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Article

An Integrated Decision-Making Model for the Location of a PV Solar Plant

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Abstract: Due to the increasing demand for electricity, the depletion of fossil fuels and the increase in environmental consciousness, generating power from renewable energy resources has become necessary. How to select the most appropriate site is a critical and foremost decision that must be made when setting up a renewable energy plant. This research proposes a two-stage framework for evaluating the suitability of renewable energy plant site alternatives. In the first stage, a fuzzy analytic hierarchy process (FAHP) is adopted to set the assurance region (AR) of the quantitative factors, and the AR is incorporated into data envelopment analysis (DEA) to assess the efficiencies of plant site candidates. A few sites are selected for further analysis. In the second stage, experts are invited to evaluate the qualitative characteristics of the selected sites, and FAHP is used to calculate the priorities of these sites. Solar energy is one of the most promising renewable energy sources, because of its abundance, inexhaustibility, safety and cleanliness. Based on the proposed integrated decision-making model, a case study for selecting the most appropriate photovoltaic (PV) solar plant site is examined.

Keywords: renewable energy plant; site selection; analytic hierarchy process (AHP); data envelopment analysis (DEA); fuzzy

1. Introduction

Energy is essential for socio-economic development and improvement of the quality of life. The use of fossil oil and other natural resources has resulted in detrimental impacts on the environment, especially through damage to the air, climate, water, land and wildlife [1]. With increasing environmental consciousness and global demand for energy, the utilization of renewable and clean energy sources is necessary. Although the global economic recession has reduced the demand for energy currently, energy generation from renewable resources is still necessary for the environment and for the economy in the long term. Solar energy, one of the best renewable energy sources with the least negative impacts on the environment, is becoming a promising renewable energy source [2].

The setup of a renewable energy power plant is a long process, from the very beginning stage of land survey and plant site selection, to the final stage of implementing and starting-up of the plant [3]. Selecting a site for a renewable energy power plant is the very first and an important task. Some relevant studies are reviewed here. Azoumah *et al.* [4] listed six parameters for selecting a site for a concentrating solar power (CSP) plant: solar resource assessment, availability of water and cooling mode, soil structure and geology, land issues, geography and topography of the site, the energy demand profile and a grid-connected system. Aragonés-Beltrán *et al.* [3] used an analytic network process (ANP) to select the best photovoltaic (PV) solar power project based on risk minimization. Noone *et al.* [5] presented a tool for locating sites in hillside terrain for central receiver solar thermal plants based on field efficiency and average annual normal insolation. The calculation of field efficiency includes three factors: cosine efficiency, which is the ratio of the projected heliostat area in the direction of beam insolation to the surface area, shading and blocking losses. Halasah *et al.* [6] employed life-cycle assessment to evaluate the energy-related impacts of PV systems at different scales of integration. The input parameters included panel efficiency, temperature coefficient, shading losses, ground cover ratio and latitude, and the input data included hourly solar radiation, wind speed and temperature. Pavlovic *et al.* [2] studied the possibilities of generating electrical energy from on-grid PV solar systems of 1 kW in the Republic of Srpska, and the factors considered included yearly average values of the optimal panel inclination, solar irradiation on the horizontal, vertical and optimally-inclined plane, the ratio of diffuse to global solar irradiation, Linke turbidity, average daytime temperature and 24-h average temperature. Besarati *et al.* [7] assessed the potential of harnessing solar radiation in different regions of Iran by generating solar radiation maps for different surface tracking modes, and the result can be used for designing PV and CSP power plants. Phillips [8] evaluated the sustainability for PV solar power plants by applying a mathematical model to the results of a qualitative-based environmental impact evaluation of the installation and operation of solar power plants. The impact categories include human health and well-being, wildlife and habitat, land use and geohydrological resources and climate change. Xiao *et al.* [9] constructed a site selection model for desert PV power plants using an analytic hierarchy process (AHP) and a geographic information system (GIS) in China. The major indices include climate, terrain, land cover and location, and each index contains several factors.

The evaluation and selection of an appropriate renewable energy plant site is a very complicated task, which involves the consideration of various qualitative and quantitative factors. In addition, if there are many plant sites available, the collection of relevant data from each site can be tedious or even impossible. Thus, this research proposes a two-stage evaluation model to evaluate the expected performance of renewable energy plant sites. In the first stage, a method that considers quantitative factors that are usually collectible is used to extract a number of candidate plant sites from many available plant sites. In the second stage, these candidate plant sites are further evaluated to consider qualitative factors and/or quantitative factors that are difficult to collect. The most suitable plant site can be selected as a result. To accomplish this goal, the comprehensive evaluation model is developed by integrating the AHP, data envelopment analysis (DEA), assurance region (AR) and fuzzy set theory. In the first stage, the ARs of the inputs and outputs are determined using fuzzy analytic hierarchy process (FAHP), and the DEA incorporated with AR is applied to evaluate the quantitative data of different sites. Based on the evaluation, the candidate plant sites are extracted. In the second stage, the FAHP is used to consider other qualitative data (or quantitative data that are difficult to collect), and the site with the highest priority is recommended for constructing the renewable energy plant. The flowchart of the proposed model is depicted in Figure 1.

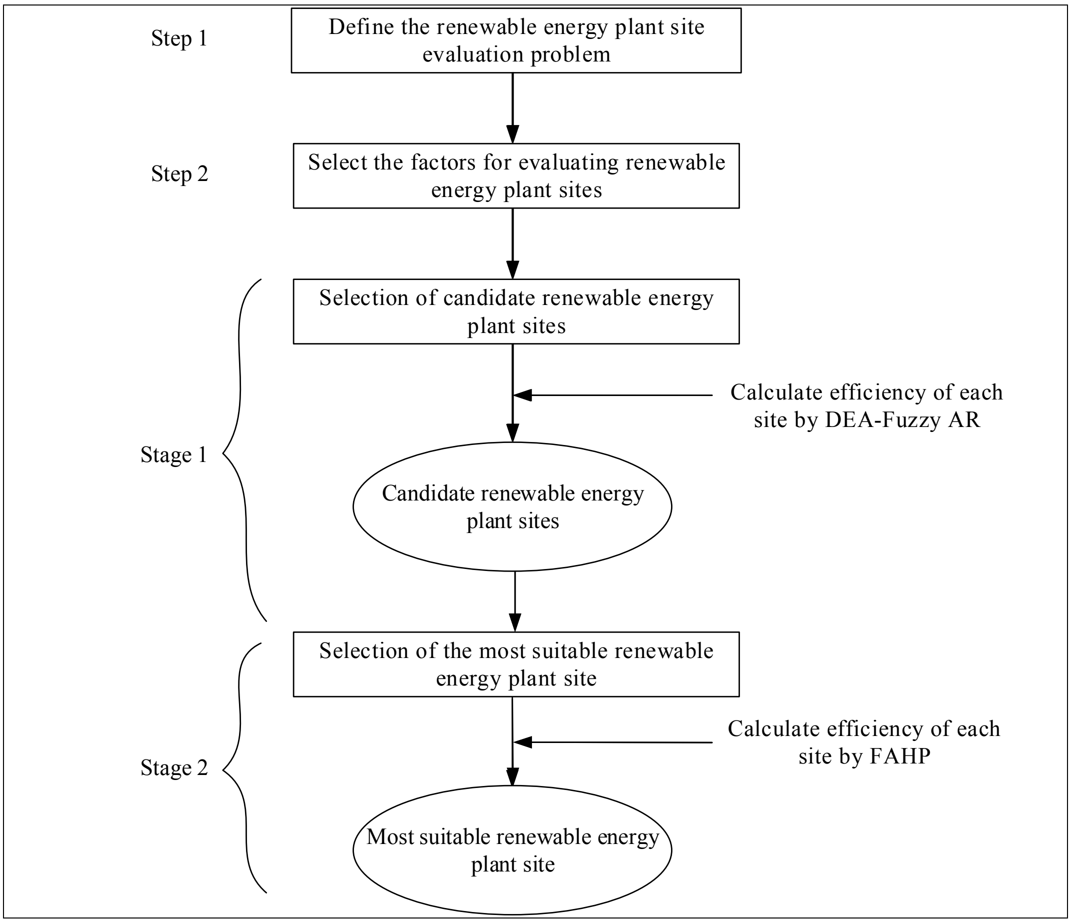

Figure 1. Flowchart of the proposed model. AR, assurance region; FAHP, fuzzy analytic hierarchy process.

The rest of this paper is organized as follows. Section 2 introduces the methodologies that are used for the model for renewable energy plant site selection. Section 3 presents a case study in Taiwan to examine the practicality of the proposed model. Some concluding remarks are made in the last section.

2. Methodologies

2.1. Data Envelopment Analysis

Data envelopment analysis (DEA) generates comprehensive performance measurement indexes for decision-making units (DMUs) through the evaluation of multiple inputs and outputs without the pre-assignment of criteria weights [10]. A DMU is a unit under evaluation, for example a process, a product, a polity or an alternative. Generally speaking, a DMU produces outputs and uses up inputs. Under DEA, inputs are factors that are smaller the better, while outputs are factors that are larger the better. The DMUs that locate on the envelopment, also called the frontier, are considered to be the most efficient. The position of a DMU relative to the efficient frontier, the envelopment constituted, is measured as efficiency. That is, the efficiency, also called the efficiency score, of a DMU depends on the location of the DMU relative to its efficient reference point, which is given by the projection on the efficient frontier. Since an efficient DMU is located on the efficient frontier, the reference point of an efficient DMU onto the efficient frontier is the DMU itself [10].

CCR, developed by Charnes, Cooper and Rhodes [10], is one of most popular DEA models and is adopted in this paper. In an input orientation (input minimization), maximal movement toward the frontier through proportional reduction of inputs is the focus [11].

The DEA ratio form, first proposed by Charnes *et al.* [10], is designed to measure the DEA efficiency of a specific DMU k' and can be expressed by [12–14]:

$$\text{Max} \quad \frac{\sum_{r=1}^{R} u_r Y_{rk'}}{\sum_{q=1}^{Q} v_q X_{qk'}} \tag{1}$$

$$\text{s.t.} \quad \frac{\sum_{r=1}^{R} u_r Y_{rk'}}{\sum_{q=1}^{Q} v_q X_{qk'}} \leq 1 \tag{2}$$

$$\frac{u_r}{\sum_{q=1}^{Q} v_q X_{qk}} \geq \varepsilon, \ r=1,\ldots r' \ldots, R \tag{3}$$

$$\frac{v_q}{\sum_{q=1}^{Q} v_q X_{qk}} \geq \varepsilon, \ q=1,\ldots q' \ldots, Q \tag{4}$$

where $X_{qk'}$ is the amount of the q-th input ($q = 1,\ldots q' \ldots,Q$) of the k'-th DMU, $Y_{rk'}$ is the amount of the r-th output ($r = 1,\ldots r' \ldots,R$) of the k'-th DMU, v_q is the weight given to the q-th input, u_r is the weight given to the r-th output, Q is the number of inputs, R is the number of outputs and K is the number of DMUs.

However, the ratio form can yield an infinite number of optimal solutions. For instance, if (u^*, v^*) is an optimal solution, then $(\gamma u^*, \gamma v^*)$ is also optimal for $\gamma > 0$. The transformation developed by Charnes and Cooper [15] for linear fractional programming was utilized in the DEA study [10] to define an equivalent relation that partitioned the set of feasible solutions into equivalence classes. The transformed DEA model can be expressed as the following linear programming (LP) problem [12–14]:

$$\text{Max } \sum_{r=1}^{R} u_r Y_{rk'} \tag{5}$$

$$\text{s.t. } \sum_{q=1}^{Q} v_q X_{qk'} = 1 \tag{6}$$

$$\sum_{r=1}^{R} u_r Y_{rk} - \sum_{q=1}^{Q} v_q X_{qk} \leq 0,\ k = 1, \ldots k' \ldots, K \tag{7}$$

$$u_r \geq \varepsilon,\ r = 1, \ldots r' \ldots, R \tag{8}$$

$$v_q \geq \varepsilon,\ q = 1, \ldots q' \ldots, Q \tag{9}$$

The above primal model is difficult to solve, and the dual problem of the LP is proposed [12–14]:

$$\text{Min } h_k = \theta_k - \varepsilon\left(\sum_{q=1}^{Q} s_q^- + \sum_{r=1}^{R} s_r^+\right) \tag{10}$$

$$\text{s.t. } \sum_{k=1}^{K} \lambda_k X_{qk} - \theta_k X_{qk} + s_q^- = 0,\ q = 1, \ldots q' \ldots, Q \tag{11}$$

$$\sum_{k=1}^{K} \lambda_k Y_{rk} - s_r^+ = Y_{rk'},\ r = 1, \ldots r' \ldots, R \tag{12}$$

$$\lambda_k \geq 0, k = 1, \ldots k' \ldots, K \tag{13}$$

$$s_q^- \geq 0, q = 1, \ldots q' \ldots, Q \tag{14}$$

$$s_r^+ \geq 0, r = 1, \ldots r' \ldots, R \tag{15}$$

$$\theta_k \ \textit{unconstrained},\ k = 1, \ldots k' \ldots, K \tag{16}$$

where ε is a non-Archimedean (infinitesimal) constant, s_q^-, s_r^+ are the slack variables of inputs and outputs, respectively, λ_k is the weight for DMU_k and $h_{k'}$ is the relative efficiency indicator of the k'-th DMU.

In Equation (10), the optimal h_k^* indicates a DEA efficiency score in a manner that $h_k^* = 1$ indicates the state of DEA efficiency, while $h_k^* < 1$ represents DEA inefficiency. Note that the primal model has $K + R + Q + 1$ constraints, whilst the dual model has $Q + R$ constraints. Since K, the number of units, is usually considerably larger than $Q + R$, the number of inputs and outputs, the primal model has many more constraints than the dual model. Generally speaking, the more constraints there are in an LP, the more difficult it is to solve. Therefore, the dual DEA model rather than the primal is usually solved.

2.2. Weights of Inputs/Outputs in DEA

Under the conventional DEA, the weights given to inputs and outputs to evaluate a DMU are chosen in a manner to maximize the efficiency score of that DMU [16]. That is, the DEA model does not require *a priori* weights on inputs and outputs, and the weights are determined by solving the DEA models, such as the models developed by Charnes *et al.* [10], so-called CCR, when efficient production is characterized by constant returns to scale, or by Banker *et al.* [13,17], so-called BCC (Banker, Charnes and Cooper), when variable returns to scale are assumed [18]. Complete input/output weight flexibility can result in inappropriate efficiency estimation [18]. Therefore, a DMU may be efficient even if it performs best in one input (output) and performs inferior in other inputs (outputs). However, in real-world problems, some factors may be more important than others, and experts' subjective opinions on the importance of the factors should be incorporated into the methodology. One of the common methods to do so in DEA is the assurance regions (ARs) model, in which the upper bound and lower bound of a ratio of the weights of two inputs (outputs) are pre-determined [19,20]. For every pair (p_x, p_y) of inputs/outputs, the ratio w_{p_x}/w_{p_y} must be bounded by $L_{p_x p_y}$ and $U_{p_x p_y}$ as [19–21]:

$$L_{p_x p_y} \le w_{p_x}/w_{p_y} \le U_{p_x p_y} \tag{17}$$

Even though many works have applied AHP to set AR, another problem with AR is that experts may have vagueness or ambiguity in expressing their opinions. Under such circumstances, the fuzzy set theory can be incorporated into the DEA/AR model. Liu [14] developed a fuzzy DEA/AR method to evaluate the performance of flexible manufacturing system (FMS) alternatives when the input and output data contained crisp and fuzzy data. A pair of two-level mathematical programs was formulated to calculate the lower and upper bounds of the fuzzy efficiency score of the alternatives based on the extension principle [22]. Liu and Chuang [23] applied the proposed fuzzy DEA/AR method to evaluate the performance of university libraries. Lee *et al.* [19] applied FAHP to set the AR of the factors, and then, DEA was carried out to assess the business performance of PV firms. That is, FAHP is used to extract experts' opinions on the AR of the factors, which is represented by Equation (17). With the addition of Equation (17) to Equations (10) to (16), this DEA/AR method can be used to evaluate the performance of the firms.

In the first stage of this research, FAHP is applied to set the AR of the quantitative factors. The calculated AR is incorporated into DEA to assess the efficiencies of renewable plant site candidates, and the most suitable candidates are selected for further evaluations.

2.3. Fuzzy Analytic Hierarchy Process

AHP, a mathematically-based multi-criteria decision-making (MCDM) tool proposed by Saaty [24], has been adopted in various academic fields and in real practice. AHP decomposes a complex problem into several factors into hierarchical levels, and each factor can be decomposed into several sub-factors at a lower level. The factors (sub-factors) of the same hierarchical level are compared relative to their impact on their higher level factor. The incorporation of the fuzzy set theory with AHP, or so-called FAHP, has been adopted abundantly in recent years. This is due to the facts that decision-makers may not have complete information or a full understanding of all aspects of the problem and that the experiences and judgments of humans are not well defined [25,26]. As a result, pairwise comparison under the conventional AHP, which requires the selection of arbitrary values in the process, may not be appropriate. Under FAHP, uncertainty can be considered in pairwise comparison values.

Different models for the FAHP have been proposed by scholars. In this study, the major steps of the FAHP are as follows [27–29]:

Step 1: Define the unstructured problem: The problem should be stated clearly and be put into a broad context, including the objectives and the outcomes.

Step 2: Decompose the problem into a hierarchical structure: The problem is decomposed into a hierarchy, like a decision tree, with the overall objective of the problem at the top level and several criteria at a lower level. Each next lower level can contain sub-criteria, and the lowest level usually contains alternatives. A standard format for an FAHP decision model is illustrated in Figure 2.

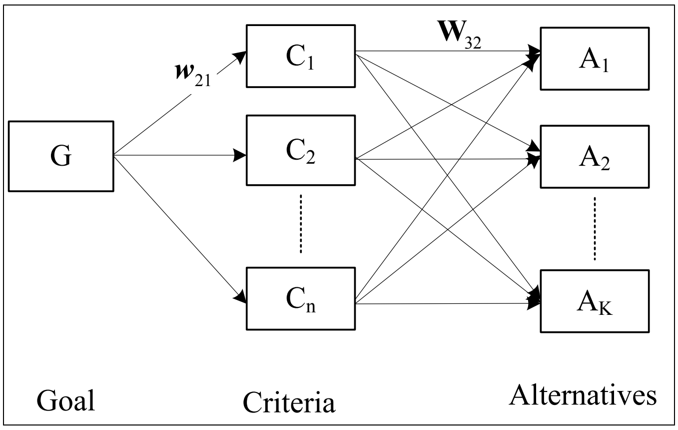

Figure 2. A hierarchy for the AHP.

Step 3: Employ questionnaires and pairwise comparisons: Experts are asked to pairwise compare the elements in a questionnaire using five linguistic levels, as shown in Table 1. The linguistic variables are transformed into triangular fuzzy numbers. For example, with pairwise comparison of criteria with respect to the objective, a matrix ($\tilde{\Lambda}_e$) for expert *e*, is as follows:

$$\tilde{\Lambda}_e = \begin{matrix} & \begin{matrix} C_1 & C_2 & \cdots & C_n \end{matrix} \\ \begin{matrix} C_1 \\ C_2 \\ \vdots \\ C_n \end{matrix} & \begin{bmatrix} 1 & \tilde{a}_{12e} & \cdots & \tilde{a}_{1ne} \\ 1/\tilde{a}_{12e} & 1 & \cdots & \tilde{a}_{2ne} \\ \vdots & \vdots & 1 & \vdots \\ 1/\tilde{a}_{1ne} & 1/\tilde{a}_{2ne} & \cdots & 1 \end{bmatrix} \end{matrix} \tag{18}$$

where *n* is the number of criteria.

Step 4: Aggregate experts' opinions and build aggregated pairwise comparison matrices: If there are *E* experts, the geometric average approach is employed to aggregate experts' responses, and a synthetic triangular fuzzy number is obtained:

$$\tilde{r}_{ij} = \left(\tilde{a}_{ij1} \otimes \tilde{a}_{ij2} \otimes \ldots\ldots \otimes \tilde{a}_{ijE}\right)^{1/E} \tag{19}$$

Each triangular fuzzy number is then defuzzified into a crisp number F_{ij} by the center of gravity (COG) method. The crisp value for a triangular fuzzy number $\tilde{r}_{ij} = \left(l_{ij}, m_{ij}, u_{ij}\right)$ is [30,31]:

$$F_{ij} = \frac{\left[\left(u_{ij} - l_{ij}\right) + \left(m_{ij} - l_{ij}\right)\right]}{3} + l_{ij} = \frac{l_{ij} + m_{ij} + u_{ij}}{3} \quad (20)$$

Then, the aggregated pairwise comparison matrix is:

$$\Lambda = \begin{bmatrix} 1 & F_{12} & \cdots & \cdots & \cdots & \cdots & F_{1j} \\ 1/F_{12} & 1 & \cdots & \cdots & \cdots & \cdots & F_{2j} \\ \vdots & \vdots & 1 & \cdots & \cdots & \cdots & \cdots \\ \vdots & \vdots & \vdots & 1 & F_{ij} & \cdots & \cdots \\ \vdots & \vdots & \vdots & 1/F_{ij} & 1 & \cdots & \cdots \\ \cdots & \cdots & \cdots & \cdots & \cdots & 1 & \cdots \\ 1/F_{1j} & 1/F_{2j} & \cdots & \cdots & \cdots & \cdots & 1 \end{bmatrix} \quad (21)$$

Table 1. Membership functions of triangular fuzzy numbers.

Fuzzy Number	Linguistic Variable	Membership Function of Fuzzy Number
$\tilde{1}$	Equally important	(1, 1, 3)
$\tilde{3}$	Moderately important	(1, 3, 5)
$\tilde{5}$	Important	(3, 5, 7)
$\tilde{7}$	Very important	(5, 7, 9)
$\tilde{9}$	Extremely important	(7, 9, 9)

Step 5: Calculate the priority vector for each aggregated pairwise comparison matrix: Derive priority vectors for all aggregated comparison matrices by:

$$\mathbf{\Lambda} \cdot \boldsymbol{w} = \lambda_{\max} \cdot \boldsymbol{w} \quad (22)$$

where $\mathbf{\Lambda}$ is the matrix of pairwise comparisons, $\boldsymbol{w}$ is the eigenvector and $\lambda_{\max}$ is the largest eigenvalue of $\mathbf{\Lambda}$.

Step 6: Check the consistency property of each aggregated pairwise comparison matrix: The consistency of judgments that experts demonstrate during the pairwise comparisons has an important impact on the quality of the outcomes. The consistency index (CI) and consistency ratio (CR) are defined as [24,32]:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \quad (23)$$

$$CR = \frac{CI}{\text{RI}} \quad (24)$$

where RI is random index, as shown in Table 2 [24]. When CR is exceeding 0.1, it is an indication of inconsistent judgment. The experts need to revise the original values in the pairwise comparison matrix. The whole process needs to be repeated again.

Table 2. Random index (RI) [24].

Order of Matrix (n)	2	3	4	5	6	7	8
RI	0.00	0.58	0.90	1.12	1.24	1.32	1.41

Step 7: Calculate the overall rating for alternatives by aggregating the relative priorities of the elements: Based on Figure 1, establish the total ranking number, $\mathbf{\Phi}$, of the alternatives by multiplying the judgment matrix $\mathbf{W}_{32}$ with the corresponding weight vector, $\boldsymbol{w}_{21}$.

$$\mathbf{\Phi} = \mathbf{W}_{32} \otimes \boldsymbol{w}_{21} = \begin{bmatrix} \phi_1 \\ \phi_2 \\ \cdot \\ \cdot \\ \phi_k \end{bmatrix} \tag{25}$$

The priority vectors for the aggregated comparison matrices are synthesized to obtain overall priorities for alternatives. The alternative with a higher rating is considered to be preferable.

3. Case Study

A two-stage evaluation model by integrating DEA and FAHP is constructed to assess various feasible sites for a renewable energy plant. In the model, the renewable energy plant site selection problem is defined first, and the factors for evaluating the suitability of various sites are selected next. Stage I is a plant site screening stage. Among many available plants sites, several candidate plant sites are selected by considering quantitative factors. This is done by applying the DEA-fuzzy AR method. In Stage II, the candidate plant sites are further evaluated to consider qualitative factors. By applying the FAHP, the most suitable plant site can be selected. A case study of the solar plant site selection in Taiwan is carried out using the proposed model.

Step 1: Define the renewable energy plant site evaluation problem: Experts in the renewable energy industry are invited to define the problem.

Step 2: Select the factors for evaluating renewable energy plant sites: A literature review, including solar energy conversion and renewable energy site selection, is carried out first [33–40], and experts in the solar energy industry in Taiwan are then interviewed to identify critical factors. The critical factors are considered and categorized into quantitative and qualitative factors. In Stage I, only quantitative factors are considered. As stated before, when applying DEA, inputs are critical factors that are smaller the better, and outputs are critical factors that are larger the better. Due to the information accessibility of various sites and the importance of various factors, we select two inputs and two outputs for the quantitative factors. The two inputs are temperature (I_1) and wind speed (I_2). The two outputs are sunshine hours (O_1) and elevation (O_2). The definitions of the inputs and outputs are listed in Table 3. Because land is abundant and less expensive in southern Taiwan and sunshine is plentiful there, five counties (cities) with 15 towns/districts that are most suitable for setting PV solar plant sites are selected, namely A_1 to A_{15}, respectively. The data for these sites are listed in Table 4. The potential locations are shown in Figure 3.

Stage I: Selection of candidate solar plant sites using DEA-fuzzy AR: The CCR model is first applied on the case study. The results are shown in Table 5. Table 5 shows the efficiency and the rank of each DMU. The "Peers" column indicates the number of reference points that the DMU used to calculate its efficiency, and the "Reference set" lists the reference points to which the DMU is compared. Among the

15 DMUs, six of them are efficient with a value of one. For example, A_4 is efficient. Thus, it ranks the first among all DMUs. Since A_4 is located on the efficient frontier, its reference point is itself, and it does not have a peer to which to compare. A_1 has an efficiency value of 87.13, and it is not efficient. Its rank is 10. Its reference set includes two peers, A_9 and A_{11}. This means that A_1 is found inefficient when compared to A_9 and A_{11}.

Table 3. Definitions of inputs and outputs.

Factors	**Definition**
	Inputs
Temperature (I_1)	A numerical measure of hot or cold by detection of heat radiation. According to Radziemska [34], temperature increases lead to a decrease of the output power and of the conversion efficiency of the PV module. That is, the more sunshine a panel receives, the hotter the panel gets, and in turn, the conversion efficiency decreases. The heat factor can reduce output power by 10% to 25%, depending on the location and the equipment [39].
Wind speed (I_2)	Wind is the flow of gases on a large scale. Wind causes small particles to be lifted, and the suspended particles may impact the solar panels and equipment, which need to resist wind loads and uplift. Wind may cause erosion and operation failures of solar plants.
	Outputs
Sunshine hours (O_1)	A climatological indicator to measure the duration of sunshine in a period (here, a year) for a given location, typically expressed as an average of several years. The sunshine duration is the period during which direct solar irradiance exceeds a threshold value of 120 W/m² [35]. A longer sunshine duration can convert to a larger amount of output power.
Elevation(O_2)	The height of a geographic location above sea level. A higher elevation means a shorter distance for solar radiation to reach the ground and a higher intensity of solar irradiance. A higher intensity of solar irradiance converts to a larger amount of output power.

Table 4. Quantitative data of the solar plant sites.

County/City	**Town/District**	**Temperature (°C)**	**Wind Speed (m/sec)**	**Sunshine Hours (h/year)**	**Elevation (m)**
Yunlin County	A_1	23.80	1.50	1779.47	31
	A_2	23.43	1.73	1915.53	4
	A_3	19.90	4.13	1452.00	8
Chiayi County	A_4	22.67	0.63	1588.63	265
	A_5	16.87	0.40	976.43	130
	A_6	23.47	3.27	2378.67	12
Tainan City	A_7	23.43	0.87	1718.00	21
	A_8	23.70	4.53	2332.63	7
	A_9	23.93	2.60	2320.03	12
Kaohsiung City	A_{10}	24.13	0.73	1605.17	51
	A_{11}	23.60	0.23	1719.27	75
	A_{12}	22.80	0.43	1605.20	253
Pingtung County	A_{13}	25.17	3.47	2029.70	27
	A_{14}	24.57	0.60	1255.60	28
	A_{15}	24.57	0.10	1560.80	16

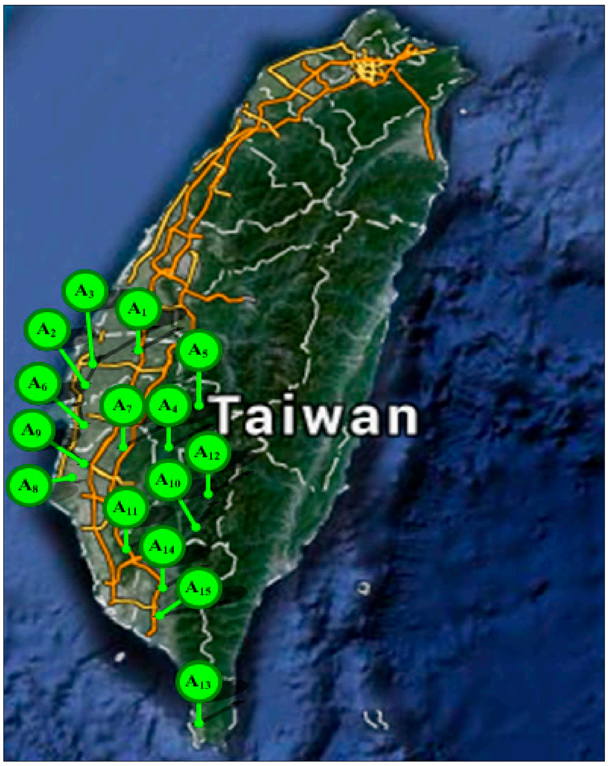

Figure 3. The potential locations in Taiwan.

Table 5. DEA performance results. DMU, decision-making unit.

DMU	Efficiency	Rank	Peers	Reference Set
A_4	100	1	0	A_4
A_6	100	1	0	A_6
A_9	100	1	0	A_9
A_{11}	100	1	0	A_{11}
A_{12}	100	1	0	A_{12}
A_{15}	100	1	0	A_{15}
A_8	97.1	7	1	A_6
A_2	92.4	8	2	A_9, A_{11}
A_7	92.27	9	2	A_9, A_{11}
A_1	87.13	10	2	A_9, A_{11}
A_{10}	85.44	11	2	A_9, A_{11}
A_{13}	81.38	12	2	A_4, A_6
A_5	80.05	13	3	A_9, A_{11}, A_{12}
A_3	72.08	14	2	A_4, A_6
A_{14}	66.9	15	2	A_9, A_{11}

As mentioned before, the conventional DEA cannot incorporate experts' opinions on the importance of the inputs/outputs; thus, DEA-fuzzy AR is applied next to the case study. The FAHP is used to set the ARs for the inputs and outputs first, and then, the DEA/AR is applied to calculate the efficiencies of the solar plant sites. Eight experts in the solar industry were asked to pairwise compare the importance of the inputs/outputs. A question, such as "which input is more important in selecting the location of the solar plant site and how much more?" was asked, and a pairwise comparison with five linguistic terms was used. The comparison matrix for the inputs by the first expert by applying Equation (18) is shown as follows:

$$\tilde{\Lambda}_{I1} = \begin{matrix} & I_1 & I_2 \\ I_1 & (1, 1, 1) & (3, 5, 7) \\ I_2 & (1/7, 1/5, 1/3) & (1, 1, 1) \end{matrix} \quad (26)$$

All experts' opinions are synthesized using the geometric average method, and the fuzzy aggregated pairwise comparison matrix of the inputs by applying Equation (19) is:

$$\tilde{\Lambda}_{I} = \begin{matrix} & I_1 & I_2 \\ I_1 & (1, 1, 1) & (2.515, 4.639, 6.293) \\ I_2 & (0.159, 0.216, 0.398) & (1, 1, 1) \end{matrix} \quad (27)$$

The fuzzy aggregated pairwise comparison matrix of the inputs is transformed into a defuzzified aggregated pairwise comparison matrix using the center of gravity (COG) method (Equation (20)). By applying Equation (21), the aggregated pairwise comparison matrix is:

$$\Lambda_{I} = \begin{matrix} & I_1 & I_2 \\ I_1 & 1 & 4.482 \\ I_2 & 0.223 & 1 \end{matrix} \quad (28)$$

By applying Equation (22), the maximum eigenvalue and the eigenvector for the defuzzified aggregated pairwise comparison matrix of the inputs are:

$$w_{I} = \begin{matrix} I_1 \\ I_2 \end{matrix} \begin{bmatrix} 0.818 \\ 0.182 \end{bmatrix} \quad (29)$$

$$\lambda_{max} = 2.00 \quad (30)$$

Because there are only two inputs, the pairwise comparison is always consistent, and the CI and CR calculations are not necessary. If the number of inputs is equal to or more than three, the consistency test must be performed.

Two matrices are formed based on the fuzzy aggregated pairwise comparison matrix in Equation (27): one contains all low values in the fuzzy matrix, and the other contains all high values in the fuzzy matrix.

$$\Lambda_{IL} = \begin{matrix} & I_1 & I_2 \\ I_1 & 1 & 2.515 \\ I_2 & 0.398 & 1 \end{matrix} \quad (31)$$

$$\Lambda_{IU} = \begin{matrix} & I_1 & I_2 \\ I_1 & 1 & 6.293 \\ I_2 & 0.159 & 1 \end{matrix} \quad (32)$$

The priorities of the inputs under the two matrices are calculated using Equation (31), and they are:

$$w_{IL} = \begin{matrix} I_1 \\ I_2 \end{matrix} \begin{bmatrix} 0.715 \\ 0.285 \end{bmatrix} \quad (33)$$

$$w_{IU} = \begin{matrix} I_1 \\ I_2 \end{matrix} \begin{bmatrix} 0.863 \\ 0.137 \end{bmatrix} \tag{34}$$

The same procedure is carried out to calculate the priorities of the outputs, and they are:

$$w_{OL} = \begin{matrix} O_1 \\ O_2 \end{matrix} \begin{bmatrix} 0.762 \\ 0.238 \end{bmatrix} \tag{35}$$

$$w_{IU} = \begin{matrix} O_1 \\ O_2 \end{matrix} \begin{bmatrix} 0.871 \\ 0.129 \end{bmatrix} \tag{36}$$

For temperature (I_1), the priority ranges from 0.715 to 0.863, *i.e.*, $I_1 = [0.715, 0.863]$. For wind speed (I_2), the priority ranges from 0.138 to 0.285, *i.e.*, $I_2 = [0.138, 0285]$. For sunshine hours (O_1), the priority ranges from 0.762 to 0.871, *i.e.*, $O_1 = [0.762, 0.871]$. For elevation (O_2), the priority ranges from 0.129 to 0.238, *i.e.*, $O_2 = [0.129, 0.238]$. Based on the AR concept discussed before [21,22,25], the AR for each pair of inputs and each pair of outputs can be calculated as shown in Table 6 and Table 7.

Table 6. Assurance range (AR) for inputs.

Input Ratio	Lower Bound	Upper Bound
w_{I1}/w_{I2}	0.715/0.285 = 2.509	0.863/0.138 = 6.254

Table 7. Assurance range (AR) for outputs.

Output Ratio	Lower Bound	Upper Bound
w_{O1}/w_{O2}	0.762/0.238 = 3.202	0.871/0.129 = 6.752

Table 8. DEA-fuzzy AR performance results.

DMU	Efficiency	Rank	Peers	Reference Set
A_{12}	100	1	0	A_{12}
A_4	94.11	2	1	A_{12}
A_{11}	91.14	3	1	A_{12}
A_5	76.55	4	1	A_{12}
A_{15}	54.43	5	1	A_{12}
A_{10}	53.28	6	1	A_{12}
A_1	39.61	7	1	A_{12}
A_{14}	35.12	8	1	A_{12}
A_{13}	34.29	9	1	A_{12}
A_7	32.21	10	1	A_{12}
A_6	20.19	11	1	A_{12}
A_9	19.92	12	1	A_{12}
A_3	14.99	13	1	A_{12}
A_8	12.26	14	1	A_{12}
A_2	7.44	15	1	A_{12}

Using the ARs in Table 6 and Table 7, DEA is run to evaluate the efficiencies of the solar plant sites. As seen in Table 8, the result shows that, considering experts' opinions on the importance of the inputs and outputs, only one plant site, A_{12}, is efficient, instead of six under the conventional DEA. Under the

DEA concept, only the DMU with an efficiency of 100% is treated as efficient. Therefore, all DMUs except A_{12} are inefficient. The results are generated from the DEA-fuzzy AR model, and only A_{12} is located on the efficient frontier. The other DMUs, when compared to A_{12} as a reference point, are found inefficient. Two other DMUs that have higher efficiency scores are A_4 and A_{11}, with efficiencies of 94.11 and 91.14, respectively. The efficiencies of all other solar plant sites are less than 77. Because the selection of solar plant site cannot only consider quantitative factors, many other qualitative factors need to be considered, too. Therefore, in this stage, three plant sites that have higher efficiency scores and that outperform others are selected for further analysis.

The selection of these three plant sites is done arbitrarily by the authors. If there are several DMUs that are 100% efficient, they will be automatically selected for the evaluation in the next stage. In this case, however, only one plant site is efficient under the first-stage analysis. Since both quantitative and qualitative factors should be considered in the problem, the selection of plant A_{12} is based on only quantitative factors, and completing the evaluation process without going through Stage II analysis is not recommended. Therefore, more efficient DMUs are selected in this stage. Since the efficiency difference between A_{11} (ranked third) and A_5 (ranked fourth) is 14.59%, a rather large number, A_5 is not selected for the next-stage evaluation.

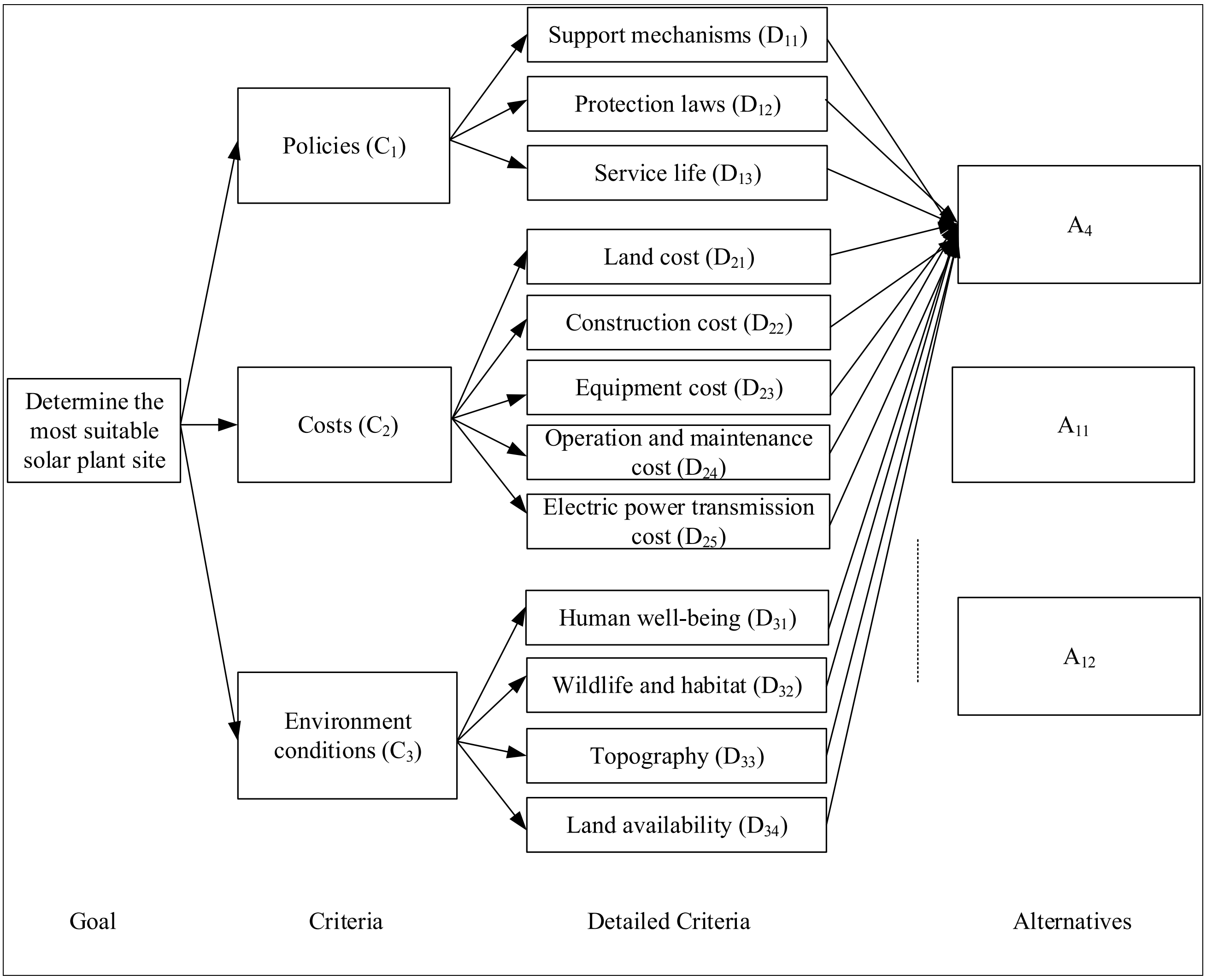

Figure 4. The hierarchy.

Stage II: Selection of the most suitable solar plant site using FAHP: In Stage I, inputs and outputs are all quantitative factors. In Stage II, factors that are qualitative in nature or quantitative but difficult to measure or collect are considered here. With a comprehensive literature review and consultation with experts in the industry, the factors for determining the suitability of solar plant sites are collected, and a hierarchy is constructed, as shown in Figure 4. Under the goal, there are three criteria, each of which has several detailed criteria. For example, under criterion costs (C_2), the detailed criteria are land cost (D_{21}), construction cost (D_{22}), equipment cost (D_{23}), operation and maintenance cost (D_{24}) and electric power transmission cost (D_{25}). The definitions of the detailed criteria are listed in Table 9. The three solar plant sites generated in Stage I are the alternatives.

Table 9. Definitions of detailed criteria.

Detailed Criteria	Definition
Support mechanisms (D_{11})	Different government policy instruments have been implemented to support solar PV power plants. Some incentives include feed-in-tariffs, investment tax credits, subsidies and favorable financing. The incentives may be different at different locations.
Protection laws (D_{12})	The existing laws and regulations might constrain the development of solar plants in different areas, such as farm land and inhabited areas.
Service life (D_{13})	Expected useful life of PV solar plant. The electricity buy-back period may be different, and the weather and geological conditions, such as temperature, humidity, salt-laden air, may affect the service life of the solar plant.
Land cost (D_{21})	The cost of obtaining the land required for setting up the solar plant.
Construction cost (D_{22})	The total cost for constructing the solar plant, including all of the capital expenses related to the initial establishment of the plant, such as buildings, roads, *etc*.
Equipment cost (D_{23})	Costs for the initial purchase and installation of the equipment and facilities.
Operation and maintenance cost (D_{24})	Costs for everyday operation of the solar plant and repair and maintenance, including labor, material, *etc*.
Electric power transmission cost (D_{25})	The transfer cost of electrical energy from the solar power plant to electrical substations located near demand centers.
Human well-being (D_{31})	The negative impacts of the solar plant on the health of the residents and aesthetics in the area.
Wild life and habitat (D_{32})	The negative impacts of the solar plant on the animal inhabitants and plants in the area.
Topography (D_{33})	A description of relief or terrain, the three-dimensional quality of the surface, and the identification of specific landforms of a place. A solar plant needs to be built in a flat place where solar radiation can be reached easily.
Land availability (D_{34})	The availability of land for setting up a solar plant with economies of scale and for future expansion.

A questionnaire is prepared, and the eight experts are invited to fill out the questionnaire; the results from each expert can then form pairwise comparison matrices. After the calculation, we can obtain the priorities of the eigenvectors for defuzzified aggregated pairwise comparison matrices, as shown in Table 10. Among the three criteria, costs (C_2) have the highest priority with 0.493, followed by policies (C_1) with 0.269 and environment conditions (C_3) with 0.238. This implies that when selecting the most appropriate solar plant site, the overall costs for constructing and running the solar plant in a certain site are considered the most important criterion by the experts. Under the policies (C_1) criterion, service life

(D_{13}), with a priority of 0.466, is the most important detailed criterion, followed by support mechanisms (D_{11}) with a priority of 0.319 and protection laws (D_{12}) with 0.215. Service life estimates the expected useful life of the PV solar plant and ultimately determines the duration and amount of power generation of the plant. Therefore, it is a rather important detailed criterion. Under the costs (C_2) criterion, operation and maintenance cost (D_{24}), with a priority of 0.382, is the most important detailed criterion. Land cost (D_{21}) ranks the second (0.190), followed by electric power transmission cost (D_{25}) with a priority of 0.177 and construction cost (D_{22}) with a priority of 0.171. Operation and maintenance cost (D_{24}) occurs continuously as long as the solar plant is under operation. The costs for everyday operation of the solar plant and repair and maintenance, including labor and material, depend on the transportation cost and the availability of human resources in that area. Therefore, a good plant site can reduce the expected long-term operation and maintenance cost. Under the environment conditions (C_3) criterion, wild life and habitat (D_{32}) has the highest priority with 0.432. Human well-being (D_{31}) with a priority of 0.362 ranked the second. Due to the rise of environmental awareness, environment impact assessment is necessary before a solar plant is allowed to be constructed. Thus, the negative impacts of the solar plant on the animal inhabitants and plants and on human well-being in the area need to be considered seriously.

The synthesized priority of a detailed criterion, which is calculated by multiplying the priority of the detailed criterion by the priority of its upper-level criterion, shows the overall importance of the detailed criterion. The most important detailed criterion is operation and maintenance cost (D_{24}), with a priority of 0.188, followed by service life (D_{13}) and wild life and habitat (D_{32}), with priorities of 0.125 and 0.103, respectively. Some other important detailed criteria include land cost (D_{21}) (0.094), electric power transmission cost (D_{25}) (0.087), support mechanisms (D_{11}) (0.086) and human well-being (D_{31}) (0.086).

Table 10. Priorities of factors.

Criteria	Detailed Criteria	Priorities	Rank	Synthesized Priorities	Synthesized Rank
Policies (C_1) (0.269)	Support mechanisms (D_{11})	0.319	2	0.086	6
	Protection laws (D_{12})	0.215	3	0.058	9
	Service life (D_{13})	0.466	1	0.125	2
Costs (C_2) (0.493)	Land cost (D_{21})	0.190	2	0.094	4
	Construction cost (D_{22})	0.171	4	0.084	8
	Equipment cost (D_{23})	0.080	5	0.040	10
	Operation and maintenance cost (D_{24})	0.382	1	0.188	1
	Electric power transmission cost (D_{25})	0.177	3	0.087	5
Environment conditions (C_3) (0.238)	Human well-being (D_{31})	0.362	2	0.086	6
	Wild life and habitat (D_{32})	0.432	1	0.103	3
	Topography (D_{33})	0.144	3	0.034	11
	Land availability (D_{34})	0.062	4	0.015	12

Table 11 shows the expected performance of the solar plant sites under each criterion. For example, under support mechanisms (D_{11}), A_{11} has the highest priority of 0.626, followed by A_{12} and A_4, with priorities of 0.231 and 0.143, respectively. The solar plant site that performs the best under a sub-criterion is highlighted in gray in Table 11. Solar plant site A_4 performs the best under five sub-criteria: service life (D_{13}), land cost (D_{21}), construction cost (D_{22}), human well-being (D_{31}) and wild life and habitat (D_{32}). Solar plant site A_{11} performs the best under six sub-criteria: support mechanisms

(D_{11}), equipment cost (D_{23}), operation and maintenance cost (D_{24}), electric power transmission cost (D_{25}), topography (D_{33}) and land availability (D_{34}). Solar plant site A_{12} performs the best under one sub-criterion only, *i.e.*, protection laws (D_{12}).

Finally, the overall priorities of the solar plant sites are obtained by synthesizing the priorities. For example, the overall priority of A_4 is calculated as follows:

$$\begin{aligned}&0.086\times0.143+0.058\times0.176+0.125\times0.478+0.094\times0.557+0.084\times0.392+0.040\times0.318+\\&0.188\times0.267+0.087\times0.300+0.086\times0.385+0.103\times0.447+0.034\times0.381+0.015\times0.277=0.353\end{aligned} \quad (37)$$

The priorities of A_{11} and A_{12} are 0.402 and 0.245, respectively. The result shows that A_{11} has the highest overall priority. Therefore, A_{11} should be selected for building the solar plant.

Table 11. Priorities of solar plant sites.

Criteria	Detailed Criteria	Synthesized Priorities	A_4	A_{11}	A_{12}
Policies (C_1)	Support mechanisms (D_{11})	0.086	0.143	**0.626**	0.231
	Protection laws (D_{12})	0.058	0.176	0.375	**0.449**
	Service life (D_{13})	0.125	**0.478**	0.333	0.189
Costs (C_2)	Land cost (D_{21})	0.094	**0.557**	0.188	0.255
	Construction cost (D_{22})	0.084	**0.392**	0.374	0.233
	Equipment cost (D_{23})	0.040	0.318	**0.465**	0.216
	Operation and maintenance cost (D_{24})	0.188	0.267	**0.539**	0.195
	Electric power transmission cost (D_{25})	0.087	0.300	**0.425**	0.275
Environment conditions (C_3)	Human well-being (D_{31})	0.086	**0.385**	0.311	0.304
	Wild life and habitat (D_{32})	0.103	**0.447**	0.304	0.250
	Topography (D_{33})	0.034	0.381	**0.394**	0.225
	Land availability (D_{34})	0.015	0.277	**0.481**	0.241
Synthesized priorities	-	-	0.353	**0.402**	0.245

4. Conclusions

To accommodate the increasing demand for electricity while confronting the finite amounts of world fossil fuel resources and environmental concerns, many countries are putting a greater effort into generating power from renewable energies. To construct a renewable energy plant, the selection of the most appropriate renewable energy plant site is the first of a series of stages, and it is a very challenging job, since the decision has a great impact on the operation outcome of the renewable energy plant. In this paper, an evaluation framework by integrating AHP, DEA, AR and fuzzy set theory is constructed to evaluate the suitability of renewable energy plant sites. Because various sites may need to be considered, a screening process is necessary to select some candidate sites first. Thus, in the first stage of the model, FAHP is adopted to set the AR of the quantitative factors, and DEA with AR is then used to select the renewable energy plant site candidates. In the second stage, FAHP is applied to find the most suitable plant site from the selected candidates.

Solar energy, one of the best renewable energy sources, is becoming a prospect of unlimited clean and safe energy. The proposed framework is applied to evaluate different districts/towns in Taiwan for constructing a PV solar plant. In the case study, A_{12} is the most efficient plant site in Phase I, which applies DEA-fuzzy AR analysis to consider quantitative factors. However, the plant site performs inferior compared to the other two sites in Phase II, which adopts FAHP to consider qualitative factors. On the other hand, A_{11}, which passes the Phase I analysis, performs rather outstanding in Phase II. Therefore, A_{11} is the most suitable plant site overall. In the future, a model that can be applied to select a specific site in a district/town will be constructed to consider more detailed factors.

Due to the size of Taiwan, and in this case only southern Taiwan is considered, the data of the inputs and outputs may not be representative enough to be decisive factors. For example, the temperature and wind speed values are rather similar in different locations. However, if the decision-making is done in a larger geographical area, more diverse data may be present, and the model can lead to a more significant result in obtaining potential solar plant locations.

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Author Contributions

The research is designed and performed by Amy H. I. Lee and He-Yau Kang. The data was collected by Chun-Yu Lin and Kuan-Chin Shen. Analysis of data was performed by He-Yau Kang, Chun-Yu Lin and Kuan-Chin Shen. Finally, the paper is written by Amy H. I. Lee and He-Yau Kang. All authors read and approved the final manuscript.

Conflicts of Interest

The authors declare no conflict of interest.

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