EFFICIENCY RANKING OF TURKISH WIND POWER PLANTS BY USING DATA ENVELOPMENT ANALYSIS AND TOPSIS

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Abstract - Energy is an indispensable and ever-growing need in our daily lives. Due to the finite nature of our planet's resources, the importance of renewable energy sources is increasing in tandem. For example, wind power plants (WPPs) are growingrapidly in use. In this studywehave calculated the relative efficiencies of 22 Turkish WPPs. As these WPPs are of different sizes, an initial cluster analysis was performed using data collected in the 2014-2016 period. For each cluster, data envelopment analysis (DEA) was conducted to calculate the relative efficiencies of the WPPs. DEA-derived weightings were then used to rank WPPs by TOPSIS (Technique for Order Preference by Similarity to Ideal Solution). Finally, DEA and TOPSIS rankings were compared.

Keywords: Wind Power Plants, Data Envelopment Analysis, TOPSIS, Efficiency

1. INTRODUCTION

Energy availability is undoubtedly a key factor in the economic and social development of a country [1]. Turkey has been developing rapidly in many areas and, accordingly, energy consumption continues to increase with each passing year. However, Turkey's heavy dependence on foreign markets to meet its energy needs carries risks in terms of energy supply security. In this context, use of domestic resources, reduction of the share of natural gas in electricity generation, and increasing the share of renewable energy sources have been gaining traction as possible solutions [2].

Figure 1 shows the change in Turkey's foreign energy dependencyfor primary consumption in the 1990-2014 period, expressed as a percentageof total consumption [3]. This table shows that Turkey remains highly dependent on foreign energy.

Apart from the foreign energy dependency problem, the distribution of primary sources for Turkey's power generation in 2017 clearly reveals that fossil fuels are still dominant (fig. 2) [4]. It is widely accepted today that the use of fossil fuels leads to increased air and environmental pollution as well as climate change [3].

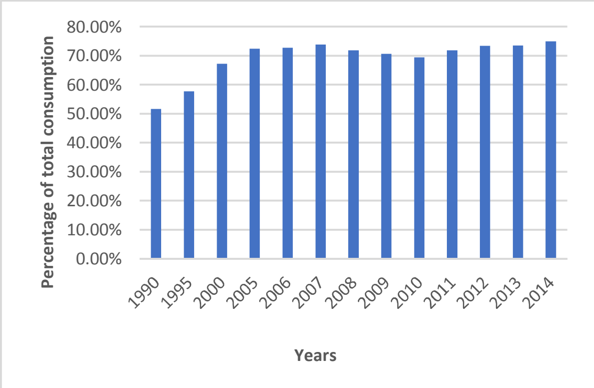

Fig. 1. Turkey's foreign dependency for primary energy consumption (1990-2014) expressed as a percentage of total consumption

The aforementioned problems constitute serious obstacles to the healthy development of the country. Therefore, future energy policy should encourage the production and consumption of renewable energy sources to reduce the use of fossil fuels and external dependency, as well as take into account environmental impacts. It should be noted thatTurkey is in a geographical region quite suitable for generation of renewable energy from almost all sources [5].

Turkey is making significant progress in the field of renewable energy. Final data for 2017 indicate that Turkey's total installed capacity is 85200 MW. Although hydropower plants make up most of the country's renewable energy sources, the total installed capacity of WPPs at the end of 2017 had reached 6872.1 MW. Figure 3 shows the change in the total installed capacity of WPPs in Turkey by year [4, 6].

Wind is horizontal air movement over the earth's surfacecaused by atmospheric pressure differences.Air moves from high-pressure to low-pressure regionsuntil the pressure is uniform [7]. Turkey's position between relatively cooler Europe and relatively warmer Asian and African systems leads to a wide temperature and climate gradient. Studies show that the Aegean, Marmara, and Eastern Mediterranean regions have high wind energy potential [8]. Turkey has an onshore wind potential of 48000 MW, assuming a wind speed above 7.0 m/s [9]. By this estimate, the total installed capacity in 2017 constitutes only 14.32% of this full potential.

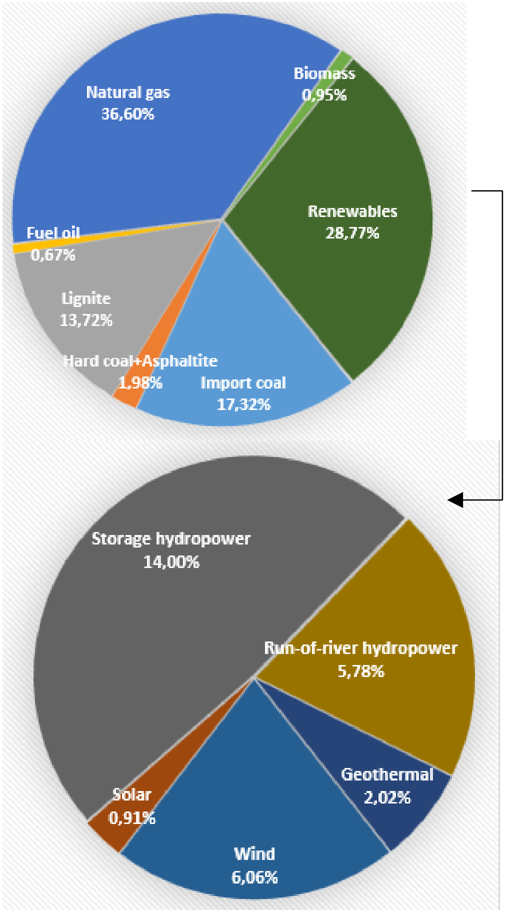

Fig. 2. Distribution of Turkey's primary power generation sources in 2017

The first commercial WPP in Turkey became operational in 1998 with 8.7 MW of installed capacity in Çeşme, İzmir. Subsequently, there was no significantdevelopment related to wind energy until 2006. However, with the enactment of the Renewable Energy Law No. 5346 in 2005, the demand for renewable energy sources increased and in parallel, an increase in the number of WPPs was observed [10].

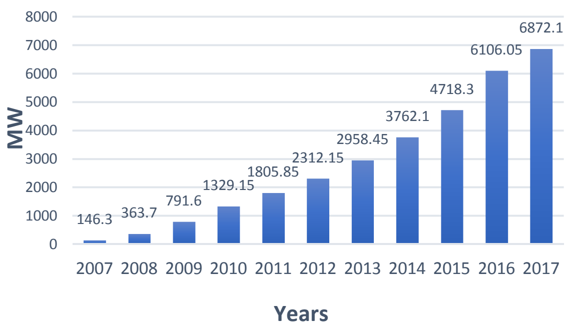

Fig. 3. Change in total installed capacity of Turkish WPPs in MW by year

2. LITERATURE REVIEW

Various studies in the literature have measuredthe relative efficiency of power plants using DEA. In Park and Lesourd's study, the efficiencies of 64 South Korean fuel power plants are measured using DEA and the stochastic frontier approach (SFA), where the inputs are fuel quantity, installed power, and total manpower. The output is the net electrical energy output [11]. Sarica and Or assess the operational performance of thermal power plants and renewable power plants by using two DEA models successively [12]. In their study, Barros and Peypoch use a two-stage procedure to analyze the technical efficiency of Portuguese thermoelectric power plants for the period 1996-2004. The DEA model in the first stage ranks the plants where the book value of physical assets, number of workers, and operational costs are inputs, and electricity production and maximum capacity are outputs. In the second stage, the Simar and Wilson procedure is used to bootstrap DEA scores [13]. In a two-step procedure, Barros analyzes the relative efficiencies of 25 Portuguese hydroelectric plants. The Malmquist productivity index is calculated first and a Tobit regression is then estimated using the efficient Malmquist score [14]. Sözen et al. assess the operational performance and the environmental performance of Turkish thermal power plants by applying two DEA models successively [15]. Liu et al. determine the efficiency of Taiwanese thermal power plants withhigh installed capacity for the period 2004-2006 usinga DEA approach. The model uses installed capacity, electricity consumption in the power plant, and heating value of fossil fuels as inputs, and net electricity produced as output [16]. Iglesias et al. measure the productive efficiency of a group of wind farms in Spainover the 2001-2004 period using both DEA and SFA. The inputs are installed capacity, number of full-time employees, and fuel; the only output is electricity produced [17]. Emre and Ömürgönülşen calculate the relative efficiency of WPPs in the Marmara region with a DEA model: installation and connection costs are inputs, with annual production, mean annual return, and return on investment as outputs [18]. Ömürgönülşen et al. measure the relative efficiency of WPPs in Turkey with DEA. The inputs are installation cost, average wind speed, and wind capacity factor, while outputs are meter capacity utilization rate and annual return [19].

3. DEA and TOPSIS

3.1 DEA

DEA is a technique based on linear programming. It incorporatesseveral entities called decision making units (DMUs) thatgenerate outputs from inputs. DEA measures the relative efficiencies of these DMUs for this activity. Essentially, it calculates a scalar measure of efficiency for DMUs having multiple inputs and outputs without preassigning weights or requiring an explicit functional relation between these inputs and outputs. A nonparametric approach, DEA creates a linear efficiency frontier consisting of the efficient DMUs and thus assesses the relative efficiency of all other DMUs. It measures the efficiency of each unit and identifieswhich DMUs act as peers if the unit under evaluation is not efficient [20, 21].

There are two common DEA models in the literature. The first one is known as the CCR model introduced by Charnes, Cooper and Rhodes [22]. The second one is the BCC model developed by Banker, Charnes and Cooper [23]. The former deals with constant return to scale (CRS) whereas the latter deals with variable return to scale (VRS). CRS means that if an activity(x, y) is feasible then the activity (kx, ky) is also feasible for every positive scalar k [24]. In other words, there is a proportional change in the outputs when the inputs are increased. This proportionality does not apply for VRS.

The ratio of the weighted sum of outputs to the weighted sum of inputs gives the relative efficiency measure of a DMU. It should be noted that this ratio is less than or equal to unity for each DMU [16].The CCR model in ratio form is given below [22,24,25]:

$$\max h_k = \frac{\sum_{r=1}^{s} u_{rk} y_{rk}}{\sum_{i=1}^{m} v_{ik} x_{ik}} \tag{1}$$

s.t.

$$\frac{\sum_{r=1}^{s} u_{rk} y_{rk}}{\sum_{i=1}^{m} v_{ik} x_{ik}} \leq 1; \quad j = 1,2, \dots, n$$

$$u_{rk}, v_{ik} \geq 0; \qquad r = 1,2, \dots, s \quad i = 1,2, \dots, m$$

where k is the considered DMU in the set of $j = 1,2, \dots, n$ DMUs; h_k the relative efficiency measure of the k-th DMU in the same set; y_{rk} the amount of output r of the k-th DMU; x_{ik} the amount of input i of the k-th DMU; y_{rj} the amount of output r of the j-th DMU; x_{ij} the amount of input i of the j-th DMU; u_{rk} the weight for output r in the solution of the model; v_{ik} the weight for input i in the solution of the model; m the number of inputs and s the number of outputs.

Because the objective function is fractional, the model (1) given above is not easy to solve. In practice, the dual of the linear model is used [25]:

$$\min \theta_k - \varepsilon\left(\sum_{i=1}^{m} s_{ik}^{-} + \sum_{r=1}^{s} s_{rk}^{+}\right) \tag{2}$$

s.t.

$$\theta_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_{ik}^{-} = 0; \qquad i = 1,2, \dots, m$$

$$y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} + s_{rk}^{+} = 0; \qquad r = 1,2, \dots, s$$

$$\lambda_j, s_{ik}^{-}, s_{rk}^{+} \geq 0 \qquad \forall i, j, r$$

In contrast to the CCR model, there is an additional convexity constraint in the BCC model, of which the dual form is given below [23]:

$$\min \theta_k - \varepsilon\left(\sum_{i=1}^{m} s_{ik}^{-} + \sum_{r=1}^{s} s_{rk}^{+}\right)(3) \tag{3}$$

s.t.

$$\theta_k x_{ik} - \sum_{j=1}^{n} \lambda_j x_{ij} - s_{ik}^{-} = 0; \qquad i = 1,2, \dots, m$$

$$y_{rk} - \sum_{j=1}^{n} \lambda_j y_{rj} + s_{rk}^{+} = 0; \qquad r = 1,2, \dots, s$$

$$\sum_{j=1}^{n} \lambda_j = 1$$

$$\lambda_j, s_{ik}^{-}, s_{rk}^{+} \geq 0 \qquad \forall i, j, r$$

This is solved for each DMU. As explained before, there is an efficiency frontier consisting of the efficient DMUs, and DEA assesses the efficiency of other DMUs relative to the efficient ones. This means that the efficiency scores are calculated by considering the distance of a DMU from this efficiency frontier: if this score is equal to unity, the DMU is efficient; if the score is less than unity, the DMU is not efficient.

Both CCR and BCC models are applied either in input-oriented (I) or output-oriented (O) fashion. An input-oriented model tries to minimize inputs subject to given output levels, and an output-oriented model tries to maximize the outputs subject to given input levels [25].

3.2 TOPSIS

Hwang and Yoon were the first to develop TOPSIS in 1981 [26]. This technique determines the best alternative by means of a compromise solution that has the shortest Euclidean distance from thepositive ideal solutionandthe farthestEuclidean distance from the negative ideal solution[27].

Seven steps of applying TOPSIS are listed below [28]:

1) A performance decision matrix $\boldsymbol{A}_{ij}$ is established.

$$\boldsymbol{A}_{ij} = \begin{bmatrix} a_{11} & a_{12} & \cdots & a_{1n} \\ a_{21} & a_{22} & \cdots & a_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ a_{m1} & a_{m2} & \cdots & a_{mn} \end{bmatrix} \tag{4}$$

2) By normalizing this decision matrix $\boldsymbol{A}_{ij}$, the matrix $\boldsymbol{R}_{ij}$ is obtained. $\boldsymbol{R}_{ij}$ consists of r_{ij} values calculated as follows:

$$r_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \quad i = 1,2, \dots, m \quad j = 1,2, \dots, n \tag{5}$$

$$\boldsymbol{R}_{ij} = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & \cdots & r_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix} \tag{6}$$

3) By weighting the columns of $\boldsymbol{R}_{ij}$, the matrix $\boldsymbol{V}_{ij}$ is obtained. $\boldsymbol{V}_{ij}$ consists of v_{ij} values calculated as follows:

$$v_{ij} = w_j r_{ij} i = 1,2, \dots, m \quad j = 1,2, \dots, n \tag{7}$$

$$\boldsymbol{V}_{ij} = \begin{bmatrix} v_{11} & v_{12} & \cdots & v_{1n} \\ v_{21} & v_{22} & \cdots & v_{2n} \\ \vdots & \vdots & \vdots & \vdots \\ v_{m1} & v_{m2} & \cdots & v_{mn} \end{bmatrix} \tag{8}$$

Here, w_j is the weight for the j-th criterion and$\sum_{j=1}^{n} w_j = 1$.

4) The positive ideal solution (A_i^{+})

$$A_i^{+} = \{(\max v_{ij} \mid j \in J), (\min v_{ij} \mid j \in J'), (i = 1,2, \dots, m)\} = \{v_1^{+}, v_2^{+}, \dots, v_n^{+}\} \tag{9}$$

and the negative ideal solution (A_i^{-})

$$A_i^- = \{(\min v_{ij} \mid j \in J), (\max v_{ij} \mid j \in J'), (j = 1,2,\ldots,m)\} = \{v_1^-, v_2^-, \ldots, v_n^-\} \quad (10)$$

are determined. Here, J is the set of criteria with positive effect and J' is the set of criteria with negative effect.

5) By using the m-dimensional Euclidean distance, D_i^+ and D_i^- are calculated. These are separation measures of each alternative from A_i^+ and A_i^- respectively. The calculation is as follows:

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2}, \quad i = 1,2,\ldots,m \quad (11)$$

$$D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2}, \quad j = 1,2,\ldots,n \quad (12)$$

6) The relative closeness value CC_i^+ is calculated as follows:

$$CC_i^+ = \left[\frac{D_i^-}{D_i^+ + D_i^-}\right]; \quad 0 \le CC_i^+ \le 1; \quad i = 1,2,\ldots,m (13)$$

7) The alternatives are ranked according to CC_i^+ value in descending order.

4. APPLICATION

In this study, we used a CCR-O model with two inputs and one output. Our reason for usingCCR-O model is to maximize the output level subject to the given input levels. The first input is annual average energy production of WPPs in MWh calculated by means of a Weibull distribution. Details of the calculations are given in Section 4.1. The second input is installed capacity of the WPPs in MW, and the output is the actual energy production of WPPs in MWh.

4.1 Data Preprocessing

Initially we chose 31 WPPs, the installed capacity of which remained unchanged and the data for which were available during the2014-2016 period. One input is the annual average energy production in MWh of the WPPs and the other input is the installed capacity in MW, as mentioned above.

The data for the installed capacity are available on the web sites of the Energy Market Regulatory Authority of the Republic of Turkey (EPDK) [29]and the Turkish Wind Energy Association (TÜREB) [30].

Below is the explanation of how the annual average energy production was calculated by means of a Weibull distribution.

Kinetic energy of airflow with a certain velocity and mass is.

$$E = \frac{1}{2}mv^2 \quad (14)$$

where m is the mass of airflow in kg and v is the velocity of airflow in m/s. Mass flow rate of airflow with a certain density through a cross-sectional area is

$$\dot{m} = \rho A v \quad (15)$$

where ρ is the air density in kg/m^3 and A is the cross-sectional area in m^2. Making use of the equations (14) and (15) the energy per unit time, power can be calculated as

$$P = \frac{1}{2}\rho A v^3 \quad (16)$$

where A now represents the swept area of turbine. Instead of utilizing the equation in (16), we opted for the the wind speed probability density function, which is usually a Weibull distribution [17].

The Weibull distribution is

$$f(v) = \frac{k}{c}\left(\frac{v}{c}\right)^{k-1} \exp\left[\left(-\frac{v}{c}\right)^k\right] \quad (17)$$

Here, c represents scale factor in m/s, k represents shape factor [31].

For the calculation of annual average energy production, the Weibull parameters at turbine tower height are required. However, the data we received from the General Directorate of Energy Affairs were for the scale and shape factors at 100 m. For this reason, we adjusted these c_a and k_a values determined at anemometer height to the tower height z by using the following relationships[32]:

$$c(z) = c_a(z/z_a)^n \quad (18)$$

$$k(z) = k_a[1 - 0.088\ln(z_a/10)]/[1 - 0.088\ln(z/10)] \quad (19)$$

where z and z_a are in m and the power law exponent $n$is given by

$$n = [0.37 - 0.088\ln c_a]/[1 - 0.088\ln(z_a/10)] \quad (20)$$

The next step was to find out how many turbines are in operationat each WPP, which model they have, and how high they are. Normally, the power curve of turbines is given for the standard air density ρ = 1.225 kg/m^3. However, the air density at tower height differs from the standard. We therefore adjusted the power curve to the air density at tower height: first, we calculated the air density at tower height by using the following equation [33]:

$$\rho(z_2) = \rho(z_1)\exp\left(\frac{-(z_2 - z_1)}{H}\right) \quad (21)$$

where H=7,4 km. To adjust the power curve of turbines used in the WPP to the air density at tower height, we used the relationship[34]:

$$v_{site} = v_{std}\left(\frac{\rho_{std}}{\rho_{site}}\right)^{\frac{1}{3}} \quad (22)$$

Average power (expected value) can be calculated by using the equation

$$\bar{P} = \int_0^{\infty} P(v)f(v)dv \qquad (23)$$

where $P(v)$ is the adjusted power curve of the turbine.

Last but not least, $\bar{P}$ should be multiplied by the total hours in a year and availability. Assuming that a wind turbine has a lifetime of 20 years, we took the average availability for the first 10 years to be approximately 97% and 94% for the second ten years [35].

As for the outputs, the data are available on the website for the Energy Market Regulatory Authority of the Republic of Turkey.

4.2 Results

There is a key DEA requirementfor DMUs to be homogeneous. In our study, there are 31 WPPs with installed capacities designated as very large, large, medium, and low. To establish homogenous DMUs, we divided these 31 WPPs into clusters by applying cluster analysis [36]. We applied the average linkage method to cluster the WPPs, and as seen in the dendrogram in Table 1,ended up with two main clusters (Cluster A and Cluster B) with 11 WPPs each. Cluster A consists of WPPs with relatively low installed capacity and Cluster B consists of WPPs with medium installed capacity. We eliminated the last nine WPPs with relatively large and very large installed capacity because the clusters they formed were too small.

Cooper et al. emphasize that the number of DMUs (n) should be much greater than the total number of inputs and outputs ($m + s$). A rough rule is to have n equal to or greater thanmax{ m x s, 3 x($m + s$) }[37].

Since we have two inputs and one output in this study, max{ 2 x 1, 3 x(2 + 1) } = 9. We have two clusters each with 11 WPPs, so $n = 11$. Therefore, the condition for the DEA model to have an efficiency discrimination among DMUs in each cluster is fulfilled.

For each cluster (Cluster A and Cluster B)the DEA CCR-O model wasapplied for the years 2014-2016.

The two inputs and one output used in DEA constitute three criteria in TOPSIS, i.e. the first criterion is the calculated annual average energy production, the second criterion the installed capacity, and the third criterion the actual energy production. The steps for deriving weights from DEA for criteria in TOPSIS are as follows:

1) The CCR weights of every individual DMU for each input and output are written in vector form, i.e. there are $m + s$ vectors in total.
2) These vectors are normalized.
3) The average of elements in the normalized vectors are calculated.
4) These averages are scaled to sum 1.

The calculated weights are given in Table 2.

The weights calculated previously were assigned to the criteria. After following the steps mentioned in 3.2 the alternatives were ranked. Rankings resulting from both DEA and TOPSIS are given in Table 3.

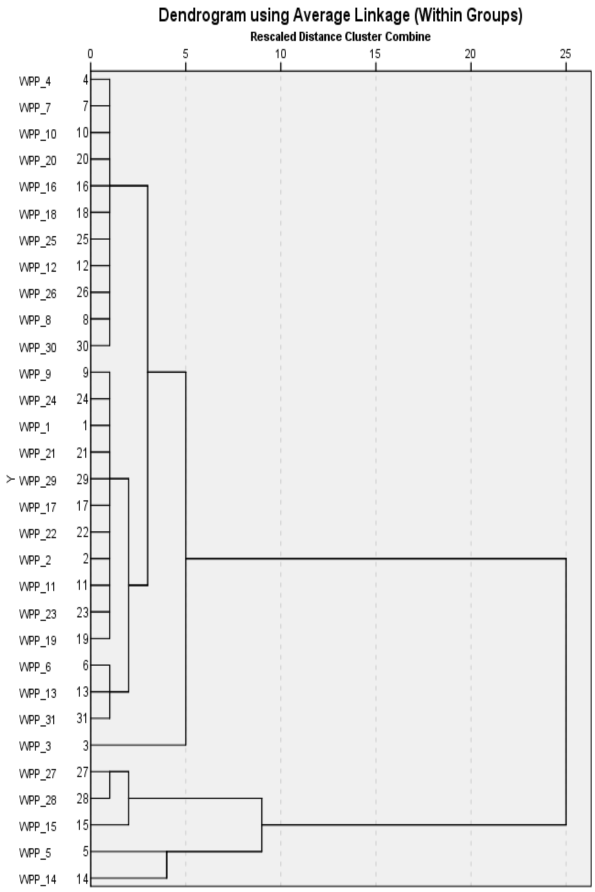

Table 1. Dendrogram of the cluster analysis applied

Cluster	Weights for year 2014			Weights for year 2015			Weights for year 2016		
	CR1	CR2	CR3	CR1	CR2	CR3	CR1	CR2	CR3
A	0.30	0.30	0.40	0.36	0.26	0.38	0.33	0.27	0.40
B	0.35	0.29	0.36	0.30	0.31	0.39	0.33	0.30	0.37

Table 2. Weights in TOPSIS derived by DEA (CR: Criterion)

CLUSTER A 2014 CRITERIA WEIGHTS 30% / 30% / 40%

DEA		TOPSIS	
WPP	RANK	WPP	RANK
WPP_4	1	WPP_30	1
WPP_30	1	WPP_4	2
WPP_12	3	WPP_12	3
WPP_8	4	WPP_8	4
WPP_7	5	WPP_7	5
WPP_20	6	WPP_26	6
WPP_26	7	WPP_16	7
WPP_16	8	WPP_20	8
WPP_25	9	WPP_10	9
WPP_10	10	WPP_25	10
WPP_18	11	WPP_18	11

CLUSTER A 2015 CRITERIA WEIGHTS 36% / 26% / 38%

DEA		TOPSIS	
WPP	RAN	WPP	RANK
WPP_4	1	WPP_4	1
WPP_8	1	WPP_8	2
WPP_30	3	WPP_30	3
WPP_12	4	WPP_7	4
WPP_20	5	WPP_26	5
WPP_26	6	WPP_20	6
WPP_7	7	WPP_12	7
WPP_10	8	WPP_10	8
WPP_18	9	WPP_16	9
WPP_25	10	WPP_18	10
WPP_16	11	WPP_25	11

CLUSTER A 2016 CRITERIA WEIGHTS 33% / 27% / 40%

DEA		TOPSIS	
WPP	RANK	WPP	RANK
WPP_4	1	WPP_4	1
WPP_16	1	WPP_30	2
WPP_30	3	WPP_16	3
WPP_12	4	WPP_7	4
WPP_8	5	WPP_8	5
WPP_7	6	WPP_12	6
WPP_26	7	WPP_26	7
WPP_10	8	WPP_10	8
WPP_25	9	WPP_20	9
WPP_18	10	WPP_25	10
WPP_20	11	WPP_18	11

Table 3. Rankings obtained by both DEA and TOPSIS

CLUSTER B 2014 CRITERIA WEIGHTS 35% / 29% / 36%

DEA		TOPSIS	
WPP	RANK	WPP	RANK
WPP_17	1	WPP_1	1
WPP_23	1	WPP_29	2
WPP_29	1	WPP_17	3
WPP_22	4	WPP_23	4
WPP_1	5	WPP_22	5
WPP_21	6	WPP_21	6
WPP_18	7	WPP_24	7
WPP_11	8	WPP_11	8
WPP_24	9	WPP_18	9
WPP_2	10	WPP_9	10
WPP_9	11	WPP_2	11

CLUSTER B 2015 CRITERIA WEIGHTS 30% / 31% / 39%

DEA		TOPSIS	
WPP	RAN	WPP	RANK
WPP_22	1	WPP_22	1
WPP_29	1	WPP_17	2
WPP_17	3	WPP_1	3
WPP_1	4	WPP_29	4
WPP_21	5	WPP_21	5
WPP_23	6	WPP_23	6
WPP_2	7	WPP_2	7
WPP_11	8	WPP_24	8
WPP_24	9	WPP_11	9
WPP_9	10	WPP_9	10
WPP_18	11	WPP_18	11

CLUSTER B 2016 CRITERIA WEIGHTS 33% / 30% / 37%

DEA		TOPSIS	
WPP	RANK	WPP	RANK
WPP_22	1	WPP_1	1
WPP_29	1	WPP_22	2
WPP_1	3	WPP_17	3
WPP_17	4	WPP_29	4
WPP_21	5	WPP_21	5
WPP_23	6	WPP_23	6
WPP_11	7	WPP_24	7
WPP_2	8	WPP_11	8
WPP_24	9	WPP_2	9
WPP_9	10	WPP_9	10
WPP_18	11	WPP_18	11

In order to test the similarity between the rankings obtained, we conducted Spearman's rank test for each group andyear. The hypotheses were as follows [38]:

H_0 : There is no correlation between the ranks of individual DMUs obtained by DEA and TOPSIS.

H_1 : There is a correlation between the ranks of individual DMUs obtained by DEA and TOPSIS.

As shown in Tables 4 - 9, there is a significant correlation between the ranks of individual DMUs obtained by DEA and TOPSIS.

Table 4. Spearman's rank test for Cluster A in 2014
Correlations

			DEA RANK	TOPSIS RANK
Spearman's rho	DEA RANK	Correlation Coefficient	1,000	,961**
		Sig. (2-tailed)	.	,000
		N	11	11
	TOPSIS RANK	Correlation Coefficient	,961**	1,000
		Sig. (2-tailed)	,000	.
		N	11	11

**. Correlation is significant at the 0.01 level (2-tailed).

Table 5. Spearman's rank test for Cluster A in 2015
Correlations

			DEA RANK	TOPSIS RANK
Spearman's rho	DEA RANK	Correlation Coefficient	1,000	,879**
		Sig. (2-tailed)	.	,000
		N	11	11
	TOPSIS RANK	Correlation Coefficient	,879**	1,000
		Sig. (2-tailed)	,000	.
		N	11	11

**. Correlation is significant at the 0.01 level (2-tailed).

Table 6. Spearman's rank test for Cluster A in 2016
Correlations

			DEA RANK	TOPSIS RANK
Spearman's rho	DEA RANK	Correlation Coefficient	1,000	,920**
		Sig. (2-tailed)	.	,000
		N	11	11
	TOPSIS RANK	Correlation Coefficient	,920**	1,000
		Sig. (2-tailed)	,000	.
		N	11	11

**. Correlation is significant at the 0.01 level (2-tailed).

Table 7. Spearman's rank test for Cluster B in 2014
Correlations

			DEA RANK	TOPSIS RANK
Spearman's rho	DEA RANK	Correlation Coefficient	1,000	,853**
		Sig. (2-tailed)	.	,001
		N	11	11
	TOPSIS RANK	Correlation Coefficient	,853**	1,000
		Sig. (2-tailed)	,001	.
		N	11	11

**. Correlation is significant at the 0.01 level (2-tailed).

Table 8. Spearman's rank test for Cluster B in 2015
Correlations

			DEA RANK	TOPSIS RANK
Spearman's rho	DEA RANK	Correlation Coefficient	1,000	,952**
		Sig. (2-tailed)	.	,000
		N	11	11
	TOPSIS RANK	Correlation Coefficient	,952**	1,000
		Sig. (2-tailed)	,000	.
		N	11	11

**. Correlation is significant at the 0.01 level (2-tailed).

Table 9. Spearman's rank test for Cluster B in 2016
Correlations

			DEA RANK	TOPSIS RANK
Spearman's rho	DEA RANK	Correlation Coefficient	1,000	,920**
		Sig. (2-tailed)	.	,000
		N	11	11
	TOPSIS RANK	Correlation Coefficient	,920**	1,000
		Sig. (2-tailed)	,000	.
		N	11	11

**. Correlation is significant at the 0.01 level (2-tailed).

5. CONCLUSION

The global demand for energy is continually increasing. While different means of energy production remain available, renewable energy isarguably the mostpromising from the standpoint of sustainability and mitigation of environmental impact. Windconstitutes a key renewable energy source of ever-growing importance. In this study, we have evaluated WPPs —in wide use globally— with respect to efficiency using the DEA technique.

Multi-criteria decision making (MCDM) techniques have been developed to make various decisions in daily life. In cases where there are multiple criteria that are often conflicting with each other, MCDM techniques help the person to scan, prioritize, rank, or select among finite decision alternatives[26]. Prioritizing means that some criteria play more important roles than others, which is apparent in the weights assigned to these criteria. Various criteria exist for weighting methods. TOPSIS is a very frequently used MCDM technique in which weights are assigned to criteria to rank the alternatives and determine the best.

In this study, weights used in TOPSIS were derived from DEA. The derivation procedure for the weights is explained in section 4.2. The rankings obtained by DEA and TOPSIS techniques were compared, and it was found that there is a significant correlation between the ranks of individual DMUs obtained by DEA and TOPSIS.

There is no study in the literature for WPP efficiency determination that combines DEA and TOPSIS techniques. Therefore, our study provides a new approach for ranking WPPs by using these two techniques.

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