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Optimal Selection of Hybrid Renewable Energy System Using Multi-Criteria Decision-Making Algorithms

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Abstract: Several models of multi-criteria decision-making (MCDM) have identified the optimal alternative electrical energy sources to supply certain load in an isolated region in Al-Minya City, Egypt. The load demand consists of water pumping system with a water desalination unit. Various options containing three different power sources: only DG, PV-B system, and hybrid PV-DG-B, two different sizes of reverse osmosis (RO) units; RO-250 and RO-500, two strategies of energy management; load following (LF) and cycle charging (CC), and two sizes of DG; 5 and 10 kW were taken into account. Eight attributes, including operating cost, renewable fraction, initial cost, the cost of energy, excess energy, unmet load, breakeven grid extension distance, and the amount of CO_2, were used during the evaluation process. To estimate these parameters, HOMER® software was employed to perform both the simulation and optimization process. Four different weight estimation methods were considered; no priority of criteria, based on a pairwise comparisons matrix of the criteria, CRITIC-method, and entropy-based method. The main findings (output results) confirmed that the optimal option for the case study was hybrid PV-DG-B with the following specification: 5 kW DG, RO-500, and load following control strategy. Under this condition, the annual operating cost and initial costs were \$ 5546 and \$ 161022, respectively, whereas the cost of energy was 0.077 \$/kWh. The excess energy and unmet loads were 40998 and 2371 kWh, respectively. The breakeven grid extension distance and the amount of CO_2 were 3.31 km and 5171 kg per year, respectively. Compared with DG only, the amount of CO_2 has been sharply reduced by 113939 kg per year.

Keywords: Al-Minya city (Egypt); energy efficiency; multi-criteria decision-making; optimization; renewable energy; reverse osmosis units

1 Introduction

Global warming is one of the greatest challenges experienced by humanity in today's era. The best way to reduce or eliminate its effects is by limiting CO_2 emissions. This can be achieved by utilizing renewable energy sources (RES) to generate electrical power instead of using fossil fuel sources, which have negative effects on the environment [1]. RES is environment-friendly and can replace all the conventional sources for power supply.

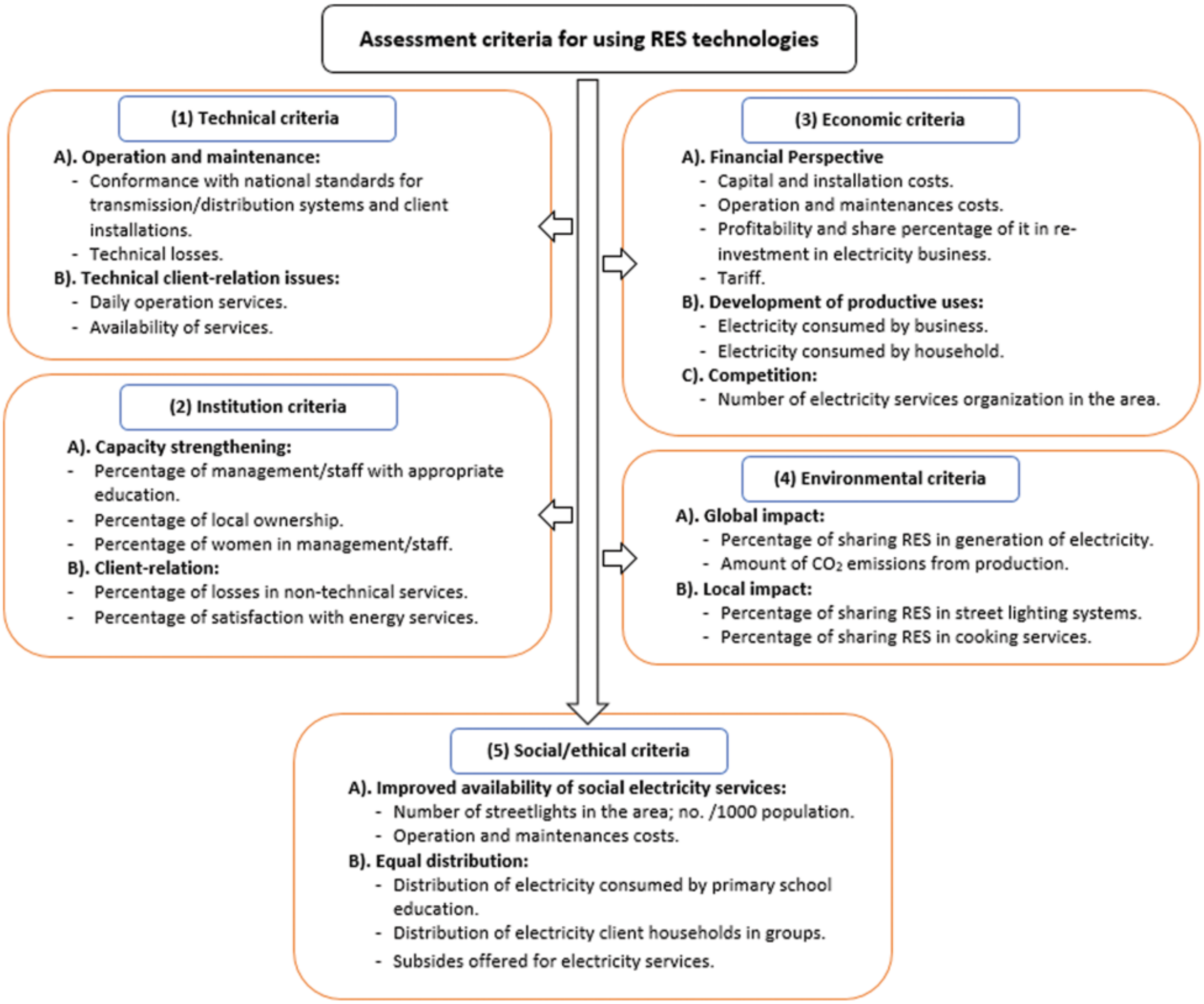


Figure 1: Assessment criteria for using RES technologies

There are several kinds of RES, which can be used in any project. Furthermore, these can be separate sources or hybrid systems which depend on the location of the case study (project) and availability of the natural sources, i.e., wind energy, solar radiation, falls or dams etc. The process of selecting the suitable kind of RES for any project is a strenuous task. For any successful RES project, decision-makers must study, analyze, and consider multiple factors such as economic, environmental, and technological factors. Decision-makers should resolve this problem in the framework to understand suitable source without concessions [2]. The design of the RES uses several technical methodologies and algorithms based on the optimal analysis. Therefore, the process of selecting a powerful and optimum RES is a complex problem that needs evidence-based decision. Furthermore, the decision of using/installing a RES normally includes various stakeholders that may have various interests and goals related to the project. An assessment criterion for using RES technologies include technical, institutional, economic, environmental, and social/ethical criteria as is illustrated in Fig. 1.

The variety of available technologies and equipment to achieve specific goals is a characteristic feature of the modern era. The ratios of parameters such as price, performance, reliability, durability, safety, environmental friendliness, ergonomics, etc. constitute the issue of optimal choice. In a situation when there are 5–7 choices with immense object attributes and competing criteria; there is no obvious choice for the optimal solution.

One of the approaches to solve this problem of optimal choice is the use of various multi-criteria solution techniques i.e., Multi-criteria decision-making (MCDM/MCDA) [3–5] and integration of methods into the engineered design process. Though, MCDM models are partially formalized and for them there is no concept of an absolute optimal solution. Nevertheless, as practice shows, MCDM models allow the selection of best option among predefined alternatives. If several alternatives have some of the attributes as "*strong*" and approximately the same part as "*week*," then the performance indicators of such alternatives will differ significantly, and the alternatives will be hardly distinguishable. This requires a comprehensive analysis using various MCDM models and solution-based sensitivity analysis, where partially formalized quantitative (or qualitative) analysis is the basis for decision-making. Tab. 1 reviews the previous literature on MCDM methods showing aim of the work, modeling, solution, and main results of the literature work [6–19].

Table 1: Literature review's summary

Authors	Method of MCDM	Aim of the work	Modeling, solution, and results
Josimović et al. [6]	Multicriteria Evaluation (MCE)	Applied for the waste management plan.	For actualizing Strategic Environmental Assessment (SEA). Findings of this study exhibited that planning arrangements assessment was accomplished zero states from the maintainability part of waste administration framework.
Levy [7]	ANP	Assessment of the flood risk management and water resources management problems.	Integrated MCA and DSS techniques to improve complex flood risk problems.
Tiwari et al. [8]	AHP	Develop environmental-economic framework, and economic in the zone of marsh irrigated agriculture framework.	Evaluate sustainability criteria in ecological and social of nearby and worldwide need of planters' perspectives among other sub-criteria based on GIS and MCDM methods.

(Continued)

Table 1: Continued

Authors	Method of MCDM	Aim of the work	Modeling, solution, and results
Tesfamariam et al. [9]	Fuzzy AHP	Utilized FAHP for Risk-based environmental evaluation and utilized MCDM instruments for the determination of models of risk ecological evaluation because of clashing and contending measures.	Used a new methodology via risk-based fuzzy AHP to indicate synthetic-based fluids (SBFs), fluids-water based fluids (WBFs) and oil-based fluids (OBFs).
Marinoni et al. [10]	Multicriteria Analysis Tool (MCAT)	Using MCAT for investment environmental aspects which is applied to natural resource management (NRM) problems.	A novel tool of Multicriteria Analysis Tool (MCAT) to measure the social and environmental issues in NRM issues, which can improve straightforwardness and suitability identified with speculation choices.
San Cristóbal [11]	VIKOR	Surveyed sustainable power source ventures by utilized VIKOR.	For taking care of these sorts of issues for the usage of sustainable power source ventures need to think about all rules, this study introduced VIKOR and AHP procedures for the choice of a sustainable power source. The biomass plan elective is the most ideal alternative, followed by solar-based thermo-electric and wind power, for the execution of a sustainable power source venture.
Govindan et al. [12]	Fuzzy TOPSIS	Using F-TOPSIS for maintainability execution estimation. Also, there is a shortage in previous studies that did not consider manageability issues in the determination of providers.	Analyzed and surveying manageable gracefully chain activities issue dependent on the Triple Bottom Line (TBL) approach. Also, it helps organizations in four unique manners including choice of the best provider among others, working with provider bunch constantly, recommending certain providers to improve a portion of their imperfections and quit working with some specific providers.
Doukas et al. [13]	TOPSIS	Surveyed RES advancement by applied TOPSIS. For maintainable advancement, RES assets to decline the carbon emanations, decrease fuel and fossil imports, and see the other vitality strategy goals.	Given the adaptable and straightforward MCDM approach for evaluation of sustainable power source assets dependent on the expansion of TOPSIS and 2-tuple portrayal, the sun-oriented authority in the family unit division is the most ideal alternative of practical sustainable power source assets.

(Continued)

Table 1: Continued

Authors	Method of MCDM	Aim of the work	Modeling, solution, and results
Streimikiene et al. [14]	TOPSIS and MULTIMOORA	Utilized TOPSIS and MULTIMOORA for supportable vitality source choice. It is essential to introduce a supportable dynamic for vitality strategy dependent on political, social, mechanical, and financial improvements.	Applied MULTIMOORA and TOPSIS for choosing the most advances concerning manageable power generation. Findings of this study demonstrated that the approach identified with future vitality must situate towards innovations with respect to the practical vitality, specifically sun-based solar thermal and water ones.
Büyüközkan et al. [15]	F-TOPSIS, FDEMATEL, and F-ANP	Applied F-TOPSIS, FDEMATEL, and F-ANP for assessment of green providers, which, nowadays find appropriate providers in the key inflexible chain of organizations because of natural execution and picture.	For the determination of proper green providers, this study has explored measurements of green SC management and proposed a system dependent on ability measurements. The proposed system has assessed the green provider for improvement of green SC the board activities.
Kannan et al. [16]	F-TOPSIS and FAHP	Applied F-TOPSIS and FAHP for assessment of RES. For the determination of providers, there are a few problems with quantitative and subjective standards because of restrictions of providers.	For choosing, rating, and assessing of the best RES using ecological and financial rules dependent on fluffy MAUT hypothesis and multi-target programming. The proposed model can help firms for making of an efficient model for the undertaking of green provider determination and issues identified with the request portion in genuine contextual analyses.
Sánchez-Lozano et al. [17]	TOPSIS and AHP	Utilize TOPSIS and AHP for evaluation of solar farms locations.	For evaluation and recognition of the best photovoltaic plant area, this investigation incorporated GIS and MCDM methods.
Perera et al. [18]	Fuzzy TOPSIS	Analyze hybrid RES by applied Fuzzy TOPSIS. Because of global issues identified with petroleum product assets consumption and ozone harming substance to select the optimal design to locate of hybrid RES.	For the configuration process of hybrid RES, this investigation incorporated the MCDM method and multi-target streamlining. Another proposed model helped decide loads of targets for present a subtlety see.

(Continued)

Table 1: Continued

Authors	Method of MCDM	Aim of the work	Modeling, solution, and results
Streimikiene et al. [19]	TOPSIS	Utilized TOPSIS for assessment technologies of road transport. Need to assess the technologies of RES with street transport segment in the European Union because of second position ozone harming substance discharges.	For assessment of vitality innovations identified with transport street area, which utilized MCDM strategies such as Interval TOPSIS. The finding of this investigation showed that; a few components effect on transportation generally level, for example, quality, degree, and limit, also; results found that; sustainable based battery-electric vehicles was the best position dependent on all-encompassing and ecological methodology.

The main contributions of this research work can be summarized as:

(1) Based on multi-criteria decision-making models, implementing the integration of MCDM rank methods into the process of engineering design of hybrid renewable energy systems.
(2) Four different methods of weight estimation are considered for usage; no priority of criteria, criteria based on a pairwise comparisons matrix, CRITIC-method, and entropy-based method.
(3) A step-by-step methodology for forming various MCDM models and subsequent analysis of the results is described.

2 Description of the Case Study

The case study represents a flat 70 acres site in the Al-Minya city (Egypt) as an example of the far region location. The latitude and longitude is 28° N and 30° E, respectively. The nearest electrical grid point was 12 km from this location. The site is wealthy with solar irradiance. The mean solar irradiance level was 5.97 kWh/m^2/day [20]. The maximum and minimum solar radiation values were 8.056 and 3.555 kWh/m^2/day, respectively, for June and December. The sunshine period was about 9 to 11 h per day all year except for a few cloudy days. The hourly solar irradiance profile for every month is presented in Fig. 2.

On the site, there was a well with the following specifications: 150 m depth, 40 m static level of water, 120 m^3 the hourly rate of discharge. The salinity of brackish water was 2500 mg/l. It had been scheduled to cultivate part of the land with crops using the raw brackish water. The reminder was cultivated with Wheat as it cannot grow with brackish water. The salinity of the water needed to be lower than 800 mg/l. The amount of desalinated water was 250 m^3/day. The required amounts of brackish water were 350–500 m^3/day and 250–300 m^3/day in the summer and winter periods, respectively.

The required energy to extract the brackish water was around 110 kWh/day with a peak of 15 kW. For desalination of the brackish water, it was scheduled to employ a reverse osmosis (RO) unit. Two different sizes of RO units, RO-250 and RO-500, were considered. The electrical peak demand values were 15 and 29.5 kW for RO-250 and RO-500 respectively [21]. To collect 250 m^3, RO-250 operates 24 h every day. So, the total required energy was 360 kWh/day. While, to collect the same amount by RO-500, 12 h of operation was required with a total consumption of 354 kWh/day.

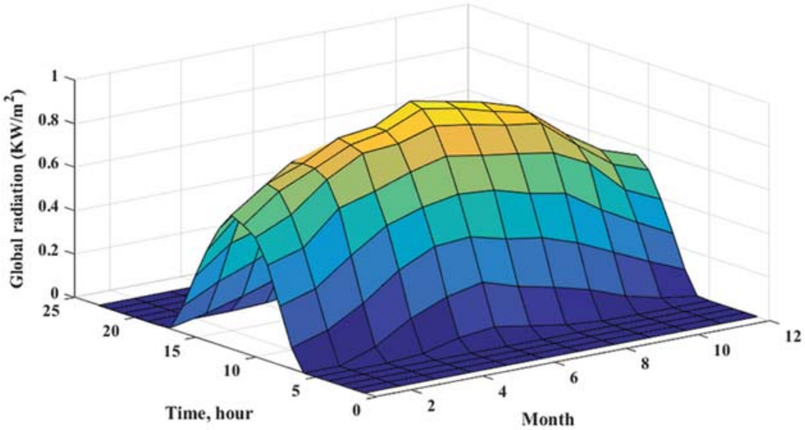


Figure 2: The solar irradiance profile for every month (kW/m^2) per day, Al-Minya city (Egypt)

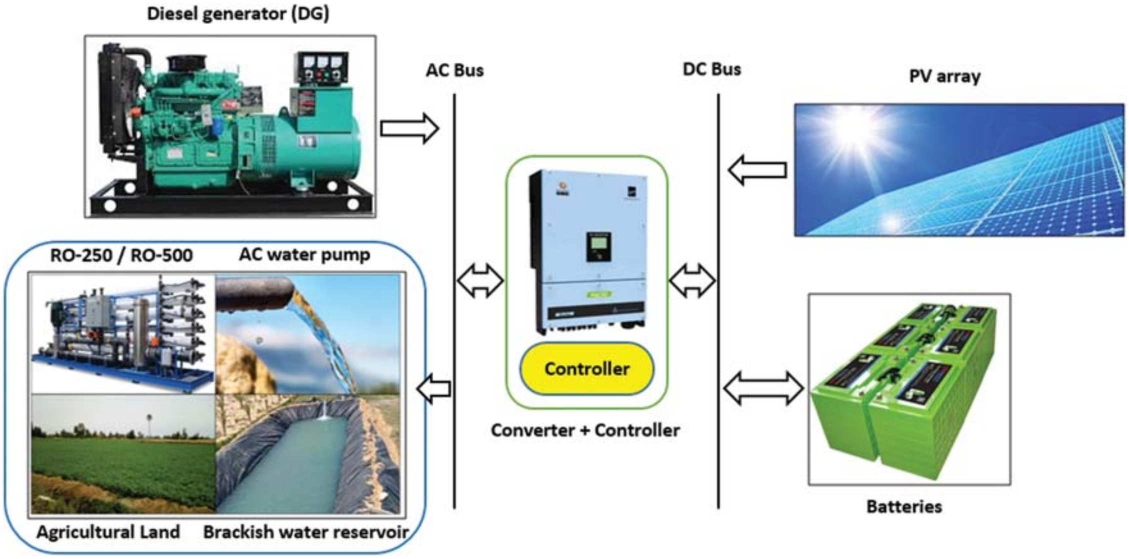


Figure 3: Renewable energy system (RES) schematic graph, Al-Minya city (Egypt)

Fig. 3 illustrates the suggested hybrid system, which contains a Fixed PV array at a tilt angle of 28-degree, DG, power conditioning unit, and battery storage bank. The model of battery was Trojan L16P (360 Ah, 2.16 kWh). The input techno-economic specification data for different elements of a hybrid system are shown in Tab. 2 [22–24]. These data were used for determining the system's best sizes using HOMER® software [25,26]. Various options containing three different power sources: only DG, PV-B system, and hybrid PV-DG-B, two different sizes of reverse osmosis (RO) units; RO-250 and RO-500, two strategies of energy management; load following (LF) and cycle charging (CC), and two sizes of DG; 5 and 10 kW were taken into account. The optimal size of each option was selected based on the minim cost of energy.

To identify the best option for the case study, MCDM tools were used. Eight parameters, including operating cost, renewable fraction, initial cost, the cost of energy, excess energy, unmet load, breakeven grid extension distance, and the amount of CO_2 were considered during the determination of the best option. Tab. 3 shows the output of eight parameters for every considered option.

Table 2: Specification of different elements of the hybrid system

Item	The element of the hybrid system			
	PV array	Battery bank	PCU	DG
Capital cost	\$1000/kW	175 \$/one unit	500 \$/kW	230 \$/kW
Replacement cost	\$1000/kW	175 \$/one unit	450 \$/kW	230 \$/kW
O&M cost	\$5/year	5 \$/year	\$5/year	0.1 \$/h
lifetime	20 years	5 years	15 years	15000 h
Efficiency (%)	14.7	–	90	–

Table 3: The eight output parameters for all alternatives

Alternatives	Operating cost \$/year	RF %	IC \$	COE \$	Excess energy (kWh)	Unmet load kWh	BED km	CO_2 kg/year
DG-250	27155	0.0	6250	0.164	5822	3460	12.3	119110
PVB-250	13994	100	204316	0.138	40294	2461	17.5	0.0
PVBDG5-250LL	13295	87	161930	0.123	14209	2903	15.5	17828
PVBDG10-250LL	12737	75	122840	0.109	16101	2770	15.9	8757
PVBDG5-250CC	14875	84	150226	0.129	34048	2486	19.9	24325
PVBDG10-250CC	15664	67	104204	0.121	24145	2319	26.3	46861
DG-500	28134	0.0	11250	0.171	737	624	11.9	117677
PVB-500	5445	100	175340	0.081	51764	2509	9.7	0.0
PVBDG5-500LL	5546	97	161022	0.077	40998	2371	3.31	5171
PVBDG10-500LL	5087	95	158636	0.074	67671	2024	4.18	8757
PVBDG5-500CC	9549	88	152386	0.099	74813	2599	19.6	22578
PVBDG10-500CC	11774	81	135568	0.108	75695	1927	27	34623

3 Basic Methods and Formulas of MCDM

3.1 Aggregation Models

3.1.1 SAW (Simple Additive Weighting) Method [3–5]

Performance indicator Q_i of the i-th alternative was determined as the entire standardized estimations of the attributes r_{ij} with the weight w_j of the j-th criteria:

$$Q_i = \sum_{j=1}^{n} w_j \cdot r_{ij}, \tag{1}$$

where; $\sum_{j=1}^{n} w_j = 1$ is the most elevated Q_i score.

3.1.2 COPRAS (Complex Proportional Assessment) Method [27]

The aggregation method uses the construction of a performance indicator of alternatives based on the homogeneous function of the two arguments S_{+i} and S_{-i}:

$$Q_i = S_{+i} + \left(\frac{\sum_{i=1}^{m} S_{-i}}{S_{-i} \sum_{i=1}^{m} \left(\frac{1}{S_{-i}} \right)} \right), \tag{2}$$

where;

$$S_{+i} = \sum_{j=1}^{n} w_j \cdot r_{ij} \,|\, for\ j \in C_j^+, \quad S_{-i} = \sum_{j=1}^{n} w_j \cdot r_{ij} \,|\, for\ j \in C_j^-, \tag{3}$$

The above equation represents the sum of the normalized attribute values with weight revenue criteria and cost criteria. The best alternative was the one with the most elevated Q_i score.

3.1.3 TOPSIS (Technique for Order of Preference by Similarity to Ideal Solution) [3]

To determine the performance indicator of the i-th alternative Q_i, a homogeneous function was used:

$$Q_i = \frac{S_i^-}{S_i^+ + S_i^-}, \tag{4}$$

where;

$$v_{ij} = r_{ij} \cdot w_j, \quad S_i^+ = d\left(v_{ij}, v_j^+\right), \quad S_i^- = d\left(v_{ij}, v_j^-\right), \tag{5}$$

$$v_j^+ = \left\{ max_i\ v_{ij}\ \middle| if\ j \in C_j^+;\ min_i\ v_{ij} \middle|\ if\ j \in C_j^- \right\}, \tag{6}$$

$$v_j^- = \left\{ min_i\ v_{ij}\ \middle| if\ j \in C_j^+;\ max_i\ v_{ij} \middle|\ if\ j \in C_j^- \right\}. \tag{7}$$

S_i^+ and S_i^- were the distances d between the ideal and anti-ideal objects respectively. Whereas, the alternative A_i in the n-dimension attributes space, which are defined in one of the L_p-metrics (Section 3.2). The TOPSIS ranking result depends on the choice of distance metric. The best alternative was the one with the highest Q_i score.

3.1.4 GRA (Gray Relation Analysis) [28]

It evaluates the effectiveness of alternatives in two groups with respect to ideal and anti-ideal objects. The sequence of calculations is as follows:

Step 1: Define two sets of attributes i.e., ideal and anti-ideal:

$$r_j^{(1)} = \begin{cases} \max\limits_i \left(r_{ij}\right), & \mathit{if}\ j \in C_j^+ \\ \min\limits_i \left(r_{ij}\right), & \mathit{if}\ j \in C_j^- \end{cases}, \quad r_j^{(2)} = \begin{cases} \min\limits_i \left(r_{ij}\right), & \mathit{if}\ j \in C_j^+ \\ \max\limits_i \left(r_{ij}\right), & \mathit{if}\ j \in C_j^- \end{cases}, \tag{8}$$

Step 2: Determine the matrix of deviations of normalized values from the ideal and anti-ideal:

$$V_{ij}^{(1)} = \left|r_j^{(1)} - r_{ij}\right|, \quad V_{ij}^{(2)} = \left|r_j^{(2)} - r_{ij}\right|, \tag{9}$$

Step 3: Determine the matrices the gray relational coefficient:

$$g_{ij}^1 = \frac{\min_i\left(\min_j V_{ij}^1\right) + \beta \cdot \max_i\left(\max_j V_{ij}^1\right)}{V_{ij}^1 + \beta \cdot \max_i\left(\max_j V_{ij}^1\right)}, \tag{10}$$

$$g_{ij}^2 = \frac{\min_i\left(\min_j V_{ij}^2\right) + \beta \cdot \max_i\left(\max_j V_{ij}^2\right)}{V_{ij}^2 + \beta \cdot \max_i\left(\max_j V_{ij}^2\right)}. \tag{11}$$

Step 4: Determination of the indicator performance for the alternative Q_i:

$$Q_i = Q_i^1 / Q_i^2, \tag{12}$$

$$Q_i^1 = \sum_{j=1}^{n} g_{ij}^1 \cdot \omega_j, \quad Q_i^2 = \sum_{j=1}^{n} g_{ij}^2 \cdot \omega_j. \tag{13}$$

Here, the best alternative was the one with the highest Q_i score.

3.1.5 VIKOR (VIsekriterijumsko KOmpromisno Rangiranje) [29]

Step 1: Determination of “*ideal*” and “*anti-ideal*” object can be expressed as:

$$a_j^+ = \left\{max_i\ a_{ij} \middle| if\ j \in C_j^+;\ min_i\ a_{ij} \middle|\ if\ j \in C_j^-\right\},$$

$$a_j^- = \left\{min_i\ v_{ij} \middle| if\ j \in C_j^+;\ max_i\ v_{ij} \middle|\ if\ j \in C_j^-\right\}, \tag{14}$$

Step 2: Weighted normalization:

$$x_{ij} = \omega_j \cdot \frac{a_j^+ - a_{ij}}{a_j^+ - a_j^-}; \tag{15}$$

Step 3: Maximal R and the group utility S strategies can be expressed as:

$$S_i = \sum_{i=1}^{n} x_{ij}; \quad S^* = min_i\, S_i; \quad S^* = max_i\, S_i;$$
$$R_i = max_i\, x_{ij}; \quad R^* = min_i\, S_i; \quad R^- = max_i\, R_i \tag{16}$$

Step 4: Calculate the values of Q_i:

$$Q_i = v \cdot \left(\frac{S_i - S^*}{S^- - S^*}\right) + (1 - v) \cdot \left(\frac{R_i - R^*}{R^- - R^*}\right), \tag{17}$$

Here, v assumes the part of balancing factor between the general advantage (S) and the maximum individual deviation (R). Smaller estimations of v accentuate bunch gain, while bigger qualities increased the weight controlled by singular deviations. "*Voting by majority rule*" ($v > 0.5$); or "*by consensus*" (for $v = 0.5$); or "*with a veto*" (for $\mathrm{v} < 0.5$).

Step 5: The aftereffect of the system is the three-rating records S, R, and Q. The options were assessed by arranging the estimations of S, R, and Q models of the base worth.

Step 6: As a compromise arrangement, option A_1 was proposed, which was best assessed by Q (*minimum*) if the accompanying two conditions were met:

Condition C_1: "*Allowable advantage*":

$$Q(A_2) - Q(A_1) \geq \frac{1}{(m-1)}, \tag{18}$$

where; A_2 is an alternative in contrast to the second situation in the Q ranking rundown:

Condition C2: "*Adequate soundness in decision-making*": Alternative A_1 ought to likewise be best assessed by S or/and R.

Step 7: If one of the conditions 1 or 2 was not fulfilled, a lot of negotiating arrangements were proposed, which comprises of:

Alternatives A_1 and A_2; if condition C_2 is not met, or

Alternatives $A_1, A_2, \ldots, A_k$; if condition C_1 is not fulfilled. Where, A_k is controlled by the connection:

$$Q\left(A_{k-1}\right) - Q(A_1) < \frac{1}{(m-1)}; \quad Q(A_k) - Q(A_1) \geq \frac{1}{(m-1)} \tag{19}$$

3.1.6 PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) [30]

Step 1: Set the inclination work for two items for every model $H_j = H\ (d_{is},\ p,\ q)$. When in doubt, they have two boundaries: p-indifference edge, it mirrors the way that if the distinction of these estimations of two options i and s are immaterial, objects by standard j were comparable. If the distinction in the limit esteem p was surpassed, an inclination connection was built up between the items. Similarly, if the distinction in edge q was surpassed, the inclination work, which compares the "*strong preference*" of variation i concerning s variation as for the j measure. With the distinction of d_{is} in the stretch from p to q, the inclination work was under 1, which compares a "*weak preference*". The decision of the inclination work was controlled by the leaders. A few sorts of capacities favored $H(d)$ were introduced in Tab. 4.

Table 4: Preference functions for PROMETHEE-method

Function	Threshold	Formula
Usual	No threshold	$f(x) = \begin{cases} 1, & x > 0 \\ 0, & x \leq 0 \end{cases};$
U-shape	q threshold	$f(x) = \begin{cases} 1, & x > q \\ 0, & x \leq q \end{cases};$
V-shape	p threshold	$f(x) = \begin{cases} x/p, & x \leq p \\ 1, & x > p \end{cases};$
Level	p and q threshold	$f(x) = \begin{cases} 0, & x \leq p \\ 0.5, & p < x < q \\ 1, & x \geq q \end{cases};$
Linear	p and q threshold	$f(x) = \begin{cases} 0, & x \leq p \\ (x-p)/(q-p), & p < x < q \\ 1, & x \geq q \end{cases};$
Russian	s threshold	$f(x) = 1 - \exp\left(-\frac{x^2}{2s^2}\right);$

Step 2: Compute the distinction in the estimations of the models for the two items and calculate the inclination records V:

$$d_{is} = a_{ij} - a_{sj}; \quad H_j(d_{is}, p, q); \quad V_{is} = \sum_{j=1}^{n} w_j \cdot H_j - [m \times n]\, matrix \tag{20}$$

Step 3: Determination of the preference factors:

$$\begin{aligned} \Phi_i^{+} &= \sum_{s=1, s \neq i}^{m} V_{is}; \\ \Phi_i^{-} &= \sum_{s=1, s \neq i}^{m} V_{si} \\ Q_i &= \Phi_i^{+} - \Phi_i^{-} \end{aligned} \tag{21}$$

The best option is the one with the most elevated Q_i score.

3.1.7 ORESTE (Organization, Arrangement to Sinteze of Relational Data) [31]

Step 1: Change from network DM to ranks matrix (the columns of the matrix are supplanted by their ranks).

$$r_{ij} = rank\left(a_{ij} \mid \left\{a_{1j}, a_{2j}, \ldots, a_{mj}\right\}\right), \quad \forall i, j \ \ (i = 1, \ldots, m; j = 1, \ldots, n). \tag{22}$$

Step 2: Determine the ranks of criteria:

$$\begin{aligned} & rc_j = rank\left(C_j \mid \{C_1, C_2, \ldots, C_n\}\right), \quad \forall j = 1, \ldots, n, \\ & \text{or } rc_j = rank\left(w_j \mid \{w_1, w_2, \ldots, w_n\}\right) \end{aligned} . \tag{23}$$

Step 3: The projections of ranks were computed:

$$d_{ij} = \left[(1-\alpha) \cdot r_{ij}{}^{p} - \alpha \cdot rc_j{}^{p}\right]^{1/p}, \quad \alpha \in (0; 1). \tag{24}$$

p-one of: $p = 1$ Average (CityBlock, TaxiCab or Manhattan) distance,
$p = 2$ Mean Square (*Euclidean*) distance,
$p = \infty$ Chebyshev distance.

Step 4: Calculating Ranks d_{ij}

$$Rd_{ij} = rank\left(d_{ij} \mid \{d_{ij}\}_{i=1:\,m; j=1:\,n}\right), \quad R_i = \sum_{j=1}^{n} Rd_{ij}. \tag{25}$$

Step 5: Calculating Ranks R_i (ORESTE 1)

$$OutR_i = rank\left(R_i \mid \{R_1, R_2, \ldots, R_m\}\right). \tag{26}$$

Step 6: Calculation of preference factors C_{ik}

$$C_{ik} = \frac{1}{2 \cdot n^2 \cdot (m-1)} \cdot \sum_{j=1}^{n} \left(Rd_{ij} - Rd_{kj} + |Rd_{ij} - Rd_{kj}|\right). \tag{27}$$

$$r_{ij} = \underset{j}{rank}\left(a_{ij}\right); \quad R_{ij} = \underset{j}{sort}\left(a_{ij}, \text{'descend' } if\, j \in C_j^{+} \text{ or 'ascend' } if\, j \in C_j^{-}\right) \tag{28}$$

The best option was the one with the **lowest** Q_i score.

3.2 Distance Metric

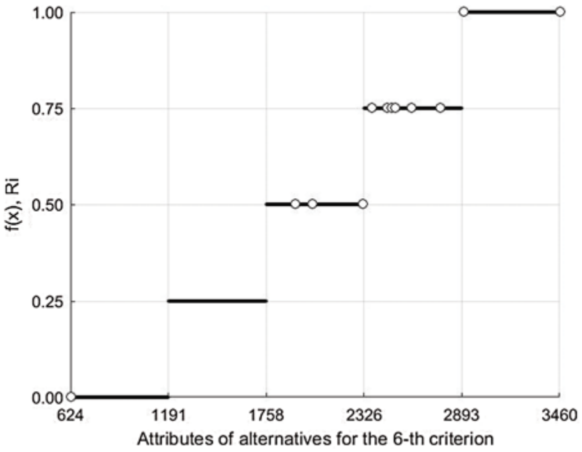
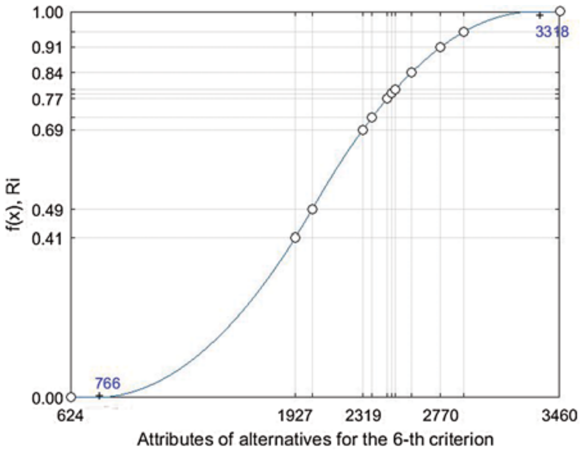
Distance metric was used to choose measurement to quantify the distance between two n-dimensional objects x and y:

$$\begin{aligned} & L_p(x, y) = \left[\sum_{j=1}^{n} \left(x_j - y_j\right)^p\right]^{1/p}, \quad 1 \le p \le \infty; \\ & L_\infty(x, y) = \max_j \left|x_j - y_j\right| \end{aligned} \tag{29}$$

3.3 Normalization Methods

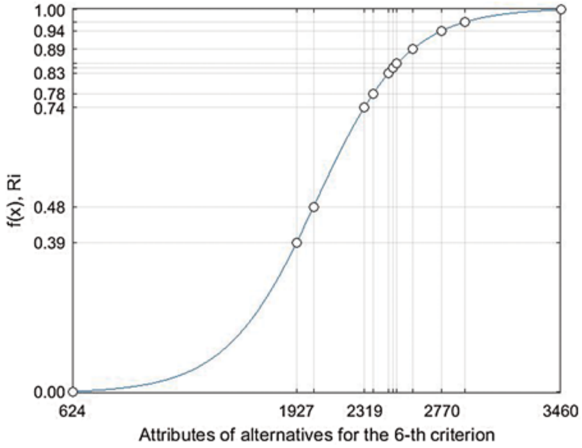
The study used the following 8-normalization methods [32,33] as listed in Tab. 5.

Table 5: The 8-normalization methods used in the study

Linear methods				
Max	Sum	Max–Min	Vec	Dea
$\frac{a_{ij}}{a_j^{\max}}$	$a_{ij}/\sum_{i=1}^{m} a_{ij}$	$\frac{a_{ij}-a_j^{\min}}{a_j^{\max}-a_j^{\min}}$	$a_{ij}/\sqrt{\sum_{j=1}^{n} a_{ij}^2}$	$1-\frac{a_j^{\max}-a_{ij}}{\sum_{i=1}^{m}\left(a_j^{\max}-a_{ij}\right)}$
Non-linear methods				
St4(a)	$r_{ij}=\begin{cases}0, & a_{ij}\le p_{1j}\\ 0,\ 25, & a_{ij}\le p_{2j}\\ 0,\ 5, & a_{ij}\le p_{3j}\\ 0,\ 75, & a_{ij}\le p_{4j}\\ 1, & a_{ij}>p_{4j}\end{cases}$			
Spl(b)	$r_{ij}=\begin{cases}0, & v_{ij}\le p_j\\ 2\cdot\left(\frac{v_{ij}-p_j}{q_j-p_j}\right)^2, & p_j<v_{ij}\le\frac{p_j+q_j}{2}\\ 1-2\cdot\left(\frac{q_j-v_{ij}}{q_j-p_j}\right)^2, & \frac{p_j+q_j}{2}<v_{ij}\le q_j\\ 1, & v_{ij}>q_j\end{cases}$ $v_{ij}=\frac{a_{ij}-a_j^{\min}}{a_j^{\max}-a_j^{\min}},$ $p_j,\ q_j\in[0;\ 1]\quad(p=0,\ 05;\ q=0,\ 95)$			

(Continued)

Table 5: Continued

Non-linear methods		
Sgm$^{(c)}$	$r_{ij} = \dfrac{1}{1 + e^{-k_j \cdot 12(v_{ij} - p_j)}}$, $k_j \approx 1 \ \ (tg45 = 1)$ $p_j \in [0.5 \pm 0.25], \quad f\left(p_j\right) = 0.5;$ $v_{ij} = \dfrac{a_{ij} - a_j^{\min}}{a_j^{\max} - a_j^{\min}}$ k_j—slope factor (0, 9); p_j—point of symmetry center (0, 5)	

$^{(a)}$**St4-method** (*Step four*) is one of the variations of the family of step functions that allows combining close (or *indistinguishable*) indicators into groups.

$^{(b)}$**Spl-method** (*spline function*) is a two-step method with a parabolic spline function, which allows to strengthen the "*strong*" attributes and weaken the "*weak*" attributes. In the first step, the Max–Min transformation is applied.

$^{(c)}$**Sgm-method** (*sigmoid function*) is also a two-step method with a sigmoid approximation that allows one to strengthen "*strong*" attributes and weaken "*weak*" attributes and eliminate "*clumps*" in the data. In the first step, the Max–Min transformation is applied.

3.4 Normalization for Cost Criteria

Two-Step Res-algorithm for inversion of cost credits into advantage ascribes [33]:

$$\begin{aligned} &1)\ r_{ij} = Norm\left(a_{ij}\right), \quad \forall j = 1, \ldots, n \\ &2)\ \widetilde{r}_{ij*} = -r_{ij*} + r_{j*}^{\max} + r_{j*}^{\min}, \quad \forall j^* \in C_j^- \end{aligned} . \tag{30}$$

where; the linear normalization method $Norm(a_{ij})$ in the first step was applied to both, the benefit attributes and the cost attributes, and index j^* meets the cost criteria.

3.5 Methods for Weight Estimation

3.5.1 No Priority of Criteria

$$w_i = 1/n \tag{31}$$

3.5.2 Estimation the Weights Based on a Pairwise Comparisons Matrix of the Criteria [34]

Step 1: Determine pairwise comparison matrix P in T, *Saaty scale*.

Step 2: Determine eigenvector (v) for max eigenvalue λ_{max} of matrix P (the calculations use the MATLAB function *eigs*( )):

$$[v, \lambda_{max}] = eigs(P, 1), \tag{32}$$

Step 3: Calculate consistency index ($C.I.$) and compare with Tab. 5 of random consistency index ($R.I.(n)$).

$$C.I. = (\lambda_{\max} - n)/(n - 1), \tag{33}$$

Step 4: Check the consistency of the pairwise comparison matrix. Compare the consistency index ($C.I.$) with the values of ($R.I.(n)$):

```
if $C.I./R.I.(n) < 0, 1$
    'Pairwise comparison matrix $P$ consistent'
else
    go to Step 1
end
```

Step 5: Calculate weights of criteria:

$$w_j = v_j / \sum_{j=1}^{n} v_j \tag{34}$$

In this case study, the values of the P were listed in Tab. 6.

Table 6: Values of the P-matrix in the case of study

P	C_1	C_2	C_3	$C4$	C_5	C_6	C_7	C_8
C_1	1	3	0,5	0,5	1/3	1/3	1/3	2
C_2	1/3	1	0,5	0,5	0,5	0,5	1/3	1
C_3	2	2	1	0,5	0,5	0,5	3	2
C_4	2	2	2	1	3	2	2	2
C_5	3	2	2	1/3	1	1	1	2
C_6	3	2	2	0,5	1	1	1	3
C_7	3	3	1/3	0,5	1	1	1	2
C_8	0,5	1	0,5	0,5	0,5	1/3	0,5	1
w	0,082	0,060	0,138	0,221	0,147	0,158	0,132	0,062

$C.I./R.I.(n) = 0{,}07.$

3.5.3 CRITIC-Method (Criteria Importance Through Intercriteria Correlation) for Weight Estimation [12]

Step 1: Determine '*best*' (b) and '*worst*' (t) solution ($[1 \times n]$-vector) for all attributes.

Step 2: Determine relative deviation matrix $V = (v_{ij})$ $[m \times n]$-matrix

$$v_{ij} = \frac{\left(a_{ij} - b_j\right)}{\left(b_j - t_j\right)}. \tag{35}$$

Step 3: Determine standard deviation (St) $([1 \times n] - \text{vector})$ for *colls* of V.

$$St = std(V) \tag{36}$$

Step 4: Determine correlation matrix (Cr) $([n \times n])$ for *colls* of V.

$$Cr = corr(V) \tag{37}$$

Step 5: Determine vector (c) and calculate the weight of criteria w_k.

$$\begin{aligned} c_k &= St_k \cdot \textstyle\sum_{j=1}^{n} \left(1 - Cr_{kj}\right), \quad k = 1, \ldots, n \\ & . \\ w_k &= c_k / \textstyle\sum_{k=1}^{n} c_k \end{aligned} \tag{38}$$

In this case study, the values of the *B, T, and w* were listed as:

$b = [5087\ 10\ 6250\ 0{,}109\ 5822\ 2319\ 12{,}3\ 1]$,

$t = [28134\ 1\ 204316\ 0{,}164\ 40294\ 3460\ 26{,}3\ 100]$, and

$w = [0.104\ 0.124\ 0.166\ 0.102\ 0.175\ 0.100\ 0.111\ 0.119]$.

3.5.4 Entropy-Based Method for Weight Estimation [13]

The step-by-step algorithm for estimating the weights of the criteria using the entropy method was presented as follows:

Step 1: Standardized decision matrix (*Max–Min method*) for benefit criteria:

$$r_{ij} = \frac{a_{ij} - a_j^{\min}}{a_j^{\max} - a_j^{\min}}, \tag{39}$$

For cost criteria:

$$r_{ij} = \frac{a_j^{\max} - a_{ij}}{a_j^{\max} - a_j^{\min}}. \tag{40}$$

Step 2: Calculate the equity contribution of the *i*-th attribute for each criterion:

$$f_{ij} = \frac{r_{ij}}{\sum_{i=1}^{m} r_{ij}}, \quad \forall i = 1, \ldots, m, \quad j = 1, \ldots, n; \quad \sum_{i=1}^{m} f_{ij} = 1, \tag{41}$$

Step 3: Calculate the entropy of each criterion:

$$e_j = -\frac{\sum_{i=1}^{m} f_{ij} \cdot \ln f_{ij}}{\ln m}, \quad \mathrm{j} = 1, \ldots, \mathrm{n}; \ \left(\text{if } r_{ij} = 0 \Rightarrow f_{ij} \cdot \ln f_{ij} = 0\right), \tag{42}$$

Step 4: Calculate the weight of each criterion:

$$\omega_j = \frac{1 - e_j}{n - \sum_{j=1}^{n} e_j}, \quad j = 1, \ldots, n, \quad \sum_{\mathrm{j=1}}^{\mathrm{n}} \omega_j = 1. \tag{43}$$

The value $(1 - e_j)$ is the internal intensity of the contrast of each criterion or is the degree of divergence of the internal information of each criterion [35,36]. The smaller value of the entropy, the larger the entropy-based weight. In this case study, the values of the w were listed as:

$w = [0{,}093\ 0{,}082\ 0{,}106\ 0{,}023\ 0{,}180\ 0{,}032\ 0{,}086\ 0{,}398]$.

4 MCDM Techniques

4.1 MCDM Rank Model

The ranking-based MCDM model for every elective A_i decides a specific exhibition level of the choices Q_i based on the ranking of the other options, and the ensuing decision-making was obtained [3–5]:

$$A_i \xrightarrow{F} Q_i, \quad i = 1, \ldots, m, \tag{44}$$

$$Q = F\left(A, C, D, \omega, \text{‘}nm\text{’}, \text{‘}dm\text{’}, \text{‘}pr\text{’}\right), \tag{45}$$

$$A_p \prec A_q \prec \ldots \prec A_r \prec A_s, \quad p, q, r, s \in \{1; 2; \ldots; m\}. \tag{46}$$

The MCDM rank model incorporates the decision of a lot of alternatives (A) and a set of criteria (C), an evaluation of the estimations of the characteristics of choices with respect to every criterion-a decision-making matrix (a_{ij}), a method for assessing the weight or priority of criteria (w), a choice of a normalization method (‘*nm*’) decision-making matrix, a choice of metric for calculating distances in n-dimensional space of criteria (‘*dm*’), a choice of preference functions (‘*pr*’), and the definition of aggregation function of alternatives’ attributes (F) to calculate efficiency indicator (Q) of each alternative. Based on the calculation of the aggregate performance indicator of alternatives Q, alternatives were ranked, i.e., SAW ranking model is simplified as:

$$Q_i = \sum_{j=1}^{n} w_j \cdot r_{ij}. \tag{47}$$

where r_{ij} are the standardized estimations of the regular estimations of the qualities a_{ij}, acquired utilizing one of the standardization techniques. None of the arguments to F were unambiguous. The choice of A and C was not formalized, the estimates a_{ij} were not accurate, the choice of the method for evaluating the weights of the criteria, the method of the standardized method, the method of aggregation, and the choice of the distance metric were not formalized, as there were no selection criteria. Therefore, different combinations of 8 basic parameters in Eqs. (44)–(46) define different MCDM models.

4.2 MCDM Formalization of the Problem of Choosing Hybrid Renewable Energy Systems

In the present study, different models were defined by combining the ‘n_m’ normalization method, the aggregation method F, the choice of different distance metrics, and different preference functions. Thus, for integration into the engineering design process of hybrid renewable energy systems, 55 models or variations of the basic ranked MCDM methods have been identified in Tab. 7.

Table 7: Constructor of alternative ranking models

Model #	Aggregation model F [3–5,27–31]	Distance metric	Normalization method [32,33]
1–8	1) SAW: Simple Additive Weighting [3–5].		Max Sum Vec Max–Min Dea St4 Spl Sgm
9–16	2) COPRAS: Complex Proportional Assessment [27].		
17–40	3–5) TOPSIS: Technique for Order of Preference by Similarity to Ideal Solution [3].	3) L1 4) L2 5) L∞	
41–48	6) GRA: Gray Relation Analysis [28].		
49	7) VIKOR: Visekriterijumsko Kompromisno Rangiranje [29].	Sum	
50–53	8) PROMETHEE, version II: Preference Ranking Organization Method for Enrichment Evaluations [30].	Set the preference function: 1) all V-shape 2) all Linear 3) all Gaussian 4) Linear–Gaussian	
54–55	9) ORESTE, version I: [31]	54) L2 55) L∞	–
Weight [12,13,34,36]			
i.	No priority of criteria		
ii.	Estimation of the weights based on a pairwise comparisons matrix of the criteria [34].		
iii.	CRITIC-method (Criteria Importance Through Intercriteria Correlation) for weight estimation [35].		
iv.	Entropy-based method for weight estimation [36].		

Combining 4 different methods for evaluating criteria weights, gives 220 options for ranking alternatives. Besides, the following model notation was used in the form of a cortege: # = {‘*F*’, ‘w’, ‘*nm*’, ‘*dm*’, ‘*pr*’}. For example, model #18 = {TOPSIS, (ii), Sum, L_1} uses the TOPSIS attribute aggregation method, (ii)-a method for evaluating criteria weights, the **Sum** normalization method and the CityBlock-metric [3–5,27–31].

How much the ranking results differ depends on many factors. First, a ranking of alternatives was determined by the partial preference of various alternatives among themselves according to individual attributes. Suppose one of the alternatives has a preference over the other alternative according to several criteria, and vice versa, the other alternative dominates over the first according to another group of criteria. In that case, the performance indicators of these alternatives differ slightly. Although the aggregation methods, normalization methods, and the choice of parameters for preference functions affect the ranking result insignificantly, their small variations, together with a weak distinction of alternatives determine the ranking results [37]. Another parameter determining the ranking is the criterion weight. The weights directly determine the preference of alternatives over each other according to certain criteria. Therefore, the assessment of the criteria weights requires a justification of the chosen method and subsequent comparative analysis and correction of the weights of various criteria. Following this, one of the tasks of the study is to determine several best alternatives based on the analysis of the ranking results when varying the methods and parameters in the MCDM models.

4.3 Description of Alternatives and Attributes of Hybrid Renewable Energy Systems; Decision Matrix

Tab. 8 presents a matrix of decisions for the selected list of alternatives and their attributes.

Table 8: Matrix of decision D $[12 \times 8]$

Alternatives		C_1^-	C_2^+	C_3^-	C_4^-	C_5^-	C_6^-	C_7^-	C_8^-
		Operating cost	RF	IC	COE	Excess energy	Unmet load	BED	CO_2
A_1	DG-250	27155	1	6250	0,164	5822	3460	12,3	100
A_2	PVB-250	13994	10	204316	0,138	40294	2461	17,5	1
A_3	PVBDG5-250LL	13295	9	161930	0,123	14209	2903	15,5	15
A_4	PVBDG10-250LL	12737	8	122840	0,109	16101	2770	15,9	8
A_5	PVBDG5-250CC	14875	9	150226	0,129	34048	2486	19,9	21
A_6	PVBDG10-250CC	15664	7	104204	0,121	24145	2319	26,3	40
A_7	DG-500	28134	1	11250	0,171	737	624	11,9	100
A_8	PVB-500	5445	10	175340	0,081	51764	2509	9,7	1
A_9	PVBDG5-500LL	5546	10	161022	0,077	40998	2371	3,31	5
A_{10}	PVBDG10-500LL	5087	10	158636	0,074	67671	2024	4,18	8
A_{11}	PVBDG5-500CC	9549	9	152386	0,099	74813	2599	19,6	19
A_{12}	PVBDG10-500CC	11774	9	135568	0,108	75695	1927	27	29

All criteria except the second (C_2^+) were "cost" criteria (C_j^-). Therefore, to aggregate the attributes of benefit and cost jointly, the inversion of the normalized values was used through the ReS-algorithm [33]. The ReS-algorithm allows the same normalization method to be applied to both benefit and cost attributes and is effective for all normalization methods.

To determine the priority of alternatives, it was not enough to compare the absolute values of the efficiency indicator Q_i. Attribute values may not be accurate due to many factors. For example, an attribute can be measured where the data source may be unreliable, there was error in measurement, the measurements for various alternatives were carried out using different methods, some attributes may be random values or determined by the values of intervals, etc. Thus, the value of the performance indicator was determined with an error of $Q_i \pm \Delta Q_i$, and the distinguishability of alternatives was determined by the error ΔQ_i.

In many cases, it was not possible to estimate the error. Then use the "*a priori*" or expert estimate, expressing it as a percentage. For example, as follows: the error in assessing the indicator of the alternative's effectiveness was 5% of its value. Considering that alternatives were ranked according to their place in the ordered list of performance indicators, it was advisable to determine a relative indicator to assess the distinguishability of alternatives:

$$\mathrm{d}Q_p = \left(Q_p - Q_{p+1}\right)/rng\,(Q) \cdot 100\%, \quad p = 1, \ldots, m-1. \tag{48}$$

where; Q_p is the value of the performance indicator corresponding to the p-rank alternative, $rng(Q) = Q_I - Q_m$. Following Eq. (48), dQ_p represents the relative (given in the Q scale) increase or decrease in the efficiency indicator for an ordered list of alternatives. Afterward, two alternatives: the relative increase in dQ of which differ less than the value of the given a priori error, should be considered indistinguishable. The dQ indicator was used to assess the distinguishability of alternatives and to compare the results of aggregation performed by different methods.

4.4 Estimation of Weights of Criteria

Tab. 9 presents the criterion weights obtained using the 4-methods of estimation [12,13,34,36].

Table 9: Values of the weighting coefficients of the criteria obtained by using various methods

Rank #	Method of the weight estimation	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8
(*i*)	No priority of criteria	0,125	0,125	0,125	0,125	0,125	0,125	0,125	0,125
(*ii*)	Based on a pairwise comparisons matrix of the criteria	0,082	0,060	0,138	0,221	0,147	0,158	0,132	0,062
(*iii*)	CRITIC-method	0,104	0,124	0,166	0,102	0,175	0,100	0,111	0,119
(*iv*)	Entropy based method	0,093	0,082	0,106	0,023	0,180	0,032	0,086	0,398
	Methods comparison	|wp-wq|/wp · 100, %							
	i–ii	34	52	10	77	18	26	6	50
	ii–iii	27	107	20	54	19	37	16	92
	iii–iv	11	34	36	77	3	68	23	234
	i–iii	17	1	33	18	40	20	11	5
	i–iv	13	37	23	90	22	80	35	542
	ii–iv	26	34	15	82	44	74	31	218

In the second part of Tab. 9, values of the relative difference (%) were given between the weights obtained by different methods. For the highlighted cells, the criteria weights differ significantly more than 70%.

For method (*iv*), the weight values for C_8 were greatly overestimated (by 4–5 times) and the weight of C_4 and C_6 was greatly underestimated (by 4–5 times) in comparison with the weights determined by other methods. This overestimates the contribution of attribute 8 to the performance indicator of alternatives. It was expected that the priority 8 attribute alternatives will receive priority in the performance indicator. These are alternatives to A_2, A_8, A_9, and A_{10}.

The weights obtained using methods (*ii*) and (*iii*) differ on average by 30%. Both methods consider the relationship between different criteria in general, rather than the difference in attributes like the entropy-based method.

5 Results and Discussion

Calculations for various models were performed using the **MCDM_tools** software (version 2020), developed in the MATLAB system. **MCDM_tools** (version 2018) were posted in the public domain in a MathWorks File Exchange service on the website of the developer company MathWorks [38]. For each MCDM model, the performance indicator of each alternative Q_i, the relative intensity iQ, the relative increment dQ were calculated and the ranks of the alternatives A_i were determined. An example of calculated indicators was presented in Tab. 9.

Tabs. 10, 11 present the synthetic results of ranking alternatives (based on Tab. 7) for various options (*i*)–(*iv*) estimates of the criterion weights obtained for 55 different MCDM models.

Table 10: Fragment of calculation results for the MCDM model #17–24 = {TOPSIS, (*i*), (Max, Sum, …, Sgm), L_1,}

Rank #	Max				Sum				…	Sgm			
	Q	iQ	dQ	A_i	Q	iQ	dQ	A_i	…	Q	iQ	dQ	A_i
1	0.731	10.96	0.000	9	0.760	11.01	0.000	9	…	0.707	10.49	0.000	9
2	0.692	10.38	0.105	10	0.711	10.30	0.115	10	…	0.696	10.33	0.031	10
3	0.663	9.94	0.078	8	0.703	10.18	0.020	8	…	0.668	9.92	0.077	4
4	0.624	9.36	0.106	4	0.671	9.72	0.075	4	…	0.650	9.65	0.051	8
5	0.586	8.79	0.103	3	0.630	9.12	0.098	3	…	0.599	8.89	0.142	3
6	0.533	7.99	0.145	2	0.589	8.53	0.096	2	…	0.554	8.23	0.125	6
7	0.529	7.93	0.011	5	0.560	8.11	0.068	5	…	0.552	8.20	0.005	12
8	0.502	7.53	0.073	11	0.529	7.66	0.074	11	…	0.519	7.70	0.093	11
9	0.499	7.49	0.007	6	0.513	7.43	0.036	6	…	0.494	7.33	0.071	5
10	0.478	7.17	0.058	7	0.478	6.92	0.083	12	…	0.477	7.08	0.046	7
11	0.467	7.01	0.029	12	0.425	6.15	0.125	7	…	0.471	6.99	0.017	2
12	0.362	5.44	0.285	1	0.336	4.87	0.209	1	…	0.349	5.18	0.341	1

Table 11: Statistics of alternatives of I–III ranks based on the results of calculations of 55 MCDM models

Rank #	(*i*)			(*ii*)			(*iii*)			(*iv*)		
	I	II	III	I	II	III	I	II	III	I	II	III
A_1	0	0	0	0	0	0	0	1	4	0	0	0
A_2	0	0	0	0	0	0	0	0	0	0	1	2
A_3	0	0	0	0	1	1	0	1	5	3	17	5
A_4	4	8	10	3	1	18	17	21	0	24	19	10
A_5	2	1	2	0	0	0	0	0	1	0	2	0
A_6	0	0	0	0	0	0	1	2	1	0	0	0
A_7	0	0	0	5	2	4	2	2	5	0	0	0
A_8	0	0	37	0	4	24	0	0	17	0	6	21
A_9	45	7	3	45	6	2	34	13	1	27	9	16
A_{10}	4	39	3	2	41	6	1	15	21	1	1	1
A_{11}	0	0	0	0	0	0	0	0	0	0	0	0
A_{12}	0	0	0	0	0	0	0	0	0	0	0	0

The numerical values in the Tab. 11 indicate how many times each of the alternatives A was ranked as I, II, III when ranks were based on 55 variants of MCDM models.

First: Let us consider the clearly "*weak*" alternatives that, according to the results of calculations, did not have high ranks. According to Tab. 8, it is A_{11} and A_{12}.

Second: The assumption (Section 3.4) that, for the method (*iv*), all alternatives with a priority on attribute #8 will also receive priority in the performance indicator.

Indeed, according to Tab. 8 alternatives, A_9 and A_8 have I and II ranks in most models, and alternative A_2 has II and III ranks in one and two cases, respectively, (and for other methods of estimating weights, I–III ranks are never achieved). The final ranks of the alternatives were presented in Tab. 12.

Table 12: Final rank of alternatives

Rank												
w_i	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XI
(*i*)	A_9	A_{10}	A_8	A_4	A_3	A_2	A_5	A_{11}	A_6	A_{12}	A_7	A_1
(*ii*)	A_9	A_{10}	A_8	A_4	A_7	A_3	A_6	A_6	A_{11}	A_5	A_1	A_1
(*iii*)	A_9	A_4	A_{10}	A_4	A_3	A_5	A_7	A_6	A_2	A_{11}	A_{12}	A_1
(*iv*)	A_9	A_4	A_8	A_{10}	A_3	A_2	A_5	A_{11}	A_{11}	A_{12}	A_7	A_1

The unconditional leader was alternative A_9. However, the alternatives A_{10}, A_7, A_4, and A_3 for some models (about 30% of variants) also had the first rank. Determining the leader by majority of votes cannot be a correct method. Additional information consists of assessing the distinguishability of alternatives using the relative performance indicators iQ and dQ.

Tab. 13 shows the ranks of alternatives (*fragment*) based on the results of calculations for 55 models in the case of determining the weights of the criteria by method (*iii*).

Table 13: Ranks of alternatives based on the results of 55 models in the case of determining the weights of criteria by method (*iii*) (*Fragment*)

Rank #	Number of alternatives											
	I	II	III	IV	V	VI	VII	VIII	IX	X	XI	XI
1	9	4	10	8	3	7	5	6	2	11	1	12
2	9	4	8	10	3	2	5	6	7	11	12	1
3	9	4	10	8	3	5	2	6	7	11	12	1
4	9	10	8	4	3	5	6	7	2	11	12	1
5	9	10	8	4	3	2	5	11	6	12	7	1
6	9	4	10	3	8	6	7	11	2	5	12	1
…	…	…	…	…	…	…	…	…	…	…	…	…
36	4	7	1	6	3	9	5	8	10	2	11	12
37	6	4	10	9	5	8	11	12	3	2	1	7
38	4	1	7	3	6	5	9	2	8	10	11	12
39	4	7	1	6	3	5	9	8	2	10	11	12
40	7	6	1	4	3	5	9	8	2	10	11	12
41	9	10	8	4	3	5	7	2	6	11	12	1
…	…	…	…	…	…	…	…	…	…	…	…	…
54	10	9	8	4	3	2	11	12	7	5	6	1
55	9	4	10	8	3	2	11	5	6	12	7	1

Tab. 13 and the data in Tab. 7 make it possible to select models for subsequent refinement of the leader. The specificity of MCDM models shows that for some models (more precisely, an unsuccessful combination of model parameters), a result is possible in which an alternative "*weak*" in terms of characteristics has a high rating (*rank*). For example, the alternative A_1 has shown II rank in the model #38 = {TOPSIS, (*iii*), St4, L_∞}, Tab. 11. In the absence of formal criteria for the selection of models, acceptance or rejection was possible if there were additional arguments (*reasons*).

Fig. 4 shows various histograms of the ranks of alternatives based on the results of calculations in 55 models (option (*ii*)). Data were collected in separate histograms considering the distinguishability of rank I–III alternatives.

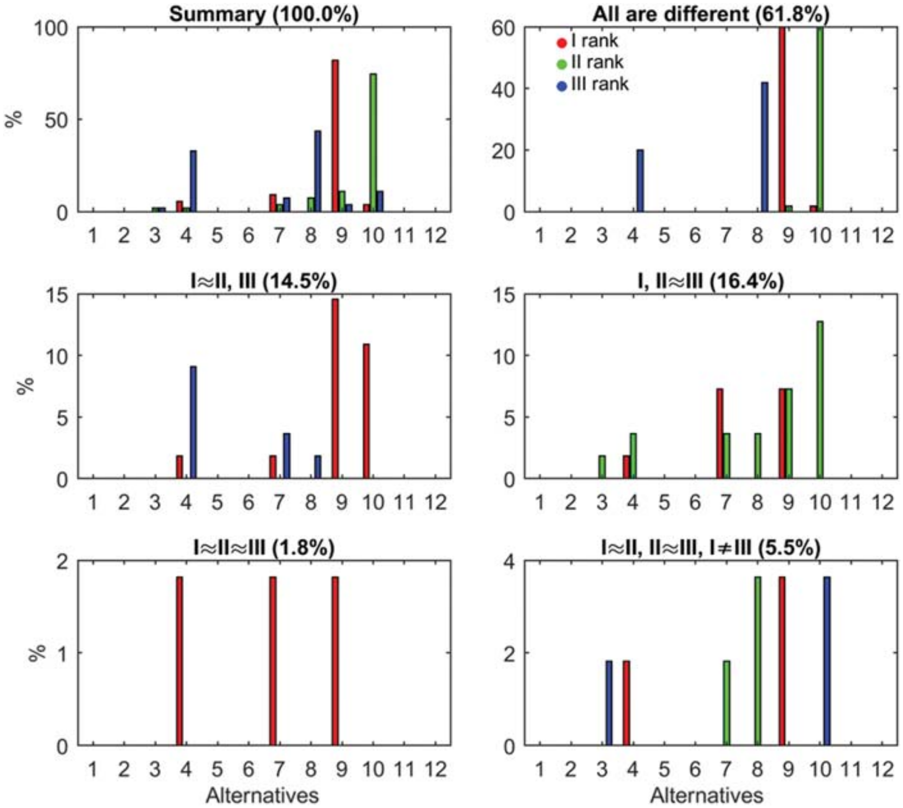


Figure 4: Distinguishability of the alternatives of rank I–III for (*ii*)-method

Fig. 5 shows the intensity of the performance indicator of alternatives of I–III ranks (points), considering their distinguishability for various models of aggregation of attributes. The results were collected in sequential groups corresponding to the eight different normalization methods as indicated in Tab. 2 (Model Builder)-{'Max,' 'Sum,' 'Vec,' 'Max–Min,' 'Dea,' 'St4,' 'Spl,' 'Sgm.'} Colored markers illustrate the distinguishability of rank I–III alternatives.

Similar Figs. 4 and 5 were obtained for all the variants for evaluating the weights of criteria (*i*)–(*iv*). Tab. 14 presents a summary of the results.

The distinguishability of alternatives of I–III ranks was no more than 61.8%, and the indifference of alternatives I, II, and III ranks above 30% cannot be made unambiguously. Alternatives

A_9, A_{10}, A_8, and A_4 were recommended as suboptimal. The final decision was made by the decision-maker.

Table 14: Distinguishability of rank I–III alternatives; statistics for 55 models

w_i	Distinguishability of the alternatives of rank I–III			
	All different	I≈II, III	I, II≈III	I≈II≈III
(*i*)	54,5	14,5	27,5	1,8
(*ii*)	61,8	14,5	16,4	1,8
(*iii*)	50,9	14,5	27,3	5,5
(*iv*)	14,5	9,1	61,8	3,6

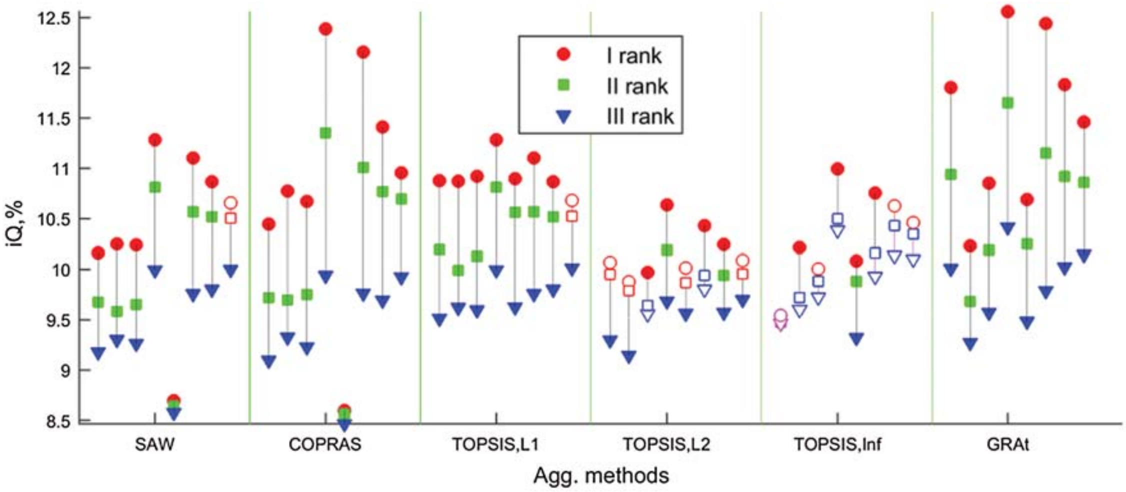


Figure 5: Distinguishability of the alternatives of rank I–III for the *ii*-method of weight estimation and linear normalization method

6 Conclusion

Based on various multi-criteria decision-making (MCDM) models, the best electrical energy source has been identified to feed both the water pumping system and the water desalination unit, respectively. The electrical energy source alternatives were suggested to consider different sizes of water desalination units, different energy management strategies, different sizes of diesel generators, and different system configurations. Four different methods of the weight estimation were considered; no priority of criteria, based on a pairwise comparisons matrix of the criteria, CRITIC-method, and entropy-based method. The results revealed that the best/optimal alternative of hybrid PV-DG-B consists of 5 kW DG, RO-500, and load following control strategy. The yearly operating cost and initial cost for such a system were \$ 5546 and \$ 161022, respectively, while the cost of energy was 0.077 \$/kWh. The excess energy and unmet loads were 40998 and 2371 kWh, respectively. The breakeven grid extension distance and the amount of CO_2 were 3.31 km and 5171 kg per year. Compared with DG only, the amount of CO_2 has been sharply reduced by 113939 kg per year.

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References

[1] D. Fernández-Cerero, A. Fernández-Montes and A. Jakóbik, "Limiting global warming by improving data-centre software," *IEEE Access*, vol. 8, pp. 44048–44062, 2020.

[2] J. R. San Cristóbal, "Multi-criteria decision-making in the selection of a renewable energy project in Spain: The VIKOR method," *Renewable Energy*, vol. 36, no. 2, pp. 498–502, 2011.

[3] C. L. Hwang and K. Yoon, *Multiple Attributes Decision Making: Methods and Applications*, Berlin, Heidelberg: Springer, 1981, ISBN: 978-3-642-48318-93.

[4] E. Triantaphyllou, *Multi-criteria Decision Making Methods: A Comparative Study*, US: Springer, 2000, ISBN: 978-1-4757-3157-6.

[5] G. H. Tzeng and J. J. Huang, *Multiple Attribute Decision Making: Methods and Application*, United Kingdom: Chapman and Hall/CRC, 2011.

[6] B. Josimović, I. Marić and S. Milijić, "Multi-criteria evaluation in strategic environmental assessment for waste management plan, a case study: The city of Belgrade," *Waste Management*, vol. 36, pp. 331–342, 2014.

[7] J. K. Levy, "Multiple criteria decisions making and decision support systems for flood risk management," *Stochastic Environmental Research and Risk Assessment*, vol. 19, no. 6, pp. 438–447, 2005.

[8] D. Tiwari, R. Loof and G. Paudyal, "Environmental-economic decision–making in lowland irrigated agriculture using multi-criteria analysis techniques," *Agricultural Systems*, vol. 60, no. 2, pp. 99–112, 1999.

[9] S. Tesfamariam and R. Sadiq, "Risk-based environmental decision-making using fuzzy analytic hierarchy process (F-AHP)," *Stochastic Environmental Research and Risk Assessment*, vol. 21, no. 1, pp. 35–50, 2006.

[10] O. Marinoni, A. Higgins, S. Hajkowicz and K. Collins, "The multiple criteria analysis tool (MCAT): A new software tool to support environmental investment decision making," *Environmental Modelling & Software*, vol. 24, no. 2, pp. 153–164, 2009.

[11] J. R. San Cristóbal, "Multi-criteria decision-making in the selection of a renewable energy project in Spain: The VIKOR method," *Renewable Energy*, vol. 36, no. 2, pp. 498–502, 2011.

[12] K. Govindan, R. Khodaverdi and A. Jafarian, "A fuzzy multi criteria approach for measuring sustainability performance of a supplier based on triple bottom line approach," *Journal of Cleaner Production*, vol. 47, no. 8, pp. 345–354, 2013.

[13] H. Doukas and J. Psarras, "A linguistic decision support model towards the promotion of renewable energy," *Energy Sources, Part B*, vol. 4, no. 2, pp. 166–178, 2009.

[14] D. Streimikiene, T. Balezentis, I. Krisciukaitienė and A. Balezentis, "Prioritizing sustainable electricity production technologies: MCDM approach," *Renewable and Sustainable Energy Reviews*, vol. 16, no. 5, pp. 3302–3311, 2012.

[15] G. Büyüközkan and G. Çifçi, "A novel hybrid MCDM approach based on fuzzy DEMATEL, fuzzy ANP and fuzzy TOPSIS to evaluate green suppliers," *Expert Systems with Applications*, vol. 39, no. 3, pp. 3000–3011, 2012.

[16] D. Kannan, R. Khodaverdi, L. Olfat, A. Jafarian and A. Diabat, "Integrated fuzzy multi criteria decision making method and multi-objective programming approach for supplier selection and order allocation in a green supply chain," *Journal of Cleaner Production*, vol. 47, no. 4, pp. 355–367, 2013.

[17] J. M. Sánchez-Lozano, J. Teruel-Solano, P. L. Soto-Elvira and M. S. García-Cascales, "Geographical information systems (GIS) and multi-criteria decision making (MCDM) methods for the evaluation of solar farms locations: Case study in southeastern Spain," *Renewable and Sustainable Energy Reviews*, vol. 24, no. 9, pp. 544–556, 2013.

[18] A. D. Perera, R. A. Attalage, K. C. Perera and V. C. Dassanayake, “A hybrid tool to combine multi-objective optimization and multi-criterion decision making in designing standalone hybrid energy systems,” *Applied Energy*, vol. 107, pp. 412–425, 2013.

[19] D. Streimikiene, T. Baležentis and L. Baležentienė, “Comparative assessment of road transport technologies,” *Renewable and Sustainable Energy Reviews*, vol. 20, no. 6, pp. 611–618, 2013.

[20] H. Rezk, M. Al-Dhaifallah, Y. B. Hassan and H. A. Ziedan, “Optimization and energy management of hybrid photovoltaic-diesel-battery system to pump and desalinate water at isolated regions,” *IEEE Access*, vol. 8, pp. 02512–102529, 2020.

[21] M. A. K. Water, [Online]. Available: https://www.makwater.com.au/products/sea-water-reverse-osmosis/ (Accessed on 24 September 2020).

[22] H. Rezk, M. Alghassab and H. A. Ziedan, “An optimal sizing of stand-alone hybrid PV-fuel cell-battery to desalinate seawater at Saudi NEOM city,” *Processes*, vol. 8, no. 382, pp. 1–17, 2020.

[23] H. Rezk, M. A. Abdelkareem and C. Ghenai, “Performance evaluation and optimal design of stand-alone solar PV-battery system for irrigation in isolated regions: A case study in Al Minya (Egypt),” *Sustainable Energy Technologies and Assessments*, vol. 36, no. 100556, pp. 1–11, 2019.

[24] A. Askarzadeh, “Distribution generation by photovoltaic and diesel generator systems: Energy management and size optimization by a new approach for a stand-alone application,” *Energy*, vol. 122, no. 1, pp. 542–551, 2017.

[25] K. Sayed, M. G. Gronfula and H. A. Ziedan, “Novel soft-switching integrated boost DC–DC converter for PV power system,” *Energies*, vol. 13, no. 3, pp. 1–17, 2020, paper no. 749.

[26] M. Abdel-Salam, A. Ahmed, H. A. Ziedan, K. Sayed, M. Amery *et al.,* “A Solar-wind hybrid power system for irrigation in Toshka area,” in *Proc. IEEE Jordan Conf. on Applied Electrical Engineering and Computing Technologies*, Amman, Jordan, 2011.

[27] L. Ustinovichius, E. K. Zavadskas and V. Podvezko, “Application of a quantitative multiple criteria decision making (MCDM-1) approach to the analysis of investments in construction,” *Control and Cybernetics*, vol. 36, no. 1, pp. 251–268, 2007.

[28] M. Archana and V. Sujatha, “Application of fuzzy MOORA and GRA in multi-criterion decision making problems,” *International Journal of Computer Applications*, vol. 53, no. 9, pp. 46–50, 2012.

[29] H. V. Dedania, V. R. Shah and R. C. Sanghvi, “Portfolio management: Stock ranking by multiple attribute decision making methods,” *Technology and Investment*, vol. 6, no. 4, pp. 141–150, 2015.

[30] J. P. Brans, Ph Vincke and B. Mareschal, “How to select and how to rank projects: The PROMETHEE method,” *European Journal of Operational Research*, vol. 24, no. 2, pp. 228–238, 1986.

[31] F. A. Al-Khayyal, “Linear, quadratic, and bilinear programming approaches to the linear complementarity problem,” *European Journal of Operational Research*, vol. 24, no. 2, pp. 216–227, 1986.

[32] A. Jahan and K. L. Edwards, “A state-of-the-art survey on the influence of normalization techniques in ranking: Improving the materials selection process in engineering design,” *Materials & Design*, vol. 65, pp. 335–342, 2015.

[33] I. Z. Mukhametzyanov, “ReS-algorithm for converting normalized values of cost criteria into benefit criteria in MCDM tasks,” *International Journal of Information Technology & Decision Making*, vol. 19, no. 5, pp. 1389–1423, 2020.

[34] T. L. Saaty, *The Analytic Hierarchy Process*, New York: McGraw-Hill, 1980.

[35] D. Diakoulaki, G. Mavrotas and L. Papayannakis, “Determining objective weights in multiple criteria problems: The CRITIC method,” *Computers & Operations Research*, vol. 22, no. 7, pp. 763–770, 1995.

[36] J. Wu, J. Sun, L. Liang and Y. Zha, “Determination of weights for ultimate cross efficiency using Shannon entropy,” *Expert Systems with Applications*, vol. 38, no. 5, pp. 5162–5165, 2011.

[37] I. Mukhametzyanov and D. Pamučar, “Sensitivity analysis in MCDM problems: A statistical approach,” *Decision Making: Applications in Management and Engineering*, vol. 1, no. 2, pp. 51–80, 2018.

[38] I. Z. Mukhametzyanov, “MCDM_tools. Mathworks,” [Online]. Available: https://www.mathworks.com/matlabcentral/fileexchange/65742-mcdm-tools (Accessed on 20 October 2020).