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An Integrated Performance Evaluation Model for the Photovoltaics Industry

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Abstract: Global warming is causing damaging changes to climate around the World. For environmental protection and natural resource scarcity, alternative forms of energy, such as wind energy, fire energy, hydropower energy, geothermal energy, solar energy, biomass energy, ocean power and natural gas, are gaining attention as means of meeting global energy demands. Due to Japan's nuclear plant disaster in March 2011, people are demanding a good alternative energy resource, which not only produces zero or little air pollutants and greenhouse gases, but also with a high safety level to protect the World. Solar energy, which depends on an infinite resource, the sun, is one of the most promising renewable energy sources from the perspective of environmental sustainability. Currently, the manufacturing cost of solar cells is still very high, and the power conversion efficiency is low. Therefore, photovoltaics (PV) firms must continue to invest in research and development, commit to product differentiation, achieve economies of scale, and consider the possibility of vertical integration, in order to strengthen their competitiveness and to acquire the maximum benefit from the PV market. This research proposes a performance evaluation model by integrating analytic hierarchy process (AHP) and data envelopment analysis (DEA) to assess the current business performance of PV firms. AHP is applied to

obtain experts' opinions on the importance of the factors, and DEA is used to determine which firms are efficient. A case study is performed on the crystalline silicon PV firms in Taiwan. The findings shall help the firms determine their strengths and weaknesses and provide directions for future improvements in business operations.

1. Introduction

The depletion of fossil fuels and the increasing consciousness about environmental degradation have led to the use of renewable energy resources in the 21st century. In December 2009, world leaders met at the United Nations Climate Change Conference (COP15) in Copenhagen to tackle with the issue of CO_2 reduction for stopping global warming before it causes irreversible damage [1]. Intense debate was centered on the challenge of reducing CO_2 emissions in each country without limiting economic growth and the ability to make life better for the citizens [2]. One of the consensuses was that renewable energy is the key to CO_2 reduction now and in the future. The main advantages of renewable energy are the reduction of harmful emissions and the conversion of infinite availability of renewable resources into electricity [3]. After Japan's Fukushima nuclear plant disaster in March 2011, people are having doubt about the safety of nuclear plants, and many countries are closing or planning to close their nuclear plants. Therefore, safety is another big concern for selecting an alternative energy source. Despite the global economic recession that has not fully recovered yet and that is bound to have an impact on the demand for clean energy, many developed and developing countries have recognized that the development of safe renewable energy sources is necessary for the environment as well as the economy [4].

While environmental friendly renewable energy sources like hydraulic, wind, ocean and solar energy have received increasing attention as alternative means of meeting global energy demands, the rapid development in photovoltaic (PV) technology has made it the most promising alternative to conventional energy systems in recent years [5]. It is the strongest-growing renewable energy technology, with recent annual growth rates of around 40% [6]. Despite the difficult worldwide economic conditions between 2008 and 2009, there was still a relatively flat growth of the PV market, with an estimate of total PV capacity installed worldwide during 2009 of a little over 7 GW [7]. In 2010, an estimated 17 GW of capacity was added worldwide, and the global cumulative installed capacity was about 40 GW, which is more than seven times the capacity five years earlier [8]. Nevertheless, solar PV only accounted for 0.1% of worldwide electricity generation in 2009 [9]. PV's share in global electricity generation was expected to pass 1% around 2030 [10]. The PV market has a tremendous growing potential, and it is driven by falling costs, new applications, strong investor interest, and continued strong policy support [8]. The major challenge for larger deployment of PV technologies is the high electricity generating cost. Whether PV can represent a significant portion of future electricity supply will depend critically on future technological learning aimed at reducing generating costs, which must be lowered sufficiently to be competitive with other generation

technologies [6]. In fact, PV power, including both crystalline and thin film technologies, is not expected to be competitive before 2020 [6,11]. Therefore, PV firms not only need to be competitive in the PV market, they also need to survive in the entire renewable energy market.

Taiwan's PV industry can achieve a strong position easily because of the large global demand from renewable energy and the technical advantages obtained from the semiconductor/TFT-LCD industries. However, currently PV products suffer a large difficulty in high production cost with low PV conversion efficiency. Hence, firms today need to stress on effective R&D to improve product quality and to achieve economic scale for cost effectiveness. Even though there were some works on the PV industry in Taiwan, most studies have focused on the industrial analysis of the entire PV industry in a qualitative way. While there were few works that did study the performance of individual PV firms, those studies were still rather rough and did not evaluate the performance of the firms comprehensively and justifiably.

This research aims to develop a systemic model to help evaluate the performance of firms in a sector in the PV supply chain. The performance evaluation model is constructed using methodologies including analytic hierarchy process (AHP) and data envelopment analysis (DEA). Conventional DEA allows each alternative to specify its own weights of inputs and outputs so as to obtain its maximum efficiency score [12]. Thus, a firm may be 100% efficient even if it performs best in one input (output) and performs inferior in other inputs (outputs). However, experts often have subjective opinions on the importance of various inputs and outputs, and a good methodology should be able to incorporate these assigned weights. AHP can fulfill this task by incorporating the experts' opinions to calculate the priorities of the inputs and outputs. Therefore, an AHP/DEA model is proposed in this research. Based on the analysis results, a strategic recommendation can be devised for firms to achieve an exponential growth in this emerging renewable energy market, and it can be a decision-making basis for continuous improvement of the firms. The rest of this paper is organized as follows: in Section 2, AHP and DEA are introduced, and the works based on these methodologies are reviewed. Section 3 proposes an AHP/DEA model for performance evaluation. The model is applied to a case study of the PV industry in Taiwan in Section 4. Some conclusion remarks are made in the last section.

2. DEA and AHP

AHP is a mathematically-based multi-criteria decision making (MCDM) tool introduced by Saaty [13] back to the early 1970s in response to the scarce resources allocation and planning needs for the military. It is popular in the academic field for data analysis and model verifications, and in real practice for providing critical information for decision making. AHP has been widely employed in decision-making analysis in political, social, economic and management sciences, etc. AHP has both qualitative and quantitative attributes [14]. It decomposes an unstructured problem into a systematic decision hierarchy qualitatively, and it then uses a quantitative way to employ pairwise comparison to determine the local and global priority weights of the alternatives [15].

DEA was first introduced in 1978 by Charnes, Cooper and Rhodes, and was applied to investigate not-for-profit organizations whose success cannot be measured by a single measure, such as profit [16]. A relative efficiency score of decision making unit (DMU) can be obtained under multiple inputs and outputs, and the DMUs that locate on the frontier, the envelopment, are considered to be the most

efficient [17]. Although there are limitations to DEA, different models of DEA have been developed for various applications in the past three decades. Two models of DEA are often adopted in research, namely, CCR and BCC. CCR, introduced by Charnes, Cooper and Rhodes, generates efficiency in ratio form by obtaining directly from the data without requiring a *priori* specification of weights nor assuming functional forms of relations between inputs and outputs [16]. One disadvantage of CCR model is that it is limited to constant returns to scale (CRS). That is, a doubling of all inputs leads to a doubling of all outputs. Under the assumption of CRS, the efficiency results obtained from input-oriented CCR and output-oriented CCR are identical. Banker, Charnes and Cooper [18] further extended the CCR model into variable returns to scale (VRS), and the model is called BCC. VRS occurs when a doubling of all inputs leads to either a more than doubling of all outputs or a less than a doubling of all outputs.

Even though DEA is usually undertaken with absolute numerical data, there are works that have used ratio variables rather than absolute numbers. Some scholars have claimed that DEA should not be applied on ratio variables [19], but others have asserted that CCR should not be used but instead BCC can be applied when input and/or output include a ratio variable [20]. Some recent works that include ratio variables in the DEA analysis are reviewed here. Wang *et al.* [21] studied the performance of banks in China and used two output ratios: return on total assets (ROA) and return on equity (ROE). Sakar [22] studied commercial banks in Turkey and chose net interest revenue to asset, net interest revenue to operating revenue, non-interest revenue to asset, ROA, and ROE as outputs. Siriopoulos and Tziogkidis [23] selected five financial ratios which are widely used by practitioners and researchers in banking efficiency, namely, ROE, financial independence ratio (FIR), gross operating margin (GOM), asset turnover ratio (ATR), service concentration index (SCI) for the output variables, and CRS is assumed in applying the DEA. Avkiran [24] studied the performance of banks and concluded that when a model comprises of key financial ratios DEA can be used to objectively identify benchmarks for ratio analysis based on actual observed data collected from peers. Shetty *et al.* [25] proposed a non-oriented, non-radial directional distance model, which measures worst relative efficiency within the range of zero to one, and assessed bankruptcy of information technology companies in India based on ten financial ratios, among which three are input variables and seven are output variables. Because the case study in this paper includes one ratio variable, BCC is applied in the analysis.

No methodology is perfect, and both AHP and DEA have their own drawbacks [17,26]. The most common mentioned problem of AHP is that too many pairwise comparisons are required to be done by experts. DEA has a drawback in the Pareto principle. That is, when almost every decision maker or most other MCDM methods may prefer one solution, DEA can consider two DMUs be both perfectly efficient [27]. In addition, a conventional DEA may produce too many and even an infinite number of optimal solutions [28]. As stated before, DEA allows each alternative to specify its own weights of inputs and outputs so as to obtain its maximum efficiency score [12]. Since experts may have subjective opinions on the importance of the inputs and outputs, a good performance evaluation methodology should be able to take this into consideration. As a result, many modified AHP and DEA have been proposed.

Although both AHP and DEA are commonly used in research and in practice, only limited literature has attempted to link AHP and DEA until recent years. Sinuany-Stern *et al.* [27] proposed an AHP/DEA methodology for ranking DMUs using a two-stage model. In the first stage, DEA was run

for each pair of DMUs separately and pairwise evaluation matrix was generated. In the second stage, AHP was applied to rank the DMUs. Cai and Wu [29] applied AHP to calculate the weights of basic indices. After the performances of enterprises under the basic indices are aggregated into various synthetic abilities, DEA was used to evaluate the performance of the firms. Yoo [30] evaluated total quality management activities in Korean companies by a combination of the AHP and the DEA methodologies. AHP was adopted to quantify the weights of success factors for TQM and to generate the input and output data, and DEA was then applied to evaluate the efficiency of TQM activities in various firms. Liu and Hai [31] presented a voting AHP method to determine the weights of criteria not by pairwise comparisons but by voting. The votes each criterion received in different ranking places were aggregated into an overall score of each criterion by the DEA method, and the overall scores were then normalized as the relative weights of the criteria. Ramanathan [32] proposed a data envelopment analytic hierarchy process (DEAHP) approach. DEA was used to derive weights from the pairwise judgment matrices of AHP and to aggregate local weights of alternatives in terms of different criteria in AHP. Ertay *et al.* [12] adopted AHP to collect qualitative data, and then used DEA to solve the layout design problem by considering the quantitative and qualitative data simultaneously. Korpela *et al.* [33] used AHP to calculate the importance weights of the outputs and the performance of warehouses under each output, and then used DEA to combine the performance information of inputs and outputs. Wang *et al.* [34] applied AHP to determine the weights of criteria, DEA to generate local risk scores of bridge structures, and simple additive weighting (SAW) method to aggregate bridge risks for each bridge structure. Wang *et al.* [35] proposed a linear programming method for generating the most favorable weights (LP-GFW) from pairwise comparison matrices. The variable weight concept of DEA is incorporated with the priority scheme of AHP to generate the most favorable weights for the criteria and alternatives based on crisp pairwise comparison matrices. Wang and Chin [36] further proposed two DEA models for priority determination in AHP. The best local priorities from a pairwise comparison matrix or a group of pairwise comparison matrices could be derived no matter the martices are perfectly consistent or inconsistent. Sueyoshi *et al.* [37] constructed a decision support framework for internal audit prioritization in a rental car company with the adoption of AHP and DEA. AHP was used to process qualitative information, while DEA was used to measure quantitative data. The AHP and DEA results were further combined in a matrix for manager inputs and efficiency analysis. Lozano and Villa [38] proposed two target-setting DEA approaches: an interactive multi-objective method and a lexicographic multi-objective approach. Both approaches used AHP to calculate the local relative priorities of the inputs and outputs. Tseng *et al.* [39] constructed a model for measuring business performance in the high-tech manufacturing by adopting DEA, AHP and technique for order preference by similarity to ideal solution (TOPSIS). AHP was applied first to calculate the weights of performance indicators, DEA was used to evaluate cost efficiency, and TOPSIS was adopted to obtain the final ranking results. Kang and Lee [17] constructed a supplier performance evaluation model based on AHP and DEA. DEA was applied first to evaluate quantitative factors, and the results were then transformed into pairwise comparison values for AHP analysis. AHP was applied to evaluate qualitative factors. Ramanathan and Ramanathan [40] proposed a qualitative DEAHP model, in which both qualitative and quantitative factors could be used to derive weights from pairwise comparison matrices by treating judgments as qualitative factors.

As stated before, under the conventional DEA, the weights given to inputs and outputs are chosen in a manner that assigns a best set of weights to each DMU, meaning that the resulting efficiency score is maximized for each DMU under the given data. However, if prior knowledge or accepted views exist for the weights of the inputs or outputs, the weight flexibility leads to produce unrealistic efficiency scores [41]. Restrictions then need to be placed on weights in DEA to reflect the preference in a real world [42]. The most common method is the assurance regions (AR) model, and AR is to impose restrictions on the upper bound and lower bound of a ratio of the weights of two variables [43]. Takamura and Tone [44] did a comparative site evaluation study for relocating Japanese government agencies out of Tokyo based on a combination of the AHP and the AR model of DEA. Sun [45] applied pairwise comparison to collect individual expert's judgments on the importance of each output, and the results from the AHP analysis are then used for setting the upper and lower bounds of the ARs of the weights of the outputs for the DEA analysis. Wang *et al.* [46] proposed a DEA/AR model, in which DEA model was incorporated with AR for weight generation in AHP. Lee *et al.* [42] evaluated the performance of national R&D programs with heterogeneous objectives using a DEA approach, and either the geometric mean or the AR for weights restriction could be obtained from pairwise comparisons of multiple experts to determine the priorities of variables.

It would be inappropriate to use DEA if too little DMUs are examined. To overcome this issue and to apply AR concurrently, this research treats each firm in each year as a DMU. This methodology has been applied in previous works. For example, Siriopoulos and Tziogkidis [23] evaluated the efficiency of Greek commercial banks through the period 1995–2003 using the DEA technique, and each bank for each year is considered as a different DMU. Chang [47] investigated technology development programs (TDP) performance over the period from 1999 to 2003 using CCR and BCC. TDPs were divided into five fields, and five years were studied; thus, the research evaluated a total of 25 DMUs. Lee and Pai [48] measured the business performance of 10 thin film transistor-liquid crystal display (TFT-LCD) manufacturers from 2002 to 2007. The data of a company in a single year is treated as a DMU, so that the benchmarking would be other nine companies within six years as well as the operation of the company in other years.

3. The Proposed AHP/DEA Model

The integrated AHP and DEA model for evaluating the firms in the PV industry is described as follows:

Step 1: ***Define the performance evaluation problem for PV firms.*** A committee of experts in the field is formed to define the problem and to determine the key competitive factors firms need to possess in the market.

Step 2: ***Select the factors for evaluating PV firms.*** Literature reviews are done first to list the factors that have been used in the past, and experts are asked to select the most important ones for business performance. The factors that are preferably minimized are treated as inputs, and those that are preferably maximized are outputs, as defined by DEA.

Step 3: ***Collect the data of the PV firms.*** The company data for the factors are collected from financial reports and websites of the firms or other resources. If one or more factors have a very close relationship with another factor, it is possible to select one factor to represent others

in the DEA analysis. Correlation analysis is performed on all the quantitative inputs and outputs selected, and some factors might be deleted.

Step 4: ***Obtain the ARs of the factors.*** A questionnaire, in the pairwise comparison form, is used to collect the opinions of experts in evaluating the importance of the factors. AHP is applied to calculate the ARs of the factors. For example, if there are n inputs, $X_1, X_2, X_3,..., X_n$ are compared in pairs according to their relative weights, denoted by w_1, w_2, w_3,..., w_n, respectively, the pairwise comparisons by expert c can be represented in the form of a matrix [13]:

$$\mathbf{A}_c = \begin{bmatrix} \dfrac{w_{1c}}{w_{1c}} & \dfrac{w_{1c}}{w_{2c}} & \cdots & \dfrac{w_{1c}}{w_{nc}} \\ \dfrac{w_{2c}}{w_{1c}} & \dfrac{w_{2c}}{w_{2c}} & \cdots & \dfrac{w_{2c}}{w_{nc}} \\ \vdots & \vdots & \vdots & \vdots \\ \dfrac{w_{nc}}{w_{1c}} & \dfrac{w_{nc}}{w_{2c}} & \cdots & \dfrac{w_{nc}}{w_{nc}} \end{bmatrix} = \begin{bmatrix} a_{11c} & a_{12c} & \cdots & a_{1nc} \\ a_{21c} & a_{22c} & \cdots & a_{2nc} \\ \vdots & \vdots & \vdots & \vdots \\ a_{n1c} & a_{n2c} & \cdots & a_{nnc} \end{bmatrix} \tag{1}$$

The maximum eigenvalue and the eigenvector are calculated to estimate the relative weights of the inputs with the following formula, where w_c is the eigenvector, the weight vector, of $\mathbf{A}_c$, and $\lambda_{\max}$ is the largest eigenvalue of $\mathbf{A}_c$:

$$\mathbf{A}_c \cdot w_c = \lambda_{\max} \cdot w_c \tag{2}$$

The consistency property of the matrix is checked by the consistency index (CI) and consistency ratio (CR) [13]:

$$CI = \frac{\lambda_{\max} - n}{n - 1} \tag{3}$$

$$CR = \frac{CI}{RI} \tag{4}$$

where RI is random index, the average random consistency index from a large sample of randomly generated reciprocal matrices using the scale 1/9, 1/8, ..., 1, ..., 8, 9 [13]. As calculated by Saaty [13], the order of the matrix and the average RI are as shown in Table 1. If CR is less than 0.1, the consistency test is passed. Otherwise, the experts would need to revise the original values in the pairwise comparison matrix.

After the priorities of the inputs are calculated for each expert, the maximum and the minimum values for each input from all the experts are selected. The lower bound and upper bound of the ratio of every two inputs is calculated as the AR. The ARs of the outputs can be calculated in the same way.

Table 1. Random index (RI) [13].

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* 5:** ***Calculate business performance of the PV firms. A modified DEA model is constructed to consider the importance of various factors in analyzing the performance of the firms in a period of time. The outcomes from Step 4 are used in the modified DEA model, and the overall performance of the firms can be generated. The DEA/AR model for measuring the AR efficiency of a selected *DMUr* is as follows [28,49,50]:

$$E_r = \max \sum_{k=1}^{t} u_k Y_{rk} \tag{5}$$

$$\text{s.t.} \quad \sum_{j=1}^{s} v_j X_{rj} = 1 \tag{6}$$

$$\sum_{k=1}^{t} u_k Y_{ik} - \sum_{j=1}^{s} v_j X_{ij} \leq 0 \,, \quad i = 1,2,3,...,n \tag{7}$$

$$u_k \geq \varepsilon > 0 \,, v_j \geq \varepsilon > 0$$

where E_r is the relative efficiency of the *r*th DMU taking into account the minimum and maximum influence that each factor can have on E_r, X_{ij} is the amount of *j*th input (*j* = 1,…,*s*) of the *i*th DMU, Y_{ik} is the amount of the *k*th output (*k* = 1,…,*t*) of the *i*th DMU, v_j and u_k are the weights of the *j*th input and the *k*th output respectively, and ε is a small non-Archimedean number. Set the relative importance elicited from the experts range from L_{Op} to U_{Op} for output *p* and from L_{Oq} to U_{Oq} for output *q*, and from L_{Ip} to U_{Ip} for input *p* and from L_{Iq} to U_{Iq} for input *q*. The associated constraints are as following:

$$L_{O_p} \big/ U_{O_q} \leq u_p \big/ u_q \leq U_{O_p} \big/ L_{O_q} \,, p < q = 2,...,t \tag{8}$$

$$L_{I_p} \big/ U_{I_q} \leq v_p \big/ v_q \leq U_{I_p} \big/ L_{I_q} \,, p < q = 2,...,s \tag{9}$$

With the above model, the efficiencies of the PV firms can be calculated.

4. A Case Study of the PV Industry in Taiwan

A case study of the performance of crystalline silicon solar firms in Taiwan is carried out using the proposed model. Because of the success of the semiconductor industry and TFT-LCD industry over the past decade, Taiwan has a concrete background and foundation for developing a PV industry, which requires very similar technology and is a less complex process than semiconductor/TFT-LCD manufacturing. Taiwan's PV industry can achieve a strong position because of the increasing global demand from renewable energy and the technical advantages obtained from the semiconductor/ TFT-LCD industries. However, PV products suffer a large difficulty in high production cost with low conversion efficiency at present. A good evaluation of the firms in the PV industry and an understanding of a firm's position in the market are important for the firm to improve its competitiveness in the market.

Through literature review of performance evaluation and interview with experts in the industry, we listed important factors. With the consideration of information accessibility from the firms under study, we selected five inputs and three outputs. The five inputs are: selling expenses (I1), general and administrative expenses (I2), fixed assets (I3), research and development expenses (I4), and cost of goods sold (I5). The three outputs are sales revenue (O1), income before income taxes (O2), and

earnings per share (O3). Theses inputs and outputs are defined in Table 2. Note that due to limited information availability of the firms in an industry, the inputs and outputs may need to be changed so that all firms can be compared justifiably.

Table 2. Definitions of inputs and outputs.

Input/Output	Definition
Selling expenses (I1)	Costs incurred to sell or distribute products. They are operating expenses incurred in a period. Some examples include advertising expense, salesperson commission, delivery expense, *etc*.
General and administrative expenses (I2)	Expenditures related to the day-to-day operations of a business. They are operating expenses incurred in a period. Some examples include managerial salaries, depreciation, insurance, rent and utilities, *etc*.
Fixed assets (I3)	Also called property, plant, and equipment. They are acquired for use in the operation of the business and have physical substances with useful lives of more than one year. Some examples are land, building, machinery and auto, *etc*.
Research and development expenses (I4)	Expenditures incurred to discover new knowledge and to develop the knowledge into a design for a new product. They are usually expensed as incurred in a period.
Cost of goods sold (I5)	Inventory costs of the goods a company has sold during a period. Costs of goods manufactured by the company include raw material, direct labor and overhead expenses. The costs of the goods that are sold are called cost of goods sold (COGS), and the cost of the goods not yet sold are called inventory.
Sales revenue (O1)	Income received from selling products over a period of time.
Income before income taxes (O2)	Net income is the difference between a company's total sales revenues and total expenses (including cost of goods sold, selling expenses, general and administrative expenses, research and development expenses) for a period of time. Income before income taxes is pretax income, which is the amount a company earned before taking taxes into account.
Earnings per share (O3)	The amount of earnings per outstanding share of a company's common stock. Earnings per share (EPS) serves as an indicator of a company's profitability.

In this study, a DMU is a company in a year, and the performance of the company in that year is evaluated with other DMUs. Six major firms in the market are studied for a period of five years. To keep anonymousness, they are identified as A, B, C, D, E and F. However, some of the data for firm C, D, E and F for the first year is missing and cannot be obtained. Therefore, only the last four years are included for the analysis. The data is as shown in Table 3. For example, DMU A1 indicates firm A in year 1, and the performance indicators include five inputs (I1 to I5) and three outputs (O1 to O3).

4.1. DEA Using BCC-I

The case study is first performed by DEA using the input-oriented BCC (BCC-I) model. The results are shown in Table 4. Among the 26 DMUs, 19 of them are efficient with a value of 1, and they are all ranked number one. In addition, only seven DMUs are not efficient.

Table 3. Data of the crystalline silicon solar firms.

Firm	Year	DMU	Selling expenses (I1) (thousand NT dollar)	General and administrative expenses (I2) (thousand NT dollar)	Fixed assets (I3) (thousand NT dollar)	Research and development expenses (I4) (thousand NT dollar)	Cost of goods sold (I5) (thousand NT dollar)	Sales revenue (O1) (thousand NT dollar)	Income before income taxes (O2) (thousand NT dollar)	Earnings per share (O3) (NT dollar)
A	1	A1	6,874	14,922	93,904	11,974	849,871	1,169,707	283,931	8.81
	2	A2	8,212	18,204	202,264	33,232	2,565,388	3,425,263	807,259	18.46
	3	A3	16,121	47,985	202,742	121,233	5,180,275	6,120,354	899,595	14.71
	4	A4	32,867	95,816	812,071	385,821	11,757,638	13,913,832	1,268,085	12.62
	5	A5	79,359	230,889	4,203,159	133,591	12,882,458	13,401,531	2,362,179	12.75
B	1	B1	90,248	113,858	830,354	34,055	2,860,744	4,326,110	1,166,619	8.52
	2	B2	78,521	205,787	2,603,988	45,198	5,618,471	8,112,714	2,262,551	13.11
	3	B3	108,875	289,089	2,921,139	193,432	12,591,624	15,755,996	2,458,800	12.55
	4	B4	189,200	403,851	3,749,677	229,737	19,351,467	23,065,224	2,352,015	7.7
	5	B5	173,029	508,728	7,609,698	216,895	17,147,009	19,058,312	102,313	0.44
C	2	C2	8,163	75,295	829,911	22,030	464,228	563,545	259	0.01
	3	C3	36,829	139,570	33,620	493,783	6,914,182	6,010,325	493,783	5.03
	4	C4	59,017	318,047	6,256,010	49,453	13,155,938	15,854,416	1,899,381	12.73
	5	C5	117,002	263,777	9,151,921	65,918	15,162,452	15,877,665	36,387	0.14
D	2	D2	2,892	22,688	419,667	20,990	350,021	380,534	10,731	0.18
	3	D3	12,008	49,388	461,556	21,336	3,075,578	3,714,250	533,347	5.81
	4	D4	30,292	203,533	2,732,806	80,967	9,358,744	10,217,290	768,395	5.66
	5	D5	76,650	149,212	4,258,524	69,845	10,273,176	10,364,909	936,596	4.92
E	2	E2	7,601	40,108	619,171	2,533	330,701	403,760	14,144	0.19
	3	E3	26,201	55,711	997,466	7,794	2,387,274	2,861,326	338,061	3.8
	4	E4	32,782	111,733	1,326,280	16,955	4,097,105	4,905,594	384,890	4.07
	5	E5	41,552	159,721	2,877,546	24,549	3,357,494	3,833,404	180,927	1.36
F	2	F2	9,636	29,739	489,257	89,773	1,430,095	1,945,754	261,215	4.99
	3	F3	21,975	67,139	1,289,924	131,178	3,003,718	3,958,736	620,550	7.62
	4	F4	32,941	99,371	1,375,177	172,677	6,213,163	7,173,656	758,815	6.28
	5	F5	28,467	78,775	1,687,820	178,777	4,183,367	4,383,501	144,894	0.99

Firm A was efficient for all the five years. Firm B was efficient for the first four years but not efficient for the last year. In the fifth year, Firm B has a score of 0.913, and the reference for DMU B5 is B2. Firm C was not efficient in the second year, with a score of 0.945; however, it became efficient for the next three years. Firm D was efficient for all the four years studied. Firm E was efficient for year 2 to 4, but it became inefficient in year 5, with a score of 0.828. Firm F did not perform well in compared with other firms. Its scores were decreasing for the four years of study. The reference set for each inefficient DMU can be found in Table 4. To illustrate this, DMU C2 has a reference set of DMU A1. That is, by compared with DMU A1, an efficient DMU, DMU C2 is relatively inefficient, with a score of 0.945. For an efficient DMU, the reference set is the DMU itself.

Table 4. Relevant results for BCC-I.

DMU	Efficiency value	Rank	Reference set
A1	1.000	1	A1
A2	1.000	1	A2
A3	1.000	1	A3
A4	1.000	1	A4
A5	1.000	1	A5
B1	1.000	1	B1
B2	1.000	1	B2
B3	1.000	1	B3
B4	1.000	1	B4
B5	0.913	23	B2
C2	0.945	22	A1
C3	1.000	1	C3
C4	1.000	1	C4
C5	1.000	1	C5
D2	1.000	1	D2
D3	1.000	1	D3
D4	1.000	1	D4
D5	1.000	1	D5
E2	1.000	1	E2
E3	1.000	1	E3
E4	1.000	1	E4
E5	0.828	25	A1
F2	0.995	20	A1
F3	0.958	21	A1
F4	0.905	24	A2
F5	0.766	26	A2

Because most of the DMUs are efficient, further analysis is necessary. With a larger number of inputs and outputs, there may be too many DMUs that are assessed to be efficient. Therefore, a correlation analysis of the factors is done to check if there is any factor that has a high correlation with other factors. The requirement for a lower correlation among factors aims to exclude inputs or outputs which are close to perfect substitutes or perfect complements. As a result, a factor that has high correlation with other factor(s) can be deleted as a result. The correlation coefficients of the input and output factors are shown in Table 5. The correlation coefficient between cost of goods sold (I5) and sales revenue (O1) is very high with 0.991. Selling expenses (I1) and general and administrative expenses (I2) are also highly correlated, with correlation coefficient of 0.906. Because sales revenue (O1) is generally higher than cost of goods sold (I5), sales revenue (O1) is selected to represent the other factor. In addition, because general and administrative expenses (I2) is basically higher than selling expenses (I1), general and administrative expenses (I2) is selected. Thus, selling expenses (I1) and/or cost of goods sold (I5) can be deleted, and the evaluation is performed again.

Table 5. Correlation analysis of the factors.

	Selling expenses (I1)	General and administrative expenses (I2)	Fixed assets (I3)	Research and development expenses (I4)	Cost of goods sold (I5)	Sales revenue (O1)	Income before income taxes (O2)	Earnings per share (O3)
Selling expenses (I1)	1.00	0.906	0.730	0.278	0.844	0.857	0.479	0.005
General and administrative expenses (I2)		1.00	0.818	0.294	0.886	0.893	0.455	−0.008
Fixed assets (I3)			1.00	0.014	0.779	0.753	0.196	−0.157
Research and development expenses (I4)				1.00	0.469	0.438	0.221	0.133
Cost of goods sold (I5)					1.00	0.991	0.542	0.164
Sales revenue (O1)						1.00	0.605	0.225
Income before income taxes (O2)							1.00	0.713
Earnings per share (O3)								1.00

After deleting selling expenses (I1), cost of goods sold (I5), and both I1 and I5, DEA is performed again, and the results are shown in Table 6. Compared to 19 efficient DMUs in the original analysis, there are 18, 19 and 17 efficient DMUs when selling expenses (I1), cost of goods sold (I5), and both I1 and I5, are removed from the analysis, respectively. Even though less DMUs are found efficient now, there are still more than half of the DMUs that are efficient. In addition, experts may think that some factors are more important than others. Thus, different weights may need to be assigned to different factors. This cannot be done by the conventional DEA, and our proposed model can then solve the problem.

Table 6. Results for BCC-I after deleting factor(s).

DMU	BCC-I		BCC-I (Delete I1)		BCC-I (Delete I5)		BCC-I (Delete I1 & I 5)	
	Efficiency value	Reference set	Efficiency value	Reference set	Efficiency value	Reference set	Efficiency value	Reference set
A1	1	A1	1	A1	1	A1	1	A1
A2	1	A2	1	A2	1	A2	1	A2
A3	1	A3	1	A3	1	A3	1	A3
A4	1	A4	1	A4	1	A4	1	A4
A5	1	A5	1	A5	1	A5	1	A5
B1	1	B1	1	B1	1	B1	1	B1
B2	1	B2	1	B2	1	B2	1	B2

Table 6. *Cont*.

B3	1	B3	1	B3	1	B3	1	B3
B4	1	B4	1	B4	1	B4	1	B4
B5	0.913	B2	0.91304	B2	0.68085	A4	0.67040	B4
C2	0.945	A1	0.93438	B1	0.62561	A1	0.36976	A1
C3	1	C3	1	C3	1	C3	1	C3
C4	1	C4	1	C4	1	C4	1	C4
C5	1	C5	1	C5	1	C5	1	C5
D2	1	D2	1	D2	1	D2	0.65769	A1
D3	1	D3	1	D3	1	D3	1	D3
D4	1	D4	0.88777	A2	1	D4	0.86649	A2
D5	1	D5	1	D5	1	D5	1	D5
E2	1	E2	1	E2	1	E2	1	E2
E3	1	E3	1	E3	1	E3	1	E3
E4	1	E4	1	E4	1	E4	1	E4
E5	0.828	A1	0.81810	B2	0.53409	C4	0.46642	C4
F2	0.995	A1	0.97003	A1	0.63961	A1	0.53973	A1
F3	0.958	A1	0.93225	A2	0.43076	A2	0.35621	A2
F4	0.905	A2	0.89399	A2	0.67752	A2	0.66808	A2
F5	0.766	A2	0.75867	A2	0.36760	A2	0.34242	A2

4.2. AHP/DEA Model

The proposed AHP/DEA model is applied to the case study. The AHP is applied to set the ARs for the factors first, and the DEA/AR is used next to calculate the efficiencies of the DMUs. Five experts in the PV industry contributed their professional experience to fill out a questionnaire to pairwise compare the importance of the factors. The question, "which input should be emphasized more in determining the performance of the firms, and how much more?" was asked, and a nine-point scale was used to do the pairwise comparison. The pairwise comparison results for the first expert are shown in Table 7. Based on the results, a comparison matrix for the inputs by the first expert can be prepared, as shown in Table 8.

Table 7. Pairwise comparison of factors by Expert 1.

In order to evaluate the performance of the firms, which input should be emphasized more?																		
	Absolute		Very strong		Strong		Weak		Equal	Weak			Strong	Very strong		Absolute		
	9:1	8:1	7:1	6:1	5:1	4:1	3:1	2:1	1:1	1:2	1:3	1:4	1:5	1:6	1:7	1:8	1:9	
Selling expenses (I1)								X										General and administrative expenses (I2)
Selling expenses (I1)								X										Fixed assets (I3)
Selling expenses (I1)													X					Research and development expenses (I4)

Table 7. *Cont.*

	Absolute		Very strong		Strong		Weak		Equal	Weak		Strong		Very strong		Absolute		
	9:1	8:1	7:1	6:1	5:1	4:1	3:1	2:1	1:1	1:2	1:3	1:4	1:5	1:6	1:7	1:8	1:9	
Selling expenses (I1)									X									Cost of goods sold (I5)
General and administrative expenses (I2)									X									Fixed assets (I3)
General and administrative expenses (I2)												X						Research and development expenses (I4)
General and administrative expenses (I2)												X						Cost of goods sold (I5)
Fixed assets (I3)												X						Research and development expenses (I4)
Fixed assets (I3)												X						Cost of goods sold (I5)
Research and development expenses (I4)									X									Cost of goods sold (I5)
In order to evaluate the performance of the firms, which output should be emphasized more?																		
	Absolute		Very strong		Strong		Weak		Equal	Weak		Strong		Very strong		Absolute		
	9:1	8:1	7:1	6:1	5:1	4:1	3:1	2:1	1:1	1:2	1:3	1:4	1:5	1:6	1:7	1:8	1:9	
Sales revenue (O1)									X									Income before income taxes (O2)
Sales revenue (O1)									X									Earnings per share (O3)
Income before income taxes (O2)									X									Earnings per share (O3)

Table 8. Comparison matrix for the inputs by Expert 1.

	Selling expenses (I1)	General and administrative expenses (I2)	Fixed assets (I3)	Research and development expenses (I4)	Cost of goods sold (I5)
Selling expenses (I1)	1	2	2	1/5	1
General and administrative expenses (I2)	1/2	1	1	1/4	1/4
Fixed assets (I3)	1/2	1	1	1/4	1/4
Research and development expenses (I4)	5	4	4	1	1
Cost of goods sold (I5)	1	4	4	1	1

An eigenvector and an eigenvalue are calculated using the eigenvalue method by Equation (2):

$$w_{\text{Expert 1}}^{\text{Inputs}} = \begin{array}{c} \text{I1} \\ \text{I2} \\ \text{I3} \\ \text{I4} \\ \text{I5} \end{array} \begin{bmatrix} 0.16362 \\ 0.07864 \\ 0.07864 \\ 0.38955 \\ 0.28955 \end{bmatrix} \text{ and } \lambda_{\max} = 5.31946$$

The eigenvector shows the priorities of the five inputs. In the opinion of the first expert, research and development expenses (I4), with a weight of 0.38955, is the most important input in determining the performance of the firms, followed by cost of goods sold (I5), with a weight of 0.28955. To check the consistency of this combination of values in the matrix, the consistency test is performed:

$$CI = \frac{\lambda_{\max} - n}{n - 1} = \frac{5.31946 - 5}{5 - 1} = 0.07986, \ CR = \frac{CI}{\text{RI}} = \frac{0.07986}{1.12} = 0.07130$$

Since *CR* is less than 0.1, the comparison matrix is consistent. If the consistency test fails, the expert is required to fill out the specific part of the questionnaire again until a consensus is met. The same procedure is carried out to calculate the priorities of the outputs determined by expert 1 and the priorities of the inputs and of the outputs for the other four experts. The results are shown in Tables 9 and 10.

Table 9. Priorities of the inputs by the experts.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Minimum priority	Maximum priority
Selling expenses (I1)	0.16362	0.1779	0.19353	0.06425	0.08353	0.06425	0.19353
General and administrative expenses (I2)	0.07864	0.07198	0.11591	0.12914	0.12638	0.07198	0.12914
Fixed assets (I3)	0.07864	0.08899	0.11265	0.28264	0.14167	0.07864	0.28264
Research and development expenses (I4)	0.38955	0.32344	0.27881	0.19847	0.28051	0.19847	0.38955
Cost of goods sold (I5)	0.28955	0.33769	0.29908	0.3255	0.36791	0.28955	0.36791

Table 10. Priorities of the outputs by the experts.

	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Minimum priority	Maximum priority
Sales revenue (O1)	0.33333	0.12632	0.33333	0.09091	0.33333	0.09090	0.33333
Income before income taxes (O2)	0.33333	0.45767	0.33333	0.45455	0.33333	0.33333	0.45767
Earnings per share (O3)	0.33333	0.41601	0.33333	0.45455	0.33333	0.33333	0.45454

For selling expenses (I1), the minimum priority and the maximum priority among all experts are 0.06425 and 0.19353, respectively. For general and administrative expenses (I2), the minimum priority

and the maximum priority among all experts are 0.07198 and 0.12914, respectively. Let the weight for input I1 to input I5 be $v_{I1},\ldots, v_{I5}$ respectively, and the weight for output O1 to output O3 be $u_{O1},\ldots, u_{O3}$ respectively. The ratio v_{I1}/v_{I2} has a lower bound of 0.49752 (0.06425/0.12914) and an upper bound of 2.6887 (0.19353/0.07198). In the same way, the AR for each pair of inputs and each pair of outputs can be calculated, as shown in Tables 11 and 12.

Table 11. Assurance ranges (AR) for inputs.

Input ratio	Lower bound	Upper bound
v_{I1}/v_{I2}	0.06425/0.12914 = 0.49752	0.19353/0.07198 = 2.6887
v_{I1}/v_{I3}	0.06425/0.28264 = 0.22732	0.19353/0.07864 = 2.4610
v_{I1}/v_{I4}	0.06425/0.38955 = 0.16493	0.19353/0.19847 = 0.9751
v_{I1}/v_{I5}	0.06425/0.36791 = 0.17464	0.19353/0.28955 = 0.6684
v_{I2}/v_{I3}	0.07198/0.28264 = 0.25467	0.12914/0.07864 = 1.6422
v_{I2}/v_{I4}	0.07198/0.38955 = 0.18478	0.12914/0.19847 = 0.6507
v_{I2}/v_{I5}	0.07198/0.36791 = 0.19565	0.12914/0.28955 = 0.4460
v_{I3}/v_{I4}	0.07864/0.38955 = 0.20187	0.28264/0.19847 = 1.4241
v_{I3}/v_{I5}	0.07864/0.36791 = 0.21375	0.28264/0.28955 = 0.9761
v_{I4}/v_{I5}	0.19847/0.36791 = 0.53945	0.38955/0.28955 = 1.3454

Table 12. Assurance ranges (AR) for outputs.

Output ratio	Lower bound	Upper bound
u_{O1}/u_{O2}	0.09090/0.45767 = 0.19861	0.33333/0.33333 = 1
u_{O1}/u_{O3}	0.09090/0.45454 = 0.19998	0.33333/0.33333 = 1
u_{O2}/u_{O3}	0.33333/0.45454 = 0.73333	0.45767/0.33333 = 1.3730

Using the ARs from Tables 11 and 12, the DEA/AR model in Step 5 is adopted to calculate the efficiencies of the DMUs, and the results are shown in Table 13. With the consideration of the experts' opinions on the importance of the inputs and outputs, the analysis shows that eight out of 26 DMUs are efficient, and the number of efficient DMUs is decreased substantially compared to the results from the conventional DEA in Section 4.1. In Section 4.1, the number of efficient DMUs is 19 when all factors are included in the analysis. The numbers are 18, 19 and 17 when selling expenses (I1), cost of goods sold (I5), and both I1 and I5 are removed from the analysis, respectively. Therefore, by using the AHP/DEA model, the number of efficient DMUs can be reduced, and experts' opinions can be considered to select the most efficient DMUs. Firm A performed relatively well in compared with other firms over the years. However, it was efficient for the first two years and became inefficient for the next three years. Fortunately, its performance improved in the fifth year. The performance of firm B was deteriorating tremendously during the five years. In fact, Firm C, D and E all performed terribly in the fifth year. The reason is basically due to the global economic downturn in that year. To summarize, the DEA/AR model can obtain the most efficient DMUs with the consideration of experts' opinions on the importance of the factors. Table 13 also shows the potential improvements of the inefficient DMUs. For example, to become efficient, DMU A5 should refer to DMU B2, B3 and C4, and should decrease its selling expenses (I1) by 28.03%, increase general and administrative expenses (I2) by 4.24%, increase fixed assets (I3) by 21.66, increase research and development expenses (I4) by

14.89%, and decrease cost of goods sold (I5) by 18.60%. In addition, it needs to decrease its sales revenue (O1) by 0.14%, increase income before income taxes (O2) by 0.11%, and increase earnings per share (O3) by 0.11%. Also note that it may be very difficult for an inefficient DMU to become efficient when its improvement level is over 100%. However, the company can use the potential improvements reported in Table 13 to identify the directions for improving its efficiency. For example, DMU B5 is very inefficient with a score of only 0.0402. In order to be efficient, the firm needs to increase its sales revenue (O1) by 1156.15%, which is simply impossible for a firm to achieve in a short time. However, the firm can improve its performance by decreasing selling expenses (I1), general and administrative expenses (I2), fixed assets (I3), research and development expenses (I4), cost of goods sold (I5), and earnings per share (O3), while increasing sales revenue (O1) and income before income taxes (O2).

Table 13. Relevant results for AHP/DEA model.

DMU	Efficiency value	Rank	Reference set	Potential improvement %							
				I1	I2	I3	I4	I5	O1	O2	O3
A1	1	1	A1								
A2	1	1	A2								
A3	0.9503	10	A2, A4	47.25	−26.68	−24.92	−36.53	−22.47	19.23	−2.18	−16.98
A4	0.9431	11	A2, B3	51.52	−75.68	40.81	25.91	−45.93	28.57	12.91	−41.87
A5	0.9973	9	B2, B3, C4	−28.03	4.24	21.66	14.89	−18.60	−0.14	0.11	0.11
B1	0.6162	14	A1, A2	−79.42	−20.48	−91.33	−84.85	−27.68	83.89	−43.79	−35.91
B2	1	1	B2								
B3	1	1	B3								
B4	0.2831	19	A2, B3	−75.27	−66.94	−81.48	−77.61	−72.93	119.3	-46.96	−70.90
B5	0.0402	26	A1, E2	−96.14	−96.14	−95.87	−95.18	−96.2	1156.15	77.09	−95.39
C2	0.6296	13	D2, E2	−28.27	−78.49	−13.78	−49.50	−28.27	1178.05	5203.52	−28.85
C3	1	1	C3								
C4	1	1	C4								
C5	0.0594	25	A1, E2	−93.34	−95.90	−93.51	−84.97	−97.76	146.59	−47.78	−97.37
D2	1	1	D2								
D3	0.5513	15	A1, A2	−75.0	−24.11	−40.54	−68.47	−61.30	84.59	−27.30	−56.46
D4	0.1928	21	A1, A2	−95.09	−75.43	−75.66	−92.07	−84.09	119.15	−37.68	−80.33
D5	0.1695	23	A1, A2	−97.04	−73.86	−90.52	−89.35	−86.79	137.06	−53.16	−82.28
E2	1	1	E2								
E3	0.7040	12	A1, E2	−87.77	33.35	−73.30	−65.65	−68.04	93.86	−29.37	−63.6
E4	0.3773	17	A1, E2	−91.16	−31.85	−78.93	−85.65	−79.82	107.07	−29.34	−76.85
E5	0.1916	22	A1, E2	−84.6	−76.8	−82.29	−80.17	−84.97	126.29	−42.23	−82.77
F2	0.4570	16	A1, D2	−71.35	−85.24	−34.53	−46.11	−45.54	51.99	−6.16	−45.64
F3	0.3317	18	A1, A2	−89.28	−84.24	−66.23	−75.77	−48.33	67.45	−19.73	−47.13
F4	0.1939	20	A1, A2	−89.85	−87.88	−77.42	−83.59	−74.69	105.0	−33.54	−70.45
F5	0.1525	24	A1, D2	−83.66	−90.49	−83.66	−75.55	−86.35	303.26	−9.03	−83.37

5. Conclusions

With natural resource scarcity and environmental protection, solar energy represents a promise of clean and plentiful energy. Even though the PV market faces a rather volatile market cycle in response

to the global economic condition, it still has a tremendous growth potential, and the firms that have a solid foundation in the aspects such as technology and finance can survive and lead the market in the future. Therefore, a good performance evaluation of firms is essential for judging the success or failure of a business. While there are abundant works on the analysis of various industries, including the PV industry, many of them are industry-based and qualitative-based. This research develops an AHP/DEA model to assist the evaluation of the performance of PV firms and empirically tests the applicability of the proposed model. The proposed model takes into account the opinions of experts about the importance of the factors by adopting AHP to set the ARs of the weights of the factors, and DEA is applied to evaluate the performance of the firms in different years. After the analysis is performed using the proposed model, the findings can help the firms determine their efficiencies in the market and provide directions for future improvements in business operations.

In the case study, research and development expenses and cost of goods sold are the most important input variables, as assessed by the experts. Such results are consistent with the current condition of the PV industry, i.e. high production cost with low PV conversion efficiency. Firms, in order to compete successfully in the industry, need to lower their production cost and must achieve R&D goals with limited expenses. Among the output variables, income before income taxes and earnings per share are the most important factors. This is basically true for all for-profit organizations. Firms need to make decent profit, and they definitely need to concern with the shareholders' welfare.

When adopting the conventional DEA, 19 out of 26 DMUs are found efficient in the case study. This is mainly due to the attribute and also a shortcoming of DEA that a DMU is efficient if it performs the best in at least one single input or output. Therefore, these efficient DMUs may not perform very well in other factors. However, in assessing whether a firm is successful or not, various factors must be considered simultaneously. Each factor should have a range of importance when calculating the overall performance of the firms. After incorporating the experts' opinions on the importance of the factors into the AHP/DEA analysis, the result shows that only 8 DMUs are efficient. Such an outcome is more reasonable in real practice.

In this study, we treat each firm in each year as a DMU. For future research directions, Malmquist index approach or window analysis may be incorporated with the AHP/DEA model to understand the performance trend of each firm. In addition, fuzzy set theory can be applied to the proposed model so that the ambiguity and uncertainty of experts' opinions can be considered.

Acknowledgements

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