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Evaluating the Efficiencies of Logistics Centers with Fuzzy Logic: The Case of Turkey †

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Abstract: The primary actor in today's economic life, forming the backbone of the production-consumption cycle, is the distribution activities. Logistics centers (LCs) are organized areas where these activities are carried out together. Therefore, the efficiency and effectiveness of distribution activities are crucial for sustainability. This study incorporates fuzzy logic theory into the framework of data envelopment analysis (DEA) to measure the efficiency of LCs. Classical DEA assumes input and output data are precisely measured, making the efficiency scores unreliable and inconsistent when data precision is not always possible. The adoption of fuzzy logic is primarily to overcome possible uncertainties, errors, and ambiguities in data acquisition, preventing incorrect results. Hence, an approach assumes the data lie within specific intervals, was adopted to calculate the efficiencies of LCs based on α-cut levels. Officially obtained data on nine input and one output variable from twelve LCs operating in Turkey were used to calculate efficiency scores. As a result of the study, Köseköy/Izmit, Halkali/Istanbul, and Yenice/Mersin LCs were found to be fully efficient considering both lower and upper bound efficiencies. Moreover, the efficiency calculations using Fuzzy-DEA allowed for a more precise evaluation of LCs with high data sensitivity.

Keywords: logistics center; fuzzy logic; data envelopment analysis (DEA); Fuzzy-DEA; efficiency analysis; membership function; α-cut level

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1. Introduction

Logistics Centers (LCs), a relatively recent concept, go by various synonymous names in different countries and regions, such as Gueterverkehrszentren (Germany), Plateformes Logistiques/Multimodale (France), Interporti (Italy), Freight Village (England), Tradeports (Denmark), Logistics Centre-Center/Logistics Park (China-Turkey), Dry Port/Distripark (United States of America), and others. LCs are essentially specialized areas near or connected to national and international transportation corridors, equipped with an intermodal transportation infrastructure. They integrate logistics activities, serving as convergence points for service providers, recipients, and relevant public and private entities [1]. The European Logistic Platforms Association (Europlatforms) defines LCs as 'defined areas where various operators carry out transport, logistics, and goods distribution activities, catering to both national and international transit on a commercial basis' [2]. Another definition linked to LCs [3] highlights their role as large logistics operation areas, purposefully situated near cities to enhance transportation activities in tandem with logistical transformations and to ensure seamless operational integration.

The concept of logistics, which functions within transportation [4], finds its place in various fields today, encompassing definitions and applications across economics, healthcare, information technology, and agriculture [5]. Moreover, the efficient development of logistical processes and activities, aimed at establishing effective supply chains, heavily depended on the pivotal role played by logistic networks. These networks consisted of nodes operated by various transportation modes and technologies, encompassing different categories and sizes of LCs and their interconnections. Consequently, LCs, as the links in the logistics chain, create a unique logistics system by interconnecting all participants into a single transport market [6]. LCs not only connect specific entities (demanders, suppliers, freight forwarders, etc.) into a single transportation chain but also undertake multiple roles that rationalize processes and operations [7]. As a result, effective and efficient LCs provide numerous advantages to all participants, including increased productivity, agility, speed, quality, competitiveness, profitability, enhanced delivery, vertical and horizontal integration, resource conservation, reduced operational costs, and improved work quality [8].

LCs constitute areas where diverse and comprehensive processes are conducted, including storage, goods transportation, handling, packaging, consolidation, cleaning, dismantling, quality control, financial, and social services [9]. They significantly impact the optimization of logistics chains by determining the quality of stock distribution and affecting order fulfillment efficiency. The execution of logistics activities through LCs enhances access to better collaboration and high-value-added services [10].

Creating value that meets customer expectations is crucial for sustaining competitiveness in the market. The primary objective is to provide logistics services that meet customers' demands to the highest degree. The significance of this aspect has been widely emphasized in recent times, particularly during the unforeseen COVID-19 pandemic, which severely challenged the sustainability of the supply chain and resulted in substantial losses [11].

LCs, the nucleus of logistics activities in terms of sustainability, play a critical role in organizing and directing the logistics operations of a country or region. These centers serve as points where various transportation modes converge, goods are stored, and distribution occurs. The contribution of LCs to sustainability goals is directly linked to their efficiency. Effectively managing these centers can reduce energy consumption, lower emissions, and enhance the overall efficiency of logistics processes by optimizing transportation activities [12]. Efficient LCs can directly support sustainability goals by enabling goods to be transported in more environmentally friendly ways at lower costs. Therefore, the efficiency of LCs is considered one of the cornerstones of sustainable logistics operations. Challenges such as climate change, energy scarcity, and the increasing world population will further expand the need for sustainability management, sustainable supply chain management, and governance in the future [13].

The eco-friendly and sustainable function of LCs is acknowledged as a strategic objective by researchers and practitioners. According to the UE (European Union) expression [14], due to the focus on optimizing space utilization, considering environmental sensitivities, diverting heavy freight traffic away from residential areas, optimizing supply chains, and storage activities to reduce all kinds of costs, etc., LCs inherently possess ecological and sustainable functions. Urban freight transport contributes to a city's economic function while also generating externalities such as congestion, noise, and hazardous situations [15]. Similarly, the Organization for Economic Co-operation and Development (OECD) report highlights urban freight consolidation and distribution are among the most important techniques for enhancing the sustainability of cities [16].

On the other hand, LCs can enhance regional sustainable economic development and distribution efficiency through eco-friendly transportation. More specifically, LCs consolidate freight flows, share common infrastructure and facilities, reorganize supply chains, and improve logistics processes in line with a value-focused perspective. Considering the nature of LCs, they are suggested as environmentally friendly solutions supporting green logistics and supply chain management, potentially providing sustainability benefits. They reduce warehouse distribution nationwide and help in reducing vehicle emissions in city centers [17].

When looking at the historical development process, LCs, which emerged in the early 20th century in the United States due to industrial growth, were implemented particularly to enhance business process efficiency and reduce costs. Subsequently, in Japan, LCs were also proposed for reasons such as reducing traffic congestion, lowering labor costs, minimizing environmental impacts, and achieving energy savings. The application of LCs transitioned to Western Europe from the second half of the 20th century, notably being extensively carried out in France. Major LCs like Sogoris (Rungis) and Garonor were established, especially in the Paris region. These centers contributed to the development of intermodal transportation by providing access to different modes of transportation, and this practice spread to countries like Germany and Italy in subsequent years. During this process, LCs evolved into structures targeting the integration of various transportation modes such as road, rail, and sea transportation [18].

In the 1980s and 90s, LCs rapidly increased globally and witnessed significant advancements in various European countries. Countries like Germany, Belgium, France, the Netherlands, Italy, and the United Kingdom played a pioneering role in the establishment and development of LCs. The concept of LCs, initially born in the US, became more widely adopted in Europe [18].

Considering the study focuses on LCs in a specific region (Turkey), it is necessary to mention the situation of these LCs in this area. Indeed, LCs initiatives in Turkey have been conducted by both public and private sectors since the early 2000s. As a result of the studies conducted by the Turkish State Railways (TCDD) under the Ministry of Transport and Infrastructure in 2006, it was decided to establish 23 LCs in various regions, and as of 2023, 12 of these LCs have become operational [19]. When all LCs that are expected to significantly contribute to Turkey's logistics sector become operational, it is anticipated approximately 73 million tons of additional transportation capacity and an additional area of 19 million square meters (open spaces, stock areas, container storage, and handling areas) are provided to the sector [20].

Today, solutions offered by LCs have gained significant prominence for both enhancing production and distribution and for the seamless integration of transportation networks. In this context, countries make substantial investments to benefit from the opportunities LCs provide, aiming to increase trade volumes and make progress in the field of logistics. Due to their ability to facilitate, expedite, and streamline integrated logistics activities in their respective regions, LCs are predicted to continue drawing considerable attention in the modern, sustainable economic era [21]. Considering all these factors, studying and conducting current situation analyses of LCs, focusing on their core aspects, and striving to achieve evidence-based tangible outcomes for improvement, underline the importance of this study.

It is widely acknowledged each system has its unique set of goals. While these goals vary, they are generally expressed in terms of performance criteria such as efficiency, effectiveness, profitability, competitiveness, satisfaction, growth, etc. Therefore, calculating performance measurements becomes necessary to understand whether the system's objectives are achieved. Efficiency analysis, among these measurements, is a method used to determine how effectively and efficiently systems utilize their resources (inputs) [22]. Efficiency analyses being used for this purpose can be categorized into three main groups: ratio analysis, parametric methods, and non-parametric methods. Ratio analysis involves comparing a single output value to a single input value. On the other hand, parametric methods rely on cause-and-effect relationships, calculating the system's efficiency value through regression analysis. Non-parametric methods are utilized when dealing with multiple input and output variables being measured in different units, where Data Envelopment Analysis (DEA) stands as one of these methods [23].

The lack of studies assessing the efficiencies of LCs in Turkey emphasizes the innovative nature of this research. What sets this study apart is its pioneering utilization of the fuzzy logic approach (Fuzzy-DEA) to measure LCs' efficiencies for the first time. As a result, the significance of this study becomes evident as it delves into the fundamental aspects of LCs, conducts current situation analyses, and strives to attain evidence-based outcomes for driving improvements.

Our main motivation for adopting the fuzzy logic approach stems from recognizing, although the obtained data are deemed precise, there might be potential undesirable situations such as deficiencies, errors, uncertainties, unknowns, and changes in the process of acquiring these data that should not be overlooked. The rationale is that in the Fuzzy-DEA approach, considering data might exist within certain intervals, interval efficiency scores can be calculated, taking into account uncertainty situations, as an alternative to the pointwise efficiency calculations of classical DEA.

Hence, data related to the 12 LCs operational in Turkey was obtained through official channels and integrated into the study using a fuzzy logic approach. The Fuzzy-DEA method was selected for efficiency calculations to assess the performance of these LCs. While there is a significant volume of literature in various fields concerning efficiency calculations, we are particularly inspired by several studies [24–28] in terms of methodology and the focal point of our study.

2. Literature Review

The research presented in this study aims to conduct a situational analysis of LC concepts amidst challenges such as exceptional growth in transportation, increasing containerization, and urban sprawl, and to propose solutions to enhance operational efficiency and minimize externalities. Essentially, the study investigates to what extent LCs efficiently manage their logistics-related activities. Therefore, highlighting the multifaceted examinations of LCs in similar studies holds significant importance for the logistics sector. LCs have been the focus of numerous research and studies due to the complexity of extensive processes, activities, and flows.

Among these studies related to LCs, various areas have been explored such as location determination problems [29,30], optimization of storage activities [31], productivity and performance research [6,32], design and planning studies [33,34], studies on management activities [35], studies in the field of sustainable supply chain practices [36], and economic studies on imports and exports [37]. Selected studies included: Taniguchi et al. [18] who developed a mathematical model using queuing theory and nonlinear programming techniques to determine the optimal size and location of public logistics terminals in the Kyoto-Osaka region of Japan. He et al. [38] assessed the efficiency of regional LCs in China using the DEA method, revealing significant differences in efficiency between the Eastern and Western regions, with a noticeable decrease in efficiency from East to West. Markovits-Somogyi et al. [39] investigated the activities of 26 LCs in Hungary, incorporating data from 12 LCs due to their completeness. They attempted to determine their efficiency using DEA analysis by considering inputs like office size, number of employees, available storage space, and outputs such as total revenue and transported cargo tonnage. A similar study on the efficiency of LCs was conducted by Kapucu [40] using the DEA method, analyzing operational and financial data from 2015 and 2016 in Turkey. The study revealed excess input factors in inefficient LCs and observed low cargo volume in these LCs. Assessing the performance rankings of LCs based on their potential efficiencies was conducted by Dumlu and Wolff [41] using the MOORA (Multi-objective Optimization by Ratio Analysis) method and by Keleş and Pekkaya [42] using the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluation)-CRITIC (Criteria Importance Through Inter-criteria Correlation) approach.

Ballis et al. [43] used the PROMETHEE method among the MCDM (Multi Criteria Decision Making) methods to design an LC considering different criteria such as efficiency, sustainability, cost, etc. Erturgut and Oğuz [44] evaluated the impact of LCs on exports in EU countries using cross-sectional data analysis, indicating a positive and significant relationship.

Studies focusing on determining the locations of LCs considering sustainability criteria utilized fuzzy theory: Elevli [45] utilized Fuzzy-PROMETHEE, Kazançoğlu et al. [46] used

Fuzzy AHP (Analytic Hierarchy Process)-PROMETHEE, Awasthi et al. [47], He et al. [48], Essaadi et al. [49] employed Fuzzy-TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), Kumar and Anbanandam [50] used IFS AHP-TOPSIS, Ulutaş et al. [9] utilized Fuzzy SWARA (Stepwise Weight Assessment Ratio Analysis)-CoCoSo (Combined Compromise Solution), Uyanık et al. [51] employed IFS (Intuitionistic Fuzzy Sets) DEMATEL (The Decision Making Trial and Evaluation Laboratory)-TOPSIS/VIKOR (Vlse Kriterijumska Optimizacija I Kompromisno Resenje), while Stojanović and Puška [52] used the CRITIC-MABAC (Multi-Attributive Border Approximation Area Comparison) method to model a decision-making process for determining the locations of LCs. Jaržemskis [53] conducted a study focusing on the benefits provided by LCs for users and potential challenges in planning and management activities, providing theoretical insights. A similar study was conducted by Kaynak and Zeybek [54] examining LCs in Turkey, highlighting the absence of LCs established as in Europe and Asia, emphasizing the need for a public-private sector model and integrated planning in a comparison with global examples.

3. Materials, Variables and Methodology

3.1. Materials

Through official correspondences related to data acquisition, raw data for the 12 LCs operational in Turkey in 2022 were obtained. The LCs under scrutiny in this study are managed by Turkish State Railways, a public institution operating under the jurisdiction of the Ministry of Transport and Infrastructure in Turkey. Therefore, the source of data concerning the LCs is this aforementioned public institution. As this study stems from a doctoral thesis, we assert there are no usage restrictions associated with the acquisition and dissemination of the obtained data, contingent upon proper attribution. Moreover, the fulfillment of the necessary procedures by the university and the subsequent publication of the final version of the doctoral thesis in an openly accessible manner through the Council of Higher Education of Turkey-Thesis Center [55] will satisfy the obligations in this regard.

The primary raw data obtained for the 12 operational LCs underwent meticulous scrutiny and necessary adjustments before being made suitable for analysis. The study further elucidates the literature-based variables being employed and the information pertaining to the LCs.

3.2. DMUs Used and Selection of Variables

A total of 12 operational LC centers in Turkey have been included in the study. Information pertaining to these LC units, termed Decision-Making Units (DMUs) and set to be assessed for efficiency in this phase of the study, was provided in Table 1. As observed from the table, among the planned 23 LC centers across the 7 geographical regions in Turkey, the distribution of the currently operational 12 LCs is as follows: 3 in the Marmara region (planned 3), 2 in the Aegean region (planned 2), 2 in the Central Anatolia region (planned 2), 1 in the Black Sea region (planned 2), 2 in the Mediterranean region (planned 0), 2 in the Eastern Anatolia region (planned 0), and 0 in the Southeastern Anatolia region (planned 2). Thus, the LCs have been dispersed across various provinces and geographical regions in Turkey. It is planned to establish only 2 LC each in the provinces of Istanbul and Izmir in Turkey [20].

The potential influence of LCs on criteria such as success, performance, or efficiency, either directly or indirectly, was considered when determining the variables, taking into account previous studies in the literature related to the subject. In this context, 1 variable was designated as the output variable, while 9 variables were included as input variables in the study. The selection of these variables involved an assessment of the availability, reliability, and suitability of the data. Initially, data obtained from relevant sources within the study's scope were considered. Subsequently, variables/criteria used in prior studies concerning LCs regarding efficiency, productivity, performance, success, etc., were evaluated through various methods in the literature. Consequently, a hybrid evaluation method supported by the literature was employed to identify the variables used in the study.

Table 1. DMUs.

No	DMUs (LCs)	City	Geographical Region
1	Gelemen	Samsun	Black Sea
2	Kosekoy/Izmit	Kocaeli	Marmara
3	Usak	Usak	Aegean
4	Halkali	Istanbul	Marmara
5	Hasanbey	Eskisehir	Central Anatolia
6	Gokkoy	Balikesir	Marmara
7	Kaklik	Denizli	Aegean
8	Turkoglu	Kahramanmaras	Mediterranean
9	Palandoken	Erzurum	Eastern Anatolia
10	Kayacik	Konya	Central Anatolia
11	Yenice	Mersin	Mediterranean
12	Kars	Kars	Eastern Anatolia

The source of all data related to the variables used in the study is Turkish State Railways Transportation Inc. For LCs, the 2022 data were designated as the output variable, representing "total revenue (turnover)", while data from 9 distinct categories were established as input variables. Detailed information about these variables and their usage in previous literature is presented in Table 2.

Table 2. Variables.

	Variables	Abbreviations	Previous References
Output	Total revenue (turnover)	Y	[39,40,56–60]
Inputs	Installed area (m^2)	X1	[40,41,59,61–69]
	Capacity (tons)	X2	[40,41,66,70–74]
	Number of personnel	X3	[39,59,60,67,68,74–78]
	Number of railway lines	X4	[40,68,79]
	Total number of engaged companies	X5	[68,71,76]
	Total railway transportations	X6	[68,72,73,80,81]
	Total handled cargo quantity (netton)	X7	[39,40,61–67,73,75,76]
	Total handled cargo quantity (netton-km)	X8	[68,73,77,82]
	Number of loaded/unloaded wagons	X9	[40,59,65,67,69,75]

The explanatory information for the variables that are provided in Table 2 is detailed below:

- Output-Total Revenue (turnover): the data obtained concerning revenue from LC activities was scrutinized. This included the annual overall revenue generated by various activities conducted by LC, comprising domestic and international transportation revenues, along with other incomes categorized under the 'other' section. The annual total revenue (turnover) was calculated in Turkish Lira (TL) for this study. Within this scope, this variable was considered the output, aiming to assess how effectively LCs utilized their inputs to generate this output.
- Input-Installed area (m^2): this variable indicates the current size of the LC area (in m^2), encompassing warehouses, terminals, road-rail connections, container loading-unloading, and stock areas, among others.

- Input-Capacity (tons): it denotes the maximum total cargo capacity (inbound and outbound cargo) that an LC can handle within a year, expressed in tons.
- Input-Number of personnel: this variable signifies the total permanent personnel actively working within the LC, including maintenance, management, and support staff.
- Input-Number of railway lines: it reflects the total count of railway tracks within the LC, encompassing loading-unloading ramp lines, main ramps, running lines, platforms, train formation, maneuvering, dispatch lines, and weighing lines.
- Input-Total number of engaged companies: this variable denoted the number of companies collaborated with, a result of the LC's conducted activities and offered services.
- Input-Total railway transportations: this variable represents the total amount of railway cargo transported from the LC in 2022, measured in tons.
- Input-Total handled cargo quantity (nett): based on 2022 data, this variable signified the total handled cargo quantity (inbound and outbound cargo) in nett tons within the LC. (netton: the ton loaded on a wagon in proportion to its capacity).
- Input-Total handled cargo quantity (netton-km): derived from 2022 data, this variable represented the distance (in km) that the total handled cargo traveled after leaving the LC in nettons. (netton-km: distance traveled in km by nettons).
- Input-Number of loaded/unloaded wagons: this variable indicated the total number of loaded and unloaded wagons for inbound and outbound cargo within the LC during 2022.

In this study, data obtained from relevant institutions underwent initial review. Only complete and relevant data aligning with the study's focus were considered. Subsequently, variables presented in the "previous references" column in Table 2, used in various similar studies in the literature, were taken into account, ultimately determining the existing variables. Additionally, the potential for LCs to enhance these variables in the future through new investments or decisions was considered in determining the variables.

3.3. Methodology

3.3.1. Classical DEA Model

DEA is a method that considers the efficiency of systems when measuring their performance, enabling the generation of results by calculating their technical efficiency, scale efficiency and overall efficiency. Here, efficiency refers to the success in obtaining outputs from the inputs being used. Technical efficiency denotes the success in producing the highest output using the most suitable input composition, while scale efficiency defines success in producing at an appropriate scale. Total efficiency, on the other hand, signifies the combined consideration (multiplication) of technical and scale efficiencies [22].

DEA, developed by Charness et al. (1978) [83] based on Farrell's (1957) [84] efficiency measurement concept, was defined as a non-parametric method used to compare the performance (efficiency) of businesses based on their inputs and outputs. The DEA model introduced by Charness et al. (1978) [83] aimed to measure performance based on the principle of "constant returns to scale" while later, Banker et al. (1984) [85] developed a new approach to measure performance based on the principle of "variable returns to scale" [86].

- CCR (Charnes, Cooper, and Rhodes) Model: this model is based on the principle of "constant returns to scale" and calculates the efficiency level between the system's inputs and outputs, aiming to achieve the best state by altering inputs to reduce or outputs to increase. This model considers only strategies for reducing inputs or increasing outputs for each business.
- BCC (Banker, Charnes, and Cooper) Model: In this model, based on the principle of "variable returns to scale" the system had the flexibility to employ strategies for both reducing inputs and increasing outputs. The BCC model calculates efficiency levels by allowing businesses to make balanced changes to inputs and outputs.

The CCR and BCC models in DEA, although differing in nuanced aspects, are models that yield similar outcomes (a unit efficient in one model is also efficient in the other).

The primary distinction between these two approaches lies in their orientations. These orientations, crucial in DEA, diverge in measuring efficiency based on inputs (input-oriented) or outputs (output-oriented) for the system's effectiveness. These orientations are outlined as follows [87]:

1. input-oriented DEA: in input-oriented DEA, a system's efficiency is assessed from the perspective of how effectively it uses the given input quantity to achieve maximum output-essentially, how efficiently it utilizes resources to generate more output. This evaluation aims to minimize the system's inputs proportionally while keeping outputs constant. The input-oriented efficiency of a system reflects its success in obtaining the highest possible output with the given input quantity.
2. output-oriented DEA: on the other hand, output-oriented DEA examines a system's ability to maximize output, focusing on how effectively it can use input to achieve the desired output quantity. This assessment aims to maximize the system's outputs proportionally while keeping inputs constant. The output-oriented efficiency of a system reflects how little input it needs to achieve the highest possible output.

Classical DEA models were highly sensitive to changes in data and reliability due to their usability only in cases where inputs used and produced outputs were precisely known. Consequently, any abnormal (outlier) value or error within the dataset can significantly impact the resulting efficiency scores. Guo and Tanaka (2001) [88], along with Kuosmanen et al. (2007) [89], have highlighted the estimated efficiency scores were biased and inconsistent when dealing with such data. Their observations bring into question the reliability of classical DEA results, leading to the exploration and utilization of different methods [86]. One of these approaches, Fuzzy-DEA, was initially developed by Sengupta (1992) [90], integrating classical DEA within Zadeh's (1965) [91] fuzzy logic framework to accommodate uncertainties and unknowns in the data.

Sengupta [90] introduced the classical DEA model into the realm of "fuzzy mathematical programming" by developing the "tolerance approach" over both the objective function and constraints through fuzziness. Following this initial step, known as Fuzzy-DEA, various advancements have occurred over time. These advancements were typically categorized based on the mathematical approaches used, generally classified into four groups as mentioned in [92,93]. Examples of these approaches and their application in studies include [94]: tolerance approach [90], α-level-based approach [95–98], fuzzy ranking approach [99,100], and possibility approach [101,102].

Besides numerous studies that prefer these different approaches in the literature, there are various unique studies that can be considered beyond this classification [103–105]. Considering all these approaches in Fuzzy-DEA, it has been noted each approach had its specific limitations. For instance, the tolerance approach uses fuzzy inequalities and equalities instead of fuzzy inputs and outputs, the α-level-based approach requires numerous linear programming models, the fuzzy ranking approach can yield different efficiency scores with different fuzzy ranking methods, and finally, the possibility approach necessitates complex computations and might not adapt to every DEA model [94].

Despite these limitations, aside from the advantages and disadvantages, it is observed the models can be successfully applied for efficiency estimation in different situations. Among the Fuzzy-DEA models in the literature, the "α-level-based approach" stood out as the most popular and has been the subject of numerous studies [94,98], followed by the fuzzy ranking approach [98]. Taking into account these considerations related to Fuzzy-DEA models, we have chosen to continue our study within the framework of the "α-level-based approach".

3.3.2. Fuzzy DEA Model

Fuzzy-DEA is considered an extension of classical DEA. Developed based on fuzzy logic and set theory [91], it held significant importance for evaluating datasets containing uncertainties. This approach represents input and output data not as precise values but as fuzzy sets. Each input or output variable is defined through a function that represents a fuzzy set instead of an exact value. These fuzzy sets allow the expression of uncertainty by defining specific membership degrees, thereby accommodating uncertainties. They aid in surpassing the limitations of classical DEA, effectively addressing uncertainties and imprecisions in the dataset. Fuzzy-DEA calculates efficiency scores while considering uncertainties in input and output data. These scores are obtained as fuzzy outputs reflecting the uncertain nature of the data [106]. For this purpose, an explanation will first be provided regarding the fundamental logic of fuzzy logic and its integration into DEA.

Definition 1. *Let E be a non-empty set and $Z \subseteq E$. For each $x \in E$, let $\mu_Z(x) : E \to [0,1]$ denote a membership (belonging) function that indicates the degree of membership of x in the set Z. Thus, a fuzzy set $\widetilde{Z}$ on the set E is represented in this manner* [91]:

$$\widetilde{Z} = \left\{ \left(x, \mu_{\widetilde{Z}}(x) \right) : x \in X \right\} \tag{1}$$

Based on this definition, for each $x \in E$ if $\mu_{\widetilde{Z}}(x) = 1$, it indicates element x completely belongs to the set $\widetilde{Z}$, if $\mu_{\widetilde{Z}}(x) = 0$, it means x does not belong to the set $\widetilde{Z}$ and when $0 < \mu_{\widetilde{Z}}(x) < 1$, it signifies element x partially belongs to the set $\widetilde{Z}$ with a certain degree of membership (μ).

Membership functions constitute the essence of fuzzy logic. These functions, determining the degree of membership, reduce the data to the [0, 1] interval by fuzzifying it. Various techniques, such as triangular, trapezoidal, exponential, bell curve, among others, are employed during this reduction process [107]. Likewise, the hybrid utilization of the mentioned methods has been employed in various studies during the selection and implementation of membership functions. One of these hybrid forms was the simple membership function and fuzzy rule generation technique (SMRGT), introduced to the literature by Toprak in 2009 [108] and subsequently favored in various studies [109]. Although numerous types of membership functions are available, it is indicated apart from variations in methodology, there is not a significant change in the outcome among these functions [107]. Therefore, within the scope of the Fuzzy-DEA analysis used in this study, the triangular membership function has been preferred for the fuzzification process.

Definition 2. *Let E be a non-empty set and $Z \subseteq E$. For each $x \in E$, let $\mu_Z(x) : E \to [0,1]$ denote a membership (belonging) function that indicates the degree of membership of x in the set Z. Consider a fuzzy set $\widetilde{Z}$ and define the triangular membership function $\mu_{\widetilde{Z}}(x)$ for any $\pi^l < \pi^m < \pi^u$ values as follows* [110]:

$$\mu_{\widetilde{Z}}\left(x; \pi^l, \pi^m, \pi^u\right) = \begin{cases} \frac{x-\pi^l}{\pi^m-\pi^l}\ if,\ \pi^l \le x \le \pi^m \\ \frac{\pi^u-x}{\pi^u-\pi^m}\ if,\ \pi^m \le x \le \pi^u \\ 0\ if,\ x > \pi^u\ ,\ x < \pi^l \end{cases} \tag{2}$$

Here, π^m denotes the membership degree of 1, representing the central value indicating full membership in the set (the point of intersection of the triangle's apex). π^l and π^u represent the left- and right-wing spans of the triangle, indicating partial memberships in the set. To provide equal wing spans in the study, for each π^m value, $\pm$standard errors $\left(S_{\widetilde{x}} = \frac{standard\ deviation\ (S)}{\sqrt{n}}, \text{where } n = \text{number of observations} \right)$ were utilized to obtain π^l and π^u, and a symmetric triangular membership function was used. Hence $(\pi^l = \pi^m - S_{\widetilde{x}})$ and $(\pi^u = \pi^m + S_{\widetilde{x}})$ are expressed. The graphical representation of the standard error-based symmetric triangular membership function is illustrated in Figure 1 [110].

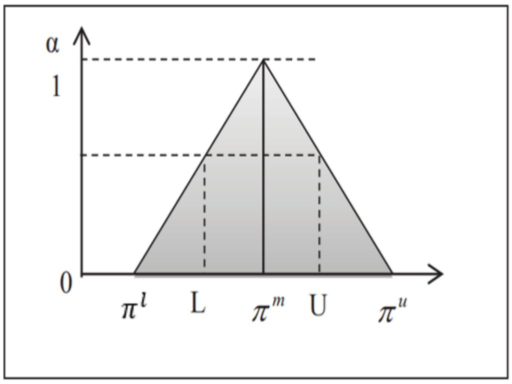

Figure 1. Triangular membership function $[L = \pi^l + \alpha(\pi^m - \pi^l), U = \pi^u - \alpha(\pi^u - \pi^m)]$.

The Fuzzy-DEA method, fundamentally a linear programming approach, cannot directly use data that involves uncertainty information by transforming it into fuzzy numbers using triangular membership functions. Hence, to adapt this fuzzy-transformed data appropriately for Fuzzy-DEA without eliminating the uncertainty information, it was necessary to utilize the method proposed by Zadeh (1965), known as the "principle of extension of fuzzy numbers" [91], along with α-cut levels. Here, α-cut level referred to defined a set $(\widetilde{A_\alpha})$ formed by elements equal to or greater than the membership degree α, representing elements in a fuzzy set whose membership degree to that set was $\alpha \in [0,1]$. It can be expressed as follows [86]:

$$\widetilde{A_\alpha} = \{(x, \mu_{\widetilde{A}}(x) \geq \alpha) : x \in X\} \tag{3}$$

As a result, fuzzy numbers are converted into crisp values within the $[L(\alpha),\ U(\alpha)]$ interval for each α-cut level. Here, $L(\alpha)$ represents the lower limit, and $U(\alpha)$ denotes the upper limit. Considering these lower and upper bounds, the confidence intervals of the data for each $\alpha \in [0,1]$ are expressed as $A_\alpha = [L(\alpha),\ U(\alpha)]$ [111]:

$$A_\alpha = [L = \pi^l + \alpha(\pi^m - \pi^l), U = \pi^u - \alpha(\pi^u - \pi^m)] \tag{4}$$

Thus, it has been observed the fuzzy data could be applied to the DEA method through the model developed by Kao and Liu [111]. In other words, assuming the fuzzy representation of input data as $\widetilde{x}_{ij}$ and output data as $\widetilde{y}_{rj}$ for the Fuzzy-DEA model, the general representation of inputs and outputs as triangular fuzzy numbers can be expressed as follows:

$$\widetilde{x}_{ij} = (x^l_{ij}, x^m_{ij}, x^u_{ij}),\ \widetilde{y}_{rj} = (y^l_{rj}, y^m_{rj}, y^u_{rj}) \tag{5}$$

The transformation of data represented in Equation (5) into triangular fuzzy numbers implied converting the data into bounded intervals using the expansion principle and α-cut level approach, such that $\widetilde{x}_{ij} \in [x^L_{ij}, x^U_{ij}]$ and $\widetilde{y}_{rj} \in [y^L_{rj}, y^U_{rj}]$.

While evaluating efficiency using the Fuzzy-DEA model, comparative results are obtained. However, to determine the unit that was relatively most efficient, Chen and Klein (1997) [112] developed an index enabling the ranking of fuzzy efficiency values. This method allows for considering the efficiency values of decision units, enabling the identification and ranking of the most efficient unit. The Chen–Klein Index (I) is expressed as follows [112]:

$$I = \frac{\sum_{i=1}^{n} \left((E_j)^U_{\alpha i} - c \right)}{\left[\left(\sum_{i=1}^{n} \left((E_j)^U_{\alpha i} - c \right) \right) - \left(\sum_{i=1}^{n} \left((E_j)^L_{\alpha i} - d \right) \right) \right]}, n \to \infty \tag{6}$$

In Equation (6), I represents the Chen–Klein Index, $(E_j)^U_{\alpha i}$ signifies the upper bound efficiency score, $(E_j)^L_{\alpha i}$ denotes the lower bound efficiency score, c refers to the lowest value of the α-cut level of all decision-making units, d indicates the highest value of the α-cut level of all decision-making units, and n represents the number of α-cuts.

A higher value of I indicates relatively higher efficiency (performance) of the decision unit. When α is taken as 1 during the calculation of the Chen–Klein Index, the Fuzzy-DEA ranking automatically transforms into the classical DEA ranking [112].

Within the scope of the study, the Fuzzy-DEA/BCC model is used since the measurement of technical efficiency with the input-oriented variable returns to scale approach is adopted. At this juncture, the extension of the DEA linear programming model to the fuzzy approach, followed by the application of Zadeh's extension principle and the α-cut level approach proposed by Kao and Liu, defined the general input-oriented Fuzzy-DEA/BCC model as presented [110]:

$$
\begin{gathered}
\text{Objective Function}: \ \mathrm{Min} Z = \theta \\
\text{Constraints:} \\
[\theta(\alpha x_{io}^{m} + (1-\alpha)x_{io}^{l}), \theta(\alpha x_{io}^{m} + (1-\alpha)x_{io}^{u})] \geq [\textstyle\sum_{j=1}^{N} \lambda_j(\alpha x_{ij}^{m} + (1-\alpha)x_{ij}^{l}), \sum_{j=1}^{N} \lambda_j(\alpha x_{ij}^{m} + (1-\alpha)x_{ij}^{u})]\forall_{\boldsymbol{i}} \\
[\theta(\alpha y_{ro}^{m} + (1-\alpha)y_{ro}^{l}, \theta(\alpha y_{ro}^{m} + (1-\alpha)y_{ro}^{u})]] \leq [\textstyle\sum_{j=1}^{N} \lambda_j(\alpha y_{rj}^{m} + (1-\alpha)y_{rj}^{l}), \sum_{j=1}^{N} \lambda_j(\alpha y_{rj}^{m} + (1-\alpha)y_{rj}^{u})]\forall_{\boldsymbol{r}} \\
\textstyle\sum \lambda_j = 1, \lambda_j \geq 0 \text{ ve } 0 \leq \theta \leq 1 \\
\widetilde{x}_{ij} = i.\ fuzzy\ input\ of\ decision\ unit\ j. \\
\widetilde{y}_{rj} = i.\ fuzzy\ output\ of\ decision\ unit\ j. \\
\lambda_j = Weight \\
o \in \{1, 2, \ldots, N\} \\
N = Number\ of\ Units\ Assessed
\end{gathered}
\quad (7)
$$

In the study, alongside the efficiency ranking results obtained through the Fuzzy-DEA/BCC model and the Chen–Klein Index for LCs, comparisons were drawn between the rankings obtained by setting $\alpha = 1$ and the classical DEA rankings for LCs. This comparison scrutinized whether there existed a statistically significant difference between the Fuzzy-DEA and classical DEA methods through the Spearman Rank Correlation test within a specific confidence interval.

Spearman Rank Correlation Test: Trend analysis was a statistical method used to identify a monotonic relationship among ordered variables and measured similarities or differences between ordered datasets. In this approach, a correlation coefficient (rho) within the range of $[-1, 1]$ was calculated based on the rankings of variables to evaluate the extent of agreement between rankings, tested for significance at a specific level. When there is statistical significance, if the Spearman correlation coefficient approaches 1, it indicates an increasingly similar trend in the same direction; as it approaches -1, it indicates an increasingly dissimilar trend in the opposite direction. When it equals 0, it suggests no consistent trend, either similar or dissimilar, between the variables [113].

Considering the explanations provided thus far regarding the Fuzzy-DEA/BCC method based on standard error, it was possible to summarize the steps to be followed and the procedures to be implemented as followed [114]:

1. identification of decision units (alternatives) involved in the research problem.
2. Classification of relevant variables for decision units into input and output variables.
3. Computation of various descriptive statistical information for input and output variables.
4. Calculation of fuzzy lower and upper bounds (intervals) of variables using symmetric triangular membership functions with standard errors for input and output variables.
5. Clarification and refinement of fuzzy lower and upper bounds of the fuzzified input and output variables using α-cut levels, followed by the computation of lower and upper bound efficiencies using classical DEA models.
6. Since there are two efficiency values for each α-cut, obtaining the final efficiencies and rankings by combining these efficiencies with the Chen–Klein Index.
7. Statistical testing of the relationship between rankings of classical DEA efficiencies and Fuzzy-DEA efficiencies using the 'Spearman Rank Correlation' test for each α-cut.

4. Results

The statistical information, including the highest value, lowest value, mean, standard deviation, and standard error for the variables used to measure the performance of the LCs (DMUs) (one output-nine inputs), is presented in Table 3.

Table 3. Summary statistics.

Variables		Minimum	Maximum	Mean	Standard Deviation	Standard Error (S_x)
Total revenue (turnover)	Y	1,042,228	84,727,941	35,345,916.4	32,585,147.2	9,406,521.7
Installed area (m^2)	X1	40,000	1,000,000	421,666.7	289,352.7	83,528.9
Capacity (tons)	X2	246,000	2,000,000	1,137,300	657,153.2	189,703.8
Number of personnel	X3	2	181	73	63.2	18.3
Number of railway lines	X4	1	26	15	7.7	2.2
Total number of engaged companies	X5	1	15	8	4.9	1.4
Total railway transportations	X6	18,056	1,155,079	401,787.8	397,100.8	114,633.1
Total handled cargo quantity (in tons)	X7	3111.1	1,070,691.7	420,360.9	372,199.5	107,444.7
Total handled cargo quantity (in ton-km)	X8	2,511,443	455,606,727	174,562,974.9	151,237,390	43,658,473.9
Number of loaded/unloaded wagons	X9	286	52,382	15,201	15,503.6	4475.5

When examining Table 3, it becomes apparent there is significant variability in the input and output variables that are related to the LCs. Specifically, the substantial variability in inputs suggests inefficient utilization of resources within these LCs. From this observation, it can be inferred LCs fall short of achieving optimal efficiency in obtaining the total revenue output. Additionally, Table 3 offers multiple interpretations of the variables. For example, in 2022, it seemed , on average, LCs managed an area of about 422 thousand m^2, employed 73 personnel, and handled over 420 thousand tons, resulting in an annual turnover surpassing 35 million TRY. Given an average annual handling capacity of 1.2 million tons, the handled tonnage (approximately 420 thousand tons) appeared notably lower than the capacity.

The data concerning the specified input and output variables of the LCs need to undergo fuzzification within the framework of the Fuzzy-DEA method. To fuzzify the variable data, the standard errors (S_x) provided for each variable in the preceding table (Table 3) were utilized to convert the data into fuzzy intervals using symmetric triangular membership functions. Due to the sensitivity of the DEA method to data accuracy, fuzzification is notably crucial in preventing inaccurate outcomes [115].

It was stated the data for inputs in the Fuzzy-DEA model were represented in triangular fuzzy form as $\widetilde{x}_{ij} = \left(x_{ij}^l, x_{ij}^m, x_{ij}^u\right)$ and for outputs as $\widetilde{y}_{rj} = \left(y_{rj}^l, y_{rj}^m, y_{rj}^u\right)$ as expressed in Equation (5). Following the acquisition of symmetrical triangular fuzzy lower and upper bounds (intervals) in the study, it is necessary to convert the data into definite intervals, that is, to refine them, to be applicable in classical DEA models. At this juncture, the α-cut approach developed by Kao and Liu [111] was employed.

In the α-cut approach, flexibility is provided when comparing decision units at specific probability levels. α-cut values, as is illustrated further, can optionally be designated as any set within the $[0, 1]$ range [114]:

$$\alpha = \{0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1\},$$
$$\alpha = \{0, 0.25, 0.50, 0.75, 1\},$$
$$\alpha = \{0, 0.30, 0.70, 1\} \text{ etc.}$$

In the study, α-cut values of $\alpha = \{0, 0.25, 0.50, 0.75, 1\}$ were used. Here $\alpha = 1$ denotes certainty among the data, while $\alpha = 0$ signifies the highest degree of uncertainty. For each α-cut level, fuzzy lower (L) and upper (U) bounds have been converted into definite intervals in the form $[L(\alpha),\ U(\alpha)]$ as shown in Equation (4), with precise lower limit $L(\alpha)$ and upper limit $U(\alpha)$.

Given the use of $\alpha = \{0, 0.25, 0.50, 0.75, 1\}$ in the study, two definite bounds emerged for each α-cut value, denoted as $L(\alpha)$ and $U(\alpha)$. In Equation (4), when $\alpha = 0$, where $L(\alpha) = \pi^l$ and $U(\alpha) = \pi^u$, the fuzzy boundaries become definitive, indicating the highest level of uncertainty. Conversely, for $\alpha = 1$, where $L(\alpha) = \pi^m$ and $U(\alpha) = \pi^m$, the data remain unchanged after fuzzification and subsequent defuzzification, representing a state of certainty without uncertainty. As defuzzification was performed for each α-cut value, considering five different α-cut values, the lower bounds $L(\alpha)$ and upper bounds $U(\alpha)$ were determined using Equation (4), followed by the calculation of lower and upper bound efficiencies.

The input-oriented Fuzzy-DEA model was utilized in the study by adopting the variable returns to scale (BCC Model) approach. It is important to highlight the reasons behind choosing this model:

- the main aim behind adopting the "variable returns to scale" approach in measuring the efficiencies of LCs is as follows. In assessing efficiency using the variable returns to scale approach, it is asserted the proportional change in inputs differs from the change in outputs. Specifically, the notion that when inputs double, outputs also double proportionally forms the basis of the "constant returns to scale (CCR Model)" approach. Conversely, the principle underlying the "variable returns to scale" approach emerges when the doubling of inputs results in a more or less than twofold change in outputs (a proportional differentiation) [40]. This understanding, considering similar efficiency measurement studies in the literature mentioned in previous sections, led to the adoption of the "variable returns to scale" approach in assessing the efficiencies of LCs in this study, considering the selected inputs (such as installed area, capacity, personnel number, etc.) and outputs (total revenue). This conclusion was influenced by the realization that changes in inputs, whether increased or decreased, might not correspond proportionally to changes in total revenue due to various internal and external factors.
- The primary purpose behind adopting the input-oriented approach is as follows. In input-oriented Fuzzy-DEA, a system is evaluated from the perspective of how efficiently it utilizes a given amount of input to achieve maximum output, i.e., how effectively it utilizes resources to generate more output. This approach is aimed at proportionally minimizing the system's inputs while keeping the outputs constant [87]. Hence, considering the relevant literature provided in the previous sections, the adoption of the input-oriented Fuzzy-DEA model in the study is aimed at determining to what extent the inputs should be minimized to achieve the output data (total revenue) for LCs in the year 2022.

The model created using the adopted approaches was presented in the Appendix A. On the other hand, the Benchmarking package in R was employed to compute the lower and upper bound efficiency scores. The calculated lower bound efficiencies were presented in Table 4, whereas the upper bound efficiencies were provided in Table 5.

Upon reviewing Tables 4 and 5, it becomes evident for the α-cut values of $\alpha = \{0, 0.25, 0.50, 0.75, 1\}$, both the efficiency scores for lower bounds and upper bounds increase progressively from α value 0 towards 1. Due to the fuzzification of input and output data, the interpreted efficiency scores should also align with a fuzzy approach. When α equals 0 for both lower and upper bounds, it indicates the highest degree of uncertainty, representing the widest range. Conversely, an α value of 1 suggests the least uncertainty, where the interval transforms into a definite value. Stated differently, as α approaches 1, the probability associated with the efficiency score increases, while the level of uncertainty decreases [110].

Table 4. Lower bound technical efficiency scores at varying α-cut levels.

	Lower Bound Efficiency Scores $\left(E_j\right)_{\alpha i}^{L}$					
	α-Cut Levels					
DMUs (LCs)	0	0.25	0.50	0.75	1	Mean
Gelemen/Samsun	0.487	0.560	0.643	0.726	0.800	0.643
Kosekoy/Izmit	1.000	1.000	1.000	1.000	1.000	1.000
Usak	1.000	1.000	1.000	1.000	1.000	1.000
Halkali/Istanbul	1.000	1.000	1.000	1.000	1.000	1.000
Hasanbey/Eskisehir	0.978	1.000	1.000	1.000	1.000	0.996
Gokkoy/Balikesir	0.664	0.754	0.849	0.911	0.957	0.827
Kaklik/Denizli	1.000	1.000	1.000	1.000	1.000	1.000
Turkoglu/Kahramanmaras	1.000	1.000	1.000	1.000	0.905	0.981
Palandoken/Erzurum	0.170	0.265	0.388	0.697	0.902	0.484
Kayacik/Konya	0.567	0.769	0.882	0.940	0.909	0.813
Yenice/Mersin	1.000	1.000	1.000	1.000	1.000	1.000
Kars	0.066	0.119	1.000	1.000	1.000	0.637
mean	0.744	0.789	0.897	0.940	0.956	0.865

Table 5. Upper bound technical efficiency scores at varying α-cut levels.

	Upper Bound Efficiency Scores $\left(E_j\right)_{\alpha i}^{U}$					
	α-Cut Levels					
DMUs (LCs)	0	0.25	0.50	0.75	1	Mean
Gelemen/Samsun	0.657	0.685	0.717	0.756	0.800	0.723
Kosekoy/Izmit	1.000	1.000	1.000	1.000	1.000	1.000
Usak	0.251	0.303	0.389	0.574	1.000	0.504
Halkali/Istanbul	1.000	1.000	1.000	1.000	1.000	1.000
Hasanbey/Eskisehir	1.000	1.000	1.000	1.000	1.000	1.000
Gokkoy/Balikesir	0.788	0.821	0.859	0.903	0.957	0.866
Kaklik/Denizli	0.633	0.704	0.838	1.000	1.000	0.835
Turkoglu/Kahramanmaras	0.518	0.569	0.638	0.742	0.905	0.674
Palandoken/Erzurum	0.255	0.306	0.390	0.554	0.902	0.481
Kayacik/Konya	0.807	0.828	0.852	0.880	0.909	0.855
Yenice/Mersin	1.000	1.000	1.000	1.000	1.000	1.000
Kars	0.103	0.131	0.186	0.335	1.000	0.351
mean	0.668	0.696	0.739	0.812	0.956	0.774

Explaining this probability approach using Tables 4 and 5, for instance, consider the case of Gelemen LC. When the α-cut value is 1, both the lower and upper bound efficiency scores are [0.800; 0.800], resulting in an efficiency score of 0.800. This assumes a precise measurement. At an α-cut value of 0.75, the range of lower and upper bound efficiency scores narrows to [0.726; 0.756]. This indicates Gelemen LC's efficiency score can lie between 0.726 and 0.756 with a 75% probability ($\alpha = 0.75$). Similarly, at an α-cut value of 0.50, the range of lower and upper bound efficiency scores further reduces to [0.560; 0.685], suggesting Gelemen LC's efficiency score might fall between 0.560 and 0.685 with a 50% probability ($\alpha = 0.50$). At the extremes where uncertainty is highest (α-cut value equals 0), it implies the lower and upper bound efficiency scores spans [0.487; 0.657]. This will suggest when comparing Gelemen LC with other LCs, the efficiency score will not surpass 0.657 or drop below 0.487, with a 0% probability. Hence, it is plausible to interpret the efficiency scores of other LCs at various probability levels in a similar manner.

When examining Tables 4 and 5, it is apparent the average lower bound efficiency scores for LCs range between 0.744 and 0.956, while upper bound efficiency scores range from 0.668 to 0.956. Considering both lower and upper efficiency scores collectively, it is established the efficiency scores of LCs vary between 0.668 and 0.956 according to this study's findings.

From the lower bound efficiency scores in Table 4, it is evident for each α-cut value, five LCs—Kosekoy/Izmit, Usak, Halkali/Istanbul, Kaklik/Denizli, and Yenice/Mersin—are fully efficient (with efficiency scores equal to one), while the remaining seven LCs exhibit inefficiency (with efficiency scores less than one).

Likewise, upon reviewing the upper bound efficiency scores in Table 5, it is notable for each α-cut value, four LCs—Kosekoy/Izmit, Halkali/Istanbul, Hasanbey/Eskisehir, and Yenice/Mersin—are fully efficient, whereas the remaining eight LCs are inefficient.

Considering both the lower and upper bound efficiency scores across these tables, it is evident three LCs (Kosekoy/Izmit, Halkali/Istanbul, and Yenice/Mersin) consistently exhibit full efficiency for each α-cut value, while six LCs (Gelemen/Samsun, Gokkoy/Balikesir, Turkoglu/Kahramanmaras, Palandoken/Erzurum, Kayacik/Konya, and Kars) consistently demonstrate inefficiency.

When examining Tables 4 and 5, it becomes apparent with the highest uncertainty the α-cut value is 0, Kars LC holds the lowest efficiency score among the LCs. For the α-cut value being 0, Kars LC's lower bound efficiency score is calculated as 0.066, while the upper bound efficiency score is 0.103. Therefore, it appears Kars LC has an excess of inputs to achieve the same output (total revenue) and to attain full efficiency, it would need to reduce its inputs. This surplus is determined to be 93.4% in the lower bound efficiency and 89.7% in the upper bound efficiency. This suggested Kars LC, in the year 2022, could have achieved its total revenue with a significant unused capacity (ineffective use of inputs).

The assessments made for the $\alpha = 0$ cut value can similarly be conducted for $\alpha = 0.25$, $\alpha = 0.50$, $\alpha = 0.75$, $\alpha = 1$ cut values. Given the unique scenario where the $\alpha = 1$ cut value has the least uncertainty, the evaluation at this point becomes significant. Upon reviewing Tables 4 and 5, it is evident for the $\alpha = 1$ cut value, the efficiency scores are precisely aligned. This indicated in the formulas utilized for the lower and upper bound calculations (Equation (4)) provided in previous sections, the $\alpha = 1$ cut value led to exact values, meaning the fuzzification process did not alter the data. Therefore, the efficiency scores calculated for the $\alpha = 1$ cut value remained the same, signifying for this value, no changes were made to the existing data during the calculation. Consequently, these scores also represented the classical DEA results obtained for the data [114].

It is observed the Gelemen/Samsun LC attains the lowest efficiency score of 0.800 for the $\alpha = 1$ cut value. Consequently, it suggested the Gelemen/Samsun LC possessed surplus inputs compared to other fully efficient LCs, necessitating a reduction in inputs to achieve full efficiency. This input surplus results in an efficiency score of 0.800, indicating an excess of 20% in inputs. This implied the Gelemen/Samsun LC could achieve its 2022 total revenue by reducing inputs by 20%, indicating considerable underutilization of its capacity (ineffective input utilization). Similar inferences can be drawn for other inefficient LCs at $\alpha = 1$.

Utilizing the Fuzzy-DEA method allows for observing efficiency changes of each LC from the most uncertain scenario ($\alpha = 0$) to the most certain scenario ($\alpha = 1$). Hence, an advantage of Fuzzy-DEA models lied in providing richer information compared to the point efficiency levels derived from classical DEA models [72].

The information presented in Tables 4 and 5 appeared considerably intricate and extensive compared to the conventional efficiency calculations (classical DEA). Therefore, providing a simplified and concise approach for interpretation and evaluation is essential. Firstly, we should consider the distinction between Fuzzy-DEA analysis and classical DEA analysis. This distinction primarily manifests in the treatment of the data. In classical DEA, the data pertaining to the LCs for which we calculate efficiencies are precise or, in other words, are composed of definite values accepted with certainty. Consequently, it was anticipated the calculated efficiencies would also be definite or point efficiencies. However, in Fuzzy-DEA, the handling of data shifts within the framework of fuzzy logic. This change can be expressed as follows. In Fuzzy-DEA, the approach to the data being related to the efficiencies of LCs is not as precise or definite but rather considers the data to exist within specific intervals. This approach involves evaluating the efficiency to be calculated by considering the data within certain intervals and probabilities (α-cut values). Hence, through fuzzy logic, there is flexibility in both approaching the data and evaluating efficiencies [110]. Based on this perspective, the data regarding LCs have been evaluated considering the accepted lower and upper limits within certain technical rules. Consequently, upper and lower bound efficiencies related to these limits have been calculated. Tables 4 and 5 encompass information concerning these interval efficiencies and the likelihood of such efficiencies within specific probabilities.

The detailed interpretations on how to assess the information within Tables 4 and 5 have been provided above. Furthermore, these insights can serve as a guiding tool for decision-makers and policymakers within the field. Indeed, higher institutions or direct management overseeing LCs can conduct comprehensive comparative assessments involving all LCs.

This study examined nine distinct input variables related to LCs, including installed area, capacity, number of personnel, number of railway lines, among others, to evaluate their influence on the total revenue (turnover) of LCs. Consequently, this study aided inefficient LCs with underutilized capacities in understanding the level of optimization required for their input usage to overcome inefficiencies, identifying potential areas for enhancement (inputs). Subsequently, prioritizing additional investments or implementing specific solutions in problematic areas (if any) allows these entities to sustain activities at their intended performance level. Leveraging both upper and lower bound efficiencies during these evaluations is possible.

By considering these tables, LCs can observe fluctuations in efficiency scores along with the flexibility of data across various probabilities. This capability allows an exploration not just into whether an LC is efficient or not, but rather into the intervals and probabilities within which its efficiency resides, presenting a crucial advantage of the fuzzy logic approach.

All these analyses can serve as a guide for organizations within the LC sector aiming to conduct comparative evaluations among institutions. It may facilitate the identification of industry best practices and enable struggling LCs aspiring to enhance their performances to align with these practices.

The subsequent step involves evaluating the final performance rankings by considering the previously calculated lower and upper bound efficiencies of LCs. Table 6 presents the calculated Chen–Klein Index values (I) for LCs, the classical DEA efficiency scores obtained with $\alpha = 1$, and the ultimate performance rankings.

Table 6. Ranking of the crisp and fuzzy efficiency scores.

Rank	DMUs (LCs)	Chen–Klein Index (I)	Classical DEA Scores (α=1)
1	Kosekoy/Izmit	1.000	1.000
2	Halkali/Istanbul	1.000	1.000
3	Yenice/Mersin	1.000	1.000
4	Kaklik/Denizli	1.000	1.000
5	Usak	1.000	1.000
6	Hasanbey/Eskisehir	0.995	1.000
7	Turkoglu/Kahramanmaras	0.968	0.905
8	Gokkoy/Balikesir	0.815	0.957
9	Kayacik/Konya	0.801	0.909
10	Gelemen/Samsun	0.635	0.800
11	Palandoken/Erzurum	0.423	0.902
12	Kars	0.406	1.000

Table 6 shows the Chen–Klein Index values of LCs, calculated by considering both lower and upper bound efficiency scores, arranged in descending order. It could be observed five LCs—Kosekoy/Izmit, Halkali/Istanbul, Yenice/Mersin, Kaklik/Denizli, and

Usak—had Chen–Klein Index values ($I = 1$) according to the Fuzzy-DEA analysis, indicating their complete efficiency compared to other LCs. Conversely, the least efficient LCs, in decreasing order, are Kars, Palandoken/Erzurum, Gelemen/Samsun, Kayacik/Konya, Gokkoy/Balikesir, Turkoglu/Kahramanmaras, and Hasanbey/Eskisehir.

Table 6 also presents the classical DEA efficiency scores. Comparing them with the Fuzzy-DEA results reveals some variations. For instance, while Fuzzy-DEA indicates five LCs as fully efficient, classical DEA identifies seven LCs as fully efficient by adding two more to the list. Notably, Kars LC, despite being classified as fully efficient in classical DEA, is identified as the least efficient in Fuzzy-DEA, accounting for uncertainty considerations. The discrepancy arose from the point efficiency values calculated in classical DEA, whereas Fuzzy-DEA accounted for interval efficiency values considering uncertainty, which was an expected divergence [110]. Therefore, the Fuzzy-DEA method yielded more detailed and precise outcomes in efficiency calculations compared to classical DEA.

Lastly, a comparison between Fuzzy-DEA and classical DEA results has been conducted. A Spearman Rank Correlation test examined whether a statistically significant difference existed between these methods within a certain confidence interval: at a 95% confidence interval ($p = 0.0208 < 0.05; n = 12$), it was statistically significant (Spearman's rho = 0.655). This indicates there is no statistically significant difference in rankings between Fuzzy-DEA and classical DEA results, suggesting a similar trend. With a Spearman's rho of 0.655, it can be inferred there is a moderate to strong level of agreement/similarity (i.e., an LC being efficient in Fuzzy-DEA also being efficient in classical DEA).

5. Discussion

The extensive assessment of Logistics Centers (LCs) in this study, conducted through the Fuzzy-DEA methodology, provided a varied range of efficiency evaluations for each center. This shed light on their operational dynamics and performance throughout Turkey.

The analysis revealed diverse efficiency levels among the 12 operational LCs. Both Kosekoy/Izmit and Halkali/Istanbul LCs exhibited full efficiency, consistent with earlier research [40,41], and highlighting their pivotal roles in Turkey's trade network—facilitating the transit of over half of the country's internationally transported goods via road and rail [116]. Positioned as crucial centers within the Marmara Region, these LCs not only demonstrated exemplary efficiency but also underscore their significance in national import/export activities and transportation management.

Yenice/Mersin LC, despite being recently established, exhibited remarkable efficiency, emphasizing its strategic significance as a pivotal hub near the Mediterranean, accommodating diverse transportation modes. Conversely, centers like Turkoglu/Kahramanmaras and Gokkoy/Balikesir demonstrated inefficiencies akin to previous studies [40,41], highlighting the imperative to rectify input redundancies for enhanced performance. On the other hand, the study emphasized Kayacik/Konya LC exhibited similar input redundancies, yet it was identified as a potential successful center in a study conducted by [42]. This evaluation took place before the center commenced operations, focusing solely on its sustainability potential.

Moreover, Hasanbey/Eskisehir LC, strategically positioned in terms of industrial potential, exhibited inefficiencies due to input surpluses (similar results [40,41]), necessitating strategic input management for enhanced efficiency. Despite its advantageous location, Gelemen/Samsun LC, the first established in Turkey, displayed notable inefficiencies, indicating the need for substantial improvements to align its performance with its potential capabilities.

The findings also underscore the imperative for LCs like Palandoken/Erzurum and Kars LC to address their inefficiencies. Palandoken/Erzurum LC's low efficiency, particularly concerning given its strategic position along a key transit route, demands significant operational enhancements. Similarly, Kars LC, despite its crucial role in transportation corridors (TRACECA, Baku-Tbilisi-Kars), requires substantial improvements to operate at optimal efficiency.

The outcomes derived from employing the Fuzzy-DEA methodology to evaluate the efficiency of LCs presented intriguing facets that warranted deeper exploration and consideration.

One significant revelation lied in the variability observed in the efficiency assessments between classical DEA and Fuzzy-DEA methods. This disparity was particularly evident in LCs rated as fully efficient by classical DEA but exhibiting differing efficiency levels when considering uncertainties, showcasing the nuanced perspective that Fuzzy-DEA offered. The shift from point efficiency values to interval efficiency values in Fuzzy-DEA illuminates the significance of accounting for uncertainties in performance evaluations.

Furthermore, the identification of certain LCs as less efficient in Fuzzy-DEA despite being rated as fully efficient by classical DEA prompts an essential discussion on the impact of uncertainty on efficiency assessments. This suggests classical DEA might overlook crucial operational aspects within LCs, highlighting the necessity of adopting more comprehensive methodologies like Fuzzy-DEA.

The capability of Fuzzy-DEA to provide a more detailed understanding of efficiency changes for each LC is a notable contribution. By capturing the transitions between states of uncertainty to certainty, this approach offers a nuanced view that enhances the precision and depth of efficiency evaluations.

Among the constraints of the study are the following: limitations in data collection regarding LCs, thereby basing the study on a specific time frame, resulting in the reliance of outcomes on the available dataset and constraining the currency of results; the restriction of variables used to evaluate the efficiency of LCs based on the dataset; the regional focus of the study (Turkey) limiting a broad generalization; and the scarcity of studies in the existing literature hindering detailed comparisons in the results. Nevertheless, despite these limitations, the established model, once specific adjustments were made, could be universally applicable and comfortably employed in both this field and other domains for efficiency research.

Given its methodological uniqueness and focus, the study interprets its comparative results in relation to a few studies examining LCs in Turkey. Therefore, we propose a favorable perspective regarding its potential to offer significant projections for future studies concerning LCs. Subsequent research could further enrich and expand upon the data-driven results provided by this study. The variability in the number of variables can be achieved by specifying multiple inputs and outputs, experimenting with output-oriented models, and exploring various methods of fuzzification, among other possibilities. Specifically, conducting comparative efficiency analyses of LCs in different countries, analyses based on datasets incorporating diverse variables, or studies employing techniques such as intuitive-fuzzy logic that elevate fuzzy logic to the next stage, could be valuable in fostering a more comprehensive understanding across the industry. Furthermore, exploring broader perspectives concerning LCs, encompassing sustainability, environmental impacts, and societal dimensions, could serve as a significant resource for deeper operational enhancements and decisions in these areas.

6. Conclusions

In this study, the evaluation of Logistics Centers' (LCs) performances/efficiencies was conducted using the Fuzzy-DEA method, applying a fuzzy approach. Thus, considering the data for the year 2022 pertaining to 12 operational LCs in Turkey, efficiency levels and comparative relationships among them were investigated through the symmetric triangular, variable returns to scale, and input-oriented Fuzzy-DEA/BCC method based on the standard error.

One variable, total revenue (turnover), was designated as an output variable, while nine variables (such as installed area, capacity, number of personnel, etc.) were incorporated as input variables in the study. These selections were made considering prior literature, which is believed to have a direct or indirect influence on the efficiency of LCs.

Upon statistical examination of the input and output variable data of LCs, it was observed there was a high degree of variation. Specifically, the presence of high variation in inputs indicated irrational resource utilization in LCs. Consequently, it was observed LCs did not achieve full efficiency in reaching the output of total revenue.

On the other hand, the efficiency changes of each LC were tracked using the Fuzzy-DEA method, observing the progression from the most uncertain state with maximum deviation in the data to the most certain (definite) state with no deviation. Consequently, interval efficiency scores were computed using the preferred Fuzzy-DEA method, and these efficiencies were interpreted at certain probability levels to identify input redundancies in the LCs. Simultaneously, the analysis results were compared with classical DEA outcomes, indicating no statistically significant difference. However, while the classical DEA analysis showed seven LCs operated at full efficiency, the Fuzzy-DEA analysis revealed five LCs operating at full efficiency. This disparity arose from the inability of LCs deemed fully efficient to maintain their efficiency when considering uncertain conditions. In essence, the primary originality of the study lies in providing concrete evidence that such differences can exist when calculating efficiencies and underscores the importance of not overlooking these factors. As a result, using the Fuzzy-DEA method, the efficiency of LCs with high data sensitivity could be calculated more accurately.

The study's outcomes allow for multifaceted and diverse recommendations for decision-makers in the logistics sector and regarding the efficiencies of LCs. These recommendations encompass various aspects of the logistics sector and the efficiencies of LCs:

- it is imperative to identify the LCs as are highlighted in these and similar studies and strategize plans to enhance the efficiency of these centers. Ensuring the efficient utilization of resources in these centers is crucial.
- The expedited execution of studies aiming to establish nine new centers in addition to the existing twelve LCs was of significant importance for completing essential railway connections among all LCs in Turkey.
- Formulating regional logistics master plans could contribute to new LC establishment plans that would be based on needs and offered a more balanced distribution, rather than being driven solely by political decisions.
- Facilitating a tighter integration, particularly through the establishment of railway connections, between LCs and production centers is essential. Various incentives should be provided in this context.
- Investments in modern equipment and cutting-edge technology tailored to the industry's needs should be made in LCs. Technologies such as automation, monitoring systems, and data analytics are pivotal in enhancing the appeal of these centers.
- Embracing a more proactive approach in managing LCs in Turkey is crucial to establish a competitive ecosystem. Increasing collaboration between the public and private sectors is vital for swiftly meeting customer needs. Furthermore, such collaboration can facilitate the more effective utilization of public resources and maximize leveraging the experiences of the private sector.

The obtained results offer valuable insights into the efficiency of logistic systems. These findings could be pivotal in establishing novel measurement indices for evaluating the sustainability performance of LCs. Additionally, they underscore the potential contributions of LCs to other industries and emphasize the importance of expanding sustainable LCs to other countries or contexts. Such outcomes could hold significant value for logistic managers and decision-makers. For instance, the recommendations aimed at enhancing the sustainability of LCs could lead to improvements in operational processes. Moreover, the practical implications of these findings might contribute to better management of LC operations and more efficient resource utilization.

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Abbreviations

AHP, Analytic Hierarchy Process; BCC, Banker, Charnes, and Cooper Model; CCR, Charnes, Cooper, and Rhodes Model; CRITIC, Criteria Importance Through Inter-criteria Correlation; DEA, Data Envelopment Analysis; DMU, Decision-Making Unit; EU, European Union; Europlatforms, The European Logistic Platforms Association; Fuzzy-DEA, Fuzzy Data Envelopment Analysis; I, Chen–Klein Index; LC, Logistics Center; MCDM, Multi Criteria Decision Making; PROMETHEE, Preference Ranking Organization Method for Enrichment Evaluation; S_x, Standard Error; TCDD, Turkish State Railways; TOPSIS, Technique for Order Preference by Similarity to Ideal Solution.

Appendix A

Lower bound technical efficiency (TE)

$$\text{TE}\ (X1,\ X2,\ X3,\ X4,\ X5,\ X6,\ X7,\ X8,\ X9,\ Y) = Min\ \theta$$

subject to:

$$\text{Constraints}\quad \begin{bmatrix} \theta\left(\alpha X1_{io}^{m} + (1-\alpha)X1_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X1_{ij}^{m} + (1-\alpha)X1_{ij}^{l}\right) \\ \theta\left(\alpha X2_{io}^{m} + (1-\alpha)X2_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X2_{ij}^{m} + (1-\alpha)X2_{ij}^{l}\right) \\ \theta\left(\alpha X3_{io}^{m} + (1-\alpha)X3_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X3_{ij}^{m} + (1-\alpha)X3_{ij}^{l}\right) \\ \theta\left(\alpha X4_{io}^{m} + (1-\alpha)X4_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X4_{ij}^{m} + (1-\alpha)X4_{ij}^{l}\right) \\ \theta\left(\alpha X5_{io}^{m} + (1-\alpha)X5_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X5_{ij}^{m} + (1-\alpha)X5_{ij}^{l}\right) \\ \theta\left(\alpha X6_{io}^{m} + (1-\alpha)X6_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X6_{ij}^{m} + (1-\alpha)X6_{ij}^{l}\right) \\ \theta\left(\alpha X7_{io}^{m} + (1-\alpha)X7_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X7_{ij}^{m} + (1-\alpha)X7_{ij}^{l}\right) \\ \theta\left(\alpha X8_{io}^{m} + (1-\alpha)X8_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X8_{ij}^{m} + (1-\alpha)X8_{ij}^{l}\right) \\ \theta\left(\alpha X9_{io}^{m} + (1-\alpha)X9_{io}^{l}\right) \geq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha X9_{ij}^{m} + (1-\alpha)X9_{ij}^{l}\right) \\ \theta\left(\alpha Y_{ro}^{m} + (1-\alpha)Y_{ro}^{l}\right) \leq \sum\limits_{j=1}^{12} \lambda_j\left(\alpha Y_{rj}^{m} + (1-\alpha)Y_{rj}^{l}\right) \\ \sum \lambda_j = 1,\ \lambda_j \geq 0,\ 0 \leq \theta \leq 1,\ o \in \{1, \ldots, 12\} \end{bmatrix}$$

Upper bound technical efficiency (TE)

$$\text{TE}\ (X1,\ X2,\ X3,\ X4,\ X5,\ X6,\ X7,\ X8,\ X9,\ Y) = Min\ \theta$$

subject to:

$$
\text{Constraints}\quad
\left[
\begin{array}{c}
\theta(\alpha X1_{io}^{m}+(1-\alpha)X1_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X1_{ij}^{m}+(1-\alpha)X1_{ij}^{u}\right) \\
\theta(\alpha X2_{io}^{m}+(1-\alpha)X2_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X2_{ij}^{m}+(1-\alpha)X2_{ij}^{u}\right) \\
\theta(\alpha X3_{io}^{m}+(1-\alpha)X3_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X3_{ij}^{m}+(1-\alpha)X3_{ij}^{u}\right) \\
\theta(\alpha X4_{io}^{m}+(1-\alpha)X4_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X4_{ij}^{m}+(1-\alpha)X4_{ij}^{u}\right) \\
\theta(\alpha X5_{io}^{m}+(1-\alpha)X5_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X5_{ij}^{m}+(1-\alpha)X5_{ij}^{u}\right) \\
\theta(\alpha X6_{io}^{m}+(1-\alpha)X6_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X6_{ij}^{m}+(1-\alpha)X6_{ij}^{u}\right) \\
\theta(\alpha X7_{io}^{m}+(1-\alpha)X7_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X7_{ij}^{m}+(1-\alpha)X7_{ij}^{u}\right) \\
\theta(\alpha X8_{io}^{m}+(1-\alpha)X8_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X8_{ij}^{m}+(1-\alpha)X8_{ij}^{u}\right) \\
\theta(\alpha X9_{io}^{m}+(1-\alpha)X9_{io}^{u}) \geq \sum_{j=1}^{12} \lambda_j\left(\alpha X9_{ij}^{m}+(1-\alpha)X9_{ij}^{u}\right) \\
\theta(\alpha Y_{ro}^{m}+(1-\alpha)Y_{ro}^{u}) \leq \sum_{j=1}^{12} \lambda_j\left(\alpha Y_{rj}^{m}+(1-\alpha)Y_{rj}^{u}\right) \\
\sum\lambda_j=1,\ \lambda_j\geq 0,\ 0\leq\theta\leq 1,\ o\in\{1,\ldots,12\}
\end{array}
\right]
$$

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