IJE TRANSACTIONS B: Applications Vol. 37, No. 05, (May 2024) 959-973

International Journal of Engineering

Journal Homepage: www.ije.ir

Performance Evaluating Energy, Economic and Environmental Performance with an Integrated Approach of Data Envelopment Analysis and Game Theory

M. Mohammadzadeh, M. Navabakhsh*, A. Hafezalkotob

Department of Industrial Engineering, Islamic Azad University, South Tehran Branch, Iran

PAPER INFO

Paper history:
Received 31 December 2023
Received in revised form 11 February 2024
Accepted 18 February 2024

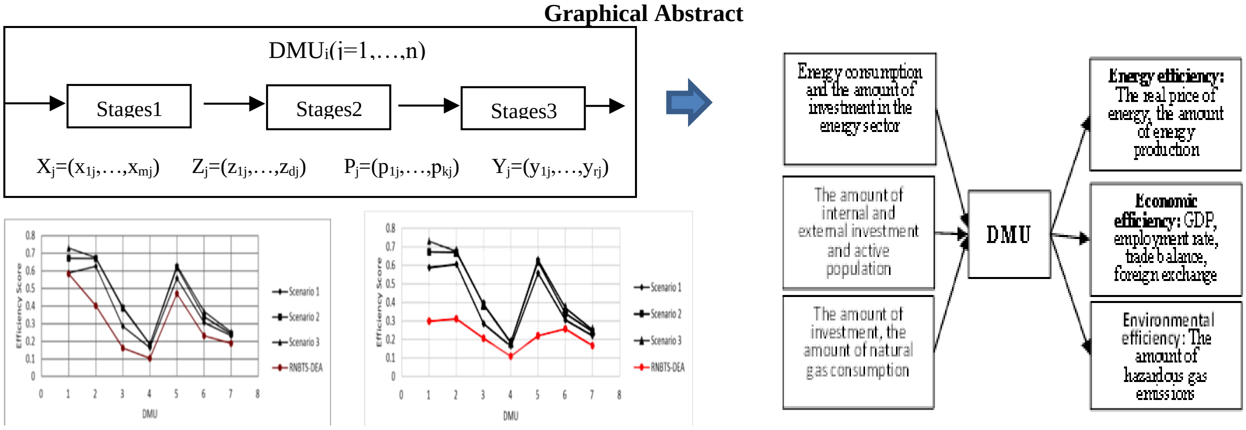
Keywords:
Performance Evaluation
Economic
Energy
Environmental
Game Theory
Data Envelopment Analysis

ABSTRACT

This research has been carried out with the aim of evaluating the energy, economic and environmental performance of selected countries that export energy resources with the integrated approach of data envelopment analysis (DEA) and game theory. The methodology of this research, including super-efficiency and cross-efficiency methods have also been used to rank efficient countries before the cooperation phase. Then, in the cooperation phase, each country is investigated using the method of cooperative games theory and Shapley's value. The resulting model was implemented and the rank of the efficient countries was compared with each other in the super-efficiency and cross-efficiency method (before cooperation) and the Shapley's value method (after cooperation). The results showed that Qatar and Yemen have the highest, Lebanon and Jordan the lowest energy efficiency; Kuwait, Qatar and Turkmenistan have the highest economic efficiency, Iran and Turkey have the lowest economic efficiency; UAE and Qatar have the highest, Iran and Jordan the lowest environmental efficiency.

doi: *10.5829/ije.2024.37.05b.13*

Graphical Abstract



NOMENCLATURE

BR	*V*	*U*	Horizontal components of velocity (m/s)
C_c	Cunningham correction factor	V	Vertical components of velocity (m/s)
c_k	Discrete lattice velocity in direction (k)	U_i, U_j	Random numbers between 0 and 1
c_s	Speed of sound in Lattice scale	**Greek Symbols**	
d^p	Particle diameter (µm)	ρ	Density (kg/m^3)
f_k^{eq}	Equilibrium distribution function	τ	Lattice relaxation time

*Corresponding Author Email: *m_navabakhsh@azad.ac.ir* (M. Navabakhsh)

Please cite this article as: Mohammadzadeh M, Navabakhsh M, Hafezalkotob A, Performance Evaluating Energy, Economic and Environmental Performance with an Integrated Approach of Data Envelopment Analysis and Game Theory. International Journal of Engineering, Transactions B: Applications. 2024;37(05):959-73.

1. INTRODUCTION

Energy consumption is an indispensable aspect of production processes across all stages, as it is imperative for the production process to function. It is impossible to carry out any production activity without the use of energy. Economic growth models that neglect the significance of energy in driving economic growth suffer imperfections. Numerous scholarly works have examined the relationship between economic growth and energy consumption, while comparatively a few studies have delved into the effects of energy on product growth (1). Energy consumption and all economic activities exert direct and indirect impacts on the environment; meaning that the process of energy production, from extraction to production, and consumption, can significantly harm the environment (2). The correlation between economic development and the environment is a major and convoluted economic concern. Energy consumption is an essential component of any economic activity. It plays a vital role in driving economic growth and enhancing the overall quality of human life while leading to the generation of environmental pollutants (3). Energy is widely acknowledged as a major constituent in the establishment and advancement of industrial societies (4). In that light, the level of access to various energy sources serves as an indicator of the political and economic development and influence of countries. The combination of high energy prices and the significant investment required in the capital sector, along with the rapid expansion of industrialization and the increasing energy demands of societies, has prompted the adoption of policies to optimize energy consumption (5). These policies aim to prevent uncontrolled and inefficient energy usage while reducing production costs and enhancing public welfare (6). Therefore, given the great importance of energy and the reduction of fossil energy sources and the increasing fuel price in production and services, as well as environmental issues, the improvement of consumption status and efficiency has given much attention as possible in its use (7). Enhancing energy efficiency is a widely used cost-effective approach to the enhancement of energy security; the promotion of industrial competitiveness, and the mitigation of climate change repercussions (8). Furthermore, with the rise in population growth and energy dependence, there has been a corresponding increase in the consumption of fossil fuels, leading to environmental challenges (9). As a result, there is a growing necessity for politicians to engage with experts and opinion leaders to formulate and execute policies that promote energy efficiency and reduce overall energy consumption (10). A significant number of developing countries are undergoing raised energy consumption as a result of economic growth and subsequent better living standards (11). Besides, this increasing trend cannot continue to rise as the available resources are limited. This is while energy security and environmental crises are other issues that have raised serious concerns. In addition, the utilization of energy often requires substantial investments, which are frequently limited in developing countries (12). Moreover, energy consumption in these nations tends to contribute to elevated levels of environmental pollution and energy inefficiency when compared to more developed countries. Consequently, improving energy, economic, and environmental efficiency emerges as a feasible solution (13).

In spite of the extensive endeavors made in developed nations to enhance awareness, adopt environmentally friendly technologies, and increase energy efficiency; the rapid pace of economic development has resulted in a substantial surge in energy consumption (14). Consequently, this has given rise to multiple environmental challenges, including the international emission of greenhouse gases. Each year, state-level meetings are convened to address environmental risks, promote stability, and mitigate greenhouse gas emissions (15, 16). Based on a comprehensive analysis of these conventions, certain countries demonstrably lack a definitive stance toward effectively attaining the objectives outlined in these conventions, evidently shunning the principle of responsibility (17). These conventions serve countries as an opportunity to be able to align their policy-making with global CO_2 emission reduction policies while interacting with credible international institutions. In recent conventions, a legally binding regime aimed at reducing emissions for all countries has been approved, indicating that in order to achieve the objectives of emission reduction, it is imperative for both developed and developing countries to establish robust policy frameworks (18). To effectively utilize emission reduction permits as a means to regulate pollution levels and align them with socially optimal standards, an exhaustive constraint has been imposed on the overall emission levels within a given region (19). This restriction enables the evaluation and allocation of permits to countries that have actively participated in the program. This limited availability serves as a driving force behind the trade and exchange of licenses (20). To ensure the efficiency of these licenses several criteria must be thoroughly examined: responsibility, qualification, equality, effectiveness, and sustainable development. In order to determine the optimal emission rate in countries to create a win-win situation in terms of environmental impact and efficiency in the study area, permits were efficiently allocated while taking into account the social and economic aspects (21, 22). To establish an appropriate setting for the achievement of Pareto optimal conditions, it is feasible to ensure that all countries are placed in a favorable position once the efficiency frontier outlined in the employed model is attained (23).

The evaluation of energy and environmental performance holds significant importance for policymakers and economists. This interest stems from two key factors: the escalating levels of greenhouse gas emissions and the limited availability of energy resources. These factors are integral in shaping the behavior of energy consumers and how they respond to energy programs. In certain instances, consumers exhibit complete responsiveness, while in others, they pose challenges to policy packages (24). In light of the escalating energy consumption and environmental pollution, and subsequently their adverse impact on health, it has become imperative to prioritize the optimization of existing resources and prevent energy waste (25). This directs the attention of energy policymakers toward the necessity of optimally exploiting energy sources. Unmistakably, relevant decision-making and planning require a full grasp of the current and final consumption of energy carriers in terms of efficiency (26). The unchecked surge in energy consumption across developing nations has made it imperative to adopt energy optimization strategies (27). As a result, in conjunction with other production factors, the efficiency and optimization of energy is a determining constituent of the economic pulse of nations (28). Accordingly, economic developments have progressively increased the significance of energy efficiency and optimization. As environmental concerns continue to rise, it is crucial to consider the negative impacts and pollutants that arise from economic activities when evaluating the efficiency of businesses at both the micro and macro levels. This is especially important in energy-intensive industries and at the macro level where pollutants can have a significant impact on the environment (29).

Besides, other methods are also available to measure efficiency. DEA has become increasingly popular in recent years as a method for measuring efficiency. It is based on mathematical programming that allows for measuring the relative efficiency of the units using the possible production set (PPS) formed by all units. This method has many significant advantages: Its main advantage is its ability to compute the efficiency of units with multiple inputs and outputs. Additionally, it does not make any assumptions about the production frontier shape or the internal structure of decision-making units (30).

In the past, classic DEA models regarded systems as a black box and to some extent ignored their internal structures. That is to say, models with network structures were treated as a single unit. This approach failed to account for the fact that real-world problems in telecommunications, such as power distribution and transportation, often have a network structure. Over the past few years, there have been advancements in the development of models that also incorporate the network structure of decision-making units. It is crucial to acknowledge that in problems with a network structure, the collaboration among subsystems leads to an increase in the overall efficiency of the system. Consequently, models should be able to effectively take this collaboration into account. Game theory is a viable methodology that can facilitate the achievement of this objective. The approach mentioned has gained popularity in recent years and is commonly referred to as centralized models in the field of data envelopment analysis. One of the main issues with these models is their inability to provide a distinct performance value for each subunit (31). It should be noted that certain researchers have adopted the leader-follower approach or the concept of achieving maximum efficiency. However, it is important to recognize that this approach is at odds with the principles of the cooperative gameplay concept. In classical DEA models, it is commonly assumed that data is certain. As a result, these models lack the capability to handle data uncertainties. In the real world, certain data are inherently inaccurate, ambiguous, and uncertain. Therefore, it is crucial to adopt approaches that can effectively manage this uncertainty during the modeling process. Numerous methods have been proposed for controlling uncertainty in optimization problems. In recent years, there has been a significant focus on approaches to addressing complex problems, such as fuzzy set theory, random programming, and optimization. These methods have proven to be effective in tackling a wide range of challenges and have garnered significant attention from researchers. It is worth noting that previous investigations into the implementation of these approaches in DEA have primarily focused on issues with simple and non-network structures. However, there is a dearth of quantitative research on the use of uncertainty control approaches in network-structured issues. It is important to mention that the existing studies are restricted to the use of fuzzy approaches, ignoring other approaches. The objective of this study is to address the aforementioned issues by first introducing a DEA model based on the Nash bargaining game, a technique in game theory. Then, in order to effectively control the uncertainty of the proposed model, three approaches are employed: fuzzy set theory, random programming, and robust optimization. In conclusion, various numerical examples and case studies were used to validate the proposed models and estimate their efficiency.

Gabriel et al. (1) reported that energy service companies face limited resources. The companies are centralized using the DEA method. The DEA model is used to limit the efficient use of resources. The results of the study demonstrated that this method demonstrated good effectiveness in improving energy consumption in energy service companies in Spain.

Amani and Bagherzadeh Valami (32) studied a thorough examination of sustainable development and sustainability using DEA analysis. They suggested that these concepts have been at the core of policy-making within multilateral agreements at a wide range of levels. Despite their importance, both concepts have been defined ambiguously. Data envelopment analysis is an increasingly used method for measuring sustainability. This paper is a review of the body of research published between 2017 and 2020 and explores the extent to which DEA has been applied to measuring sustainability. Previous research demonstrated that social capital remains a key factor in measuring sustainability. Furthermore, process indicators are also being treated as an alternative measure. Despite their significance, these measures fail to fully capture the multidimensional nature of sustainability and sustainable development. The findings of this research reveal that the majority of programs are focused on Asian countries or Chinese regions, while it seems to be a significant research gap in European territories.

Maddi et al. tried to analyze and forecast the relative efficiency of multiple branches of the Social Security Organization throughout Iran. A framework was developed in this study to estimate the future value of unit efficiency using artificial neural networks. This research delves into the measurement of cost and technical efficiency in a two-tier supply chain under both stable and unstable price conditions. To achieve this, we utilized the non-parametric method of DEA and game theory. By doing so, we were able to address research gaps in this field and provide valuable insights. First, branch efficiency was assessed using the DEA method, followed by the classification of the efficiency level. We used time series functions to predict the future efficiencies of units based on their previous efficiencies and cost-efficiency calculations over several consecutive years. By analyzing historical data and using advanced forecasting techniques, we were able to accurately predict the future efficiencies of these units. The findings of this research suggest that managers must implement a data collection and processing system and consistently perform clustering and efficiency prediction for upcoming months and years based on whose results they must concentrate on enhancing and optimizing inputs and outputs.

Amani and Bagherzadeh Valami (32) report that DEA is a linear programming-based approach utilized in economics to measure the efficiency of decision-making units. In classical models of data envelopment analysis, the efficiency of a system is typically calculated by treating the entire system as a decision-making unit (DMU) and disregarding the inter-process relationships within the system. However, the internal relationships of different parts of a DMU may have diverse structures that can complicate the evaluation of its efficiency. A network perspective is a viable solution to model inter-unit relationships (33). The relationship between subunits in a DMU may occur in series, parallel, or mixed states. The objective of this study is to address the aforementioned issues by introducing a DEA model based on the Nash bargaining game, a technique in game theory. In the next stage, in order to effectively control uncertainty, three approaches are employed: fuzzy set theory, random programming, and robust optimization.

1. 1. Research Questions

1. What is the energy efficiency of the selected countries?
2. What is the economic efficiency of the selected countries?
3. What is the environmental efficiency of the selected countries?
4. What is the integrated efficiency rate of selected countries in cooperative game conditions?

1. 2. Research Objectives

1. Design a model to overcome the limitations of standard DEA analysis
2. Application of the game theory method and how to integrate them with the DEA model
3. Determine factors influencing energy, economic, and environmental efficiency

2. METHODOLOGY

This is a development-oriented study in which the main approach is based on mathematical modeling. This research paper proposes a parametric linear mathematical programming model to analyze a three-stage data envelope problem with a series structure. The proposed model is based on game theory and the system identifies uncertainties. Additionally, various approaches were employed to control uncertainty. The data in this study is quantitative-qualitative. The data were collected using the library survey method. The library method was used for general data collection. The employed data analysis methods are stated as follows:

1. Data coverage analysis: to identify units whose decision-making is carried out effectively. This article estimates efficiency using linear programming dual. The dual problem imposes a minimum requirement on the quantities of inputs, which is conditioned by specific amounts of the product, as outlined below:

$$MIN = \theta_0 - \varepsilon\left(\sum_{i=1}^{m} s^{-}{}_{i} + \sum_{r=1}^{s} s_r{}^{+}\right)$$

Provided that the "DEA model" is its returns to scale structure, which includes:

$$\sum_{j=1}^{n} x_{ij}\lambda_j + s^{-}{}_i = \theta_0 x_{io}$$

$$\sum_{j=1}^{n} y_{rj}\lambda_j - s_r{}^{+} = y_{ro}$$

$$\lambda_j \geq 0 \;\; s_r{}^{+} \geq 0 \;\; s_i{}^{-} \geq 0$$

- The CCR constant returns of scale;
- The BCC variable returns of scale;

The proposed robust bargaining model is based on the scenario-based discrete robust optimization approach. Another feature of this model is that it uses the proposed solution to improve inefficient units and achieve the efficiency frontier. These solutions include input-oriented DEA and output-oriented DEA models.

The selection between an input-oriented or output-oriented perspective is contingent upon the level of management control over the inputs or outputs. When management lacks control over the outputs and their quantity is predetermined and fixed, the reduction in input quantity is regarded as a managerial viewpoint. Consequently, the model is approached as an input-oriented model. Conversely, if management lacks control over the inputs and their quantity is predetermined and fixed, the reduction in output quantity is considered a managerial viewpoint. In this case, the model is approached as an output-oriented model.

2. Collaborative Game Theoretical Model: In non-cooperative games, players may adopt a strategy that ultimately results in the least possible outcome, based on the opponent's chosen strategy, in order to maximize their own outcome. Therefore, in peer games, players try to cooperate with the player or other players of the game to achieve more benefits. In this case, a set of singles, duets, or multiple players is called a coalition. In cooperative game theory, the primary emphasis is on the formation of feasible coalitions and the calculation of surplus that accrues to the set of players in each coalition. Next, the obtained surplus must be allocated among the players, which is mentioned in cooperative games with transferable utility. The allocation of surplus encourages players to join feasible coalitions. The cooperative game is displayed as (N, v). In every specific game and per coalition T, the security level can be defined with respect to (T)v. It is referred to as the characteristic function game (CFG). The characteristic function is assumed to have no information asymmetry. Per each coalition T, T can be defined as the function (T)v. This demonstrates the total surplus that the coalition members receive through cooperation regardless of the strategies adopted by the players outside the coalition. In a cooperative game, for the selected action of coalition members and the complementary coalition, the outcome of the coalition T versus those outside equals the sum of the outcomes of each coalition member. It is calculated as follows:

$$u(T) = \sum_{i \in T} u_i(a_1.a_2 \ldots\ldots a_k). \quad i = 1.2.\ldots.n$$

3. The Nash product: Suppose there will be increased mutual benefits resulting from cooperation between two countries in reducing energy consumption and CO_2 emissions. When the level of cooperation is strong, the interests of both countries will significantly increase. Conversely, if the level of cooperation is low, the impact on their interests will be minimal. The Nash product, which represents the product of the multiplication of their combined additional benefits, is derived from their collaborative efforts. Due to the assumption that cooperation between the two sides will generate additional interests, the interests of both countries exceed their individual interests at the point of threat. The disparity between the interests at the threat point and the interests resulting from mutual cooperation leads to the acquisition of supplementary interests. The Nash product is obtained by utilizing the coordinate system. As depicted below, moving from point A upwards along line AB increases the value of the country's interests. However, in a competitive scenario, the value of the interests of the first country remains constant. Similarly, moving from point A to the right along line AC enhances the value of the first country's interests, while the value of the second country's interests remains unaltered in the competitive state. The interests of the second country under a competitive state is shown in Figure 1.

In the event of competitive conditions and lack of cooperation between two countries, their interests can be demonstrated by A. However, if these countries choose cooperation over competition, they can enjoy additional interests beyond point A. For instance, at point N, both countries can agree on the amount of energy consumption and emissions, resulting in increased interest for each country. The value of these benefits can be represented as V1 and W1, respectively. By agreeing to cooperate, both countries can increase their interests.

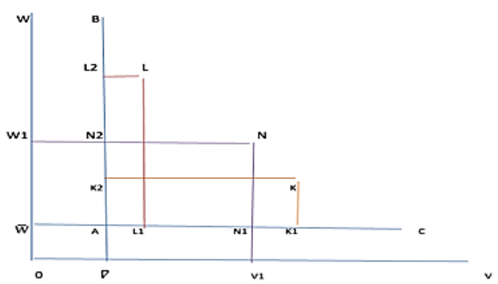


Figure 1. The interests of the second country under a competitive state

The increase in interests is equal to N_1 for the first country and N_2 for the second country. The level of cooperation can be determined by comparing the interests of cooperation to those of competitive conditions.

4. The relationship between DEA and game theory: DEA is a non-parametric method used to evaluate the relative efficiency of decision-making units. DEA is a powerful tool that uses all collected observations to measure efficiency and optimizes each observation in comparison to the optimal efficient frontier, unlike regression analysis, which obtains the best performance available in the study set of units by averaging. In regression analysis, the performance of each unit is estimated relative to an optimized regression equation, while in DEA, the performance of units is examined by constructing and solving n models.

The primary DEA model is founded on the principles of inclusive observations, convexity, constant returns to scale, feasibility, and minimal extrapolation. The concept of production possibility set is essential in this analysis, as it should comprise all inputs and corresponding outputs that are realistically feasible. Additionally, this set should generally include the set of observations of the units under evaluation. The problem can be posited mathematically as follows:

Suppose X is the input vector for a decision-making unit and Y is its output vector. Then, the production possibility set is introduced as follows:

$$T = \{(X.Y)| Non-negative\ x\ can\ produce\ non-negative\ y.\}$$

To establish a comprehensive set of principles, we acknowledge these principles that are at the core of data coverage analysis models.

The principle I is based on the argument that the inputs received are aligned with the desired outputs. This principle is widely accepted. To put it differently, it serves as the real production possibility of the society. Mathematically, this principle can be represented as $(X_j.Y_j) \in T;\ j = 1.\dots.n$, where n represents the number of units.

(Principle II) Feasibility: It states that if $(X.Y) \in T$, then X has the ability to produce Y. This means that any input greater than X can also result in the production of Y, and any output less than Y can still be produced from X. The principle can be expressed mathematically as follows:

$$\forall(X.Y)\forall\bar{X}\forall\bar{Y}\{(X.Y) \in T \& \bar{X} \geq X \& \bar{Y} \leq Y\} \Rightarrow (\bar{X}.\bar{Y}) \in T$$

(Principle III) Convexity: It states that if $(\acute{X}.\acute{Y}) \in T\ .(X.Y) \in T$, then we will have:

$$[\lambda(X.Y) + (1-\lambda)(\acute{X}.\acute{Y})] \in T \qquad 0 \leq \lambda \leq 1$$

According to the convexity principle, if Y, X produce $\acute{Y}.\acute{X}$, then, the input $\lambda X + (1-\lambda)\acute{X}$ can generate an output of $\lambda Y + (1-\lambda)\acute{Y}$, where $0 \leq \lambda \leq 1$.

(Principle IV) Constant scale return: It states that if X is added with a coefficient of λ, the value of Y will also grow with the same coefficient λ.

(Principle V) Minimal extrapolation T: This set is taken as the smallest set of values that satisfy the first four principles.

In DEA, units strive to determine the optimal weight combination for measuring their performance. The efficiency measurement method in this analysis is based on the minimal distances of each unit from the production set frontier. This approach is essentially a form of minimization, which is a subset of optimization

In this section of the article, the primary approach under consideration is the integration of the bargaining game with DEA. It is worth noting that the solutions derived from the bargaining game exhibit Pareto optimality. These principles can be subject to modification depending on various assumptions. The model is outlined as follows:

$$T= (K.L.E.GDP.CO_2): (K.L.E) \Rightarrow (GDP.CO_2)$$

As the data results in the production of limited outputs, T is regarded as the production function. The objective of this study was to employ a methodology that aligns with production theory concepts while simultaneously minimizing undesirable outputs and maximizing desirable outputs. Mathematically, the representation of robust data access and desired outputs is as follows:

$$(K.L.E.GDP.CO_2) \epsilon\ T (or\ (K.L.E.G\check{D}P.CO_2)\ \epsilon T)$$

$$If (K.L.E.GDP.CO_2)\ \epsilon T\ and (\acute{K}.\acute{L}.\acute{E}) \geq (K.L.E)\ (or\ G\check{D}P \leq GDP)$$

In 1951, Nash introduced the Nash Equilibrium, also known as the Nash Solution, which outlines three essential features for resolving any problem. These conditions include:

- Pareto efficiency
- the independence of solutions from alternative options
- symmetry

In order to obtain the Nash solution of the bargaining game, it is necessary for the solution space to be compact, convex, and inclusive of the payoff vectors. These payoff vectors should ensure that the payoffs for each player exceed the values of their corresponding breakpoints. Suppose utility functions v(x) and U(x) for actors 1 and 2, respectively. In the context of the bargaining game, if we assume V and U, the logical decision would be to maximize the product of the multiplication of the difference between the utility functions and the breakpoint values for each actor. In simpler terms, the following conditions must be met:

Maximize$|U(x)-u_d|\ |V(y)-v_d|$

The solution acquired is called Nash solution and the product of the multiplication is called Nash product. The Nash relation can be extended to more than two actors. Now, if it is assumed that Ui(x) is the utility function for

the i^{th} player and Ui is the value of the breakpoint for the i^{th} player -when they have not entered the game; then:
Maximize$\Pi^{n}_{i=1} |u_i\text{-}(x)\text{-}u_i(d)|$

Below is an illustration of a PSTS process model. As shown, each DMU j comprises three interconnected series stages. Furthermore, the outputs generated by each stage serve as the sole inputs for the subsequent stage. This implies that stages 1 and 2 do not produce any external outputs, while stages 2 and 3 do not receive any external inputs. Figure 2 shows DMU of three interconnected stages in series.

Return to scale represents the link between changes in inputs and outputs of a system.

2. 1. Research Findings In this part, in order to demonstrate the efficiency and applicability of the proposed models, various numerical examples and case studies are utilized, and their results are thoroughly examined and analyzed.

In the field of choosing appropriate indicators to evaluate energy, economic and environmental performance of countries, some researchers have put forward suggestions that are mentioned in the second part. Based on them, Figure 3 shows the impact of input variables on specified efficiencies and their selected indicators was prepared, which is stated as follows:

2. 1. 2. The Answers to Questions 1 to 3 are Explained below The data presented in this article pertains to a comprehensive evaluation of selected countries (Azerbaijan, Kuwait, Qatar, Turkey, Yemen, Emirates, Lebanon, Saudi Arabia, Turkmenistan, Jordan, Iran, and Bahrain) from 2014 to 2019. The data was carefully analyzed using energy, economic, and environmental input data, taking into account similar conditions. The entire data is presented in the following. The efficiency values for energy, economics, and the environment were calculated for each DMU. Table 1 specifies the results.

Overall, it can be stated that most countries have a high level of efficiency, averaging around 50%, and none of the DMUs have completely undesirable efficiency. In other words, DMUs have been able to achieve relatively desirable outcomes from their inputs. It can be

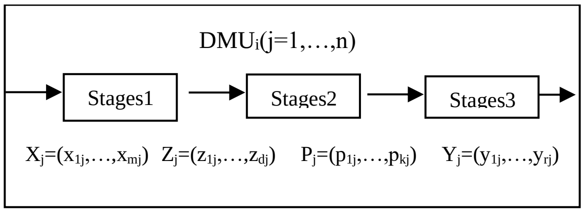


Figure 2. DMU of three interconnected stages in series

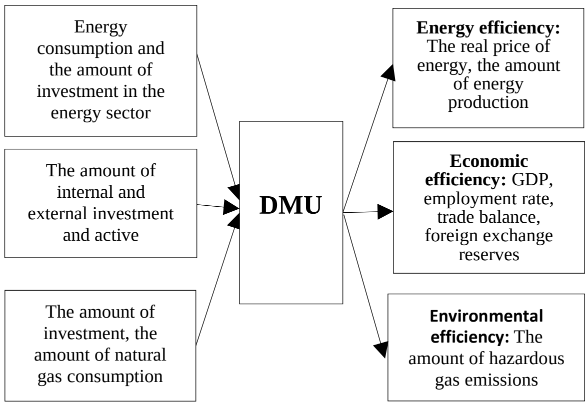


Figure 3. Selected inputs and outputs

TABLE 1. The energy, economic, and environmental efficiency scores of DMUs

DMU	Energy efficiency, %	Economic efficiency, %	Environmental efficiency, %	Total efficiency
Azerbaijan	82.1	84	66.41	77.5
Kuwait	91	100	74.4	88.4
Qatar	100	100	79	93
Türkiye	80	86	62	76
Yemen	100	93	71.3	88.1
United Arab Emirates	92.8	96	83.8	90.8
Lebanon	78.5	83	71.4	77.6
Saudi Arabia	93	98.9	78.9	90.2
Turkmenistan	94.6	100	72.6	89
Jordan	73.2	89	61.2	74.4
Iran	90.7	86	58.6	78.4
Bahrain	91	100	63.3	84.7

acknowledged that these DMUs have prevented resource and input waste and have had proper management of their outputs and inputs. On the other hand, the values obtained for each of the lines represent the economic scale compared to the constant efficiency. These values indicate the economies of scale of each DMU in terms of CRS, increasing efficiency to scale (IRS), and decreasing efficiency to scale (DRS). In simpler terms, if $\sum_{j=1}^{n} \lambda j^* = 1$, the economies of scale of lines will be constant, if $\sum_{j=1}^{n} \lambda j^* > 1$, the economies of scale will be decreasing, and if , $\sum_{j=1}^{n} \lambda j^* < 1$, the economies of scale will be increasing. Table 2 displays the λ values obtained for each company.

As shown in Table 2, DMUs 3 and 11 exhibit a constant return to scale, indicating a linear relationship between institutions and outputs. On the other hand, DMUs 2, 8, and 10 demonstrate an increasing return to scale, where an increase in inputs results in a relatively greater increase in outputs. Conversely, DMUs 1, 4, 6, 7, 9, 12, and 5 display diminishing returns to scale, meaning that increasing inputs by one unit leads to a smaller relative increase in output.

Computational results of the NBTS-DEA model under uncertainty conditions

In this section, the validity and accuracy of the NBTS-DEA model are assessed under uncertain conditions. This analysis is based on the following relationship:

$$MAX \quad F_{So} = \left(\sum_{i} \theta_i X_i + \sum_{l} \theta_l W_l + \sum_{r} \theta_r U_r \right)$$

TABLE 2. The λ values of DMUs

DMU	$\sum_{j=1}^{n} \lambda j^*$
DMU1	3.462
DMU2	0.854
DMU3	1
DMU4	3.531
DMU5	0
DMU6	2.077
DMU7	3.723
DMU8	0.861
DMU9	3.112
DMU10	0.915
DMU11	1
DMU12	2.058

where x represents the decision-making unit, W denotes the computational efficiency value, and U represents the estimated efficiency value under future uncertainty conditions. Table 3 summarizes the efficiency values obtained from the centralized model and the Nash bargaining model at breakpoints (0.0.0) , ($\theta^1_{\min}.\theta^2_{\min}.\ \theta^3_{\min}$).

According to the findings presented in Table 3, the outcomes of the centralized model are nearly identical to those of the bargaining model at (0.0.0) breakpoint. As it is anticipated that the NBTS-DEA model at breakpoint (0.0.0) will exhibit similar behavior to the centralized

TABLE 3. The results of the centralized model versus the Nash bargaining model

DMU	Centralized Model				Ba rgaining Model Brealodown Point (0.0.0)				Ba rgaining Model Brealodown Point ($\boldsymbol{\theta^1_{\min}.\theta^2_{\min}.\ \theta^3_{\min}}$)			
	Energy efficiency	Economic efficiency	Enviornmental efficiency	Total efficiency	Energy efficiency	Economic efficiency	Enviornmental efficiency	Total efficiency	Energy efficiency	Economic efficiency	Enviornmental efficiency	Total efficiency
1	0.906	1.000	0.572	0.518	0.906	1.000	0.572	0.518	0.906	1.000	0.572	0.518
2	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000	1.000
3	0.515	0.392	0.501	0.100	0.516	0.388	0.497	0.099	0.517	0.348	0.549	0.099
4	0.666	0.505	0.425	0.143	0.667	0.504	0.425	0.143	0.669	0.502	0.425	0.143
5	0.769	0.191	1.000	0.147	0.769	0.191	1.000	0.147	0.769	0.191	1.000	0.147
6	1.000	0.206	0.468	0.096	1.000	0.206	0.468	0.096	1.000	0.206	0.468	0.096
7	1.000	0.219	1.000	0.219	1.000	0.220	0.997	0.219	1.000	0.224	0.979	0.219
8	0.693	0.172	0.832	0.099	0.690	0.172	0.832	0.099	0.690	0.172	0.832	0.099
9	0.467	0.594	0.862	0.239	0.467	0.592	0.863	0.239	0.466	0.570	0.897	0.238
10	0.356	1.000	0.738	0.262	0.356	1.000	0.737	0.262	0.381	0.907	0.738	0.255
11	0.637	0.174	0.835	0.092	0.629	0.174	0.835	0.091	0.629	0.174	0.835	0.091
12	1.000	0.241	0.726	0.175	1.000	0.240	0.728	0.175	1.000	0.212	0.819	0.174

model. The congruence of the results between these two models, particularly in terms of overall efficiency and the efficiency of each stage, validates the proposed model. That DMU 2 is the only efficient entity across all parts in both models.

Based on the analysis of Table 3, it can be inferred that the total efficiency scores derived from the centralized model are nearly identical to those of the Nash bargaining model at breakpoint ($\theta^1_{\min}.\theta^2_{\min}.\ \theta^3_{\min}$) for all DMUs. Consequently, it can be deduced that the Nash bargaining model proposed offers the same benefits as the centralized model in assessing the overall efficiency of the process. Furthermore, as shown that the efficiency scores of stages II and III in DMUs 3, 9, and 12, as well as the efficiency scores of stages I and II in DMU 10, calculated by the centralized model, differ from the efficiency scores calculated by the proposed non-parametric model. Additionally, in the centralized model, stage II of DMU 10 is efficient, whereas it is inefficient in the non-parametric model at breakpoint ($\theta^1_{\min}.\theta^2_{\min}.\ \theta^3_{\min}$). It should be noted that, unlike the centralized model, the non-parametric model provides a fair and unique decomposition of overall performance scores into component efficiencies.

2. 2. Results of NBTS-DEA Model under Robust Conditions To assess the efficiency of the supply chain depicted in Figure 4, analysis was conducted using two models: the centralized model and the proposed Nash bargaining game model. The objective was to calculate the total efficiency values and the efficiency of each component of the DMUs for each scenario at the (0.0.0) breakpoint and $\varepsilon = 0.001$ step size. The total efficiency scores of all DMUs using both the centralized model and the Nash bargaining game model at breakpoint (0.0.0) are nearly identical. This outcome serves as an indication of the validity of the proposed Nash bargaining game model. The results of centralized scenario model are summarized in Table 4.

Here, the method of DMU which involves constructing the most anti-ideal DMU, was employed to identify breakpoints (see Table 5 for the breakpoints obtained in each stage of the process and scenario).

These breakpoints are utilized in the proposed robust bargaining model to determine the total efficiency scores and the efficiency of the process components for each scenario (see Table 6 for the results). As shown, the total efficiency scores were decomposed into the components uniquely and equitably. This highlights one of the key advantages of the proposed bargaining model.

In order to utilize the proposed DEA RNBTS model, its parameters should be configured. These parameters should be set in a manner that does not impact the overall problem and aligns with the specific constraints. The values for these parameters are specified in Table 7.

TABLE 4. The results of centralized scenario model

DMUs	Scenario 1				Scenario 2				Scenario 3			
	Step 1	Step 2	Step 3	All system	Step 1	Step 2	Step 3	All system	Step 1	Step 2	Step 3	All system
1	1.000	0.589	1.000	0.589	1.000	0.672	1.000	0.672	1.000	0.731	1.000	0.731
2	0.975	0.880	0.730	0.626	0.859	0.990	0.787	0.670	0.898	1.000	0.751	0.675
3	0.808	0.699	0.505	0.286	0.764	0.816	0.622	0.388	0.665	0.926	0.640	0.394
4	1.000	0.660	0.249	0.164	1.000	0.697	0.261	0.182	1.000	0.724	0.254	0.184
5	0.948	0.967	0.609	0.558	0.920	0.938	0.717	0.619	0.833	0.929	0.817	0.632
6	0.787	1.000	0.389	0.307	0.693	1.000	0.490	0.340	0.755	1.000	0.490	0.370
7	0.825	0.579	0.487	0.232	0.729	0.647	0.515	0.243	0.678	0.678	0.548	0.252
8	0.832	0.172	0.693	1.000	0.219	0.979	0.224	1.000	0.219	0.997	0.220	1.000
9	0.862	0.594	0.467	0.690	0.099	0.832	0.172	0.690	0.099	0.832	0.172	0.690
10	0.738	1.000	0.356	0.467	0.238	0.897	0.570	0.466	0.239	0.863	0.592	0.467
11	0.835	0.174	0.637	0.356	0.255	0.738	0.907	0.381	0.262	0.737	1.000	0.356
12	0.726	0.241	1.000	0.629	0.091	0.835	0.174	0.629	0.091	0.835	0.174	0.629

TABLE 5. The breakpoints of each step for each scenario

Step	Scenario		
	1	2	3
1	0.566	0.573	0.543
2	0.529	0.619	0.638
3	0.154	0.175	0.166

TABLE 6. The results of the NBTS DEA model

DMUs	Scenario 1				Scenario 2				Scenario 3			
	Step 1	Step 2	Step 3	All system	Step 1	Step 2	Step 3	All system	Step 1	Step 2	Step 3	All system
1	1.000	0.588	1.000	0.588	1.000	0.672	1.000	0.672	1.000	0.730	1.000	0.730
2	0.974	0.937	0.664	0.606	0.861	0.988	0.787	0.670	0.898	1.000	0.751	0.675
3	0.781	0.722	0.505	0.285	0.764	0.816	0.622	0.388	0.691	0.882	0.640	0.390
4	1.000	0.659	0.249	0.164	1.000	0.696	0.261	0.182	1.000	0.724	0.254	0.184
5	0.975	0.939	0.609	0.558	0.921	0.937	0.717	0.619	0.832	0.927	0.817	0.630
6	0.787	1.000	0.389	0.306	0.693	1.000	0.490	0.340	0.755	1.000	0.490	0.370
7	0.729	0.651	0.466	0.221	0.728	0.646	0.515	0.242	0.678	0.678	0.548	0.252
8	1.000	0.340	1.000	0.340	1.000	0.763	1.000	0.763	1.000	0.550	1.000	0.550
9	0.986	0.945	0.897	0.540	0.931	0.943	0.767	0.606	0.823	0.931	0.807	0.604
10	0.778	1.000	0.345	0.301	0.687	1.000	0.487	0.324	0.766	1.000	0.487	0.369
11	1.000	0.567	0.234	0.165	1.000	0.767	0.245	0.165	1.000	0.870	0.202	0.168
12	0.890	0.701	0.499	0.276	0.756	0.818	0.640	0.390	0.689	0.878	0.650	0.387

TABLE 7. The values of the RNBTS-DEA model parameters

Parameters	W_1 W_6	W^+_7	W^-_7	W^+_8	W^-_8	W^+_9	W^-_9	W^+_{10}	W^-_{10}	λ
Amounts	1	8	1	8	1	8	2	8	2	**0.4**

In Table 7, Columns 2 to 6 display the weighted average efficiency scores for each stage, as well as the total efficiency score and rank for each DMU in the DEA model of the Nash bargaining game at breakpoint (0.0.0) Similarly, in Table 8, Columns7 to 11 present the efficiency scores for each step, the total efficiency score, and the rank for each DMU in the RNBTS-DEA model at breakpoint (0.0.0) .Table 8 also summarizes the results for the same breakpoint ($\theta^1{}_{\min}.\theta^2{}_{\min}.\ \theta^3{}_{\min}$) ,as shown in Table 8.

TABLE8. Weighted average results of the NBTS-DEA model under the scenario versus the results of the RNBTS-DEA model

DMUs	Weighted average results of the VBTS-DEA model under the scenario					RENBTS-DEA Model				
	Step 1	Step 2	Step 3	All system	Rank	Step 1	Step 2	Step 3	All system	Rank
1	1.000	0.666	1.000	0.666	**1**	0.945	0.647	0.954	0.583	**1**
2	0.891	0.971	0.764	0.660	**2**	0.596	0.874	0.772	0.402	**3**
3	0.744	0.821	0.598	0.364	**4**	0.406	0.743	0.537	0.162	**6**
4	1.000	0.694	0.256	0.178	**7**	0.761	0.634	0.215	0.104	**7**
5	0.913	0.934	0.715	0.607	**3**	0.830	0.759	0.748	0.471	**2**
6	0.732	1.000	0.465	0.339	**5**	0.635	0.859	0.423	0.231	**4**
7	0.740	0.637	0.516	0.242	**6**	0.661	0.591	0.480	0.188	**5**
8	1.000	0.659	0.249	0.164	**9**	1.000	0.770	0.202	0.102	**8**
9	1.000	0.567	0.261	0.132	**11**	0.504	0.436	0.453	0.101	**9**
10	1.000	0.659	0.254	0.146	**10**	0.406	0.438	0.221	0.098	**10**
11	1.000	0.567	0.234	0.165	**8**	0.346	0.548	0.201	0.095	**12**
12	0.165	1.000	0.567	0.121	**12**	0.254	0.387	0.168	0.097	**11**

The above tables illustrate that the per breakpoints (0.0.0) and ($\theta^1_{min}.\theta^2_{min}.\ \theta^3_{min}$), total efficiency scores of all DMUs in the RNBTS-DEA model are lower compared to the total efficiency scores obtained from the weighted average of the NBTS-DEA model in the study scenarios. This discrepancy arises due to the inclusion of the 2nd moment of the NBTS-DEA model and a penalty for deviating from the limits in the RNBTS-DEA model, in addition to the weighted average of the NBTS-DEA model in the given scenarios. The tables also suggest that the robust optimization model presented exhibits a significant sensitivity to breakpoints. Consequently, both the efficiency scores and the ranking of DMUs have experienced considerable fluctuations with the alteration of breakpoints from (0.0.0) to ($\theta^1_{min}.\theta^2_{min}.\ \theta^3_{min}$). Figure 4 visually represents the overall performance scores acquired from the RNBTS-DEA model and the NBTS-DEA model for each scenario at breakpoint (0.0.0). The figure above illustrates the identical observations at breakpoint ($\theta^1_{min}.\theta^2_{min}.\ \theta^3_{min}$).

As shown in Figures 4 and 5, the efficiency scores obtained from the RNBTS-DEA mode are less than or equal to the NBTS-DEA model for all DMUs and in all scenarios. It should be noted that the results obtained from the RNBTS-DEA model are robust in terms of both feasibility and optimality.

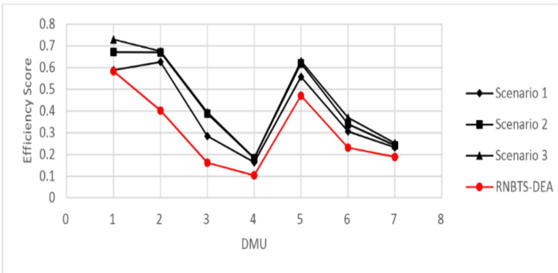


Figure 4. Total efficiency scores of the proposed NBTS-DEA model under different scenarios versus the proposed RNBTS-DEA model at breakpoint **(0.0.0)**

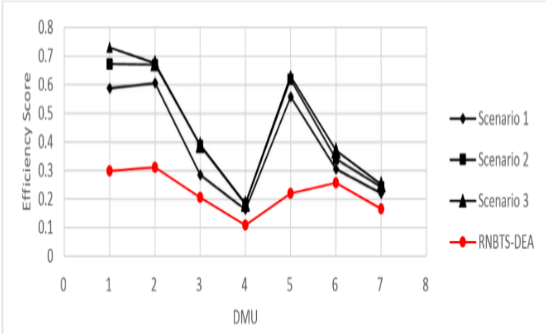


Figure 5. Total efficiency scores of the proposed NBTS-DEA model under different scenarios versus the proposed RNBTS-DEA model at breakpoint **(0.0.0)**

2. 4. Answer to Question 4 it is Explained below

The evaluation of countries' efficiencies indicated that only Azerbaijan, Kuwait, Qatar, and Turkey have demonstrated level 1 efficiency and are acknowledged as such among the 12 countries evaluated. As a result, a collaborative game theory is developed for the mentioned countries.

2. 4. 1. First Step: Formation of Coalitions

The first step in the process is to establish coalitions. Each efficient country is assigned a unique symbol based on Table 8. There will be as many as P possible coalitions equal to 1 to 4. Coalition formation is stated in Table 9. Formation of the coalition and the resulting cohesive efficiency stated in Table 10.

TABLE 9. Coalition formation

Türkiye	Qatar	Kuwait	Azerbaijan	Country
D	C	B	A	Symbol

2. 4. 2. Step Two: Calculating the Profit of Coalitions

TABLE 10. Formation of the coalition and the resulting cohesive efficiency

Integrated functionality, %	Profit	Coalition	Integrated functionality, %	Profit	Coalition	Integrated functionality, %	Profit	Coalition
95	1.211	A-D	73	0.677	A-C	40	0.458	A-B
99	1.415	A-C-D	39.5	0.452	A-B-D	62	0.622	A-B-C
25	0.365	B-C	27	0.205	B-C	90.5	1.012	B-A
16	0.225	B-C-D	36.5	0.384	B-A-D	46	0.514	B-A-C
86	0.921	C-D	89	0.941	C-B	80.5	0.717	C-A
27	0.415	C-B-D	92	1.124	C-A-D	89	1.009	C-A-B
12	0.112	D-C	75.5	0.696	D-B	93.5	1.201	D-A
60.5	0.620	D-B-C	76	0.709	D-A-C	70	0.650	D-A-B

2. 4. 3. Step Three: Calculating the Shapley value

Based on the evaluation of coalition values, the value of decision-making units in each coalition was evaluated and calculated using the Shapley value formula (Table 11).

Therefore, the countries were compared and evaluated based on the obtained Shapley value achieved through different coalitions using the cross-efficiency and super-efficiency methods (Table 12).

3. DISCUSSION

The 2025 Vision Document positions Iran as a developed, active, and influential participant in the global economy. To achieve the goals outlined in the document, Iran must have substantial economic growth. However, economic growth and development in any country are inextricably linked to energy consumption, which has negative environmental impacts. Therefore, it is crucial to consider technical, economic, and environmental factors when setting energy production and consumption patterns. By doing so, Iran can ensure sustainable economic growth while minimizing its environmental footprint**.** This research investigates the relationship between economic activities, carbon dioxide emissions, and energy consumption during the production process. Using the data envelopment analysis method, the study measures the level of energy efficiency in Iran and neighboring countries from 2012 to 2019. Additionally, the study evaluates the extent to which the goals outlined in the vision document for energy efficiency have been achieved. By analyzing these factors simultaneously, In response to the questions of the thesis, the findings showed that among the 12 selected countries (Azerbaijan, Kuwait, Qatar, Turkey, Yemen, UAE, Lebanon, Saudi Arabia, Turkmenistan, Jordan, Iran and Bahrain), the highest energy efficiency is related to the countries of Qatar and Yemen and the lowest The efficiency is related to Lebanon and Jordan; The highest environmental efficiency is related to the UAE and Qatar and the lowest efficiency is related to Iran and Jordan; The highest economic efficiency is related to the countries of Kuwait, Qatar and Turkmenistan, and the lowest efficiency is related to Iran and Turkey.

TABLE 11. The calculated Shapley value after the cooperation and coalition phase

Türkiye	Qatar	Kuwait	Azerbaijan	Country
0.236	0.222	0.325	0.125	P=1
0.333	0.625	0.229	1.425	P=2
0.620	0.632	0.111	0.425	P=3
0.659	0.325	0.222	0.701	P=4
1.848	1.807	0.887	1.676	Shapley value

TABLE 12. The calculated Shapley value after the cooperation and coalition phase

Türkiye	Qatar	Kuwait	Azerbaijan	Country
0.938	0.800	0.857	0.947	Super efficiency
0.960	0.927	0.934	0.900	Cross-functionality
1.848	1.807	0.887	1.676	Shapley value
1	2	4	3	Ranking

The findings related to the efficiency rating of 5 countries of Qatar, UAE, Saudi Arabia, Turkmenistan, Kuwait and Yemen are more efficient. Kuwait, UAE and Qatar have been the same in the assessment of super-efficiency and alliance, and the changes are related to the countries of Saudi Arabia and Turkmenistan. This case shows that the efficiency score of each decision-making country in the super-efficiency method does not necessarily cause its rank after the cooperation phase.

The findings of this work showed that the country of Qatar with the highest efficiency also has the most effect in the coalition and its rank remains unchanged, but the efficiency score of the country of Saudi Arabia is lower than that of Turkmenistan, but its impact on the coalition is greater, so the score of Saudi Arabia in the Shapley method is increased and Its ranking has been improved compared to the ranking in the super performance method. Also, the country of Turkmenistan, which was higher than Saudi Arabia in the super efficiency method, has decreased in the Shapley method.

The research aims to provide a comprehensive understanding of the energy efficiency landscape in the region. The results of this research demonstrate that the current state of energy efficiency in Iran is suboptimal. Therefore, Iran must implement programs aimed at enhancing energy efficiency. This will not only enable the country to expand its economic development capabilities but also ensure the preservation of existing resources and prevent any harm to the environment and human health. As data coverage analysis is a comparative approach, it is recommended that future studies in Iran should include a comparison with developed countries. This will help portray a more accurate picture of energy efficiency.

In recent years, DEA researchers have shown great interest in developing models to calculate the efficiency of network-structured processes. Classical models have proven inadequate in this regard, prompting the seeking of new DEA models to overcome this weakness. One such model is the multi-stage structure - a particular type of network structure - where the outputs of each stage serve as inputs for the next stage. The most widely used type of model developed in this field is the two-stage data DEA model. These models are able to calculate the efficiency scores of each step in addition to the total efficiency score. The network structure known as the three-stage process is a unique and prevalent phenomenon in the real world, with multiple applications. A three-level supply chain consisting of suppliers, manufacturers, and distributors can exemplify these processes.

There are different methods available for modeling three-stage processes, which are derived from generalizing the approaches used in two-stage process modeling. The game theory approach, also used here, is one of the most commonly used such approaches. This approach mainly involves non-cooperative and cooperative games. The first category of models is known as leader-follower or decentralized models, and the second category of models is known as centralized models. In centralized models, the system's overall efficiency is prioritized before evaluating the efficiency of individual components. This is while decentralized models prioritize the efficiency of the most significant or leading component, followed by the subordinate components and ultimately determine the overall system efficiency. Centralized and decentralized models have different assumptions regarding the importance of components. In centralized models, all components are considered equally important, while in decentralized models, components have equal priority. In real-world problems with network structures, calculating the overall efficiency of the process is more important than calculating the efficiency of the components. Therefore, methods based on this approach attract more attention from company managers. However, in non-collaborative models, the leader component is more important than the follower components, and calculating the efficiency of the components has a higher priority than determining the efficiency of the overall process. This approach is less favored by managers. Non-collaborative models can be used in specific cases where the value of the components is not equal, such that the leader has more power than the other component (follower), and the follower has no control over the leader. The sub-process under the leader determines the optimal weights related to intermediate criteria (optimal strategy), making it a useful approach in certain scenarios. In centralized models, a serious challenge is the fair and unique decomposition of the overall efficiency score into component efficiency scores. However, many developed models have struggled to provide a satisfactory solution. To address this issue, a data envelopment analysis model is necessary. This model should calculate overall and three-stage process component efficiency scores while preserving the advantages of previous models and providing a fair and unique decomposition of component efficiency.

A DEA model based on the game theory approach is considered a viable choice for this objective. In this study, the overall efficiency and efficiency of the components of the three-stage processes with a net structure, in which the outputs of each stage are used as the only inputs of the next stage, were calculated. To that end, we used a three-stage data envelopment analysis model based on the non-cooperative game theory approach. The proposed model is able to provide a fair and unique decomposition of overall efficiency into component efficiencies while maintaining the advantages of cooperative games. As game theory models are generally nonlinear, finding global optimal solutions in such difficult models can be challenging. Hence, multiple transformations were used to convert the aforementioned nonlinear game theory model into a linear parametric programming model.

To identify the breaking points of each stage, the study utilized an anti-ideal DMU approach. The values of breaking points can significantly impact the optimal solutions of bargaining models, and selecting inappropriate values can render the model infeasible. Therefore, here, various scenarios were developed to perform a sensitivity analysis on breaking point values and the extent to which they impact the proposed model. This analysis provides valuable insights into the optimal selection of breaking point values for slicing models.

DEA models rely on the efficiency frontier formed by the available data to calculate the efficiency of DMUs. In that light, any uncertainty can threaten the validity of the efficiency scores calculated. To overcome this uncertainty challenge, three approaches were employed: fuzzy set theory, robust optimization, and stochastic optimization.

The optimization approach used in this study is based on the stable scenario method. To achieve the objective, several scenarios with specified probable occurrence values were applied to a case study of a cement supply chain consisting of the supplier, producer, and distributor. The proposed robust DEA model was solved for each scenario with different breakpoints. The results were compared with the centralized model. The total efficiency scores obtained from both methods for all DMUs were almost equal, indicating the validity of the proposed model in an uncertain state. Finally, the proposed robust DEA model was implemented on the dataset of the study supply chain, and its results were analyzed.

The $-\alpha$ -cuts method was utilized in the fuzzy approach to develop two bargaining DEA models in the fuzzy form. These models are used to calculate the lower and upper bounds of the efficiency of the three pure development process stages. These models were converted into a linear form. For the random state, the stochastic programming approach was employed, using the proposed random bargaining model to evaluate the efficiency of the three-stage processes with random outputs.

4. CONCLUSION AND FUTURE RESEARCH

In the following, to check the validity and efficiency of the proposed models, some numerical examples were presented, and the results were analyzed. The results indicate the energy efficiency of Azerbaijan, Kuwait, Qatar, Turkey, Yemen, UAE, Lebanon, Saudi Arabia, Turkmenistan, Jordan, Iran, and Bahrain as follows: 82.1%, 85.7%, 100%, 83.5%, 100%, 90.8%, 78.5%, and 87.3%.

The future research suggestions are proposed in the following section:

The focus here is on models that operate under constant return-to-scale conditions. However, it is worth exploring the potential for developing models that can accommodate variable return-to-scale conditions in future research endeavors. The proposed model cannot be utilized for general three-stage processes that involve the presence of external outputs for Stages 1 and 2, or external inputs for Stages 2 and 3. Hence, it is recommended to develop a modeling approach for assessing processes with such structures as a foundation for future research.

In this study, the fuzzy, stable, and random approaches were employed to address the data uncertainty of PSTS processes. Since each approach was implemented individually, future research could explore the potential benefits of combining them to enhance the management of uncertainty in real-world problems.

It is suggested to develop the proposed models to evaluate processes with unfavorable data.

The robust bargaining model proposed in this research is based on the discrete robust optimization approach (scenario-based). Future research can address the use of robust continuous approaches.

Another avenue for future research is the development of a stochastic bargaining model that can effectively handle uncertainty in all PSTS process data.

5. REFERENCES

1. Villa G, Lozano S, Redondo S. Data envelopment analysis approach to energy-saving projects selection in an energy service company. Mathematics. 2021;9(2):200.
2. Wang C-N, Dang T-T, Wang J-W. A combined Data Envelopment Analysis (DEA) and Grey Based Multiple Criteria Decision Making (G-MCDM) for solar PV power plants site selection: A case study in Vietnam. Energy Reports. 2022;8:1124-42.
3. Tsaples G, Papathanasiou J. Data envelopment analysis and the concept of sustainability: A review and analysis of the literature. Renewable and Sustainable Energy Reviews. 2021;138:110664. https://doi.org/10.1016/j.rser.2020.110664
4. Arouri MEH, Youssef AB, M'henni H, Rault C. Energy consumption, economic growth and CO2 emissions in Middle East and North African countries. Energy policy. 2012;45:342-9. https://doi.org/10.1016/j.enpol.2012.02.042
5. Singh G, Singh P, Sodhi G, Tiwari D. Energy auditing and data envelopment analysis (DEA) based optimization for increased energy use efficiency in wheat cultivation (Triticum aestium L.) in north-western India. Sustainable Energy Technologies and Assessments. 2021;47:101453. https://doi.org/10.1016/j.seta.2021.101453
6. Bampatsou C, Papadopoulos S, Zervas E. Technical efficiency of economic systems of EU-15 countries based on energy consumption. Energy Policy. 2013;55:426-34. https://doi.org/10.1016/j.enpol.2012.12.021
7. DeBenedictis LF, Giles DE, Policy P, Branch L. Diagnostic Testing in Econometrics: Variable Addition, RESET, and Fourier Approximations: Department of Economics, University of Victoria; 1996.
8. Ren J, Gao B, Zhang J, Chen C. Measuring the energy and carbon emission efficiency of regional transportation systems in China: chance-constrained DEA models. Mathematical Problems in Engineering. 2020;2020:1-12. https://doi.org/10.1155/2020/9740704
9. Chen C-K. CONSTRUCT MODEL OF THE KNOWLEDGE-BASED ECONOMY INDICATORS. Transformations in Business & Economics. 2008;7(2).
10. Ito K. CO2 emissions, renewable and non-renewable energy consumption, and economic growth: Evidence from panel data for developing countries. International Economics. 2017;151:1-6. https://doi.org/10.1016/j.inteco.2017.02.001
11. Chen CK. Causal modeling of knowledge-based economy. Management Decision. 2008;46(3):501-14. https://doi.org/10.1108/00251740810863915
12. Fukuyama H, Matousek R. Modelling bank performance: A network DEA approach. European Journal of Operational Research. 2017;259(2):721-32. https://doi.org/10.1016/j.ejor.2016.10.044
13. Huang D, Li G, Chang Y, Sun C. Water, energy, and food nexus efficiency in China: a provincial assessment using a three-stage data envelopment analysis model. Energy. 2023;263:126007. https://doi.org/10.1016/j.energy.2022.126007
14. Collard F, Fève P, Portier F. Electricity consumption and ICT in the French service sector. Energy Economics. 2005;27(3):541-50. https://doi.org/10.1016/j.eneco.2004.12.002
15. Kamarudin F, Sufian F, Nassir AM, Anwar NAM, Hussain HI. Bank efficiency in Malaysia a DEA approach. Journal of Central Banking Theory and Practice. 2019. 10.2478/jcbtp-2019-0007
16. Li F, Zhu Q, Liang L. Allocating a fixed cost based on a DEA-game cross efficiency approach. Expert Systems with Applications. 2018;96:196-207. https://doi.org/10.1016/j.eswa.2017.12.002
17. Antonakakis N, Cunado J, Filis G, Gabauer D, de Gracia FP. Oil and asset classes implied volatilities: Investment strategies and hedging effectiveness. Energy Economics. 2020;91:104762. https://doi.org/10.1016/j.eneco.2020.104762
18. Odhiambo NM. Energy consumption, prices and economic growth in three SSA countries: A comparative study. Energy policy. 2010;38(5):2463-9. https://doi.org/10.1016/j.enpol.2009.12.040
19. Liu H, Zhang R, Zhou L, Li A. Evaluating the financial performance of companies from the perspective of fund procurement and application: New strategy cross efficiency network data envelopment analysis models. Energy. 2023;269:126739. https://doi.org/10.1016/j.energy.2023.126739
20. Zhou W, Chen Q, Luo D, Jiang R, Chen J. Global energy consumption analysis based on the three-dimensional network model. IEEE Access. 2020;8:76313-32. 10.1109/ACCESS.2020.2989186

21. Lu C-C, Lin I-F, Lin T-Y, Chiu Y-h. Two-stage dynamic data envelopment analysis measuring the overall efficiency and productivity changes of industry and agriculture in EU countries. Journal of Cleaner Production. 2023;382:135332.
22. Narayan PK, Narayan S. Estimating income and price elasticities of imports for Fiji in a cointegration framework. Economic Modelling. 2005;22(3):423-38. https://doi.org/10.1016/j.econmod.2004.06.004
23. Leng Y-J, Zhang H. Comprehensive evaluation of renewable energy development level based on game theory and TOPSIS. Computers & Industrial Engineering. 2023;175:108873. https://doi.org/10.1016/j.cie.2022.108873
24. Toloo M, Nalchigar S, Sohrabi B. Selecting most efficient information system projects in presence of user subjective opinions: a DEA approach. Central European Journal of Operations Research. 2018;26:1027-51. https://doi.org/10.1007/s10100-018-0549-4
25. Wu J, Liang L, Yang F, Yan H. Bargaining game model in the evaluation of decision making units. Expert Systems with Applications. 2009;36(3):4357-62. https://doi.org/10.1016/j.eswa.2009.05.001
26. Shi X. Environmental efficiency evaluation of Chinese industry systems by using non-cooperative two-stage DEA model. Mathematical Problems in Engineering. 2019;2019:1-10. https://doi.org/10.1155/2019/9208367
27. Halkos GE, Tzeremes NG. Oil consumption and economic efficiency: A comparative analysis of advanced, developing and emerging economies. Ecological Economics. 2011;70(7):1354-62.
28. Yanqing X, Mingsheng X. A 3E Model on Energy Consumption, Environment Pollution and Economic Growth---An Empirical Research Based on Panel Data. Energy Procedia. 2012;16:2011-8. https://doi.org/10.1016/j.egypro.2012.01.306
29. Zuo Y, Shi Y-l, Zhang Y-z. Research on the sustainable development of an economic-energy-environment (3E) system based on system dynamics (SD): A case study of the Beijing-Tianjin-Hebei Region in China. Sustainability. 2017;9(10):1727. https://doi.org/10.3390/su9101727
30. Zhang X-P, Cheng X-M, Yuan J-H, Gao X-J. Total-factor energy efficiency in developing countries. Energy Policy. 2011;39(2):644-50. 10.1016/j.enpol.2010.10.03
31. Zhou P, Ang B, Han J. Total factor carbon emission performance: a Malmquist index analysis. Energy Economics. 2010;32(1):194-201. https://doi.org/10.1016/j.eneco.2009.10.003
32. Amani N, Bagherzadeh Valami H. Efficiency Evaluation of regional electronic companies in Iran by Network DEA: A based on the Conversion of the Structures into a uniform structure. Journal of decisions and operations research. 2018;3(3):249-80. https://doi.org/10.22105/dmor.2018.81213
33. Wu Y, Li K, Fu X. An integrated zero-sum game and data envelopment analysis model for efficiency analysis and regional carbon emission allocation. Decision Analytics Journal. 2024;10:100387. https://doi.org/10.1016/j.dajour.2023.100387

Persian Abstract

چکیده

هدف: این پژوهش با هدف ارزیابی عملکرد انرژی، اقتصاد و زیست محیطی کشورهای منتخب صادر کننده منابع انرژی با رویکرد یکپارچه تحلیل پوششی داده‌ها و نظریه بازی انجام شده است. روش‌شناسی پژوهش: روش ابرکارایی و کارایی متقاطع نیز به منظور رتبه‌بندی کشورهای کارآمد قبل از فاز همکاری مورد استفاده قرار گرفته است. سپس در فاز همکاری، هر کشور با استفاده از روش نظریه بازی‌های همکارانه و ارزش شاپلی مسئله مورد بررسی قرار می‌گیرد. یافته‌ها: نتایج نشان داد که قطر و یمن بیشترین و لبنان و اردن کمترین کارایی انرژی؛ کویت، قطر و ترکمنستان بیشترین و به ایران و ترکیه کمترین کارایی اقتصادی؛ امارات و قطر بیشترین و ایران و اردن کمترین کارایی زیست محیطی را دارند.