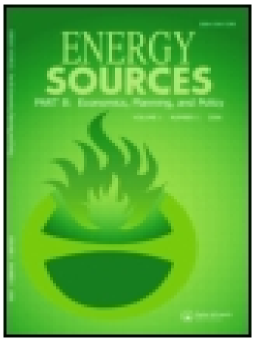

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Evaluation of sustainable energy performance for OECD countries

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ABSTRACT

This study aims to evaluate the sustainable energy performance of 36 OECD (Organization for Economic Cooperation and Development) countries. The sustainable energy performance evaluation of the countries was made with linear programming-based "DEA (Data Envelopment Analysis)" and multi-criteria decision-making-based "PROMETHEE (The Preference Ranking Organization Method for Enrichment Evaluation)". Spearman Correlation Coefficients were calculated for the relationships between the rankings obtained from all methods. According to the Spearman's Rank Correlation Coefficients (R) calculated for the performance rankings of OECD countries, the relations between all rankings of OECD countries were positive moderate (R = +0.6952) and positive high (R = +0.7959; R = +0.8919). The novelty of this article is to verify that DEA models and PROMETHEE technique, which are different from each other in terms of structure, algorithms, and basic purposes, can be used as an alternative performance evaluation tool.

KEYWORDS

Sustainable energy; performance evaluation; data envelopment analysis (dea); promethee method; OECD countries

1. Introduction

Energy is one of the basic inputs of production that plays an important role in the economic, sociocultural, and political progress of countries. The development and implementation of energy policies, which can balance the energy supply and demand, are becoming a strategic issue, especially for energy-dependent countries (Uludag and Dogan 2018). The need for energy is increasing day by day with the population, industrialization, and economic growth all around the world (Sharma et al. 2019).

Today, nonrenewable energy sources, external dependence on nonrenewable energy sources, the security of supply, and global warming are the most fundamental global issues (Anwar et al. 2020; Sadorsky 2009). Many countries in the world are in search of alternative energy sources to solve all these issues. Renewable energy, which replaces nonrenewable energy, also reduces countries' dependence on the energy exporting countries. Renewable energy is produced from natural resources that are constantly renewed and are harmless environmental conditions (Gokgoz and Guvercin 2018). Energy obtained from renewable sources is an important element of sustainable development. The use of renewable energy means both achieving higher economic growth and keeping the environment clean and healthy for present and future generations (Aceleanu et al. 2017). As new productive sectors require a more qualified workforce and high technology, renewable energy will create environmentally friendly economic growth and sustainable development (Cerqueira, Soukiazis, and Proença 2020).

The International Energy Agency (IEA) estimates the consequences resulting from the depletion of energy resources that cannot be renewed regularly. The recently envisaged exhaustion has been linked to other economic activities, including the unbalanced distribution of limited energy sources, rapid

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population growth, and industrial development. Governments and other relevant stakeholders are concerned not only about the depletion of energy resources, but also about the destruction of biodiversity, destruction of forests, its effect on global warming, public health, and natural disaster (Adedoyin et al. 2020; Alola and Alola 2018; Edenhofer et al. 2011). The design of sustainable renewable energy systems requires socio-economic decoupling of the relevant decision-making process. The interactions of the participating actors (e.g. regional development, private economic interests, protection of the environment, building a market, etc.) occur along with relevant basic socio-economic features and indicators. It is important to successfully promote renewable energy systems (Polatidis and Haralambopoulos 2007).

The link between sustainability and renewable energy is evident in the literature. Mathematical modeling, multi-criteria decision-making, and data mining techniques are frequently used in this field. DEA and PROMETHEE techniques are two members of this approach, which are included in the methodology adopted in this study. DEA is a non-parametric approach that can be widely used to evaluate the relative efficiency of Decision-Making Units (DMUs) by considering multiple variables. PROMETHEE is a multi-criteria decision-making technique used to evaluate alternatives according to the determined decision criteria. There are several studies in the literature on the use of renewable energy and the measurement of sustainable energy performance.

For instance, the energy efficiency in GDP for China's 29 regions using Data Envelopment Analysis (DEA) was examined (Hu and Wang 2006). The effects of renewable energy on the efficiency of macroeconomic techniques in 45 countries that are OECD members and not OECD members were examined with three inputs and one output using the DEA approach to compare the effectiveness of technology at the country level (Chien and Hu 2007). Honma and Hu (2008) analyzed regional energy efficiency on the economic growth of 47 Japanese regions using DEA for the period 1993–2003 (Honma and Hu 2008). In another study, the Malmquist index was used to examine the change in energy efficiency in Chinese regions between 2000–2004 and it was found that China's total factor energy efficiency decreased by an average of 1.4% annually (Chang and Hu 2010). Woo et al. (2015) examined the environmental efficiency scores of 31 OECD countries in renewable energy. DEA was used as a non-parametric methodology to evaluate environmental efficiency with multiple parameters (input and output). Labor, capital and renewable energy supply were determined as input, GDP, and carbon emissions were determined as output. Then, they used the Malmquist efficiency index to evaluate the dynamic environmental efficiency of renewable energy (Woo et al. 2015). The Sustainable Energy Index (SEI) for 109 countries in the period 2005–2010 was established and the countries with the best sustainable energy performance were determined among the three country groups using the Malmquist index (Wang 2015). Alidrisi and Al-Sasi (2017) used the TOPSIS technique to rank the energy policies of G20 countries that contribute to a sustainable economy. Their study aimed to give a clearer idea of the aspect that should be considered when formulating a future energy policy (Alidrisi and Al-Sasi 2017). In another study, the renewable energy performance of OECD and BRICS countries over the period 2009–2013 was evaluated using DEA and Malmquist Productivity Indexes (Sozen and Karik 2017). Zurano-Cervelló et al. (2019) proposed a new approach to compare and optimize electricity production and consumption according to sustainability criteria and implemented the proposed approach for 28 EU members. Their approach has included combining life cycle assessment, DEA and meticulous mathematical programming tools in three main steps (Zurano-Cervelló et al. 2019). In a recent study, Vavrek and Chovancová (2019) made a quantitative evaluation of the economic and environmental performance of EU countries in sustainable energy using the TOPSIS technique, one of the MCDM methods, where they have used weighted criteria with the Variance Coefficient (VC) (Vavrek and Chovancová 2019). Solangi et al. (2019) proposed a methodology based on Strengths, Weaknesses, Opportunities, and Threats (SWOT), AHP, and Fuzzy TOPSIS to evaluate sustainable energy strategies in energy planning. They used SWOT analysis to determine main and sub-criteria using weighted criteria with AHP and ranked sustainable energy strategies with Fuzzy TOPSIS (Solangi et al. 2019). Neofytou et al. (2020) highlighted areas of improvement for 14 countries with different profiles and levels of progress toward sustainable energy. In order to support policymakers to design a more environmentally friendly economy, they ranked countries using PROMETHEE II and AHP methods from the perspective of decision analysis (Neofytou et al. 2020). A multi-criteria decision-making framework based on the Triple Bottom Line principles and AHP methodology in sustainable supply chain development for the renewable energy sector was also proposed by the researchers (Mastrocinque et al. 2020). Wang, Xu, and Solangi (2020) used SWOT analysis to evaluate internal and external factors affecting renewable energy technologies, which play an important role in sustainable development. Technologies were evaluated with Fuzzy AHP after the criteria were determined (Wang, Xu, and Solangi 2020). Ibrahim and Alola (2020) offered an efficiency calculation approach for MENA countries to analyze the efficiency of fossil energy and renewable energy for economic development and environmental sustainability. DEA has been used to estimate traditional and renewable energy efficiency put on multiple networks (Ibrahim and Alola 2020). In another study, a multi-criteria decision-making model for the design of energy efficiency policies in Greece by selecting the most effective measures for sustainable development using a new model was proposed, and a sensitivity analysis was performed based on the combination of PROMETHEE and SIMOS methods (Neofytou et al. 2020). Phillis, Grigoroudis, and Kouikoglou (2020) evaluated the sustainability of national energy systems of 43 European countries using the PROMETHEE method; then, they made a sensitivity analysis for the main parameters of this method (Phillis, Grigoroudis, and Kouikoglou 2020). In a recent study, a new framework to evaluate renewable energy from a sustainable development perspective was proposed, to contribute to the renewable energy management. Network Analysis Process (ANP) was used to determine the weight of each criterion. To quantitatively evaluate renewable energy alternatives, the success of the methods has been investigated by using multi-criteria decision-making (MCDM) methods such as WSM, TOPSIS, PROMETHEE, ELECTRE and VIKOR (Li, Li, and Guo 2020). The main topics, methods and the origin of the sustainable energy studies reviewed in this section are summarized in Table 1.

In this study, DEA and PROMETHEE methods were used to investigate whether the steps taken by OECD countries on sustainable energy are effective and to compare the sustainable energy performances of these countries. Each of the OECD countries was modeled as “DMU” for DEA and “Alternative” for PROMETHEE. Finally, the energy sustainability performance rankings of the OECD countries obtained were examined together. Energy sustainability performance rankings were selected based on the sustainability criteria. When the studies on the subject in the literature were examined, it was seen that similar methods were used when hybridizing more than one method (AHP, TOPSIS, etc., or only DEA). DEA is a relative efficiency analysis method and is based on “Linear Programming”. PROMETHEE method is one of the “Multi-Criteria Decision-Making Methods”. The innovative aspect of this study was to reveal that these two methods, which are included in different analysis method groups, can be used for the same purpose and to analyze to what extent the methods support each other. In order to use methods used for different purposes for the same purpose, some assumptions should be made. In the study, it is aimed to obtain the relative efficiency of the sustainable energy performance of OECD countries with DEA models. At the same time, a performance ranking has been reached with DEA models. A performance evaluation was made with the PROMETHEE method from the decision analysis perspective. Analyzing the relationship between the performance rankings to be obtained from the methods used is the main purpose of the study.

2. Material and methods

The analysis made in this study consists of three stages. These stages are given as follows:

(i) The effectiveness of OECD countries was examined, and country rankings were obtained with the DEA Models.
(ii) PROMETHEE method was used from the perspective of decision analysis.
(iii) Energy sustainability performance rankings obtained from different methods were examined.

Table 1. Literature review.

Focus topic for Sustainable Energy	Methods	Country	Reference
Energy efficiency in GDP	DEA	China	Hu and Wang 2006
Renewable energy efficiencies of OECD and not OECD countries	DEA	China	Chien and Hu 2007
The regional energy efficiency of 47 Japanese regions	DEA	Japan	Honma and Hu 2008
Examining the change in the energy efficiency of the regions of China by periods	Malmquist Index	China	Chang and Hu 2010
Review of the environmental efficiency scores of 31 OECD countries in renewable energy	Malmquist Index	Korea	Woo et al. 2015
Determining the Sustainable Energy Index for 109 countries	Malmquist Index	Singapore	Wang H., 2015
To rank the energy policies of G20 countries that contribute to a sustainable economy	TOPSIS	Saudi Arabia	Alidrisi and Al-Sasi 2017
Evaluation of OECD and BRICS countries' performance in sustainable energy	DEA, Malmquist Index	Turkey	Sozen and Karik 2017
To compare electricity production and consumption according to sustainability criteria for 28 EU members	DEA, Mathematical Programming	Spain	Zurano-Cervelló et al. 2019
Evaluation of EU countries' economic and environmental performance in sustainable energy	TOPSIS, Variance Coefficient (VC)	Czech Republic	Vavrek and Chovancová 2019
Evaluating sustainable energy strategies in energy planning	SWOT, AHP, Fuzzy TOPSIS	China, Pakistan	Solangi et al. 2019
Performance assessment for 14 countries with different levels of progress in sustainable energy	PROMETHEE II, AHP	Greece	Neofytou et al, 2020
Sustainable supply chain development for the renewable energy sector	Triple Bottom Line principles, AHP	United Kingdom	Mastrocinque et al. 2020
Evaluating renewable energy technologies that play an important role in the sustainable economy	SWOT, Fuzzy AHP	China	Wang, Xu, and Solangi 2020
Efficiency analysis of renewable energy in MENA countries for economic development and environmental sustainability	DEA	United Arab Emirates	Ibrahim and Alola 2020
Selecting renewable energy efficiency policies in Greece and sensitivity analysis	PROMETHEE, SIMOS	Greece	Neofytou et al., 2020
Evaluating the energy sustainability performance of 43 European countries	PROMETHEE	Greece	Phillis, Grigoroudis, and Kouikoglou 2020
Evaluation of renewable energy alternatives from a sustainable development perspective	ANP, WSM, TOPSIS, PROMETHEE, ELECTRE, and VIKOR	China	Li, Li, and Guo 2020

2.1. DEA models

DEA is an efficiency assessment method that allows using inputs and outputs that cannot be compared with each other. DEA was first described in the literature by Charnes et al. (Charnes, Cooper, and Rhodes 1978). This study was based on Farrell's seminal work on the measurement of productive efficiency (Farrell 1957; Visani and Boccali 2020). The objective of the DEA model is to maximize the ratio of weighted output to weighted inputs for decision-making units (DMUs). Coelli (1995) indicated that the DEA approach has two main advantages in estimating efficiency scores (Coelli 1995). One of them is no requirement for the assumption of a functional form to specify the relationship between inputs and outputs. Second, it does not require the distributional assumption of the inefficiency term (Tipi et al. 2009). DEA is a linear programming-based technique that has received much attention recently due to its distinct advantages over traditional methods for evaluating the relative efficiency of DMUs (Demirbag, Tatoglu, and Glaister 2009; Emrouznejad and Tavana 2014). In DEA, each linear programming model is solved separately for DMUs. These solutions are generally obtained from software developed for DEA (Akgobek et al. 2015).

The first basic models developed for DEA are CCR models based on constant return assumption and developed by Charnes, Cooper, and Rhodes (Charnes, Cooper, and Rhodes 1978). These models were used in the first periods only to measure the relative effectiveness of the units involved in public efficiencies, and then their use in different areas became widespread. Another model variant developed for DEA was Banker, Charnes, and Cooper (BCC), and BCC models based on scale-based variable return (Banker, Charnes, and Cooper 1984). The BCC model is derived by adding a "convexity constraint" to the CCR model. The convexity constraint causes the effective frontier of the CCR model that connects the origin with the northwestern unit to pass through the origin, causing the BCC effective frontier to envelop the DMUs more tightly than the CCR effective frontier (Yenioglu and Ates 2019). DEA models are formed according to the constant and variable return assumptions in terms of return to scale, and the focus of analysis in the processes of the model can differ as input-oriented, output-oriented, and non-oriented (Charnes 1994). The DEA model is input-oriented if it is required to minimize the level of input without reducing the level of output. However, if the level of output is to be maximized without reducing the level of input, the DEA model is output-oriented (Khare, Villuri, and Chaurasia 2020; Ozcan 2014).

Efficiency score refers to the efficiency levels of DMUs in DEA. The efficiencies calculated using the CCR model depict the Overall Efficiency (O.E.) scores and those obtained from the BCC model depict the Pure Efficiency (P.E.) scores (Dutta, Jain, and Gupta 2020). The efficiency score is the ratio of the total weighted output to the total of the weighted inputs. In the input-oriented approach, DMUs with an efficiency score of "1" are effective and located on the border. Those not included in the effective border take values less than "1". These scores are calculated according to their distance from the effective frontier (Cooper, Seiford, and Zhu 2011). In the output-oriented approach, the effective DMUs take the value of "1" as the efficiency score; ineffective DMUs take value above 1. Since this score is obtained by dividing the weighted sum of the inputs by the weighted sum of the outputs, it is the opposite of the efficiency score in the input-oriented approach compared to the division (Soylemez 2015).

Since DEA is a relative efficiency analysis, it offers potential improvement opportunities for ineffective DMUs. Potential improvements show how much output must be increased in an input-oriented model for the DMU to achieve maximum efficiency, or how much input must be minimized in an output-oriented model. There is no way to change only one variable for effectiveness to achieve efficiency (except that only one variable appears as a possible improvement). There should be a change in the set of all variables that minimizes input variables and maximizes output variables (Lepchak and Voese 2020).

In this study, four different DEA models were applied in terms of being input and output-oriented and the return to the scale is constant or variable. The assumption in this matter is left to the decision-makers' choice. For OECD countries, if outputs are to be maximized without changing the input

Table 2. CCR models (Atan and sahin 2017; Kumar and gulati 2014; Luptáčik 2010; Ozden 2008).

CCR Models	
Input-Oriented	Output-Oriented
Objective Function $\max \sum_{r=1}^{s} u_r y_{ro}$ Restrictive Conditions $\sum_{r=1}^{s} u_r y_{rj} - \sum_{i=1}^{m} v_i x_{ij} \leq 0; j = 1, 2, ., n \sum_{i=1}^{m} v_i x_{io} = 1 u_r \geq 0; r = 1, 2, \ldots, s v_i \geq 0; i = 1, 2, \ldots, m$	Objective Function $\min \sum_{i=1}^{m} v_i x_{io}$ Restrictive Conditions $\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0; j = 1, 2, ., n \sum_{r=1}^{s} u_r y_{ro} = 1$ $u_r \geq 0; r = 1, 2, \ldots, s v_i \geq 0; i = 1, 2, \ldots, m$

u_r= weight given to output by DMUo, v_i= weight given to input by DMUo,
y_{ro} = produced output by DMU_0, x_{io}= used input by DMUo, y_{rj}= produced output by DMU_j, x_{ij}=used input by DMU_j, n = number of DMU

variables determined in sustainable energy, the output-oriented DEA model can be used. Otherwise, an input-oriented DEA model can be used. In the same logic, if the return to scale is constant, the CCR model can be preferred; otherwise, the BCC model can be preferred. In this study, four "basic" DEA models have been studied in terms of scenarios that decision practitioners may encounter. Super-efficiency models were used for four basic DEA models. The reason why the super-efficiency model is used in this way is that it can also provide rankings for effective DMUs.

2.1.1. The CCR model

The CCR model assumes that all DMUs in the analysis operate on an optimum scale that provides constant returns to scale (Fancello, Carta, and Serra 2020). The input-oriented CCR model is the DEA model that investigates how much the input amount should be reduced to reach the current output level by keeping the output level constant. The output-oriented CCR model is the model that investigates how much the output composition should be increased to achieve this input level by keeping the input level constant. The difference between the output-oriented CCR model and the input-oriented model is that the ratio of weighted input to weighted output is minimized (Charnes et al. 1997; Guler, Kandemir Yerel, and Acikkalp 2020). Mathematical representations of the CCR models are given in Table 2 (Taskopru 2014). In these models, s is the number of outputs, m is the number of inputs and n is the number of DMUs.

2.1.2. The BCC model

The BCC model is the proposed DEA model to deal with situations where the proportionality between input and output variables is not constant across the efficient frontier. A variable return occurs according to the scale (VRS) frontier **(de** Mello et al. 2013). BCC model is a DEA model based on technical efficiency rather than O.E. in the CCR model and assumes variable returns to scale. The efficiency limit defined by the CCR model reveals constant returns to scale. As a different version of the CCR model, Banker et al. proposed a BCC model that adds the $\sum^{\lambda_j} = 1$ constraint (Ervural, Zaim, and Delen 2018; Li 2020). Mathematical representations of the BCC models are given in Table 3. In these models, s is the number of outputs, m is the number of inputs and n is the number of DMUs.

2.1.3. Super efficiency model

A recommended method for ranking effective DMUs within Data Envelopment models is the Super-efficiency model (SEM) developed by Andersen and Petersen (Andersen and Petersen 1993). The super-efficiency model, which allows effective DMUs to score more than 1, can rank effective DMUs, and produces the same result as classic DEA models for non-effective DMUs (Ekiz and Tuncer Sakar 2020). In the SEM, a decision-making unit is compared with the linear combination of all other DMUs in the relevant DEA model. The examined decision-making unit is excluded from the evaluation by keeping it separate from the reference set. Thus, while maintaining the efficiency scores of the effective DMUs, the maximum rate of increase is obtained for the input variables of efficient DMUs. DMUs are ranked from large to small according to their efficiency score (Ervural, Zaim, and Delen 2018). In the SEM, the constraint included in the DEA model and ensuring the efficiency scores to be maximum 1 is not included in the model created for the DMU to be analyzed (Ozveri and Kabak 2018). There is a constraint that the weights of input and output variables are greater than a coefficient (Ɛ). The solution is made by including the "$u_r and\, v_i \geq \varepsilon$" constraint in all other traditional DEA models (CCR and BCC models). Also, package programs include a super-efficiency model plug-in for each traditional DEA model.

The SEM has a similar function formula with the CCR model (Yang et al. 2015). The technique changes the constraint from CCR models to enable an efficient unit to achieve an efficiency score that is greater than or equal to 1. All traditional DEA super-efficiency models contain "j≠o" in addition to the constraints (Bagherikahvarin and De Smet 2016).

The efficiency index is θ = 1, which makes it impossible to further evaluate the effectiveness of DEA. Therefore, the use of an SEM allows for a more in-depth production efficiency ranking of all DEA

Table 3. BCC Models (Atan and Sahin 2017; Kumar and Gulati 2014; Luptáčik 2010; Ozden 2008).

BCC Models	
Input-Oriented	Output-Oriented
Objective Function max $\sum_{r=1}^{s} u_r y_{ro} + u_o$ **Restrictive Conditions**	**Objective Function** min $\sum_{i=1}^{m} v_i x_{io} + v_o$ **Restrictive Conditions**

u_r= weight given to output by DMUo, v_i= weight given to input by DMUo,
y_{ro} = produced output by DMUo, x_{io}= used input by DMUo, y_{rj}= produced output by DMU_j, x_{ij}=used input by DMU_j, n = number of DMU

effective DMUs (Shuai and Fan 2020). The most important point that distinguishes the SEM is that it can more accurately reflect the differences between active DMUs and provide a precise ranking (Hong and Jeong 2020).

2.2. PROMETHEE method

The PROMETHEE method is one of the decision-making techniques first developed by J.P. Brans in 1982. In the method based on ranking logic, the aim is to determine the most appropriate result among the alternatives based on the criteria (Aladag et al. 2018). The PROMETHEE method is a multi-criteria decision-making method that uses the transition principle to order alternatives due to its ease of use and less complexity. In the method, binary comparisons are made to rank the alternatives according to a set of criteria (Brans, Vincke, and Mareschal 1986). In the PROMETHEE method, after the definition of the decision-making problem and the basic components of the problem (alternatives, decision criteria, etc.), analyzes can be performed. PROMETHEE method consists of seven stages (Ozkale et al. 2017).

(i) Determining the criteria and weights of the alternatives and forming the data matrix (this matrix is given in Table 4).
(ii) Determination of preference functions for criteria in Table 3,
(iii) Determination of common preference functions,
(iv) Calculation of preference indices for alternative pairs,
(v) Calculation of positive and negative advantages,
(vi) Determining partial priorities via PROMETHEE I,
(vii) Determining clear priorities and ranking alternatives via PROMETHEE II.

In the PROMETHEE method, preference function $(\mathrm{Pj}(\mathrm{a},\mathrm{b}))$, which is a function of *dj* difference between any two alternatives, is used for any criterion j. dj is the difference function, denoted by $\mathrm{f}(\mathrm{a},\mathrm{j}) - \mathrm{f}(\mathrm{b},\mathrm{j})$. Here $\mathrm{f}(\mathrm{a},\mathrm{j})$ and $\mathrm{f}(\mathrm{b},\mathrm{j})$ are the value of alternatives (a and *b*) for criterion *j* (Pohekar and Ramachandran 2004).

The PROMETHEE method provides a preference function to determine the decision-maker's choice between alternative pairs for each criterion (Dagdeviren 2008). There are six different preference functions presented in the literature. Preference functions used for the PROMETHEE method are given in Table 5.

Type I Preference function takes values between 0 and 1 and is a linear segmented function where the limit from the right is zero,

Type II is Quasi-function, almost similar to the Type 1 function except that the limit from the right is 0,

Type III is linear preference function or V type function,

Type IV is level preference function,

Type V is the function with linear preference and indifference area,

Type VI is a Gaussian function.

The differences in preference functions depend on the specific features of their functions. (Abdullah, Chan, and Afshari 2019).

Table 4. The data matrix (Ozkale et al. 2017).

Criteria	a	b	c	…	w
f_1	$f_1(a)$	$f_1(b)$	$f_1(c)$	…	w_1
f_2	$f_2(a)$	$f_2(b)$	$f_2(c)$		w_2
…	…	…	…	…	…
f_k	$f_k(a)$	$f_k(b)$	$f_k(c)$	…	w_k

Table 5. Preference functions for PROMETHEE (Brans and mareschal 2005; Gervásio and da silva 2012).

Type of Preference Functions	Definition of the Function	Parameter
Type I (Classic)	$p(d) = \begin{cases} 0 d \leq 0 \\ 1 d > 0 \end{cases}$	-
Type II (U Type)	$p(d) = \begin{cases} 0 d \leq q \\ 1 d > q \end{cases}$	q
Type III (V Type)	$p(d) = \begin{cases} 0 d \leq 0 \\ \frac{d}{p} 0 < d \leq p \\ 1 d > p \end{cases}$	p
Type IV (Level)	$p(d) = \begin{cases} 0 d \leq 0 \\ \frac{1}{2} 0 < d \leq p \\ 1 d > p \end{cases}$	p, q
Type V(Linear)	$p(d) = \begin{cases} 0 d \leq 0 \\ \frac{1}{2} 0 < d \leq p \\ 1 d > p \end{cases}$	p, q
Type VI (Gaussian)	$p(d) = \begin{cases} 0 d \leq q \\ 1 - e^{\frac{-d^2}{2s^2}} d > q \end{cases}$	s

In the PROMETHEE method, the multi-criteria preference index representation is $\pi(\mathrm{a,b})$ (Ren et al. 2016). This value is the weighted average of preference functions $(\mathrm{Pj(a,b)})$. Equation representations are given in eq.1, eq.2, eq.3, and eq.4.

$$\pi(\mathrm{a,b}) = \frac{\sum_{j=1}^{J} w_j P_j(\mathrm{a,b})}{\sum_{j=1}^{J} w_j} \tag{1}$$

$$\phi^{+}(\mathrm{a}) = \sum_{A} \pi(\mathrm{a,b}) \tag{2}$$

$$\phi^{-}(a) = \sum_{A} \pi(b,a) \tag{3}$$

$$\phi(a) = \phi^{+}(a) - \phi^{-}(a) \tag{4}$$

While a and b are two alternatives in the alternative decision set, the following decisions are made according to their net priority values.

If (a)> Φ (b), alternative a has priority, otherwise, alternative b prevails.

If (a) = Φ (b), alternatives a and b are not superior to each other.

2.3. Spearman's rank correlation coefficient

Spearman's rank correlation coefficient is a measure of the statistical dependence between two different stochastic sequences. This measure is not parametric (Liu et al. 2010). The notation of Spearman's rank correlation coefficient is designated as "ρ" when considered for a population and "r" when considered for a sample taken from the population. Spearman's Rank Correlation Coefficient is used when one or both of the variables subject to analysis show ordinal properties (Mukaka 2012). The formula for the correlation between x and y variable calculation of sample Spearman's correlation coefficient is given in eq.5.

$$\mathrm{p} = 1 - \frac{6\sum^{\mathrm{d}^2}}{\mathrm{n}(\mathrm{n}^2 - 1)} \tag{5}$$

Table 6. Linguistic expressions for the size of Spearman's rank correlation coefficient (Hinkle, wiersma, and Jurs 2003; Mukaka 2012).

Size of Correlation	Linguistic Expressions
± 0.90 to ± 1.00	very high (+ or -)
± 0.70 to ± 0.90	high positive (+ or -)
± 0.50 to ± 0.70	moderate positive (+ or -)
± 0.30 to ± 0.50	low positive (+ or -)
± 0.00 to ± 0.30	negligible

where d is the difference between different stochastic sequences. n is the total number of sequences. Considering two sequences, $n = 2$. ρ is Spearman's rank correlation coefficient as mentioned before. The variables must have the same number of observations. The p value takes place in the range value $[-1, 1]$. The higher the absolute value of p, the stronger the relationship between the two variables is considered. Positive p values indicate a positive relationship between variables, while negative p values indicate a negative relationship between variables (Chiang et al. 2016; Puth, Neuhäuser, and Ruxton 2015). Table 6 contains the linguistic expressions of the correlation degrees for the correlation coefficients.

3. Empirical analysis: an application for OECD countries

DEA models recommend a set of weights for each DMU to reach its maximum viable efficiency. Therefore, DEA can identify ineffective DMUs with low performance even while taking the best weights imaginable. In real decision-making problems, the weighting of criteria is insufficient due to the lack of information and in such cases, the use of DEA will be extremely useful. On the other hand, in MCDM techniques such as PROMETHEE, the weight of each decision criterion is determined by the DM according to the state of the system (Mousavi-Nasab and Sotoudeh-Anvari 2017). The ranking of alternatives in the PROMETHEE method is extremely sensitive to changes in criterion weights. This fundamental difference distinguishes the methods from each other and requires analysis of the preferability situation. Results from PROMETHEE are based on weighted criteria and the result of the DEA models is independent of DM's preferences. Therefore, the different results obtained provide a broader view of decision criteria and the weights of these criteria. Also, as exemplified in the literature, the more effective techniques included in the decision procedure, the more reasonable the results will be (Kou, Peng, and Wang 2014; Wang, Zhu, and Wang 2016). As a result, ranking according to DEA models and PROMETHEE from multi-criteria decision-making techniques is much more accurate than sorting materials with only one MCDM technique or with a DEA model.

In DEA models, if output variables are kept constant, input-oriented models should be used, if input variables are kept constant, output-oriented models should be used. CCR or BCC models are preferred depending on whether the returns to the scale are constant or variable. The weighting algorithm of input-output variables is different in each DEA model. Traditional DEA models and performance rankings for OECD countries were presented in the study. In the PROMETHEE technique, preference functions, criteria are cost or benefit-oriented, and criteria are weighted. The analysis approach for DEA models and PROMETHEE is given in Figure 1.

In this study, a three-stage methodology is used. In the first stage, DEA models were used to analyze the sustainable energy performance of 36 OECD member countries. In this context, the statuses of OECD countries were examined from different perspectives. In the second stage, the PROMETHEE method has been used in performance evaluation for sustainable energy. In the third stage, the similarity of the country performance rankings obtained from each method was revealed by correlation analysis. It has been questioned that the methods used are alternatives to each other.

PROMETHEE		DEA
Alternatives	→	DMUs
Maximization Criteria	→	Outputs
Minimization Criteria	→	Inputs
Criteria weights by DM	→	Inputs and Outputs weights by DEA model

Figure 1. DEA and PROMETHEE in the decision context (Sarkis 2000).

3.1. Data collection

The Organization of Economic Cooperation and Development (OECD) is composed of 37 member countries. The main purpose of the organization is to provide financial support and economic programs to its members (Selam, Ozel, and Akan 2014).

The use of renewable energy is important for the OECD countries for the following three main reasons:

(i). To create social awareness and support these policies to reduce the effects of climate change,

(ii). The use of renewable energy in clean energy to ensure energy security in carbon-constrained economies,

(iii). Seeing renewable energy production as an opportunity for development for developing countries.

In this study, OECD countries represent Decision-Making Units (DMUs). OECD countries subjected to performance evaluation in sustainable energy are given in Table 7. Since the data of 1 OECD country (United Kingdom) could not be fully reached in the study, it was excluded from the scope of this study.

In this study, three input variables and one output variable were determined for DEA analysis. For the PROMETHEE method, each of these four variables was defined as "criteria". Input variables are determined as "Renewable Energy Consumption (TJ)", "Energy Intensity Level of Primary Energy (MJ/2011USD PPP)", "Total Electricity Production (GWh)", and output variable as "Renewable Electricity Share of Total Electricity Output (%)". Data for OECD countries for relevant variables were obtained from the official website of the World Bank [https://databank.worldbank.org/source/sustainable-energy-for-all#]. Details of the input and output variables are given in Table 8. Also, indicator attributes (input or output) for DEA models are included in Table 8.

Table 7. OECD countries.

No	DMUs	No	DMUs
1	Turkey	**19**	Italy
2	United States	**20**	Japan
3	Germany	**21**	Iceland
4	Australia	**22**	Canada
5	Austria	**23**	Colombia
6	Belgium	**24**	Latvia
7	Czech Republic	**25**	Luxembourg
8	Denmark	**26**	Hungary
9	Estonia	**27**	Mexico
10	Finland	**28**	Norway
11	France	**29**	Poland
12	Korea, Dem. Rep.	**30**	Portugal
13	Netherlands	**31**	Slovak Republic
14	Ireland	**32**	Slovenia
15	Spain	**33**	Chile
16	Israel	**34**	New Zealand
17	Sweden	**35**	Greece
18	Switzerland	**36**	Lithuania

Table 8. Inputs and output of sustainable energy performance evaluation (Yulek 2018, http://www.unece.org/info/ece-homepage.html; Cîrstea et al. 2018; Ibrahim and alola 2020).

Layer of Variables	Indicator Attribute	Details
Renewable Energy Consumption	Input	Final consumption of energy obtained from renewable energy sources by consumers
Energy Intensity Level of Primary Energy	Input	Intensity calculated as a result of the ratio of primary energy consumption to GDP (Gross Domestic Product)
Total Electricity Production	Input	Total electricity production from all nonrenewable energy sources
Renewable Electricity Share of Total Electricity Output	Output	Percentage share of electricity produced from renewable energy sources

According to the studies in the literature, the number of DMUs for the DEA model should be at least twice the sum of variables (Zhu and Cook 2007). In this study, the total number of input and output variables was 4 and DMUs consist of 36 countries. Descriptive statistics for input and output variables are shown in Table 9.

In this study, CCR, BCC, and SEM from DEA models were used to evaluate the sustainable energy performance of OECD countries and to examine their efficiency status. In the second stage, sustainable energy performance evaluation was examined from the perspective of decision analysis, and the performance ranking of OECD countries was obtained with the PROMETHEE method. The similarity between all the obtained performance rankings was analyzed with the calculated Spearman's rank correlation coefficients.

4. Results and discussion

Renewable energy resources are of great importance to effectively use energy resources, which have been scarce in the competitive environment between countries in recent years. Minimizing the input variables determined for sustainability in the energy, and maximizing the output variables are among the aims of the countries. In the study, these objectives were determined as input and output orientation for DEA. The variables determined for the PROMETHEE method, another method in the study, were considered as criteria and the performance rankings of OECD countries were obtained from the decision analysis perspective. In this context, the sustainable energy performance of OECD countries has been evaluated with different analyses. The following subsections detail the data analysis used in this study.

4.1. Efficiencies of OECD countries via DEA

The equations in Tables 2 and Tables 3 are used to derive efficiency scores and reference sets for DMUs. Reference sets consist of DMUs with an efficiency score of 1. In this study, efficiency scores were obtained depending on whether the scale returns are constant or variable.

As shown in Table 10, Denmark, Korea Dem. Rep., Switzerland, Colombia, and Luxembourg were determined as effective DMUs for the input-oriented CCR model. The calculated O.E. values confirm

Table 9. Descriptive statistics of input and output variables (Ervural, zaim, and delen 2018).

Layer of Variables	Unit	Maximum	Minimum	Mean	Standard Deviation
Renewable Energy Consumption	TJ	5097931.000	13392.290	452719.938	855472.539
Energy Intensity Level of Primary Energy	MJ/2011USD PPP	16.557	1.948	4.388	2.361
Total Electricity Production	GWh	4297048.000	1331.000	279438.917	715417.680
Renewable Electricity Share of Total Electricity Output	%	99.979	1.890	39.161	25.741

Table 10. Input-oriented DEA model results.

DMU	O.E. % (CCR)	CCR Rank	P.E. % (BCC)	BCC Rank	S.E. Model + CCR	S.E. Model + CCR rank	S.E. Model + BCC	S.E. Model + BCC rank
Turkey	35.89%	18	67.09%	15	35.89%	18	67.09%	15
United States	8.09%	35	36.02%	34	8.09%	35	36.02%	34
Germany	26.85%	24	54.33%	21	26.85%	24	54.33%	21
Australia	10.84%	33	38.73%	32	10.84%	33	38.73%	32
Austria	79.39%	8	89.22%	10	79.39%	8	89.22%	10
Belgium	20.46%	25	41.09%	31	20.46%	25	41.09%	31
Czech Republic	9.71%	34	35.37%	35	9.71%	34	35.37%	35
Denmark	100.00%	1	100.00%	1	108.87%	3	113.09%	7
Estonia	19.84%	26	45.01%	30	19.84%	26	45.01%	30
Finland	28.19%	23	36.77%	33	28.19%	23	36.77%	33
France	12.79%	30	47.50%	28	12.79%	30	47.50%	28
Korea Dem. Rep.	100.00%	1	100.00%	1	144.91%	2	187.59%	4
Netherlands	14.72%	27	49.49%	27	14.72%	27	49.49%	27
Ireland	69.47%	10	100.00%	1	69.47%	10	139.59%	5
Spain	34.76%	20	60.06%	17	34.76%	20	60.06%	17
Israel	4.50%	36	78.49%	13	4.50%	36	78.49%	13
Sweden	49.04%	14	51.67%	26	49.04%	14	51.67%	26
Switzerland	100.00%	1	100.00%	1	101.71%	5	104.88%	9
Italy	41.66%	17	65.93%	16	41.66%	17	65.93%	16
Japan	14.13%	28	52.06%	25	14.13%	28	52.06%	25
Iceland	50.89%	13	100.00%	1	50.89%	13	big	1
Canada	28.40%	22	30.01%	36	28.40%	22	30.01%	36
Colombia	100.00%	1	100.00%	1	106.63%	4	109.87%	8
Latvia	92.64%	6	100.00%	1	92.64%	6	116.25%	6
Luxembourg	100.00%	1	100.00%	1	279.12%	1	398.63%	3
Hungary	11.52%	32	54.39%	20	11.52%	32	54.39%	20
Mexico	13.63%	29	52.11%	24	13.63%	29	52.11%	24
Norway	86.14%	7	100.00%	1	86.14%	7	407.30%	2
Poland	12.56%	31	47.11%	29	12.56%	31	47.11%	29
Portugal	59.14%	12	67.30%	14	59.14%	12	67.30%	14
Slovak Republic	31.94%	21	54.07%	22	31.94%	21	54.07%	22
Slovenia	45.16%	15	57.30%	18	45.16%	15	57.30%	18
Chile	44.63%	16	55.36%	19	44.63%	16	55.36%	19
New Zealand	67.84%	11	88.54%	11	67.84%	11	88.54%	11
Greece	35.30%	19	53.14%	23	35.30%	19	53.14%	23
Lithuania	78.55%	9	79.27%	12	78.55%	9	79.27%	12

O.E.: Overall Efficiency **P.E.**: Pure Efficiency **S.E.**: Super Efficiency

this situation. In these OECD countries, the efficiency score was 1. In other inefficient OECD countries, P.E. values were less than 1. In the BCC model, Denmark, Korea Dem. Rep., Ireland, Switzerland, Iceland, Colombia, Latvia, Luxembourg, and Norway were determined as input-oriented effective DMUs. P.E. values of these countries were calculated as 1. In other inefficient OECD countries, P.E. values were less than 1. When examining the results obtained from the SEM for the exact ranking of DMUs, Luxembourg was determined as the OECD country with the highest efficiency score for the CCR input-oriented model. Iceland was the most effective OECD country for the BCC input-oriented model.

Reference sets should be considered for other ineffective countries to have an efficiency score equal to 1, that is, to be fully effective DMUs.

With the adaptation of the SEM to input-oriented CCR and BCC models, full rankings of OECD countries in sustainable energy performance have been achieved. These rankings are also included in Table 10.

If it is considered as an objective for decision-makers to increase the output variables by keeping the number of input variables in Table 8 constant, output-oriented CCR and output-oriented BCC models can be studied. In this context, models are created using the mathematical representations in Tables 2

Table 11. Output-oriented DEA model results.

DMU	O.E. % (CCR)	CCR rank	P.E. % (BCC)	BCC rank	S.E. Model + CCR	S.E. Model + CCR rank	S.E. Model + BCC	S.E. Model + BCC rank
Turkey	278.66%	18	256.01%	21	278.66%	18	256.01%	19
United States	1235.51%	35	740.84%	35	1235.51%	35	740.84%	33
Germany	372.49%	24	324.12%	24	372.49%	24	324.12%	22
Australia	922.24%	33	667.20%	32	922.24%	33	667.20%	30
Austria	125.96%	8	106.83%	11	125.96%	8	106.83%	9
Belgium	488.80%	25	381.46%	26	488.80%	25	381.46%	24
Czech Republic	1029.44%	34	717.15%	33	1029.44%	34	717.15%	31
Denmark	100.00%	1	100.00%	1	91.85%	3	78.00%	3
Estonia	504.03%	26	333.84%	25	504.03%	26	333.84%	23
Finland	354.71%	23	199.53%	18	354.71%	23	199.53%	16
France	781.69%	30	616.56%	29	781.69%	30	616.56%	27
Korea, Dem. Rep.	100.00%	1	100.00%	1	69.01%	2	66.54%	1
Netherlands	679.21%	27	613.99%	28	679.21%	27	613.99%	26
Ireland	143.95%	10	100.00%	1	143.95%	10	big	35
Spain	287.70%	20	255.54%	20	287.70%	20	255.54%	18
Israel	2223.56%	36	1964.16%	36	2223.56%	36	1964.16%	34
Sweden	203.93%	14	154.60%	13	203.93%	14	154.60%	11
Switzerland	100.00%	1	100.00%	1	98.32%	5	93.29%	7
Italy	240.03%	17	217.90%	19	240.03%	17	217.90%	17
Japan	707.51%	28	609.90%	27	707.51%	28	609.90%	25
Iceland	196.51%	13	100.00%	1	196.51%	13	74.02%	2
Canada	352.09%	22	156.08%	14	352.09%	22	15608%	12
Colombia	100.00%	1	100.00%	1	93.79%	4	93.23%	6
Latvia	107.94%	6	100.00%	1	107.94%	6	93.18%	5
Luxembourg	100.00%	1	100.00%	1	35.83%	1	big	36
Hungary	867.85%	32	730.58%	34	867.85%	32	730.58%	32
Mexico	733.90%	29	632.81%	30	733.90%	29	632.81%	28
Norway	116.09%	7	100.00%	1	116.09%	7	78.58%	4
Poland	796.07%	31	649.18%	31	796.07%	31	649.18%	29
Portugal	169.10%	12	161.03%	15	169.10%	12	161.03%	13
Slovak Republic	313.05%	21	276,10%	23	313.05%	21	276.10%	21
Slovenia	221.43%	15	186,72%	16	221.43%	15	186.72%	14
Chile	224.08%	16	194,57%	17	224.08%	16	194.57%	15
New Zealand	147.40%	11	102,76%	10	147.40%	11	102.76%	8
Greece	283.26%	19	266,37%	22	283.26%	19	266.37%	20
Lithuania	127.30%	9	113,62%	12	127.30%	9	113.62%	10

O.E.: Overall Efficiency **P.E.**: Pure Efficiency **S.E.**: Super Efficiency

and Tables 3. As shown in Table 11, Denmark, Korea Dem. Rep., Switzerland, Colombia, and Luxembourg were effective for the output-oriented CCR model; and Denmark, Korea Dem. Rep., Ireland, Switzerland, Iceland, Colombia, Latvia, Luxembourg, and Norway were effective for the output-oriented BCC model.

As shown in Tables 10 and Tables 11, with the inclusion of the SEM in the CCR and BCC models, the sustainable energy full potential rankings of OECD countries were obtained. These rankings are important in terms of giving decision-makers a clear rank among the effective countries as well as giving performance rankings among all OECD countries.

There was no difference in terms of efficiency and inefficient OECD countries and the number of these countries in input or output-oriented DEA models. However, the ranking of OECD countries varied. Efficiency scores of the inefficient units do not vary in the super-efficiency model. The super-efficiency model changes the scores of the efficiency units and allows these units to be ranked among them.

4.2. Evaluation of OECD countries via PROMETHEE method

In this part of the study, based on the variables used for efficiency analysis in the previous section, the sustainable energy performances of the OECD countries subject to the analysis were compared using the PROMETHEE method.

While the 36 OECD countries given in Table 7 create DMUs in the analysis, all of the input and output variables in Table 9 (Renewable Energy Consumption, Energy Intensity Level of Primary Energy, Total Electricity Production, Renewable Electricity Share of Total Electricity Output) were defined as decision criteria (Cîrstea et al. 2018; Mahlknecht and González-Bravo 2018).

In DEA application, decision qualities are accepted as outputs and inputs, respectively, instead of benefit (maximization) criteria or cost (minimization) criteria. Therefore, while minimization criteria for the PROMETHEE method are inputs in DEA, maximization criteria for the PROMETHEE method are outputs in DEA (Bagherikahvarin and De Smet 2016; Mousavi-Nasab and Sotoudeh-Anvari 2017). The direction of criteria, preference functions determined for each criterion, and criterion weights are given in Table 12.

As all criteria have quantitative properties, Type Five (Linear) preference function was used. Since the consumption issue is a situation to be minimized for decision analysis, the criterion aspect for the "Renewable Energy Consumption" criterion has been determined as minimization. Likewise, since there are nonrenewable energy sources other than renewable energy among primary energy sources (such as coal, oil, natural gas), "Energy Intensity Level of Primary Energy" and "Total Electricity Production" were also minimized criteria. "Renewable Electricity Share of Total Electricity Output" was determined to be maximized. In the analysis, the weights of the decision criteria were considered equal (0.25) with their sum being 1.00.

As a result of the implementation of PROMETHEE method steps, the positive (ϕ^+), negative (ϕ^-), and net (ϕ) advantage values of OECD countries and the country rank obtained are given in Table 13.

4.3. Evaluation of DEA and PROMETHEE methods

The ability to use the methods as alternatives to each other depends on providing close results based on purpose. Country rankings derived from the methods used for sustainable energy performance assessment of OECD countries were examined. The rankings obtained as a result of the methods used in the study are collectively given in Table 14.

Figure 2 shows the graphical representation of the ranks.

When Figure 2 is examined, OECD countries with high sensitivity for rankings can be interpreted. For example, the differences in the rankings obtained from the methods in countries such as Luxembourg, Canada, Ireland, and Sweden are striking. The main reason for this situation can be shown as the countries' openness to different interpretations in terms of input/output variables (criteria).

When the countries of Luxembourg and Ireland are examined, a difference in the ranking obtained from DEA models is observed. For example, Luxemburg, which has a low population in renewable energy use, is the last country in the ranking according to the output-oriented BCC model, while it is

Table 12. Criteria attributes for PROMETHEE method.

	Criteria			
	Renewable Energy Consumption	Energy Intensity Level of Primary Energy	Total Electricity Production	Renewable Electricity Share of Total Electricity Output
Selected Preference Function	Linear	Linear	Linear	Linear
Direction of Criterion (Purpose)	Minimization	Minimization	Minimization	Maximization
Criterion Weight	0.25	0.25	0.25	0.25

Table 13. Results of PROMETHEE method.

Rank	OECD Countries	ϕ	ϕ^+	ϕ^-
1	Norway	0.2565	0.2736	0.0171
2	Colombia	0.2535	0.2683	0.0147
3	Switzerland	0.2336	0.2533	0.0197
4	Denmark	0.2307	0.2449	0.0142
5	Korea, Dem. Rep.	0.2281	0.2397	0.0115
6	Austria	0.2259	0.2384	0.0125
7	New Zealand	0.1682	0.2328	0.0646
8	Sweden	0.1386	0.1805	0.0418
9	Latvia	0.1204	0.1601	0.0397
10	Portugal	0.1133	0.154	0.0407
11	Ireland	0.0958	0.17	0.0742
12	Chile	0.0769	0.1287	0.0518
13	Lithuania	0.0712	0.1266	0.0554
14	Luxembourg	0.0699	0.1332	0.0633
15	Italy	0.0339	0.116	0.0822
16	Iceland	0.0156	0.2659	0.2503
17	Greece	0.0154	0.0938	0.0784
18	Turkey	0.0108	0.103	0.0922
19	Spain	0.0093	0.0991	0.0898
20	Slovenia	0.0012	0.0897	0.0885
21	Slovak Republic	−0.0282	0.0764	0.1046
22	Finland	−0.0525	0.1111	0.1636
23	Belgium	−0.0549	0.0648	0.1196
24	Netherlands	−0.0694	0.0622	0.1315
25	Hungary	−0.0733	0.0634	0.1367
26	Poland	−0.0829	0.054	0.1369
27	Israel	−0.0875	0.0723	0.1598
28	Mexico	−0.0942	0.0539	0.1482
29	Germany	−0.0993	0.0718	0.1711
30	Australia	−0.1349	0.0412	0.1761
31	Czech Republic	−0.1394	0.049	0.1884
32	France	−0.15	0.0424	0.1924
33	Estonia	−0.1674	0.0591	0.2265
34	Japan	−0.2259	0.0449	0.2709
35	Canada	−0.2488	0.1553	0.4041
36	United States	−0.6603	0.0112	0.6714

a country that is effective in terms of renewable energy performance according to the results of other DEA models. In the PROMETHEE method, an average ranking result was obtained for Luxemburg. In this context, it can be said that the sequencing result obtained from the PROMETHEE method has a unifying effect. DEA models provide a relative efficiency analysis. In DEA models, input and output variables are evaluated relatively for all DMUs. The fact that Luxemburg is an effective country for the 3 DEA model despite its low population is due to the use cases of renewable energy inputs and the efficient production of the outputs compared to the population. "Variable returns to scale" and "stability of inputs" may not be a logical option for Luxembourg for decision-makers. For other OECD countries, interpretations can be made by taking country-specific assumptions into account.

In this part of the study, the Spearman's Rank Correlation Coefficient was calculated in pairs for the ranks obtained. Spearman's rank correlation coefficients of the rankings between the full rankings obtained by the DEA Models and the PROMETHEE method are found in Table 15.

When the models were evaluated mutually, a low, or negligible correlation coefficient was not calculated as shown in Table 15. The fact that all correlation coefficients were positive indicates that the directions of the rankings obtained were the same and the relationship between rankings was positive. The highest correlation coefficient 1.0000 CCR output and CCR were obtained from input-oriented DEA models. The OECD country rankings derived from these models were the same. The lowest value among the correlation coefficients obtained in the calculation was 0.6952. There was a moderate positive correlation between the rankings obtained from the output-oriented BCC model and the PROMETHEE method.

Table 14. The rank results of OECD countries.

Methods	Input-oriented DEA models		Output-oriented DEA models		PROMETHEE
DMUs	S.E. Model +CCR Rank	S.E. Model +BCC Rank	S.E. Model +CCR Rank	S.E. Model +BCC Rank	PROMETHEE Rank
Turkey	18	15	18	19	18
United States	35	34	35	33	36
Germany	24	21	24	22	29
Australia	33	32	33	30	30
Austria	8	10	8	9	6
Belgium	25	31	25	24	23
Czech Republic	34	35	34	31	31
Denmark	3	7	3	3	4
Estonia	26	30	26	23	33
Finland	23	33	23	16	22
France	30	28	30	27	32
Korea. Dem. Rep.	2	4	2	1	5
Netherlands	27	27	27	26	24
Ireland	10	5	10	35	11
Spain	20	17	20	18	19
Israel	36	13	36	34	27
Sweden	14	26	14	11	8
Switzerland	5	9	5	7	3
Italy	17	16	17	17	15
Japan	28	25	28	25	34
Iceland	13	1	13	2	16
Canada	22	36	22	12	35
Colombia	4	8	4	6	2
Latvia	6	6	6	5	9
Luxembourg	1	3	1	36	14
Hungary	32	20	32	32	25
Mexico	29	24	29	28	28
Norway	7	2	7	4	1
Poland	31	29	31	29	26
Portugal	12	14	12	13	10
Slovak Republic	21	22	21	21	21
Slovenia	15	18	15	14	20
Chile	16	19	16	15	12
New Zealand	11	11	11	8	7
Greece	19	23	19	20	17
Lithuania	9	12	9	10	13

In the literature, hybridization of similar techniques (from MCDM techniques) is mentioned for sustainable energy performance evaluation (Li, Li, and Guo 2020; Neofytou et al. 2020; Vavrek and Chovancová 2019). The main motivation in this study is to analyze whether methods with different algorithm structures (DEA and PROMETHEE) could achieve the same purpose of performance evaluation. This analysis was verified by calculating the Spearman's Correlation Coefficients (R). Also, the relationship between DEA models was examined in terms of giving an idea of method similarities. Moderate (R =0.6952) and high (R =0.7959; R =0.8919) relationships have been determined between DEA models and the PROMETHEE.

5. Conclusion

In this study, a sustainable energy performance assessment of OECD countries was made. OECD countries that were efficient and inefficient in terms of sustainable energy were considered as DMUs and their efficiency scores were calculated with DEA models. Full performance rankings of all OECD countries had been obtained with Super Efficiency Models. Luxemburg was determined as the most efficient OECD country in sustainable energy for the input-oriented CCR model and the output-oriented CCR model. The most effective OECD country for the input-oriented BCC model was

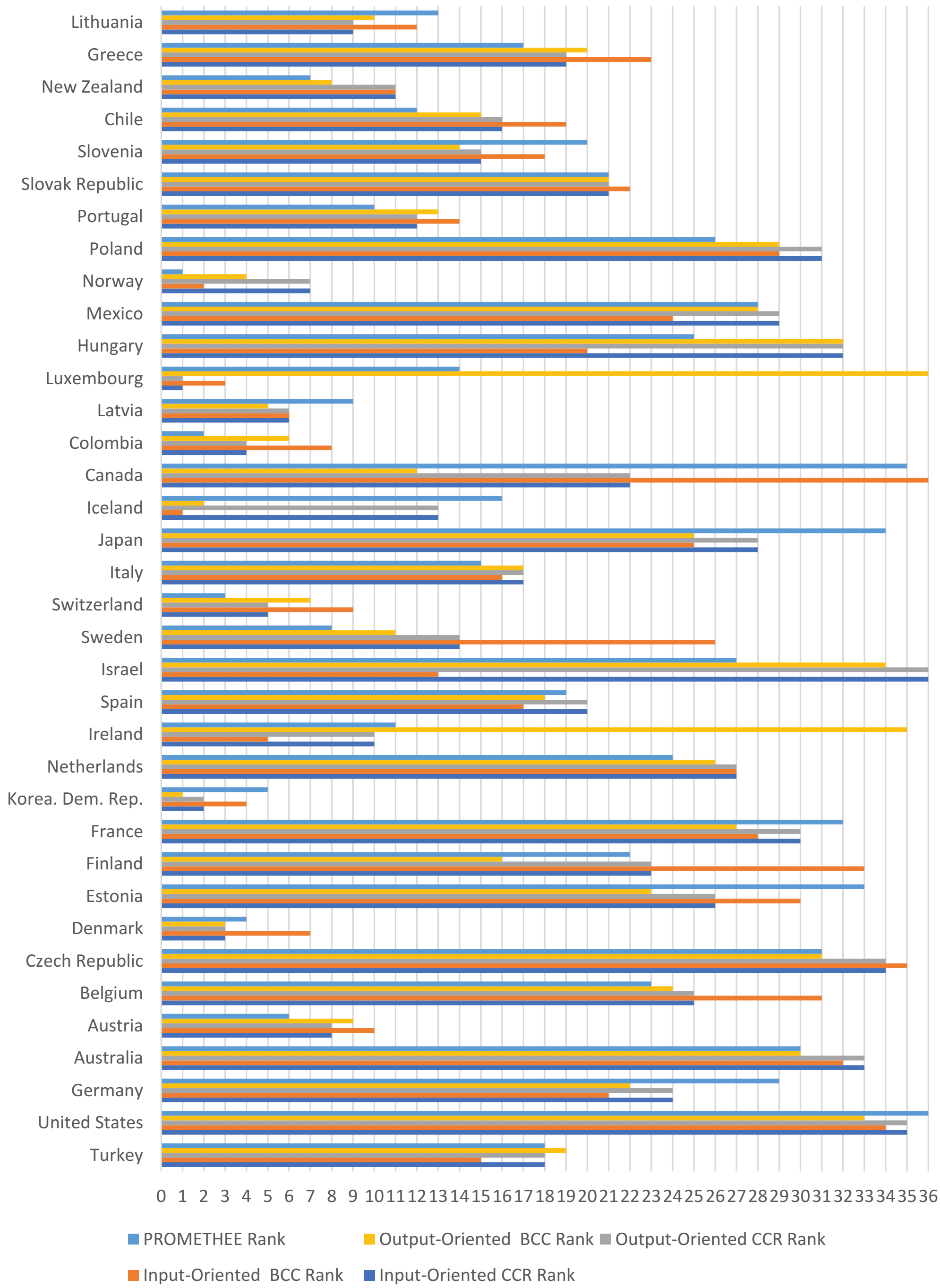

Figure 2. Chart of rank results.

Iceland. Korea was determined as the most effective OECD country for the output-oriented BCC model. After this analysis, the efficiency status of the countries was evaluated using the PROMETHEE method from the decision analysis perspective. Countries were listed in terms of sustainable energy performance according to decision criteria. According to the PROMETHEE method, the country with the highest performance ranking in sustainable energy was determined as Norway. Afterward, the

Table 15. The spearman's correlation coefficients.

	Input-oriented CCR Model	Input-Oriented BCC Model	Output-Oriented CCR Model	Output-Oriented BCC Model	PROMETHEE
Input-Oriented CCR Model	1	0.8018	10000	0.9537	0.8919
Input-Oriented BCC Model		1	0.8018	0.7647	0.7959
Output-Oriented CCR Model			1	0.9537	0.8919
Output-Oriented BCC Model				1	0.6952
PROMETHEE					1

Spearmans' rank correlation coefficient was calculated in order to compare the rankings obtained from all methods and to determine the degree of relationship between the rankings. The correlation coefficients obtained vary between 0.6952 and 1.0000. In this context, there are "positive" and "moderate and high" level relationships between the DEA models and the PROMETHEE method. Although the basic algorithm of the methods is different, the high correlated performance rankings obtained reveal the applicability of the methods as an alternative. Spearman's rank correlation coefficient is a coefficient that determines the strength and direction of the relationship between rankings. The difference in the study is that the rankings obtained from all the methods used are evaluated together.

This study is important as it presents an alternative performance evaluation for countries in the field of sustainable energy. With the DEA model, an analysis based on Linear Programming can be made by considering more than one input and output variables. Decision-makers can choose input or output-oriented models according to the constant state of input or output variables. Decision-makers may prefer CCR or BCC models depending on whether the return on the scale is constant or variable. DEA also provides potential improvement values for inefficient DMUs. With various formulations, ineffective DMUs are compared to effective decision-making units. In this study, input or output variables of inefficient OECD countries can be improved by taking effective OECD countries as references. Continuous renewable energy sustainability improvements are also required for effective OECD countries in the long term. In this context, continuous observations and similar relative analysis can be made for input or output variables that may change. In addition, it is assumed that the input and output variables used in the DEA model are decision criteria for PROMETHEE. Because the data related to sustainable energy obtained for OECD countries are also a decision criterion. In future studies, hybrid fuzzy models that provide more reliable results for uncertain decision environments can be used by including the linguistic expressions of decision-makers.

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