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ARTICLE

CRITIC-CoCoSo Model Application in Hybrid Solar-Wind Energy Plant Location Selection Problem: A Case Study in Vietnam

Viet Tinh Nguyen and Rujira Chaysiri*

Sirindhorn International Institute of Technology, Thammasat University, Pathum Thani, 12000, Thailand

*Corresponding Author: Rujira Chaysiri. Email: rchaysiri@siit.tu.ac.th

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ABSTRACT

This paper presents a novel multi-criteria decision-making (MCDM) model for selecting optimal locations for a solar-wind hybrid energy plant in Vietnam. The study employs the Criteria Importance Through Intercriteria Correlation (CRITIC) and Combined Compromise Solution (CoCoSo) methods to address the challenge of evaluating potential sites based on a range of economic, technical, environmental, and social criteria. By integrating CRITIC for criteria weighting and CoCoSo for ranking alternatives, the study underscores the importance of objective, data-driven approaches in the strategic planning and implementation of sustainable energy projects. The results identify Ham Thuan Nam District in Binh Thuan Province (DA4) as the most suitable site for the solar-wind hybrid energy plant, with a performance score of 2.0919. Phan Thiet City (DA3) and Ninh Phuoc District (DA6) rank second and third, with scores of 2.0655 and 1.8723, respectively. Sensitivity analysis confirms the robustness of the model, showing stable rankings under various scenarios.

KEYWORDS

Multi-criteria decision making; renewable energy; CRITIC; CoCoSo

1 Introduction

Fossil fuels, including oil, gas, and coal have dominated global energy supply in the last century. However, the rapid consumption of these resources is leading to depletion, and their extraction and use have significant environmental impacts. These challenges are driving countries to transition towards clean, sustainable energy, making the development of renewable sources an inevitable trend. As countries globally pivot towards sustainable energy sources, there's been a marked increase in the production capacity of renewable energy (Fig. 1). This shift goes beyond the adoption of greener energy; it reflects a broader transformation in our societies and economies.

Vietnam is emerging as a powerhouse in the sustainable energy sector, thanks to its rich reserves of renewable resources with increasing production of renewable energy over the years (Fig. 2). The country owns a vast array of renewable energy sources, including but not limited to hydropower, wind, solar, and biomass energy [1]. Vietnam's solar energy potential is particularly noteworthy, with market projections estimating its capacity to be between 260–280 TWh per year [2]. The country's advantageous solar energy prospects are bolstered by an even distribution of sunlight throughout the year, making it an ideal candidate for solar energy projects [3].

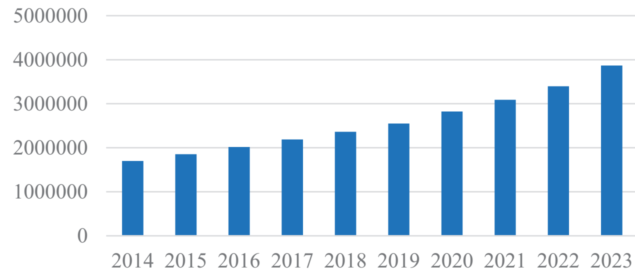

Figure 1: World renewable power energy capacity (in MW) [4]

Beyond solar power, Vietnam's renewable energy spectrum also has abundant of potential in wind power with a technical capacity potential estimated at 26,763 GW [5] with offshore wind power potential is over 600 GW [6]. This significant potential not only opens doors for economic growth but also strengthens Vietnam's energy security, showcasing the nation's vibrant and diverse renewable energy landscape.

However, integrating renewable energy sources into the current national power grid has been challenging due to the inconsistency in their output. To address this issue, hybrid energy systems are being considered to enhance the stability of renewable energy production. By combining two complementary energy sources, such as solar and wind, a hybrid renewable energy model can provide a more stable and continuous power supply. Given Vietnam's abundant solar and wind resources, this approach offers a promising solution for optimizing energy generation [7].

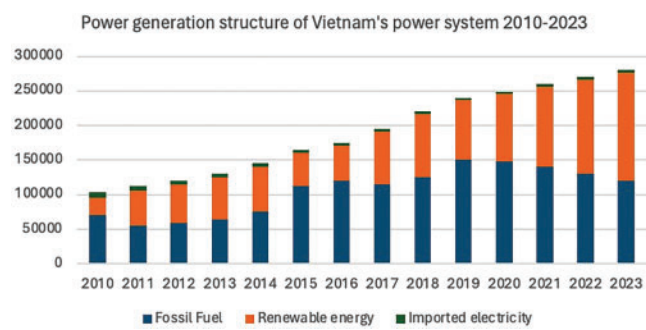

Figure 2: Power generation structure of Vietnam's power system 2010–2023 (in MWh) [8]

Selecting the location of a renewable energy plant is identified as an important issue that can affect the performance of renewable energy projects. The most widely applied model in this regard is the MCDM model [9–12].

This research will focus on the development of a MCDM model to assist the location selection process of a potential solar-wind hybrid energy plant in Vietnam using Criteria Importance Through Intercriteria Correlation (CRITIC) and Combined Compromise Solution (CoCoSo) methods. CRITIC method is implemented to assess the importance of each criterion based on two main factors: the variability of the data (the dispersion of criterion values among choices) and the degree of correlation between criteria (measuring the level of independent information between them). Thus, CRITIC provides an objective approach to quantify the information value of each criterion, helping to improve the quality and transparency of the final decision. CoCoSo focuses on finding a balanced solution between conflicting or complementary criteria to achieve an optimal or near-optimal result.

It helps decision-makers comprehensively evaluate options based on a diverse set of criteria, thereby identifying the most suitable solution for their specific goals and requirements. The main purpose of the CoCoSo method is to provide a multi-criteria decision-making technique to determine and evaluate optimal choices or solutions based on a range of evaluation criteria [13].

The study aims to apply decision-making methodologies to evaluate and prioritize possible sites for a future solar-wind energy facility, emphasizing the robustness, and practical applicability of the results within the context of Vietnam's renewable energy industry. While MCDM methods have been extensively applied in renewable energy planning, there remains a gap in their application to hybrid solar-wind energy plant location selection in the Vietnam. Furthermore, few studies in this field employ the CRITIC and CoCoSo methods in combination, which offer a more balanced and data-driven approach to decision-making. This gap is especially pronounced in Vietnam, where limited research has been conducted on adapting MCDM models to the country's specific geographical and environmental conditions.

The structure of the rest of the paper is as follows: Section 2 offers an extensive review of relevant literature. Section 3 details the methodologies employed, while Section 4 showcases a real-world case study to illustrate the viability of the approach proposed. Finally, conclusions are drawn in Section 6.

2 Literature Review

Applications of MCDM span various industries, including supply chain management [14], engergy managment [15], sustainability research [16–18], risk management [19,20], information technology [21,22], and healthcare [23]. MCDM methods have been employed across a broad spectrum of applications, from selecting alternative marine fuel technology [24], construction cost optimization [25], optimizing distribution center locations [26], and material assessment and selection [27]. These applications demonstrate the versatility and effectiveness of MCDM in addressing complex decision-making processes across diverse sectors.

MCDM methods are also widely used in the development of renewable energy projects, commonly applied in energy planning, sustainability assessment, and the ranking of renewable energy sources [28]. The use of MCDM techniques in renewable energy development projects also assists in decision-making processes from supplier selection for a particular project [29] to the evaluation of a suitable national sustainable energy strategy [30]. Researchers have emphasized the importance of MCDM methods in addressing energy sustainability issues and have highlighted their practical utility in solving such problems [31] and interest in the application of MCDM techniques in renewable energy have been increasing in recent years [32–35]. Within the expansive array of decision-making challenges encountered by renewable energy projects, the selection of a location stands out as a critical factor due to its direct influence on the project's potential performance. Moreover, location selection issues often encompass a multitude of evaluation criteria, encompassing both quantitative and qualitative dimensions. In response to these complex challenges, recent years have witnessed the development of numerous MCDM models. These models have significantly contributed to a growing body of literature dedicated to addressing such multifaceted issues.

Wang et al. [36] conduct a study on the development of a Fuzzy MCDM model for solar power plant location selection in Vietnam. The research highlighted the use of the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and the Analytic Hierarchy Process (AHP) methodologies in evaluating and selecting suitable locations for solar power plants. The study provided insights into the decision-making process involved in renewable energy project location selection, emphasizing the importance of considering multiple sustainable criteria and objectives. Nuriyev [37] explores the efficiency and applicability of a unified approach based on Fuzzy logic, Z-information, and the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS). The study focuses on renewable energy resources and plant location selection, emphasizing the integration of these methodologies to streamline decision-making processes. By utilizing fuzzy logic and TOPSIS, the research aims to enhance the robustness and effectiveness of selecting optimal renewable energy resources and plant locations. Solangi et al. [38] conduct a study on the selection of wind power project locations in the southeastern corridor of Pakistan. The research utilized Factor Analysis, AHP, and Fuzzy TOPSIS to prioritize sites in the region. The research findings emphasize the importance of economic considerations and land availability as the most important factors in the decision-making process for selecting wind power project locations in the southeastern corridor of Pakistan.

In this research, an MCDM model employing CRITIC and CoCoSo methods is developed to assist with the location selection of a solar-wind hybrid energy plant in the southern region of Vietnam. CRITIC methods have been applied to several studies about renewable energy to calculate the weighting of quantitative criteria. Shao et al. [39] discuss the utilization of the Criteria Importance Through Intercriteria Correlation (CRITIC) method in conjunction with Geographic Information System (GIS) for identifying optimal sites for tidal current power plants in China. The CRITIC method is employed to evaluate the significance of criteria by analyzing their interrelationships. Through the incorporation of the CRITIC method into the GIS-MCDM approach, the study aims to improve the precision and efficiency of site selection for tidal current power plants. Saraji et al. [40] delve into the use of the CRITIC method for exploring the challenges in adopting renewable energy technologies in rural areas. This research combines the CRITIC method with the VIKOR technique to identify and evaluate the barriers to deploying renewable energy solutions in less urbanized regions. Through the application of the CRITIC-VIKOR framework, the study aims to offer an in-depth examination of the obstacles encountered in the implementation of renewable energy technologies in rural areas. Alkan [41] investigates the evaluation of sustainable development and the application-oriented use of renewable energy systems. This analysis integrates the CRITIC method with SWARA and CODAS approaches, utilizing interval-valued picture fuzzy sets to establish a comprehensive framework for the assessment and selection of renewable energy systems. In this context, the CRITIC method is used for the objective weighting of criteria, highlighting its effectiveness and ease of use. The research underscores the necessity of incorporating sustainability and practical usage considerations in the decision-making processes concerning renewable energy systems.

The Combined Compromise Solution (CoCoSo) method has been utilized in numerous studies within the renewable energy sector to evaluate the performance of various potential options. The study by Van Thanh [42] examines an optimal location for a waste-to-energy plant using a Fuzzy MCDM model. The research incorporates the CoCoSo method along with Fuzzy AHP to evaluate and prioritize location alternatives for a waste-to-energy project. The study by Wang et al. [43] presents a model focused on selecting a biomass furnace supplier by considering both qualitative and quantitative factors. The research highlights the challenges posed by the complex decision-making environment in renewable energy, particularly in scenarios where factors interact in a fuzzy decision-making setting.

CRITIC and CoCoSo methods have several advantages in comparison with similar MCDM methods. CRITIC was introduced by Diakoulaki et al. [44] and was highlighted for its ability to generate more balanced criteria weights as the method incorporates information from all objectives within the decision objective matrix into its calculation. Wang et al. [45] analyze weighting and selection methods for Pareto-optimal solutions in multiobjective optimization within chemical engineering applications. In this research, five objective weighting methods (CRITIC, mean, entropy, StDev, StatVar) were tested and compared using several chemical engineering and mathematical problems.

CRITIC, along with the entropy method, was recommended because it includes correlations among criteria, which becomes crucial when dealing with three or more criteria. Nabavi et al. [46] examine the sensibility of the entropy method and CRITIC methods in combination with eight popular MCDM methods with different types of modification to the data (linear transformation of objectives, reciprocal objective reformulation, and removal of alternatives). The results show models that employ CRITIC provide robust results against the modifications. CoCoSo method also demonstrates robustness in decision-making models. The study by Wen et al. [47] examines the cold chain logistics management of medicine using an integrated multi-criteria decision-making method. The research covers topics such as refrigeration, ranking, antineoplastic agents, neoplasms, delivery of health care, pharmaceutical preparations, and economics. Through comparative analysis of different MCDM methods, the results suggest that CoCoSo method, in comparison with VIKOR, TOPSIS and other MCDM methods, provide results that are robust and less sensitive to changes such as adding or removing options, or altering the weights of the criteria.

In this study, a MCDM framework that utilizes a novel combination of CRITIC and CoCoSo techniques has been formulated to aid in selecting a site for a solar-wind hybrid energy facility in Vietnam's southern region. While MCDM methods are widely used, the combination of CRITIC and CoCoSo specifically for renewable energy project location selection, demonstrates an innovative approach as few studies specifically use these methods together to solve decision making problems in renewable energy development. The case study also offers new insights into applying MCDM techniques within the specific context of Vietnam's renewable energy sector, especially regrading hybrid renewable energy solutions. The results provide practical recommendations for location selection based on quantitative data from a set of unique criteria.

3 Materials & Methods

3.1 Research Process

The research process consists of three main phases, shown in Fig. 3.

- *Phase 1:* In the Pre-processing phase, the problem is defined, and a list of evaluation criteria is formed based on existing literature and expert opinions. Then, the relevant data is collected.
  - A list of potential criteria is identified by reviewing existing literature and interviewing a board of experts.
  - A definitive list of criteria is determined by a Delphi process proposed by Frinsdorf et al. [48], where a group of academic and industry experts are interviewed and asked to rate each of the potential criteria and sub-criteria. The rating step will repeat until a consensus of the list of criteria and sub-criteria is reached.
  - Data relevant to each alternative is collected for all criteria.
- *Phase 2:* In this phase, the collected data is used to calculate the criteria weights using the CRITIC method. Subsequently, CoCoSo is applied to determine the performance score of each alternative. The detailed of calculation steps of CRITIC and CoCoSo methods are described in Sections 3.2 and 3.3 of this research, respectively.
- *Phase 3:* In the final phase, a ranking of alternatives is obtained based on the calculated performance scores. Sensitivity analysis is performed to evaluate the results of the proposed model.

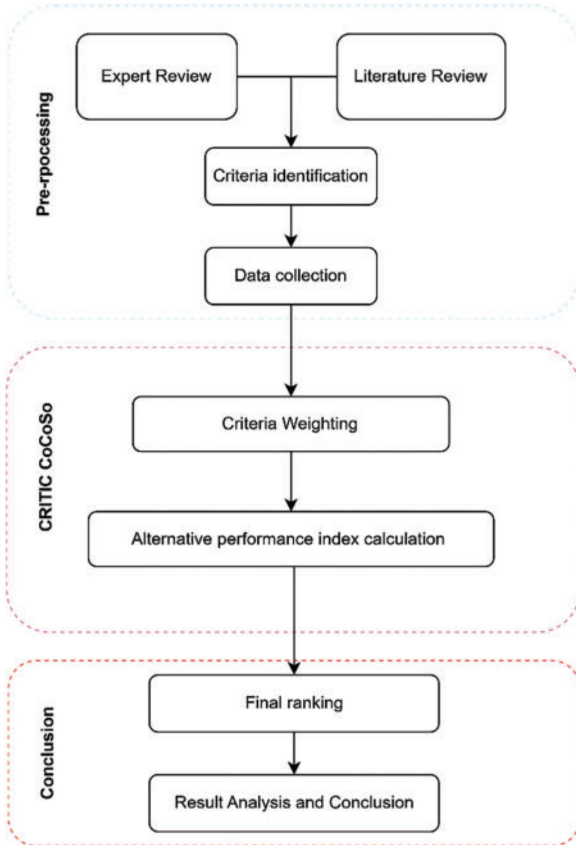

Figure 3: Research process

3.2 Criteria Importance through Intercriteria Correlation (CRITIC) Method

In this research, CRITIC method is employed to calculate the weights of the relevant decision-making criteria. The advantages of CRITIC is that the method accounts for both the variability and correlation of criteria, as well as being effective for cases where there are potential correlations between criteria. CRITIC is also relatively simple to calculate and interpret. As such it is suitable for the problem at hand, where multiple criteria with potential complex relationships must be considered.

The CRITIC method is introduced by Diakoulaki et al. [44] as a quantitative technique to calculate criteria weights based on their contrast intensity and correlation among the criteria. The multicriteria problem can be characterized as follows for a finite set A of n choices and a given system of m assessment criteria f_j:

$$Max\left\{f_1(a), f_2(a), \ldots, f_m(a), a \in A\right\} \tag{1}$$

A membership function x_j for each criterion f_j is built in this multicriteria problem, which maps the values of f_j to the interval (0, 1). The idea of the ideal point serves as the foundation for this transition. Accordingly, the number x_{aj} below indicates how much the alternative a deviate from the anti-ideal value f_{j*}, which represents the worst performance in criterion j, and approaches the ideal value f_j^*, which represents the best performance in criterion j. At least one of the options under consideration is able to accomplish both f_j^* and f_{j*}.

$$x_{aj} = \frac{f_j(a) - f_{j*}}{f_j^* - f_{j*}} \tag{2}$$

This process transforms the original evaluation matrix into a matrix of relative scores with generic element x_{ij}. A vector x_j is created that represents the scores of all n possibilities that were taken into consideration by looking at the jth criterion separately.

$$x_j = \left(x_j(1), x_j(2), \ldots, x_j(n)\right) \tag{3}$$

The standard deviation, σ_j, quantifies the contrast strength of the corresponding criterion for each vector x_j. Therefore, a measure of the importance of that criterion to the decision-making process is the standard deviation of x_j. It is obvious that the standard deviation might be substituted with any other indicator of the dispersion in scores, such as variance or entropy.

The linear correlation coefficient between the vectors x_j and x_k, represented by the generic element r_{jk}, is then built into a symmetric matrix with dimensions of $m \times m$. It is evident that the value of r_{jk} decreases with increasing discordance between the scores of the options in criteria j and k. In this way, the total indicated in Eq. (4) serves as a gauge for the degree of conflict that criterion j creates in relation to the decision-making scenario that is determined by the remaining criteria.

$$\sum_{k=1}^{m} \left(1 - r_{jk}\right) \tag{4}$$

It should be noted that in order to offer a broader measure of the link connecting the rank orders of the items included in the vectors x_j and x_k, the Spearman rank correlation coefficient R_{jk}^s might be used in place of r_{jk}.

The information found in MCDM problems relates to the decision criteria's conflict and contrast intensity. Therefore, the quantity of data C_j released by the jth criterion can be ascertained by assembling the measurements that measure the two concepts using the subsequent multiplicative aggregation formula:

$$C_j = \sigma_j \times \sum_{k=1}^{m} \left(1 - r_{jk}\right) \tag{5}$$

The preceding analysis states that the greater the value C_j the more information the relevant criterion transmits and the greater its relative significance for the decision-making process. By normalizing these values to unity using the following equation, objective weights are produced:

$$w_j = \frac{C_j}{\sum_{k=1}^{m} C_k} \tag{6}$$

3.3 Combined Compromise Solution (CoCoSo) Method

Yazdani et al. [49] devised the CoCoSo MCDM technique, which combines the exponentially weighted product model with the simple additive weighting method. The CoCoSo approach in this study is employed to determine the ranking of the alternatives. There are five steps in a typical CoCoSo model with m choices and n criteria:

Step 1: The decision-making matrix $X = \left(x_{ij}\right)_{m \times n}$ is calculated for the ith alternative and the jth criterion as follows:

$$x_{ij} = \begin{bmatrix} x_{11} & x_{12} & \dots & x_{1n} \\ x_{21} & x_{22} & \dots & x_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & & x_{mn} \end{bmatrix} \tag{7}$$

With $i = 1, 2, \dots, m$ and $j = 1, 2, \dots, n$.

Step 2: The decision-making matrix is then normalized accordingly [30]:

For beneficial criterion:

$$r_{ij} = \frac{x_{ij} - \min_i x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{8}$$

For non-beneficial criterion:

$$r_{ij} = \frac{\max_i x_{ij} - x_{ij}}{\max_i x_{ij} - \min_i x_{ij}} \tag{9}$$

Step 3: Calculate each of the alternative's power weight of comparability (S_i) and the total of the power weight of comparability (P_i) sequence using Eqs. (10) and (11):

$$S_i = \sum_{j=1}^{n} \left(w_j r_{ij}\right) \tag{10}$$

$$P_i = \sum_{j=1}^{n} \left({r_{ij}}^{w_j}\right) \tag{11}$$

Step 4: Determine three aggregated performance scores. Calculate the arithmetic mean of sums of S_i and P_i scores to determine the k_{ia} as the relative performance scores of the ith alternative.

$$k_{ia} = \frac{P_i + S_i}{\sum_{i=1}^{m} (P_i + S_i)} \tag{12}$$

Calculate the sum of relative scores of S_i and P_i scores in comparison to the ideal performance values where k_{ib} is the relative performance scores of the ith alternative.

$$k_{ib} = \frac{S_i}{\min_i S_i} + \frac{P_i}{\min_i P_i} \tag{13}$$

Calculate the compromise of S_i and P_i performance scores for k_{ic} is the relative performance scores of the ith alternative. In Eq. (14), the λ value is selected by the decision makers and has a value between 0 and 1 (usually $\lambda = 0.5$).

$$k_{ic} = \frac{\lambda(S_i) + (1 - \lambda) P_i}{\lambda \max_i S_i + (1 - \lambda) \max_i P_i} \tag{14}$$

Step 5: Alternative's performance score (k_i) is then calculated by:

$$k_i = (k_{ia}k_{ib}k_{ic})^{\frac{1}{3}} + \frac{1}{3}(k_{ia} + k_{ib} + k_{ic}) \tag{15}$$

Alternatives are subsequently ranked based on their performance scores; an alternative with a higher score is ranked more favorably.

4 Case Study

In this section, the proposed model is applied to the location selection problem of a potential solar-wind energy plant in Vietnam using available quantitative criteria. After reviewing relevant literature and discussing with industry experts and academics through a Delphi process, a list of 4 criteria and 13 sub-criteria is obtained (Table 1).

Table 1: List of evaluation criteria

Code	Criteria	Sub-criteria	Literature	Description
C11	Economic	Regional populace	Wang et al. [50]	The size of the local population indicates potential local energy consumption and manpower accessibility. The higher the better. In this case, provincial population is used. Data published by the General Statistics Office of Vietnam [51]
C12		Investment environment		Investment environment is assessed using the Provincial Competitiveness Index (PCI), a thorough index that evaluates the competitiveness of provinces by examining their economic, administrative, and governance aspects. Higher PCI scores are preferable. Data published by Vietnam Chamber of Commerce and Industry (VCCI) and USAID [52]
C21	Technical	Wind speed	Wang et al. [53], Samanlioglu et al. [54]	Average annual wind speed, measured in meter per second. The higher the better. Data taken from Wind Atlas [55]
C22		Wind speed variation	Wang et al. [53]	Variation of monthly wind speed index. A smaller variation is desirable as it suggests higher output stability. Data taken from Wind Atlas [55]
C23		Average solar radiation	Samanlioglu et al. [54], Ghose et al. [56], Al Garni et al. [57]	Average annual direct normal radiation measured in kWh/m2 per year. The higher the better. Data taken from Solar Atlas [58]
C24		Solar seasonality		Variation of monthly direct normal radiation. A lower variation is preferable as it indicates greater output stability, ensuring grid safety [59]. Data taken from Solar Atlas [58]

(Continued)

Table 1 (continued)

Code	Criteria	Sub-criteria	Literature	Description
C25		Transmission grid accessibility	Wang et al. [36], Wang et al. [50], Chatterjee et al. [60], Garni et al. [57]	The distance to the nearest substation is measured in kilometers. Proximity is beneficial as it enhances grid accessibility, potentially reducing costs and simplifying project execution. The data are gathered from ground measurements.
C26		Elevation	Wang et al. [36], Chatterjee et al. [60], Ghose et al. [56]	Geographic elevation is measured in meters. A higher elevation is preferable as it enhances both wind speed and solar radiation. Data taken from Solar Atlas [58]
C27		Distance to nearest settlement	Wang et al. [53], Chatterjee et al. [60], Garni et al. [57]	Distance to the nearest city is measured in kilometers. A shorter distance is advantageous as it enables local consumption of the project's output, potentially reducing stress on the grid network. The data are gathered from ground measurements.
C28		Slope	Wang et al. [50], Al Garni et al. [57]	Geographic slope is measured in degrees. A lower slope is preferable as it facilitates construction and reduces the risk of flash flooding. The data are gathered from ground measurements.
C31	Environmental	Distance to conservation area	Chatterjee et al. [60]	Distance to the nearest conservation area is measured in kilometers. A greater distance is preferable, as it reduces the project's impact on the local environment. The data are gathered from ground measurements.
C32		Land use	Wang et al. [50], Al Garni et al. [57], Chatterjee et al. [60], Wang et al. [61]	Land availability, as outlined in the most recent official land use plan, is measured in hectares. Greater availability is considered more advantageous. Data published by provincial governments.
C41	Social	Population density		District population density is expressed in persons per square kilometer. A lower density is preferable, as it minimizes the potential impact of the project on communities nearby the potential site. Data published by the General Statistics Office of Vietnam [51]

In this case, six potential locations were identified through expert discussions and were considered in this case (Table 2). The map of these locations is shown in Fig. 4.

Table 2: List of potential locations

No.	Location	Symbol	Coordinate	General information
1	Cu Kuin District, Dak Lak Province	DA1	12°34′5.916″ N, 108°7′38.2584″ E	Dak Lak Province currently hosts 9 solar energy projects and 6 wind energy projects. Cu Kuin and Krong Pac Districts, situated in close proximity to Buon Ma Thuot City, the economic hub of the

(Continued)

Table 2 (continued)

No.	Location	Symbol	Coordinate	General information
2	Krong Pac District, Dak Lak Province	DA2	12°42′43″ N, 108°23′23″ E	Central Highlands region, offer strategic locations for renewable energy development.
3	Phan Thiet City, Binh Thuan Province	DA3	10°49′31″ N, 108°01′21″ E	Over the past decade, Binh Thuan Province has emerged as a significant hub for renewable energy development, hosting 25 solar energy projects
4	Ham Thuan Nam District, Binh Thuan Province	DA4	10°46′14″ N, 107°58′08″ E	and 13 wind energy projects. Phan Thiet City, La Gi District, and Ham Thuan Nam District have been identified as favorable locations for
5	La Gi District, Binh Thuan Province	DA5	10°43′44″ N, 107°49′17″ E	both existing and prospective renewable energy initiatives.
6	Ninh Phuoc District, Ninh Thuan Province	DA6	11°30′08″ N, 108°58′10″ E	Ninh Phuoc District, located in Ninh Thuan Province, is also regarded as a potential key region for renewable energy development. The province is currently home to 33 solar energy projects and 13 wind energy projects.

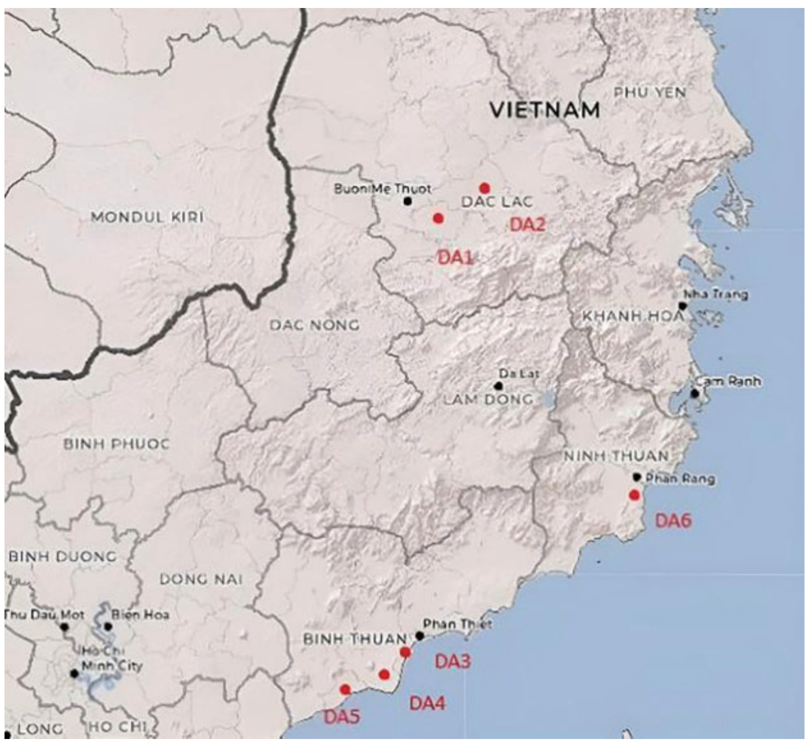

Figure 4: Potential locations map

The relevant data of corresponding to these locations are collected as of June 2024 and shown in Table 3.

Table 3: Decision making data

Alternative	C11	C12	C21	C22	C23	C24	C25	C26	C27	C28	C31	C32	C41
DA1	1,869,322	60.91	7.92	0.09703	1373.40	755.04	6.00	445	15.74	2.9514	43.00	35.70	360
DA2	1,869,322	60.91	7.36	0.04398	1341.10	800.92	33.00	467	37.17	2.4880	19.00	515.58	331
DA3	1,230,808	64.39	7.44	0.02041	1660.20	758.76	18.00	87	13.40	2.1913	157.00	301.44	1083
DA4	1,230,808	64.39	7.80	0.02511	1634.10	799.43	26.00	75	23.30	3.6014	165.00	835.51	98
DA5	1,230,808	64.39	6.61	0.02189	1691.10	838.33	13.00	15	37.97	2.6171	181.00	825.79	582
DA6	590,467	65.43	8.62	0.03853	1790.30	796.05	11.00	32	6.73	3.7551	30.00	2043.64	380.9

Next, CRITIC method is applied to calculate the weight of each criterion. The data is then normalized using Eq. (2) and used to calculate the weight of each sub-criterion using CRITIC. The normalized data is shown in Table 4 and the weight of each sub-criterion is shown in Table 5.

Table 4: Normalized data

Alternative	C11	C12	C21	C22	C23	C24	C25	C26	C27	C28	C31	C32	C41
DA1	1.0000	0.0000	0.6517	0.0000	0.0719	1.0000	1.0000	0.9513	0.7116	0.5139	0.1481	0.0000	0.7340
DA2	1.0000	0.0000	0.3731	0.6923	0.0000	0.4492	0.0000	1.0000	0.0256	0.8103	0.0000	0.2390	0.7635
DA3	0.5007	0.7698	0.4129	1.0000	0.7104	0.9553	0.5556	0.1593	0.7865	1.0000	0.8519	0.1323	0.0000
DA4	0.5007	0.7698	0.5920	0.9387	0.6523	0.4670	0.2593	0.1327	0.4696	0.0983	0.9012	0.3983	1.0000
DA5	0.5007	0.7698	0.0000	0.9806	0.7792	0.0000	0.7407	0.0000	0.0000	0.7277	1.0000	0.3935	0.5086
DA6	0.0000	1.0000	1.0000	0.7635	1.0000	0.5076	0.8148	0.0376	1.0000	0.0000	0.0679	1.0000	0.7128

Table 5: CRITIC result

Sub-criterion	Weight
C11	0.0875
C12	0.0767
C21	0.0590
C22	0.0748
C23	0.0710
C24	0.0696
C25	0.0683
C26	0.1054
C27	0.0691
C28	0.0892
C31	0.0926
C32	0.0644
C41	0.0724

At this stage, the CoCoSo method is utilized to determine the ranking of potential solar-wind energy plant locations. The Weighted comparability sequence (S_i), and the Exponentially weighted comparability sequence (P_i) are displayed in Tables 6 and 7, respectively.

Table 6: Weighted comparability sequence (S_i)

	C11	C12	C21	C22	C23	C24	C25	C26	C27	C28	C31	C32	C41	S_i
DA1	0.0875	0.0000	0.0385	0.0000	0.0051	0.0696	0.0683	0.1003	0.0492	0.0458	0.0137	0.0000	0.0532	0.5311
DA2	0.0875	0.0000	0.0220	0.0518	0.0000	0.0312	0.0000	0.1054	0.0018	0.0722	0.0000	0.0154	0.0553	0.4427
DA3	0.0438	0.0590	0.0244	0.0748	0.0505	0.0665	0.0380	0.0168	0.0544	0.0892	0.0788	0.0085	0.0000	0.6046
DA4	0.0438	0.0590	0.0349	0.0702	0.0463	0.0325	0.0177	0.0140	0.0325	0.0088	0.0834	0.0257	0.0724	0.5412
DA5	0.0438	0.0590	0.0000	0.0734	0.0553	0.0000	0.0506	0.0000	0.0000	0.0649	0.0926	0.0253	0.0368	0.5018
DA6	0.0000	0.0767	0.0590	0.0571	0.0710	0.0353	0.0557	0.0040	0.0691	0.0000	0.0063	0.0644	0.0516	0.5502

Table 7: Exponentially comparability sequence (P_i)

	C11	C12	C21	C22	C23	C24	C25	C26	C27	C28	C31	C32	C41	P_i
DA1	1.0000	0.0000	0.9751	0.0000	0.8295	1.0000	1.0000	0.9948	0.9768	0.9424	0.8380	0.0000	0.9779	9.5343
DA2	1.0000	0.0000	0.9435	0.9729	0.0000	0.9458	0.0000	1.0000	0.7762	0.9814	0.0000	0.9119	0.9806	8.5124
DA3	0.9413	0.9801	0.9491	1.0000	0.9760	0.9968	0.9606	0.8240	0.9835	1.0000	0.9853	0.8779	0.0000	11.4747
DA4	0.9413	0.9801	0.9695	0.9953	0.9701	0.9484	0.9119	0.8083	0.9491	0.8131	0.9904	0.9424	1.0000	12.2200
DA5	0.9413	0.9801	0.0000	0.9985	0.9824	0.0000	0.9797	0.0000	0.0000	0.9721	1.0000	0.9417	0.9522	8.7481
DA6	0.0000	1.0000	1.0000	0.9800	1.0000	0.9539	0.9861	0.7077	1.0000	0.0000	0.7796	1.0000	0.9758	10.3831

Finally, the performance scores of each alternative are calculated (Table 8 and Fig. 5). In this case, Ham Thuan Nam District of Binh Thuan Province (DA4) is the optimal location for a hybrid solar-wind energy plant.

Table 8: Alternative performance and ranking results

Alternative	k_{ia}	k_{ib}	k_{ic}	k_i	Final ranking
DA1	0.1572	2.3198	0.7849	1.7463	4
DA2	0.1398	2.0000	0.6983	1.5262	6
DA3	0.1886	2.7137	0.9419	2.0655	2
DA4	0.1993	2.6582	0.9951	2.0919	1
DA5	0.1444	2.1612	0.7213	1.6173	5
DA6	0.1707	2.4627	0.8525	1.8723	3

Ham Thuan Nam District (DA4) secured the top rank due to its high scores in solar radiation (C23), wind speed (C21), lower slope (C28) and low population density (C41). In contrast, Phan Thiet City (DA3) ranked second, benefiting from higher solar radiation (C23) and lower solar variation (C24), but its significantly higher population density negatively impacted its overall ranking. Ninh Phuoc District (DA6) ranked third, performing well in areas such as investment environment (C12), wind speed (C21), solar radiation (C23), proximity to settlements (C27), and land use (C32). However, its lower regional population (C11), higher slope (C28), and lower elevation (C26) contributed to its reduced overall score.

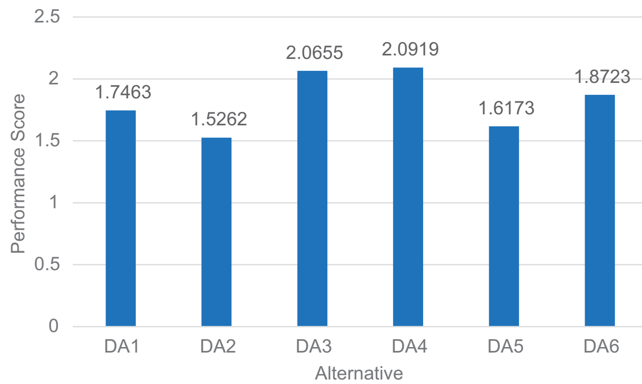

Figure 5: Alternatives' performance scores

5 Sensitivity Analysis

5.1 Criteria Weight Alteration

In this session, a sensitivity analysis is performed to examine the behavior of results when changes in criteria are introduced. Various methods are used for robust testing and sensitivity analysis, including evaluating how changes in criteria weight affect alternative rankings. Firstly, the impact of removing the Regional Populace (C11) sub-criterion is examined, using the method proposed by Alinezhad et al. [62]. The criteria weights after the removal of C11 criterion are shown in Table 9.

Table 9: Criteria weights after the removal of C11

Criteria	Weight
C11	0.00000
C12	0.07052
C21	0.07856
C22	0.07260
C23	0.06407
C24	0.08855
C25	0.10692
C26	0.07911
C27	0.09246
C28	0.06494
C31	0.11549
C32	0.06752
C41	0.09926

As a result, the performance scores and rankings of the alternatives in this scenario are displayed in Table 10.

Table 10: Alternatives' performance scores and ranking after the removal of C11

Alternative	k_{ia}	k_{ib}	k_{ic}	k_i	Final ranking
DA1	0.1571	2.6765	0.7746	1.8908	4
DA2	0.1366	2.0000	0.6734	1.5054	6
DA3	0.1881	3.0163	0.9272	2.1845	2
DA4	**0.2023**	**3.1739**	**0.9971**	**2.3196**	**1**
DA5	0.1444	2.4357	0.7120	1.7277	5
DA6	0.1714	3.0420	0.8450	2.1138	3

The final performance scores of the alternatives (k_i) have changed, but the rankings remain consistent, with DA4 as the optimal location for a solar-wind energy plant in this case. This indicates that the ranking of alternatives is stable, regardless of the removal of the Regional Populace sub-criterion (C11).

Next, the impact of removing each remaining sub-criterion on the final ranking is examined. In total, 13 scenarios are considered. The weights of each sub-criterion for each scenario are presented in Table 11, while the performance scores and rankings of the alternatives are displayed in Table 12 and Fig. 5.

Table 11: Criteria weights in considered scenarios

Criteria	Weights													
	Original	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13
C11	0.0875	0.0000	0.0948	0.0930	0.0614	0.0942	0.0940	0.0939	0.0978	0.0940	0.0961	0.0964	0.0935	0.0943
C12	0.0767	0.0840	0.0000	0.0815	0.0714	0.0825	0.0824	0.0823	0.0857	0.0823	0.0842	0.0845	0.0819	0.0826
C21	0.0590	0.0647	0.0639	0.0000	0.0795	0.0635	0.0634	0.0633	0.0660	0.0634	0.0648	0.0650	0.0631	0.0636
C22	0.0748	0.0820	0.0810	0.0795	0.0000	0.0806	0.0804	0.0803	0.0836	0.0804	0.0822	0.0825	0.0800	0.0807
C23	0.0710	0.0778	0.0769	0.0755	0.0648	0.0000	0.0763	0.0762	0.0794	0.0763	0.0780	0.0783	0.0759	0.0766
C24	0.0696	0.0762	0.0753	0.0739	0.0896	0.0749	0.0000	0.0747	0.0778	0.0747	0.0764	0.0767	0.0744	0.0750
C25	0.0683	0.0749	0.0740	0.0726	0.1082	0.0736	0.0734	0.0000	0.0764	0.0734	0.0750	0.0753	0.0730	0.0737
C26	0.1054	0.1155	0.1141	0.1120	0.0801	0.1135	0.1133	0.1131	0.0000	0.1132	0.1157	0.1161	0.1127	0.1136
C27	0.0691	0.0757	0.0749	0.0735	0.0936	0.0744	0.0743	0.0742	0.0773	0.0000	0.0759	0.0762	0.0739	0.0745
C28	0.0892	0.0977	0.0966	0.0948	0.0657	0.0960	0.0958	0.0957	0.0997	0.0958	0.0000	0.0983	0.0953	0.0961
C31	0.0926	0.1014	0.1002	0.0984	0.1169	0.0996	0.0995	0.0993	0.1035	0.0994	0.1016	0.0000	0.0989	0.0998
C32	0.0644	0.0706	0.0697	0.0684	0.0683	0.0693	0.0692	0.0691	0.0720	0.0692	0.0707	0.0710	0.0000	0.0694
C41	0.0724	0.0794	0.0784	0.0770	0.1005	0.0780	0.0778	0.0777	0.0810	0.0778	0.0795	0.0798	0.0774	0.0000

Table 12: Alternative's performance scores in considered scenarios

Alternatives	Performance score													
	Original	Scenario 1	Scenario 2	Scenario 3	Scenario 4	Scenario 5	Scenario 6	Scenario 7	Scenario 8	Scenario 9	Scenario 10	Scenario 11	Scenario 12	Scenario 13
DA1	1.7463	1.7615	1.7500	1.7316	1.9287	1.7656	1.7060	1.6738	1.7643	1.6871	1.7923	1.7980	1.7577	1.7602
DA2	1.5262	1.5193	1.5286	1.5289	1.5144	1.5271	1.5291	1.5249	1.5097	1.5436	1.5173	1.5628	1.5296	1.5241
DA3	2.0655	2.1627	2.0104	2.0730	2.1634	2.0179	2.0343	2.0301	2.2399	1.9976	2.0632	2.0298	2.0851	2.1497
DA4	2.0919	2.1720	2.0337	2.0795	2.2188	2.0466	2.0983	2.0818	2.2507	2.0477	2.1997	2.0418	2.0793	2.0791
DA5	1.6173	1.6912	1.5631	1.6415	1.6783	1.5649	1.6544	1.5678	1.7623	1.6094	1.6326	1.5572	1.6100	1.6514
DA6	1.8723	2.0032	1.7945	1.8318	2.0539	1.7987	1.8772	1.8141	2.0628	1.7869	1.9691	1.9411	1.8132	1.8903

To further verify the robustness of the sensitivity analysis results, a statistical test was applied to examine whether the changes in criteria weights significantly influenced the performance scores of the alternatives. An one-way Analysis of Variance (ANOVA) test is conducted with the null hypothesis as following: "The changes in criteria weights do not significantly affect the performance scores of alternatives". The results are shown in Table 13.

Table 13: One-way ANOVA results

Source of variation	SS	df	MS	F	*p*-value	F crit
Between groups	0.203324	13	0.01564	0.268104	0.994276	1.862661
Within groups	4.083575	70	0.058337			
Total	4.286899	83				

With a 5% level of significant, the results suggest that there is no significant difference of performance scores between scenarios (p-value = 0.994276 > 0.05, fail to reject the null hypothesis). The results in Fig. 5 and Table 12 indicate that the proposed model's outcome is highly robust to changes in criteria weights. In most scenarios, the final rankings of the alternatives stay the same, with the exception of scenario 11 where DA2 and DA5 exchange rankings. DA4 remains the consistently optimal location across most scenarios, except in scenarios 12 and 13, where DA3 (Phan Thiet City) becomes the optimal location. This is reasonable since DA3 had weak performance in criteria C32 (Land use) and C41 (Population density). Thus, removing these criteria led to a significant improvement in DA3's performance. The top three locations remain unchanged, consisting of DA4, DA3 and DA6 in all cases.

The results in Fig. 6 and Table 12 indicate that the proposed model's outcome is highly robust to changes in criteria weights. In most scenarios, the final rankings of the alternatives stay the same, with the exception of scenario 11 where DA2 and DA5 exchange rankings. DA4 remains the consistently optimal location across most scenarios, except in scenario 12 and 13, where DA3 (Phan Thiet City) becomes the optimal location. This is reasonable since DA3 had weak performance in criteria C32 (Land use) and C41 (Population density). Thus, removing these criteria led to a significant improvement in DA3's performance. The top three locations remain unchanged, consisting of DA4, DA3 and DA6 in all cases.

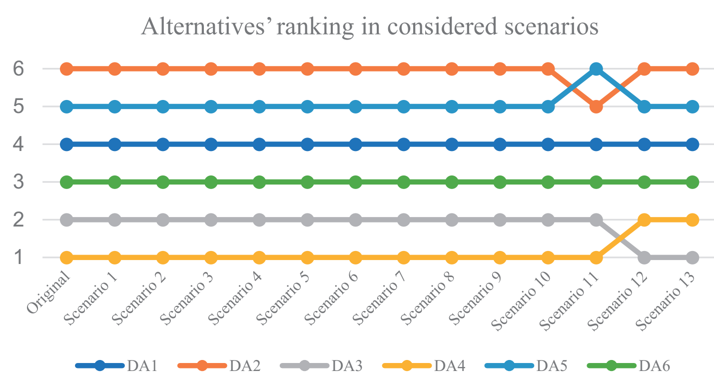

Figure 6: Alternatives' ranking in considered scenarios

5.2 Compromise Coeficient Value Alteration

Another sensitivity test is performed to show the robustness of the proposed method by changing the value of the compromise coefficient (λ) which reflects the decision maker's preference for compromise solutions. Let the value of λ changing from 0.1 to 0.9 (with 0.5 is the default value), the performance of the alternatives is shown in Table 14.

Table 14: Alternatives' performance scores in considered scenarios

Alternatives	Performance score								
	$\lambda = 0.1$	$\lambda = 0.2$	$\lambda = 0.3$	$\lambda = 0.4$	$\lambda = 0.5$	$\lambda = 0.6$	$\lambda = 0.7$	$\lambda = 0.8$	$\lambda = 0.9$
DA1	1.7437	1.7441	1.7447	1.7453	1.7463	1.7476	1.7496	1.7534	1.7619
DA2	1.5253	1.5254	1.5256	1.5259	1.5262	1.5267	1.5274	1.5288	1.5319
DA3	2.0640	2.0642	2.0645	2.0649	2.0655	2.0663	2.0676	2.0699	2.0752
DA4	**2.0946**	**2.0941**	**2.0936**	**2.0929**	**2.0919**	**2.0906**	**2.0884**	**2.0845**	**2.0754**
DA5	1.6144	1.6149	1.6155	1.6162	1.6173	1.6188	1.6213	1.6256	1.6355
DA6	1.8708	1.8710	1.8714	1.8718	1.8723	1.8731	1.8744	1.8767	1.8819

Consequentially, the ranking of the alternatives corresponding to different λ values are shown in Fig. 7.

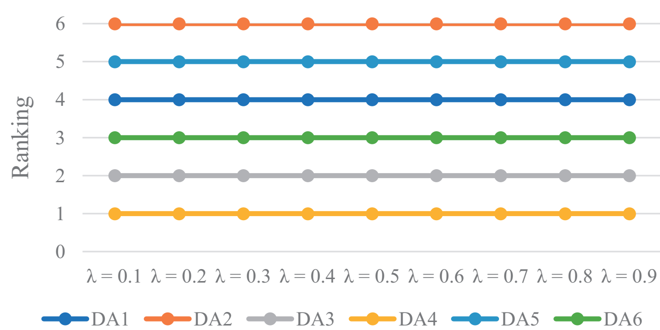

Figure 7: Alternatives' ranking with different λ values

A one-way ANOVA statistical test is carried out to verify the robustness of the sensitivity test results. With the null hypothesis stated as: "The changes in the value of the compromise coefficient do not significantly affect the performance scores of alternatives". The results are shown in Table 15 below:

Table 15: One-way ANOVA results

Source of variation	SS	df	MS	F	*p*-value	F crit
Between groups	0.000338	8	4.22E−05	0.000789	1	2.152133
Within groups	2.408082	45	0.053513			
Total	2.40842	53				

With a 5% level of significant, the results suggest that there is no significant difference of performance scores between with different compromise coefficient values (p-value = 1 > 0.05, fail to reject the null hypothesis). Fig. 7 also shows that the rankings in all cases remain unchanged regardless of the value of the compromise coefficient. As such, the model's results are robust against changing preference for compromise solutions.

6 Conclusions

As climate change becomes an ever-growing concern, there has been a notable acceleration in the development of renewable energy projects worldwide over the past decade. Vietnam is a country with substantial renewable energy resources has also saw an increase in renewable energy output in this time period. To enhance the success of renewable energy projects, the use of MCDM models in addressing complex decision-making challenges has also risen. This study developed a CRITIC-CoCoSo based MCDM model to support the location selection process for a hybrid solar-wind energy plant in Vietnam. The model identified Ham Thuan Nam District (DA4) as the most suitable site, with a performance score of 2.0919. Phan Thiet City (DA3) and Ninh Phuoc District (DA6) followed closely, with scores of 2.0655 and 1.8723, respectively. Sensitivity analyses confirmed the stability of the rankings under various scenarios, demonstrating the robustness of the model.

While the model has successfully assisted decision makers in identifying optimal location for a solar-wind hybrid energy plan based on quantitative data, it may overlook qualitative aspects like political risks or community acceptance of the problem. As such, future research should address these limitations by incorporating qualitative criteria by employing methods such as Fuzzy AHP or Fuzzy ANP. Comparative studies with other MCDM approaches, such as VIKOR or TOPSIS, could provide further validation to the results. Additionally, applying the proposed model to other similar renewable energy decision making problems would help verify its broader applicability.

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Availability of Data and Materials: The data that supports the findings of this study are available from the corresponding author, Rujira Chaysiri, upon reasonable request.

Ethics Approval: Not applicable.

Conflicts of Interest: The authors declare no conflicts of interest to report regarding the present study.

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