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ORIGINAL ARTICLE

An assessment model for national sustainable development based on the hybrid DEA and modified TOPSIS techniques

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Abstract
Assessing and improving energy efficiency is crucial for addressing the problems of climate change and global warming. This study evaluates the performance of each Organisation for Economic Cooperation and Development (OECD) nation based on the weights obtained by Data Envelopment Analysis (DEA), combined with a modified Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS) method based on the concept of the aspiration level (called modified TOPSIS-AL). Objective weights are obtained for each country through DEA. This method offers an effective improvement over the previous methods which only use the same subjective weights for the calculation. In addition, our model is also able to account for negative environmental externalities generated during development and provides a comprehensive assessment system for the evaluation of national sustainable development. The findings indicate that the member nations are gradually adopting policies to reduce fossil fuel consumption. However, regional analysis showed that the overall performance of the G7 nations differed significantly from that of the non-G7 nations. The importance of this study lies in the fact that energy consumption not only creates environmental burdens but also affects resource production patterns and productivity. By evaluating the performance of nations in terms of energy efficiency and environmental impact, we aim to address the challenges posed by energy consumption for sustainable development. The proposed hybrid model offers several advantages, including a comprehensive assessment system, consideration of negative externalities, and practical policy recommendations.

Keywords Energy environmental efficiency · Data envelopment analysis · TOPSIS · OECD

Introduction

Global warming has had a massive impact on the environment. In response to climate change and the consequent environmental problems, the sustainable development of industries has become a common global trend. Key discussion points are the development of a circular economy and ensuring the sustainable utilization of limited resources. The circular economy aims to generate renewable resources through waste reuse, effective waste management, and renewable energy use. In the context of industry, the application of sustainable energy and environmental management seeks to maximize economic benefits, while at the same time minimizing negative impacts on the environment.

However, despite these efforts, national economic development and technological progress are usually accompanied by negative environmental impacts at the macro level. For example, environmental pollution and the loss of resources due to increased greenhouse gas emissions. The Sustainable Development Goals (SDGs) (17 goals and 169 targets) proposed by the United Nations in September 2015 were designed to reduce the severity of these impacts and incorporate sustainable development into the existing economic,

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environmental, and social development frameworks. However, as the SDGs are global guidelines, actual implementation depends on each nation's efforts and priorities [35].

Environmental issues have also aroused the increasing attention of academia both for the developing methods to evaluate the problems and devising measures that can be used to manage them. Energy and environmental efficiency have been suggested as strategies that can be taken for reducing the discharge of pollutants during manufacturing. Data Envelopment Analysis (DEA) and Multiple Criteria Decision-Making (MCDM), which have emerged as the two fastest-growing research methods in operations research, have already been widely applied to several management problems [26]. MCDM has proven effective for analysis in complex systems and environments because it does not require the linearized relations needed within traditional statistical analyses or extensive sample data [3]. When relations and mechanisms are unknown or incomplete, MCDM can combine objective survey data with the subjective judgments of experts to obtain adequate management information that will allow decision-makers to formulate optimal strategies [16]. For example, Leung and Wang [17] proposed a new method, the Collaborative Neurodynamic (CND) approach, for solving multi-objective optimization problems. This method utilizes neural networks to approximate the objective functions, and dynamic programming to find the optimal solutions. Their results show that the CND approach can effectively solve multi-objective optimization problems with multiple objectives and constraints.

However, as pointed out in past studies, energy and environmental performance indicators differ significantly by industry and it is difficult to make cross-industry comparisons [26]. The method commonly used in cross-industry comparisons is to conduct static assessments of energy and environmental performance to obtain performance scores at the enterprise level [18]. These scores are then input into a DEA to evaluate energy and environmental performance, and improvement measures to minimize deficiencies in environmental management and improve environmental performance are proposed accordingly [12, 19, 21, 24]. However, in energy and environmental efficiency evaluations, enterprises with fewer inputs, more outputs, and lower pollution emissions are generally considered to be more efficient. Less efficient enterprises need to continue improving production technology, management, and labor productivity [21]. The maturation of DEA, incorporating concepts from operations research, mathematics and management, has proven to be a good method for measuring the efficiency and revealing the shortcomings of inefficient enterprises [6]. Hence, DEA helps to guide inefficient enterprises toward more efficient operations by providing a limited basis for adjustment and production improvement [4].

Another widely accepted MCDM technique is the Technique for Order Preference by Similarity to an Ideal Solution (TOPSIS), developed by Hwang and Yoon [13]. The TOPSIS technique is capable of highlighting, from among all the considered criteria, through comparisons with the positive-ideal and negative-ideal solutions, which may result in the best performance and which may bring the worst performance [46]. The positive-ideal solution is that which maximizes benefits and minimizes costs, while the negative-ideal solution minimizes benefits and maximizes costs [2]. Like DEA, TOPSIS can produce an efficiency ranking for Decision-Making Units (DMUs). Furthermore, both TOPSIS and DEA utilize similar decision-making processes [37], and both aim to maximize the output and minimize the input of the model. The difference is that, in DEA, when determining the relative importance of each criterion (e.g., benefits and costs, or inputs and outputs), the weights are derived from the efficiency frontier. The TOPSIS technique has often been used in the energy sciences for determining energy and environmental efficiency [6]. For example, Wang [37] applied TOPSIS to analyze the overall efficiency of Canadian hydroelectric power plants from the comprehensive perspectives of profitability, environmental benefit, and social responsibility. The study found that the factors affecting the efficiency of hydropower generation also contributed to sustainable hydropower production in Canada. In addition, they found that energy conservation and social responsibility played a crucial role in the overall efficiency of the hydropower industry.

Energy and environmental efficiency assessment systems generally consider pollution an undesirable output [4]. The desired scenarios in efficiency analysis are generally those which create more outputs and fewer inputs. However, undesirable outputs enhance research by shifting its scope from intended outputs to output minimization [36, 39, 47]. Hence, undesirable outputs are a key point to consider when analyzing energy and environmental efficiency.

Furthermore, although most past studies have relied on subjective judgements of decision-makers subjective to determine the ranking of item weights, the present study uses the Data-Driven Decision-Making (DDDM) method to calculate the weights for decision analysis. In the era of big data, it has frequently been pointed out that enterprises should shift their decision-making processes from an experience intuition-based orientation to an analytical data-based orientation. In the past, decision-making has relied chiefly on experience and intuition, but the process may be influenced by personal biases and incomplete information. Decision-making effectiveness can be significantly improved by basing enterprise decisions on data rather than intuition [34].

To the best of our knowledge, although both the DEA and TOPSIS modeling approaches have been used together, this is the first time these methods have been applied to analyze

the energy and environmental efficiency of the member states of the Organisation for Economic Cooperation and Development (OECD) and their respective sustainable development programs. The aim of this study is to evaluate the performance of each OECD nation based on the weights obtained by DEA in combination with TOPSIS-AL. The modified TOPSIS-AL considers the aspiration level of each criterion and analyzes efficiency through consideration of both energy and environmental indicators to obtain the optimal adjustment setting.

The motivation for combining the DEA and modified TOPSIS-AL is the desire to provide a more comprehensive evaluation of energy efficiency and environmental impact. DEA is useful for assessing the relative efficiency of DMUs based on a set of inputs and outputs, but it does not consider environmental impact of the production process. The modified TOPSIS-AL provides a comprehensive evaluation of the alternatives but does not supply information about their relative efficiency. Thus, the two are combined to overcome the limitations of each individual method and provide a more comprehensive evaluation of environmental impact and energy efficiency for each OECD nation. The weights obtained from the DEA are used to evaluate the relative importance of each input variable in the modified TOPSIS-AL, which considers the concept of the aspiration level as well as negative environmental externalities. This hybrid model provides a more robust evaluation of energy efficiency and environmental impact, which can inform decision-makers and help with the development of effective policies and strategies to promote sustainable development. In addition, the introduction of undesirable outputs into the evaluation of efficiency in the present study has significant academic and practical value.

In short, this study proposes a novel hybrid model for evaluation of the national sustainable development performance. The contributions and innovativeness of this method are explained below:

(i) Past research on energy and environmental efficiency has only compared efficiency values. The method developed in this present study reveals the direction of such values. The performance of each OECD member state is evaluated based on the DEA weights obtained, followed by calculation with the modified TOPSIS-AL. This hybrid model considers the level of each criterion in relation to the desired level, overcoming the limitations of traditional DEA, in which efficiency frontiers are restricted to the original value of the evaluated unit [26], thereby providing a more objective developmental evaluation method. The study also combines the energy and environmental indicators with a regional-analysis perspective to obtain efficient adjustment measures which can be used to develop corresponding improvement strategies for each OECD member state.

(ii) This work extends the existing research on the integration of the DEA and modified TOPSIS-AL techniques. A DEA–TOPSIS model has been proposed in [5], where the DEA is used to evaluate the relative efficiency of the DMUs, and TOPSIS is used to rank the DMUs based on their performance. The authors used this method to evaluate the performance of emergency management systems in 10 provinces in China based on the DMUs, using multiple criteria such as emergency warning, emergency response, and emergency recovery. In our work, DEA is used to obtain the weights for the hybrid model. This hybrid model is an improvement upon traditional DEA, where only efficient DMUs are ranked by using the efficiency values obtained from the DEA.

(iii) Although there has been a lot of work evaluating environmental energy performance from the perspectives of the product [30], green supply chains [16] and green manufacturing [18] and these studies have provided a theoretical basis for the research of environmental performance evaluation, no one has yet taken a comprehensive look at the relationship between a nation's environmental and economic performance. Furthermore, few past studies on regional and national development have considered the externalities generated by development, often completely excluding negative externalities, which distorts the calculation. Since sustainable development is an essential subject of current concern to global economic development, undesirable outputs were introduced to measure efficiency by considering the external costs of production processes and economic development.

(iv) Using the aspiration level concept in TOPSIS is also beneficial, as it allows for consideration of what is the desired level of environmental impact rather than just evaluating environmental impact based on the current level of performance. This provides a more nuanced evaluation, which in turn can inform the development of more effective policies and strategies for sustainable development. The modified TOPSIS-AL is an excellent evaluation tool for complex environments, as it requires only expert interview data rather than directional hypotheses of traditional statistical methods [3]. The modified TOPSIS-AL combines objective survey data with the subjective judgments of experts to provide practical management information to support decision-makers in formulating the best strategies [16].

(v) However, the subjective assignment of weights ignores internal criteria [32]. Therefore, in this study, DEA is used to obtain objective criteria weights. DEA requires

actual performance evaluation data but not expert interviews. This is essential, since expert interviews provide only one set of weights, while the proposed method allows for broad optimal weight sets to be generated for each OECD member state to evaluate their energy and environmental performance. This allows for a more comprehensive and accurate evaluation. The weights reflect the relative importance of each input variable, which helps ensure that the evaluation considers only the most critical factors affecting energy efficiency and environmental impact.

The rest of the paper is organized as follows. Sect. "Literature Review" presents a brief literature review. The proposed model is described in Sect. "Data and Methods" and the empirical results are reported in Sect. "Results". Concluding remarks and policy implications are discussed in Sect. "Conclusion".

Literature review

Sustainable development and environmental protection

Cooperation and coordination between policy and technology are essential to reduce the risk of climate change, and to significantly reduce pollution caused by fossil fuels. Of equal importance is to develop technology and procedures for economic development and environmental sustainability [7]. The transition from fossil fuels to renewable energy is of great assistance to reducing greenhouse emissions, solving fuel shortages in certain areas [25], and ensuring sustainable economic development. With the rapid growth of energy demand, exhaust emissions and air pollution have rapidly increased. Improving energy efficiency requires effective resource allocation that can contribute to improving local air quality and ensuring environmental sustainability [44]. It is well accepted academically that a decline in energy use would significantly impact economic and environmental quality in a positive way. It has been observed that, as nations consume energy for economic activities, thereby increasing their GDP, carbon dioxide emissions are produced. Hence, economic development and energy consumption are closely related to the environment and energy efficiency.

While global warming has already caused problems worldwide, more energy consumption would likely to lead to more problems, such as further ecological deterioration [41] and energy shortages [11]. Since most energy-intensive industries cause harm to the climate and environment, to improve, either existing technologies must be upgraded, or new types of eco-innovative technologies used in production [7]. For that reason, it is worthwhile investigating how resources can be used more efficiently to protect the environment and achieve financial benefits.

Iram [14] used DEA to assess the environmental quality of some OECD member states. They found that Brunei, Australia, Singapore, and Hong Kong were the most efficient regions during the study period in terms of energy efficiency and reduction of carbon dioxide emissions. In addition, they found a strong correlation between energy efficiency and carbon emissions. However, the link between economic and environmental efficiency was weak. They suggested that, for OECD member states, the optimization of energy efficiency was more critical than achieving economic efficiency for improving environmental efficiency.

In striving toward establishing low-carbon economies, nations are scrambling to develop and put in place low-carbon industry innovations. This has emerged as one of the main directions of modern economic development. Since more than 50% of the world's population lives in cities, population size and economic development needs have led to extremely high energy consumption in urban areas [39]. Although nations are continuously attempting to develop technology that improves energy use to ensure sustainability, the International Energy Agency has pointed out that energy-intensive industries are only at 50% energy efficiency, the implication being that further innovation is needed to improve energy and environmental efficiency and to reduce the negative impact of technological progress on the environment.

Energy and environmental efficiency

On the path to sustainable development, it is necessary to conserve energy and natural resources while minimizing waste and pollution. Various analytical methods have been developed to facilitate strategies to reduce the adverse effects of operating activities on the environment, including DEA, a non-parametric mathematical method for measuring the efficiency performance of DMUs. It has been widely used in past studies in various fields related to cultural tourism [42], energy efficiency [47], ecological innovation [20], and energy and environmental efficiency [41]. The OECD and European Union (EU) member states regularly conduct environmental energy efficiency analyses of their regional economies, focusing on comparing energy efficiency, energy impact, and environmental efficiency factors.

It is the responsibility of government to guide economic development for individual nations and stimulate economic growth by strengthening domestic demand and innovative development [44]. While developed countries suggest that government supervision remains an indispensable tool for national economic development, it should be balanced with market mechanisms. However, when pursued with the maximization of self-interest, development is achieved at the high price of environmental pollution and energy depletion, which

limits the scope of and sustainability of the development process. Thus, government supervision mechanisms are still required to ensure sustainable economic growth [36, 47].

The measurement of energy and environmental efficiency involves multiple aspects, such as the health of the economy, energy consumption, and environmental impact, all of which should be considered simultaneously; it is impossible to construct a comprehensive measurement model using a single indicator. The advantage of DEA, as a non-parametric method, lies in its ability to perform simultaneous multi-objective performance evaluations, and it does not require preset functions or estimation of the function parameters, hence, many different data types can be used [23].

Unlike stochastic frontier analysis, neither DEA nor TOPSIS requires functional conversion of the data or data allocation assumptions during efficiency value calculations [37]. The TOPSIS basically assumes that the selected alternative should have the shortest distance to the positive-ideal solution and the longest distance to the negative-ideal solution. While DEA optimizes the distance from each evaluated unit to the efficiency frontier by finding an appropriate set of weights for input and output items [1], TOPSIS determines the Euclidean distance between the normalized vector of the positive (output) and negative (input) criteria, adjusted by the weights initially determined by the decision-maker.

Rakhshan [33] further developed the model, proposing the combined TOPSIS–DEA method to rank efficiency units. This model was applied by Wang [38], who used DEA to measure efficiency, and TOPSIS to implement the multi-attribute decision-making process. To verify the stability of multi-attribute decision-making, they used an additive weighting and weighted product to rank decision-making schemes. Djordjević and Krmac [6] evaluated changes in the energy and environmental efficiency of the European road, aviation, and railway transportation sectors. Specifically, the decision-maker would assign weights to each efficiency value, with TOPSIS introduced to rank the DMUs.

From the above, it can be concluded that DEA can serve as an effective to measure the performance of OECD member states. DEA allows the simultaneous introduction of varied input and output indicators so is a more balanced evaluation method than those that use single indicators. The results can reduce issues such as unnecessary labor time and human resource inefficiencies while quantifying energy and performance to obtain specific and valid results.

Data and methods

This section describes the research process (Fig. 1) and the steps of the methods involved.

Data description

Performance evaluation uses scientific methods, standards, and procedures to accurately assess the organizations' performance, achievements, and actions [9]. Although past studies have evaluated environmental energy performance from the perspectives of the product life cycle [30] and green manufacturing [18], providing a theoretical basis for research on environmental performance evaluation models, they have not been able to comprehensively consider the relationship between environmental and economic performance. International indicators for measuring sustainable development, be they from the perspective of the circular economy (resource investment, recycling production, and resource consumption) or energy and environmental efficiency (input and output), require the consideration of multi-objective measurement [14].

The determination of inputs and outputs should be based on evaluation targets and organizational goals. Specific selection methods include interviewing experts from different organizations, analyzing the organizational and management objectives, and reviewing the literature [9]. The initial definition of productivity is the ratio of outputs to inputs. Geng [8] argued that economic, environmental, and human factors, as well as pollutant data, should be considered as input data to increase the accuracy of results. In other words, inputs are a crucial factor in modeling, which directly affects outputs and indirectly influences productivity. This study defines labor as a representative indicator of human resource inputs. Since the present study uses national energy and environmental efficiency as units of analysis, energy consumption is also introduced as an input.

Environmental pollutant emissions are generally considered to be an output item. However, given that "undesirable outputs" do not fully explain the burden on the environment caused by a nations' consumption of resources, environmental risk costs were used in the present study, to reflect the expenditure incurred by the nation for the damage to human health and the ecological environment, given the risk of exposure to environmental stressors, as well as the impacts of managing such risk.

The research subjects were the 34 OECD member states, and the research period was from 2013 to 2017. A hybrid assessment model, combining DEA and modified TOPSIS-AL, was proposed to evaluate energy and environmental performance. The OECD was established in 1961 and is one of the world's largest and most reliable sources of global economic and social statistics for all 34 member states and other vital economies.

An attempt is made to construct an energy and environmental performance evaluation model for all 34 OECD member states, all of which have aligned goals to promote sustainable development. Past studies have usually included

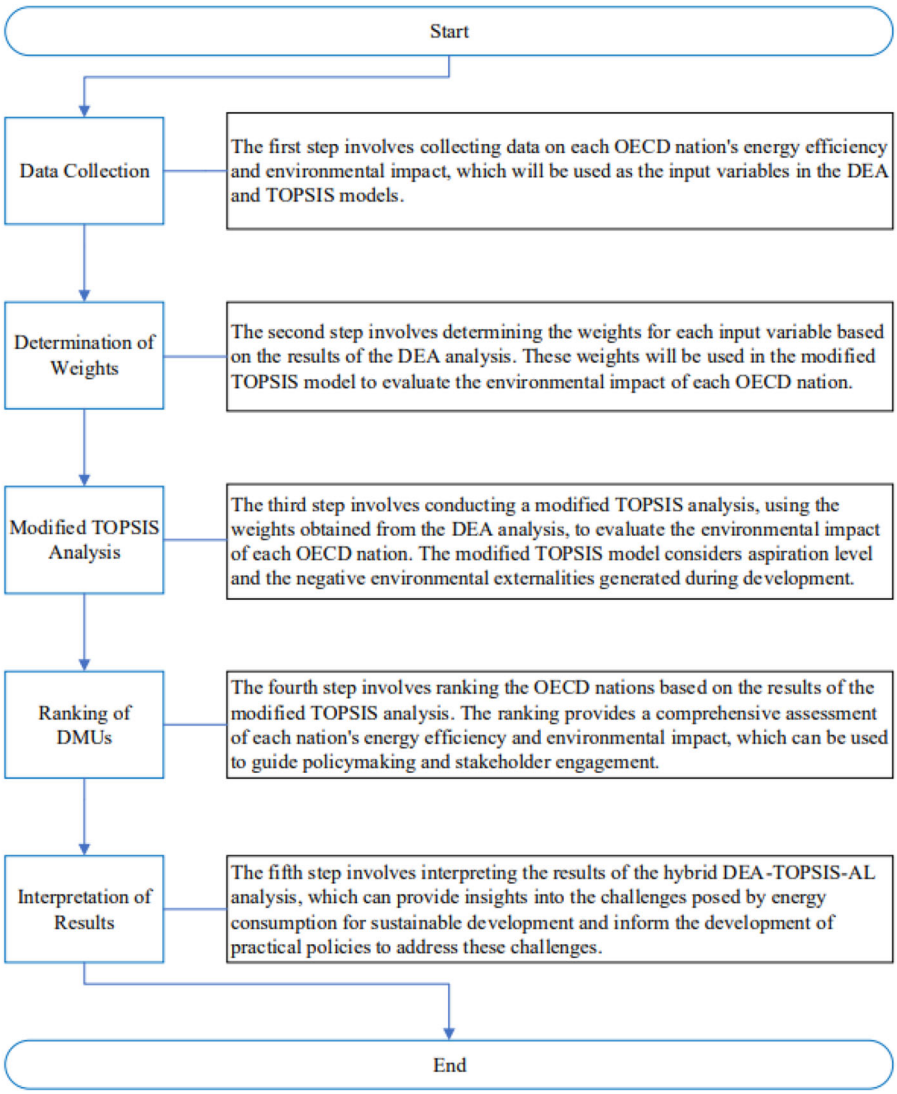


Fig. 1 The research process of this study

energy and labor as production inputs, the GDP as the desired output, and air pollutants as undesirable outputs. To ensure that the energy consumption results are comparable and focused on minimizing pollution while incorporating natural resources into the efficiency assessment, we selected labor, energy consumption, and natural resource consumption as the initial input items. At the same time, GDP, greenhouse gas emissions, and environmental risk costs are defined as the initial output items (Table 1). Table 2 presents the descriptive statistics.

Hybrid DEA–TOPSIS-AL model

The TOPSIS uses the distance between the evaluated solution and the ideal solution to eliminate the impact of variance in the internal and external environment on the evaluation [10]. This subsection outlines the method used to rank DMUs. In the hybrid model proposed in the present study, DEA is used to obtain the weights. This is an improvement over traditional DEA, where only efficient DMUs are ranked [33]. The efficiency values obtained from the DEA are used to rank the inefficient DMUs. The hybrid method is divided into nine steps as follows.

Step 1: Generate a non-parametric weight matrix

The existing methods for evaluating efficiency can be divided into two types (parametric and non-parametric) depending upon whether weights are assigned in advance or not. The non-parametric methods do not define weights in advance; instead, they are selected according to the relationships between the variables. In the parametric methods, weights are assigned in advance based on expert and decision-maker recommendations and the desired goals. Weights can be

Table 1 List of input and output items

Category	Item	Measurement
Input	Labor	Population over 15 years of age who are allowed to work legally (employed and unemployed)
Input	Energy consumption	Energy consumption of oil, natural gas, coal, and electricity
Input	Natural resource consumption	Natural resources, such as metals, minerals, and wood, form the basis of economic development
Output	GDP	The market value of all final products produced by an economy (a state/region) using production factors within a given period
Output	Greenhouse gas emissions	Emissions of greenhouse gases, including carbon dioxide, methane, nitrous oxide, perfluorocarbon, hydrofluorocarbon, and sulfur hexafluoride. The equivalent amount of carbon dioxide determines the emission unit
Output	Environmental risk costs	Expenses incurred by exposure to environmental stressors that have harmful effects on human health or the ecological environment, and expenses incurred in managing risks

determined subjectively or objectively, with the most common determination methods being the analytic hierarchy process, analytic network process, and best–worst method [3].

Objective weighting methods determine weights based on the information provided by each indicator, while subjective weighting overlooks internal information regarding the criteria [32]. For this reason, an objective weighting method was adopted to generate the required input and output weights, following the creation of the first decision matrix from all DMUs, which are then used to calculate the weights of each indicator. DEA can be considered a representative non-parametric efficiency evaluation method, allowing each DMU to select the optimal weights and be evaluated accordingly. DEA is, therefore, an ideal objective weighting method for obtaining relative efficiency in a group of DMUs, while avoiding the disadvantages of expert questionnaires and other subjective weight assignment methods.

Generally, the efficiency of a given DMU increases as fewer inputs generate more outputs. Therefore, the inputs are set to have negative characteristics, and the outputs positive characteristics. This step is represented by a matrix (decision matrix) based on all the information available about the DMU inputs and outputs. Each row of the matrix shows a DMU, and each column shows either an input or an output. There are n DMUs ($DMU_j (j = 1, \cdots, n)$) that use i input items ($x_i (i = 1, \cdots, m)$) to produce r output items ($y_r (r = 1, \cdots, s)$); u_r represents the rth output item; and v_i represents the weight of the i th input item; h_o symbolizes the relative efficiency; and e is the non-Archimedean number. The objective weight of each input (output) item can then be calculated using Eq. (1).

.

$$
\begin{aligned}
&Max h_0 = \sum_{r=1}^{s} u_r y_{r0}.\\
&Subject\ to:\\
&\sum_{i=1}^{m} v_i x_{ij} - \sum_{r=1}^{s} u_r y_{rj} \geq 0;\ \ j = 1, 2, \ldots, n;\\
&\sum_{i=1}^{m} v_i x_{i0} = 1;\\
&u_r \geq \varepsilon > 0;\ \ r = 1, 2, \ldots, s;\\
&v_i \geq \varepsilon > 0;\ \ i = 1, 2, \ldots, m.
\end{aligned}
\tag{1}
$$

The input/output weights of each assessed unit are as follows:

$$
V_{j,input} = \begin{pmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{pmatrix};\quad U_{j,output} = \begin{pmatrix} u_{11} & \cdots & u_{1n} \\ \vdots & \ddots & \vdots \\ u_{s1} & \cdots & u_{sn} \end{pmatrix}.
$$

Step 2: Normalize the input/output weights

Normalization involves using each input/output weight as the unit for calculation of the ratio of the input/output weight (for each nation) to the sum of the input/output weights of all nations, as shown in Eq. (2).

$$
V_{ij} = \frac{v_{ij}}{\sum_{i=1}^{m} v_{ij}},\ i = 1, \ldots, m;\quad U_{rj} = \frac{u_{rj}}{\sum_{r=1}^{s} u_{rj}},\ r = 1, \ldots, s. \tag{2}
$$

Table 2 Descriptive statistics

	Input items			Output items		
	NRC	EC	Labor	ERC	GGE	GDP (USD)
2013						
Max	6241.47	2196.25	143,800.00	1779.06	5133.44	58,502.06
Min	21.86	4.40	621.35	410.72	5.75	15,472.83
Average	542.79	155.60	16,560.41	1159.38	356.02	33,969.25
SD	1080.37	371.05	26,648.70	357.95	873.62	10,435.86
2014						
Max	6346.57	2216.76	146,800.00	1770.32	5176.43	58,923.94
Min	24.66	4.40	624.83	412.54	6.08	15,690.89
Average	554.13	154.01	16,777.43	1145.36	351.42	34,616.22
SD	1104.40	374.05	27,118.06	350.99	878.96	10,516.63
2015						
Max	6204.17	2193.68	149,000.00	1843.21	5033.93	60,208.27
Min	24.69	4.30	640.90	418.13	6.14	15,991.90
Average	549.53	154.19	17,000.30	1183.59	348.82	35,595.80
SD	1084.47	370.20	27,494.61	382.91	854.93	11,076.30
2016						
Max	6098.91	2172.33	150,800.00	1852.27	4927.44	62,863.84
Min	23.11	4.30	644.63	428.14	6.22	16,246.26
Average	548.38	154.39	17,240.80	1156.58	347.05	36,241.87
SD	1071.73	366.58	27,843.02	379.50	837.92	11,191.63
2017						
Max	5996.12	2180.41	153,800.00	1932.65	4962.86	66,900.09
Min	23.98	4.50	658.58	443.07	6.21	16,374.16
Average	553.81	156.05	17,520.07	1197.21	351.30	37,175.37
SD	1059.35	368.00	28,350.69	390.19	843.90	11,376.15

NRC Natural resource consumption (million tons), *EC* Energy consumption (million tons), *ERC* Environmental risk cost (USD), *GGE* Greenhouse gas emissions (million tons), *GDP* Gross domestic product (USD)

Step 3: Determine the aspiration and worst levels of the input/output items

An efficient DMU has a broader output value and a smaller input value in DEA. An inefficient DMU has a smaller output value and a broader input value. Each DMU is considered as a separate unit in this step, for calculation of the aspiration and worst levels for each input/output attribute. In quality management, three sigma represents a definition of quality that limits the deviations to only 3 in 1000, or three standard deviations of the mean, within a normal distribution. That probability reduces to 2.0 parts per billion for six sigma, which confines deviations in quality to six standard deviations and is a reasonably low defect rate. Referring to quality control constructs, the aspiration level of an output item is defined as the mean plus six standard deviations for all enterprises, while the worst level is defined as the mean for all enterprises minus six standard deviations. The aspiration level for the input items is defined as the mean minus six standard deviations for all enterprises. The worst level is defined as the mean plus six standard deviations.

The aspiration and worst levels of a given input can be expressed as in Eq. (3).

$$\begin{aligned} &A_{j,input}^{aspira} = v_i - 6\sigma_i \geq 0, \\ &A_{j,input}^{worst} = v_i + 6\sigma_i, \\ &v_i = \overline{x_{ij}},\ \sigma_i = \sqrt{\textstyle\sum_{i=1}^{m} \left(x_{ij} - v_i\right) \Big/ m},\ i = 1, \ldots, m;\ j = 1, \ldots, n. \end{aligned} \tag{3}$$

The aspiration and worst levels of output can be expressed by

$$A_{j,output}^{aspira} = u_r + 6\sigma_r,$$
$$A_{j,output}^{worst} = u_r - 6\sigma_r \geq 0,$$
$$u_r = \overline{y_{rj}},\ \sigma_r = \sqrt{\sum_{r=1}^{s}\left(y_{rj} - u_r\right)/s},\ r = 1, \ldots, s;\ j = 1, \ldots, n. \tag{4}$$

Step 4: Build a decision matrix

A decision matrix can then be built according to the input and output data, as shown in Eq. (5).

$$A_{j,input} = \begin{pmatrix} A_{11} & \cdots & A_{1n} \\ \vdots & \ddots & \vdots \\ A_{m1} & \cdots & A_{mn} \end{pmatrix};\quad A_{j,output} = \begin{pmatrix} A_{11} & \cdots & A_{1n} \\ \vdots & \ddots & \vdots \\ A_{s1} & \cdots & A_{sn} \end{pmatrix}. \tag{5}$$

Step 5: Calculate the normalized decision matrix

The purpose of normalization is to standardize variable units across all input and output terms by converting them all to values t between 0 and 1. Following normalization, a greater value for the input and output terms is considered more desirable. When the value is greater than 0.5, the evaluation performance is considered satisfactory. The formulas for normalization of the input and output items, are as follows:

$$A_{j,input}^{*} = \frac{A_{j,input}^{worst} - x_{ij}}{A_{j,input}^{worst} - A_{j,input}^{aspira}};\quad A_{j,output}^{*} = \frac{y_{rj} - A_{j,output}^{worst}}{A_{j,output}^{aspira} - A_{j,output}^{worst}}. \tag{6}$$

Step 6: Build a weighted normalized decision matrix

Considering the importance of each input and output item, the weighted value of the standard evaluation (V_{ij}, U_{rj}) is multiplied by the normalized decision matrix to obtain the weighted normalized decision matrix.

$$A_{j,input}^{**} = V_{ij} \cdot A_{j,input}^{*};\quad A_{j,output}^{**} = U_{rj} \cdot A_{j,output}^{*}. \tag{7}$$

Step 7: Obtain positive and negative-ideal solutions (PIS and NIS)

Based on the aspiration level construct, the evaluated unit's PIS and NIS should be 1 and 0, respectively, following normalization. Therefore, the calculation of PIS (PIS_j) and NIS (NIS_j) can be expressed as follows:

$$PIS_j = \max A_j^{**};\quad NIS_j = \min A_j^{**}. \tag{8}$$

Step 8: Calculate the distance between each assessed unit and PIS and NIS

Based on the squared Euclidean distance, the distances between the input and output items and the corresponding PIS and NIS are calculated by

$$d_i^{*} = \sqrt{\sum_{j=1}^{n}\left(PIS_j - A_j^{**}\right)^2};\quad d_i^{-} = \sqrt{\sum_{j=1}^{n}\left(A_j^{**} - NIS_j\right)^2}, \tag{9}$$

where d_i^{*} represents the distance between the input/output items of the i-th assessed item and PIS; and d_i^{-} represents the distance between the input/output item of the i-th assessed item and NIS.

Step 9: Calculate the closeness coefficient (CC_i)

CC_i is a reliable ranking score, as shown in Eq. (10). The model respectively considers the distance between all alternatives and PIS and NIS, to compensate for the traditional TOPSIS [22].

$$CC_i = NISw\left(\frac{d_i^{-}}{\sum_{i=1}^{m} d_i^{-}}\right) - PISw\left(\frac{d_i^{*}}{\sum_{i=1}^{m} d_i^{*}}\right),$$
$$\begin{cases} -1 \leq CC_i \leq 1 \\ 0 \leq PISw \leq 1 \\ 0 \leq NISw \leq 1 \end{cases},\ i = 1, 2, \ldots, m. \tag{10}$$

The $PISw$ and $NISw$ weights reflect the relative importance of PIS and NIS. Usually, both $PISw$ and $NISw$ are set to 0.5. The closer CC_i is to 1, the closer it is to the aspiration level; whereas, the closer it is to -1, the closer it is to the worst level.

Results

Overall performance and performance by nation

The CC_i scores for the OECD member states are shown in Table 3. As can be seen in Fig. 2 there was a great difference in the performance of the OECD member states from 2013 to 2014. In 2015, the United Nations Climate Change Conference (COP 21) concluded the Paris Agreement, aimed at reducing greenhouse gas (mainly carbon dioxide) emissions, to limit temperature increases to below 2 °C while

Table 3 CC_i for the OECD member states

Country	2013	2014	2015	2016	2017
Australia	0.0027	0.0026	0.0023	0.0024	0.0024
Austria	− 0.0029	− 0.0024	− 0.0010	− 0.0012	− 0.0011
Belgium	− 0.0011	− 0.0005	0.0004	0.0003	0.0004
Canada	0.0006	0.0005	− 0.0004	0.0002	0.0001
Chile	0.0038	0.0033	0.0009	0.0009	0.0009
Czech Republic	0.0000	0.0002	0.0008	0.0008	0.0008
Denmark	0.0007	0.0008	0.0010	0.0010	0.0010
Estonia	0.0042	0.0040	0.0011	0.0011	0.0011
Finland	0.0026	0.0023	0.0009	0.0009	0.0009
France	− 0.0008	− 0.0007	− 0.0008	− 0.0006	− 0.0006
Germany	− 0.0027	− 0.0024	− 0.0007	− 0.0006	− 0.0006
Greece	0.0007	0.0008	0.0009	0.0010	0.0010
Hungary	0.0006	0.0007	0.0009	0.0010	0.0009
Ireland	0.0019	0.0019	0.0009	0.0010	0.0010
Israel	0.0020	0.0017	0.0008	0.0009	0.0008
Italy	− 0.0016	− 0.0013	− 0.0002	− 0.0002	− 0.0002
Japan	− 0.0042	− 0.0039	− 0.0009	− 0.0008	− 0.0007
Korea	− 0.0034	− 0.0033	− 0.0005	− 0.0009	− 0.0007
Latvia	0.0021	0.0022	0.0011	0.0011	0.0011
Lithuania	0.0015	0.0015	0.0011	0.0011	0.0011
Mexico	0.0037	0.0029	0.0001	0.0003	0.0002
Netherlands	− 0.0002	0.0000	0.0002	0.0004	0.0003
New Zealand	0.0048	0.0043	0.0011	0.0010	0.0010
Norway	0.0018	0.0019	0.0010	0.0010	0.0011
Poland	− 0.0003	− 0.0001	0.0006	0.0007	0.0006
Portugal	0.0017	0.0017	0.0010	0.0010	0.0010
Slovak Republic	0.0007	0.0011	0.0009	0.0010	0.0009
Slovenia	0.0023	0.0025	0.0010	0.0010	0.0010
Spain	0.0008	0.0008	0.0002	0.0004	0.0003
Sweden	0.0019	0.0017	0.0008	0.0009	0.0009
Switzerland	− 0.0013	− 0.0019	− 0.0009	− 0.0014	− 0.0012
Turkey	0.0000	− 0.0001	0.0004	0.0004	0.0003
United Kingdom	− 0.0009	− 0.0006	− 0.0001	0.0001	0.0001
United States	− 0.0217	− 0.0220	− 0.0151	− 0.0160	− 0.0159

continuing to strive for no more than a 1.5 °C increase. This agreement was tantamount to proclaiming the end of the post-industrial revolution era, which relied heavily on fossil fuels (natural resources, e.g., coal, oil, and natural gas) for growth, and to the commencement of a low-carbon production and sustainability era. From 2016 to 2017, national performance remained consistently stable. These findings are consistent with those obtained in recent studies. Specifically, Ozcan [27] studied the data for OECD member states from 2000 to 2014 and found that economic growth and energy consumption patterns were conducive to improving environmental performance and that the nations' economic development and energy consumption patterns gradually began to align with their environmental policies. As the research period of this study was extended to include 2017, the results reveal that, in 2016, nations began to adopt practical policies to reduce fossil fuel consumption and improve energy and environmental efficiency to better achieve sustainable development goals. Even nations which had performed poorly in the past, such as Japan, South Korea, and Germany, showed considerable improvement over the last two years of the research period.

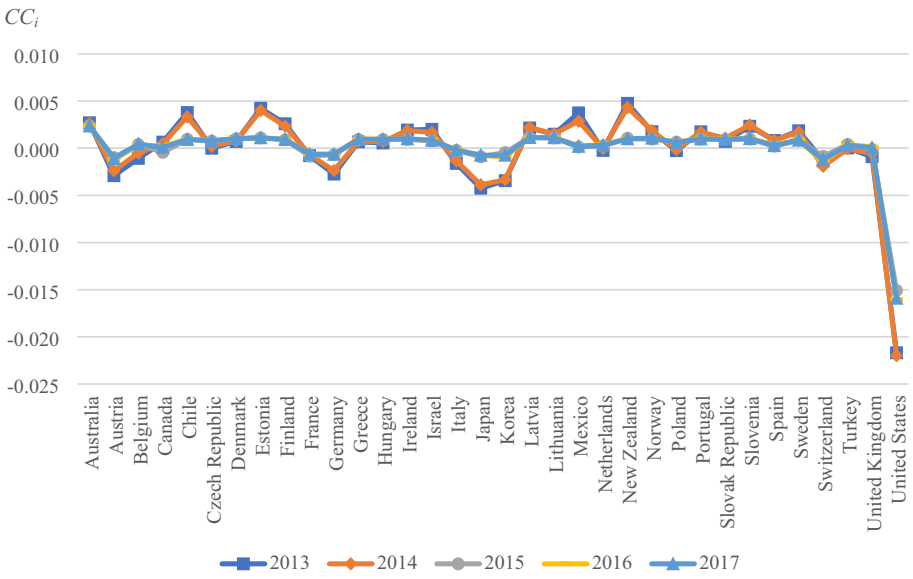


Fig. 2 Changes in the CC_i for OECD member states

Analysis by region

In their analysis of China's thermal power industry, Wang [38] emphasized the continuous deterioration of the environment caused by human activity, making environmental sustainability an important goal in industrial development. However, industrial production remains an unavoidable cause of greenhouse gas emissions [12, 19, 21, 24].

First, the OECD member nations were first divided into two groups, the G7 and non-G7 nations. Figure 3 shows the mean CC_i values for the G7 nations from 2013 to 2017.

It can be seen that the overall performance of the G7 nations was quite from that of the non-G7 nations. The environmental damage caused by the greenhouse gas emissions produced by the G7 nations remained large during this time period. To further explore the individual performance of the seven nations, more detailed data were analyzed. Figure 4 reveals that, in addition to the US, which had the worst performance (− 0.0181), Japan (− 0.0021) and Germany (− 0.0014) were also poor performers; Canada was the only nation that had a positive CC_i (0.0002).

As shown in Fig. 5, the United Kingdom (UK, − 0.0003), Italy (− 0.0007), Germany (− 0.0014), France (− 0.0007), Belgium (− 0.0001), and Austria (− 0.0017) had the worst performances, with negative CC_i. In contrast, the performances of Estonia (0.0023), Slovenia (0.0016), Latvia (0.0015), and Finland (0.0015) were generally better. In terms of geographical location, nations closer to the periphery, such as Finland and Sweden, appeared to perform better, followed by Italy and France. In contrast, nations in the center of Europe, such as Germany, Switzerland, and Austria, performed worse. Thus, the nations' energy and environmental efficiency presented as a semi-radial shape.

Past research has pointed out that differences in regional performance and population growth in Western Europe have significantly impacted carbon dioxide emissions and urban land use [40]. Natural resources are the foundation of economic and social development. Excessive consumption of these resources leads to environmental degradation and economic loss. For EU members in the OECD, improving resource efficiency in the European economy and society is of paramount importance. The six nations with the worst performance (including the UK) should be the first to review their resource efficiency systems.

Efficiency improvement

To better understand the energy and environmental efficiency performance of underperforming nations relative to the other nations and to provide a benchmark as a reference, this study charts a comparison chart based on the *CCi* means and standard deviations from 2013 to 2017. The 34 nations were divided into four groups (Table 4); suggestions were then proposed for each group.

The first group included nations with positive mean values and stable performance. Nearly 60% of OECD members were in this group. Australia remained in the top five throughout the research period. Portugal was active in developing renewable energy (especially, hydropower and wind power). Portugal's promotion of climate policy goals, fossil fuel prices, energy efficiency, and carbon taxes played essential roles. In 2015, the Portuguese government began incorporating the goals mentioned above and directions for improvement into its national policy and promulgated a new carbon tax system [29]. The government strove to improve energy efficiency. The rapid growth of renewable energy

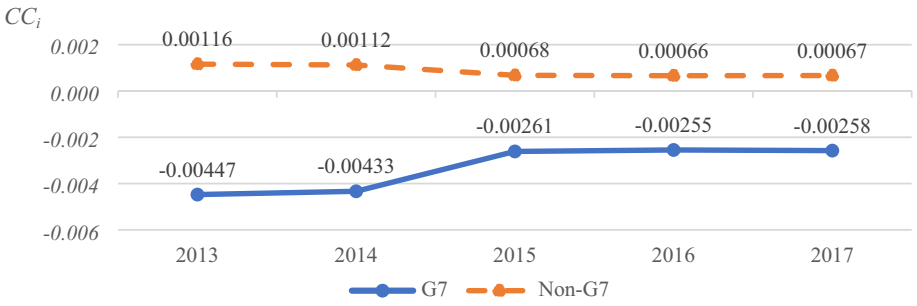


Fig. 3 Comparison of CC_i between G7 and non-G7 nations (from 2013 to 2017)

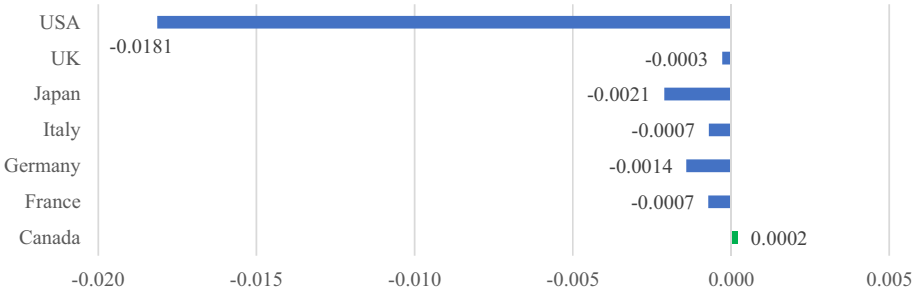


Fig. 4 Comparison of the CC_i of the G7 nations

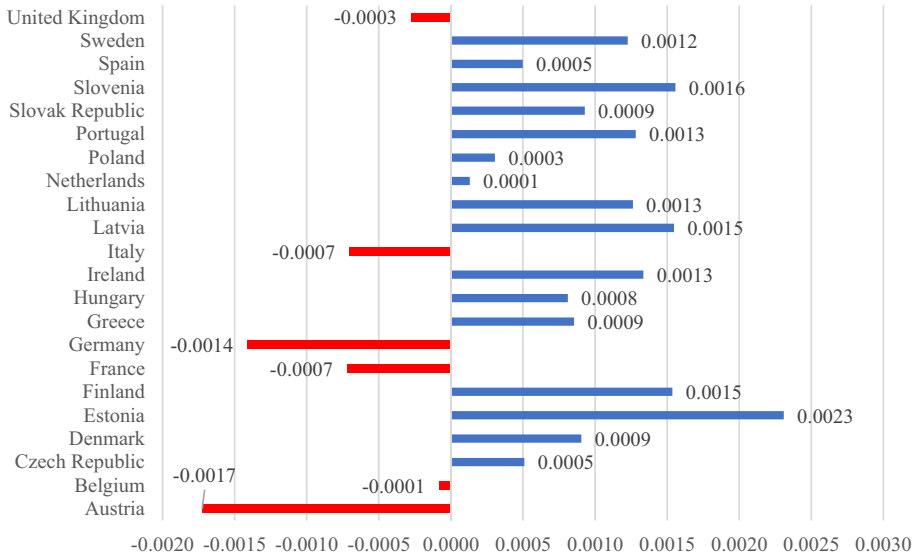


Fig. 5 Comparison of the *CCi* of EU nations

Table 4 Efficiency improvement groups

Category	Criteria	Nation	Mean	SD
Group 1	Positive and stable	Australia, Canada, Czech Republic, Denmark, Greece, Hungary, Ireland, Israel, Latvia, Lithuania, Netherlands, Norway, Poland, Portugal, Slovakia, Spain, Sweden, and Turkey	0.00095	0.00030
Group 2	Positive and unstable	Chile, Estonia, Finland, Mexico, New Zealand, and Slovenia	0.00188	0.00125
Group 3	Negative and unstable	Austria, Belgium, Germany, Italy, Japan, South Korea, and the US	− 0.00371	0.00127
Group 4	Negative and stable	France, Switzerland, and the UK	− 0.00078	0.00027

sources released Portugal from its dependence on imported fossil fuels and contributed to the further vigorous development of such energy sources, leading to a decline in the retail price of renewable energy and acceleration in replacing traditional fossil fuels [43].

The second group included nations with positive mean values and unstable performance. This study suggests that these nations should review their policies and the effectiveness of implementing energy and environmental policies to increase the stability of their performance.

The performance of Finland worsened from 2013 to 2017. Some have suggested that cogeneration of heat and electricity would solve Finland's energy and environmental efficiency problems. In a case study on Helsinki, it was found that implementing the cogeneration method halved emissions and operating costs, showing this to be an effective method for reducing carbon dioxide emissions [31]. Such low-carbon or zero-carbon solutions have positively impacted energy use elasticity.

The third group included nations with negative mean values and unstable performance. Based on the overall performance of the nations in this group, more effort is needed to improve energy and environmental efficiency and promote relevant policies. It is worth noting that all those in this group were G7 member states. The study results confirm that these nations have yet to achieve the goals set out by the G7. In Japan, thermal power plants provide over 80% of their primary energy. More than two-thirds of these plants have remained in operation for more than 30 years [45]. Japan was also the only nation that continued to build thermal power plants and invest heavily in such plants abroad, especially in Southeast Asia.

Studies on the efficiency of energy applications in the US from 2012 to 2015 showed that a large amount of energy was wasted due to low technical efficiency. Thus, the US Department of Energy, working with affiliated research institutes, promoted the National Action Plan for Energy Efficiency, aimed at developing more efficient technologies to improve energy and environmental efficiency. The benefits of such an approach include lower energy costs, cleaner air, and better corporate competitive advantages [24].

The fourth group included nations with negative means and stable performance. This study suggests that nations in this group should examine whether their current policies facilitate the desired goals. Switzerland has been recognized as a climate leader, as it utilizes both hydroelectric power resources and is a nation with nuclear and renewable energy resources an strong supporting policies [28]. However, Switzerland has no natural resources, so must rely on imports for 80% of its energy needs. Switzerland's power supply consists of 54% hydropower, 40% nuclear power, 4% other sources, and only 2% renewable energy. The Swiss government has provided subsidies to large-scale green energy power plants and recently, investments made in large-scale hydroelectric power plants have also been included in the subsidy scheme.

Weight analysis

The previous subsections dealt with the efficiency performance demonstrated by each nation. This subsection explores the optimal weights developed for each OECD member state through analysis of the weight differences. This approach avoids the shortcoming of relying upon expert assigned weights in which only one set of weights is obtained. First, the inputs of the model were evaluated (Fig. 6). There was minimal difference between nations for the labor weighting among the input items, while natural resources and energy consumption were important factors that affected performance. Nations with more unsatisfactory performance, such as the US and the UK, could improve their energy consumption performance more than nations with better overall performance, which is indicative of the issues faced by major industrialized nations aiming to improve energy and environmental efficiency. In most nations, the weighting for energy consumption was greater than that of natural resource consumption. South Korea and Switzerland were the only exceptions, indicating that they had more energy consumption problems than the other nations. Past studies have proposed policy suggestions aimed at maintaining a balance between economic development and environmental protection, as well as reaching a mutual agreement with other nations to develop practices for industrial transformation, improvement of energy efficiency, and policy control [8, 11].

In terms of outputs (Fig. 7), the differences in the GDP between nations were relatively small. In contrast, greenhouse gas emissions and environmental risk costs (undesirable outputs) were essential performance factors. Undesirable outputs played a more significant role in measuring energy and environmental efficiency than the desired outputs, which should serv as a reference for energy policy formulation. Since sustainable development is a core focus of economic development, ensuring that undesirable outputs are considered when evaluating energy, environmental efficiency permits policymakers to consider the external costs of economic development and production processes, identify more efficient economic areas, and determine directions for improvement. The concept of the undesirable output could also be extended to the development of industry, energy, and natural resources, as well as local, regional, and national development. This study applied the undesirable output construct for the analysis of member nations to yield appropriate improvement strategies corresponding to the OECD nations. Although the US, Japan, South Korea, and Canada led in terms of GDP performance, their greenhouse gas

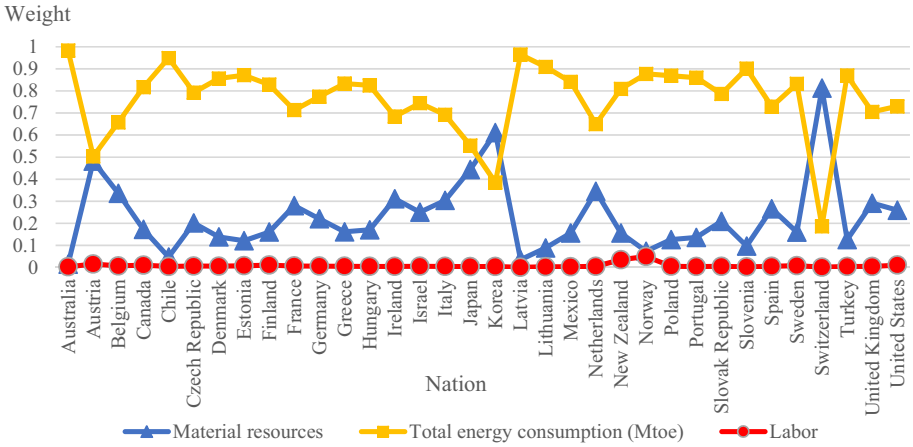


Fig. 6 Input weights for the OECD member states

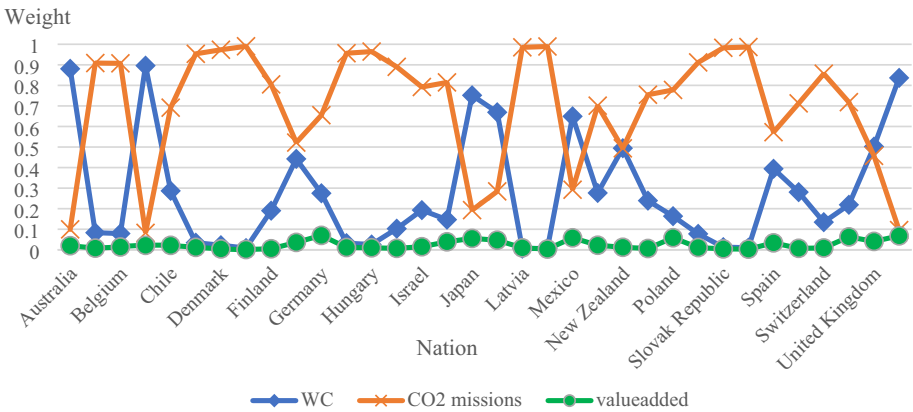


Fig. 7 Output weights for the OECD member states

emission performance remained poor, resulting in poor overall performance. Therefore, these nations should prioritize reducing waste emissions to improve energy and environmental efficiency. Meanwhile, Slovakia, Slovenia, Estonia, Latvia, and Lithuania had fewer greenhouse gas emissions overall, while their corresponding weight scores were relatively high. However, only Estonia, Latvia, and Slovenia had good overall performance, suggesting that fewer greenhouse gas emissions did not necessarily lead to better energy and environmental efficiency, as improvements in other areas were still necessary.

Method comparisons and sensitivity analysis

This subsection presents the results of multiple method comparisons and sensitivity analyses. Of the five years of data used in this case, the most recent year, 2017, is taken as an example. A model comparison was performed, including the modified TOPSIS-AL (used in this study), Simple Additive Weighting (SAW), TODIM (an acronym in Portuguese for Interactive Multi-criteria Decision-Making), Gray Relational Analysis (GRA), COmplex PRoportional Assessment (COPRAS), VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR), and the Performance Calculation technique of the Integrated Multiple multi-attribute decision-making (PCIM) methods. The calculation results obtained with the multiple methods are shown in Table 5. Obviously, the ranking produced by each method is not exactly the same, but the first and last countries are still Australia and the United States, respectively. The modified TOPSIS-AL used in this study not only incorporates the concept of the aspiration level, but also utilizes the relative distance of each country to the PIS and NIS to obtain more potential information. In addition, the modified TOPSIS-AL can be applied to produce a schematic diagram, like that shown in Fig. 5, that can help decision-makers more clearly understand which countries have relatively good performance and which have relatively poor performance.

In addition, a sensitivity analysis was conducted in order to check whether a change of some parameters will affect the analysis results. In the ranking index of the modified TOPSIS-AL, the *NISw* and *PISw* are the two most important parameters. Here, the most objective method is to set these two parameters to 0.5. The values of *NISw* and *PISw* are adjusted nine times, from 0.42 to 0.58, to explore if the ranking of a country changes. Figure 8 shows the sensitivity analysis results. The ranking of the first and last countries

Table 5 Calculation results obtained with multiple methods

	Modified TOPSIS-AL	SAW	TODIM	GRA	COPRAS	VIKOR	PCIM
Australia	1	1	1	1	1	1	1
Austria	32	33	24	24	33	33	33
Belgium	20	14	20	20	14	28	29
Canada	25	4	33	33	4	22	22
Chile	14	16	18	18	16	4	8
Czech Republic	18	32	19	19	32	20	23
Denmark	7	29	8	8	29	7	10
Estonia	4	28	3	3	28	6	7
Finland	15	26	17	17	26	11	16
France	28	20	31	31	20	27	32
Germany	29	5	32	32	5	24	26
Greece	11	27	14	14	27	12	13
Hungary	13	30	16	16	30	13	17
Ireland	8	15	6	6	15	16	11
Israel	17	13	15	15	13	23	19
Italy	27	17	27	27	17	29	31
Japan	30	3	30	30	3	32	21
Korea	31	2	10	10	2	17	2
Latvia	2	22	2	2	22	2	5
Lithuania	3	21	4	4	21	5	6
Mexico	24	9	29	29	9	21	27
Netherlands	22	11	22	22	11	30	28
New Zealand	9	18	9	9	18	10	12
Norway	5	12	12	12	12	3	3
Poland	19	7	23	23	7	8	4
Portugal	10	19	11	11	19	9	9
Slovak Republic	12	31	7	7	31	19	18
Slovenia	6	24	5	5	24	18	15
Spain	23	10	25	25	10	25	25
Sweden	16	25	21	21	25	14	20
Switzerland	33	23	13	13	23	31	30
Turkey	21	8	26	26	8	15	14
United Kingdom	26	6	28	28	6	26	24
United States	34	34	34	34	34	34	34

has not changed, but there are slight changes in the rankings of other countries. This indicates that the most appropriate settings for these two parameters is 0.5, because this is the only way we can pay attention to both PIS and NIS.

Conclusion

Statistical methods and econometric models have been widely used in energy and environmental efficiency studies. This study also utilized and obtained weights for input/output items which can be utilized to propose suggestions for underperforming nations and set benchmarks according to each nations national development priorities. The concept of the aspiration level and the introduction of the six sigma methodology were used to overcome the shortcomings of the traditional DEA, where the best evaluation results are limited by the original data, while retaining the advantages of the DEA in terms of maximizing the characteristics of each evaluated nation. The proposed hybrid model which combines DEA and modified TOPSIS-AL was applied to evaluate the energy and environmental performance of the

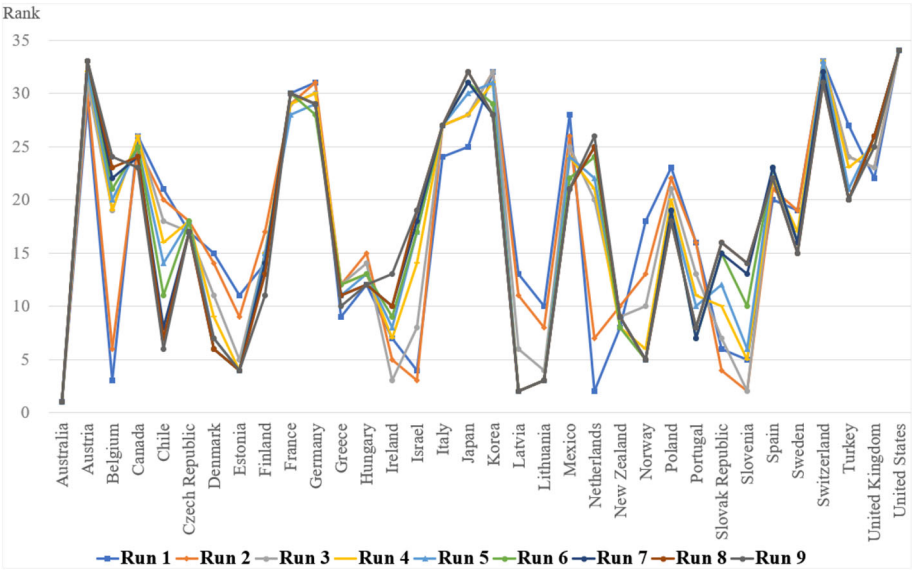


Fig. 8 Results of nine sensitivity analysis runs

OECD member states without the need of a hypothesis, as required in traditional statistical analysis or extensive sample data [3]. Based on the findings, the following suggestions are proposed.

(i) In terms of national policy implementation, it has been pointed out that advances in global climate models have improved the understanding of future climate scenarios. However, higher-quality observational data on the current state of the environment are needed [15]. Science and economics related to climate change involve winners and losers, burden-sharing, and bargaining. A perspective that supersedes pure science is required, as issues demand government action, especially cooperation between governments. Decisions made by companies and governments should stimulate low-carbon consumption and technology, such as reducing carbon dioxide emissions and reducing coal-fired thermal power generation. The environmental problems caused by energy consumption and the lack of supporting monitoring policies pose a significant challenge to sustainable development. This study suggests that nations should ensure that the economy develops in a way that has the most negligible impact on the environment. The suggestions on the input/output items proposed in this study could be used as a reference to modify and improve related policies. Hence, it is recommended that nations utilize lean management practices in renewable energy and waste management to ensure the safe acquisition of needed resources and cope with climate change and global warming.

(ii) From the perspective of academic research, this study extends the application of the DEA. It provides a valuable reference for estimating weights for the input and output items. Past research on energy and environmental efficiency has only compared values, while the method developed in the present study can reveal the direction of such values. According to the results, the US had the worst performance among the investigated nations, while the performance of Switzerland, South Korea, Japan, Italy, Germany, France, and Austria was also underwhelming. The performance of these nations significantly reduced the OECD's ability to achieve sustainable development and energy and environmental efficiency goals. In particular, improving government efficiency in energy consumption reduced the energy intensity of OECD members. In addition, the results showed that higher GDP per capita and total capital contributed to energy efficiency, which may present a shortcut for industrial powers, led by the US, to improve energy and environmental efficiency.

(iii) In terms of climate change, past studies have shown that the number of local climate adaptation programs has increased with the increasing threat of climate change. City governments and various institutions have provided new insights into national climate adaptation planning methods. This study takes the stance that national governments should be committed to a solid response to climate change, while actively participating in related programs, introducing new carbon reduction and industrial adjustment policies, and organizing independent climate change committees. Although there many climate conferences have been held and agreements made, there remains a gap between agreeing to participate in a program and actually implementing effective policies. Nations should not blindly focus on reducing emissions but rather consider the direction national development should take and the availability

of resources. Assessing and referring to national needs and attainable goals should be the first step toward energy and environmental efficiency and sustainable development. The calculation and evaluation of statistical models should be utilized to understand better a given nation's advantages and disadvantages compared to other nations so that more targeted measures can be formulated.

Despite the contributions mentioned above, this study has several limitations. Based on the research model proposed in the present study, future research could adopt an analysis of variance approach using future improvement data for inefficient DMUs following the calculation of efficient values by the DEA. Future studies could also introduce the network and continuous-time to expand further the dimensions measured by the model. Another issue encountered is that the weights calculated by the DEA might be 0, which could be addressed in future research. Moreover, more comprehensive greenhouse gas reduction measures should be considered, such as reduction targets, alternative energy sources, methods, supporting measures, and social and economic impact. Future studies should include more input/output items to improve the model's integrity further. Furthermore, time complexity analysis can be incorporated into follow-up studies.

Author contributions S-WL and H-WL conceived the study and were responsible for the design and development of the data analysis. MG performed the review and editing work. All authors have read and agreed to the final version of the manuscript.

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Data availability This study's research subjects were the 34 OECD member states, and the research period was from 2013 to 2017. The statistics provided by the OECD include those for all 34 member states as well as other vital economies. Data are available within the article or in supplementary materials. The authors confirm that the data supporting the findings of this study are available at https://data.oecd.org/.

Declarations

Conflict of interest None of the authors declare any conflicts of interest.

Ethical approval This study does not include any data from studies with humans or animals.

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