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A CRITIC–TOPSIS Multi-Criteria Decision-Making Approach for Optimum Site Selection for Solar PV Farm

Imad Hassan [1,2,*], Ibrahim Alhamrouni [1,*] and Nurul Hanis Azhan [1]

[1] Renewable Energy Research Laboratory (RENERAL), Electrical Engineering Section, British Malaysian Institute, Universiti Kuala Lumpur, Selangor 53100, Malaysia; nurulhanis@unikl.edu.my
[2] Department of Energy Engineering Technology, University of Technology Nowshera, Nowshera 24100, Pakistan
* Correspondence: imad.hassan@s.unikl.edu.my (I.H.); ibrahim.mohamed@unikl.edu.my (I.A.)

Abstract: This research work proposes a new hybrid framework to assess suitable sites and technical potentials for large-scale solar photovoltaic (PV) systems by integrating two multi-criteria decision-making (MCDM) techniques. The evaluation of sites for PV plants was performed using the MCDM method, taking into account a wide range of variables, including climate, technical, geographical, and economic variables, with factor weights determined using the CRITIC technique. Five Saudi Arabian cities with abundant solar radiation served as illustrations of this study's framework. For classification, the TOPSIS method was employed to rank the five alternatives. The results show that Riyadh is ranked first with a performance score of 72%, followed by Jeddah with a performance score of 65%, and the remaining three cities, namely, Al Ahsa, Dammam, and Abha scored less than 50%. Lastly, the reliability and robustness of the results obtained were examined using sensitivity analysis. The findings of this study can be used to pinpoint possible places that could be used to build solar power plants and to promote the expansion of generating facilities and electrical grids.

Keywords: PV system; multi-criteria decision making; CRITIC; TOPSIS; sustainable cities

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Citation: Hassan, I.; Alhamrouni, I.; Azhan, N.H. A CRITIC–TOPSIS Multi-Criteria Decision-Making Approach for Optimum Site Selection for Solar PV Farm. *Energies* **2023**, *16*, 4245. https://doi.org/10.3390/en16104245

Academic Editor: Jesús Polo

Received: 24 April 2023
Revised: 12 May 2023
Accepted: 16 May 2023
Published: 22 May 2023

1. Introduction

It is well-acknowledged that solar energy is a strong, dependable, and convenient source of power. Along with other renewable energy sources, including wind, hydro, biomass, and geothermal energy, it is viewed as a clean and sustainable alternative that is essential in tackling the growing environmental problems [1]. Due to the various problems caused by climate change, rising greenhouse gas emissions, environmental pollution, and depleting fossil fuel reserves, the use of renewable energy, especially solar energy, for electricity generation has drawn significant attention on a global scale [2]. Solar energy is a plentiful resource that depends on the average daily sunlight hours in a certain place and solar irradiation. Any city that receives a sufficient quantity of global horizontal irradiance (GHI) year-round is deemed to be an excellent choice for solar photovoltaic (PV) system installation [3,4].

Solar power projects have positive effects on the economy, society, and environment [5]. Additionally, the effectiveness, operating costs, and final energy yields of solar power systems are significantly influenced by the sites selected [6]. In order to increase its capacity for the production of electricity, Saudi Arabia recently implemented a number of renewable energy (RE) projects [7]. Government-set plans will soon see a variety of RE-based power plants installed across the country [8].

The Kingdom of Saudi Arabia has traditionally relied heavily on oil as its primary source of energy. However, the nation is attempting to diversify its energy mix as worries about climate change and energy security increase. Because Saudi Arabia is situated in a region with abundant solar resources and receives high levels of solar radiation [9], solar energy has a significant potential to meet the country's energy needs. As a result, the nation has recently made large investments in solar power research and is seeking to increase the proportion of solar power in its energy mix [10].

Solar energy's affordability is one of its key benefits. Solar energy is now substantially more affordable than traditional energy sources, thanks to recent price reductions. This indicates that solar energy is becoming increasingly appealing as a solution to Saudi Arabia's energy demands. In addition, solar energy is a clean, renewable energy source with no air pollution or greenhouse gas emissions. Saudi Arabia may lessen its carbon impact and enhance air quality by using more solar energy [11]. This is critically important for a nation that is particularly susceptible to the effects of climate change, such as rising temperatures, water scarcity, and extreme weather events [12].

Investing in sustainable energy sources, such as solar energy, can also be very advantageous for Saudi Arabia's economy. Large solar power plants can be installed to boost local economies, employment, and investment. The local economy can be boosted, and sustainable development can be supported by choosing a location that maximizes the potential for these economic benefits. Large-scale solar power plant investments can also help Saudi Arabia diversify its energy mix and lessen its reliance on fossil fuels, which can help to reduce the risks associated with oil price fluctuations and supply disruptions and guarantee a more reliable and secure energy supply for the nation [13].

Investments in renewable energy provide advantages for Saudi Arabia's economy as well as its standing as a responsible global citizen and as a regional leader in clean energy. As a signatory to the Paris Agreement, Saudi Arabia has committed to reducing its greenhouse gas emissions. Investing in solar power can help the country to meet its climate change commitments and demonstrate its leadership in addressing global environmental challenges [14]. Furthermore, the installation of large solar power plants can help promote innovation and technology development in the country, including the development of new solar technologies, energy storage solutions, and smart grid systems. This can encourage economic diversification and foster the development of a local clean energy sector [15].

While large solar power plants can provide significant benefits, it is also important to ensure that they are developed in a way that is sustainable and environmentally responsible. Careful site selection and planning can help minimize the environmental impacts of large solar power plants. The main issue with choosing the location for such projects is that it is one of the crucial choices that necessitates taking into account a number of factors and conducting a preliminary study [16].

PV systems work most effectively in vast land areas with abundant solar irradiation throughout the year. However, there is a number of major obstacles impeding the development of PV technology, one of which is the difference in solar irradiation brought on by various geographical factors in various places. As a result, selecting and installing a solar PV project requires considerable thought and evaluation of numerous parameters. These variables include increasing solar energy output, lowering the overall solar power project costs, and other essential factors. Numerous variables can affect the site selection for a solar PV power project, and the application of multi-criteria decision-making (MCDM) methodologies is essential in assessing the significant variables involved in the installation and positioning of a solar PV plant [17].

Due to its advantages, importance, and necessity, the usage of multicriteria decision-making techniques for solar photovoltaic (PV) site selection is becoming more prevalent. Multiple criteria and aspects that affect the performance of a solar PV system are taken into account by MCDM approaches, which offer an organized and thorough approach to site selection. Solar irradiation, temperature, wind speed, and other variables are some of these criteria and parameters. All of these criteria and aspects must be taken into account in order to choose the best location for solar PV installation. They must also be thoroughly and systematically evaluated. This is where MCDM techniques can help by offering a structured strategy that considers all pertinent criteria and aspects and aids in choosing the best installation site.

When choosing an optimal spot for a solar PV project, MCDM approaches have a number of advantages. They initially allow a thorough study of numerous criteria and parameters that affect a solar PV system's performance; this helps in making a well-informed decision on an appropriate construction place for solar projects. Secondly, objective and transparent mathematical models serve as the foundation for MCDM procedures. As a result, the impact of individual biases and subjective evaluations on the decision-making process is minimized. Thirdly, using a methodical approach, MCDM procedures increase the decision-making process' precision. This greatly aids in precisely identifying the best location for the installation of solar PV. Finally, by offering a structured approach that eliminates the need for trial-and-error tactics, MCDM techniques save time. This facilitates in quickly finding the best location for solar PV installation [18,19].

Additionally, it has been acknowledged that MCDM approaches are helpful in solving energy-planning problems [20,21]. Site selection for a solar PV power plant is a critical decision that necessitates careful consideration of numerous vital steps. When putting up solar PV projects, constraints, requirements, and pertinent decision criteria must first be carefully considered. A methodology is then used to rank the suggested sites. To further understand and get new insights into the results, a sensitivity analysis can be performed [22].

A thorough analysis of Saudi Arabia's solar PV potential demonstrates that solar energy is the most advantageous option for electricity generation [23]. This study aims to investigate MCDM methodologies in order to identify the best location within Saudi Arabia for a grid-connected solar PV installation. A utility-scale solar project involves generating solar power, transmitting it to an on-grid facility, and supplying energy to the utility. Thus, this research proposes a decision model that combines MCDM approaches, specifically the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) and Criteria Importance Through Intercriteria Correlation (CRITIC), using data collected from various sources on potential sites. These MCDM methods will offer valuable insights into a range of appropriate decision criteria to assist the government and policymakers in solar PV system site selection and development. The study focuses on five Saudi Arabian cities: Dammam, Jeddah, Abha, Riyadh, and Al Ahsa, aiming to determine the optimal locations for constructing grid-connected solar PV systems. Additionally, the literature review was conducted to identify the primary criteria (5) and sub-criteria (16) for this study. The CRITIC and TOPSIS methods were employed to achieve the research objective. The TOPSIS approach is utilized to rank the five alternatives, while the CRITIC method is employed to assign weights to the criteria and sub-criteria by using a normalized matrix and estimating the standard deviation from the normalized matrix.

One limitation of the previously applied multi-criteria decision-making techniques for selecting suitable sites for solar system installation is that subjective methods were used for weighting the criteria. In most of the previously published literature, the AHP technique, which is based on subjective values, is typically used to give weights to the criteria. However, the CRITIC method, which is based on objective values, is now being used in this work for the first time to do so for PV system site selection. The CRITIC method determines the relative importance of criteria by analyzing their intercorrelations and impact on the overall decision without relying on subjective judgments. The advantage of the CRITIC technique is that it helps to provide an objective and unbiased approach, ensuring that the selected sites are technically feasible, socially and environmentally responsible, and economically viable. The incorporation of objective criteria weighting also increases the credibility and reliability of the decision-making process, leading to more sustainable and efficient use of resources [24].

The existing literature categorizes criteria-weighting techniques into two main groups, objective and subjective methods [25,26]. Subjective techniques require decision-makers to provide initial information based on their knowledge or experience before determining criteria weights [27]. Pairwise comparison-based methods are popular subjective weighting techniques, such as the Analytic Hierarchy Process (AHP), Decision-Making Trial and Evaluation Laboratory (DEMATEL), Stepwise Weight Assessment Ratio Analysis (SWARA), and Analytic Network Process (ANP) [28,29]. While subjective approaches benefit from gathering data from knowledgeable decision-makers, there is a potential for bias in outcomes as certain criteria may be favored due to preexisting views of decision-makers [30]. Additionally, decision-makers who lack familiarity with the specific problem at hand may struggle to provide the necessary initial information. Moreover, the process of conveying complex information becomes challenging when the MCDM problem involves numerous criteria [31].

In contrast to subjective methods, objective methods merely assess the organization of the data present in the decision matrix to determine the weights [32]. They do not rely on any prior knowledge or judgment from the decision-makers [33]. These techniques are renowned for removing any potential bias related to subjective assessment, thereby increasing objectivity [34].

CRITIC and entropy-based techniques are among the most often employed objective methods for weighing criteria, according to our analysis of the currently available literature. Contrary to the Shannon entropy technique, which simply addresses the contrast intensity [35], CRITIC is shown to have additional worth because it takes into account both the contrast intensity and the conflicting relationships held between criteria [36,37].

(a) Contrast intensity of decision criteria

The contrast intensity in the CRITIC approach indicates the level of variability observed in the local scores for each criterion. The standard deviation is utilized to measure how distinctly each criterion contrasts with the others [38]. By employing this approach, criteria with higher standard deviations or contrast intensities are assigned greater weights. The rationale behind this approach can be illustrated with an example. If a criterion exhibits greater variation in scores across alternatives, it is considered to provide more valuable and insightful information. Therefore, in the context of decision-making, such a criterion should be accorded more consideration or weight compared to criteria with identical scores [39].

(b) Conflicting relationships between the decision criteria

Conflicting criteria are frequently used in an MCDM scenario to distinguish between alternatives [40]. As a result, an alternative may not always be able to completely satisfy all set criteria [41]. To account for these contradicting relationships, the CRITIC approach uses the Pearson correlation coefficient, which has a range of −1 to 1. The two criteria, cj and cj', are independent of one another when the coefficient is zero. When the coefficient is negative, the criteria are moving against one another. The contradiction between the two criteria gets worse as the co-efficient gets closer to 1. In contrast, a positive coefficient shows a parallel relationship between the two criteria and, when both have significant positive coefficient values, implies a disproportionate overlap. A criterion that has a high positive correlation with other criteria does not add new information and is, therefore, viewed as having less value overall. The CRITIC approach assures that a criterion with a larger degree of conflict or a lower degree of recurrence has a higher weight by adhering to this concept, which is based on specific formulas [42].

By analyzing the selection criteria for solar photovoltaic (PV) sites and creating a decision-support system, our study significantly contributes to the field. It is worthwhile to note that no previous study has offered objective weights to the factors considered in selecting a solar PV location utilizing the objective CRITIC approach. Our main goal is to use the CRITIC–TOPSIS decision-making approach to evaluate the significance of factors impacting the site selection of solar PV projects in order to fill the research gap. The block diagram of the MCDM technique used in this study is shown in Figure 1.

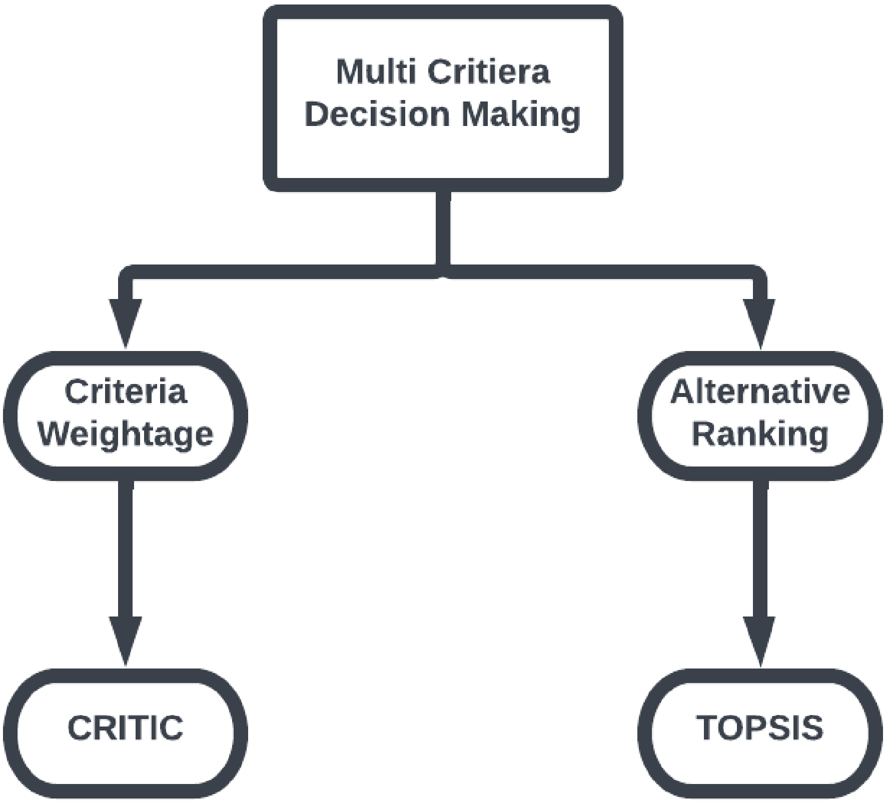

Figure 1. CRITIC–TOPSIS MCDM Approach.

The remainder of the paper is divided into the following sections. An overview of earlier research on the use of multi-criteria decision-making is given in Section 2. We go into detail about how we came up with and chose the criteria for our study in Section 3, along with the description of criteria and sub-criteria. The potential for solar energy in Saudi Arabia is covered in Section 4, along with a description of the site identification procedure. Section 5 provides more information on the CRITIC and TOPSIS techniques we employed in our study. The findings are presented in Section 6, along with performance ratings for each alternative. In Section 7, the proposed approach for ranking alternatives is compared with the Simple Additive Weightage (SAW) and Multi-Objective Optimisation based on Ratio Analysis (MOORA) methodologies. A sensitivity analysis is conducted in Section 8 to assess the robustness and reliability of the model. Finally, in Section 9, we draw conclusions regarding the effectiveness of our model, discuss limitations, and suggest future research directions.

2. Multi-Criteria Decision-Making Approaches in Solar PV Site Selection

To obtain a substantial amount of energy generation, it is crucial to choose the best sites for constructing solar PV power plants [43]. There has been a lot of fascinating research on this subject that has been undertaken and written about. In these pieces of research, the optimal location or alternative is typically determined using a geographic information system (GIS) and the multi-criteria decision-making (MCDM) technique.

Decision-makers can use MCDM approaches as useful tools to prioritize acceptable options based on a variety of criteria for a particular purpose [44]. MCDM approaches are frequently used by planners and policymakers in the field of renewable energy (RE). Given that multiple criteria or alternatives may lead to various outcomes among decision-makers, group decision-making becomes crucial to the decision-making process. It is insufficient to choose several sites for a RE project exclusively based on one criterion [45]. Table 1 provides a summary of previous studies that have utilized hybrid MCDM and GIS techniques to determine the optimal locations for solar PV plants.

Table 1. Hybrid MCDM and GIS methods for PV site selection.

Authors	Year	RE Source	Case Study	Proposed Methodologies
[46]	2021	CSP	Algeria	GIS and AHP
[47]	2021	PV	Sweden	GIS
[48]	2020	Solar PV	Malaysia	ForgeSolar software
[49]	2020	Solar PV	Turkey	GIS and AHP
[50]	2019	Solar PV	Mauritius	GIS and AHP
[51]	2019	CSP	China	PROMETHEE
[52]	2019	Solar PV	Pakistan	AHP and fuzzy VIKOR
[53]	2018	Rooftop PV	China	ANP and VIKOR
[54]	2018	PV	Morocco	GIS and AHP
[55]	2018	Solar PV	Iran	GIS and Boolean–fuzzy logic model
[56]	2017	Solar PV	Saudi Arabia	GIS and AHP
[57]	2017	Solar PV-CSP	Tanzania	GIS and AHP
[58]	2017	Solar PV-Wind	Afghanistan	GIS
[59]	2016	Solar PV	Spain	GIS, AHP, TOPSIS, and ELECTRE TRI
[60]	2016	Solar PV-CSP	Morocco	GIS
[61]	2015	Solar PV–Wind	UK	GIS and AHP
[62]	2015	Solar PV	Morocco	AHP and GIS
[63]	2014	Solar PV	Spain	GIS and ELECTRE
[64]	2014	Solar PV	Iran	Fuzzy AHP and GIS
[65]	2013	Solar	Turkey	GIS and AHP
[66]	2008	Solar PV	Spain	GIS
[67]	2010	Solar PV	Spain	AHP and ANP
[68]	2014	Solar PV–Wind	China	ELECTRE-II
[69]	2014	Solar	Iran	SWARA, WASPAS, and Delphi
[70]	2016	Solar PV	Korea	Fuzzy AHP and GIS
[71]	2017	Solar PV	Serbia	GIS and AHP

The data presented in Table 1 demonstrate the variation in the number of alternatives and criteria employed in previous studies. For instance, ref. [67] utilized the Analytic Network Method (ANP) to analyze 4 alternatives based on 12 main criteria and 50 sub-criteria for PV site selection. Study [68] focused on solar PV-wind site selection, considering 7 possibilities based on 5 criteria and 13 sub-criteria. In [69], the suitability of 25 solar projects in Iran was evaluated using 4 criteria and 14 sub-criteria. Study [70] employed fuzzy AHP and GIS to assess the potential of solar farms in South Korea, considering six primary and eight sub-criteria for three alternatives.

In the context of specific regions, studies have been conducted to determine the suitability of certain areas for solar PV projects. For instance, a GIS-AHP study in southern Morocco revealed that 24% of the region is suitable for the construction of PV farms [62]. Similarly, in eastern Morocco, 19% of the land was found to be suitable for large-scale solar PV projects using the AHP approach [54]. In Saudi Arabia, researchers computed a land suitability index using the AHP approach to identify the best location for solar PV sites [56]. In Serbia, the AHP approach was utilized to assess the natural solar PV potential, highlighting the impact of climate, vegetation, and orography on ground-mounted PV installations [71].

Table 1 also highlights the widespread use of the AHP method for criteria weighting and ranking in the selection of solar PV sites. GIS applications have frequently been combined with the AHP method compared to other decision-making approaches. Various MCDM methods, such as TOPSIS, ELECTRE, and VIKOR, have been employed for alternative ranking.

To the best of our current understanding, this research is the first effort to apply the CRITIC–TOPSIS techniques to Saudi Arabia for the purpose of assessing and prioritizing the site selection of solar PV generating plants. The chosen criteria were ranked according to their weights using the CRITIC methodology, while TOPSIS was used as a second method. Calculating the Euclidean distance allows TOPSIS to ascertain how close each alternative is to the ideal solution. The approach ranks alternatives according to how close they are to the preferred outcome and how far they are from the undesirable outcome [72]. Alternatives for the site selection of solar PV power projects in Saudi Arabia were categorized using the TOPSIS approach.

3. Criteria Identification and Selection

It is imperative to carefully assess and analyze several decision criteria when choosing a location for a solar PV power facility. This strategy guarantees the development of a highly effective and environmentally sustainable energy generation system. Based on the research carried out by [73–75], decision criteria and their associated sub-criteria were chosen in this study for the site selection of solar PV power projects. Five main criteria were established by the study: climatic; technical; economic; environmental; and social. A total of 16 sub-criteria were created by further evaluating each criterion based on numerous sub-criteria. Figure 2 gives a thorough summary of the chosen criterion and sub-criteria for the project's location.

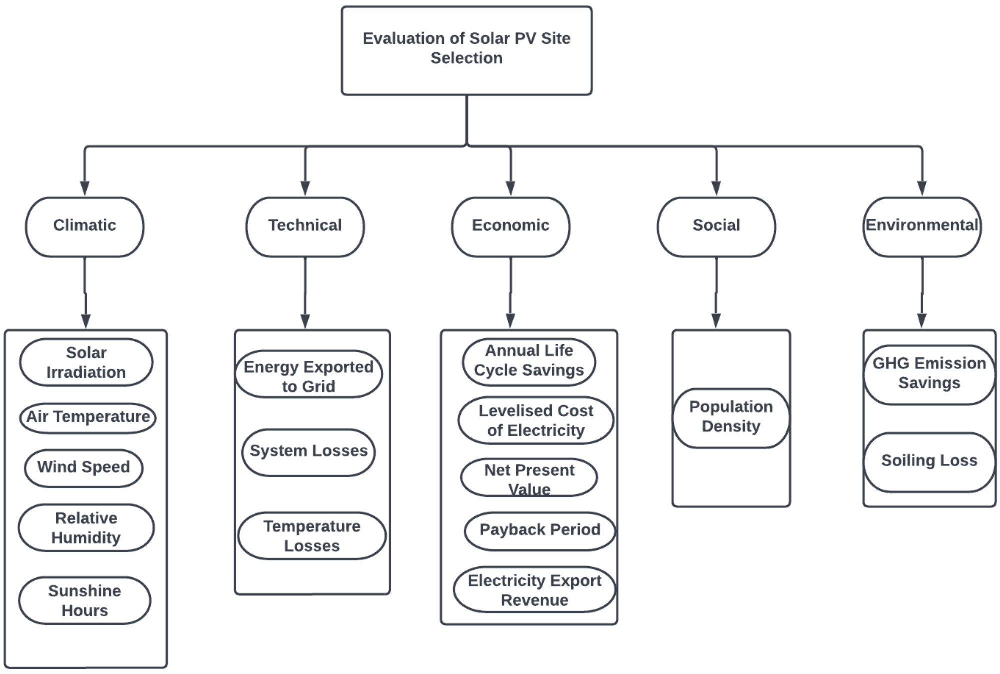

Figure 2. Selected criteria and sub-criteria for this work.

In the following section, a concise description of the criteria and sub-criteria identified for the study discussed in this paper are provided.

(a) Climatic Criterion:

This criterion is significant when evaluating the viability and potential output of a solar energy system at a specific site since it relates to area weather and climate trends.

Solar Irradiation: A PV plant's ability to run continuously is typically determined by the annual solar radiation, a meteorological factor used to assess the site's sunshine intensity. Solar radiation has a proportionate relationship with the PV power output. RETSCREEN was used to determine the yearly average daily sun irradiation for each of the selected locations.

Air Temperature: Owing to the science involved in how solar panels produce electricity, when a solar panel becomes too hot, its efficiency decreases. On the other hand, lower temperatures increase the effectiveness of solar panels. In a nutshell, colder panels enable more energy to pass through than hot panels when it comes to solar cell performance. The average yearly temperature for all sites in this work was calculated using RETSCREEN software.

Wind Speed: Wind causes solar panels to cool. This does make a difference, even if it does not significantly affect the overall solar panel productivity. Solar panels are 0.05 percent more efficient when cooled by 1 °C. Over time, this percentage increases.

Relative Humidity: On the surfaces of solar panels, minute water droplets or water vapors may gather and deflect or refract light away from the solar cells. Consequently, less sunlight strikes them, generating less electricity. During their lifetime, solar panels can deteriorate under hot, humid conditions.

Sunshine Duration: This is an essential indicator of the amount of solar energy a place receives. It is described as the interval during which direct sun irradiation of 1200 W/m^2 or higher is received by a place. With an increase in the number of hours of sunshine, more solar irradiation is received, resulting in increased generation of electricity from the PV system.

(b) Technical Criterion

This criterion is related to the technical aspects of solar energy systems, and it is important in determining the technical feasibility of the generation, installation, and operation of a solar energy system at a particular site.

Electricity Exported to Grid: This is the total power of the PV system sent to the grid. The value was determined by simulating a 5 MW grid-connected PV system using real-time meteorological data in the PVSYST software for all sites.

System Losses: The system losses include array mismatch, ohmic wiring, and inverter losses. This value is calculated by PVSYST software.

Temperature Losses: This criterion represents the decrease in energy yield due to the increase in temperature above the nominal rating.

(c) Economic Criterion

This criterion refers to the financial aspects of solar energy projects, and it is essential in evaluating the economic viability of a solar energy project at a specific site.

Annual Life-Cycle Savings: The yearly life-cycle savings are the levelized nominal annual savings with the same net present value and life as the project. Using the project life, discount rate, and net present value, the yearly life-cycle savings were calculated using RETSCREEN.

Levelized Cost of Electricity (LCOE): The export rate of electricity needed to achieve a zero Net Present Value (NPV) is represented as LCOE.

Payback Period: This is the time period the facility will take to generate the revenue or savings needed to cover its initial costs. The underlying tenet of the simple payback approach is that an investment is more desirable if its cost can be returned quickly.

Electricity Export Revenue: This value is calculated by multiplying the electricity exported to the grid by the electricity export rate.

(d) Environmental Criterion

This criterion is related to the environmental impacts of solar energy projects and is important in determining the environmental sustainability of a solar energy project at a particular site.

GHG Emissions: These are the net GHG emissions per year resulting from the use of fossil fuel for the generation of electricity instead of the PV system.

Soiling Loss: This is the power loss due to the accumulation of dirt on the PV panels. This can degrade the performance of the PV systems over time. The value for soiling loss was obtained using the PVSYST software.

(e) Social Criterion

This criterion refers to the social impacts of solar energy projects, and it is significant in evaluating the social acceptability of a solar energy project at a particular location.

Population Density: The installation of a PV system must be nearby to a place with enough consumers and skilled labor to reduce the expense of hiring labor to build, run, and maintain the PV system. The KAPSARK data portal was used to obtain the population data for each alternative in this analysis.

The next phase of the research involves gathering data after the criteria have been determined. In this context, the emphasis was on looking for reliable data sources that could give us the details we needed to fill up Table 2. RETSCREEN, PVSYST, and KAPSARC were among the data sources that were taken into consideration. Numerous studies have confirmed the usage of the widely utilized software programs RET-SCREEN and PVSYST for analyzing renewable energy systems. KAPSARC is a reputable energy research organization, and studies involving energy frequently use its data.

Table 2. Calculated values of criteria.

Criteria	Sub-Criteria	References	Data	Abha	Jeddah	Dammam	Riyadh	Al Ahsa
Climatic	Solar Irradiation ($kwh/m^2/day$)	[73,74]	RETSCREEN	5.43	5.94	5.6	5.78	5.85
	Air Temperature (°C)	[73,74]	RETSCREEN	18.6	28.2	26.5	25.7	26.8
	Wind Speed (m/s)	[73,75]	RETSCREEN	3.1	3.6	4.4	3	3.57
	Relative Humidity (%)	[73,74]	RETSCREEN	54.9	60.4	52	26.6	39.1
	Sunshine Duration (h)	[73]	PVSYST	8.7	9.2	9.2	9.2	9.4
Technical	Energy Exported to Grid (Mwh)	[73]	RETSCREEN	11,020	9505	8808	10,074	9220
	System Losses (Mwh)	[73]	PVSYST	519.6	435.09	395.043	467.45	428.92
	Temperature Losses (Mwh)	[73]	PVSYST	877.56	1072.6	930.8	1144.3	1072.9
Economic	Annual Life-Cycle Savings ($)	[73,74]	RETSCREEN	287,476	202,147	162,935	234,207	186,117
	Levelized Cost of Electricity ($/Mwh)	[73,74]	RETSCREEN	30	35	38	33	36
	NPV ($)	[73]	RETSCREEN	2,624,238	1,845,308	1,487,360	2,137,970	1,698,977
	Payback Period (Year)	[73,74]	RETSCREEN	4.8	5.8	6.5	5.4	6.1
	Electricity Export Revenue ($/Mwh)	[73,74]	RETSCREEN	528,964	45,6221	422,793	483,552	442,555
Environmental	GHG Emissions (tCO2/year)	[73,74]	RETSCREEN	8314	7170	6645	7600	6956
	Soiling Loss (kwh/m^2)	[73,74]	PVSYST	76.393	67.801	62.45	72.379	66.632
Social	Population Density	[73,74]	KAPSARC	2,354,320	9,261,257	1,304,688	8,660,885	858,935

The software tool RETScreen is frequently used to assess the viability of projects, including renewable energy and energy conservation. Solar radiation, air temperature, wind speed, relative humidity, and other pertinent parameters are among the capabilities it offers for calculating and analyzing technical and financial data linked to energy projects. RETScreen has been used to obtain data on meteorological, technical, and economic aspects. RETScreen gathers and computes the data using a combination of satellite and ground-based data sources. In order to guarantee the correctness and dependability of the data collected from these sources, the software employs a strict validation process. This includes comparing data derived from satellites with measurements taken on the ground to ensure the data is accurate and consistent. The use of reputable and trusted data sources, such as NASA and the National Oceanic and Atmospheric Administration (NOAA), which give data that is widely used and acknowledged in the field of renewable energy, can also show the correctness and reliability of the data [76].

Solar energy systems are designed and simulated using the software program PVsyst. It offers a variety of tools and capabilities for modeling solar energy systems and evaluating their performance, and it is widely used in the solar energy sector. PVsyst was used to determine sunshine duration (h), system losses (MWh), temperature losses (MWh), and soiling loss (kWh/m^2) in order to acquire and interpret the data shown in Table 2. To produce precise and trustworthy statistics on solar resources, PVsyst draws on a range of data sources, including measurements made on the ground and data collected from satellites. Additionally, PVsyst uses a strict methodology for data validation and quality control, which includes sensitivity analysis, input data quality control, and model calibration and validation. Additionally, PVsyst models have been calibrated and validated using real-world field data to guarantee that they appropriately depict how solar energy systems behave in various scenarios. For the most part, PVsyst is a trustworthy and accurate tool for simulating solar energy systems, and the information gleaned from it can be regarded as trustworthy and accurate for the purposes of this study. However, the results should always be interpreted with a certain degree of caution and awareness of the limits of the underlying data and models, as no simulation tool can guarantee complete accuracy [77].

King Abdullah Petroleum Studies and Research Centre, or KAPSARC, is a well-known and highly regarded energy research organization that has been carrying out thorough studies on a variety of energy-related topics for many years. KAPSARC is widely regarded as a top source of trustworthy and accurate data in the area of energy research, notably in the Middle East region, as a result of its competence and reputation.

KAPSARC provided the information for the population density sub-criteria shown in Table 2. This information's use and acceptance in several studies and research projects on energy attests to its dependability and accuracy. In order to guarantee that the data they provide are of the highest quality and accuracy, KAPSARC has a well-established reputation for adhering to strict and open data gathering and analysis processes [78].

It should be emphasized that the information in Table 2 is particular to Abha, Jeddah, Dammam, Riyadh, and Al Ahsa in Saudi Arabia. As a result, the information might not be relevant in other places.

Topographical coordinates of the five selected cities were obtained using Google Earth software, and the solar data for the chosen cities were obtained using RETSCREEN software. Data on latitude, longitude, average relative humidity (%), average air temperature (°C), annual average GHI (kWh/m^2/day), and average GHI (kWh/m^2/year) were gathered. Figure 3 illustrates the solar statistics for the five selected Saudi Arabian cities.

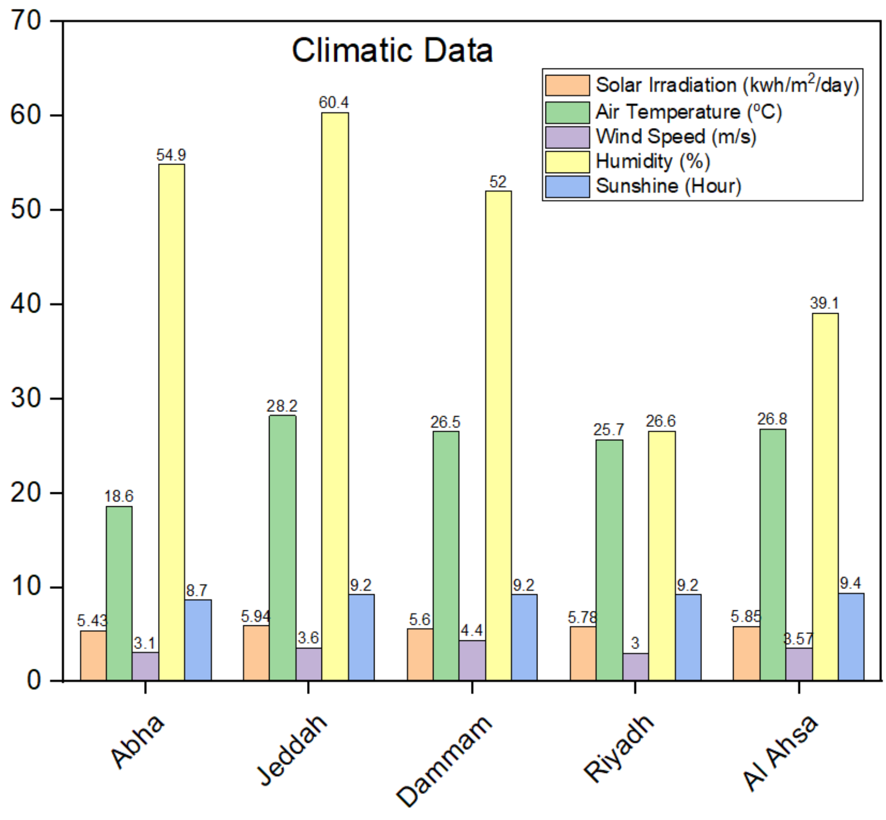

Figure 3. Climatic data of selected cities.

4. Saudi Arabia's Solar Energy Potential

Saudi Arabia is the GCC nation with the highest potential for solar energy production. The need for energy in Saudi Arabia is increasing every year, which has led to the burning of numerous tons of oil and carbon-rich fuel to produce electricity. As oil is the country's main source of revenue, this has a negative impact on the Saudi economy. Furthermore, the release of CO_2 has an adverse impact on human health [79]. Saudi Arabia has thus made tremendous efforts to move away from its present situation of complete reliance on oil and towards new frontiers of investigation for other forms of renewable energy. PV solar energy is the most desirable to be harvested in Saudi Arabia among all the renewable energy sources. Thankfully, Saudi Arabia's location is among the best in the world for solar insolation. Figure 4 shows the average daily and yearly solar radiation for all regions of Saudi Arabia. When the sky is clear, Saudi Arabia's lands receive an average daily global horizontal irradiance (GHI) of roughly 6.2 kWh/m^2 [80].

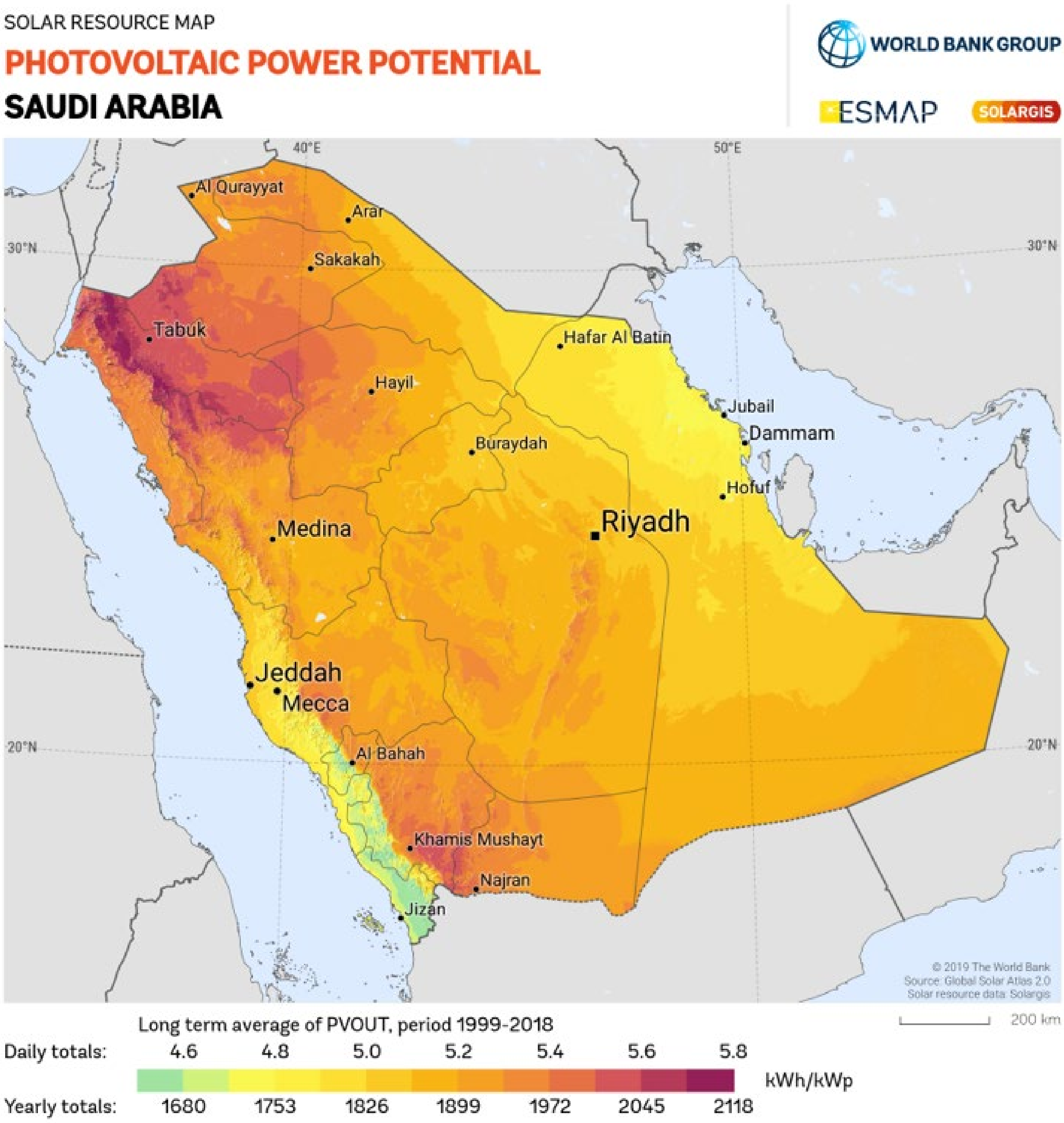

Figure 4. Solar radiation map of Saudi Arabia.

In addition, while the lifespan of PV modules has extended to approximately 30 years, the cost of producing PV modules has reduced internationally over the past ten years to an affordable level [81]. The cumulative installed capacity of the PV solar energy indicator increased with the passage of time; it increased from 40 GW to 480 GW in the period from 2010 to 2018. However, it is predicted that more capacity will be built over the following ten years to create roughly 3200 TWh by 2030, which would be approximately six times the 580 TWh produced in 2018 [82]. The performance of the PV module can be impacted by Saudi Arabia's warmer climate and the elevated outer surface temperature of the module. Fluctuation in line losses, changes in the network voltage profiles, prospective node voltage threshold errors, and raised fault current levels may result from the inverted power flow from the PV system to the conventional power flow. Thus, depending on the network structure and the area's solar resources, adding large-scale PV systems to Saudi Arabia's current electrical power networks could have either beneficial or negative effects.

To integrate several solar projects with the current Saudi Arabian network, new rules and procedures must be developed and adopted. In a similar vein, conducting research studies with the aid of cutting-edge software tools and programs for the analysis of future risks, evaluating their technical detrimental effects on the existing network, and exploring the financial feasibility of implementing such projects will unquestionably clear the way for policy-makers to eventually arrive at the right solution [83].

Most regions in Saudi Arabia receive sufficient solar irradiation throughout the year, which creates very good geographic conditions for solar system installation. The primary criterion used to select the cities for this study was that each site must receive a minimum of 5 kwh/m^2/day of solar irradiation. Therefore, in this work, Dammam, Riyadh, Abha, Jeddah, and Al Ahsa were identified as the chosen cities of Saudi Arabia to study, as indicated in Figure 5. In addition, various other factors, such as their location, size, and economic importance, were also considered. The fact that the chosen cities are spread throughout different regions of Saudi Arabia enables a more thorough evaluation of the viability and potential of solar PV power projects throughout the entire country. Additionally, due to their immense scale and economic significance, they are appropriate for research on how solar PV power plants can have a significant impact on Saudi Arabia's economy. A brief description of each of the five chosen cities can be found in the paragraph that follows.

Saudi Arabia's capital and largest city, Riyadh, is situated in the country's central area. As a result of its strategic location and convenient access to neighboring Saudi Arabian provinces and cities, it serves as a major financial and transportation hub. Jeddah is the second-largest city in Saudi Arabia, which is located in the western part of the country, overlooking the Red Sea. Jeddah, a significant port city, acts as a crucial entry point for trade and commerce between Saudi Arabia and other nations. The third-largest city in Saudi Arabia, Dammam, sits in the country's eastern area. It is a significant industrial and commercial hub noted for its oil industry and sizable seaport. Abha, which is located in southern Saudi Arabia, is a fairly small city when compared to the other chosen cities. It is a well-liked tourist attraction in the nation due to its scenic beauty and temperate environment. Lastly, Al Ahasa, well known for the agricultural sector, is a city in eastern Saudi Arabia. Numerous colleges and research centers are also located in the city. By selecting these particular cities, the study can offer a more thorough analysis of the potential benefits as well as challenges of putting solar PV power projects into practice in Saudi Arabia. Additionally, it can shed light on the best practices for project execution and highlight the obstacles to deployment that must be removed to enable the development of renewable energy in the country [84].

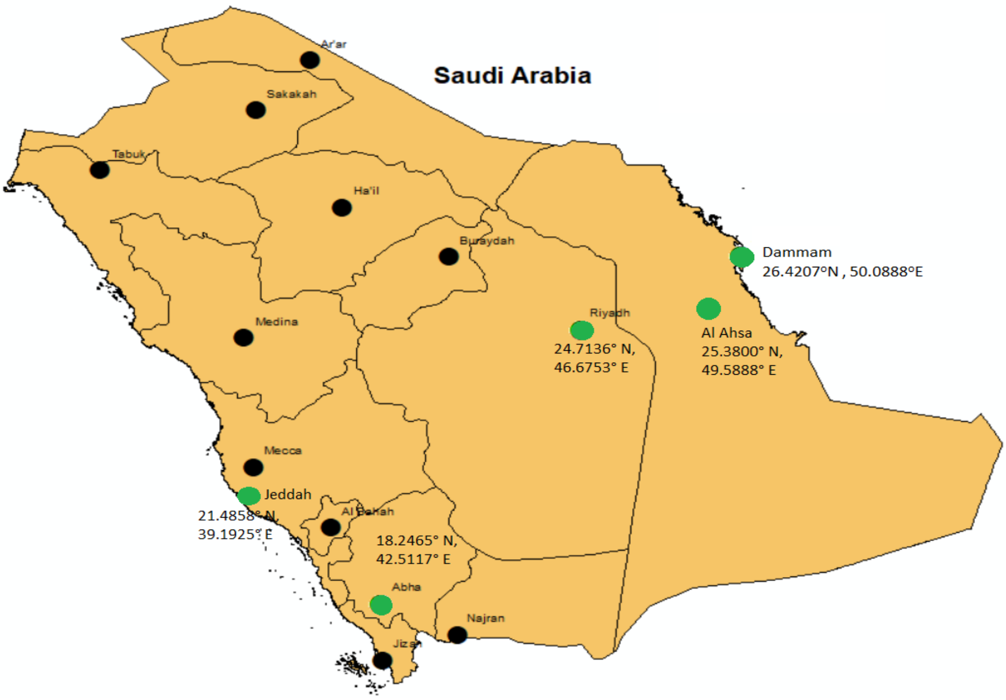

Figure 5. Map of five selected cities.

5. Methodology

This study's framework uses the CRITIC and TOPSIS approaches to evaluate and select the best location for the construction of solar PV power projects in Saudi Arabia. Figure 6 illustrates the study's research framework. The CRITIC and TOPSIS approaches are discussed in detail in the next section.

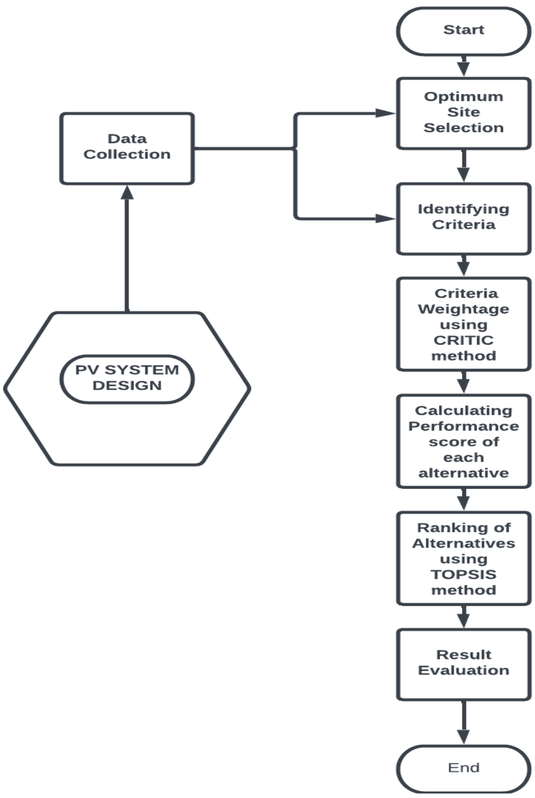

Figure 6. Methodology of the research work.

5.1. CRITIC Method for Determining Criteria Weights

One of the weighting techniques that establishes objective weights for criteria is the CRITIC (Criteria Importance Through Inter-criteria Correlation) method. Diakoulaki et al. proposed the CRITIC technique in 1995. This approach considers the degree of conflict and contrasts in the structure of a decision-making problem. Discrepancies between the criteria are discovered using correlation analysis. According to this method, the decision matrix is assessed along with the standard deviation of the normalized criterion values by columns and the correlation coefficients of all pairs of columns to determine the criteria contrast [85,86].

The proposed methodology in this work consists of six steps.

Step 1. In the first step, the decision matrix is formed, and the performance values of all the alternatives are measured.

$$x = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mm} \end{bmatrix}$$

Step 2. Calculate the transformation of performance values. Using the ideal point concept, the decision matrix values are transformed. We determined the ideal best solution (x_j^*) and ideal worst solution (x_j^-) for all criteria and then calculated the relative deviation matrix.

$$x_{ij}^T = \frac{x_{ij} - x_j^-}{x_j^* - x_j^-} \quad if\ j \in B \tag{1}$$

$$x_{ij}^T = \frac{x_{ij} - x_j^-}{x_j^- - x_j^*} \quad if\ j \in NB \tag{2}$$

${x_{ij}}^T$ is the normalized performance value of the criteria, and xj^- and ${x_j}^*$ are the minimum and maximum values of the criteria, respectively. Equations (1) and (2) are for beneficial criteria $(j \in B)$ and non-beneficial criteria $(j \in NB)$, respectively.

Step 3. Calculate the standard deviation (s) of each criterion using their corresponding vectors.

$$s_j = \sqrt{\frac{1}{m-1} \cdot \sum_{i=1}^{m} \left(x_{ij} - \overline{x_j}\right)^2} \tag{3}$$

Step 4. Construct m × m square matrix R. The elements of the square matrix R are the linear correlation coefficients between x_j and $x_{k.}$

$$R = \left[\, r_{jk} \,\right]_{mxm} \tag{4}$$

$$r_{jk} = \frac{\sum_{i=1}^{m}\left(x_{ij} - \overline{x_J}\right)\left(x_{ik} - \overline{x}_k\right)}{\sqrt{\sum_{i=1}^{m}\left(x_{ij} - \overline{x_J}\right)^2 \ \sum_{i=1}^{m}\left(x_{ik} - \overline{x_k}\right)^2}} \tag{5}$$

r_{jk} is the correlation between the criteria. Both a criterion's standard deviation and its correlation to other criteria are taken into consideration when calculating the criteria weights.

Step 5. Calculate the information measure of each criterion (H_j)

$$H_j = s_j \ \sum_{k=1}^{m}\left(1 - r_{jk}\ \right) \tag{6}$$

The CRITIC method employs the standard deviation as an indicator of the importance of each criterion. To account for inter-criterion relationships, the correlation matrix is used to allocate weight among correlated criteria using reduction coefficients $(1 - r_{jk})$. The value expressed in Equation (6) represents the level of conflict that arises from the jth criterion relative to the other criteria. Finally, the information content of the jth criterion is calculated through the multiplicative combination of measures according to Equation (6).

Step 6. Determine the criteria weights w_j.

$$w_j = \frac{H_j}{\sum_{k=1}^{m} H_k} \tag{7}$$

where H_k is the sum of the information measure of all criteria. This strategy, it may be said, provides more weight to criteria with high standard deviation and little association with other criteria. In other words, a larger value of Hj indicates that more information may be gleaned from the provided criterion, thereby increasing the criterion's relative importance for the decision-making problem.

5.2. TOPSIS Method for Ranking Alternatives

Ranking the alternatives comes next after the weights of the criteria have been determined. To achieve this, the TOPSIS technique was used. The TOPSIS approach determines the closeness of each alternative to the ideal option based on the concepts of ideal and anti-ideal solutions. The TOPSIS technique offers a systematic way to assess and rank options based on overall performance, making it an effective MCDM tool for making decisions [87].

The TOPSIS method is implemented by following these steps:

Step 1. In the first step, the decision matrix is created, which shows how each alternative performs in relation to each criterion.

$$x = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1m} \\ x_{21} & x_{22} & \cdots & x_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mm} \end{bmatrix}$$

Step 2. Normalize the decision matrix by calculating as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{1}^{n} x_{ij}^2}} \tag{8}$$

where r_{ij} is the normalized decision matrix and x_{ij} is the performance value of alternative i on criterion j.

Step 3. In this step, determine the weighted normalized decision matrix (v_{ij}), the weighted normalized decision matrix assigns weights to each criterion based on their relative importance using Equation (9).

$$v_{ij} = r_{ij} \times w_j \tag{9}$$

Step 4. Next, determine positive (A^{+}) and negative ideal solutions (A^{-}). A negative ideal solution represents the poorest possible performance, whereas an ideal solution reflects the best possible performance for each criterion.

$$A^{+} = \{\ (\max v_{ij} \mid j \in J\ ,\ (\min v_{ij} \mid j \in J^{-})\}. \tag{10}$$

$$A^{-} = \{\ (\min v_{ij} \mid j \in J\ ,\ (\max v_{ij} \mid j \in J^{-})\} \tag{11}$$

Step 5. Next, calculate the Euclidean distances between each alternative and the positive ideal solution and negative ideal solution.

$$s_i^+ = \sqrt{\sum_i^n \left(v_{ij} - v_j^+\right)^2} \quad (12)$$

$$S_i^- = \sqrt{\sum_i^n \left(v_{ij} - v_j^-\right)^2} \quad (13)$$

where s_i^+ is the distance of the alternative from the positive ideal solution and S_i^- is the distance of the alternative from the negative ideal solution.

Step 6. Calculate the relative closeness of each alternative to the ideal solution. The ratio of the distance to the negative ideal solution to the total distances to the ideal and negative ideal solutions represented as C_i in Equation (14) is used to determine how close each alternative is to the ideal answer.

$$C_i = \frac{S_i^-}{S_i^- + S_i^+} \quad (14)$$

Step 7: The final step involves ranking the alternatives. The alternatives are ranked based on their relative closeness values, with higher values indicating better performance.

6. Results and Discussion

A hybrid decision-support system is developed in this section using the above-discussed CRITIC and TOPSIS approaches. A total of 16 criteria were defined. Criteria C1, C3, C5, C6, C9, C11, C13, C14, and C16 are considered beneficial, meaning that higher values are preferred, whereas criteria C2, C4, C7, C8, C10, C12, and C15 are considered non-beneficial, favoring lower values. Following the determination of the decision matrix and the normalized decision matrix illustrated in steps 1 and 2 of the CRITIC approach, the standard deviation for each criterion is calculated using its corresponding vectors, as shown in Table 3. The standard deviation represents the variability or diversity of the values for each criterion across the alternatives being evaluated. The values of the decision matrix and normalized decision matrix are provided in Tables S1 and S2 of the Supplementary Materials.

Table 3. Standard Deviation Values of each criterion.

	C1	**C2**	**C3**	**C4**	**C5**	**C6**	**C7**	**C8**	**C9**	**C10**	**C11**	**C12**	**C13**	**C14**	**C15**	**C16**
STDV	0.401	0.393	0.396	0.404	0.373	0.388	0.377	0.416	0.388	0.381	0.388	0.384	0.388	0.388	0.386	0.491

A high standard deviation indicates that the values for a criterion are widely spread out and hence, will be assigned a higher priority, while a low standard deviation suggests that the values are relatively close together and, therefore, a low priority is assigned to such criteria. In this case study, the highest value of standard deviation was obtained for population density, and hence, a higher priority was assigned to this criterion in the decision-making process, followed by wind speed and GHG emissions. Then, the correlation matrix and information measure of each criterion were calculated using Equations (5) and (6), respectively. The correlation matrix is calculated by comparing the performance of each criterion with every other criterion, and the information measure (H) represents the degree of redundancy or overlap between the criterion and all the other criteria. The higher the information measure, the less redundant the criterion is with respect to the other criteria and, therefore, the more important it is in the decision-making process. In this work, the highest value of H was obtained for criterion C16 (population density), followed by C3 (wind speed) and C15 (GHG emission). The H values for all criteria are given in Table 4.

Table 4. Criteria weights.

H	6.687	5.719	7.149	6.277	6.522	5.383	6.829	6.683	5.383	5.28	5.383	5.317	5.383	7.026	7.02	7.389
W	0.067	0.058	0.072	0.063	0.066	0.054	0.069	0.067	0.054	0.053	0.054	0.054	0.054	0.071	0.071	0.074

In the final step, the weight of each criterion is calculated using Equation (7). The findings shown in Table 4 indicate that population density has the highest weight in this study (0.07431), followed by wind speed (0.072) and GHG emission reductions (0.0707). The weights for all other criteria are listed in Table 4.

The CRITIC technique assigns weights to criteria by considering both the contrast intensity and inter-criteria correlation. The contrast intensity of each criterion was measured using the standard deviation values, whereas the inter-criteria correlation was determined using the information measure of each criterion. The calculated values of the inter-criteria correlation are given in Table S3 of the Supplementary Material. The results in our model are consistent, as the values for both the standard deviation and information measure were higher for population density, wind speed, and GHG emission reductions. Hence, higher priority was assigned to these criteria, as illustrated in Figure 7.

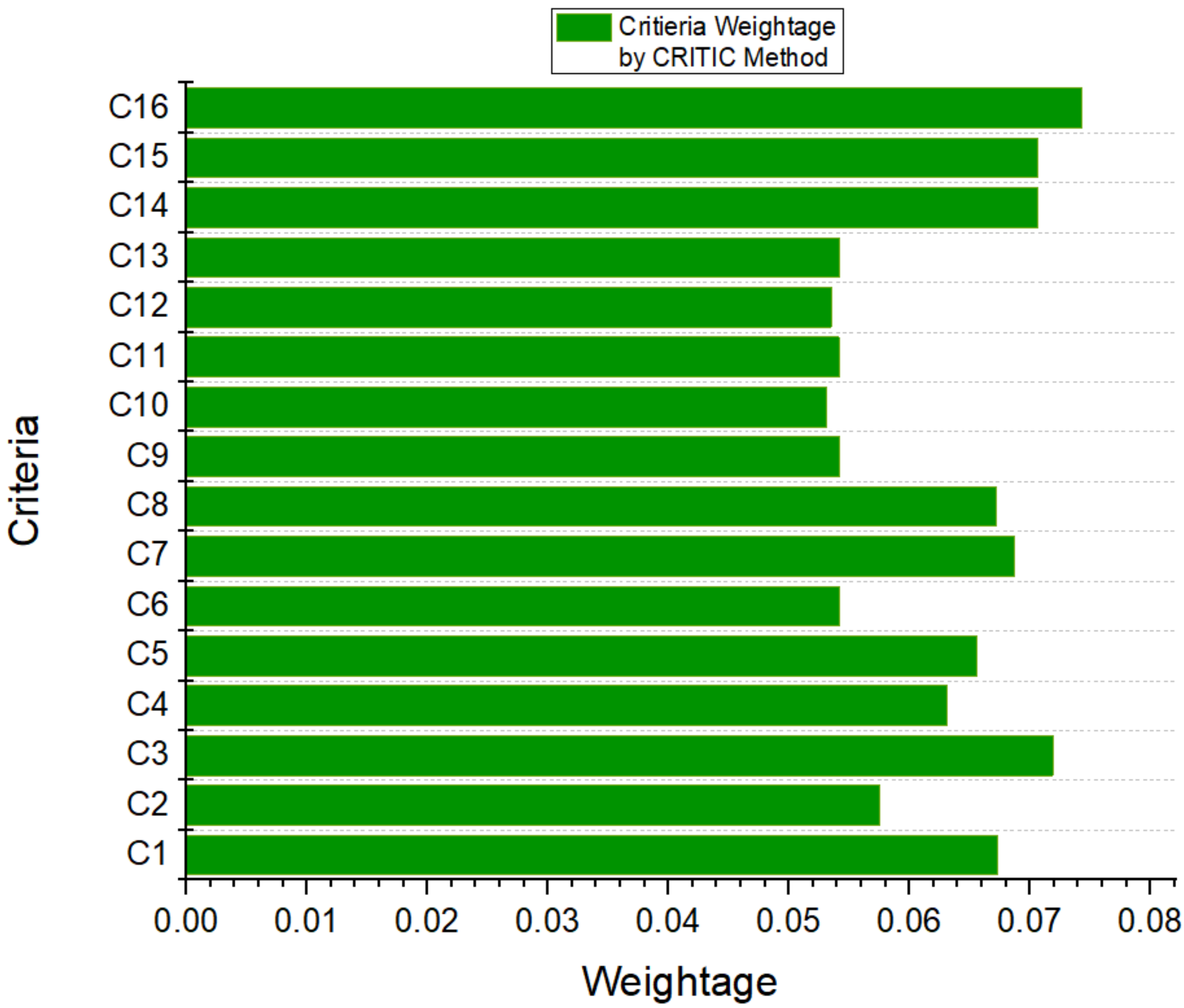

Figure 7. Criteria weights.

After the weights for criteria have been established, the subsequent step involves ranking the alternatives using the TOPSIS technique. TOPSIS uses the decision matrix as the performance matrix. The normalized performance matrix and the weighted normalized matrix are obtained using Equation (8) and Equation (9) respectively. The calculated values of the normalized performance matrix and weighted normalized matrix can be found in Tables S4 and S5 of the Supplementary Material, respectively.

The values of the ideal best solution (A^{+}) and ideal worst solution (A^{-}) were calculated using Equations (10) and (11), respectively. Both the A^{+} and A^{-} were used as reference points to measure the relative performance of each alternative. The A^{+} and A^{-} values for each criterion are listed in Table 5.

Table 5. Positive and negative ideal solutions.

A^{+}	0.031	0.019	0.04	0.016	0.03	0.027	0.03	0.026	0.032	0.021	0.032	0.02	0.027	0.029	0.028	0.053
A^{-}	0.029	0.029	0.027	0.035	0.028	0.022	0.04	0.034	0.018	0.026	0.018	0.027	0.022	0.036	0.035	0.005

In the next step, we calculated the distances between each alternative and the A^{+} and A^{-} values. The distance between an alternative and the ideal best solution is calculated using the Euclidean distance formula given in Equation (12), whereas the distance between an alternative and the ideal worst solution is calculated using the same formula but with the signs of the values in the matrix reversed, as shown in Equation (13). Alternatives with smaller Euclidean distances are considered more similar to the ideal solution and are ranked higher.

Next, the TOPSIS method was used to calculate a performance score for each alternative by employing Equation (14). The alternative with the highest score is considered to be the best alternative. Table 6 presents the performance scores and the Euclidean distances of all the chosen alternatives.

Table 6. Euclidean distances of each alternative.

	S^{+}	S^{-}	C
A1	0.046	0.028	0.373
A2	0.029	0.055	0.658
A3	0.054	0.033	0.38
A4	0.021	0.056	0.727
A5	0.054	0.03	0.362

Finally, the alternatives were ranked based on their performance scores. The final ranking shows that A4, with a performance score of 72.7%, is ranked first, followed by A2, with a performance score of 65.8%. A3, A1, and A5 were ranked third, fourth, and fifth, with performance scores of 38%, 37.3%, and 36.2%, respectively.

This study illustrates how energy planners and policy-makers can implement and evaluate a strategic decision-making process by combining CRITIC and TOPSIS approaches. This work was implemented in Saudi Arabia, where five cities had their potential for solar PV project development assessed. In order to provide the research framework for this study, which would provide an appropriate justification for the site selection of a solar PV power project, the current analysis lays the groundwork for the government and decision-makers.

On a scale from zero to one, Figure 8 illustrates the performance score of each alternative, as determined in Equation (13), with Riyadh receiving the highest value. These findings demonstrate the potential of Saudi Arabia's location for hosting PV system facilities. Based on the established criteria, Jeddah and Riyadh outperform the other three of the five possibilities, scoring above 50%.

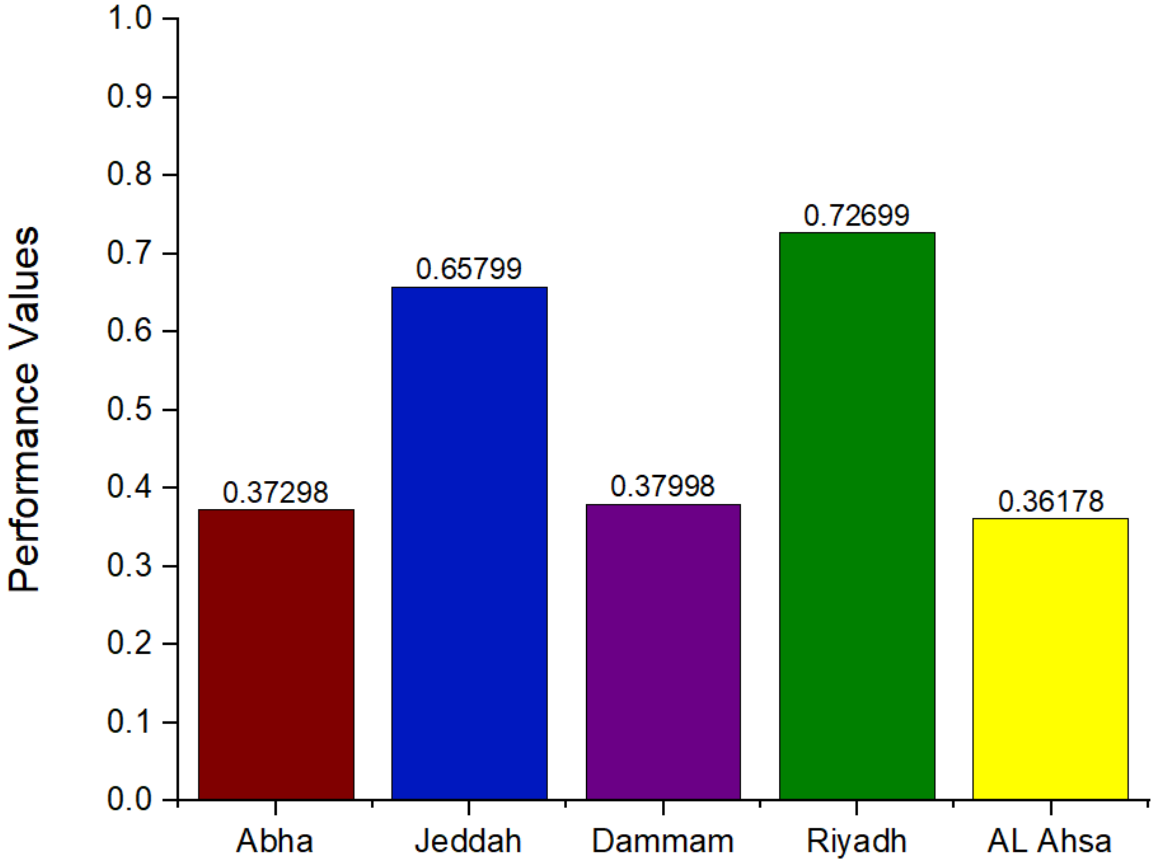

Figure 8. Performance values of selected cities.

7. Comparison of Results

In this work, the results of the TOPSIS method were compared with those of the Simple Additive Weightage (SAW) [88] and Multi-Objective Optimization on the basis of Ratio Analysis (MOORA) [89] methods. The results of the comparison are presented in Table 7, using the weights derived by the CRITIC method. We chose to compare our results with SAW and MOORA methods because our model relies on objective values, and these methods are also objective and are commonly used for ranking alternatives based on quantitative attributes. The variation in the values of each alternative among the three methods can be explained by the use of different mathematical models for calculating the performance values. Each method has its own approach to evaluating the criteria, resulting in a distinct set of values for each alternative. The step by step calculations for SAW and MOORA methods are provided in Sections S3 and S4 of the Supplementary Materials respectivley.

Table 7. Comparison of Results.

Alternatives	Proposed Method	Rank	SAW	Rank	MOORA	Rank
Abha	0.3730	4	0.8366	3	−0.0071	3
Jeddah	0.6580	2	0.8375	2	0.0031	2
Dammam	0.3800	3	0.7853	4	−0.0359	4
Riyadh	0.7270	1	0.8682	1	0.0205	1
AL Ahsa	0.3618	5	0.7789	5	−0.0362	5

In the SAW method, the performance scores of each alternative on each criterion are multiplied by their respective weights and then added up to produce a single score for each alternative. The alternative with the highest score is ranked as the best.

On the other hand, MOORA uses a ratio-based approach to rank alternatives. MOORA calculates ratios by dividing each alternative's performance score on each criterion by the sum of the performance scores of all alternatives on that criterion. These ratios are then multiplied by their respective weights to determine each alternative's overall score. The alternative with the highest overall score is ranked as the best. A negative performance value indicates that an alternative has a performance value that is lower than the best performance value observed for that criterion. Therefore, the negative values for Abha, Al Ahsa, and Dammam in the MOORA table indicate that their performance in at least one criterion is worse than the reference level used to calculate the performance value.

The results presented in Table 7 indicate that the ranking of the alternatives Riyadh, Jeddah, and Al Ahsa remain consistent across all three methods. Riyadh is ranked as the best alternative among all the five options, followed by Jeddah in second place and Al Ahsa in fifth place. However, there are some differences in the rankings for the third and fourth-place alternatives. According to the Proposed Method, Dammam is ranked in the third position, and Abha is in the fourth position. In contrast, both the SAW and MOORA methods rank Abha in the third position and Dammam in the fourth position. This indicates some sensitivity to the choice of the decision-making method. It is important to note that the rankings of the alternatives are slightly different across the three methods, highlighting the need for careful consideration of the specific requirements of the problem when selecting an appropriate method for decision-making.

8. Sensitivity Analysis

Sensitivity analysis is an important part of Multi-Criteria Decision Making (MCDM) that aids in evaluating the stability and validity of the decision model. It entails assessing the effects of adjustments to the decision variables, preferences, and criterion weights. Sensitivity analysis enables decision-makers to pinpoint the crucial elements that significantly influence a decision's outcome and modify the model as necessary. By examining the effects of changes in the input data on the output findings, sensitivity analysis in TOPSIS aids in understanding the robustness of the decision-making process.

In this work, the sensitivity analysis with the TOPSIS method was performed by varying the weights assigned to the criteria and observing the change in the ranking of alternatives. This analysis will help with understanding the impact of the weights on the final decision, and we will be able to check the robustness of the decision-making model. The sensitivity analysis was performed by the following three methods:

- Case 1: By assigning equal weights to all criteria;
- Case 2: By assigning 60% weights to beneficial criteria and 40% weights to non-beneficial criteria;
- Case 3: By assigning 70% weights to beneficial criteria and 30% weights to non-beneficial criteria.

The weights of the criteria for all three cases are shown in Figure 9. In Case 1, all criteria were given equal weights of 0.0625, and the TOPSIS method was used to calculate the positive and negative ideal solutions, as well as the Euclidean distance, resulting in the ranking of the alternatives in the following order: Riyad > Jeddah > Abha > Dammam > Al Ahsa. For Case 2 of the sensitivity analysis, beneficial criteria (C1, C3, C5, C6, C9, C11, C13, C16) were assigned a weight of 0.075, and non-beneficial criteria (C2, C4, C7, C8, C10, C12, C14, C15) were assigned a weight of 0.050. After applying the TOPSIS method, the rankings remained the same as those in Case 1. In Case 3 of the sensitivity analysis, the weights were changed again, with the beneficial criteria receiving a weight of 0.0875 and the non-beneficial criteria receiving a weight of 0.0375. The TOPSIS technique resulted in the same ranking order as in Cases 1 and 2: Riyad > Jeddah > Abha > Dammam > Al Ahsa.

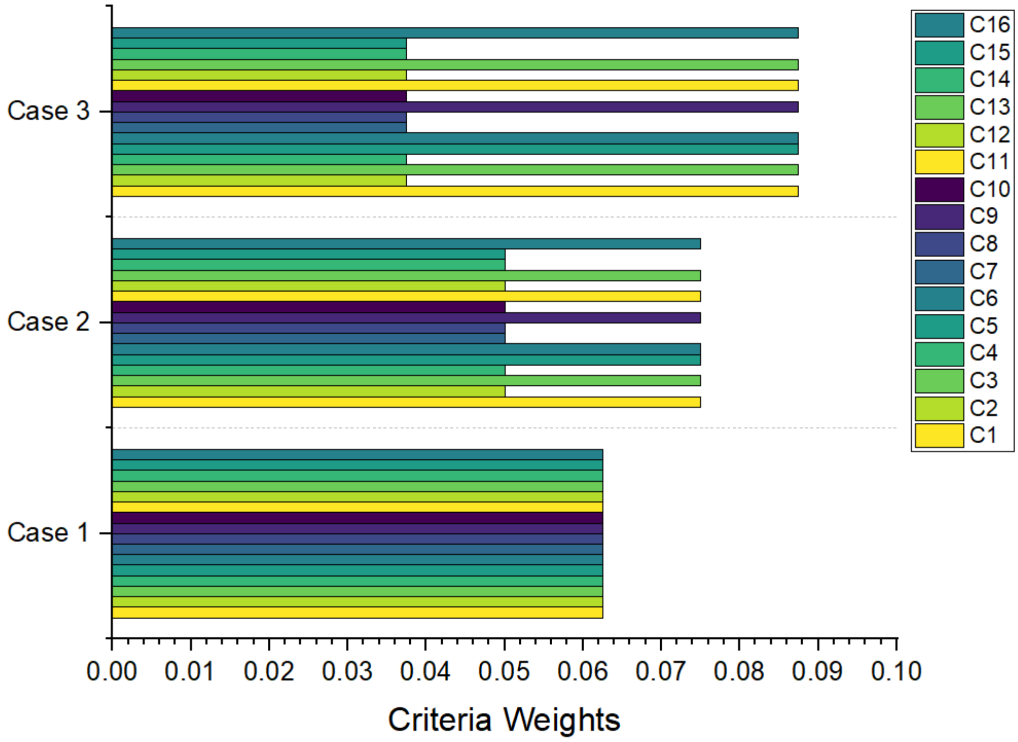

Figure 9. Criteria weights for sensitivity analysis.

Figure 10 displays the performance values of all five alternatives for the three cases of the sensitivity analysis. The results demonstrated a high degree of consistency with the changes made to the model inputs, suggesting that the model presented in this study is both reliable and robust.

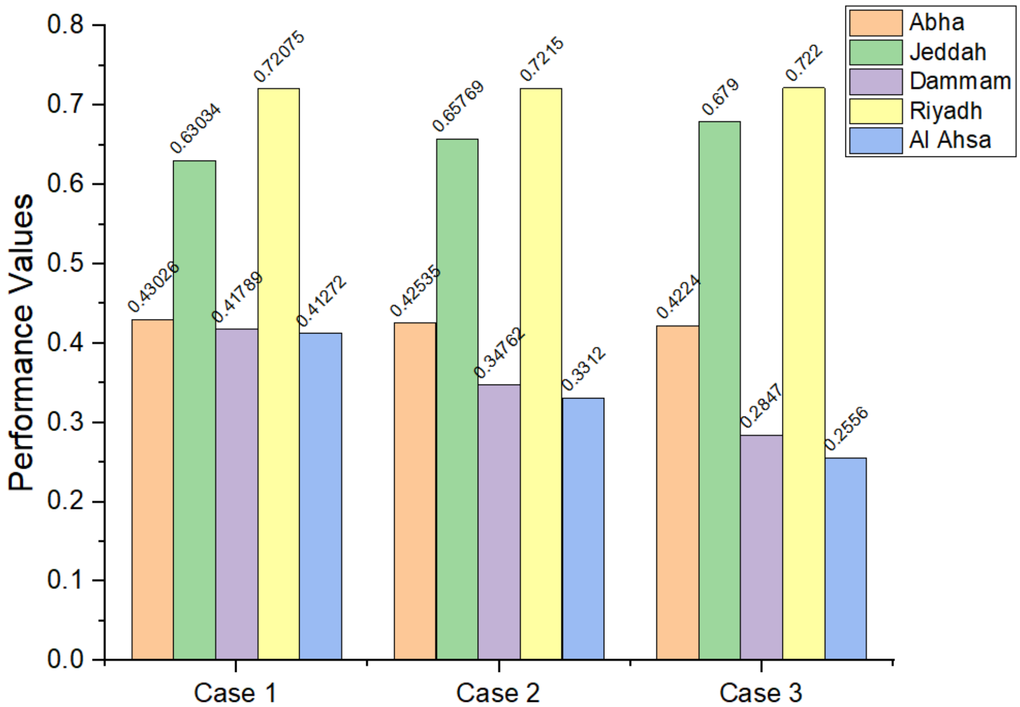

Figure 10. Performance values of alternatives for three cases of sensitivity analysis.

9. Conclusions

The potential of solar energy to produce electricity for sustainable development in Saudi Arabia is enormous. The use of solar energy instead of fossil fuels provides several advantages, including increased employment prospects and increased regional and national economic development.

Ranking the regions for building solar PV power projects in Saudi Arabia is, therefore, a crucial step. A difficult decision dilemma exists when selecting the location for solar power installation. As a result, this study has attempted to address this issue and offers a novel hybrid research methodology for Saudi Arabia's selection of solar PV project sites.

To determine the best site, this study investigated a variety of locations that would be appropriate for the construction of solar PV power projects and then applied the CRITIC and TOPSIS approaches for optimum site selection. Initially, 5 main criteria (climatic, technical, economic, environmental, and social) were identified with a total of 16 sub-criteria. Then, in the second step, weights were assigned to each sub-criterion. This work is the first instance in which the CRITIC method, which is based on objective values, was used to assign weights to the 16 sub-criteria, as in all previous studies, subjective methods were used for assigning weights to criteria. The TOPSIS method was employed for ranking the five alternatives. Of the 5 selected cities, the performance scores of 2 sites, i.e., Riyadh and Jeddah, were greater than 50%, whereas the remaining 3 cities scored less than 50%. The Riyadh site was ranked first with a performance score of 72%, followed by the Jeddah site, which is ranked second with a performance score of 65%. By varying the weights of the criteria, a sensitivity analysis was also carried out to verify the robustness of the model. In every trial for the three separate scenarios, the optimum cities were A4 and A2. Consequently, it has been demonstrated that this method is reliable and valid and can be used in any area where solar PV power projects have the potential to be installed.

The data-driven hybrid model developed in this work offers increased transparency by using objective values for all criteria. This could help build trust with stakeholders as they can see how exactly each site was evaluated and why certain sites were chosen over others. Moreover, this model can help reduce the time and cost associated with the decision-making process. This is because stakeholders can quickly evaluate multiple sites and compare them based on objective criteria without having to rely on subjective or time-consuming evaluations. Furthermore, the hybrid model is easily scalable and adaptable to other similar problems. The combination of CRITIC and TOPSIS criteria can be used in other site selection problems, providing a solid framework to analyze and evaluate options. Although the hybrid model in this work offers, a number of advantages but one of the limitations of the model is its limited scope. As the model is tested on a specific set of criteria that were chosen for this work, which means that further testing may be required if new criteria are added to the model for site evaluation. Since the model is data-driven, therefore, the accuracy and reliability of the data are of utmost importance, as the uncertainties and gaps in data could lead to inaccurate results. The CRITIC–TOPSIS model for solar PV site selection is a promising approach that has many potential applications in the field. In future work, the model could be integrated with machine learning techniques, such as neural networks or decision trees, to improve its accuracy and predictive power. This could help to identify patterns in the data that may not be apparent in this hybrid model. Moreover, for the model to handle data that has different levels of uncertainty, other probabilistic methods or fuzzy approaches could be combined with this model to make a more informed decision under the condition of uncertainty. The hybrid CRITIC–TOPSIS model can be generalized to other renewable energy sources, such as wind or hydro-power. Future research can focus on adapting the model to these other sources and identifying any necessary modifications.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/en16104245/s1, Table S1: Decision matrix; Table S2: Normalization matrix; Table S3: Correlation between Criteria; Table S4: Normalized Performance matrix; Table S5: Weighted Normalized Matrix; Table S6: Normalized Decision Matrix; Table S7: Weighted Sum Matix; Table S8: Decision Matrix; Table S9: Performance score; Table S10: Normalized Matrix; Table S11: Weigthed Normalized Matrix.

Author Contributions: Conceptualization, I.H.; investigation, I.H.; methodology, I.H.; resources, N.H.A.; formal analysis, N.H.A.; supervision I.A.; validation I.A.; funding acquisition, I.A.; All authors have read and agreed to the published version of the manuscript.

Funding: This research work was funded by Universiti Kuala Lumpur under grant no UniKL/CoRI/UER20003.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Hassan, A.; Al-Abdeli, Y.M.; Masek, M.; Bass, O. Optimal Sizing and Energy Scheduling of Grid-Supplemented Solar PV Systems with Battery Storage: Sensitivity of Reliability and Financial Constraints. *Energy* **2022**, *238*, 121780. [CrossRef]
2. Rezaei, M.; Mostafaeipour, A.; Qolipour, M.; Tavakkoli-Moghaddam, R. Investigation of the Optimal Location Design of a Hybrid Wind-Solar Plant: A Case Study. *Int. J. Hydrogen Energy* **2018**, *43*, 100–114. [CrossRef]
3. Saracoglu, B.O.; Ohunakin, O.S.; Adelekan, D.S.; Gill, J.; Atiba, O.E.; Okokpujie, I.P.; Atayero, A.A. A Framework for Selecting the Location of Very Large Photovoltaic Solar Power Plants on a Global/Supergrid. *Energy Rep.* **2018**, *4*, 586–602. [CrossRef]
4. Najafi Ashtiani, M.; Toopshekan, A.; Razi Astaraei, F.; Yousefi, H.; Maleki, A. Technoeconomic Analysis of a Grid Connected PV/Battery System Using the Teaching Learning-Based Optimization Algorithm. *Sol. Energy* **2020**, *203*, 69–82. [CrossRef]
5. Perpiña Castillo, C.; Batista e Silva, F.; Lavalle, C. An Assessment of the Regional Potential for Solar Power Generation in EU-28. *Energy Policy* **2016**, *88*, 86–99. [CrossRef]
6. Shiva Kumar, B.; Sudhakar, K. Performance Evaluation of 10 MW Grid Connected Solar Photovoltaic Power Plant in India. *Energy Rep.* **2015**, *1*, 184–192. [CrossRef]
7. Zell, E.; Gasim, S.; Wilcox, S.; Katamoura, S.; Stoffel, T.; Shibli, H.; Engel-Cox, J.; Al Subie, M. Assessment of solar radiation resources in Saudi Arabia. *Sol. Energy* **2015**, *119*, 422–438. [CrossRef]
8. Almasoud, A.H.; Gandayh, H.M. Future of Solar Energy in Saudi Arabia. *J. King Saud Univ. Eng. Sci.* **2015**, *27*, 153–157. [CrossRef]
9. Zubair, M.; Awan, A.B.; Praveen, R.P.; Abdulbaseer, M. Solar Energy Export Prospects of the Kingdom of Saudi Arabia. *J. Renew. Sustain. Energy* **2019**, *11*, 045902. [CrossRef]
10. Mosly, I.; Makki, A.A. Current Status and Willingness to Adopt Renewable Energy Technologies in Saudi Arabia. *Sustainability* **2018**, *10*, 4269. [CrossRef]
11. Barhoumi, E.M.; Okonkwo, P.C.; Zghaibeh, M.; Belgacem, I.B.; Alkanhal, T.A.; Abo-Khalil, A.G. Renewable Energy Resources and Workforce: Case Study Saudi Arabia—Review and Recommendations. *J. Therm. Anal. Calorim.* **2020**, *141*, 221–230. [CrossRef]
12. Al-Wabel, M.I.; Sallam, A.; Ahmad, M.; Elanazi, K.; Usman, A.R.A. Extent of Climate Change in Saudi Arabia and Its Impacts on Agriculture: A Case Study from Qassim Region. In *Environment, Climate, Plant and Vegetation Growth*; Springer: Cham, Switzerland, 2020; pp. 339–356. [CrossRef]
13. Asif, S.M.; Khan, S.A. Transition towards Sustainable Energy Production—A Review of the Progress for Solar Energy in Saudi Arabia. *Energy Explor. Exploit.* **2018**, *36*, 3–27.
14. Praveen, R.P.; Keloth, V.; Abo-Khalil, A.G.; Alghamdi, A.S.; Eltamaly, A.M.; Tlili, I. An insight to the energy policy of GCC countries to meet renewable energy targets of 2030. *Energy Policy* **2020**, *147*, 111864. [CrossRef]
15. Obaideen, K.; AlMallahi, M.N.; Alami, A.H.; Ramadan, M.; Abdelkareem, M.A.; Shehata, N.; Olabi, A.G. On the contribution of solar energy to sustainable developments goals: Case study on Mohammed bin Rashid Al Maktoum Solar Park. *Int. J. Thermofluids* **2021**, *12*, 100123. [CrossRef]
16. Soydan, O. Solar Power Plants Site Selection for Sustainable Ecological Development in Nigde, Turkey. *SN Appl. Sci.* **2021**, *3*, 41. [CrossRef]
17. Wang, C.-N.; Kao, J.-C.; Wang, Y.-H.; Nguyen, V.T.; Nguyen, V.T.; Husain, S.T. A Multicriteria Decision-Making Model for the Selection of Suitable Renewable Energy Sources. *Mathematics* **2021**, *9*, 1318. [CrossRef]
18. Pohekar, S.D.; Ramachandran, M. Application of Multi-Criteria Decision Making to Sustainable Energy Planning—A Review. *Renew. Sustain. Energy Rev.* **2004**, *8*, 365–381. [CrossRef]
19. Al-Shammari, S.; Ko, W.; Al Ammar, E.A.; Alotaibi, M.A.; Choi, H.-J. Optimal Decision-Making in Photovoltaic System Selection in Saudi Arabia. *Energies* **2021**, *14*, 357. [CrossRef]
20. Mateo, J.R.S.C. Multi Criteria Analysis in the Renewable Energy Industry. In *Green Energy and Technology*; Springer: London, UK, 2012. [CrossRef]

21. Keshavarz-Ghorabaee, M.; Amiri, M.; Zavadskas, E.K.; Turskis, Z.; Antucheviciene, J. Determination of Objective Weights Using a New Method Based on the Removal Effects of Criteria (MEREC). *Symmetry* **2021**, *13*, 525. [CrossRef]
22. Bhutto, A.W.; Bazmi, A.A.; Zahedi, G. Greener Energy: Issues and Challenges for Pakistan-Solar Energy Prospective. *Renew. Sustain. Energy Rev.* **2012**, *16*, 2762–2780. [CrossRef]
23. Ko, W.; Al-Ammar, E.; Almahmeed, M. Development of Feed-in Tariff for PV in the Kingdom of Saudi Arabia. *Energies* **2019**, *12*, 2898. [CrossRef]
24. Zhou, B.; Chen, J.; Wu, Q.; Pamučar, D.; Wang, W.; Zhou, L. Risk Priority Evaluation of Power Transformer Parts Based on Hybrid FMEA Framework under Hesitant Fuzzy Environment. *Facta Univ. Ser. Mech. Eng.* **2022**, *20*, 399–420. [CrossRef]
25. Wang, T.-C.; Lee, H.D. Developing a Fuzzy TOPSIS Approach Based on Subjective Weights and Objective Weights. *Expert Syst. Appl.* **2009**, *36*, 8980–8985. [CrossRef]
26. Krylovas, A.; Dadelienė, R.; Kosareva, N.; Dadelo, S. Comparative Evaluation and Ranking of the European Countries Based on the Interdependence between Human Development and Internal Security Indicators. *Mathematics* **2019**, *7*, 293. [CrossRef]
27. Deng, H.; Yeh, C.H.; Willis, R.J. Inter-company Comparison using Modified TOPSIS with Objective Weights. *Comput. Oper. Res.* **2000**, *27*, 963–973. [CrossRef]
28. Hovanov, N.V.; Kolari, J.W.; Sokolov, M. Deriving Weights from General Pairwise Comparison Matrices. *Math. Soc. Sci.* **2008**, *55*, 205–220. [CrossRef]
29. Saaty, T.L.; Kearns, K.P. *The Analytic Hierarchy Process*; Elsevier BV: Amsterdam, The Netherlands, 1985; pp. 19–62.
30. Odu, G.O. Weighting Methods for Multi Criteria Decision Making Technique. *J. Appl. Sci. Environ. Manag.* **2019**, *23*, 1449–1457. [CrossRef]
31. Ma, J.; Fan, Z.P.; Huang, L.H. A Subjective and Objective Integrated Approach to Determine Attribute Weights. *Eur. J. Oper. Res.* **1999**, *112*, 397–404. [CrossRef]
32. Vanolya, N.M.; Jelokhani-Niaraki, M. The use of Subjective–Objective Weights in GIS-based Multi-Criteria Decision Analysis for Flood Hazard Assessment: A case study in Mazandaran, Iran. *GeoJournal* **2019**, *86*, 379–398. [CrossRef]
33. Al-Aomar, R. A Combined AHP-Entropy Method for Deriving Subjective and Objective Criteria Weights. *Int. J. Ind. Eng. Theory Appl. Pract.* **2010**, *17*, 12–24.
34. Krishnan, A.R.; Mat Kasim, M.; Hamid, R. An Alternate Unsupervised Technique Based on Distance Correlation and Shannon Entropy to Estimate λ^0-Fuzzy Measure. *Symmetry* **2020**, *12*, 1708. [CrossRef]
35. Li, L.-H.; Mo, R. Production Task Queue Optimization Based on Multi-Attribute Evaluation for Complex Product Assembly Workshop. *PLoS ONE* **2015**, *10*, e0134343. [CrossRef]
36. Peng, X.; Zhang, X.; Luo, Z. Pythagorean fuzzy MCDM method based on CoCoSo and CRITIC with score function for 5G industry evaluation. *Artif. Intell. Rev.* **2020**, *53*, 3813–3847. [CrossRef]
37. Krishnan, A.R.; Hamid, R.; Kasim, M.M. An Unsupervised Technique to Estimate λ0-Fuzzy Measure Values and Its Application to Multi-criteria Decision Making. In Proceedings of the IEEE 7th International Conference on Industrial Engineering and Applications (ICIEA), Bangkok, Thailand, 16–21 April 2020; pp. 969–973.
38. Vujicic, M.; Papic, M.; Blagojevic, M. Comparative analysis of objective techniques for criteria weighing in two MCDM methods on example of an air conditioner selection. *Tehnika* **2017**, *72*, 422–429. [CrossRef]
39. Zhu, Y.; Tian, D.; Yan, F. Effectiveness of Entropy Weight Method in Decision-Making. *Math. Probl. Eng.* **2020**, *2020*, 3564835. [CrossRef]
40. Jahan, A.; Edwards, K.; Bahraminasab, M. Chapter 3-Multi-criteria Decision-Making for Materials Selection. In *Multi-Criteria Decision Analysis for Supporting the Selection of Engineering Materials in Product Design*; Butterworth-Heinemann: Oxford, UK, 2013; pp. 31–41.
41. Hwang, K.; Ching-Lai, Y. *Multiple Attribute Decision Making: Methods and Applications. A State-of-the-Art Survey*; Springer: Berlin/Heidelberg, Germany, 1981; Volume 186.
42. Tus, A.; Adalı, E.A. The New Combination with CRITIC and WASPAS Methods for the Time and Attendance Software Selection Problem. *Opsearch* **2019**, *56*, 528–538. [CrossRef]
43. Zambrano-Asanza, S.; Quiros-Tortos, J.; Franco, J.F. Optimal Site Selection for Photovoltaic Power Plants Using a GIS-Based Multi-Criteria Decision Making and Spatial Overlay with Electric Load. *Renew. Sustain. Energy Rev.* **2021**, *143*, 110853. [CrossRef]
44. Afsordegan, A.; Sánchez, M.; Agell, N.; Zahedi, S.; Cremades, L.V. Decision Making under Uncertainty Using a Qualitative TOPSIS Method for Selecting Sustainable Energy Alternatives. *Int. J. Environ. Sci. Technol.* **2016**, *13*, 1419–1432. [CrossRef]
45. Loken, E. Use of Multicriteria Decision Analysis Methods for Energy Planning Problems. *Renew. Sustain. Energy Rev.* **2007**, *11*, 1584–1595. [CrossRef]
46. Haddad, B.; Díaz-Cuevas, P.; Ferreira, P.; Djebli, A.; Pérez, J.P. Mapping Concentrated Solar Power Site Suitability in Algeria. *Renew. Energy* **2021**, *168*, 838–853. [CrossRef]
47. Lindberg, O.; Birging, A.; Widén, J.; Lingfors, D. PV Park Site Selection for Utility-Scale Solar Guides Combining GIS and Power Flow Analysis: A Case Study on a Swedish Municipality. *Appl. Energy* **2021**, *282*, 116086. [CrossRef]
48. Sreenath, S.; Sudhakar, K.; Yusop, A.F. Technical Assessment of Captive Solar Power Plant: A Case Study of Senai Airport, Malaysia. *Renew. Energy* **2020**, *152*, 849–866. [CrossRef]
49. Colak, H.E.; Memisoglu, T.; Gercek, Y. Optimal Site Selection for Solar Photovoltaic (PV) Power Plants Using GIS and AHP: A Case Study of Malatya Province, Turkey. *Renew. Energy* **2020**, *149*, 565–576. [CrossRef]

50. Doorga, J.R.; Rughooputh, S.D.; Boojhawon, R. Multi-Criteria GIS-Based Modelling Technique for Identifying Potential Solar Farm Sites: A Case Study in Mauritius. *Renew. Energy* **2019**, *133*, 1201–1219. [CrossRef]
51. Wu, Y.; Zhang, B.; Wu, C.; Zhang, T.; Liu, F. Optimal Site Selection for Parabolic Trough Concentrating Solar Power Plant Using Extended PROMETHEE Method: A Case in China. *Renew. Energy* **2019**, *143*, 1910–1927. [CrossRef]
52. Solangi, Y.A.; Shah, S.A.A.; Zameer, H.; Ikram, M.; Saracoglu, B.O. Assessing the Solar PV Power Project Site Selection in Pakistan: Based on AHP-Fuzzy VIKOR Approach. *Environ. Sci. Pollut. Res.* **2019**, *26*, 30286–30302. [CrossRef]
53. Wu, Y.; Zhang, B.; Xu, C.; Li, L. Site Selection Decision Framework Using Fuzzy ANP-VIKOR for Large Commercial Rooftop PV System Based on Sustainability Perspective. *Sustain. Cities Soc.* **2018**, *40*, 454–470. [CrossRef]
54. Merrouni, A.A.; Elalaoui, F.E.; Mezrhab, A.; Mezrhab, A.; Ghennioui, A. Large Scale PV Sites Selection by Combining GIS and Analytical Hierarchy Process. Case Study: Eastern Morocco. *Renew. Energy* **2018**, *119*, 863–873. [CrossRef]
55. Yousefi, H.; Hafeznia, H.; Yousefi-Sahzabi, A. Spatial Site Selection for Solar Power Plants Using a GIS-Based Boolean-Fuzzy Logic Model: A Case Study of Markazi Province, Iran. *Energies* **2018**, *11*, 1648. [CrossRef]
56. Al Garni, H.Z.; Awasthi, A. Solar PV Power Plant Site Selection Using a GIS-AHP Based Approach with Application in Saudi Arabia. *Appl. Energy* **2017**, *206*, 1225–1240. [CrossRef]
57. Aly, A.; Jensen, S.S.; Pedersen, A.B. Solar Power Potential of Tanzania: Identifying CSP and PV Hot Spots through a GIS Multicriteria Decision Making Analysis. *Renew. Energy* **2017**, *113*, 159–175. [CrossRef]
58. Anwarzai, M.A.; Nagasaka, K. Utility-Scale Implementable Potential of Wind and Solar Energies for Afghanistan Using GIS Multi-Criteria Decision Analysis. *Renew. Sustain. Energy Rev.* **2017**, *71*, 150–160. [CrossRef]
59. Sánchez-Lozano, J.M.; García-Cascales, M.S.; Lamata, M.T. Comparative TOPSIS-ELECTRE TRI Methods for Optimal Sites for Photovoltaic Solar Farms: Case Study in Spain. *J. Clean. Prod.* **2016**, *127*, 387–398. [CrossRef]
60. Merrouni, A.A.; Mezrhab, A.; Mezrhab, A. PV Sites Suitability Analysis in the Eastern Region of Morocco. *Sustain. Energy Technol. Assess.* **2016**, *18*, 6–15. [CrossRef]
61. Watson, J.J.; Hudson, M.D. Regional Scale Wind Farm and Solar Farm Suitability Assessment Using GIS-Assisted Multi-Criteria Evaluation. *Landsc. Urban Plan.* **2015**, *138*, 20–31. [CrossRef]
62. Tahri, M.; Hakdaoui, M.; Maanan, M. The Evaluation of Solar Farm Locations applying Geographic Information System and Multi-Criteria Decision-Making Methods: Case study in southern Morocco. *Renew. Sustain. Energy Rev.* **2015**, *51*, 1354–1362. [CrossRef]
63. Sánchez-Lozano, J.M.; Antunes, C.H.; García-Cascales, M.S.; Dias, L.C. GIS-Based Photovoltaic Solar Farms Site Selection Using ELECTRE-TRI: Evaluating the Case for Torre Pacheco, Murcia, Southeast of Spain. *Renew. Energy* **2014**, *66*, 478–494. [CrossRef]
64. Asakereh, A.; Omid, M.; Alimardani, R.; Sarmadian, F. Developing a GIS Based Fuzzy AHP Model for Selecting Solar Energy Sites in Shodirwan Region in Iran. *Int. J. Adv. Sci. Technol.* **2014**, *68*, 37–48. [CrossRef]
65. Uyan, M. GIS-based Solar Farms Site Selection using Analytic Hierarchy Process (AHP) in Karapinar region, Konya/Turkey. *Renew. Sustain. Energy Rev.* **2013**, *28*, 11–17. [CrossRef]
66. Carrión, J.A.; Estrella, A.E.; Dols, F.A.; Ridao, A.R. The Electricity Production Capacity of Photovoltaic Power Plants and the selection of Solar Energy Sites in Andalusia (Spain). *Renew. Energy* **2008**, *33*, 545–552. [CrossRef]
67. Aragonés-Beltrán, P.; Chaparro-González, F.; Pastor-Ferrando, J.P.; Rodríguez-Pozo, F. An ANP-based approach for the Selection of Photovoltaic Solar Power Plant Investment Projects. *Renew. Sustain. Energy Rev.* **2010**, *14*, 249–264. [CrossRef]
68. Jun, D.; Tian-Tian, F.; Yi-Sheng, Y.; Yu, M. Macro-Site Selection of Wind/Solar Hybrid Power Station based on ELECTRE-II. *Renew. Sustain. Energy Rev.* **2014**, *35*, 194–204. [CrossRef]
69. Vafaeipour, M.; Zolfani, S.H.; Varzandeh, M.H.M.; Derakhti, A.; Eshkalag, M.K. Assessment of regions priority for implementation of solar projects in Iran: New application of a Hybrid Multi Criteria Decision Making Approach. *Energy Convers. Manag.* **2014**, *86*, 653–663. [CrossRef]
70. Suh, J.; Brownson, J.R. Solar Farm Suitability Using Geographic Information System Fuzzy Sets and Analytic Hierarchy Processes: Case Study of Ulleung Island, Korea. *Energies* **2016**, *9*, 648. [CrossRef]
71. Doljak, D.; Stanojević, G. Evaluation of Natural Conditions for Site Selection of Ground-Mounted Photovoltaic Power Plants in Serbia. *Energy* **2017**, *127*, 291–300. [CrossRef]
72. Sánchez-Lozano, J.M.; Teruel-Solano, J.; Soto-Elvira, P.L.; García-Cascales, M.S. Geographical Information Systems (GIS) and Multi-Criteria Decision Making (MCDM) Methods for the Evaluation of Solar Farms Locations: Case Study in South-Eastern Spain. *Renew. Sustain. Energy Rev.* **2013**, *24*, 544–556. [CrossRef]
73. Deveci, M.; Cali, U.; Pamucar, D. Evaluation of Criteria for Site Selection of Solar Photovoltaic (PV) Projects Using Fuzzy Logarithmic Additive Estimation of Weight Coefficients. *Energy Rep.* **2021**, *7*, 8805–8824. [CrossRef]
74. Al Garni, H.Z.; Awasthi, A. Chapter 2—Solar PV Power Plants Site Selection: A Review. In *Advances in Renewable Energies and Power Technologies*; Elsevier: Amsterdam, The Netherlands, 2018; pp. 57–75.
75. Ali, M.; Iqbal, M.H.; Sheikh, N.A.; Ali, H.M.; Manzoor, M.S.; Khan, M.M.; Tamrin, K.F. Performance Investigation of Air Velocity Effects on PV Modules under Controlled Conditions. *Int. J. Photoenergy* **2017**, *2017*, 3829671. [CrossRef]
76. Owolabi, A.B.; Nsafon, B.E.K.; Roh, J.W.; Suh, D.; Huh, J.S. Validating the techno-economic and environmental sustainability of solar PV technology in Nigeria using RETScreen Experts to assess its viability. *Sustain. Energy Technol. Assess.* **2019**, *36*, 100542. [CrossRef]

77. Kumar, R.; Rajoria, C.S.; Sharma, K.A.; Suhag, S. Design and simulation of standalone solar PV system using PVsyst Software: A case study. *Mater. Today Proc.* **2021**, *46 Pt 11*, 5322–5328. [CrossRef]
78. Matar, W. A look at the response of households to time-of-use electricity pricing in Saudi Arabia and its impact on the wider economy. *Energy Strategy Rev.* **2017**, *16*, 13–23. [CrossRef]
79. Annual Report. Saudi Electricity Company, Saudi Arabia. 2021. Available online: https://www.se.com.sa/en-us/Pages/AnnualReports.aspx (accessed on 3 March 2023).
80. Global Carbon Atlas. 2018. Available online: http://www.globalcarbonatlas.org/en/content/welcome-carbon-atlas (accessed on 3 March 2023).
81. IRENA. Renewable Energy Cost Analysis—Solar Photovoltaics. Available online: https://www.irena.org/publications/2012/Jun/Renewable-Energy-Cost-Analysis---Solar-Photovoltaics (accessed on 5 March 2023).
82. IRENA. Renewable Power Generation Costs in 2019. Available online: https://www.irena.org (accessed on 30 July 2020).
83. Cohen, M.A.; Callaway, D.S. Effects of Distributed PV Generation on California's Distribution System, Part 1: Engineering Simulations. *Sol. Energy* **2016**, *128*, 126–138. [CrossRef]
84. Al-Khraif, R.M.; Al-Mogarry, M.; Elsegaey, I.; Salam, A.A. Saudi Arabia's City-Ranking Index (SACRI) methodology executed: Preliminary findings. *J. Econ. Manag.* **2022**, *44*, 376–392. [CrossRef]
85. Diakoulaki, D.; Mavrotas, G.; Papayannakis, L. Determining Objective Weights in Multiple Criteria Problems: The CRITIC Method. *Comput. Oper. Res.* **1995**, *22*, 763–770. [CrossRef]
86. Mukhametzyanov, I. Specific character of objective methods for determining weights of criteria in MCDM problems: Entropy, CRITIC, SD. *Decis. Mak. Appl. Manag. Eng.* **2021**, *4*, 76–105. [CrossRef]
87. Hajduk, S.; Jelonek, D. A Decision-Making Approach Based on TOPSIS Method for Ranking Smart Cities in the Context of Urban Energy. *Energies* **2021**, *14*, 2691. [CrossRef]
88. Widarma, A.; Dedi Irawan, M.; Nurhidayahti, F.; Hsb, R. Decision Support System Determining Computer Virus Protection Applications Using Simple Additive Weighting (SAW) Method. *J. Comput. Netw. Archit. High Perform. Comput.* **2021**, *3*, 68–79. [CrossRef]
89. Dhanalakshmi, C.S.; Mathew, M.; Madhu, P. Biomass Material Selection for Sustainable Environment by the Application of Multi-Objective Optimization on the Basis of Ratio Analysis (MOORA). In *Materials, Design, and Manufacturing for Sustainable Environment*; Mohan, S., Shankar, S., Rajeshkumar, G., Eds.; Springer: Singapore, 2021; pp. 345–354.