Heliyon 10 (2024) e32430

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Performance evaluation of facility locations using integrated DEA-based techniques

Sirawadee Arunyanart

Supply Chain and Logistics System Research Unit, Faculty of Engineering, Khon Kaen University, Khon Kaen, 40002, Thailand

ARTICLE INFO

Keywords:
Inverted DEA
Assurance region
Weight restrictions
Discrimination power
PEST analysis
Site selection

ABSTRACT

Facility location, particularly in the context of international investments by global enterprises, stands out as a paramount concern within the purview of top management's strategic decision-making process. The selection of a suitable location plays a pivotal role in determining the ultimate achievement of organizational objectives. The process of selecting an appropriate location requires the comprehensive analysis of a substantial volume of data, encompassing diverse tangible and intangible evaluation criteria that may exhibit inherent conflicts. This paper addresses the challenge of determining the best location for a manufacturing facility by employing alternative performance measures within the framework of the data envelopment analysis (DEA) model. In a performance evaluation process, not only positive but also negative aspects should be determined. This paper, therefore, proposes a double-frontier DEA-AR model, which is an integrated approach that incorporates the efficient frontier, anti-efficient frontier, and assurance region weight restrictions, with the aim of increasing the discrimination ability of the DEA method. An efficient frontier evaluates the information of each location from a positive viewpoint, while the worst side is evaluated by an anti-efficient frontier. The technique of weight restrictions, which allows incorporating expert opinion into the assessment, is also applied with both frontiers to restrict the regions of weights to some specific area. The prescribed approach is illustrated by a numerical example of selecting the best location among ten different countries under consideration of 22 selection criteria obtained from PEST analysis. The results show that the proposed alternative performance measures significantly improve discrimination capability, enabling the ranking of candidates based on their suitability for the optimal location.

1. Introduction

The proliferation of intense market competition, both domestically and globally, has compelled numerous manufacturing firms to accord substantial importance to the strategic decision-making process regarding the location or relocation of manufacturing facilities. This imperative arises from the recognition that a favorable location offers not only a strategic advantage against competitors but also holds the potential to play a critical role in shaping future success. Furthermore, the decision is characterized by its long-term nature and entails significant challenges in terms of flexibility, as its alteration necessitates a substantial capital outlay [1]. Moreover, the changing world economic scenario for international business, coupled with the emergence of effective supply chain management practices, has underscored the significance of strategically considering the geographic dispersion of a firm's manufacturing operations on an international scale [2]. To attain a competitive advantage, numerous manufacturing firms have considered the option of

E-mail address: sirawadee@kku.ac.th.

https://doi.org/10.1016/j.heliyon.2024.e32430
Received 25 October 2023; Received in revised form 12 May 2024; Accepted 4 June 2024
Available online 4 June 2024

establishing production sites overseas.

Several reasons contribute to the advantages that prompt a significant number of firms to choose overseas production. The principal rationale revolves around the objective of mitigating expenses associated with production, especially labor costs. By establishing manufacturing operations in some countries, firms can avail themselves of a labor market characterized by cost-effectiveness, thereby realizing substantial financial savings. Not only the cost-benefit that firms consider in strategic decision-making when choosing to manufacture overseas but also other advantageous aspects such as advanced manufacturing infrastructure and favorable regulations. Over the years, many countries have emerged as prominent manufacturing destinations, characterized by substantial investments and the establishment of world-class manufacturing facilities and infrastructure. These developments aim to simplify the manufacturing process and entice foreign companies to establish their manufacturing operations within their borders. Numerous countries make concerted efforts to optimize their laws and regulations to provide the most favorable conditions and introduce lucrative tax incentives to incentivize foreign investments. As a result, these countries represent a strategic advantage for firms seeking to optimize their manufacturing and procurement processes.

However, the process of evaluating and selecting a destination country for a manufacturing facility is intricate, as it involves a whole range of criteria that are mostly difficult to quantify. The assessment of relevant criteria that exert influence on the selection of a suitable location represents one of the formidable challenges encountered in facility location problem. Management must also examine each potential location while simultaneously considering several different criteria in order to ensure the effectiveness of the manufacturing location decision. In situations where numerous alternatives within the manufacturing and production sectors necessitate assessment and selection while being governed by conflicting criteria, the implementation of a multi-criteria decision-making (MCDM) approach demonstrates its practicality and efficacy as a productive strategy [3]. Hence, effective multi-criteria decision analysis (MCDA) plays a critical role and is necessary for supporting this strategic decision-making process. A number of different methods based on the MCDM process have been proposed as researchers and practitioners attempt to apply them to different applications of location decision problems, ranging from warehouse [4], logistics center [5], hotel [6], hospital [7], EV charging station [8], and solar power plant [9]. In this study, data envelopment analysis (DEA) is employed to evaluate the appropriate country for manufacturing locations. DEA is one of the most widely used MCDM approaches for the solution of facility location selection problems. The method is considered one of the most powerful management analysis tools. Based on mathematical programming, DEA possesses the capability to assess the efficiency or performance of homogeneous entities, often known as decision-making units (DMUs), by taking into account multiple input and output criteria [10]. There are several applications of DEA in the literature for solving location decision problems [11–14]. However, the method has a limitation in terms of poor discrimination when applied to problems involving a number of multiple inputs and multiple outputs.

This paper, therefore, presents an enhanced DEA performance measurement efficiency, as a systematic decision support framework, by integrating performance measures from both positive and negative perspectives while also incorporating management viewpoints into the analysis. A notable contribution of this paper is the integration of various techniques within the framework of the DEA model, including the combinations of efficient frontier from DEA and anti-efficient frontier from Inverted DEA, both with assurance region (AR) weight restrictions, referred to as the DEA-AR model and the Inverted DEA-AR model, respectively. The proposed approach, called the double-frontier DEA-AR model, which is an integration of the DEA-AR model and the Inverted DEA-AR model, serves as an alternative efficiency measure, particularly useful for solving the complex problem of selecting overseas manufacturing locations. Moreover, in multiple-criteria location selection, the evaluation criteria to be considered in the decision-making process are important and have an influence on determining the solution. Thus, this paper further introduces an analytical method known as PEST analysis, which encompasses political, economic, social, and technological factors, to analyze the important criteria affecting international manufacturing site selection that should be addressed by firms. The proposed method is illustrated through a numerical example, wherein 22 important criteria are employed as input and output indicators to assess the performance of ten countries using proposed DEA integration approaches.

The subsequent sections of this paper are structured as follows: Section 2 reviews the literature on an improvement of the DEA model based on the concepts of assurance region and double frontier. Section 3 outlines the DEA methodology, including discussions on efficient and anti-efficient frontiers as well as weight restrictions. The proposed approaches for performance measurement achieved through the integration of DEA techniques to solve the location selection problem are provided in Section 4. Section 5 illustrates an application of the proposed approach to a site selection problem. The study's implications are also provided in this section. Section 6 offers the concluding remarks, summarizing the findings of this study. Subsequently, Section 7 provides limitations and suggestions for future research.

2. Literature review

This section provides a review of the relevant literature on extensions of the DEA model, focusing on applications of assurance regions and double-frontier techniques that aim at enhancing the original DEA model's efficacy. The review studies cover diverse applications of performance evaluation and decision-making.

Lai et al. [15] evaluated the efficiency of 24 major international airports using the DEA-AR model. Analytic Hierarchy Process (AHP) was applied to determine the weights of input and output variables. Keskin and Köksal [16] assessed and compared the efficiency of publicly and privately operated airports in Turkey. AHP was also employed to find the relative weights of criteria, followed by DEA and AR methods to calculate efficiency scores. Their findings revealed similarities between DEA-BCC and DEA-CCR methods in efficiency scores, with 14 airports identified as efficient. However, under the AR method, only two privately operated airports were deemed efficient. Wang et al. [17] combined DEA and AR to address shortcomings in the DEAHP (combination of DEA and AHP) model. By resolving issues like illogical local weights and information loss, the DEA/AR model produced more precise priority estimation and decision findings. Numerical examples, including a real application in research fellow recruitment, illustrated the advantages of the DEA/AR model in MCDA. Wey [18] selected the optimal site for a new metro transit station in Taipei, Taiwan, using a combined fuzzy AHP and DEA model with an AR approach. The method provided actionable strategies for public sectors in urban planning and transportation. Similarly, Lee et al. [19] selected suitable sites for renewable energy plants, focusing on photovoltaic solar plants. A fuzzy AHP was also applied to set assurance regions, which were then integrated into DEA to assess site efficiencies.

Ebrahimi and Khalili [20] proposed a mixed integer assurance-region imprecise DEA model to tackle the supplier selection problem. The model incorporated weight restrictions, providing a single solution for finding the best DMU. Singh [21] presented the intuitionistic fuzzy DEA/AR approach to handling imprecise input/output data represented as intuitionistic fuzzy sets which considers degrees of hesitation in defining impreciseness. The approach was demonstrated and validated using a case study on flexible manufacturing systems. Theodoridis et al. [22] explored the technical efficiency of 66 mussel farms using the DEA and AR weight restriction model. By imposing weight restrictions on the main production factors, the model provided more comprehensive efficiency estimates. Wu et al. [23] evaluated the energy security performances of 125 countries by combining principal component analysis (PCA) and DEA-AR with the use of 18 indicators in the evaluation. Chen and Chang [24] examined resource utilization efficiency in academic departments at National Chung Cheng University in Taiwan. Their study employed DEA and AR concepts, considering aggregate, technical, and scale efficiencies.

Various applications and extensions of double-frontier DEA models have emerged in recent literature. Khanjarpanah et al. [25] determined suitable locations for hybrid power plants in Iran based on geographical and sustainability criteria. Double frontier network data envelopment analysis (NDEA) was proposed to evaluate and rank candidate locations' efficiency. Shabanpour et al. [26] selected sustainable suppliers using two levels of improvement plans. They employed goal programming and DEA at the first level, with a robust CCR model handling imprecise inputs and outputs. The second level built upon the first-level goals, utilizing a robust CCR inefficiency model to rank suppliers by considering both efficiency and inefficiency frontiers. Amirteimoori and Kordrostami [27] focused on enhancing efficiency analysis in two-stage fuzzy DEA models. Their study proposed defining the overall efficiency scores of DMUs as the total weight of stage efficiencies. The performance of DMUs was also evaluated from both optimistic and pessimistic viewpoints. The proposed approach was illustrated by investigating a Taiwanese non-life insurance company. Mavi et al. [28] assessed the efficiency trends in freight transportation in Iran over consecutive periods. The issue of undesirable outputs was addressed by proposing a novel common set of weights (CSW) model for double frontier DEA, and subsequently derived a CSW for Malmquist productivity index (MPI) analysis.

Seyedalizadeh and Rassafi [29] evaluated the effectiveness of Iranian regional safety programs in reducing road fatalities using a double-frontier DEA model to assess safety efficiencies from both optimistic and pessimistic perspectives. Efficiency values were aggregated using the Evidential Reasoning (ER) approach, and provinces were then ranked. Ganji and Rassafi [30] evaluated road safety performance (RSP) using DEA and the cross-efficiency method (CEM). Their study introduced a double-frontier CEM aggregated by the evidential reasoning approach (ERA) to consider decision-makers' preference structures. Two case studies were presented to illustrate ERA's application in aggregating cross-efficiency and anti-efficiency matrices for evaluating RSP. They also conducted another study to analyze RSP in developing countries, employing the Slacks-Based Measure (SBM) in the DEA to measure efficiency and inefficiency. A proposed double frontier approach was employed to analyze efficiency and technological changes in safety performance over time. This involved computing optimistic and pessimistic MPIs using standard SBM and inverted SBM models, which were then combined to obtain the overall MPI [31]. Later, Ganji et al. [32] proposed a double-frontier CEM that assesses DMUs relative to both frontiers to evaluate the RSP of EU nations and Serbian police departments. The minimax entropy approach (MEA) and the maximum disparity approach (MMDA) were applied to determine the weighted averaging for cross-efficiency aggregation.

Tavassoli et al. [33] introduced a double frontier fuzzy network data envelopment analysis (FNDEA) model to evaluate the sustainability of tomato paste supply chains, considering both optimistic and pessimistic scenarios. The α-cut approach was employed to solve the models and incorporate undesirable outputs. Saen et al. [34] evaluated sustainability of supply chain management in intercity passenger transportation. They proposed a MPI based on a Network DEA (NDEA) model, considering integer data, undesirable outputs, and non-discretionary inputs. NDEA models analyzed the internal structure of DMUs and assessed productivity changes over time. Ganji et al. [35] incorporated prospect theory into the double-frontier CEM to evaluate the performance of 17 Iranian airlines. Subjective preferences of decision-makers were integrated by utilizing an aggregation method based on prospect theory and consensus degree (APC). The APC was then incorporated into optimistic and pessimistic CEMs. Recently, Ganji et al. [36] introduced Regret-Consensus Aggregation (RCA) into the Game Cross-Efficiency (GCE) to capture decision-makers' preferences. GCE-RCA and Game Cross In-Efficiency (GCIE) with RCA (GCIE-RCA) integrated RCA into the GCE framework. A double-frontier GCE with RCA (DFGCE-RCA) was developed to assess the Iranian Inter-City Road Passenger Transportation system.

While assurance region DEA-AR and double-frontier DEA models have gained attention in research, there remains a notable gap in their application to evaluating international facility locations. This study aims to address this gap by introducing a double-frontier DEA-AR approach for site selection. The novelty lies in incorporating assurance regions to constrain weight regions in efficient frontier and anti-efficient frontier DEA models. Assurance regions reflects decision-makers' subjective judgments from both optimistic and pessimistic viewpoints. Additionally, an aggregation process for DEA-AR and Inverted DEA-AR is proposed to produce more realistic results. This paper contributes to alternative performance measures for the location selection problem, allowing decision-makers and management to incorporate their judgments on criteria for both positive and negative perspectives, thus enabling preferred weights within a reasonable range. By introducing the Inverted DEA-AR, insights into DMUs' performance are enhanced. Moreover, the integration strengthens the DEA model's discrimination power, offering valuable supplementary data for evaluating DMUs. This comprehensive approach enables full ranking of candidate locations and identification of the most suitable manufacturing site.

3. DEA methodology

3.1. Performance measured from a positive perspective

DEA, introduced by Charnes et al. [37], is a non-parametric mathematical programming approach to evaluate each DMU's ability to transform inputs into outputs effectively. It generates a best practice production frontier, representing the maximum output achievable given input levels, with DMUs on the frontier considered efficient [38]. Efficiency scores of other DMUs are determined by comparing them to this frontier [39]. The relative efficiency score of DMU_p, while p is a DMU being evaluated among n DMUs, is defined as E_p and computed by comparing weighted sums of outputs to inputs using the model proposed by Charnes et al. [37].

$$E_p = max \frac{\sum_r u_r y_{rp}}{\sum_i v_i x_{ip}}$$

subject to:

$$\frac{\sum\limits_r u_r y_{rj}}{\sum\limits_i v_i x_{ij}} \leq 1 \quad \forall_j \tag{1}$$

$$u_r, v_i \geq 0 \quad \forall_{r,i}$$

Assume that each DMU operates with m inputs and s outputs. j is the index assigned to all DMUs other than the DMU_p being assessed. Parameters x_{ij} ($i = 1,2, \ldots, m$) and y_{rj} ($r = 1,2, \ldots, s$) are respectively i^{th} input amounts and r^{th} output amounts of DMU_j ($j = 1, \ldots, n$), which are all known and are in positive numbers. Decision variables v_i and u_r represent the input weights or multipliers given to the i^{th} input and the output weights or multipliers given to the r^{th} output. The main goal is to maximize the efficiency value E_p for a specific DMU, with constraints ensuring the ratio of weighted outputs to inputs must not exceed one and weights are non-negative. Equation (1) is the basic DEA model, which can be reformulated as a linear programming version as follows [37].

$$E_p = max \sum_r u_r y_{rp}$$

subject to:

$$\sum_i v_i x_{ip} = 1 \tag{2}$$

$$\sum_r u_r y_{ri} - \sum\limits_i v_i x_{ij} \leq 0 \quad \forall_j$$

$$u_r, v_i \geq 0 \quad \forall_{r,i}$$

Each DMU undergoes repeated calculations n times to identify the set of input and output weights that gives the highest efficiency score for the DMUs being assessed, without any DMU exceeding a score of unity for that specific weight set. Consequently, each DMU is assigned a unique set of non-negative weights aimed at maximizing its efficiency score. As a result, each DMU obtains the highest possible score, and the argument that various weights are used is invalid when comparing final scores [40]. The final result of the DEA analysis is a ranking of DMUs based on their efficiency scores.

DEA offers the advantage of maximizing each DMU's efficiency without predetermining the weights of evaluation criteria. However, this full-weight flexibility can lead to two main drawbacks: poor discrimination power in evaluating different alternatives and impractical values of weights being assigned to input and output indicators [41,42]. Poor discrimination often arises when the number of DMUs to be evaluated is small compared to the total count of evaluation criteria. Many DMUs are then identified as efficient. Consequently, the method may fail to provide a solution, especially for selecting or ranking DMUs. Unrealistic weight occurs when excessively high or low weight values are assigned to specific criteria, or when large variance weight values for the same criterion are assigned to different DMUs [43,44]. This can be unacceptable to decision-makers as DMUs typically share identical inputs and outputs for the same overall objectives [45]. In extreme cases, values of zero are given to the weights, leading to ignorance of some criteria. As a result, an unsuitable determination of efficiency scores through the full freedom of weight assignment turns out to be illogical or nonsensical from a management perspective when implementing the model in some particular applications [46,47]. These problems have led to the development of various approaches for improved discrimination and weight control in the standard DEA model. Nevertheless, each approach has its utility in specific contexts, and none can offer a complete solution to all problems.

3.2. Performance measured from a negative perspective

The worst-side approach, an extension of DEA, was first introduced by Yamada et al. [48] as Inverted DEA (IDEA). Unlike DEA, which evaluates the efficiency of DMUs against the efficient frontier, Inverted DEA assesses DMU inefficiency against a bad reference using the anti-efficient frontier. Several studies have proposed the use of additional information from the anti-efficient frontier to improve the discrimination power of standard DEA analysis [47,49,50]. Furthermore, various applications have utilized information from both the efficient and anti-efficient frontiers to address distinct problems. For instance, Dehghani et al. [51] utilized this approach to evaluate appropriate locations for solar plants, while Zhang and Zhang [52] evaluated the performance of logistics companies. DiMaria [53] conducted an assessment of country efficiency, considering GDP creation, sustainability, and welfare. Additionally, Ganji et al. [54] assessed the performance of road safety, and Zhang et al. [55] evaluated the efficiency of industrial parks. However, most of the research on DEA for location selection has primarily focused on evaluating the efficiency of DMUs with good references. In practice, more than one reference perspective should be considered for a thorough evaluation to arrive at the best solution. This means not only the optimistic perspective but also the pessimistic perspective of DMUs should be compared. An assessment that encompasses both superior and inferior aspects is more comprehensive and reasonable than one that only relies on one aspect [52]. Comparing the DMUs with optimistic and pessimistic points of view is also one of the possible techniques for increasing discrimination power in DEA evaluation.

According to the standard DEA concept, each DMU is compared to the best performing or most efficient DMUs on the best practice frontier or efficient frontier. In essence, each alternative, utilizing varying amounts of input resources to produce varying amounts of outputs, is evaluated from its efficient or positive perspective. However, unlike efficiency measurement, the inefficiency of DMUs can be measured using the worst practice frontier, also known as anti-efficient frontier, derived from the worst performing DMUs. As more resources or inputs are consumed to produce a fixed number of outputs, the DMU becomes less efficient. Thus, the inefficiency score of each DMU is quantified as the ratio of the weighted sum of inputs to the weighted sum of outputs. The primary aim is to maximize this ratio to determine the inefficiency score, I_p, of the DMU being evaluated, DMU_p. The following formulas, introduced by Yamada et al. [48], are used to determine the inefficiency of DMU_p.

$$I_p = max \frac{\sum_i v_i x_{ip}}{\sum_r u_r y_{rp}}$$

subject to:

$$\frac{\sum_i v_i x_{ij}}{\sum_r u_r y_{rj}} \leq 1 \quad \forall_j \tag{3}$$

$$u_r, v_i \geq 0 \quad \forall_{r,j}$$

By using the reverse practice of DEA, the goal of Eq. (3) is to maximize the efficiency value for a specific DMU while adhering to the constraints that the ratio of the weighted sum of inputs to the weighted sum of outputs is limited to one or less, and the weight values are greater than or equal to zero. The inverted frontier, or anti-efficient frontier, is constructed from the worst performing or most inefficient DMUs; that is, the inefficiently performed DMUs are those that lie on the anti-efficient frontier, obtaining an inefficiency score equal to one. Subsequently, other DMUs not on the frontier are compared with the worst performing DMU to determine their respective inefficiency scores. A DMU deviating from the frontier will obtain an inefficiency score of less than one, denoted as $I_p < 1$. This means that the lower the score and the closer it is to zero, the better DMU's performance. The programming problem represented by Eq. (3) can be converted into a linear programming problem to derive the inefficiency score for a particular DMU, as illustrated below.

$$I_p = max \sum\nolimits_i v_i x_{ip}$$

subject to:

$$\sum\nolimits_r u_r y_{rp} = 1 \tag{4}$$

$$\sum\nolimits_i v_i x_{ij} - \sum_r u_r y_{ri} \leq 0 \quad \forall_j$$

$$u_r, v_i \geq 0 \quad \forall_{r,i}$$

Traditional DEA evaluates the performance of DMUs from a positive viewpoint, focusing on efficiency measurement. In contrast, Inverted DEA evaluates DMUs' performance from a negative viewpoint, emphasizing inefficiency measurement. More information regarding performance can be obtained by utilizing both efficient and anti-efficient frontiers, which are generated by the best and worst practice DMUs, respectively.

3.3. Incorporating viewpoints through weight restrictions

During analysis, management often holds specific opinions on the relative importance of various criteria, and in many cases, decision-makers may wish to include additional information or assumptions into the model. Weight restrictions represent one of the methods developed to address the issue of weight flexibility in DEA by incorporating decision-makers' viewpoints into the relative significance of input and output criteria [56]. The concept involves imposing direct limitations on weights by including extra weight-related constraints in the standard DEA model. Among the various forms of weight restrictions in DEA models, assurance regions (ARs) hold a prominent position as an approach widely examined and implemented in real-world applications to measure efficiency or performance [57]. The ARs approach facilitates the inclusion of management viewpoints, prior information, knowledge, or value judgments of decision-makers by establishing bounds on the relative magnitude of input and output weights, thereby restricting the feasible regions of weights to some specific area. One particular type of ARs approach is assurance regions of type I, commonly referred to as ARI. The technique of ARI was originated by Thompson et al. [58] to assist in selecting the optimum location for a high-energy physics laboratory when other conventional techniques proved inadequate in evaluating criteria and alternatives. The study revealed that ARI is accepted as being simple to combine with the DEA model.

The technique of ARI involves imposing upper and lower limits on the ratios of input weights and output weights. This is accomplished by adding constraints to the standard DEA model in the following form:

$$a_{ii'} \le v_i / v_{i'} \le b_{ii'} \text{ for input criteria} \tag{5}$$

$$c_{rr'} \le u_r / u_{r'} \le d_{rr'} \text{ for output criteria} \tag{6}$$

where the variables $a_{ii'}$ and $b_{ii'}$ are respectively the lower and upper limits, respectively, of the ratio between each pair of input weights. Similarly, $c_{rr'}$ and $d_{rr'}$ indicate the lower and upper limits of the ratio between each pair of output weights. These constraints, including values of $a_{ii'}$, $b_{ii'}$, $c_{rr'}$, and $d_{rr'}$, are specified by the decision-makers to reflect their judgments or opinions that they wish to incorporate into the evaluation. Rearranging the terms (5) and (6), the following linear inequalities are added to the DEA model.

$$v_i - b_{ii'} v_{i'} \le 0, -v_i + a_{ii'} v_{i'} \le 0 \text{ for input criteria} \tag{7}$$

$$u_r - d_{rr'} u_{r'} \le 0, -u_r + c_{rr'} u_{r'} \le 0 \text{ for output criteria} \tag{8}$$

The addition of these constraints generally worsens the DEA efficiency score, and DMUs that were previously defined as efficient

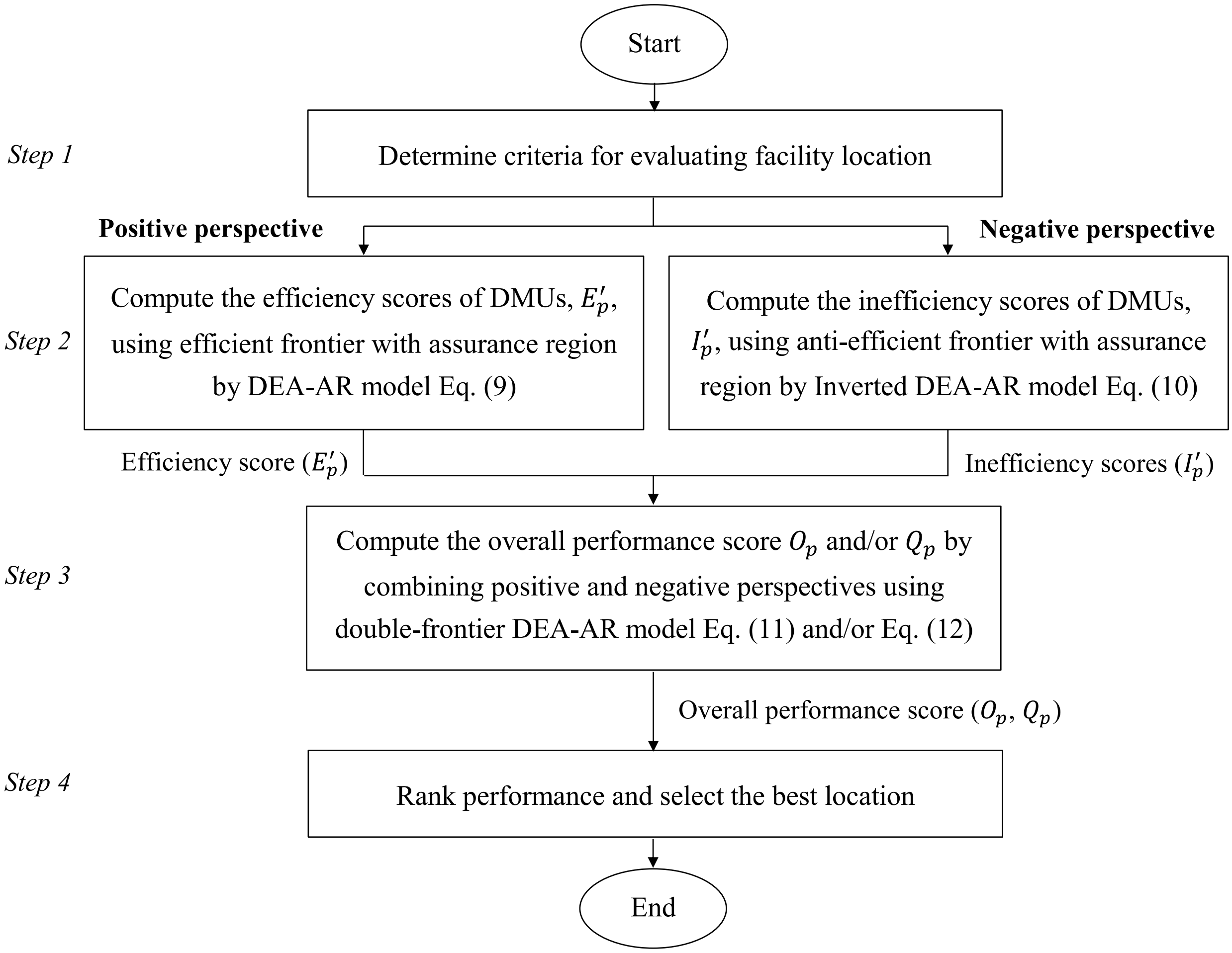

Fig. 1. Framework for alternative performance measures.

may subsequently be deemed inefficient once these constraints are imposed [59].

4. Research methodology

The selection of a suitable location is a complex process for management or decision-makers since it requires different pieces of information to address the problem. Moreover, it involves several choices, which are different candidate locations for a new facility, each requiring a simultaneous assessment of its performance. DEA is employed as the chosen method to address the problem, as it serves as a valuable tool in management analysis, utilized for assessment of efficiency or performance across a set of candidate alternatives. The DEA approach not only considers several input and output criteria from various facets, but it also allows these inputs and outputs to be explicated in different dimensions using different units of measurement [60]. However, as discussed in previous sections, the standard DEA model does not always give quality results for selection problems since it regularly provides poor discrimination among alternatives, or DMUs. Consequently, it may fail to identify the best alternative through the assessment process.

In this study, techniques to improve DEA for more effective evaluation and efficient computational solution for the location selection problem are presented. The approach integrates measurement from a positive perspective using an efficient frontier, measurement from a negative perspective using an anti-efficient frontier, as well as the opinions of decision-makers in the determination of criteria weight bounds. Considering that the decision of location selection is crucial to the company and requires extensive analysis and evaluation, examining only the positive side to find the efficiency of alternatives may be insufficient and may not always provide a solution to the selection problem. The negative side or weakness of alternatives should additionally be evaluated in order to explore the performance of alternatives under adverse circumstances. Moreover, due to the importance of the strategic decision of location selection, management usually holds strong opinions regarding the relative importance of various aspects in an analysis. In many instances, additional data or information becomes available, and management or decision-makers are willing to make assumptions or incorporate them into the model. Therefore, it is appropriate to apply management viewpoints in a location decision.

This section introduces the double-frontier DEA-AR model, which combines the use of AR based on the efficient frontier (DEA-AR model) and the anti-efficient frontier (Inverted DEA-AR) to address issues of low discrimination and illogical weighting in DEA. The proposed decision support framework for alternative performance measures in location evaluation and selection is illustrated in Fig. 1. Subsequently, a step-by-step elaboration of the procedure will be provided.

Step 1. Determine criteria for the facility location problem using PEST analysis.

The first step involves identifying the criteria influencing the location selection problem. When analyzing the establishment of a new facility from an investment standpoint, it is critical for the company to conduct a comprehensive assessment of factors that will impact the decision. This study employs the PEST analysis technique to identify criteria used in making manufacturing location decisions at the country level.

PEST analysis, widely used in business, serves as a framework for helping to comprehend the external macro-environment of an organization. It focuses on the examination of external forces and their potential impact on an organization [61]. This analysis technique, integral to strategic planning and management, assesses the business environment in which the company operates [62]. The acronym PEST represents Political, Economic, Social and Technological factors, which constitute the four main aspects identified in the analysis.

While economic performance traditionally serves as a key determination for location selection, international manufacturing location decisions necessitate consideration of a nation's political climate, as government policies and legislation may affect an organization. Additionally, social issues have gained prominence in recent years as organizations strive for competitive advantage, while technological advancements enable and expedite manufacturing processes. Consequently, it is imperative for manufacturing firms to incorporate all dimensions of the PEST into their manufacturing facility location decisions.

In this initial step, evaluation criteria or performance indicators for overseas production locations should be derived from the dimensions of the PEST concept—political, economic, social, and technological. Through PEST analysis, various external evaluation criteria affecting business activities and performance in the company's operational environment or planned project can be systematically uncovered.

Step 2. Measure the performance of potential locations from both positive and negative perspectives, using efficient frontier and anti-efficient frontier with assurance region.

Once the evaluation criteria influencing location selection are obtained from Step 1, it is necessary to categorize them into two groups: input criteria x_i and output criteria y_r, in order to serve as parameters in DEA analysis. Here, indices i and r represent the number of input and output criteria, respectively. The input criteria are considered negative criteria, representing undesirable events or factors associated with or used in a business. Hence, a lower value of inputs is desirable. Conversely, the output criteria denoted beneficial or positive attributes. In this case, a larger value of outputs is preferable.

The performance of each alternative location is measured from both positive and negative perspectives using efficient and anti-efficient frontiers, each incorporating assurance region weight restrictions. To assess performance from a positive perspective, the DEA-AR model, which is a hybrid approach combining efficient frontier in Eq. (2) with additional assurance region constraints in Eq. (7) and/or (8), is utilized. This DEA-AR model identifies the most efficient DMUs situated on the efficient frontier within restricted bounds. The total efficiency score for a particular DMU_p, denoted as E_p', is calculated using the following model.

$$E_p' = max \sum_r u_r y_{rp}$$

subject to:

$$\sum_i v_i x_{ip} = 1$$

$$\sum_r u_r y_{ri} - \sum_i v_i x_{ij} \le 0 \quad \forall_j \tag{9}$$

$$v_i - b_{ii'} v_{i'} \le 0, -v_i + a_{ii'} v_{i'} \le 0$$

$$u_r - d_{rr'} u_{r'} \le 0, -u_r + c_{rr'} u_{r'} \le 0$$

$$u_r, v_i \ge 0 \quad \forall_{r,i}$$

Similarly, the Inverted DEA-AR model is designed to evaluate performance from a negative perspective. This model combines the anti-efficient frontier from Eq. (4) with the assurance region constraints from Eq. (7) and/or (8) to identify the most inefficient DMUs situated on the anti-efficient frontier within a specific region. The total inefficiency score for a particular DMU_p, defined as I_p', is derived by computing the following Inverted DEA-AR model.

$$I_p' = max \sum_i v_i x_{ip}$$

subject to:

$$\sum_r u_r y_{rp} = 1$$

$$\sum_i v_i x_{ij} - \sum_r u_r y_{ri} \le 0 \quad \forall_j \tag{10}$$

$$v_i - b_{ii'} v_{i'} \le 0, -v_i + a_{ii'} v_{i'} \le 0$$

$$u_r - d_{rr'} u_{r'} \le 0, -u_r + c_{rr'} u_{r'} \le 0$$

$$u_r, v_i \ge 0 \quad \forall_{r,i}$$

Step 3. Combine positive and negative perspectives for overall performance.

The information gathered from both efficiency and inefficiency measurements is utilized to conduct a comprehensive evaluation of all locations from both optimistic and pessimistic perspectives. The DEA-AR model in Eq. (9) determines the total efficiency scores E_p' of DMUs that are relatively performing well, while the Inverted DEA-AR model in Eq. (10) determines the total inefficiency scores I_p' of DMUs that are relatively performing poorly. These efficiency and inefficiency scores are calculated using different frontiers, resulting in two distinct DMU rankings. The idea of an alternative performance measure is to consider information from both DMU's positive and negative performances. In order to obtain an overall performance score, this paper therefore proposes a technique called double-frontier DEA-AR to aggregate the efficiency score from the DEA-AR model and the inefficiency score from the Inverted DEA-AR model. The ideas of two approaches to double-frontier DEA-AR are as follows.

In the first approach, since the worst performing DMU situated on the anti-efficient frontier holds a score of one ($I_p' = 1$), a DMU farther away from this anti-efficient frontier with a score less than one and closer to zero ($I_p' < 1$) is considered the better performing DMU. The first approach of the double-frontier DEA-AR is to convert I_p' to keep the same orientation as E_p' by subtracting I_p' from the value of one before combining the two scores. The overall performance score of a particular DMU is calculated as follows.

$$O_p = E_p' + \left(1 - I_p'\right) \tag{11}$$

where O_p is the overall performance score of a specific DMU under evaluation, E_p' is the efficiency score obtained from an efficient measurement model with weight restriction constraints, and I_p' is the inefficiency score obtained from an inefficient measurement model with weight restriction constraints.

The second approach of double-frontier DEA-AR involves transforming the inefficiency score by taking the inverse of I_p', denoted as $1/I_p'$. Subsequently, the overall performance score of a particular DMU, Q_p, is calculated using the following formula.

$$Q_p = E_p' + \left(1 \middle/ I_p'\right) \tag{12}$$

It should be noted that both E_p' and I_p' have a range of (0,1]. The disparity between Eq. (11) and Eq. (12) lies in their calculation methods. Regardless of the approach used, the DMU with the highest overall performance score among all other DMUs is regarded as the best performing DMU.

Step 4. Rank alternative locations and select the best one.

The ranking of potential locations is determined based on the overall performance scores obtained in Step 3, represented by O_p and Q_p. The best location is identified as the one with the highest overall performance score.

For illustrative purposes, let us consider a scenario with one input and two outputs to illustrate the concept of the double-frontier DEA-AR model as an alternative performance measure through the integration of efficient and anti-efficient frontiers with assurance region weight restrictions. In Fig. 2a, the original DEA model employs the best practice DMUs (A, B, C, D, and H) to form the efficient frontier. These DMUs represent the most optimal performances and serve as reference points for assessing the efficiency of other units in the analysis. On the contrary to efficiency measurement, the Inverted DEA model uses the worst practice DMUs (A, E, F, G, and H) to establish the anti-efficient frontier, as depicted in Fig. 2b. These DMUs represent the poorest performances and are utilized to evaluate the inefficiency of other units. The discrimination power of both DEA and Inverted DEA analysis is enhanced when weight bounds are imposed on the efficient and anti-efficient frontiers, respectively. This allows for a more precise evaluation of DMU performance. The most performed DMUs are reduced to two, namely DMUs B and C, from the DEA-AR model as depicted in Fig. 2a. When using the Inverted DEA-AR model, DMU F remains the only one least efficient DMU, as shown in Fig. 2b. Applying weight restrictions reveals a clearer distinction between the better-performing and poorer-performing DMUs. By integrating efficient and anti-efficient frontiers with weight restrictions, a more comprehensive understanding of the performance of DMUs from both positive and negative aspects can be achieved. This integration enhances the discrimination power of the analysis, resulting in a more refined raking of the DMUs into consideration. As a result, the decision-makers gain valuable insights into the relative efficiency and inefficiency of the alternatives under evaluation.

5. Case study and implications

This section provides an example of applying a decision-making model for international manufacturing site selection. The case study focuses on the location selection process for a Japanese multinational company intending to establish a manufacturing plant abroad. The crucial question of determining the optimal country for locating this manufacturing facility, considering various critical criteria, still remains unanswered. To accomplish this, the proposed double-frontier DEA-AR approach, which is an alternative performance measure that combines DEA techniques, is applied to identify the most suitable country for a Japanese company to set up its manufacturing plant. Potential countries are considered DMUs in the analysis, and the overall performance of each country is measured with respect to specified evaluation criteria.

5.1. Criteria and data collection

Numerous empirical studies have been conducted with a specific focus on examining the criteria influencing the location selection process across diverse business sectors. MacCarthy and Atthirawong [63] conducted an exhaustive literature review with the aim of identifying and understanding the nature and various criteria that play a significant role in influencing the strategic decisions of international locations for business and manufacturing operations. There were 13 main criteria, divided into several sub-criteria, that have been discovered. Badri [64] identified 14 significant criteria impacting industrial location selections by combining the opinions of

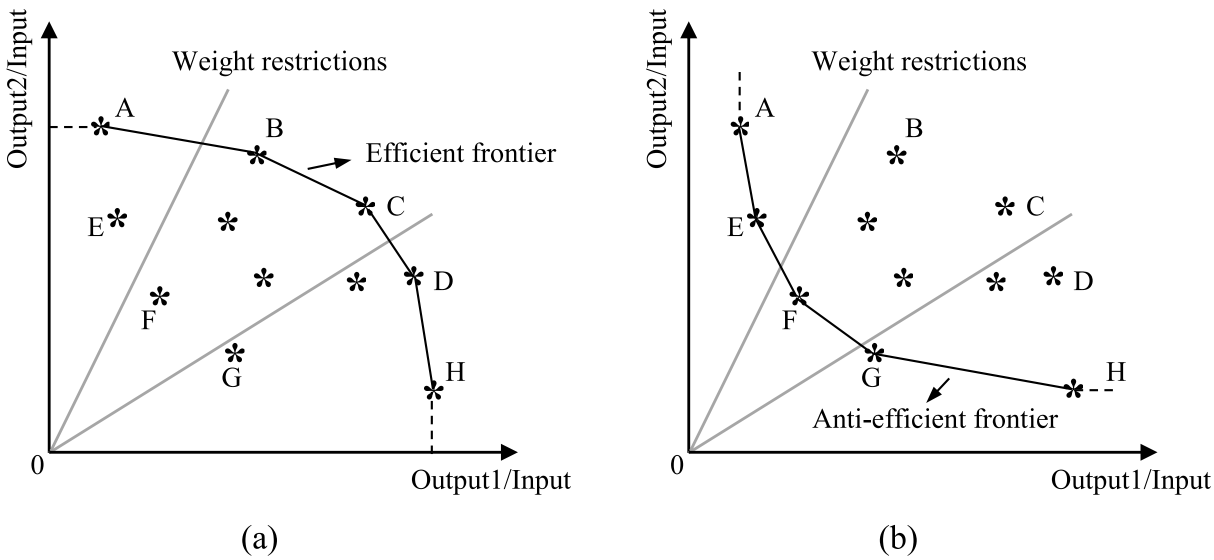

Fig. 2. Efficient frontier with weight restrictions and anti-efficient frontier with weight restrictions.

the authors with those of a group of industry executives from around the world. Four main criteria were highlighted in considering international location: foreign country political situations, worldwide competitiveness and survival, government laws, and economic reasons. Da Silveira [65] used data from an international manufacturing strategy survey, which included characteristics of different countries, to identify competitive criteria for offshoring manufacturing sites. Quality, cost, delivery, and flexibility were the four main criteria of the investigation. Additionally, Johansson and Olhager [2] utilized survey data from several Swedish factories to explore the major criteria influencing location decisions. The result revealed that access to development competencies, proximity to market, and access to low-cost manufacturing were the three primary criteria highlighted.

In this study, the application of PEST analysis was employed to identify essential criteria that necessitate consideration when evaluating different countries as potential manufacturing locations. The four main aspects of PEST, namely political, economic, social, and technological, were divided into a total of 22 important criteria for location selection decisions, which can be summarized as follows.

- The political aspect encompasses four criteria concerning governmental influence on business and industry, such as government policies and regulations, legal issues, and taxation.
- The economic aspect consists of six criteria related to economic performance factors that directly have an impact on the company.
- The social aspect encompassing three criteria addressing threats to peace and security.
- The technological aspect comprises nine criteria pertaining to innovation and development in technology that affect operations in the industry.

These 22 criteria, which can either have a positive or negative impact on the company, were used to assess each location as a viable option for the organization. All criteria were categorized into two groups: input criteria and output criteria, and their respective classifications are presented in Table 1.

According to data collection for the criteria represented in Table 1, seven criteria, namely tax system and corporate tax, capital expenditures, corruption perceptions, labor cost, public security, world risk index, and world peace index, are categorized as input performance indicators (x_i). The remaining 15 criteria, namely customs clearance efficiency, value added by industry, infrastructure, urbanization, industry growth rate, gross national income per capita, skill and quality of workers, delivery punctuality, power supply efficiency, water supply efficiency, trade and logistics infrastructure, efficiency of road transport, port capacity, shipment tracking capability, and availability of transport, are classified as output performance indicators (y_r). It is worth noting that the list of criteria for the model can be varied according to the specific considerations of each company.

As previously mentioned, this case study aims to establish strategies for identifying a suitable overseas location for the manufacturing facility of a Japanese company. While certain prominent Japanese companies are limited to operating solely within Japan, a significant number of companies have adopted a global approach, spanning their operations across numerous countries worldwide. For this applicational example, ten potential countries in Asia were considered for the selection process of the most suitable one. The potential candidate countries for the manufacturing facility location are Cambodia, China, India, Indonesia, Lao PDR,

Table 1
Input and output criteria for location selection.

	Performance indicator	Type	Codes	References
Political				
	Tax system & corporate tax	Input	x_1	[63,64,66–71]
	Capital expenditures	Input	x_2	[63,64,66,67,69–71]
	Customs clearance efficiency	Output	y_1	[2,63,68,71]
	Corruption perceptions	Input	x_3	[64,66–68,71]
Economic				
	Labor cost	Input	x_4	[2,63,64,66–71]
	Value added by industry	Output	y_2	[63,66,67]
	Infrastructure	Output	y_3	[63,66,68,70,71]
	Urbanization	Output	y_4	[63,64,67,68,70]
	Industry growth rate	Output	y_5	[63,64,67,70]
	Gross national income per capita	Output	y_6	[63,64,68,70,71]
Social				
	Public security	Input	x_5	[63,67,68,70]
	World risk index	Input	x_6	[2,67,69–71]
	World peace index	Input	x_7	[63,69]
Technological				
	Skill & quality of workers	Output	y_7	[2,63,64,66–71]
	Delivery punctuality	Output	y_8	[2,63,68,69]
	Power supply efficiency	Output	y_9	[63,64,66–68,71]
	Water supply efficiency	Output	y_{10}	[63,64,67,68,71]
	Trade & logistics infrastructure	Output	y_{11}	[63,64,66–68,70]
	Efficiency of road transport	Output	y_{12}	[63,64,66,71]
	Port capacity	Output	y_{13}	[63]
	Shipment tracking capability	Output	y_{14}	[64,66–68,71]
	Availability of transport	Output	y_{15}	[63,64,66–71]

Table 2
Input and output data for the numerical example of ten countries.

Criteria		DMUs									
		DMU$_1$	DMU$_2$	DMU$_3$	DMU$_4$	DMU$_5$	DMU$_6$	DMU$_7$	DMU$_8$	DMU$_9$	DMU$_{10}$
Inputs	x_1	20	25	42	25	24	25	35	30	30	22
	x_2	139.5	0.9	12.2	21.1	5.7	7.2	155.9	16.6	6.6	5.4
	x_3	36	40	36	32	26	50	21	36	35	31
	x_4	101	411.13	226.8	241	137	429	71	272	366	155
	x_5	4	4	4	3	3	2	3	4	3	2
	x_6	16.9	6.91	7.17	10.54	5.71	6.45	9.1	27.52	6.34	12.81
	x_7	2.201	2.207	2.571	1.853	1.723	1.659	2.473	2.456	2.395	1.792
Outputs	y_1	2.67	3.21	2.72	2.87	2.45	3.37	1.97	3	3.21	2.81
	y_2	1.52E+10	9.24E+12	1.88E+12	8.68E+11	1.11E+10	3.12E+11	1.46E+12	2.72E+11	3.87E+11	1.71E+11
	y_3	2.953	2.633	9.478	0.357	6.4	2.105	5.821	2.933	2.185	6.595
	y_4	21	54	32	53	38	74	34	44	49	33
	y_5	7.015	7.671	4.351	5.781	8.2	4.687	7.5	7.163	2.872	5.421
	y_6	950	6560	1570	3580	1460	10400	3877	3270	5370	1730
	y_7	2.67	3.46	3.03	3.21	2.31	3.47	2.07	2.93	3.29	3.09
	y_8	2.75	3.87	3.51	3.53	2.65	3.92	2.83	3.07	3.96	3.49
	y_9	3.494	4.289	3.489	4.18	3.856	4.724	3.094	4.334	4.66	4.008
	y_{10}	4.858	4.811	4.6	4.732	4.834	4.912	4.778	4.76	4.854	4.808
	y_{11}	2.58	3.67	2.88	2.92	2.21	3.56	2.14	2.6	3.4	3.11
	y_{12}	6.3	53.5	49.5	56.9	13.7	82.8	11.9	9.9	98.5	47.6
	y_{13}	246	155017	9827	9325	0	20867	209	5721	7372	6589
	y_{14}	2.92	3.5	3.11	3.11	2.2	3.58	2.36	3	3.45	3.19
	y_{15}	2.83	3.5	3.2	2.87	2.5	3.64	2.14	3.33	3.3	3.22

Malaysia, Myanmar, the Philippines, Thailand, and Vietnam, which are denoted as DMU1, DMU2, DMU3, DMU4, DMU5, DMU6, DMU7, DMU8, DMU9, and DMU10, respectively. The performance of each of the ten countries was evaluated based on the aforementioned 22 criteria. The input and output data for these ten countries in the numerical example are presented in Table 2.

5.2. Results and discussion

The dataset provided in Table 2 was utilized to assess the performance of the ten DMUs using DEA, Inverted DEA, DEA-AR, Inverted DEA-AR, and double-frontier DEA-AR model as outlined in Sections 3 and 4. In this study, a computer software program, i.e., Microsoft Excel Solver, was used to perform all numerical calculations. For each performance measure, the model was run individually for each of the ten DMUs to obtain their respective scores. The comparison of the resulting scores and ranks of the DMUs based on the different models is presented in Table 3.

The results of the efficiency scores (E_p) obtained from the DEA model and the inefficiency scores (I_p) from the Inverted DEA model are presented in the second and third columns of Table 3, respectively. It becomes apparent from the analysis that both DEA and Inverted DEA exhibit notably poor discrimination power in this particular empirical study. Among the ten DMUs under evaluation, nine of them are classified as efficient since they attained efficiency scores equal to one ($E_p = 1$) when assessed from the positive side using the efficient frontier of the standard DEA model. This indicates that 90 % of the DMUs exhibit no discrimination among them. Similarly, upon evaluating the DMUs from a negative perspective using the anti-efficient frontier to gather additional information, all ten DMUs are found to be inefficient, as indicated by their inefficiency scores equal to one ($I_p = 1$).

This outcome demonstrates that the DEA alone, including an evaluation of inefficiency using Inverted DEA, fails to provide good discrimination among the DMUs when applied to this particular numerical example. The lack of discrimination observed in the DEA models may be attributed to either characteristics inherent in the dataset itself or the theoretical minimum number of DMUs involved in the calculation. The established guideline for the minimum number of DMUs (n) required in DEA models, as proposed by Cooper et al. [72], suggests that $n \geq \max\{m \times s, 3(m+s)\}$, where m represents the number of inputs and s represents the number of outputs. Insufficient discrimination ability often arises when the number of DMUs is relatively small compared to the number of input and output criteria [73,74]. Consequently, the DMUs in this example cannot be ranked, primarily due to the relatively small sample size (ten DMUs) being considered in comparison to the numerous input and output performance indicators (22 criteria), thus violating the rule of thumb. In such a scenario, standard DEA models faced limitations in discriminating among the DMUs. With the exception of DMU8, all other DMUs were found to lie on both efficient and anti-efficient frontiers. Consequently, the identification of the best location and the resolution of the selection problem were hindered, leading to an inconclusive outcome.

The inability to acquire sufficient discrimination among the DMUs led to the adoption of the AR model. By imposing constraints on the weight values, the model aimed to reduce weight flexibility and prevent the occurrence of zero weights, which generally leads to an improvement in discrimination. In doing so, the DEA-AR model and the Inverted DEA-AR model were executed according to Eqs. (9) and (10), respectively. The results of the total efficiency scores (E'_p) from the optimistic viewpoint and total inefficiency scores (I'_p) from the pessimistic viewpoint, along with their respective ranking orders, are provided in columns four to seven of Table 3.

The analysis reveals that only three DMUs, specifically DMU5, DMU6, and DMU9, exhibit a total efficiency score of one ($E'_5 = E'_6 = E'_9 = 1$) when evaluating their performance from a positive aspect. These DMUs are ranked first and are regarded as the best performing DMUs. Nevertheless, the performance of these DMUs lacks discrimination when ranked solely based on their efficiency scores. DMU10 exhibits slightly lower performance compared to those three DMUs, with a total efficiency score of 0.99. On the other hand, DMU8 is identified as the least efficient among the ten DMUs. For the negative measurement, the number of inefficient DMUs with a total inefficiency score equal to one ($I'_p = 1$), is also reduced from ten to four, i.e., DMU1, DMU3, DMU7, and DMU8. In this case of a negative measure, DMU6 is considered the least inefficient because its score is the lowest or closest to zero; therefore, it is ranked first.

The results from employing the DEA-AR and Inverted DEA-AR models show that discrimination among the DMUs is increased when incorporating weight restriction constraints into both efficiency and inefficiency evaluation models. However, it is observed in this study that the ranking results obtained from positive and negative evaluations are not identical, aligning with findings from several

Table 3
Results of the performance measures.

DMU	DEA	Inverted DEA	DEA-AR		Inverted DEA-AR		Double-frontier DEA-AR			
	E_p	I_p	E'_p		I'_p		O_p		Q_p	
	Score	Score	Score	Rank	Score	Rank	Score	Rank	Score	Rank
DMU_1	1	1	0.69	9	1	10	0.69	9	1.69	9
DMU_2	1	1	0.95	5	0.94	6	1.01	6	2.01	6
DMU_3	1	1	0.81	7	1	10	0.81	7	1.81	7
DMU_4	1	1	0.84	6	0.74	3	1.10	5	2.19	3
DMU_5	1	1	1	1	0.86	4	1.14	3	2.16	4
DMU_6	1	1	1	1	0.61	1	1.39	1	2.64	1
DMU_7	1	1	0.80	8	1	10	0.80	8	1.80	8
DMU_8	0.95	1	0.62	10	1	10	0.62	10	1.62	10
DMU_9	1	1	1	1	0.87	5	1.13	4	2.15	5
DMU_{10}	1	1	0.99	4	0.70	2	1.29	2	2.42	2

previous studies [58,75]. It has been suggested that positive and negative evaluation approaches may not invariably yield the same ranking outcomes. Furthermore, it is noteworthy to mention that comprehensive rankings from either model are still not fully available. From the existing ranking, it could be inferred that DMU6 emerges as the most favorable performing DMU, holding the first position on both evaluations. However, it is important to emphasize that decision-makers often seek a complete ranking of the DMUs to obtain a more precise and thorough evaluation, as asserted in the study conducted by Adler et al. [73].

To further enhance the discrimination capacity, the two approaches of the double-frontier DEA-AR technique, which integrate performance measures from both positive and negative perspectives, were employed to calculate the overall performance scores O_p and Q_p according to Eqs. (11) and (12), respectively. The resulting overall performance scores and corresponding rankings for each DMU are presented in the last four columns of Table 3. Both O_p and Q_p of the double-frontier DEA-AR not only offer comprehensive evaluations of DMUs by integrating information from both their best and worst sides, taking into account the viewpoints of decision-makers or practitioners, but they also effectively discriminate among the DMUs, enabling a complete ranking to be established. This leads to significantly enhanced discrimination power compared to the results obtained from all previous models, allowing for the identification of the most well-performing DMU. With the inclusion of performance measurement from the negative aspect in the analysis, DMU6 obtains the highest overall performance scores of both O_p and Q_p. Consequently, it is regarded as the most efficient DMU among the evaluated candidates. DMU10 ascends to the second rank due to its fewer weak points compared to DMU5 and DMU9. A slight discrepancy in ranks exists from third to fifth place for both overall performance scores. In terms of O_p, DMU5 occupies the third rank, followed by DMU9 in fourth place, and DMU4 in fifth place. On the other hand, when considering Q_p, DMU4 holds the third rank, followed by DMU5 in the fourth place, and DMU9 in the fifth place. Among the remaining DMUs, there is a tie in rank, with DMU8 being identified as the least performed DMU.

From the two approaches of double-frontier DEA-AR, the analysis suggests that the total inefficiency score I_p' (from Inverted DEA-AR) in Q_p exerts a more substantial influence compared to those in O_p. Consequently, it can be inferred that the overall performance score Q_p of Eq. (12) places a greater emphasis on inefficiency scores or pessimistic perspective, while the overall performance score O_p of Eq. (11) places a greater emphasis on efficiency scores or positive perspective. As a result, decision-makers have the flexibility to choose between the two approaches based on their specific requirements and preferences.

To provide a more comprehensive understanding and enable the comparison of locations, a two-dimensional plane is constructed by plotting two performance measures of the DEA-AR and Inverted DEA-AR models for each DMU. One axis represents the total efficiency score E_p', while the other axis displays the total inefficiency score I_p' of each DMU, as illustrated in Fig. 3.

In Fig. 3, DMU6 and DMU10 are depicted in the upper left corner, indicating their superior performance compared to the other potential DMUs. The remaining DMUs are positioned behind these top two performers. As such, DMU6, which represents Malaysia, emerges as the most promising candidate country for the location selection problem. The observed result can be substantiated from the standpoint of the Japanese government, as Malaysia emerges as an appealing investment hub and destination for Japanese companies, attributable to several compelling factors. Notably, Malaysia boasts robust infrastructure, and its bureaucratic system is well-established and reliable. Furthermore, the country's political stability serves as an encouraging factor for investors seeking to establish and conduct operations in the country.

Overall, while the original DEA is simple and offers a basic assessment, it may lack discrimination power, leading to limited differentiation among DMUs. The DEA-AR improves discrimination by incorporating decision-makers' preferences. However, the model may still have limitations in fully ranking alternative DMUs due to its focus on either efficiency or inefficiency alone. The double-frontier DEA-AR further enhances the analysis by integrating both positive and negative perspectives through the efficient and

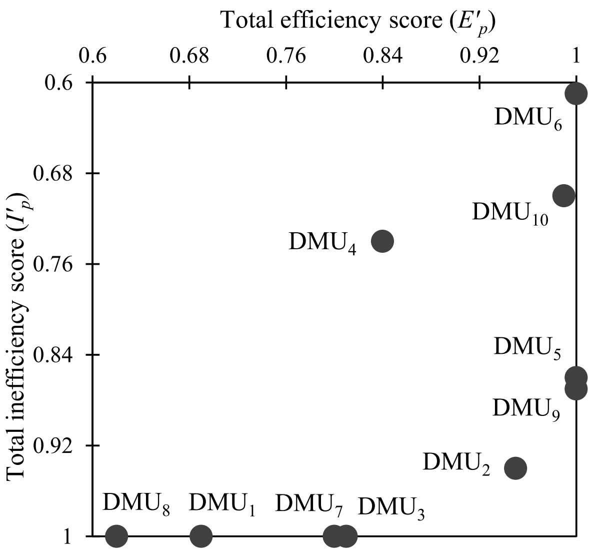

Fig. 3. Efficiency and inefficiency of the ten DMUs.

anti-efficient frontiers, providing decision-makers with a better understanding of alternative DMUs' performance. Moreover, it had the ability to increase discrimination power and ultimately provide the full ranking result. However, the two approaches within the model may yield slightly different ranking results, requiring careful consideration by decision-makers.

5.3. Implications for theory and practice

This study contributes to theoretical advancements in the application of DEA techniques in performance evaluation by providing empirical evidence on the real impact of subjective judgments and the utilization of double-frontier evaluation methods. The integration of decision-makers' preferences into both the efficiency and inefficiency evaluation processes through the assurance region represents a significant theoretical advancement in DEA methodology. By incorporating decision-makers' subjective viewpoints on both efficient and anti-efficient frontiers, this study demonstrates that greater efficiency and inefficiency scores can be achieved compared to traditional DEA and Inverted DEA models. Furthermore, the proposed double-frontier DEA-AR model, which integrates both positive and negative evaluations, enhances discrimination capability, leading to more comprehensive ranking results.

The findings of this study also have significant implications for decision-makers involved in location selection. By integrating the DEA techniques of the DEA-AR and Inverted DEA-AR models, this study provides insightful performance evaluations and offers decision-makers a more comprehensive approach to evaluating potential manufacturing site performance. The integrated approach allows for a thorough evaluation of both the strengths and weaknesses of alternative locations. This comprehensive assessment enables decision-makers to better understand the comparative advantages and disadvantages of each option, leading to more informed and effective decision-making processes when selecting suitable locations for manufacturing facilities. Moreover, by incorporating decision-makers' judgments on both positive and negative perspectives into the evaluation process through the assurance region, it ensures that the evaluation reflects the specific preferences and priorities of decision-makers, leading to more tailored and relevant results. In summary, the implications of this study highlight the importance of evaluation techniques in guiding strategic decisions related to location selection, offering decision-makers valuable tools for performance evaluation.

6. Conclusions

The selection of the optimal manufacturing location is crucial for gaining a competitive advantage and ensuring overall business success. To address this concern, this paper introduces enhanced business analysis approaches that incorporate DEA techniques to comprehensively assess potential manufacturing sites. By integrating DEA methods, the proposed framework aims to offer more insightful assessments to support informed decisions regarding location selection. The study illustrates the feasibility of incorporating decision-makers' perspectives on the relative importance of different criteria through the application of weight restrictions. Furthermore, the research emphasizes the importance of considering both positive and negative aspects of alternatives by employing efficient and anti-efficient frontiers within DEA analysis. These approaches are particularly relevant when the number of alternative locations is relatively small compared to the multitude of input and output criteria to be assessed in the performance analysis.

This study investigates the proposed decision support models through a numerical example involving location selection based on a specified set of criteria related to political, economic, social, and technological aspects. The example reveals that conventional DEA and Inverted DEA models lack the ability to distinguish the performances of alternative locations effectively. However, introducing additional weight assurance region constraints enhances their discrimination capability, although complete discrimination remains unachievable. The proposed double-frontier DEA-AR model, which integrates efficient and anti-efficient frontiers along with assurance region weight restrictions, serves as an overall performance measure. This approach enables a full ranking of all alternative locations. This double-frontier DEA-AR analysis provides a rational approach for obtaining a complete rank in scenarios where effective discrimination among DMUs is difficult to achieve.

The proposed alternative performance measures offer decision-makers and management the flexibility to incorporate their judgments on the criteria, enabling the determination of preferred weights within a reasonable range. By leveraging the anti-efficient frontier, constructed from the worst practice DMUs, further insights into the performance of DMUs can be gained. This integration of weight restrictions and additional information from a negative perspective serves as valuable supplementary data for evaluating DMUs, substantially bolstering the discrimination power of the DEA model. Consequently, management is able to gain a comprehensive understanding of each location's strengths and weaknesses, allowing for a full ranking of candidate locations and the identification of the most suitable site. Importantly, this application is not limited to site selection alone but can be extended to other assessments involving multiple criteria, where effective decision-making is crucial.

7. Limitations and future studies

This study faces limitations concerning the determination of the assurance region and the integration of the DEA-AR and Inverted DEA-AR models. Both models rely on incorporating the relative weights of input and output criteria based on decision-makers' judgments or preferences into the evaluation process. However, determining the appropriate relative importance of criteria can be subjective and may vary across decision-makers. This subjectivity introduces potential biases in the model's results, which could impact the analysis outcomes and final rankings.

Moreover, this study proposes two approaches to aggregate the efficiency score from the DEA-AR model and the inefficiency score from the Inverted DEA-AR model to form the double-frontier DEA-AR model. The first approach emphasizes efficiency scores or a positive perspective, while the second approach emphasizes inefficiency scores or a pessimistic perspective. Decision-makers have the flexibility to choose between these approaches based on their requirements and preferences. However, these approaches produce different ranking results, which may have an impact on evaluations that require comprehensive rankings.

Therefore, future studies might investigate alternative techniques to combine the DEA-AR and Inverted DEA-AR models, considering other mathematical methods. Additionally, other techniques could be explored to reach a consensus on setting the assurance region, especially in situations involving multiple decision-makers. Furthermore, comparative studies may be conducted to compare the results obtained by the proposed double-frontier DEA-AR model with those of other alternative decision-making approaches, such as MCDA methods or other optimization techniques. Comparative analyses can help evaluate the relative advantages and limitations of each approach in terms of accuracy, computational efficiency, and practical usability. By addressing these recommendations, future studies can advance the application of assurance region techniques in conjunction with the combination DEA and Inverted DEA models, ultimately improving the effectiveness and reliability of decision support systems in various domains.

Data availability statement

Data will be made available on request.

Ethics statement

Review and/or approval by an ethics committee was not needed for this study as it did not utilize any animal or human based experiments.

CRediT authorship contribution statement

Sirawadee Arunyanart: Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This research was supported by Research and Graduate Studied, and Supply Chain and Logistics System Research Unit, Khon Kaen University.

References

[1] M. Gylling, J. Heikkilä, K. Jussila, M. Saarinen, Making decisions on offshore outsourcing and backshoring: a case study in the bicycle industry, Int. J. Prod. Econ. 162 (2015) 92–100, https://doi.org/10.1016/j.ijpe.2015.01.006.
[2] M. Johansson, J. Olhager, Comparing offshoring and backshoring: the role of manufacturing site location factors and their impact on post-relocation performance, Int. J. Prod. Econ. 205 (2018) 37–46, https://doi.org/10.1016/j.ijpe.2018.08.027.
[3] C. Achillas, D. Aidonis, E. Iakovou, M. Thymianidis, D. Tzetzis, A methodological framework for the inclusion of modern additive manufacturing into the production portfolio of a focused factory, J. Manuf. Syst. 37 (1) (2015) 328–339, https://doi.org/10.1016/j.jmsy.2014.07.014.
[4] F. Kutlu Gündoğdu, C. Kahraman, A novel VIKOR method using spherical fuzzy sets and its application to warehouse site selection, J. Intell. Fuzzy Syst. 37 (1) (2019) 1197–1211, https://doi.org/10.3233/JIFS-182651.
[5] İ. Önden, A.Z. Acar, F. Eldemir, Evaluation of the logistics center locations using a multi-criteria spatial approach, Transp 33 (2) (2018) 322–334, https://doi.org/10.3846/16484142.2016.1186113.
[6] E. Ulucan, The hotel site selection: determining locational factors by Fuzzy TOPSIS, Eur. J. Tour. Hosp. Recreat. 10 (3) (2020) 213–228, https://doi.org/10.2478/ejthr-2020-0019.
[7] E.A. Adalı, A. Tuş, Hospital site selection with distance-based multi-criteria decision-making methods, Int. J. Healthc. Manag. 14 (2) (2021) 534–544, https://doi.org/10.1080/20479700.2019.1674005.
[8] Ö. Kaya, A. Tortum, K.D. Alemdar, M.Y. Çodur, Site selection for EVCS in Istanbul by GIS and multi-criteria decision-making, Transp. Res. Part D: Transp. Environ. 80 (2020) 102271, https://doi.org/10.1016/j.trd.2020.102271.
[9] S. Ozdemir, G. Sahin, Multi-criteria decision-making in the location selection for a solar PV power plant using AHP, Meas 129 (2018) 218–226, https://doi.org/10.1016/j.measurement.2018.07.020.
[10] R.D. Banker, A. Charnes, W.W. Cooper, Some models for estimating technical and scale inefficiencies in data envelopment analysis, Manag. Sci. 30 (9) (1984) 1078–1092, https://doi.org/10.1287/mnsc.30.9.1078.
[11] G. Pambudi, N. Nananukul, A hierarchical fuzzy data envelopment analysis for wind turbine site selection in Indonesia, Energy Rep. 5 (2019) 1041–1047, https://doi.org/10.1016/j.egyr.2019.08.002.
[12] Y. Takamura, K. Tone, A comparative site evaluation study for relocating Japanese government agencies out of Tokyo, Soc. Econ. Plann. Sci. 37 (2) (2003) 85–102, https://doi.org/10.1016/S0038-0121(02)00049-6.
[13] C.N. Wang, T.T. Dang, J.W. Wang, 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 Rep. 8 (2022) 1124–1142, https://doi.org/10.1016/j.egyr.2021.12.045.
[14] M. Yazdani, P. Chatterjee, D. Pamucar, S. Chakraborty, Development of an integrated decision making model for location selection of logistics centers in the Spanish autonomous communities, Expert Syst. Appl. 148 (2020) 113208, https://doi.org/10.1016/j.eswa.2020.113208.
[15] P.L. Lai, A. Potter, M. Beynon, A. Beresford, Evaluating the efficiency performance of airports using an integrated AHP/DEA-AR technique, Transport Pol. 42 (2015) 75–85, https://doi.org/10.1016/j.tranpol.2015.04.008.

[16] B. Keskin, C.D. Köksal, A hybrid AHP/DEA-AR model for measuring and comparing the efficiency of airports, Int. J. Prod. Perform. Manag. 68 (3) (2019) 524–541, https://doi.org/10.1108/IJPPM-02-2018-0043.
[17] Y.M. Wang, K.S. Chin, G.K.K. Poon, A data envelopment analysis method with assurance region for weight generation in the analytic hierarchy process, Decis. Support Syst. 45 (4) (2008) 913–921, https://doi.org/10.1016/j.dss.2008.03.002.
[18] W.M. Wey, Smart growth and transit-oriented development planning in site selection for a new metro transit station in Taipei, Taiwan, Habitat Int. 47 (2015) 158–168, https://doi.org/10.1016/j.habitatint.2015.01.020.
[19] A.H. Lee, H.Y. Kang, C.Y. Lin, K.C. Shen, An integrated decision-making model for the location of a PV solar plant, Sustain. Times 7 (10) (2015) 13522–13541, https://doi.org/10.3390/su71013522.
[20] B. Ebrahimi, M. Khalili, A new integrated AR-IDEA model to find the best DMU in the presence of both weight restrictions and imprecise data, Comput. Ind. Eng. 125 (2018) 357–363, https://doi.org/10.1016/j.cie.2018.09.008.
[21] S. Singh, Intuitionistic fuzzy DEA/AR and its application to flexible manufacturing systems, RAIRO-Oper. Res. 52 (1) (2018) 241–257, https://doi.org/10.1051/ro/2017081.
[22] A. Theodoridis, A. Ragkos, G. Koutouzidou, Revealing the profile of economically efficient mussel farms: a restricted data envelopment analysis application, Aquacult. Int. 28 (2) (2020) 675–689, https://doi.org/10.1007/s10499-019-00490-3.
[23] T.H. Wu, Y.F. Chung, S.W. Huang, Evaluating global energy security performances using an integrated PCA/DEA-AR technique, Sustain. Energy Technol. Assessments 45 (2021) 101041, https://doi.org/10.1016/j.seta.2021.101041.
[24] S.P. Chen, C.W. Chang, Measuring the efficiency of university departments: an empirical study using data envelopment analysis and cluster analysis, Scientometrics 126 (6) (2021) 5263–5284, https://doi.org/10.1007/s11192-021-03982-3.
[25] H. Khanjarpanah, A. Jabbarzadeh, S.M. Seyedhosseini, A novel multi-period double frontier network DEA to sustainable location optimization of hybrid wind-photovoltaic power plant with real application, Energy Convers. Manag. 159 (2018) 175–188, https://doi.org/10.1016/j.enconman.2018.01.013.
[26] H. Shabanpour, S. Yousefi, R.F. Saen, Future planning for benchmarking and ranking sustainable suppliers using goal programming and robust double frontiers DEA, Transp. Res. Part D: Transp. Environ. 50 (2017) 129–143, https://doi.org/10.1016/j.trd.2016.10.022.
[27] A. Amirteimoori, H. Azizi, S. Kordrostami, Double frontier two-stage fuzzy data envelopment analysis, Intern. J. Uncertain. Fuzziness Knowl.-Based Syst. 28 (1) (2020) 117–152, https://doi.org/10.1142/S0218488520500063.
[28] R.K. Mavi, A. Fathi, R.F. Saen, N.K. Mavi, Eco-innovation in transportation industry: a double frontier common weights analysis with ideal point method for Malmquist productivity index, Resour. Conserv. Recycl. 147 (2019) 39–48, https://doi.org/10.1016/j.resconrec.2019.04.017.
[29] S.R. Seyedalizadeh Ganji, A.A. Rassafi, Measuring the road safety performance of Iranian provinces: a double-frontier DEA model and evidential reasoning approach, Int. J. Inj. Control Saf. Promot. 26 (2) (2019) 156–169, https://doi.org/10.1080/17457300.2018.1535510.
[30] S.S. Ganji, A.A. Rassafi, Road safety evaluation using a novel cross efficiency method based on double frontiers DEA and evidential reasoning approach, KSCE J. Civ. Eng. 23 (2019) 850–865, https://doi.org/10.1007/s12205-018-0401-3.
[31] S.S. Ganji, A.A. Rassafi, DEA Malmquist productivity index based on a double-frontier slacks-based model: Iranian road safety assessment, Eur. Transp. Res. Rev. 11 (2019) 1–32, https://doi.org/10.1186/s12544-018-0339-z.
[32] S.S. Ganji, A.A. Rassafi, S.J. Bandari, Application of evidential reasoning approach and OWA operator weights in road safety evaluation considering the best and worst practice frontiers, Soc. Econ. Plann. Sci. 69 (2020) 100706, https://doi.org/10.1016/j.seps.2019.04.003.
[33] M. Tavassoli, A. Fathi, R.F. Saen, Assessing the sustainable supply chains of tomato paste by fuzzy double frontier network DEA model, Ann. Oper. Res. (2021) 1–33, https://doi.org/10.1007/s10479-021-04139-4.
[34] R.F. Saen, B. Karimi, A. Fathi, Assessing the sustainability of transport supply chains by double frontier network data envelopment analysis, J. Clean. Prod. 354 (2022) 131771, https://doi.org/10.1016/j.jclepro.2022.131771.
[35] S.S. Ganji, M. Najafi, A. Mora-Cruz, A. Awasthi, S.F. Ajirlu, Assessment of airline industry using a new double-frontier cross-efficiency method based on prospect theory, Ann. Oper. Res. (2023) 1–61, https://doi.org/10.1007/s10479-023-05225-5.
[36] S.S. Ganji, A. Dehghani, S.F. Ajirlu, Evaluation of intercity road passenger transportation using a novel double-frontier game-regret-cross-efficiency, Soc. Econ. Plann. Sci. 93 (2024) 101869, https://doi.org/10.1016/j.seps.2024.101869.
[37] A. Charnes, W.W. Cooper, E. Rhodes, Measuring the efficiency of decision making units, Eur. J. Oper. Res. 2 (6) (1978) 429–444, https://doi.org/10.1016/0377-2217(78)90138-8.
[38] A. Charnes, W. Cooper, A.Y. Lewin, L.M. Seiford, Data envelopment analysis theory, methodology and applications, J. Oper. Res. Soc. 48 (3) (1997) 332–333, https://doi.org/10.1057/palgrave.jors.2600342.
[39] W. Liu, X. Li, L. Qi, D. Zhang, DEA Analysis Based on Both Efficient and Anti-efficient Frontiers, University of Kent, 2007.
[40] S. Tandon, Performance Measurement of Bus Routes Using Data Envelopment Analysis, University of Illinois at Chicago, 2006.
[41] X.B. Li, G.R. Reeves, A multiple criteria approach to data envelopment analysis, Eur. J. Oper. Res. 115 (3) (1999) 507–517, https://doi.org/10.1016/S0377-2217(98)00130-1.
[42] H. Moheb-Alizadeh, S.M. Rasouli, R. Tavakkoli-Moghaddam, The use of multi-criteria data envelopment analysis (MCDEA) for location–allocation problems in a fuzzy environment, Expert Syst. Appl. 38 (5) (2011) 5687–5695, https://doi.org/10.1016/j.eswa.2010.10.065.
[43] E. Thanassoulis, Introduction to the Theory and Application of Data Envelopment Analysis, Kluwer Academic Publishers, Dordrecht, 2001.
[44] E. Thanassoulis, M.C. Portela, R. Allen, Incorporating Value Judgments in DEA, Handbook on Data Envelopment Analysis, 2004.
[45] F. Pedraja-Chaparro, J. Salinas-Jimenez, P. Smith, On the role of weight restrictions in data envelopment analysis, J. Prod. Anal. 8 (2) (1997) 215–230.
[46] R. Allen, A. Athanassopoulos, R.G. Dyson, E. Thanassoulis, Weights restrictions and value judgements in data envelopment analysis: evolution, development and future directions, Ann. Oper. Res. 73 (1997) 13–34.
[47] W.F. Shen, D.Q. Zhang, W.B. Liu, G.L. Yang, Increasing discrimination of DEA evaluation by utilizing distances to anti-efficient frontiers, Comput. Oper. Res. 75 (2016) 163–173, https://doi.org/10.1016/j.cor.2016.05.017.
[48] Y. Yamada, T. Matsui, M. Sugiyama, An inefficiency measurement method for management systems, J. Oper. Res. Soc. Jpn. 37 (2) (1994) 158–167.
[49] J.C. Paradi, M. Asmild, P.C. Simak, Using DEA and worst practice DEA in credit risk evaluation, J. Prod, Anal. 21 (2004) 153–165.
[50] M.J. Rezaeiani, A.A. Foroughi, Ranking efficient decision making units in data envelopment analysis based on reference frontier share, Eur. J. Oper. Res. 264 (2) (2018) 665–674, https://doi.org/10.1016/j.ejor.2017.06.064.
[51] E. Dehghani, M.S. Jabalameli, M.S. Pishvaee, A. Jabarzadeh, Integrating information of the efficient and anti-efficient frontiers in DEA analysis to assess location of solar plants: a case study in Iran, J. Ind. Syst. Eng. 11 (1) (2018) 163–179. https://dorl.net/dor/20.1001.1.17358272.2018.11.1.9.9.
[52] Q. Zhang, B. Zhang, Comprehensive evaluation of logistics enterprise performance based on DEA and inverted DEA model, Am. J. Appl. Math. 6 (2) (2018) 48–54.
[53] C.H. DiMaria, Sustainability, welfare and efficiency of nations, Qual. Quantity 53 (3) (2019) 1141–1163, https://doi.org/10.1007/s11135-018-0809-3.
[54] S.S. Ganji, A. Rassafi, D.L. Xu, A double frontier DEA cross efficiency method aggregated by evidential reasoning approach for measuring road safety performance, Meas 136 (2019) 668–688, https://doi.org/10.1016/j.measurement.2018.12.098.
[55] B. Zhang, J. Guo, Z. Wen, Z. Li, N. Wang, Ecological evaluation of industrial parks using a comprehensive DEA and inverted-DEA model, Math. Probl Eng. 2020 (2020), https://doi.org/10.1155/2020/9397806.
[56] R.G. Dyson, E. Thanassoulis, Reducing weight flexibility in data envelopment analysis, J. Oper. Res. Soc. 39 (6) (1988) 563–576, https://doi.org/10.1057/jors.1988.96.
[57] R.G. Dyson, R. Allen, A.S. Camanho, V.V. Podinovski, C.S. Sarrico, E.A. Shale, Pitfalls and protocols in DEA, Eur. J. Oper. Res. 132 (2) (2001) 245–259, https://doi.org/10.1016/S0377-2217(00)00149-1.
[58] R.G. Thompson, F.D. Singleton Jr., R.M. Thrall, B.A. Smith, Comparative site evaluations for locating a high-energy physics lab in Texas, Interfaces 16 (6) (1986) 35–49, https://doi.org/10.1287/inte.16.6.35.

[59] W.W. Cooper, L.M. Seiford, J. Zhu, Data envelopment analysis: history, models, and interpretations, in: Handbook on Data Envelopment Analysis, Springer, 2011.

[60] A. Charnes, W.W. Cooper, A.Y. Lewin, L.M. Seiford, The DEA process, usages, and interpretations, in: Data Envelopment Analysis: Theory, Methodology, and Applications, Springer, 1994.

[61] J. Cox, The higher education environment driving academic library strategy: a political, economic, social and technological (PEST) analysis, J. Acad. Librariansh. 47 (1) (2021) 102219, https://doi.org/10.1016/j.acalib.2020.102219.

[62] T. Sammut-Bonnici, D. Galea, PEST analysis, in: Wiley Encyclopedia of Management, John Wiley & Sons, Ltd, Hoboken, 2015.

[63] B.L. MacCarthy, W. Atthirawong, Factors affecting location decisions in international operations–a Delphi study, Int. J. Oper. Prod. Manag. 23 (7) (2003) 794–818.

[64] M.A. Badri, Dimensions of industrial location factors: review and exploration, J. Bus. Publ. Aff. 1 (2) (2007) 1–26.

[65] G.J. Da Silveira, An empirical analysis of manufacturing competitive factors and offshoring, Int. J. Prod. Econ. 150 (2014) 163–173, https://doi.org/10.1016/j.ijpe.2013.12.031.

[66] L. Boardman Liu, P. Berger, A. Zeng, A. Gerstenfeld, Applying the analytic hierarchy process to the offshore outsourcing location decision, Supply Chain Manag. Int. J. 13 (6) (2008) 435–449, https://doi.org/10.1108/13598540810905697.

[67] Y. Dou, J. Sarkis, A joint location and outsourcing sustainability analysis for a strategic offshoring decision, Int. J. Prod. Res. 48 (2) (2010) 567–592, https://doi.org/10.1080/00207540903175145.

[68] W. Atthirawong, B. MacCarthy, An application of the analytical hierarchy process to international location decision-making, in Gregory, Mike. Proceedings of the 7th Annual Cambridge International Manufacturing Symposium: Restructuring Global Manufacturing, University of Cambridge, Cambridge, England, 2002.

[69] L.M. Ellram, W.L. Tate, K.J. Petersen, Offshoring and reshoring: an update on the manufacturing location decision, J. Supply Chain Manag. 49 (2) (2013) 14–22, https://doi.org/10.1111/jscm.12019.

[70] M. Şahin, Hybrid multicriteria group decision-making method for offshore location selection under fuzzy environment, Arabian J. Sci. Eng. 45 (8) (2020) 6887–6909, https://doi.org/10.1007/s13369-020-04534-2.

[71] S. Arunyanart, P. Sureeyatanapas, K. Ponhan, W. Sessomboon, T. Niyamosoth, International location selection for production fragmentation, Expert Syst. Appl. 171 (2021) 114564, https://doi.org/10.1016/j.eswa.2021.114564.

[72] W.W. Cooper, L.M. Seiford, K. Tone, Data Envelopment Analysis: a Comprehensive Text with Models, Applications, References and DEA-Solver Software, Springer, 2007.

[73] N. Adler, L. Friedman, Z. Sinuany-Stern, Review of ranking methods in the data envelopment analysis context, Eur. J. Oper. Res. 140 (2) (2002) 249–265, https://doi.org/10.1016/S0377-2217(02)00068-1.

[74] M. Toloo, E. Keshavarz, A. Hatami-Marbini, Selecting data envelopment analysis models: a data-driven application to EU countries, Omega 101 (2021) 102248, https://doi.org/10.1016/j.omega.2020.102248.

[75] W.M. Wey, Y.H. Chang, A comparative location study for the joint development station of a mass rapid transit system: a case in Taichung City in Taiwan, Environ. Plan. B: plan, Des. 36 (4) (2009) 573–587, https://doi.org/10.1068/b33135.