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Regional Efficiency Analysis of an International Logistics Company: A Case Study

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Abstract

This study, conducted in collaboration with a US-based multinational logistics company, investigates the operational efficiency of cargo transportation firms in managing package collection and distribution. The primary objective is to identify areas for enhancing effectiveness. The research encompasses key variables such as delivered packages, pickups, truck numbers, couriers, delivery and pickup stops, total costs, daily delivery and pickup compensation. The study's focus centers on analyzing the operations of an international logistics firm in Izmir, Turkey, using the Data Envelopment Analysis (DEA) method which helps identify regions effectively managing processes. The frontier analyst program assessed the company's operations across 19 Izmir regions, leading to recommendations based on efficient regions. The research aims to provide a comprehensive roadmap for similar Third-Party Logistics Service Providers (3PLs) seeking to optimize cargo pickup operations. By adopting the study's suggested strategies and best practices, other 3PLs can enhance their package collection management and overall operational efficiency. In conclusion, the study underscores the value of employing the DEA method for evaluating cargo transportation operational efficiency, offering insights for improvement. The specific recommendations derived from efficient regions in Izmir serve as a guideline for logistics service providers looking to optimize package collection and distribution activities.

Key words: Cargo Companies, 3PL, Data Envelopment Analysis (DEA), Efficiency, Logistics, Performance

JEL Code: L91; L87; L10; L25

1. Introduction

In the contemporary dynamic market environment, corporate entities necessitate the implementation of efficient procurement methodologies in order to ascertain a sustainable competitive edge. Many studies have been carried out to analyze these processes while mathematical models and software tools can now help companies and managers make tactical, operational and strategic decisions. One such approach available to managers and companies for achieving these goals

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is data environment analysis (DEA). DEA measures operational efficiency in terms of various inputs and outputs and applies linear programming for every decision-making unit (DMU) (Chen et al., 2010). It also uses various ratios to measure efficiency with inputs and outputs (Min and Joo, 2006). DEA is used in various industries to evaluate efficiency and find the best solution in each case (Charnes et al., 1978). DEA results can range from 0 to 1, with 0 indicating the worst case or lowest efficiency and 1 indicating the best case or highest efficiency (Sherman and Ladino, 1995).

DEA is considered the best practice for defining product or service quality standards and a useful DMU for comparing efficient and inefficient practices. DMU is also used for measuring capacity, performance, and output efficiency (Sherman and Ladino, 1995). DEA has several advantages: it can represent multiple aspects of organizational performance, it does not require the basic weight of performance measurements, and it can provide suggestions for increasing operational efficiency (Zhou et al., 2008). DEA is a nonparametric mathematical instrument for evaluating the general effectiveness of homogeneous basic DMUs. DEA can be applied across quite a wide range of areas, including training, medicine, nursing, banking, agriculture, transportation, logistics, and retailing (Gao and Zhang, 2022; Mirhedayatian et al., 2014; Zhou et al., 2008;). In particular, Third-Party Logistics Service Providers (3PLs) generally use DEA to streamline their operations and increase their competitiveness.

3PL companies can use DEA to provide information about the efficiency or productivity of their processes (Zhou et al., 2008). The best way to measure actual productivity is to analyze input and output ratios by minimizing input and maximizing outputs (Pratap et al., 2021). Efficiency analysis can be used for many purposes, such as determining the capacity utilization rate, calculating vehicle usage efficiency, and measuring customer service levels (Liu et al., 2013; Zhou et al., 2008). Generally, 3PLs use DEA to evaluate customer or company service levels.

The general performance of 3PLs can be estimated from their operating income, which best reflects their operational efficiency. The DEA model not only enables 3PLs to define clear rules for organizing the utilization of financial assets but also encourages them to assess the impacts of financial ventures on their profitability (Min and Joo, 2006).

By examining the case of one international logistic company, the present study attempts to determine how such organizations can perform their logistics activities more efficiently and effectively. The aim is to identify the specific activities that increase, decrease, or have no effect on the company's efficiency, and hence profitability.

The structure of this paper entails five sections, encompassing a literature review, methodology, problem definition, results, conclusion and suggestions. Additionally, a comprehensive evaluation and recommendations section is included to provide thorough analysis and guidance.

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2. Literature Review

DEA and its decision techniques are frequently used in both the public and private sectors to evaluate organizational performance. DEA is a non-parametric technique used for maximizing objectives and minimizing resources (Fancello et al., 2020). This non-parametric method was first developed by Charnes et al. (1978) to avoid the need for parametric practical-type decisions in estimating the efficiency of decision-making units (DMUs) in a multi-input and multi-output production environment. Like other non-parametric techniques, it avoids the usual difficulties of using parametric methods (Bera et al., 2021; Mansour and Moussawi, 2020). Instead, it identifies both the most efficient units and their distance from inefficient units (Fancello et al., 2020). DEA is also the most efficient method for industries to find optimal solutions and the most efficient DMUs (Toloo and Nalchigar, 2009).

DEA, as a robust methodology for measuring efficiency and performance, has found application across a wide range of industries. In the healthcare sector, Banker, Charnes, and Cooper (1984) explored models for estimating technical and scale inefficiencies using DEA. Chen and Liang (2007) employed DEA to analyze the productivity of Taiwanese banks in the banking and finance industry.

The manufacturing sector has been a focal point of extensive research utilizing Data Envelopment Analysis (DEA), as evidenced by Cooper et al. (2011)'s comprehensive handbook on the subject. In education, Paradi et al. (2013) employed DEA alongside hierarchical Bayes methodology to evaluate regional and school performance. Hirsch and Lev (1971) explored DEA's application in sales forecasting within the transportation and logistics industry. Sueyoshi and Goto (2010) investigated DEA models for unified efficiency in the energy and utilities sector. Additionally, Zhu and Liu (2014) applied DEA to assess environmental performance across OECD countries in environmental management. Building on this foundation, recent studies have shown the versatility of DEA in logistics and transportation contexts. See et al. (2024) illustrated how countries can enhance their Logistics Performance Index (LPI) through targeted indicators using DEA-based country comparisons. Li et al. (2022) focused on improving logistics efficiency in China's coastal ports using a DEA model. Furthermore, Dini et al. (2024) developed a DEA-based mathematical model to optimize transport routes for Logistics Companies (LCs), emphasizing factors such as cost, time, reliability, and environmental sustainability. Quan et al. (2022) assesses the operational efficiency and social responsibility impact of logistics firms, using DEA, highlighting its crucial role in enhancing sustainability in the industry.

These studies demonstrate the diverse range of industries in which DEA has been successfully employed, showcasing its versatility as an analytical tool for assessing efficiency and performance.

One method for enhancing the operational efficiency of 3PLs and providing a method for designing survival techniques or a case study is to imitate best practice firms that can be identified by defining a solid solution (Li and Chen, 2019). For this solution, industry norms and standards, specifically a logistics company's performance or efficiency measurement tools, can be used as a benchmark. Benchmarking is the best way for 3PLs to identify which tool or solution can increase efficiency. DEA is especially used as benchmarking tool for comparatively evaluating the efficiency of different countries', cities or industries' performance (Fancello et al., 2020).

Accordingly, the present research provides a roadmap and a benchmarking tool for different companies to indicate how they can improve their processes.

3. Methodology

DEA is a linear programming-based technique that aims to measure the relative effectiveness of decision-making units when measured at multiple different scales or where comparison is more difficult because the inputs and outputs are measured in different units. To do so, it calculates relative efficiency values (between 0 and 1) by comparing multi-factor and homogeneous decision-making units.

DEA encompasses various models that cater to the diverse production types and characteristics of input-output data. The commonly used models include the Charnes, Cooper, and Rhodes (CCR) model, the Banker, Charnes, and Cooper (BCC) model, and the free disposal hull model. In this study, particular attention is given to the CCR and BCC models, which have been adapted to handle input-output data without any predetermined arrangement. The CCR model assumes consistent returns to scale across activities, implying that changes in inputs and outputs occur in a proportional manner. In contrast, the BCC model acknowledges the possibility of variable returns to scale, indicating that activity levels can lead to either increasing or decreasing returns. By utilizing these adapted CCR and BCC models, the study aims to effectively assess efficiency and performance, considering the varying scaling characteristics inherent in the analyzed industries.

By applying these DEA models, this research endeavors to gain a comprehensive understanding of efficiency levels and shed light on the influence of returns to scale on operational processes. The adapted CCR and BCC models provide a robust framework for evaluating the relative efficiency of decision-making units in the context of this study, enabling a thorough analysis of the input-output relationships.

The CCR (Charnes, Cooper, and Rhodes) model and the BCC (Banker, Charnes, and Cooper) model are two distinct approaches within Data Envelopment Analysis (DEA) used to evaluate the efficiency of Decision-Making Units (DMUs) in various industries.

The CCR model assumes constant returns to scale, meaning that if a DMU increases its input, its output will also increase proportionally. In this model, DMU's efficiency is determined as the maximum weighted output to weighted input ratio, subject to the constraint that this ratio must be less than or equal to 1 for all DMUs.

On the other hand, the BCC model, developed by Banker et al. (1984), allows for variable returns to scale. This means that a DMU may exhibit increasing, decreasing, or constant efficiency to scale, and a relative change in input may result in a different magnitude of change in outputs. The BCC model identifies the pure technical efficiency of DMUs concerning the efficient frontier.

Both the CCR and BCC models are widely used in the assessment of operational efficiency, including applications in the road transportation industry. Many studies have demonstrated the effectiveness of DEA as a powerful method for evaluating performance in various domains, such as road transportation performance. Notable research works by Li and Reeves (1999), Karsak and Ahiska (2005), Ertay et al. (2006), Hermans et al. (2008), and Seyedalizadeh Ganji and Rassafi (2019) have further highlighted the versatility and applicability of DEA in performance evaluation across different industries.

For this reason, in this study DEA used to measure input- and output-oriented efficiency and identify opportunities for minimizing or maximizing the variable to determine the efficiency of International Logistics Company's efficiency in each region. BCC was chosen for the present study because it generates comparative results by considering the inputs and outputs. It is thus the most appropriate method for this data set analyzing a cargo company case.

3.1. Problem Definition

In today's market, every logistics company faces almost the same issues and expenses. The international logistics company considered in this case plans to reduce these expenses by improving its processes, thereby decreasing its input and/or increasing its output. That is, the firm expects solutions to either reduce input costs, which will reduce resource use, or to increase profits and output. In general, since all companies aim to reduce costs, this company wants to both improve its processes and reduce costs.

The company identifies solutions for reducing costs by considering the packages in its processes, the number of vehicles/trucks, the number of employees, and the collected packages. The company has eight agencies conducting courier activities in İzmir. For this study, the agencies' activities were observed for three months. The region involved has sixteen localities and three shopping malls. The company wants to identify the optimal solution for the number of trucks and couriers based on delivery stops, quantity of deliveries, and quantity of pick-up packages.

Since DEA is the best tool to measure process efficiency in terms of the number of inputs and outputs, it was used in this study. The company wishes to determine where and how it can increase its effectiveness by making improvements. The data provided in the study include delivered packages, picked up packages, number of trucks, number of couriers, delivery stops, pick up stops, total cost (fuel, salary, depreciation, maintenance, etc.), daily delivery compensation, and daily pick-up compensation.

3.2. Formulation

For this firm, the inputs are the number of trucks, number of couriers, delivery stops, pick-up stops and daily costs. The outputs are delivered packages, received packages, daily delivery compensation, and daily pick-up compensation.

The firm's inputs are fixed, so it wishes these variables to be considered as constant and does not want to change them. Therefore, the input variables are constant for all cases. Thus, the only way to improve the company's processes is to focus on how it can change the output variables.

Accordingly, this study examines output-oriented solutions. The output-oriented model changes the output while controlling the input. An output-oriented analysis determines how much output these inputs can achieve while keeping them constant, and how much output these inputs can achieve for maximum efficiency. The output-oriented model indicates how an inefficient unit of output can become efficient without changing the input level.

The formulas to be used in the BCC output-oriented model are shown below.

Output Oriented BCC Model

$$E_k = Min\left(\sum_{i=1}^{m} v_i X_{ik}\right) - \rho_o$$

$$\left(\sum_{r=1}^{p} u_r Y_{rj}\right) - \left(\sum_{i=1}^{m} v_i X_{ij}\right) + \rho_o \leq 0$$

$$u_r \geq \varepsilon$$

$$v_i \geq \varepsilon$$

$$j = 1, \dots, n$$

$$r = 1, \dots, p$$

$$i = 1, \dots, m$$

$$\rho_0 = Unconstrained$$

u_r: $By\ the\ decision\ unit\ of\ k, given\ weight\ to\ output\ r.,$
v_i : $By\ the\ decision\ unit\ of\ k\ given\ weight\ to\ input\ i,$
Y_{rk}: $By\ the\ decision\ unit\ of\ k\ , produced\ output\ r\ ,$
X_{ik}: $By\ the\ decision\ unit\ of\ k\ , used\ input\ i,$
Y_{rj}: $By\ the\ decision\ unit\ of\ J\ , produced\ output\ r\ ,$
X_{ij}: $By\ the\ decision\ unit\ of\ J\ , used\ input\ i,$
ε: $Minimum\ possible\ positive\ number\ (Ex: 0{,}00001)$
o: $variable\ about\ the\ direction\ of\ return\ on\ scale.$

Regional Formulation of BCC Output Oriented Model

U_1; Delivered Packages

U_2; Picked Up Packages

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W_1; Truck Numbers

W_2; Courier Numbers

W_3; Delivery Stops

W_4; Pick Up Stops

W_5; Cost

W_6; Daily Delivery Compensation

W_7; Daily Pick-Up Compensation

U_0; Free

Region 1

Max = $148{,}851u_1 + 91{,}86u_2 - u_0$

St. $1w_1 + 1\,w_2 + 14{,}236w_3 + 3{,}11w_4 + 312w_5 + 330{,}93w_6 + 144{,}97w_7 = 1$

$148{,}851u_1 + 91{,}86u_2 - 1w_1 - 1w_2 - 14{,}236w_3 - 3{,}11w_4 + 312w_5 + 330{,}93w_6 + 144{,}97w_7 - u_0 \leq 0$

Region 2 (Shopping Mall)

Max : $141{,}83u_1 + 91.08u_2 - u_0$

St : $1w_1 + 1w_2 + 22w_3 + 1w_4 + 312w_5 + 321.96w_6 + 144.81w_7 = 1$

$141.83u_1 + 91.08u_2 - 1w_1 - 1w_2 - 22w_3 - 1w_4 + 312w_5 + 321.96w_6 + 144{,}81w_7 - u_0 \leq 0$

Region 3

Max : $93.92u_1 + 130.82u_2 - u_0$

St : $1w_1 + 1w_2 + 21w_3 + 1w_4 + 312w_5 + 213.20w_6 + 208w_7 = 1$

$93.92u_1 + 130.82u_2 - 1w_1 - 1w_2 - 21w_3 - 1w_4 + 312w_5 + 213.20w_6 + 208w_7 - u_0 \leq 0$

Region 4

Max: $64.03u_1 + 4.08u_2 - u_0$

St: $1w_1 + 1w_2 + 16w_3 + 1w_4 + 514{,}65w_5 + 145{,}34w_6 + 6{,}49w_7 = 1$

$64.03u_1 + 4.08u_2 - 1w_1 - 1w_2 - 16w_3 - 1w_4 + 514{,}65w_5 + 145.34w_6 + 6.49w_7 - u_0 \leq 0$

Region 5 (Shopping Mall)

Max: $154.39u_1 + 96.01u_2 - u0$

St: $1w_1 + 1w_2 + 65.99w_3 + 3w_4 + 326.15w_5 + 350.47w_6 + 152.65w_7 = 1$

$154.39u_1 + 96.01u_2 - 1w_1 - 1w_2 - 65.99w_3 - 3w_4 + 326.15w_5 + 350.47w_6 + 152.65w_7 - u_0 \leq 0$

Region 6

Max: $63.45u_1 + 12.45u_2 - u_0$

St: $1w_1 + 1w_2 + 27.90w_3 + 0.10w_4 + 392.15w_5 + 212.14w_6 + 28.26w_7 = 1$

$63.45u_1 + 12.45u_2 - 1w_1 - 1w_2 – 27.90w_3 – 0.10w_4 +392.15w_5 + 212.14w_6 + 28.26w_7 - u_0 \leq 0$

Region 7

Max: $70.03u_1 + 10.67u_2 - u_0$

St: $1w_1 + 1w_2 + 47.88w_3 + 1.37w_4 + 411{,}00w_5 + 158.97w_6 + 16.97w_7 = 1$

$70.03u_1 + 10.67u_2 - 1w_1 - 1w_2 - 47.88w_3 - 1.37w_4 +411{,}00w_5 + 158.97w_6 + 16.97w_7 - u_0 \leq 0$

Region 8

Max = $73.75u_1 + 15.68u_2 - u_0$

St. $1w_1 + 1w_2 + 55w_3 + 3w_4+ 345w_5 + 167.41w_6 + 24.94w_7 = 1$

$73.75u_1 + 15.68u_2 -1w_1 - 1w_2 - 55w_3 - 3w_4+ 345w_5 + 167.41w_6 + 24.94w_7 - u_0 \leq 0$

Region 9

Max: $142.67u_1 + 61.01u_2 -u_0$

st: $1w_1 + 1w_2 + 24.21w_3 + 4.95w_4 + 345w_5 + 323.86w_6 + 97w_7 = 1$

$142.67u_1 + 61.01u_2 -1w_1 -1w_2 – 24.21w_3 – 4.95w_4 + 345w_5 + 323.86w_6 + 97w_7 - u_0 \leq 0$

Region 10

Max: $68.35u_1 + 18.40u_2 -u_0$

st: $1w_1 + 1w_2 + 49w_3 + 3w_4 + 363w_5 + 155.15w_6 + 29.25w_7 = 1$

$68.35u_1 + 18.40u_2 -1w_1 -1w_2 – 49w_3 – 3w_4 + 363w_5 + 155.15w_6 + 29.25w_7 -u_0 \leq 0$

Region 11

Max: $56.18u_1 + 12.40u_2 - u_0$

st: $1w_1+1w_2+55.11w_3+3.09w_4 + 363w_5 + 127.52w_6 + 19.71w_7 = 1$

$56.18u_1 + 12.40u_2 - 1w_1- 1w_2- 55.11w_3- 3.09w_4 + 363w_5 + 127.52w_6 + 19.71w_7 - u_0 \leq 0$

Region 12 (Shopping Mall)

Max: $50.85u_1 + 6.33u_2 - u_0$

st: $1w_1 + 1w_2 + 51w_3 + 2w_4 + 524.10w_5 + 155.44w_6 + 10.06w_7 = 1$

$50.85u_1 + 6.33u_2 - 1w_1 - 1w_2 - 51w_3 - 2w_4 + 524.10w_5 + 155.44w_6 + 10.06w_7 - u_0 \leq 0$

Region 13

Max: $44.04u_1 + 9.83u_2 - u_0$

st: $1w_1 + 1w_2 + 21.76w_3 + 1.30w_4 + 401.55w_5 + 99.97w_6 + 15.62w_7 = 1$

$44.04u_1 + 9.83u_2 - 1w_1 - 1w_2 – 21.76w_3 – 1.30w_4 + 401.55w_5 + 99.97w_6 + 15.62w_7 - u_0 \leq 0$

Region 14

Max: $74.72u_1 + 12.05u_2 - u_0$

St: $1w_1 + 1w_2 + 59w_3 + 2w_4 + 514.65w_5 + 169.61w_6 + 19.17w_7 = 1$

$74.72u_1 + 12.05u_2 - 1w_1 - 1w_2 - 59w_3 - 2w_4 + 514.65w_5 + 169.61w_6 + 19.17w_7 - u_0 \leq 0$

Region 15

Max: $112.36u_1 + 33.36u_2 - u_0$

st: $1w_1 + 1w_2 + 24.55w_3 + 1.96w_4 + 297.90w_5 + 255.06w_6 + 53.05w_7 = 1$

$112.36u_1 + 33.36u_2 - 1w_1 - 1w_2 – 24.55w_3 – 1.96w_4 + 297.90w_5 + 255.06w_6 + 53.05w_7 - u_0 \leq 0$

Region 16

Max: $234.62 + 177.68u_2 – u_0$

St.: $1w_1 + 1w_2 + 26.30w_3 + 1.21w_4 + 476.95w_5 + 532.58w_6 + 287.70w_7 = 1$

$234.62u_1 + 177.68u_2 - 1w_1 – 1w_2 – 26.30w_3 – 1.21w_4 + 476.95w_5 + 532.58w_6 + 287.70w_7 – u_0 \leq 0$

Region 17

Max: $72.86u_1 + 2.02u_2 - u_0$

st: $1w_1 + 1w_2 + 52.84w_3 + 0.32w_4 + 514.65w_5 + 160.85w_6 + 3.21w_7 = 1$

$72.86u_1 + 2.02u_2 - 1w_1 - 1w_2 – 52.84w_3 – 0.32w_4 + 514.65w_5 + 160.85w_6 + 3.21w_7 - u_0 \leq 0$

Region 18

Max: $116.08u_1 + 47.86u_2 – u_0$

St: $1w_1 + 1w_2 + 45.82w_3 + 1.19w_4 + 363,85w_5 + 263.49w_6 + 76.12w_7 = 1$

$116.08u_1 + 47.86u_2 - 1w_1 - 1w_2 – 45.82w_3 - 1.19w_4 + 363,85\ w_5 + 263.49w_6 + 76.12w_7 – u_0 \leq 0$

Region 19

Max: $74.93u_1 + 22.46u_2 - u_0$

st: $1w_1 + 1w_2 + 34.40w_3 + 1.54w_4 + 476.95w_5 + 170.09w_6 + 35.71w_7 = 1$

$74.93u_1 + 22.46u_2 - 1w_1 - 1w_2 – 34.40w_3 – 1.54w_4 + 476.95w_5 + 170.09w_6 + 35.71w_7 - u_0 \leq 0$

These equations represent the mathematical formulation of the BCC output-oriented model for each region, with respective objective functions, constraints, and variables involved. This study was solved using Banxia Software with Frontier Analyst software. Frontier Analyst is a windows-based productivity analysis tool that uses DEA to measure the performance of each DMU that implements similar functions.

Frontier Analyst enables units to be compared to dividing resources more efficiently, increase the performance of planning strategies, and identify strengths and weaknesses (Hussain and Jones, 2001).

This software was chosen because it makes the inter-unit comparisons clear and understandable, reveals inefficient DMUs, and suggests improvement options for these units. It is easy to use with an easily understood language.

4. Results

The data set used in this study is shown in Table 1. The input variables are the number of trucks, couriers, delivery stops, pick-up stops, and the daily cost. The output variables are packages delivered, packages received, daily delivery compensation, and daily pick-up compensation. As seen in Table 1, the number of vehicles and couriers are equal and constant in all regions. However, the regions differ in terms of the other variables.

Table 1. Exporting Data to Frontier

Regions	Truck Number	Courier Number	Delivery Stop	Pick Up Stop	Daily Cost	Delivered Packages	Pick Up Packages	Delivery Cost	Pick Up Cost
Region 1	1,00	1,00	14,23	3,11	312,00	148,85	91,86	330,93	144,97
Region 2	1,00	1,00	22,00	1,00	312,00	141,83	91,08	321,96	144,81
Region 3	1,00	1,00	21,00	1,00	312,00	93,92	130,82	213,20	208,00
Region 4	1,00	1,00	16,00	1,00	514,65	64,03	4,08	145,34	6,49
Region 5	1,00	1,00	65,99	3,00	326,15	154,39	96,01	350,47	152,65
Region 6	1,00	1,00	27,90	0,10	392,15	63,45	12,45	212,14	28,26
Region 7	1,00	1,00	47,88	1,37	411,00	70,03	10,67	158,97	16,97
Region 8	1,00	1,00	55,00	3,00	345,00	73,75	15,68	167,41	24,94
Region 9	1,00	1,00	24,21	4,95	345,00	142,67	61,01	323,86	97,00
Region 10	1,00	1,00	49,00	3,00	363,00	68,35	18,40	155,15	29,25

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Region 11	1,00	1,00	55,11	3,09	363,00	56,18	12,40	127,52	19,71
Region 12	1,00	1,00	51,00	2,00	524,10	50,85	6,33	155,44	10,06
Region 13	1,00	1,00	21,76	1,30	401,55	44,04	9,83	99,97	15,62
Region 14	1,00	1,00	59,00	2,00	514,65	74,72	12,05	169,61	19,17
Region 15	1,00	1,00	24,55	1,96	297,90	112,36	33,36	255,06	53,05
Region 16	1,00	1,00	26,30	1,21	476,95	234,62	177,68	532,58	287,70
Region 17	1,00	1,00	52,84	0,34	514,65	70,86	2,02	160,85	3,21
Region 18	1,00	1,00	45,82	1,19	363,85	116,08	47,86	263,49	76,12
Region 19	1,00	1,00	34,40	1,54	476,95	74,93	22,46	170,09	35,71

Table 2 shows the Frontier Analyst results, which indicate how input- or output-oriented computation changes efficiency. Whether input-oriented or output-oriented, the program produces tables of maximum efficiency. Therefore, Table 2 shows both the input- and output-oriented results.

Table 2. Efficiency Scores of Regions

	Input Oriented		Output Oriented	
Regions	Score	Efficient	Score	Efficient
Region 1	100,0%	✓	100,0%	✓
Region 2	100,0%	☐	98.5%	☐
Region 3	100,0%	✓	100,0%	✓
Region 4	100,0%	✓	100,0%	✓
Region 5	100,0%	☐	61.1%	☐
Region 6	100,0%	✓	100,0%	✓
Region 7	100,0%	✓	100,0%	✓
Region 8	100,0%	✓	100,0%	✓
Region 9	100,0%	✓	100,0%	✓
Region 10	100,0%	✓	100,0%	✓
Region 11	100,0%	✓	100,0%	✓
Region 12	100,0%	☐	67.7%	☐
Region 13	100,0%	✓	100,0%	✓
Region 14	100,0%	✓	100,0%	✓
Region 15	100,0%	☐	69,1%	☐
Region 16	100,0%	✓	100,0%	✓
Region 17	100,0%	✓	100,0%	✓
Region 18	100,0%	✓	100,0%	✓
Region 19	100,0%	✓	100,0%	✓

All regions are grouped based on daily cost and distance. Each color represents a different group, while their operational efficiency is compared within the group. The input-oriented results indicate that there are no efficiency problems in any region as all are 100% efficient. On the other hand, the output-oriented efficiency results show that Regions 2, 5, 12, and 15 are operationally inefficient and require improvement to reach a 100% efficiency score. Tables 3-6 and Figures 1-4 present the improvements suggested by the analysis results for these regions.

Table 3. Potential improvements in region 2

Region 2	Actual	Goal	Improvement
Trucks	1	1	0
Couriers	1	1	0
Delivery stops	61.92	35.29	-43%
Pick up stops	1.56	1.56	0%
Daily cost	401.55	365.41	-9%
Delivered packages	74.72	75.47	1%
Picked up packages	12.05	23.26	93%
Daily delivery compensation	169.61	171.3	1%
Daily pick up compensation	19.17	36.99	93%

In table 3. the results represent a comparison of actual performance (in Region 2) with the predefined goals or benchmarks. The "Improvement" column shows the percentage difference between the actual values and the target/goal values for each performance metric. Therefore, the number of trucks and the number of couriers is fixed in all regions, no improvement is suggested.

The analysis of the results for region 2:

Delivery Stops: The actual number of delivery stops (61.92) is 43% higher than the goal (35.29). This suggests that the company is making more delivery stops than desired, and there is a need to optimize delivery routes or increase efficiency in this area.

Pick-up Stops: The actual number of pick-up stops (1.56) is exactly the same as the goal (1.56), indicating that the company is meeting its pick-up stop targets, and there is no improvement needed in this aspect.

Daily Cost: The actual daily cost (401.55) is 9% higher than the goal (365.41). This implies that the company is incurring slightly higher costs than desired, and there is room for improvement to reduce expenses.

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Delivered Packages: The actual number of delivered packages (74.72) is 1% less than the goal (75.47). The company is falling slightly short of its target for delivered packages, and efforts can be made to improve delivery efficiency.

Picked up Packages: The actual number of picked-up packages (12.05) is 93% lower than the goal (23.26). This indicates a significant shortfall in the number of packages picked up, and the company should focus on increasing the efficiency of its pick-up operations.

Daily Delivery Compensation: The actual daily delivery compensation (169.61) is 1% higher than the goal (171.3). The company is paying slightly more than the desired compensation for deliveries, and improvements can be made to manage costs in this area.

Daily Pick-up Compensation: The actual daily pick-up compensation (19.17) is 93% lower than the goal (36.99). This shows a substantial discrepancy in the compensation for pick-up operations, and efforts should be made to meet the desired compensation levels for pick-ups.

Overall, the analysis reveals areas where the cargo transportation company is performing well and areas where improvements are needed to align with predefined goals and increase operational efficiency. By addressing these discrepancies, the company can enhance its overall performance and effectiveness in Region 2. The detailed improvement graph for Region 2 is shown in Figure 1.

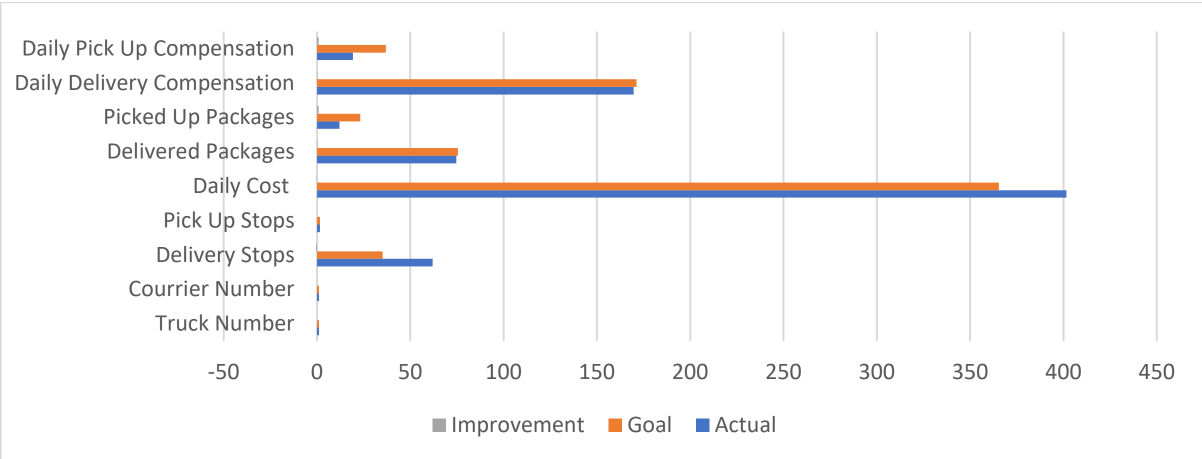

Figure 1. Region 2 Improvement Graph

Table 4. Potential improvements in region 5

Region 5	Actual	Goal	Improvement
Truck number	1	1	0%
Courier number	1	1	0%
Delivery stops	56.37	35.51	-37%

Pick up stops	3.54	3.54	0%
Daily cost	345	345	0%
Delivered packages	73.75	106.2	44%
Picked up packages	15.68	40.3	157%
Daily delivery compensation	167.41	241.07	44%
Daily pick-up compensation	24.94	64.09	157%

The analysis of the results for region 5:

Delivery Stops: The actual number of delivery stops (56.37) is 37% higher than the goal (35.51). This suggests that the company is making more delivery stops than desired, and there is a need to optimize delivery routes or increase efficiency in this area.

Pick-up Stops: The actual number of pick-up stops (3.54) is exactly the same as the goal (3.54), indicating that the company is meeting its pick-up stop targets, and there is no improvement needed in this aspect.

Daily Cost: The actual daily cost (345) is exactly the same as the goal (345), indicating that the company's cost management is aligned with the desired level, and there is no need for improvement in this area.

Delivered Packages: The actual number of packages delivered (73.75) is 44% less than the goal (106.2). The company is falling short of its target for delivered packages, and there is a significant scope for improvement in delivery efficiency.

Picked up Packages: The actual number of picked-up packages (15.68) is 157% higher than the goal (40.3). This indicates that the company has surpassed its target for picked-up packages, which is a positive performance aspect in this region.

Daily Delivery Compensation: The actual daily delivery compensation (167.41) is 44% less than the goal (241.07). The company is paying less than the desired compensation for deliveries, and efforts can be made to meet the target compensation levels.

Daily Pick-up Compensation: The actual daily pick-up compensation (24.94) is 157% higher than the goal (64.09). This shows that the company is compensating more than the desired amount for pick-up operations, and efforts can be made to manage costs in this area.

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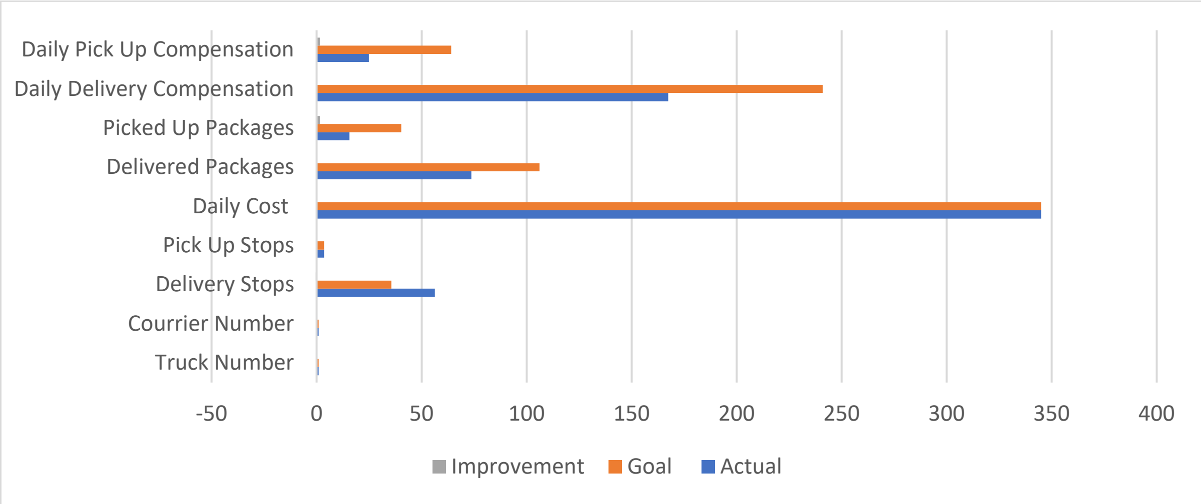

Figure 2. Region 5 Improvement Graph

Table 5. Potential improvements in Region 12

Region 12	**Actual**	**Goal**	**Improvement**
Truck number	1	1	0%
Courier number	1	1	0%
Delivery stops	69.87	15.37	-78%
Pick up stops	3.18	3.18	0%
Daily cost	392.15	329.4	-16%
Delivered packages	93.45	152.32	63%
Picked up packages	12.45	94.62	660%
Daily delivery compensation	212.14	345.79	63%
Daily pick up compensation	19.8	150.48	660%

The analysis of the results for region 12:

Delivery Stops: The actual number of delivery stops (69.87) is 78% higher than the goal (15.37). This indicates that the company is making significantly more delivery stops than desired, and there is a need to optimize delivery routes or increase efficiency in this area.

Pick-up Stops: The actual number of pick-up stops (3.18) is exactly the same as the goal (3.18), indicating that the company is meeting its pick-up stop targets, and there is no improvement needed in this aspect.

Daily Cost: The actual daily cost (392.15) is 16% higher than the goal (329.4). This suggests that the company's daily cost management needs improvement, as it exceeds the desired cost target in this region.

Delivered Packages: The actual number of packages delivered (93.45) is 63% less than the goal (152.32). The company is falling short of its target for delivered packages, and there is a significant scope for improvement in delivery efficiency.

Picked up Packages: The actual number of picked-up packages (12.45) is 660% higher than the goal (94.62). This indicates that the company has surpassed its target for picked-up packages, which is a positive performance aspect in this region.

Daily Delivery Compensation: The actual daily delivery compensation (212.14) is 63% less than the goal (345.79). The company is paying less than the desired compensation for deliveries, and efforts can be made to meet the target compensation levels.

Daily Pick-up Compensation: The actual daily pick-up compensation (19.8) is 660% higher than the goal (150.48). This shows that the company is compensating more than the desired amount for pick-up operations, and efforts can be made to manage costs in this area.

Figure 3 presents the detailed improvement graph for region 12.

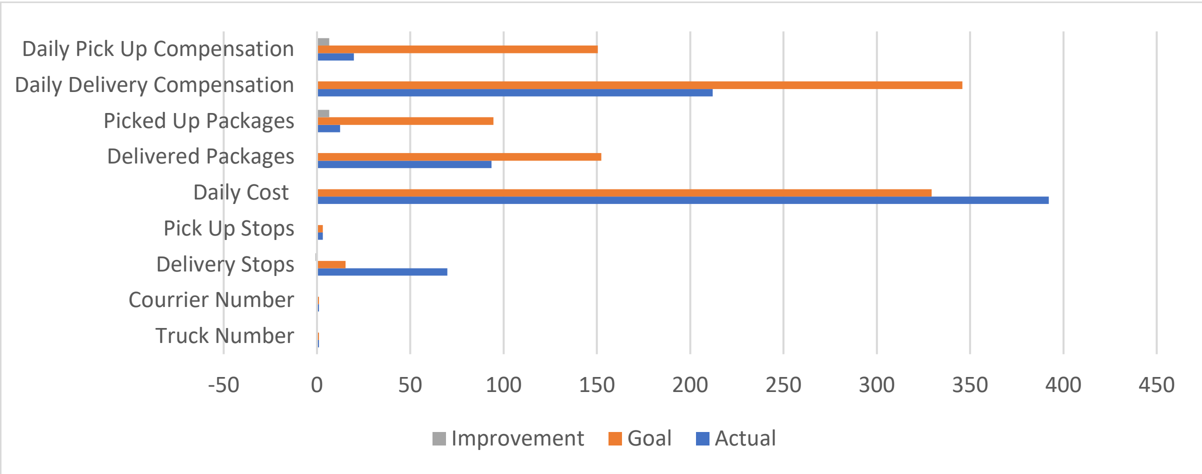

Figure 3. Region 12 Improvement Graph

Table 6. Potential improvements in region 15

Region 15	**Actual**	**Goal**	**Improvement**
Truck number	1	1	0%
Courier number	1	1	0%

Delivery stops	47.5	34.68	-27%
Pick up stops	2.6	2.6	0%
Daily cost	363.85	360.22	-1%
Delivered packages	56.18	82.58	47%
Picked up packages	12.40	25.42	105%
Daily delivery compensation	127.52	187.45	47%
Daily pick up compensation	19.71	40.4	105%

The analysis of the results for region 15:

Delivery Stops: The actual number of delivery stops (47.5) is 27% higher than the goal (34.68). This indicates that the company is making more delivery stops than desired, and there is a need to optimize delivery routes or increase efficiency in this area.

Pick-up Stops: The actual number of pick-up stops (2.6) is exactly the same as the goal (2.6), indicating that the company is meeting its pick-up stop targets, and there is no improvement needed in this aspect.

Daily Cost: The actual daily cost (363.85) is only 1% higher than the goal (360.22). This suggests that the company's daily cost management is relatively close to the desired target in this region, and there is a minor scope for improvement in managing costs.

Delivered Packages: The actual number of delivered packages (56.18) is 47% less than the goal (82.58). The company is falling short of its target for delivered packages, and there is a need to increase delivery efficiency or improve delivery operations.

Picked up Packages: The actual number of picked-up packages (12.40) is 105% higher than the goal (25.42). This indicates that the company has surpassed its target for picked-up packages, which is a positive performance aspect in this region.

Daily Delivery Compensation: The actual daily delivery compensation (127.52) is 47% less than the goal (187.45). The company is compensating less than the desired amount for deliveries, and efforts can be made to meet the target compensation levels.

Daily Pick-up Compensation: The actual daily pick-up compensation (19.71) is 105% higher than the goal (40.4). This shows that the company is compensating more than the desired amount for pick-up operations, and efforts can be made to manage costs in this area.

Overall, the analysis reveals areas where the cargo transportation company is performing well, such as having the desired number of trucks and couriers, meeting pick-up stop targets, and surpassing the target for picked-up packages. However, there are areas that require improvement, such as optimizing delivery stops, increasing the number of delivered packages, and aligning delivery and pick-up compensation with the desired levels. By addressing these aspects, the company can enhance its overall performance and effectiveness in region 5, Region 12 and Region15.

Figure 4 presents the detailed improvement graph for region 15.

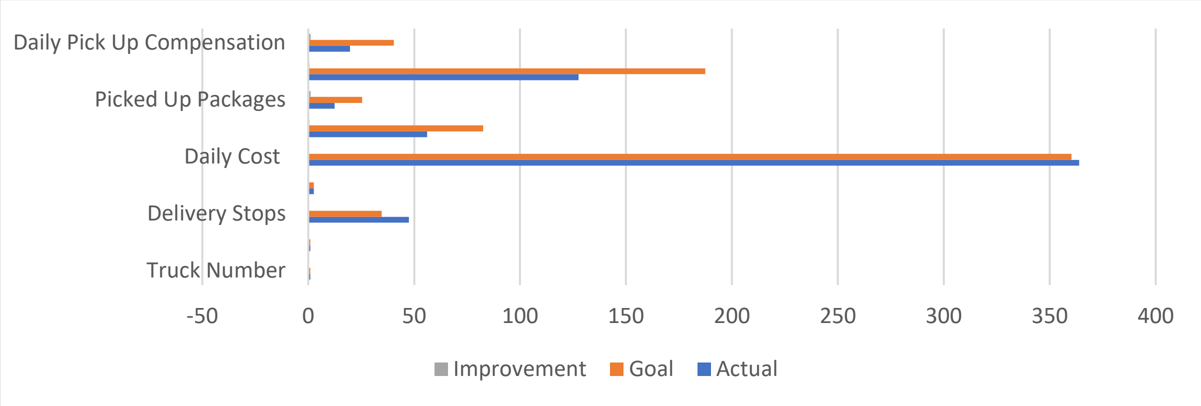

Figure 4. Region 15 Improvement Graph

To address the identified problems in regions 2, 5, 12, and 15, the company should implement specific strategies and improvements. Below are some suggested solutions for each region:

Region 5, Region 12 and Region 15:

Delivered packages and pick up packages are the main issues for Region 5, Region 12 and Region 15.

Delivered Packages: Implement process improvements to enhance delivery efficiency and meet the delivery targets. This may include better coordination between drivers, more efficient loading/unloading processes, and reducing delivery time per package.

Picked Up Packages: Reevaluate the allocation of resources and prioritize delivery and pick-up operations based on demand and capacity. Ensure that the focus on pick-ups does not compromise overall efficiency.

Region 2, Region 12 and Region 15:

The number of delivery stops is the main problem of region 2, Region 12 and Region 15. Optimizing delivery routes by using advanced route planning software to minimize unnecessary stops and improve overall efficiency. Consider grouping deliveries to reduce the number of stops in certain areas.

Region 2 and Region 15:

Daily Cost is the last problem of region 2 and Region 15. Identify cost-saving opportunities, such as optimizing fuel consumption, vehicle maintenance, and resource allocation. Conduct regular cost analysis to identify areas where cost reduction is feasible.

In summary, the main problems in these regions are related to overcapacity in delivery stops, deviations from the target for delivered packages, and an excessive focus on pick-up operations, which may lead to imbalances and inefficiencies in resource allocation. The company needs to optimize its delivery route planning, improve delivery efficiency, and balance pick-up and delivery operations to enhance overall performance in these regions.

5. Conclusion and Suggestions

After the data obtained from the logistics company were processed using the Frontier Analyst program, the results were analyzed comparatively. Regarding the efficiency of the 19 regions, 15 regions were shown to be 100% efficient, whereas four regions (2, 5, 12, and 15) were less than 100% efficient. The analysis indicated that these four regions could improve their efficiency by reducing the number of stops. For example, if the company can combine stops in nearby locations, it can reduce the inefficiency due to stopping and start movements.

The calculations indicate that the company needs to reduce the number of vehicles stops by adopting joint distribution and collection procedures in regions where these can be merged appropriately. Where the number of packages collected does not cover the cost, the company should either find ways to increase the number of packages, such as finding new customers, or merging regions with low package numbers.

Regarding the region's characteristics, Region 15 is a resort zone. The company can reduce daily costs by 60% if it cuts the number of delivery and collection days per week to this region from five to three in winter. In current economic conditions, a 60% saving is significant.

Regions 2 and 12 include shopping malls, collection and distribution are only performed during the morning. Thus, salary costs can be reduced by about 50% by recruiting part-time workers in these regions.

The increased profits that the company will gain by making these improvements in specific regions can be used for process improvements or technological developments.

The company's main problem concerns last-mile delivery processes. Currently, there are too many stops at this stage, which slows down processes while increasing the company's carbon footprint.

It is very important for companies to develop environmental approaches by considering this situation. The solutions can include joint delivery and distribution points, vehicle or product assembly, joint distribution, etc.

In order for the company to reduce its carbon footprint and manage its processes more effectively, it is important both for the profitability of the company and for the circular economy to combine deliveries at certain points and to benefit from part-time labor at certain points.

5.1. Managerial Implications

The main problem facing this logistics company is that it divides nearby areas into different regions, which causes too many stops and starts movements in each region. Therefore, the first recommendation is to reschedule the delivery vehicle's stop and start zones by using small carriers within these areas.

Recent research in logistics underscores the importance of route planning to minimize stop and start movements. Wang et al. (2022) conducted a study on urban delivery route optimization using advanced algorithms and small carriers. Their findings demonstrate that incorporating small carriers within specific areas can significantly reduce unnecessary stops and improve overall efficiency, leading to cost savings and enhanced customer satisfaction (Wang et al., 2022).

Another suggestion is to combine nearby regions, as inactive regions are very close to each other with few packages in each. Combining nearby regions will increase the number of packages processed, thereby increasing efficiency. Similarly, combining two zones can reduce the number of vehicles stop and start movements. Zhao and Zhang (2023) investigated the benefits of region consolidation in the logistics industry. Their study revealed that merging nearby regions with low package volumes into a single operational area can lead to considerable cost reductions, resource optimization, and reduced stop and start movements, resulting in enhanced operational efficiency (Zhao & Zhang, 2023).

Combining inactive areas and only employing workers at certain hours in shopping centers increases efficiency and benefits the company by reducing costs, unnecessary labor costs, and fuel costs while increasing time efficiency. Li et al. (2021) explored workforce management strategies in logistics operations. Their research demonstrates that implementing time-based workforce allocation in specific regions, such as shopping centers, leads to enhanced operational efficiency by reducing labor costs and idle time while ensuring timely deliveries (Li et al., 2021). Regarding distribution regions, the basic problem is that certain regions are unnecessarily divided. By combining these, the company can increase its overall effectiveness by reducing resource costs like labor and vehicles allocated to the area. Studies by Kumar et al. (2020) emphasize the importance of efficient distribution region design. Their research highlights that eliminating unnecessary divisions and consolidating regions can lead to resource optimization, cost savings, and improved delivery performance, supporting the company's objective of enhancing overall effectiveness (Kumar et al., 2020). At a time when resources are continuously decreasing, companies need to take responsibility to use them more efficiently. Doing so in their daily shipments should be more important than delivery speed or number. By organizing its processes in this way, the company can use both resources more efficiently while reducing its costs. Zhang and Chen (2023) investigated sustainable logistics practices in the face of resource constraints. Their study underscores the need for companies to prioritize resource optimization over speed and volume, aligning with the recommendation to enhance resource utilization for cost savings and operational sustainability (Zhang & Chen, 2023).

Similarly, conducting distribution processes in shopping centers during certain times can reduce the costs of vehicles, resources, and labor allocated to this region on a full-day basis. A half-day planning is sufficient for these regions. Recent research by Kim and Park (2022) investigated time-based distribution planning for shopping centers. Their findings reveal that adopting a half-day planning approach can lead to significant cost reductions by optimizing vehicle utilization and labor allocation while maintaining timely deliveries within shopping center regions. Incorporating the insights from these recent studies reinforces the recommendations for the logistics company, emphasizing the potential benefits of route optimization, region consolidation, time-based workforce allocation, and resource efficiency to improve operational effectiveness and reduce costs.

5.2 Limitations and Future Research

Recent studies indicate the use of Data Envelopment Analysis (DEA) to measure social and environmental performance impacts (Hatami-Marbini et al., 2024; Nannar et al., 2024; Kim et al., 2024). One limitation of these studies is that they are primarily focused on firm-level efficiency and do not incorporate social and environmental impacts at this stage. Future research could enhance these studies by integrating these parameters.

This study was conducted specifically in Izmir, revealing factors influencing firms' efficiency. A benchmarking exercise with applications in different cities or across different firms could highlight variations. Another constraint is that the study relied on primary data obtained from the firms, where certain parameters defined as inputs were fixed and could not be altered. Therefore, the study was conducted solely in an output-oriented manner. Future research could explore different datasets and conduct input-oriented analyses to compare results effectively.

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