Journal of Applied Informatics Research Vol 2 No 1 (2026) pp. 57~72

Journal of Applied Informatics Research
Fakultas Vokasi, Kampus Unesa 1, Ketintang, Surabaya, Indonesia
Website: https://journal.unesa.ac.id/index.php/jair/ | E-mail: jair@unesa.ac.id

Implementation of Data Envelopment Analysis (DEA) for Vehicle Efficiency Analysis in Fleet Management System Design at PT Fesa Antaran Logistik

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ARTICLE INFORMATION

Article history:

Received July 24, 2026
Revised July 28, 2026
Accepted July 28, 2026

Keywords:

Data Envelopment Analysis;
DEA BCC;
Fleet Management System;
Logistics;
Operational Efficiency

ABSTRACT

Fleet management systems play a vital role in improving logistics operations by supporting operational data management and decision-making. However, many logistics companies still rely on fragmented administrative processes and lack analytical tools for objectively evaluating fleet operational efficiency. This study proposes a web-based Fleet Management System integrated with the Data Envelopment Analysis (DEA) BCC input-oriented model to support operational management and efficiency assessment. The system was developed using the Waterfall methodology with Laravel as the web framework, MySQL as the database management system, and Python as the DEA computational engine. Operational data collected from PT. Fesa Antaran Logistik between January and June 2025 were analyzed using 10 selected fleet units as Decision Making Units (DMUs). Functional testing achieved a 100% success rate, while validation against MaxDEA demonstrated high computational consistency with a maximum deviation of 0.000043. The DEA analysis identified four relatively efficient fleets and six relatively inefficient fleets, with an indicative potential operational cost saving of IDR 75,918,125 to support managerial evaluation. Due to the relative nature of DEA, this estimate should not be interpreted as a definitive cost reduction target. The findings are limited by the relatively small sample size, purposive DMU selection, and a six-month observation period. Future research should employ larger and more homogeneous datasets while incorporating CCR comparison, slack variable analysis, and robustness testing to improve the reliability of efficiency assessment.

1. INTRODUCTION

Global logistics and supply chain management plays a crucial role in facilitating the movement of goods, supporting business operations, and driving economic growth [1]. The rapid advancement of information technology has accelerated the digital transformation of logistics services, encouraging companies to adopt integrated information systems to improve operational efficiency and decision-making [2], [3]. Among these technologies, Fleet Management Systems (FMS) have become an essential component for managing vehicle operations, monitoring fleet performance, optimizing delivery routes, and maintaining operational records [4]. The integration of information systems with data analytics further enables logistics companies to improve operational transparency and resource utilization. Nevertheless, the increasing cost of transportation and logistics operations remains a major challenge, particularly in developing countries, where effective cost control and operational efficiency have become critical factors for maintaining business competitiveness [5].

PT. Fesa Antaran Logistik, a logistics service provider, relies heavily on its vehicle fleet to support daily distribution activities. However, operational management is still constrained by fragmented documentation of delivery orders, vehicle maintenance records, and operational expenditures, making reporting and managerial evaluation less efficient. The absence of an integrated information system also limits the company's ability to monitor fleet performance comprehensively and support data-driven decision-making. To address these challenges, implementing a web-based Fleet Management System is considered an effective solution for integrating operational data management into a centralized platform. The Laravel framework provides a suitable development environment for enterprise-scale web applications because of its modular architecture, security features, and maintainability [6]-[9].

Besides improving administrative processes, logistics companies also require objective methods to evaluate the operational efficiency of each fleet unit. Conventional performance evaluation often relies on descriptive indicators, making it difficult to determine whether operational costs are proportional to the resulting operational outputs. Data Envelopment Analysis (DEA), originally introduced by Charnes, Cooper, and Rhodes, is a non-parametric mathematical approach designed to measure the relative efficiency of Decision Making Units (DMUs) using multiple input and output variables [10], [11]. Compared with traditional ratio-based performance measurements, DEA can simultaneously evaluate multiple operational factors without requiring a predefined production function, making it particularly suitable for logistics and transportation performance assessment [12]. The widespread application of DEA has demonstrated its effectiveness in evaluating operational efficiency in various strategic sectors, particularly in transportation and logistics. Previous studies have shown that DEA can provide reliable efficiency evaluations for transportation companies and logistics distribution systems based on objective operational data [13], [14].

This study adopts the input-oriented BCC model because fleet operations are characterized by Variable Returns to Scale (VRS), where operational efficiency is influenced by differences in vehicle utilization, transportation demand, and operating conditions. Under these circumstances, reducing operational inputs while maintaining service outputs is considered more relevant than assuming Constant Returns to Scale (CRS). Therefore, the BCC model provides a more appropriate analytical framework for evaluating fleet efficiency in the operational context of PT. Fesa Antaran Logistik.

Despite the growing adoption of Fleet Management Systems and DEA in logistics applications, relatively few studies have integrated both approaches into a unified decision-support platform capable of simultaneously managing operational data and evaluating fleet efficiency. Therefore, this study develops a web-based Fleet Management System integrated with the DEA BCC input-oriented model to support operational data management while providing objective efficiency evaluation for logistics fleet operations. The discussion of related studies and the research gap is presented in the following section.

2. LITERATURE REVIEW

2.1. Previous Research

The literature review in this study covers the concepts of Fleet Management Systems (FMS), Data Envelopment Analysis (DEA), and supporting web technologies for logistics management. Fleet Management Systems have been widely adopted to improve vehicle administration, maintenance scheduling, operational monitoring, and reporting through integrated information systems. The Laravel framework is commonly employed for developing enterprise-scale web applications due to its modular architecture, security, and maintainability, while MySQL serves as a reliable relational database for managing operational data. Furthermore, the DEA BCC input-oriented model has been extensively utilized as a quantitative approach for evaluating the relative efficiency of Decision Making Units (DMUs) based on multiple input and output variables.

Previous studies have demonstrated the effectiveness of Fleet Management Systems in improving operational administration and vehicle monitoring. A fleet management application was developed to support vehicle condition monitoring, tax management, and complaint reporting, significantly improving fleet administration; however, the system focused primarily on operational management without incorporating efficiency evaluation capabilities [6]. Similarly, a web-based car rental information system developed using the Waterfall methodology enhanced rental management processes through a structured development approach but did not provide analytical support for operational performance evaluation [15]. In the field of efficiency assessment, the DEA BCC model has been successfully applied to evaluate the performance of state-owned banks [16], while DEA has also been employed to assess logistics distribution efficiency based on multiple operational indicators [14]. Furthermore, the deaR-Shiny web application was introduced to facilitate DEA computation through an interactive web interface; however, it functions primarily as a standalone analytical tool rather than an integrated operational information system [17].

Despite these advancements, existing studies have generally focused either on developing Fleet Management Systems for operational administration or on applying DEA as an independent efficiency evaluation method. Limited research has integrated DEA directly into a web-based Fleet Management System that simultaneously manages logistics operational data and performs objective fleet efficiency analysis within a unified decision-support environment. Therefore, this study develops a web-based Fleet Management System integrated with the DEA BCC input-oriented model to support administrative processes while providing data-driven evaluation of vehicle operational efficiency for logistics companies.

3. RESEARCH METHODS

The following are the research stages in the implementation of data envelopment analysis (DEA) for vehicle efficiency analysis in the design of a fleet management system at PT. FESA ANTARAN LOGISTIK.

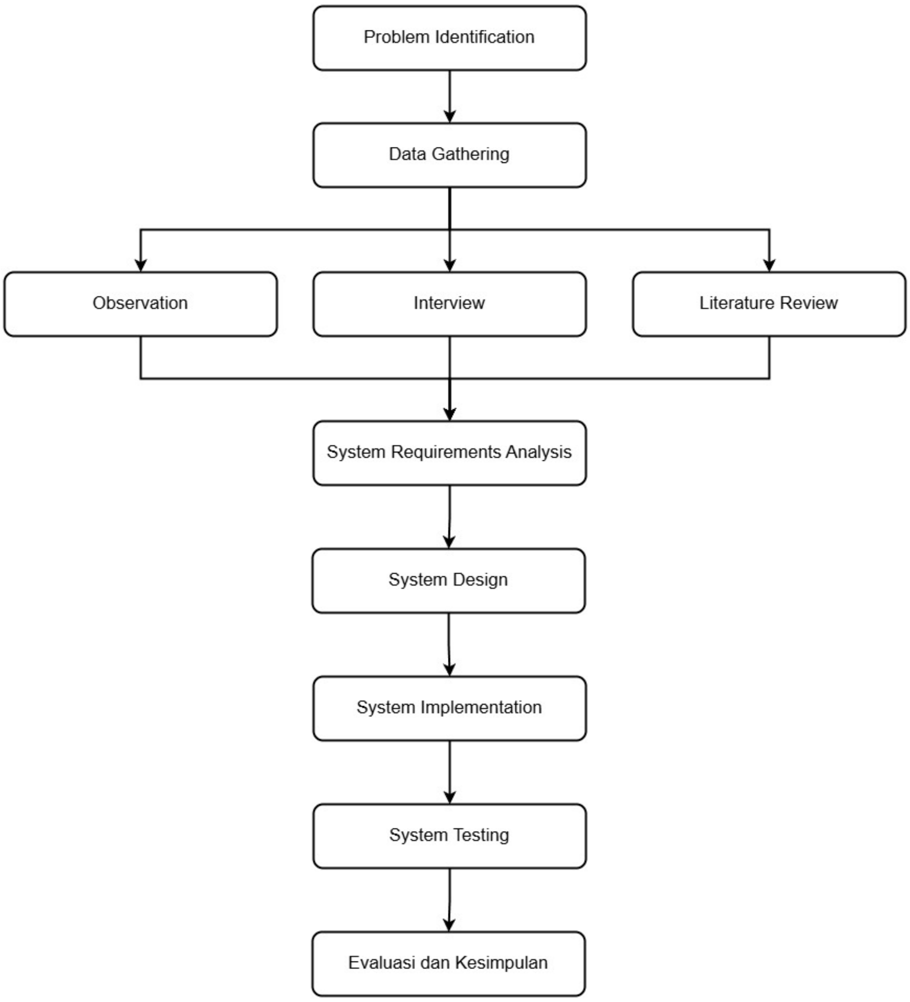

Figure 1. Research Stages

3.1. Problem Identification

Based on observations of business processes at PT. Fesa Antaran Logistik, there are two main problems facing the company:

1) Unintegrated Recording System: Operational documentation such as Delivery Orders (DO) and fleet maintenance costs are still recorded separately (partially). This slows down the flow of information, is prone to manual input errors, and complicates the preparation of management reports.
2) Lack of Objective Efficiency Evaluation Tools: Management lacks data-based benchmarks for assessing vehicle performance. As a result, the company struggles to identify productive versus inefficient fleets (increasing costs), hampering informed asset renewal decisions.

3.2. Data Collection

To obtain the concrete information and data needed to develop the application and run the mathematical modeling, this study employed three main approaches, as described below:

1) The first approach was field observation, where researchers directly observed the daily workflow of operational staff, including managing DO documents, distributing driver allowances, and handling vehicles entering the workshop for routine maintenance.
2) The second approach was conducted through structured interviews with operational administration staff and management. These interviews aimed to understand specific user needs, identify technical challenges encountered, and determine the most relevant operational variables for the company.
3) The third approach was a documentation study, which involved collecting historical operational documents on PT. Fesa Antaran Logistik's vehicles. The data collected included a summary of road costs (such as fuel, tolls, and driver allowances), maintenance costs (periodic repairs and spare part replacement), total trip distance, and total revenue (income) generated by each fleet within a specific evaluation period (monthly or every 6 months).

Although PT. Fesa Antaran Logistik operates approximately 90 active fleets, this study employed purposive sampling to select 10 Decision Making Units (DMUs) for the primary analysis. The selected fleets were required to satisfy predefined criteria, including complete operational records, identical observation periods (January–June 2025), comparable operational characteristics, and consistent service activities. This sampling strategy was intended to ensure data consistency and comparability among DMUs. However, the findings should be interpreted within the context of the selected sample and may not be directly generalized to the entire fleet population.

3.3. System Requirements Analysis

The requirements analysis phase is conducted to determine the software's primary functions, technical requirements, and the analytical computing parameters to be developed. In terms of functional requirements, the system must be able to provide an interface for user authentication (login), a vehicle data management module, a Delivery Order (DO) data input and recapitulation module, and a maintenance cost recording module. Furthermore, the required core functionality includes a main computing module for automatically executing efficiency calculations and a reporting dashboard for management. In terms of non-functional requirements, the system must have login security and access restrictions based on user roles. The system must be easy to use by Admins and Staff without requiring additional training. The system must be able to consistently process large amounts of fleet operational data. The system must be responsive and reliably accessible through a browser. The system must ensure data integrity between modules to avoid inconsistencies. The system must be able to integrate with Python modules to run the DEA process. Regarding the need for analysis using the Data Envelopment Analysis (DEA) method, evaluation parameters have been established based on company agreements. The input variables used are the total vehicle operating costs, which are the accumulation of road costs and maintenance costs, while the output variables are measured based on vehicle productivity results, namely the total revenue generated and the total fleet mileage. Overall, the development of this fleet management system adopts the Waterfall Software Development Life Cycle (SDLC) model because of its systematic and sequential nature [18].

3.4. System Design

The system design stage is a crucial phase that translates all requirements analysis results into a technical blueprint before the coding process begins. This section encompasses the overall functional architecture of the logistics system and the design of analytical components based on linear programming using the input-oriented Data Envelopment Analysis (DEA) model (Banker, Charnes, Cooper) [19].

1) Use Case Diagram

   The Fleet Management System Use Case Diagram shows the interactions between Staff and Admin with the system. Staff can manage operational data and run DEA analyses, while Admin has all Staff access plus user data management. All use cases are connected to the login process as the initial authentication step. This diagram illustrates the interaction flow and user access rights in a concise and structured manner. The Use Case Diagram below shows an image:

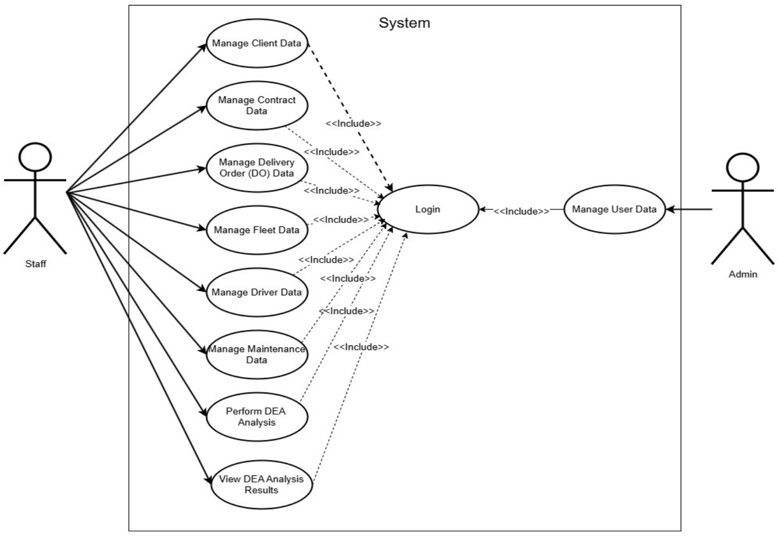

Figure 2. Use Case Diagram

2) Class Diagram

The system's relational database structure is modeled through a class diagram that integrates user management, logistics operations, and analytical computing into a single, unified data ecosystem. Operationally, the Client class relates to the Contract and DeliveryOrder classes, where the latter records all delivery variables such as distance, payload, road fares, and revenue, and is directly connected to the Driver and Fleet classes. To support vehicle maintenance management, the Fleet class relates to the Maintenance class, which records maintenance history and costs based on the MaintenanceType class's classification as an operational cost component. Meanwhile, in the analytical module, the Fleet class is connected to the DEAResult class, which stores input parameters, outputs, and scores from Data Envelopment Analysis (DEA) calculations. All efficiency evaluation results are periodically managed by the DEAAnalysis class, which records time parameters and the user actors who execute the computations. This comprehensive integration between classes results in a tightly bound data model that supports both logistics administration governance and structured vehicle performance evaluation. The class diagram below shows:

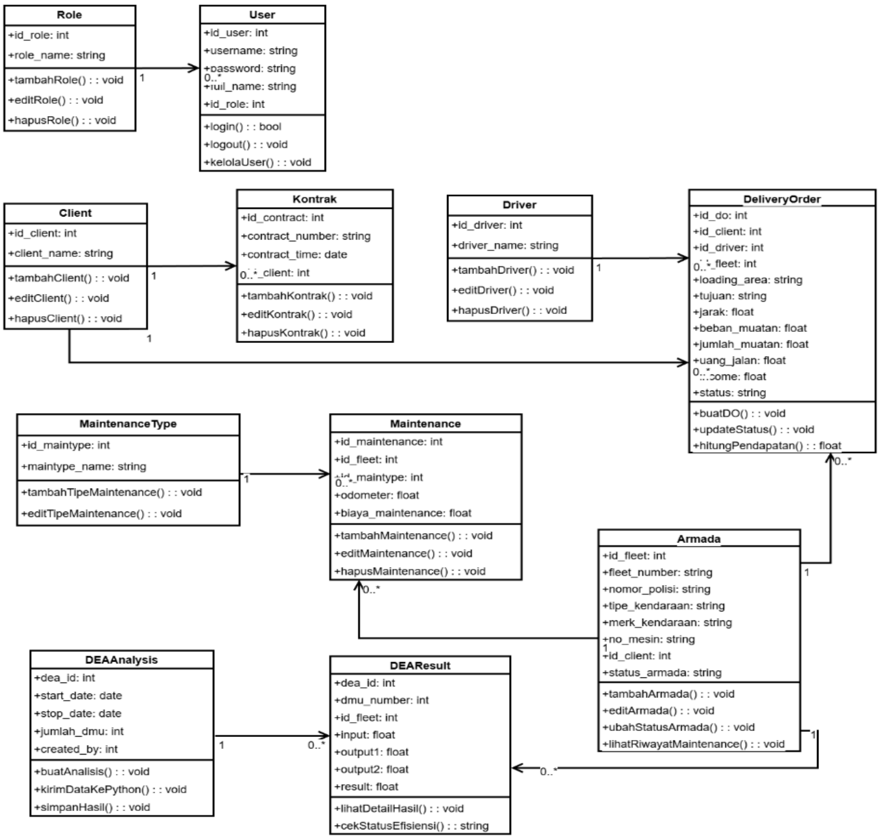

Figure 3. Class Diagram

3) Decision Making Unit (DMU)

A Decision-Making Unit (DMU) represents an operational entity whose efficiency is evaluated relative to other comparable units using the DEA model. In this study, the trucking fleet of PT. Fesa Antaran Logistik serves as the DMU because each vehicle operates under the same organizational management, performs comparable logistics distribution activities, and consumes similar categories of operational resources while generating comparable service outputs. From approximately 90 active fleets, 10 DMUs were selected using purposive sampling based on data completeness, identical observation periods, operational consistency, and comparable fleet characteristics. Although one vehicle belongs to a different truck category, it performs the same logistics distribution function under identical operational policies and was therefore retained in the analysis. Nevertheless, fleet heterogeneity may influence the efficiency frontier and should be considered in future studies by evaluating homogeneous fleet classes separately.

4) Variabel Input and Output

The determination of input and output variables in the DEA model is based on fleet evaluation needs, system data availability, and interviews with the Head of Operations of PT. Fesa Antaran Logistik for the period January to June 2025.

- Input Variables: Represent the sacrifice of economic resources in the form of total vehicle operating costs per period, which includes accumulated road costs (fuel, tolls, driver allowances) and maintenance costs (repairs and spare parts).
- Output Variables: Represent the fleet's physical and financial productivity results, expressed in total revenue from deliveries and total vehicle mileage (kilometers).

5) Matriks Input and Output

Before performing the DEA calculation, the system first compiles the input and output data from the fleet selected by the user. The data used is the aggregation of operational costs, kilometers traveled, and fleet revenue during the analysis period. At this stage, each fleet is treated as a Decision-Making Unit (DMU) whose efficiency level will be compared with other fleets. For each DMU or vehicle (j), the data used consists of one input variable and two output variables. The input variable used is the total vehicle operational costs, while the output variables used are the total kilometers traveled and the total vehicle revenue. Mathematically, this data can be written as follows:

A. Input

$x_{1,jj}$ = Total operational costs of the jj vehicle

B. Output

$y_{1,jj}$ = Total distance traveled (km) of the jj vehicle

$y_{2,jj}$ = Total income of the jj vehicle

The results of data collection and aggregation then form two main matrices used in DEA optimization modeling: the input matrix (X) and the output matrix (Y). The input matrix (X) contains the operational costs for each vehicle, while the output matrix (Y) contains the kilometers traveled and revenue for each vehicle. The general form of these matrices is as follows:

$$XX = \{xi,jj\} \quad (1)$$

$$Y = \{yr,jj\} \quad (2)$$

Where:

i is the number of inputs (1 input),
r is the number of outputs (2 outputs),
jj is the number of vehicles (DMU).

With this arrangement, the (X) matrix contains the operational costs of each vehicle, while the (Y) matrix contains the kilometers traveled and revenue of each vehicle. These input and output matrices are then used as the basis for input-oriented DEA BCC optimization modeling to compare the relative efficiency between vehicles.

6) Selection of the DEA Model

This study adopts the input-oriented BCC model because fleet operations are characterized by Variable Returns to Scale (VRS). Vehicle utilization, transportation demand, and operational workload vary among fleets, making the assumption of Constant Returns to Scale (CRS) less appropriate. Furthermore, the company primarily seeks to minimize operational costs while maintaining delivery performance and revenue. Therefore, the input-oriented BCC model was selected because it better reflects actual fleet operating conditions and supports cost-efficiency evaluation under varying operational scales.

7) Input-Oriented DEA BCC Optimization Formulation

Each DMU will be evaluated using the input-oriented DEA BCC model. The objective of this model is to minimize the input of vehicle 0 (the DMU being analyzed) while maintaining a minimum output equal to that of the other vehicles. The optimization formula is as follows:

$$min\ \theta\theta \tag{3}$$

$$\sum_{jj=1}^{n} \lambda_{jj} x_{1,jj} \leq \theta\theta x_{1,k} \tag{4}$$

$$\sum_{jj=1}^{n} \lambda_{jj} y_{1,jj} \leq y_{1,k} \tag{5}$$

$$\sum_{jj=1}^{n} \lambda_{jj} y_{2,jj} \leq y_{2,k} \tag{6}$$

$$\sum_{jj=1}^{n} \lambda_{jj} = 1 \tag{7}$$

$$\lambda_{jj} \geq 0,\ jj = 1,2,3,\dots,n \tag{8}$$

Description:

a) $X_{1,k}$ = operational costs of the kth fleet being evaluated.
b) $Y_{1,j}$ = kilometers traveled by the jth fleet.
c) $Y_{1,k}$ = kilometers traveled by the kth fleet being evaluated.
d) $Y_{2,j}$ = revenue of the jth fleet.
e) $Y_{2,k}$ = revenue of the kth fleet being evaluated.
f) λ_j = comparative weight of each fleet.
g) n = number of fleets or DMUs being analyzed.

Equation (1) shows the objective function of the input-oriented DEA BCC model, which is to minimize the value of $\theta\theta$. The value of $\theta\theta$ is used to indicate the level of fleet efficiency. Equation (2) is an input constraint indicating that the combined operating costs of the comparison fleet must not exceed the operating costs of the fleet being evaluated after being multiplied by the value of $\theta\theta$. Equations (3) and (4) are output constraints, namely that the combined output of the comparison fleet must be able to generate kilometers traveled and revenue at least equal to the fleet being evaluated. Equation (5) is a convexity constraint that characterizes the BCC model or Variable Returns to Scale (VRS). This constraint is used so that efficiency comparisons are conducted taking into account differences in operational scale between fleets. Equation (6) is a non-negativity constraint, meaning the comparison weight value λjj cannot be negative. The resulting $\theta\theta$ value ranges from 0 to 1. If $\theta\theta$ = 1, then the fleet is declared relatively efficient. Conversely, if $\theta\theta$ < 1, then the fleet is declared inefficient because there is still an opportunity to reduce operational costs without reducing kilometers traveled and revenue generated.

8) Flowchart DEA

Once the input-oriented DEA BCC optimization formulation is determined, the next step is to explain the DEA calculation flow in the system. This flow includes fleet operational data collection, data validation, DEA model development, the optimization process using a solver, and the presentation of vehicle efficiency results.

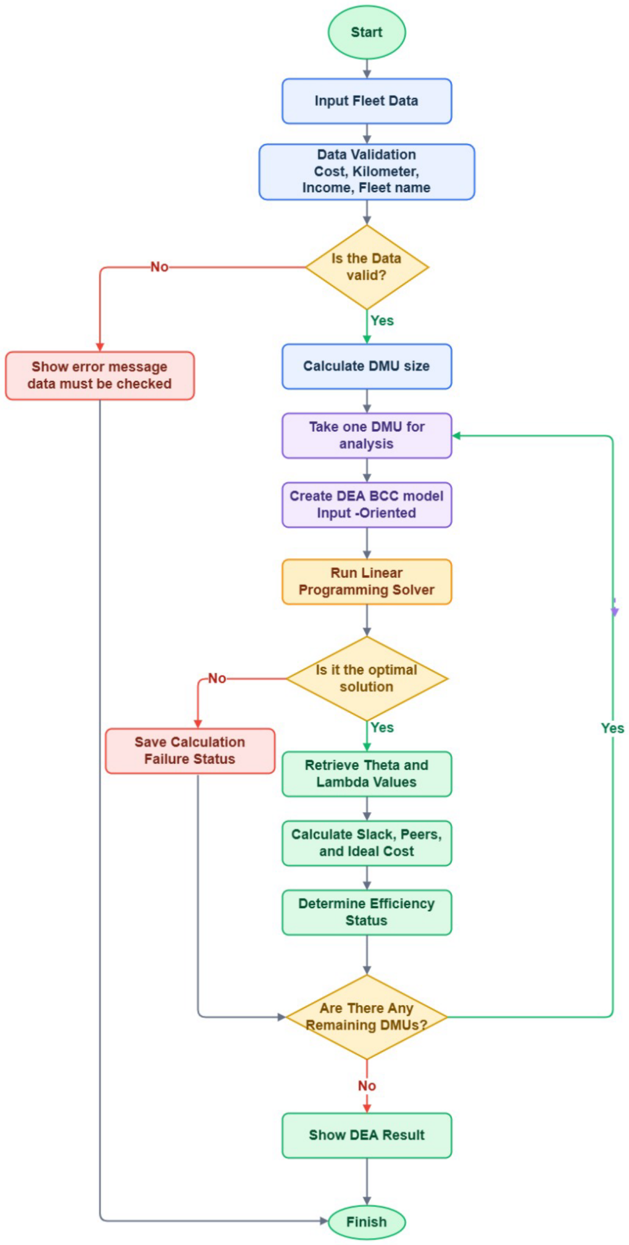

Figure 4. Flowchart DEA

9) Interpretation and Output of DEA Analysis Results

The primary performance indicator generated by the proposed system is the radial efficiency score (θ), ranging from 0 to 1. A value of $\theta = 1$ indicates that the evaluated fleet is radially efficient under the input-oriented BCC model, whereas $\theta < 1$ indicates that operational inputs can still be proportionally reduced without decreasing output levels. The current implementation focuses on radial efficiency evaluation. Slack variable analysis, which provides additional information regarding Pareto-Koopmans efficiency, is beyond the scope of the present system implementation and is recommended for future development.

10) System Implementation

System implementation is the stage of realizing the previously created design into an application that can be used by users. In this study, a fleet management system and vehicle efficiency analysis module based on Data Envelopment Analysis (DEA) were implemented using a combination of Laravel [20], MySQL [21], and Python technologies. This section describes the development environment used, the implementation architecture, and the implementation of each of the system's main components.

11) System Testing

The final stage of this research methodology is system testing, which aims to validate software quality, functional accuracy, and the alignment of analytical computing performance to user needs. The functionality testing approach was rigorously implemented using the Black-Box Testing method, developing structured test scenarios to verify the functionality of the authentication component, the accuracy of storing delivery order data forms, the reliability of maintenance cost recording calculations, and the execution of the DEA module.

In addition to interface testing, this study also conducted algorithm validation testing to ensure accuracy. Testing was conducted by preparing a set of test data containing operational costs, mileage, and revenue. This data was then calculated using MaxDEA software outside the system as reference values. The same data was then processed through the system's DEA module, and the resulting efficiency results were compared to these reference values. If the results were the same or within a reasonable difference, the DEA module was deemed to be functioning correctly.

4. RESULT AND DISCUSSION

4.1. System Implementation

At this stage, the DEA system is implemented to analyze vehicle efficiency. The system provides two main roles: admin and staff. The admin can manage staff data.

1) DEA Analysis Page

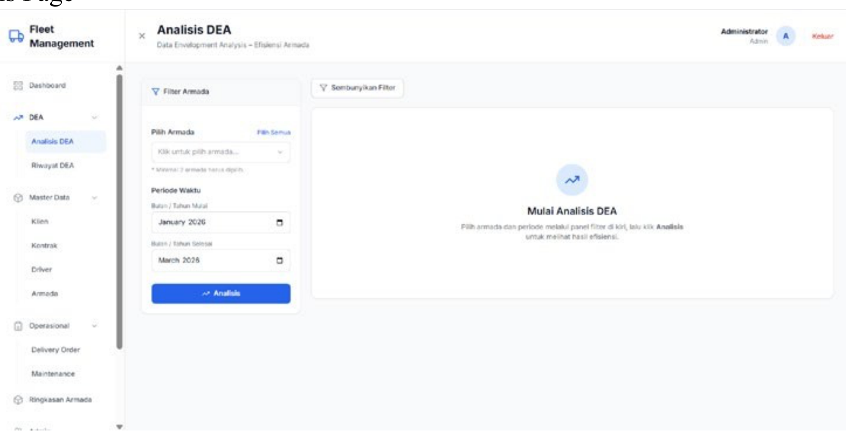

Figure 5. DEA Analysis Page

The DEA analysis module is the main component that connects operational data to the vehicle efficiency evaluation process. This page displays the DEA Analysis page, which is used to select the period and fleet to be analyzed as DMUs.

2) DEA Analysis Results Page

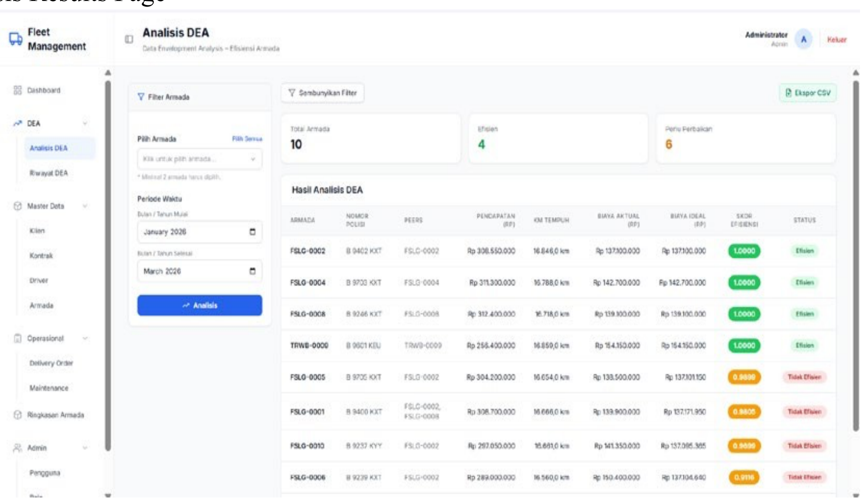

Figure 6. DEA Analysis Page

This page displays calculation results such as efficiency score, status, peers, ideal cost, and potential savings and this page also has a filter feature that contains fleet options, start year period, and end year period.

3) DEA History Page

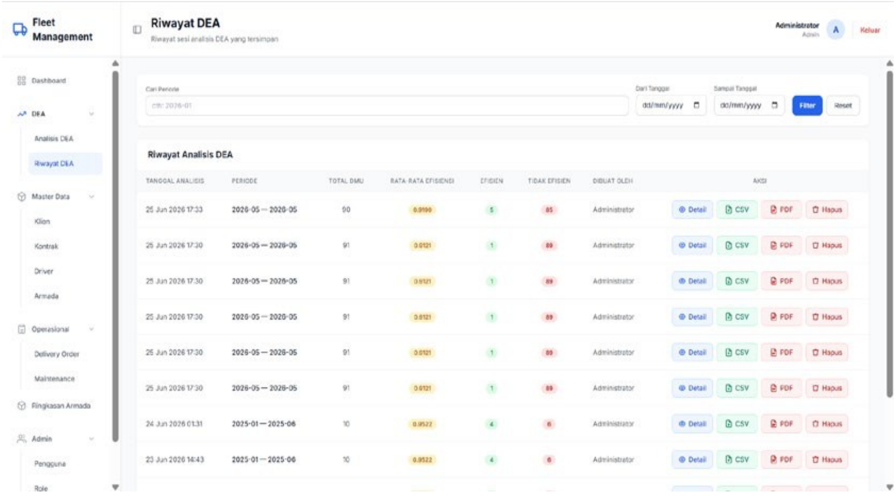

Figure 7. DEA History Page

This page displays the history of DEA analysis results for review. It includes the DEA analysis date, period, total score, details, CSV export, PDF export, and deletion.

4) DEA History Detail Page

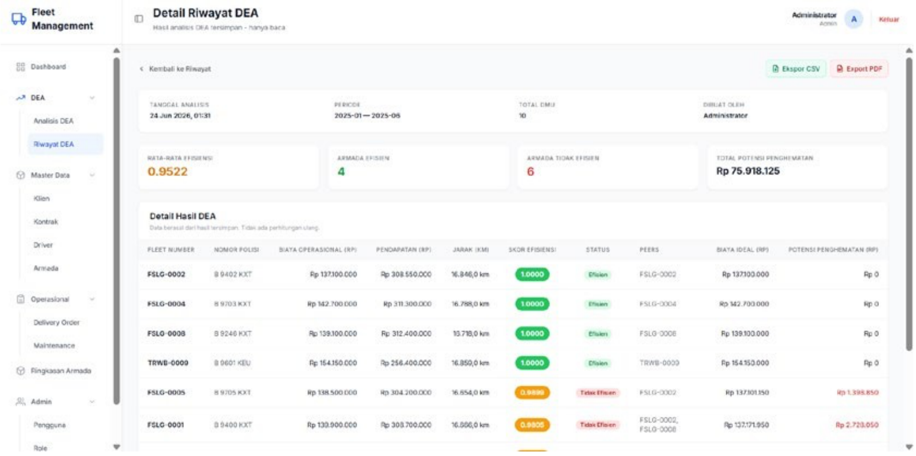

Figure 8. DEA History Detail Page

This page displays the results of the DEA analysis through the system interface, the DEA History module is also equipped with efficiency data, date, period, total potential savings, PDF export features, and CSV export.

5) Implementation of the DEA Code

```
# Python solver: stapp.py
theta = pl.LpVariable("theta", lowBound=0, upBound=1, cat="Continuous")
lamda = [
    pl.LpVariable(f"lamda_{j}", lowBound=0, cat="Continuous")
    for j in range(n)
]

prob += theta
prob += pl.lpSum(lamda[j] * x[j] for j in range(n)) <= theta * x[k]
prob += pl.lpSum(lamda[j] * y1[j] for j in range(n)) >= y1[k]
prob += pl.lpSum(lamda[j] * y2[j] for j in range(n)) >= y2[k]
prob += pl.lpSum(lamda[j] for j in range(n)) == 1
prob.solve(pl.PULP_CBC_CMD(msg=False))

theta_val = pl.value(theta)
peers = [names[j] for j in range(n) if pl.value(lamda[j]) > 0.001]

# Laravel enrichment: DeaAnalysisController.php
$theta = $res["Efisiensi"];
$biayaIdeal = $theta * $actualCost;
$potensiPenghematan = $actualCost - $biayaIdeal;
return compact("theta", "peers", "biayaIdeal", "potensiPenghematan");
```

Figure 9. Code Implementation DEA

Figure 9 shows the core DEA implementation in the system. The process begins with Laravel collecting operational data based on the fleet and analysis period selected by the user. The data is then compiled into a DMU payload and sent to a Python service for processing.

The calculated results from Python are then returned to Laravel to be displayed in a more user-friendly format. The theta value is multiplied by the actual cost to yield the ideal cost, while the difference between the actual and ideal costs is displayed as potential savings.

4.2. Implementation of DEA Calculation Results

1) Research Data

The research data were obtained from the operational records of PT. Fesa Antaran Logistik from January to June 2025. Although the company operates approximately 90 active fleets, this study employed purposive sampling to select 10 fleets as Decision Making Units (DMUs). The selected fleets met predefined criteria, including complete operational records, identical observation periods, and comparable operational characteristics, ensuring consistency during DEA evaluation. While this sampling strategy improves data quality and comparability, the findings should be interpreted within the context of the selected DMUs and may not be generalized to the entire fleet population.

Table 1. Characteristics of 10 Research DMUs

No	DPU Name	Plate Number	Fleet Type	Fleet Brand	Capacity
1	FSLG-0001	B 9400 KXT	Long	Hino	55-60
2	FSLG-0002	B 9402 KXT	Long	Hino	55-60
3	FSLG-0003	B 9702 KXT	Long	Hino	55-60
4	FSLG-0004	B 9703 KXT	Long	Hino	55-60
5	FSLG-0005	B 9705 KXT	Long	Hino	55-60
6	FSLG-0006	B 9239 KXT	Long	Hino	55-60
7	FSLG-0007	B 9991 KXS	Long	Hino	55-60
8	FSLG-0008	B 9246 KXT	Long	Hino	55-60
9	TRWB-0009	B 9601 KEU	Tronton	Hino	35-50
10	FSLG-0010	B 9237 KYY	Long	Hino	55-60

AAlthough TRWB-0009 belongs to a different truck category with a lower carrying capacity than the other fleets, it performs the same logistics distribution function under identical operational management. Therefore, it was retained in the DEA model to represent the company's operational fleet. Nevertheless, differences in vehicle characteristics may influence the efficiency frontier and should be considered in future studies by grouping fleets according to vehicle class.

2) Aggregation of DEA Input and Output Variables

Before the Data Envelopment Analysis (DEA) calculation process is carried out, the system first aggregates data based on fleet and analysis period so that each fleet has a single data set ready for calculation. Operational costs are obtained by adding up road costs on delivery orders and vehicle maintenance costs. Kilometers traveled are obtained from the total distance on delivery orders, while revenue is obtained from the total fleet income from January to June 2025. The aggregated data is then used as input and output in the DEA calculation process.

Tabel 2. Aggregation of DEA Input and Output Variables

No	DMU	Actual Cost	KM Mileage	Revenue
1	FSLG-0002	Rp 137.100.000	16.846	Rp 308.550.000
2	FSLG-0004	Rp 142.700.000	16.788	Rp 311.300.000
3	FSLG-0008	Rp 139.100.000	16.718	Rp 312.400.000
4	TRWB-0009	Rp 154.150.000	16.859	Rp 256.400.000
5	FSLG-0005	Rp 138.500.000	16.654	Rp 304.200.000
6	FSLG-0001	Rp 139.900.000	16.666	Rp 308.700.000
7	FSLG-0010	Rp 141.350.000	16.661	Rp 297.050.000
8	FSLG-0006	Rp 150.400.000	16.560	Rp 289.000.000
9	FSLG-0003	Rp 161.150.000	16.409	Rp 288.000.000
10	FSLG-0007	Rp 167.300.000	16.412	Rp 282.350.000

The table above shows that each fleet has a different combination of inputs and outputs. These differences form the basis for DEA to compare the relative efficiency between fleets. Using the input-oriented BCC approach, the system looks not only at costs but also compares operational costs against two outputs: kilometers traveled and revenue.

3) Initial Analysis of Fleet Data Characteristics

The initial analysis in Table 2 reveals considerable variation in operational costs, mileage, and revenue among the selected fleets. Interestingly, TRWB-0009 recorded the highest mileage but generated the lowest revenue. This discrepancy suggests that operational performance cannot be adequately represented by a single indicator. It may also reflect differences in fleet utilization or operational assignments, reinforcing the need for a multi-input and multi-output evaluation method such as DEA. Consequently, the efficiency results should be interpreted as relative performance within the selected DMU set rather than absolute operational performance.

4) Implementation of DEA Calculations in the System

The DEA calculation implementation process in the system begins when the user selects a period and fleet as the DMU in the DEA Analysis module, which then triggers the system to retrieve and aggregate delivery order and maintenance data into operational cost, mileage, and revenue variables. This aggregated data is sent to a Python-based analytics service to be evaluated using the input-oriented DEA BCC model to minimize operational costs without reducing the achieved output [11]. Through this optimization process, an efficiency score is obtained to determine fleet status, peer values for comparison, and ideal cost calculations and potential savings. All calculation results from this Python service are finally returned to the Laravel system to be displayed on the analysis results page and stored as a history, thus transforming the system not only as an operational recording medium but also as a data-based vehicle efficiency analysis tool.

5) Fleet Efficiency Analysis Results

The results of the fleet efficiency analysis are presented in Table 3. An efficiency score of 1.0000 indicates that the fleet is on the relative efficiency frontier. Conversely, a score below 1.0000 indicates that the fleet is inefficient relative to other fleets in the same DMU group and analysis period. The efficiency score is obtained based on a comparison of input and output variables processed using the DEA method. These results serve as the basis for identifying fleets requiring operational efficiency improvements.

Tabel 3. Fleet Efficiency Analysis Results

No	DMU	Peers	Ideal Cost	Potential Savings	Score	Status
1	FSLG-0002	FSLG-0002	Rp 137.100.000	Rp 0	1,0000	Efficient
2	FSLG-0004	FSLG-0004	Rp 142.700.000	Rp 0	1,0000	Efficient
3	FSLG-0008	FSLG-0008	Rp 139.100.000	Rp 0	1,0000	Efficient
4	TRWB-0009	TRWB-0009	Rp 154.150.000	Rp 0	1,0000	Efficient
5	FSLG-0005	FSLG-0002	Rp 137.101.150	Rp 1.398.850	0,9899	Inefficient
6	FSLG-0001	FSLG-0002, FSLG-0008	Rp 137.171.950	Rp 2.728.050	0,9805	Inefficient
7	FSLG-0010	FSLG-0002	Rp 137.095.365	Rp 4.254.635	0,9699	Inefficient
8	FSLG-0006	FSLG-0002	Rp 137.104.640	Rp 13.295.360	0,9116	Inefficient
9	FSLG-0003	FSLG-0002	Rp 137.106.420	Rp 24.043.580	0,8508	Inefficient
10	FSLG-0007	FSLG-0002	Rp 137.102.350	Rp 30.197.650	0,8195	Inefficient

It is important to note that an efficiency score of 1.0000 under the input-oriented BCC model indicates radial efficiency relative to the observed DMUs. It does not necessarily imply Pareto-Koopmans efficiency because slack variables were not evaluated in the current system implementation. Therefore, the identified efficient fleets should be interpreted as relatively efficient within the analyzed dataset.

Meanwhile, six fleets scored below 1.0000: FSLG-0005, FSLG-0001, FSLG-0010, FSLG-0006, FSLG-0003, and FSLG-0007. These fleets are categorized as relatively inefficient because they still have potential for reducing operational costs compared to fleets on the efficiency frontier.

6) Analysis of Ideal Costs and Potential Savings

   The cumulative potential operational cost saving for the six relatively inefficient fleets was estimated at IDR 75,918,125. This value should be interpreted as an indicative managerial reference derived from the DEA model rather than a guaranteed or definitive cost reduction target. Since DEA evaluates relative efficiency within a specific set of DMUs, the estimated savings may vary if different fleet compositions, operational periods, or evaluation models are applied.

7) Initial Interpretation of DEA Calculation Results

   The dominance of FSLG-0002 as the primary peer indicates that this fleet consistently demonstrates the most favorable input-output relationship among the selected DMUs. However, because DEA efficiency is relative to the observed dataset, peer relationships may change if additional fleets are included or different operational periods are analyzed. Consequently, the efficiency frontier identified in this study should be interpreted within the scope of the selected sample.

4.3. Testing

The testing phase is conducted to determine whether all features and systems are running according to design. Testing is conducted using the Black Box Testing method and algorithm validity testing to evaluate the algorithm.

1) Black Box Testing

   In system testing, testing is conducted using the Black Box Testing method, a software testing method that focuses on examining system functions based on input and output without examining the program code structure within it [22], [23]. This testing is conducted to ensure that the main functions of the Fleet Management System and the Data Envelopment Analysis (DEA) module are running properly and meet user functional requirements. Testing is conducted on several main modules, including authentication functions (login/logout), master data management (clients, contracts, drivers, fleets), operational activity recording (delivery orders and maintenance), access rights restrictions, and DEA analysis execution. The validation percentage is calculated using the following formula:

$$system\ suitability\ level = \frac{16}{16}\ x\ 100\% = 100\% \tag{9}$$

   These results indicate that the system's core functions met the tested functional requirements. The system is capable of performing login and logout processes, managing client data, contracts, delivery orders, fleets, drivers, maintenance, and users, limiting access rights based on user roles, and performing DEA analysis, from selecting a timeframe and fleet selection to data processing and displaying the analysis results.

2) DEA Calculation Results using MaxDEA

   Validation of DEA calculation results was performed to ensure that the analysis module in the system produces efficiency scores consistent with the comparison software. In this study, validation was performed by comparing the DEA calculation results from the system with the calculation results using MaxDEA. The data used in both calculations were the same input-output data, namely operational costs as input and kilometers traveled and revenue as output. The model used was also the same, namely input-oriented DEA BCC. The validation results of the DEA calculation using MaxDEA are shown in Table 4.

Table 4. DEA Calculation Results

No	DMU	System Results	MaxDEA Results	Difference
1	FSLG-0002	1,0000	1,000000	0,000000
2	FSLG-0004	1,0000	1,000000	0,000000
3	FSLG-0008	1,0000	1,000000	0,000000
4	TRWB-0009	1,0000	1,000000	0,000000
5	FSLG-0005	0,9899	0,989892	0,000008
6	FSLG-0001	0,9805	0,980543	0,000043
7	FSLG-0010	0,9699	0,969933	0,000033
8	FSLG-0006	0,9116	0,911569	0,000031
9	FSLG-0003	0,8508	0,850760	0,000040
10	FSLG-0007	0,8195	0,819486	0,000014

Based on Table 4, all 10 DMUs had consistent calculation results between the system and MaxDEA. Four DMUs, namely FSLG-0002, FSLG-0004, FSLG-0008, and TRWB-0009, had a difference of 0.000000 because the system and MaxDEA results both showed an efficiency score of 1.0000. Meanwhile, the other six DMUs had very small differences. The largest difference was found in FSLG-0001, at 0.000043. This difference did not change the DMU's efficiency status and was due to differences in decimal rounding between the system and MaxDEA results. These validation results demonstrate that the DEA calculation module

In the system is consistent with MaxDEA for the research data used. Thus, the system not only succeeded in terms of interface functionality and data management, but also produced efficiency calculations that matched the benchmarking tools. However, this validation remains limited to the data, models, and scenarios tested, so it cannot be interpreted as general validity for all possible operational data outside the scope of the research.

Although the validation confirms the computational accuracy of the proposed DEA implementation, it does not represent robustness validation of the efficiency conclusions. Future research should investigate the stability of the efficiency frontier through robustness analyses, such as jackknife procedures or DEA window analysis.

5. CONCLUSION

This study successfully developed and implemented a web-based Fleet Management System integrated with the input-oriented Data Envelopment Analysis (DEA) BCC model to support operational data management and fleet efficiency evaluation at PT. Fesa Antaran Logistik. The proposed system integrates Laravel as the web platform, MySQL for operational data management, and Python for DEA computation, enabling automated efficiency analysis within a unified operational environment. Functional testing achieved a 100% success rate, while validation against MaxDEA demonstrated high computational consistency with a maximum deviation of 0.000043, confirming the reliability of the implemented DEA algorithm.

The DEA analysis identified four relatively efficient fleets and six relatively inefficient fleets based on the selected Decision Making Units (DMUs). In addition, the system generated an indicative estimate of potential operational cost savings that can be used as a managerial reference for evaluating fleet performance and identifying opportunities for operational improvement.

This study is subject to several limitations. First, the DEA analysis was conducted using 10 purposively selected DMUs from approximately 90 operational fleets, which may limit the discriminatory power and generalizability of the efficiency results. Second, although the selected fleets perform comparable logistics distribution activities, differences in vehicle categories may influence the efficiency frontier. Third, the analysis was limited to a six-month observation period and employed the input-oriented BCC model without evaluating CCR efficiency, slack variables, or robustness analyses.

Future research should incorporate larger and more homogeneous fleet datasets, compare CCR and BCC models to distinguish technical and scale efficiency, evaluate slack variables for Pareto-Koopmans efficiency, and perform robustness analyses such as jackknife testing, DEA window analysis, or the Malmquist Productivity Index to investigate changes in fleet efficiency over time.

ACKNOWLEDGEMENTS

The authors would like to express their sincere gratitude to PT. Fesa Antaran Logistik for providing the data, facilities, and support required to conduct this research. The authors also appreciate all individuals who contributed to the successful completion of this study.

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