significance for the COMET method, while for the SPOTIS method, the most locally relevant criterion is C_5. The results obtained indicate that the preference for each alternative depends on

the values of the criteria that are most relevant not only globally, according to the weights determined by an objective weighting technique. Furthermore, of great importance are the local weights, which are different for each alternative but are dependent on the global weights. The COMET method indicated A_4 as the best alternative, which does not have the most attractive value of the globally most important criterion, price (C_5), but has a very advantageous value of the second most important criterion (C_1). The SPOTIS method, on the other hand, indicated A_{24} as the leader of the ranking, which has the lowest price, even though the value of C_1 is not among the most favorable in its case compared to the other alternatives. The results obtained suggest that, in this case, the decision-maker, in addition to considering the rankings provided by both methods, should take into account their individual preferences regarding the relevance of the decisive criteria in the final decision.

5. Discussion

This article is intended to present an approach based on two innovative rank-reversal-free MCDM methods, COMET and SPOTIS, which could be applied in a decision support system for multi-criteria selection of solar panels for photovoltaic systems. The proposed approach is demonstrated with an illustrative example of selecting the most advantageous solar panel option from thirty available alternatives, taking into account six criteria relevant to the decision-makers. The obtained results confirmed the well-known fact that the same decision problem could be evaluated differently if different MCDM methods are used for this purpose. Due to the various algorithms of the methods and the different ways they scale the targets, choosing the most appropriate method for a particular problem is not straightforward. In this situation, a comparative analysis of the methods is suggested to identify fields for their applicability [42]. A practical approach to selecting MCDM methods for benchmarking considers selecting methods with similar assumptions and algorithms. In this paper, whose subject was multi-criteria wind farm site selection, the problem was evaluated using three methods: TOPSIS, VIKOR, and COMET. Algorithms based on distance measurement and using reference points in the problem space are their common features, making their selection for comparative analysis justified [8]. Furthermore, the same set of MCDM methods was chosen to evaluate the sustainable transportation problem in [62]. Ease of application and adaptation of the method to the problem under consideration is also significant in the choice of methods, for example, usefulness in evaluating quantitative data, which are often found in renewable energy problems [31]. In selecting an MCDM method, it is also essential to consider whether the ranking that the method returns provides comparability with the other methods [42].

The authors of this paper took into account the suggestions for the adequate choice of MCDM methods present in the literature review and decided to use in the proposed approach two methods, COMET and SPOTIS. Their common features are robustness to rank reversal paradox, use of reference objects, measurement of distances from reference objects, high accuracy, and ability to work with data in the form of decision matrix with numerical values and return results in quantitative form. The mentioned advantages of both methods are useful in case of intention to use them in practice as a decision support system engine, as they enable easy, automated, and objective evaluation considering both multiple alternatives and numerous criteria. An aspect that seems to be advantageous from the point of view of attempting to develop an automated DSS that is objective and easy to use for the decision-maker is the replacement of the laborious step of pairwise comparison of characteristic objects by an expert with the evaluation of a set of COs objects using the TOPSIS method. The COMET method retains its main advantage, which is rank-reversal-free because the TOPSIS method combined with COMET operates on characteristic objects and not on alternatives [41]. For the multi-criteria problem solved in this paper, with six criteria and three characteristic values for each criterion, 729 characteristic objects are generated. It follows that if the monolithic structure of this problem were used in the classical version of COMET, 265,356 pairwise comparisons by an expert would be required. However, the number of pairwise comparisons can be obviously reduced by using

a decomposition procedure that divides the criteria into modules to obtain a hierarchical structure of the problem [64]. Such a hierarchical model with ten decision criteria divided into three modules was created for offshore wind farm site selection using COMET in [29]. However, subjective comparisons performed manually by an expert are still necessary, while replacing this step with the TOPSIS method makes the proposed hybrid approach more compatible with the authors' attempt to create a fully automated and objective system for evaluating solar panels.

When a significant effect of criterion weights on rankings is observed, it is advisable to conduct a selected kind of sensitivity analysis that supports analysis and more accurately determines the influence of criterion weights on rankings [45]. Sensitivity analysis performed in this study, providing local weights for the individual alternatives concerning the criteria, demonstrated that criterion C_1, which is Open Circuit Voltage, is more relevant for determining preferences for the COMET method. In contrast, the SPOTIS method takes more C_5 (Cost per m^2) into account.

Despite the observed differences in the rankings, the values of both r_w and WS ranking similarity coefficients showed their high correlation. Thus, the results demonstrate that both methods were appropriately selected for the problem to be solved, and they have high potential as the basis of DSS for solar panel selection.

6. Conclusions

This paper aimed to present the application of two innovative rank-reversal-free MCDM methods, which are COMET and SPOTIS, on the example of a multi-criteria solar panel selection problem. In addition, the COMET method was combined with the TOPSIS method to replace the labor-intensive and subjective step of pairwise comparison of characteristic objects by an expert with an automatic and objective evaluation of the set of characteristic objects. Criteria weights were determined using an objective entropy weighting technique and were identified as the most relevant two following selection criteria: cost per m^2 (C_5) and open circuit voltage (C_1).

The COMET method identified A_4 with an advantageous C_1 value as the best alternative, while the SPOTIS ranking indicated A_{24} with a very favorable C_5 value as the best variant. The discrepancies in obtained rankings are caused by different considerations of the significance of the criteria weights at the local level by both methods, as demonstrated in the sensitivity analysis procedure. COMET prefers alternatives with advantageous C_1 values, and SPOTIS favors alternatives with attractive C_5 values. Identification of such properties can be useful in supporting the selection of the more favorable alternative in terms of the criteria that are more important to the decision-maker.

The obtained results proved that the approach proposed by the authors is suitable and applicable as the basis of a DSS supporting the selection of solar panels. Its main advantages include ease of use, the objectivity of the obtained rankings with respect to the relevance of the criteria, and full automation of all procedures. Solar panel technology is becoming more popular and available as prices drop and the number of attributes that characterize it is large. The presented advantages of the approach, which is the subject of this article, make it seem promising and future-proof for supporting the decision of choosing solar panels both for individual customers representing households and for companies needing complex photovoltaic systems. Furthermore, the obtained results encourage the continuation of the presented research, involving the study of other techniques for criteria weighting—for example, CRITIC [65], IDOCRIW [66], CILOS [67], and extending the scope of the performed research to other fields, including the problem of renewable energy sources and, depending on the obtained results, other MCDM methods.

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Abbreviations

The following abbreviations are used in this manuscript:

AHP	Analytical Hierarchy Process
ANP	Analytic Network Process
BWM	Best-Worst Method
CO	Characteristic Object
COMET	Characteristic Object METhod
COPRAS	COmplex PropoRtional ASsessmen
DEMATEL	Decision Making Trial and Evaluation Laboratory
DSS	Decision Support System
ELECTRE	ELimination Et Choix Traduisant la REalité
ISP	Ideal Solution Point
LBWA	Level Based Weight Assessment
MABAC	Multi-Attributive Border Approximation area Comparison
MAIRCA	Multi Attributive Ideal-Real Comparative Analysis
MCDA	Multi-Criteria Decision-Analysis
MCDM	Multi-Criteria Decision-Making
MEJ	Matrix of Expert Judgement
NIS	Negative Ideal Solution
PIS	Positive Ideal Solution
PROMETHEE	Preference Ranking Organization METHod for Enrichment of Evaluation
PROSA	PROMETHEE for Sustainability Assessment
PV	Photovoltaic
RAFSI	Ranking of Alternatives through Functional mapping of criterion sub-intervals into a Single Interval
RES	Renewable Energy Supply
rw	Weighted Spearman's Rank Correlation Coefficient
SIMUS	Sequential Interactive Model of Urban Systems
SJ	vector of the Summed Judgements
SPOTIS	Stable Preference Ordering Towards Ideal Solution
TOPSIS	Technique for Order of Preference by Similarity to Ideal Solution
VIKOR	VlseKriterijumska Optimizacija I Kompromisno Resenje
WASPAS	Weighted Aggregated Sum Product Assessment
WS coefficient	Weighted Similarity Coefficient

References

1. Lak Kamari, M.; Isvand, H.; Alhuyi Nazari, M. Applications of multi-criteria decision-making (MCDM) methods in renewable energy development: A review. *Renew. Energy Res. Appl.* **2020**, *1*, 47–54.
2. Rani, P.; Mishra, A.R.; Mardani, A.; Cavallaro, F.; Štreimikienė, D.; Khan, S.A.R. Pythagorean fuzzy SWARA–VIKOR framework for performance evaluation of solar panel selection. *Sustainability* **2020**, *12*, 4278. [CrossRef]
3. Van de Kaa, G.; Rezaei, J.; Kamp, L.; de Winter, A. Photovoltaic technology selection: A fuzzy MCDM approach. *Renew. Sustain. Energy Rev.* **2014**, *32*, 662–670. [CrossRef]
4. Seker, S.; Kahraman, C. Socio-economic evaluation model for sustainable solar PV panels using a novel integrated MCDM methodology: A case in Turkey. *Socio-Econ. Plan. Sci.* **2021**, *77*, 100998. [CrossRef]
5. Govindarajan, U.; Ramachandaramurthy, V.K. Multiple criteria decision making (MCDM) based economic analysis of solar PV system with respect to performance investigation for Indian market. *Sustainability* **2017**, *9*, 820.
6. Wang, T.C.; Tsai, S.Y. Solar panel supplier selection for the photovoltaic system design by using fuzzy multi-criteria decision making (MCDM) approaches. *Energies* **2018**, *11*, 1989. [CrossRef]
7. Gnanasekaran, S.; Venkatachalama, N. A review on applications of multi-criteria decision making (MCDM) for solar panel selection. *Int. J. Mech. Prod. Eng. Res. Dev.* **2019**, *9*, 11–20.
8. Kizielewicz, B.; Wątróbski, J.; Sałabun, W. Identification of relevant criteria set in the MCDA process—Wind farm location case study. *Energies* **2020**, *13*, 6548. [CrossRef]
9. Nesticò, A.; Somma, P. Comparative analysis of multi-criteria methods for the enhancement of historical buildings. *Sustainability* **2019**, *11*, 4526. [CrossRef]
10. Nesticò, A.; Elia, C.; Naddeo, V. Sustainability of urban regeneration projects: Novel selection model based on analytic network process and zero-one goal programming. *Land Use Policy* **2020**, *99*, 104831. [CrossRef]
11. Wątróbski, J.; Jankowski, J.; Ziemba, P.; Karczmarczyk, A.; Zioło, M. Generalised framework for multi-criteria method selection. *Omega* **2019**, *86*, 107–124. [CrossRef]
12. Wątróbski, J.; Jankowski, J.; Ziemba, P.; Karczmarczyk, A.; Zioło, M. Generalised framework for multi-criteria method selection: Rule set database and exemplary decision support system implementation blueprints. *Data Brief* **2019**, *22*, 639. [CrossRef]
13. Wątróbski, J.; Jankowski, J. Guideline for MCDA method selection in production management area. In *New Frontiers in Information and Production Systems Modelling and Analysis*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 119–138.
14. Wątróbski, J.; Małecki, K.; Kijewska, K.; Iwan, S.; Karczmarczyk, A.; Thompson, R.G. Multi-criteria analysis of electric vans for city logistics. *Sustainability* **2017**, *9*, 1453. [CrossRef]
15. Sałabun, W.; Ziemba, P.; Wątróbski, J. The rank reversals paradox in management decisions: The comparison of the AHP and COMET methods. In *International Conference on Intelligent Decision Technologies*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 181–191.
16. Dezert, J.; Tchamova, A.; Han, D.; Tacnet, J.M. The SPOTIS Rank Reversal Free Method for Multi-Criteria Decision-Making Support. In Proceedings of the 2020 IEEE 23rd International Conference on Information Fusion (FUSION), Rustenburg, South Africa, 6–9 July 2020; pp. 1–8.
17. Žižović, M.; Pamučar, D.; Albijanić, M.; Chatterjee, P.; Pribićević, I. Eliminating rank reversal problem using a new multi-attribute model—The RAFSI method. *Mathematics* **2020**, *8*, 1015. [CrossRef]
18. Munier, N. A new approach to the rank reversal phenomenon in MCDM with the SIMUS method. *Multiple Criteria Decis. Mak.* **2016**, *11*, 137–152. [CrossRef]
19. De Farias Aires, R.F.; Ferreira, L. A new approach to avoid rank reversal cases in the TOPSIS method. *Comput. Ind. Eng.* **2019**, *132*, 84–97. [CrossRef]
20. Seiti, H.; Hafezalkotob, A. Developing the R-TOPSIS methodology for risk-based preventive maintenance planning: A case study in rolling mill company. *Comput. Ind. Eng.* **2019**, *128*, 622–636. [CrossRef]
21. Yang, W.; Wu, Y. A new improvement method to avoid rank reversal in VIKOR. *IEEE Access* **2020**, *8*, 21261–21271. [CrossRef]
22. Mokarram, M.; Mokarram, M.J.; Gitizadeh, M.; Niknam, T.; Aghaei, J. A novel optimal placing of solar farms utilizing multi-criteria decision-making (MCDA) and feature selection. *J. Clean. Prod.* **2020**, *261*, 121098. [CrossRef]
23. Akkas, O.P.; Erten, M.Y.; Cam, E.; Inanc, N. Optimal site selection for a solar power plant in the Central Anatolian Region of Turkey. *Int. J. Photoenergy* **2017**, *2017*, 7452715.
24. Wang, C.N.; Nguyen, V.T.; Thai, H.T.N.; Duong, D.H. Multi-criteria decision making (MCDM) approaches for solar power plant location selection in Viet Nam. *Energies* **2018**, *11*, 1504. [CrossRef]
25. Finn, T.; McKenzie, P. A high-resolution suitability index for solar farm location in complex landscapes. *Renew. Energy* **2020**, *158*, 520–533. [CrossRef]
26. Suuronen, A.; Lensu, A.; Kuitunen, M.; Andrade-Alvear, R.; Celis, N.G.; Miranda, M.; Perez, M.; Kukkonen, J.V. Optimization of photovoltaic solar power plant locations in northern Chile. *Environ. Earth Sci.* **2017**, *76*, 1–14. [CrossRef]
27. Sindhu, S.; Nehra, V.; Luthra, S. Investigation of feasibility study of solar farms deployment using hybrid AHP-TOPSIS analysis: Case study of India. *Renew. Sustain. Energy Rev.* **2017**, *73*, 496–511. [CrossRef]
28. Peña, K.; Sosa, I.; Suero, D.; Cruz-Diloné, P.; Faxas, J. A MCDA for Selecting Photovoltaic System in a Caribbean Country. In Proceedings of the IIE Annual Conference, Institute of Industrial and Systems Engineers (IISE), Pittsburgh, PA, USA, 20–23 May 2017; pp. 1625–1630.

29. Sałabun, W.; Wątróbski, J.; Piegat, A. Identification of a multi-criteria model of location assessment for renewable energy sources. In *Proceedings of the International Conference on Artificial Intelligence and Soft Computing*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 321–332.

30. Kizielewicz, B.; Szyjewski, Z. Handling economic perspective in multicriteria model-renewable energy resources case study. *Proc. Comput. Sci.* **2020**, *176*, 3555–3562. [CrossRef]

31. Wątróbski, J.; Ziemba, P.; Jankowski, J.; Zioło, M. Green energy for a green city—A multi-perspective model approach. *Sustainability* **2016**, *8*, 702. [CrossRef]

32. Ziemba, P.; Wątróbski, J.; Zioło, M.; Karczmarczyk, A. Using the PROSA method in offshore wind farm location problems. *Energies* **2017**, *10*, 1755. [CrossRef]

33. Gigović, L.; Pamučar, D.; Božanić, D.; Ljubojević, S. Application of the GIS-DANP-MABAC multi-criteria model for selecting the location of wind farms: A case study of Vojvodina, Serbia. *Renew. Energy* **2017**, *103*, 501–521. [CrossRef]

34. Pamučar, D.; Gigović, L.; Bajić, Z.; Janošević, M. Location selection for wind farms using GIS multi-criteria hybrid model: An approach based on fuzzy and rough numbers. *Sustainability* **2017**, *9*, 1315. [CrossRef]

35. Pamučar, D.; Behzad, M.; Božanić, D.; Behzad, M. Decision making to support sustainable energy policies corresponding to agriculture sector: Case study in Iran's Caspian Sea coastline. *J. Clean. Prod.* **2021**, *292*, 125302. [CrossRef]

36. Chatterjee, K.; Kar, S. A multi-criteria decision making for renewable energy selection using Z-numbers in uncertain environment. *Technol. Econ. Dev. Econ.* **2018**, *24*, 739–764. [CrossRef]

37. Rathi, R.; Prakash, C.; Singh, S.; Krolczyk, G.; Pruncu, C.I. Measurement and analysis of wind energy potential using fuzzy based hybrid MADM approach. *Energy Rep.* **2020**, *6*, 228–237. [CrossRef]

38. Sałabun, W.; Karczmarczyk, A.; Wątróbski, J.; Jankowski, J. Handling data uncertainty in decision making with COMET. In Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence (SSCI), Bangalore, India, 18–21 November 2018; pp. 1478–1484.

39. Watróbski, J.; Sałabun, W. The characteristic objects method: A new intelligent decision support tool for sustainable manufacturing. In *Proceedings of the International Conference on Sustainable Design and Manufacturing*; Springer: Berlin/Heidelberg, Germany, 2016; pp. 349–359.

40. Sałabun, W. The Characteristic Objects Method: A New Distance-based Approach to Multicriteria Decision-making Problems. *J. Multi-Criteria Decis. Anal.* **2015**, *22*, 37–50. [CrossRef]

41. Kizielewicz, B.; Shekhovtsov, A.; Sałabun, W. A New Approach to Eliminate Rank Reversal in the MCDA Problems. In *Proceedings of the International Conference on Computational Science*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 338–351.

42. Sałabun, W.; Wątróbski, J.; Shekhovtsov, A. Are MCDA methods benchmarkable? a comparative study of TOPSIS, VIKOR, COPRAS, and PROMETHEE II methods. *Symmetry* **2020**, *12*, 1549. [CrossRef]

43. Shekhovtsov, A.; Kizielewicz, B.; Sałabun, W. New Rank-Reversal Free Approach to Handle Interval Data in MCDA Problems. In *Proceedings of the International Conference on Computational Science*; Springer: Berlin/Heidelberg, Germany, 2021; pp. 458–472.

44. Şengül, Ü.; Eren, M.; Shiraz, S.E.; Gezder, V.; Şengül, A.B. Fuzzy TOPSIS method for ranking renewable energy supply systems in Turkey. *Renew. Energy* **2015**, *75*, 617–625. [CrossRef]

45. Lee, H.C.; Chang, C.T. Comparative analysis of MCDM methods for ranking renewable energy sources in Taiwan. *Renew. Sustain. Energy Rev.* **2018**, *92*, 883–896. [CrossRef]

46. Sun, Y.; Wang, R.; Li, J.; Liu, J. GIS-based multiregional potential evaluation and strategies selection framework for various renewable energy sources: a case study of eastern coastal regions of China. *Energy Sci. Eng.* **2017**, *5*, 123–140. [CrossRef]

47. Štreimikienė, D.; Šliogerienė, J.; Turskis, Z. Multi-criteria analysis of electricity generation technologies in Lithuania. *Renew. Energy* **2016**, *85*, 148–156. [CrossRef]

48. Tsai, C.T.; Beza, T.M.; Wu, W.B.; Kuo, C.C. Optimal configuration with capacity analysis of a hybrid renewable energy and storage system for an island application. *Energies* **2020**, *13*, 8. [CrossRef]

49. Ilbahar, E.; Cebi, S.; Kahraman, C. A state-of-the-art review on multi-attribute renewable energy decision making. *Energy Strategy Rev.* **2019**, *25*, 18–33. [CrossRef]

50. Xu, X.; Niu, D.; Qiu, J.; Wu, M.; Wang, P.; Qian, W.; Jin, X. Comprehensive evaluation of coordination development for regional power grid and renewable energy power supply based on improved matter element extension and TOPSIS method for sustainability. *Sustainability* **2016**, *8*, 143. [CrossRef]

51. Faizi, S.; Sałabun, W.; Ullah, S.; Rashid, T.; Więckowski, J. A new method to support decision-making in an uncertain environment based on normalized interval-valued triangular fuzzy numbers and COMET technique. *Symmetry* **2020**, *12*, 516. [CrossRef]

52. Faizi, S.; Sałabun, W.; Rashid, T.; Wątróbski, J.; Zafar, S. Group decision-making for hesitant fuzzy sets based on characteristic objects method. *Symmetry* **2017**, *9*, 136. [CrossRef]

53. Sałabun, W.; Karczmarczyk, A.; Wątróbski, J. Decision-making using the hesitant fuzzy sets COMET method: An empirical study of the electric city buses selection. In Proceedings of the 2018 IEEE Symposium Series on Computational Intelligence (SSCI), Bangalore, India, 18–21 November 2018; pp. 1485–1492.

54. Sałabun, W. Reduction in the number of comparisons required to create matrix of expert judgment in the COMET method. *Manag. Prod. Eng. Rev.* **2014**, *5*, 62–69. [CrossRef]

55. Sałabun, W.; Karczmarczyk, A. Using the COMET method in the sustainable city transport problem: An empirical study of the electric powered cars. *Procedia Comput. Sci.* **2018**, *126*, 2248–2260. [CrossRef]

56. Kizielewicz, B.; Kołodziejczyk, J. Effects of the selection of characteristic values on the accuracy of results in the COMET method. *Procedia Comput. Sci.* **2020**, *176*, 3581–3590. [CrossRef]

57. Shekhovtsov, A.; Kołodziejczyk, J.; Sałabun, W. Fuzzy Model Identification Using Monolithic and Structured Approaches in Decision Problems with Partially Incomplete Data. *Symmetry* **2020**, *12*, 1541. [CrossRef]

58. Wątróbski, J.; Sałabun, W.; Karczmarczyk, A.; Wolski, W. Sustainable decision-making using the COMET method: An empirical study of the ammonium nitrate transport management. In Proceedings of the 2017 Federated Conference on Computer Science and Information Systems (FedCSIS), Prague, Czech Republic, 3–6 September 2017; pp. 949–958.

59. Zolfani, S.; Yazdani, M.; Pamucar, D.; Zarate, P. A VIKOR and TOPSIS focused reanalysis of the MADM methods based on logarithmic normalization. *arXiv* **2020**, arXiv:2006.08150.

60. Sałabun, W. The mean error estimation of TOPSIS method using a fuzzy reference models. *J. Theor. Appl. Comput. Sci.* **2013**, *7*, 40–50.

61. Li, H.; Wang, W.; Fan, L.; Li, Q.; Chen, X. A novel hybrid MCDM model for machine tool selection using fuzzy DEMATEL, entropy weighting and later defuzzification VIKOR. *Appl. Soft Comput.* **2020**, *91*, 106207. [CrossRef]

62. Shekhovtsov, A.; Kozlov, V.; Nosov, V.; Sałabun, W. Efficiency of Methods for Determining the Relevance of Criteria in Sustainable Transport Problems: A Comparative Case Study. *Sustainability* **2020**, *12*, 7915. [CrossRef]

63. Sałabun, W.; Urbaniak, K. A new coefficient of rankings similarity in decision-making problems. In *Proceedings of the International Conference on Computational Science*; Springer: Berlin/Heidelberg, Germany, 2020; pp. 632–645.

64. Sałabun, W. Fuzzy Multi-Criteria Decision-Making Method: The Modular Approach in the Characteristic Objects Method. *Stud. Proc. Polish Assoc. Knowl. Manag.* **2015**, *77*, 54–64.

65. Tuş, A.; Adalı, E.A. The new combination with CRITIC and WASPAS methods for the time and attendance software selection problem. *Opsearch* **2019**, *56*, 528–538. [CrossRef]

66. Alao, M.A.; Popoola, O.M.; Ayodele, T.R. Selection of waste-to-energy technology for distributed generation using IDOCRIW-Weighted TOPSIS method: A case study of the City of Johannesburg, South Africa. *Renew. Energy* **2021**, *178*, 162–183. [CrossRef]

67. Zavadskas, E.K.; Podvezko, V. Integrated determination of objective criteria weights in MCDM. *Int. J. Inf. Technol. Decis. Mak.* **2016**, *15*, 267–283. [CrossRef]