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Integrating information of the efficient and anti-efficient frontiers in DEA analysis to assess location of solar plants: A case study in Iran

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Abstract

The solar photovoltaic (PV) energy is one of the most promising sources of energy, which has attracted many interests. It is potentially the largest source of energy in the world and is capable to mitigate greenhouse gas (GHG) emissions significantly in comparison with fossil fuels. Location optimization of solar plants can play a vital role to rise the efficiency and performance of the solar PV systems. In this regard, this study aims at evaluating different areas for solar plants according to a set of social, geographical and technical criteria through a data envelopment analysis (DEA) model. The proposed DEA model considers both information of the efficient and anti-efficient frontiers in order to rise discrimination power in DEA analysis. The proposed approach is evaluated and validated via studying a real case study in Iran. The extracted results reveal the usefulness and applicability of the proposed DEA model in choosing appropriate locations for solar plants.

Keywords: Data envelopment analysis, efficient frontier, anti-efficient frontier, photovoltaic, solar plant.

1-Introduction

In the last years, the requirement to implement energy sources that are substitute to fossil fuels, whose usage is the main reason of air pollution, climate changes and global warming, is becoming very prominent. Public and political consciousness, technological progression and environmental degradation are factors that, at the dawn of third millennium, open real outlooks for development of the so-called renewable energies. Renewable energies derive from limitless sources and consequently all come directly or indirectly from the sun, which is the most abundant and the most widely distributed renewable energy in the world. Specially, PV technology converts solar energy directly into electrical energy employing the PV effect (Desideri et al., 2012). The solar PV energy is taken into account as one of the most promising options for future energy. The following are its advantages: (1) large availability of solar energy; (2) no noise and substantial emissions realizing during the function phase; (3) little needs for freshwater sources for the goal

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of mirror washing and cooling; (4) application, where the power supply is not desirable and possible via network (5) high ability to mitigate GHG emissions; and (6) easy development of its grid system since fast implementation of PV plants.

However, solar PV energy has not still attained sufficient maturity and the high costs of PV systems in contrast to other electricity generation alternatives have until now hampered its rapid deployment (Bazilian et al., 2013; Chen et al., 2014). Therefore, great efforts must be performed for alleviating manufacturing costs and rising efficiencyin order to expedite the commercialization of the PV industry(Chen et al., 2014).

Large-scale PV installations, as one of the most important applications of solar energy,can play an important role in energy supply, especially in shiny and remote regions (Azadeh et al., 2011). One of the main needs for successful large-scale PV installations is determining the optimal locations in order to achieve higher returns and maximize the performance of solar PV systems. However, different factors are responsible in this problem, which make decision making a complex task (Jun et al., 2014; Sabo et al., 2016).Indeed, locations with higher solar radiation are not necessarily suitable for solar plants when other criteria are also considred(Sabo et al., 2016).Accordingly, different methods are utlized in the literatere to cope with this problem. In this sense,Kengpol et al. (2013) used Geographical Information System (GIS) method to specify the optimum site for a solar power plant. Likewise, they proposed a hybrid method of AHP and fuzzy logic for evaluating the selected alternatives. Sánchez-Lozano et al. (2016) applied a two-stage approach for selecting the best locations of solar PV farms. In the first stage, they utlized a GIS method to obtain the suitable locations. Then, a multi-criteria decision modelis exploited for evaluating the seleted alternative. Using a GIS method, Sabo et al. (2016) determined optimal sites for large-scale PV systems installation in Peninsular Malaysia. In addition, they derived accurate predictions from optimal sites for three other important parameters including carbon emission reduction, energy generation potential and installation capacity.

DEA, as a powerful optimization tool, is a mathematical model in order to assess the performance of homogeneous decision-making units (DMUs) according to theavailable data. This method is known as a non-parametric approach and it has been broadly exploited for the goal of specifying the locations of renewable energy facilities (see e.g., Azadeh et al. (2011),Azadeh et al. (2008)Yokota and Kumano (2013),Sueyoshi and Goto (2014),Babazadeh et al. (2015),Wu et al. (2016) and Babazadeh et al. (2016)). It is capable to conduct the complex nature of the relations between the multiple inputs and multiple outputs, whilst it does not need predetermined weights for the inputs and the output criteria. Furthermore, the normalizing of variable dimensions is unnecessary for the method in efficiency computation. Two significant early contributions in this issue are the works of Farrell (1957) and Charnes et al. (1978)**.** Hitherto, many applications and extensions of DEA models have been proposed based on the model presented by Charnes et al. (1978) that takes into account constant return to scale. In the literature, this model is known as the CCR model. Thereinafter, Banker (1984) developed this model by considering variable returns to scale, which the resulted model is known as the BCC model. Recognizing the production frontier, i.e., where DMUs will be regarded as efficient, is primary concept behind these classic DEA models. Likewise, through comparing those DMUs, which are not on the frontier, with their peerson production frontier, the other scores are also attained. Noteworthy, it is deemed that all the DMUs, which are on the frontier, have the same performance level as well as highest score. As mentioned before, one of the importantcharacters of the DEA models is that they do not need predetermined weights. Indeed, the weights of the criteria are decision variables and their values are specified by maximizing the efficiency scores. Nonetheless, this full flexibility may much decline the discrimination power of DEA models. The relational behind this is that too many DMUs may existon the frontier, which leads to alleviatethe performance ranking of DMUs. Thus, many scholars have tried to propose different methods with the aim of enhancing discrimination power of DEA models. These methods can be categorized into four classes as follows:

(1) Applying prior or preferential information from pertaining decision makers (Allen et al., 1997; Paradi et al., 2004; Thanassoulis et al., 2004; Zhang et al., 2009)

(2) Utilizing cross efficiency method and evaluating each DMU through both itself and other peers(Doyle and Green, 1994; Sexton et al., 1986)

(3) Employing super efficiency method, in which the DMU under evaluation, itself is excluded from the reference set and its efficiency is estimated with a linear fit of all other units (Andersen and Petersen, 1993; Banker and Chang, 2006; Banker and Gifford, 1988)
(4) Comparing the DMUs with good and bad references simultaneously(Shen et al., 2016; Sueyoshi and Goto, 2011)

In this study, we implement the methods of fourth group to evaluate different areas for solar plants according to a set of social, geographical and technical criteria. Unlike the methods of other mentioned groups, the main merit of these methods is that they are not limited to a specific issue and can be utilized in many problems (Shen et al., 2016). Indeed, the proposed DEA model using the information of both efficient and anti-efficient frontiers increases the discrimination power in DEA analysis. The application and usefulness of the proposed approach are validated and verified in a real case study in Iran. Likewise, some interesting managerial implications are extracted based on numerical results.

The remainder of this paper is structured as follows. In the next Section, the proposed DEA model for assessing the solar plants is explained in details. Section 3 proposes the studied case and addresses the considered criteria. Section 4 discusses the computational results and insights and finally concluding remarks and possible future research avenues are presented in section 5.

2-The proposed DEA model

In this section, we introduce the implemented DEA model, first proposed by Shen et al. (2016), for the goal of performance ranking of DMUs. It is worthy to note that each solar plant is considered as a DMU. Utilizing the distances to both efficient and the anti-efficient frontiers, the proposed DEA model aims to improve distinction power in DEA analysis. Indeed, the proposed approach applies the standard DEA model, presented by Charnes et al. (1978), and the inverted DEA model, presented by Yamada et al. (1994), to respectively trace the efficient and the anti-efficient frontiers. Afterwards, the obtained information are integrated employing an indicator. Graphical illustrations of the efficient and anti-efficient frontiers are represented in figure 1. From this figure, the best practice DMUs F, E, D and A are obtained by the standard DEA model. As such, the worst practice DMUs D, C, B and A are proposed by the inverted DEA model.

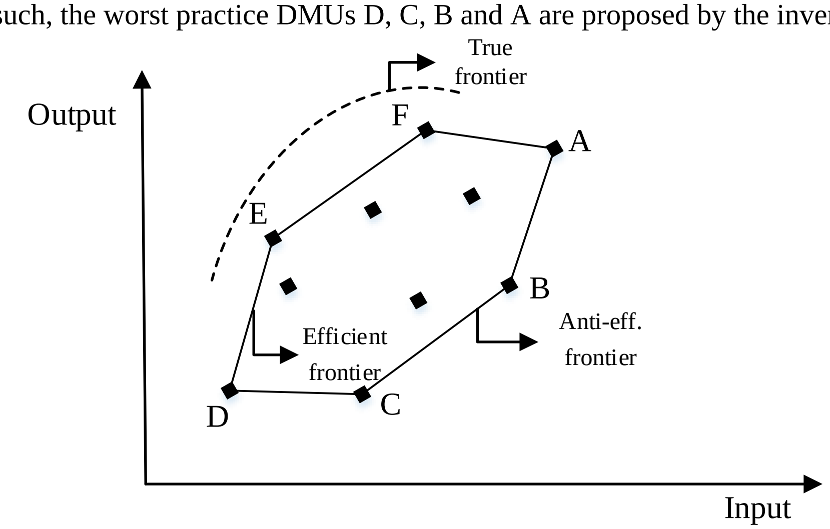

Fig 1. Graphical illustrations of the efficient and anti-efficient frontiers

The implemented approach is addressed as follow. To do so, the following indices, parameters and variables in problem formulation are first introduced.

Indices	
c, l	Index of candidate locations for solar plant (DMUs) $c, l = 1, \ldots, n$,
d	Index of inputs $d = 1, \ldots, g$,
e	Index of outputs $e = 1, \ldots, q$.
Parameters	
x_{dc}	Amount of input d for DMU c,
y_{ec}	Amount of output e for DMU c.
Variables	
θ_l	The measure of efficiency of DMU l,
λ_c	The dual weight assigned to all inputs and outputs of DMU "c".

The standard DEA model is given in model (1)-(4). As mentioned previously, this model traces the efficient frontier. In other words, the distances to good references are obtained by solving this model.

$$Min\, h_{bl}^* = \theta_l \tag{1}$$

$$\sum_{c=1}^{n} x_{dc}\lambda_c \leq \theta_l x_{dl}, \; d = 1, \ldots, g \tag{2}$$

$$\sum_{c=1}^{n} y_{ec}\lambda_c \geq y_{el}, \; e = 1, \ldots, q \tag{3}$$

$$\begin{aligned} &\lambda_c \geq 0, \; c = 1, \ldots, n \\ &\theta_l \text{ unconstrained.} \end{aligned} \tag{4}$$

In addition, the model (5)-(8) represents the inverted DEA model, which offers the distances to bad references.

$$Max\, h_{wl}^* = \theta_l \tag{5}$$

$$\sum_{c=1}^{n} x_{dc}\lambda_c \geq \theta_l x_{dl}, \; d = 1, \ldots, g \tag{6}$$

$$\sum_{c=1}^{n} y_{ec}\lambda_c \leq y_{el}, \; e = 1, \ldots, q \tag{7}$$

$$\begin{aligned} &\lambda_c \geq 0, \; c = 1, \ldots, n \\ &\theta_l \text{ unconstrained.} \end{aligned} \tag{8}$$

By solving the standard DEA model and the inverted DEA model for the l th DMU, the efficiency scores h_{bl}^*, h_{wl}^* are reached. Therefore, to obtain the efficiency scores for all DMUs, the models should be solved n times.

For the goal of calculating the distances to the good and bad references simultaneously and integrating the information of both efficient and anti-efficient frontiers, an indicator is computed as follows:

$$hi_l^* = \frac{\left[h_{bl}^* + (1 - \frac{1}{h_{wl}^*}) \right]}{2} \tag{9}$$

In the event that DMU_l is only on the efficient frontier (e.g., DMUs E and F), hi_l^* will be higher than $\frac{1}{2}$ and also if it is only on the anti-efficient frontier (e.g., DMUs B and C), $h_{wl}^* = 1$ and consequently $hi_l^* = \frac{h_{bl}^*}{2} \leq \frac{1}{2}$. Furthermore, if it is on both the efficient and anti-efficient frontiers (e.g., DMUs A and D), i.e., $h_{bl}^* = 1$ and $h_{wl}^* = 1$, then $hi_l^* = \frac{1}{2}$ .According to the presented descriptions, the approach can distinguish between the DMUs noting their positions on the frontiers.

3- Case study description

The proposed DEA model is utilized to evaluate different places for solar plants in Iran, which is one of the world's supplies of fossil energy. There are many motivations to implement the solar PV energy in Iran. Excessive use of fossil energy in Iran has created many environmental problems. One of the most prominent of these problems is the pollution of big cities in Iran such as Tehran, Esfahan, Tabriz and Mashhad. Moreover, Iran is also very talented to the use of the PV systems since the average annual solar radiation is very high in Iran and there are vast unused lands, which the systems can be installed in them. Moreover, by exploiting new energies, the country can enhance its energy diversity. Iran's government and parliament have also passed approvals and laws to encourage investment in renewable energies.

We introduce a set of social, geographical and technical criteria in order to assess different locations for solar plants. Locations with higher scores are more appropriate for establishing solar plants. It is worth noting that the criteria with increasing trend is considered as output critera and those with decreasing trend are implemented as input criteria. The considered criteria is explained in details as follows.

- **Distance of power distribution network**
  This criterion has a great impact on the amount of electrical pressure drop. In other words, if the distance between solar plant and grid is high, the pressure drop increases dramatically. Thus, less distance is more favorable and therefore it is as an input criterion.
- **Natural disasters occurrence**
  By this viewpoint, security of solar plant is taken into account. In fact, the combination of earthquake and torrent, as two important disasters, are defined as an input criterion.
- **Population density**
  Higher value of this criterion is more plus because the locations with more population, have a more electricity demand. As a result, this criterion has an increasing trend and it is regarded as an output indicator.
- **Topography feature**
  This matter considers characters and shape of the surface of the Earth. Specially, choosing rough and rocky lands for establishing solar plants is unreasonable or even inconceivable. This factor can play an important role to select solar plants and has as increasing trend. Hence, it is an output criterion.
- **Beam radiation**
  This criterion is defined as a proportion of solar radiation that is reached on the earth's surface. Assuredly, the locations with more annual radiation can yield more electrical energy. Consequently, this criterion is taken into account as an output indicator.

3-1- Data gathering

Gathering and estimating of parameter values have been done based on available historical data. Different locations, which are considered for solar plant centers, are given in table 1. Responsible organizations for input criteria of the proposed DEA model encompassing “natural disasters occurrence” and “distance of power distribution network” are repectively Disaster Management Organization (http://www.ndmo.ir) and Iran Grid Management Company (http://www.igmc.ir). Table 2 represents the collected data corresponding to input criteria for all DMUs. As such, the values of output criteria, i.e., “topography feature”, “population density” and “beam radiation” have been provided from Geological Survey of Iran (http://www.gsi.ir), National Statistical Center of Iran (http://www.amar.org.ir), and Renewable Energy Organization of Iran (http://www.suna.org.ir), respectively. The values of output criteria for DMUs are presented in table 3.

Table 1. Introducing the considered DMUs

DMU	City	DMU	City
DMU1	Ahwaz	DMU23	Lordegan
DMU 2	Amol	DMU24	Mahabad
DMU3	Anzali	DMU25	Malayer
DMU4	Arak	DMU26	Mashhad
DMU5	Ardebil	DMU27	Masjedsolieman
DMU6	Astara	DMU28	Nahavand
DMU7	Birjand	DMU29	Noshahr
DMU8	Bndarabass	DMU30	Oroomieh
DMU9	Bojnord	DMU31	Qom
DMU10	Bushehr	DMU32	Rasht
DMU11	Esfahan	DMU33	Sabzevar
DMU12	Ghazvin	DMU34	Sanandaj
DMU13	Gonbad-e Kāvus	DMU35	Sari
DMU14	gorgan	DMU36	Semnan
DMU15	Hamedan	DMU37	Share kord
DMU16	Ilam	DMU38	Shiraz
DMU17	Karaj	DMU39	Tabriz
DMU18	Kashan	DMU40	Tehran
DMU19	Kerman	DMU41	Yasuj
DMU20	Kermanshah	DMU42	Yazd
DMU21	Khoram Abad	DMU43	Zahedan
DMU22	Khoy	DMU44	Zanjan

Table 2. Values of input criteria for DMUs

DMU	Natural disasters occurrence	Distance of power distribution network	DMU	Natural disasters occurrence	Distance of power distribution network
DMU1	8.2	15	DMU23	17.2	31
DMU 2	13.2	28	DMU24	22.2	44
DMU3	15.3	39	DMU25	16.3	41
DMU4	5.2	17	DMU26	20.4	10
DMU5	20.4	39	DMU27	4.8	31
DMU6	21.2	46	DMU28	18.9	28
DMU7	12	17	DMU29	16.7	35
DMU8	14.9	18	DMU30	8.9	17
DMU9	20.3	51	DMU31	5.6	12
DMU10	8.7	16	DMU32	19.5	32
DMU11	8.3	15	DMU33	20.8	28
DMU12	14	22	DMU34	21.1	41
DMU13	14.1	15.2	DMU35	21.2	29
DMU14	19.8	43	DMU36	4.8	31
DMU15	3	15	DMU37	3.7	27
DMU16	5	18	DMU38	8.1	25
DMU17	5.6	10	DMU39	7.8	17
DMU18	8.3	10	DMU40	5.6	15
DMU19	12.9	15	DMU41	21.1	43
DMU20	3.2	15	DMU42	3.6	14
DMU21	5.1	25	DMU43	7.6	16
DMU22	8.9	21	DMU44	4.2	21

Table 3. The values of output criteria for DMUs

DMU	Topography feature	Population density	Beam radiation	DMU	Topography features	Population density	Beam radiation
DMU1	1349	2	1723	DMU23	1460	3	1541
DMU 2	843	1	1350	DMU24	1700	2	1430
DMU3	841	1	1300	DMU25	657	1	1420
DMU4	1237	2	1920	DMU26	1861	5	1692
DMU5	223	1	1340	DMU27	1359	2.5	1813
DMU6	241	1.5	1380	DMU28	970	1	1450
DMU7	1150	2.5	2062	DMU29	1200	2	1600
DMU8	1359	3	2101	DMU30	2000	2	1977
DMU9	550	2	1560	DMU31	1325	3	1853
DMU10	1255	3	1864	DMU32	451	2	1410
DMU11	1349	5	2064	DMU33	745	2	1550
DMU12	1200	2	1857	DMU34	1172	2	1893
DMU13	471	1.5	1560	DMU35	542	1	1400
DMU14	742	1	1380	DMU36	1236	3	1924
DMU15	1446	4	1853	DMU37	1030	1	1863
DMU16	1380	2	1960	DMU38	1105	5	2197
DMU17	1150	3	1806	DMU39	1317	5	1884
DMU18	911	3	2008	DMU40	1358	10	1835
DMU19	1262	3	2103	DMU41	741	1	1500
DMU20	1479	2.5	1899	DMU42	1596	4	2104
DMU21	1560	2	1964	DMU43	1757	3	2135
DMU22	1100	2	1750	DMU44	1358	2	1862

4-Results and discussions

The proposed algorithm for the purpose of obtaining corresponding scores, i.e., efficiency and anti-efficiency scores, is coded in General Algebraic Modeling System $(\text{GAMS}^{\circledR})$ software and the CPLEX solver is employed to solve the models. The overall procedure of the implemented algorithm is explained in figure 2. As it can be seen from figure 2, for all DMUs, the standard and the inverted DEA models are solved. Afterward, the proposed indicators are computed and pertaining ranking for each DMU is determined. In addition, all the empirical experiments are performed by a Pentium five-core 2.53 GHz computer with 4 GB RAM.

```
Input (x_dc : d = 1,...,g, c = 1,...,n; y_ec : c = 1,...,n)
For l=1 to number of DMUs{
        Solve the standard DEA model for DMU l;
        Obtain the amount of h*_bl;
        Solve the inverted DEA model for DMU l;
        Obtain the amount of h*_wl;
  Calculate the indicator hi*_l
}
Rank DMUs according to the obtained indicators;
```

Fig 2. Pseudo code of the implemented algorithm

The obtained efficiency scores and ranks of DMUs, acquired by standard DEA model, are illustrated in table 4. What is seen from this table is that some of DMUs have a same score and we cannot discriminate between them. For example, DMU#15(i.e., Hamedan), DMU#17(i.e., Karaj), DMU#26 (i.e., Mashhad), DMU#40 (i.e., Tehran) and DMU#42 (i.e., Yazd) obtain the same score equal to 1, which ranking between them is impossible. To increase discrimination power of the standard DEA model, the information of anti-efficient frontier is also determined. Table 5 represents the anti-efficient scores acquired by the inverted DEA model. Now, in order aggregate the information of both efficient and anti-efficient frontiers, the indictor proposed in equation 9 is calculated for the all DMUs. The obtained scores and ranks of DMUs are reported in table 6.

Table 4. Scores and rankings of DMUs obtained through the standard DEA model

DMU	h_{bl}^{*}	Rank	DMU	h_{bl}^{*}	Rank
DMU1	0.727	15	DMU23	0.374	29
DMU 2	0.281	34	DMU24	0.312	30
DMU3	0.203	39	DMU25	0.211	38
DMU4	0.728	14	DMU26	1.000	1
DMU5	0.194	41	DMU27	0.612	24
DMU6	0.176	44	DMU28	0.288	31
DMU7	0.641	21	DMU29	0.286	32
DMU8	0.635	23	DMU30	0.943	8
DMU9	0.186	43	DMU31	0.939	9
DMU10	0.670	19	DMU32	0.239	37
DMU11	0.829	11	DMU33	0.285	33
DMU12	0.466	28	DMU34	0.262	35
DMU13	0.511	26	DMU35	0.250	36
DMU14	0.188	42	DMU36	0.649	20
DMU15	1.000	1	DMU37	0.815	12
DMU16	0.715	17	DMU38	0.581	25
DMU17	1.000	1	DMU39	0.713	18
DMU18	1.000	1	DMU40	1.000	1
DMU19	0.745	13	DMU41	0.201	40
DMU20	0.981	7	DMU42	1.000	1
DMU21	0.639	22	DMU43	0.894	10
DMU22	0.499	27	DMU44	0.718	16

Table 5. The scores of DMUs obtained through the inverted DEA model

DMU	h_{wl}^{*}	DMU	h_{wl}^{*}
DMU1	3.239	DMU23	1.387
DMU 2	1.487	DMU24	1.000
DMU3	1.048	DMU25	1.033
DMU4	3.734	DMU26	1.288
DMU5	1.000	DMU27	1.949
DMU6	1.000	DMU28	1.121
DMU7	2.653	DMU29	1.478
DMU8	2.189	DMU30	3.409
DMU9	1.020	DMU31	5.091
DMU10	3.326	DMU32	1.120
DMU11	3.861	DMU33	1.153
DMU12	2.040	DMU34	1.379
DMU13	1.695	DMU35	1.000
DMU14	1.000	DMU36	2.069
DMU15	4.118	DMU37	1.593
DMU16	3.586	DMU38	2.929
DMU17	5.007	DMU39	3.694
DMU18	3.756	DMU40	4.078
DMU19	2.531	DMU41	1.000
DMU20	4.220	DMU42	5.010
DMU21	2.586	DMU43	4.331
DMU22	2.778	DMU44	2.949

Table 6. The scores and rankings of DMUs obtained through the proposed DEA model

DMU	hi_l^*	Rank	DMU	hi_l^*	Rank
DMU1	0.709	14	DMU23	0.327	29
DMU 2	0.304	31	DMU24	0.156	36
DMU3	0.124	38	DMU25	0.121	39
DMU4	0.730	11	DMU26	0.612	21
DMU5	0.097	42	DMU27	0.549	26
DMU6	0.088	44	DMU28	0.198	34
DMU7	0.632	18	DMU29	0.305	30
DMU8	0.589	23	DMU30	0.825	9
DMU9	0.103	40	DMU31	0.871	6
DMU10	0.685	16	DMU32	0.173	35
DMU11	0.785	10	DMU33	0.209	33
DMU12	0.488	27	DMU34	0.268	32
DMU13	0.461	28	DMU35	0.125	37
DMU14	0.094	43	DMU36	0.583	24
DMU15	0.879	3	DMU37	0.594	22
DMU16	0.718	13	DMU38	0.620	20
DMU17	0.900	2	DMU39	0.721	12
DMU18	0.867	7	DMU40	0.877	4
DMU19	0.675	17	DMU41	0.101	41
DMU20	0.872	5	DMU42	0.900	1
DMU21	0.626	19	DMU43	0.832	8
DMU22	0.570	25	DMU44	0.689	15

To validate and verify the obtained rankings by the proposed DEA model, a nonparametric measure namely Spearman's rank correlation method (Sheskin, 2003) is adopted.This method evaluates the positive correlation between the proposed sets of ranks, i.e., reached by the standard DEA model and the proposed DEA modelby applying the following measure:

$$\rho = \frac{6\sum_i d_i}{n\left(n^2 - 1\right)} \tag{10}$$

Note that d_i represents difference between ranks of the mentioned procedures for DMU i, and n denotes the total number of DMUs. In this regard, we test the null hypothesis $\mathbf{H_0}$ in contrast to the alternative hypothesis $\mathbf{H_1}$ as follows:

$\mathbf{H_0}$: Correlation between the ranks obtained by the proposed DEA model and the standard DEA model does not exist.
$\mathbf{H_1}$: A positive correlation between the ranks obtained by the proposed DEA model and the standard DEA model exists.

For this experiment, the confidence level (i.e.,$1-\alpha$) is considered 0.95. The Spearman's rank correlation coefficient and pertaining P-value are respectively obtained0.946 and 0.000. Since P-value is smaller than the value of α (i.e., 0.05), then the null hypothesis $\mathbf{H_0}$ is rejected and therefore it can be implied that a strong relationship between the ranks reached by the standard DEA model and the proposed DEA model exists. Overall, it can be concluded that the ranks reached by the proposed DEA model are compatible with the ones in the standard DEA model. That is, the obtained results by the proposed DEA model are verified. As such, figure 3 compares the scores acquired by the standard DEA model and the scores acquired by the proposed DEA model. It is clear that the proposed DEA model increases the difference between DMUs and consequently rankings between the DMUs are easily carried out. In other words, this highlights the validation of the results obtained by the proposed DEA model.

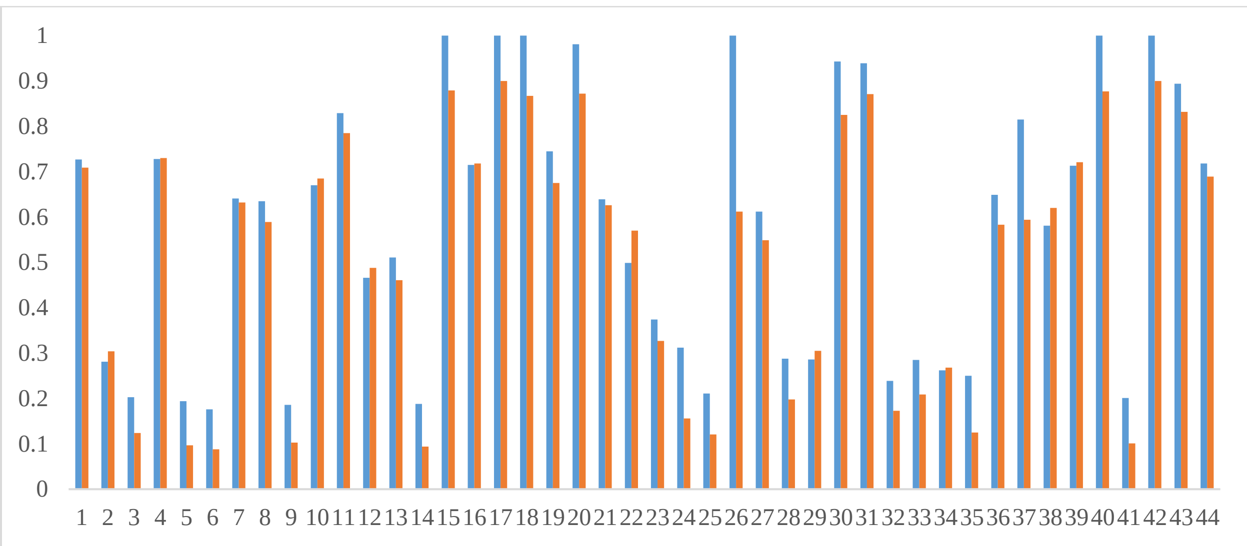

Fig 3. Comparison between the scores reached by the proposed DEA model and the standard DEA model

4-1- Sensitivity analysis

In this section, we aim to recognize the influential criteria on efficiency of DMUs using sensitivity analysis to help decision makers for the goal proposing appropriate strategies in decision-makings. To do this, the implemented algorithm explained in figure 2 is run 2 and 3 times to identify the influences of the input and output criteria, respectively. In other words, for studying the impact of each criterion, other criteria that are in a same class, i.e., input or output class, with considered criterion are omitted. For input criteria, the results obtained from this experiment is summarized in table 7. Additionally, the percentage of change in the efficiency scores, which is caused by omitting other criterion are represented in figure 4. The result shows that “natural disasters occurrence” are more effective than “distance of power distribution network”. It means that mangers and policymakers by selecting the safe and secure places for solar plants can improve efficiency of selected locations significantly. In conjunction of the output criteria, table 8 shows the related efficiency to each criterion by omitting other output criteria. Figure 5 also illustrates the importance of output criteria. What is evident from these results is that the most important output criterion is “population density”. Thus, by choosing location with higher “population density”, most return can be achieved.

Table 7. Technical efficiency of DMUs for each input criterion by omitting other criteria

	Input criteria		Considering all inputs simultaneously
	Distance of power distribution network	Natural disasters occurrence	
Average value of efficiencies	0.547	0.249	0.521

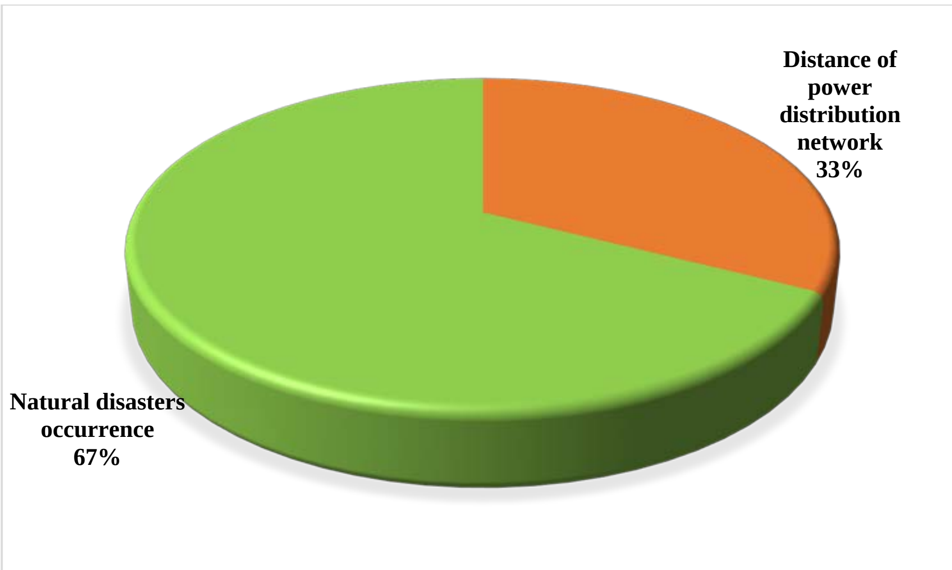

Fig 4. The importance of each input criterion in this special case study

Table 8. Technical efficiency of DMUs for each output criterion by omitting other criteria

	Output criteria			Considering all outputs simultaneously
	Beam radiation	Population density	Topography features	
Average value of efficiencies	0.547	0.249	0.507	0.521

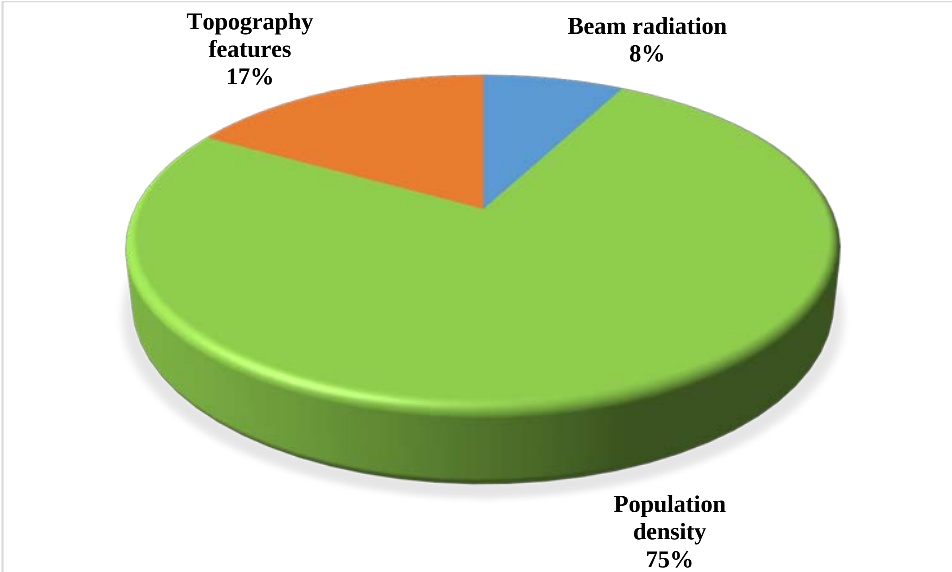

Fig 5. The importance of each output criterion in this special case study

5- Conclusion

Economic motivations, environmental concerns as well as energy security are major triggers for the development of renewable energy resources. Among the renewable energy resources, the solar PV energy has attracted many interests because it is potentially largest source of energy in the world and capable to mitigate GHG emissions significantly. Since the high costs of PV in contrast to other electricity generation alternatives, the solar PV energy has not still attained sufficient maturity. In order to bestead the commercialization of solar PV industry, great efforts must be performed for alleviating manufacturing costs and rising the efficiency. In this regard, this paper applies a DEA model to assess different sites for solar plants according to a set of social, geographical and technical criteria. Places that earn higher efficiency scores are more appropriate for establishing solar plants. The proposed DEA model is able to exploit simultaneously information of the efficient and anti-efficient frontiers. The matter contributes to rise the discrimination power in DEA analysis.

The application and usefulness of the proposed approach are studied in a real case study in Iran and some interesting insights are extracted. Specially, we showed (1) strong relationship between the ranks reached by standard DEA model and the proposed approach in this paper exists; (2) the proposed approach increases the difference between DMUs and consequently rankings between them are easily carried out; (3)“natural disasters occurrence” and “population density” are the most influential criteria among the input and output criteria, respectively.

Many extensions on the current paper could be pointed for future research. Proposing a multi-layer projection and applying geographic information system principles to specify the most appropriate areas for solar plants can be suggested as an interesting direction for future research. Likewise, the proposed DEA model can be developed under uncertainty of indicators.

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