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Evaluation of Efficiency in Logistics Company: An Analysis of Last-Mile Delivery

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Abstract: Major developments in the e-commerce business have an impact on supporting industries, such as the logistics industry. Logistics service providers for e-commerce consumers must focus on the quality of their services. Service quality is determined by meeting customer expectations, including on-time delivery, parcel security, and customer service. In the process of sending parcels, one thing that affects the timeliness of delivery is the last-mile delivery stage. Due to a large number of last-mile stations and the geographic dispersion of their locations throughout Indonesia, the service quality between stations becomes inhomogeneous. The performance of the last-mile station can be measured by comparing the relative efficiency between stations. In this study, the initial stage of the efficiency analysis of the last-mile delivery station is by conducting a cluster analysis that divides the station into two groups, namely the Leader and Majority clusters, which aim to group homogeneous DMUs. Efficiency analysis with DEA is given for each cluster. The result shows that 94 of the 133 stations are relatively efficient for the Leader cluster stations, and 136 of the 466 stations are relatively efficient for the Majority cluster stations. A decision tree method is used for classification modeling to determine the characteristics of a relatively efficient station. Total daily delivery becomes the initial variable that determines the station to enter the Leader or Majority cluster. The second criterion is the variable number and quantity of goods delivered on time.

Keywords: last-mile delivery, data envelopment analysis, cluster analysis, decision tree

1. Introduction

E-commerce is one of the fastest-growing businesses in Indonesia[1)], and the growth from 2015 to 2019 increased by almost 500% based on data from the Indonesian E-Commerce Association (idEA). The development of the e-commerce business contributes to the expansion of the logistics market and forces the logistics business to develop technology[2)].

With this growth, logistics companies must focus on improving service quality in every stage of their operations, including the first-mile (handover from a seller to logistics), middle-mile (transportation from warehouse to retail location), and last-mile delivery (delivery from a retail location to customer)[3)]. In the last-mile stage, a large number of retail points are located near the final destination, allowing for coverage in both urban and rural areas. However, there are several challenges in delivering goods through home delivery services, including inefficient regulation of urban goods transportation, a limited fleet size leading to delays, inconsistent timing of goods receipt, and high shipping costs[4,5)].

Last-mile delivery is often called one of the most expensive, inefficient, and polluting parts of the environment[6,7)]. Since it has to be close to the customer's location, there are many retail locations or what will be called last-mile stations. Due to a large number of last-mile stations and the geographic dispersion of their locations throughout Indonesia, the service quality between stations becomes inhomogeneous.

Due to these challenges, logistics companies must focus on improving the quality of their services, especially in the face of the rapid growth of home delivery services, which has also led to an increase in demand for last-mile deliveries[4)]. Focusing on service quality allows logistics companies to demonstrate their capability and reliability and improve their public image with consumers[8)].

Service quality is measured by comparing customer expectations and actual service[9)]. Previous research on the service industry has shown that efficiency and service quality have a positive correlation[10)]. For logistics customers, service quality is measured by on-time delivery, safety, and customer service. Reliability is one of the variables used to determine service quality, which is seen from the promised service performance reliably and accurately[11)]. The more efficient the process, the faster the parcel can be delivered than initially promised.

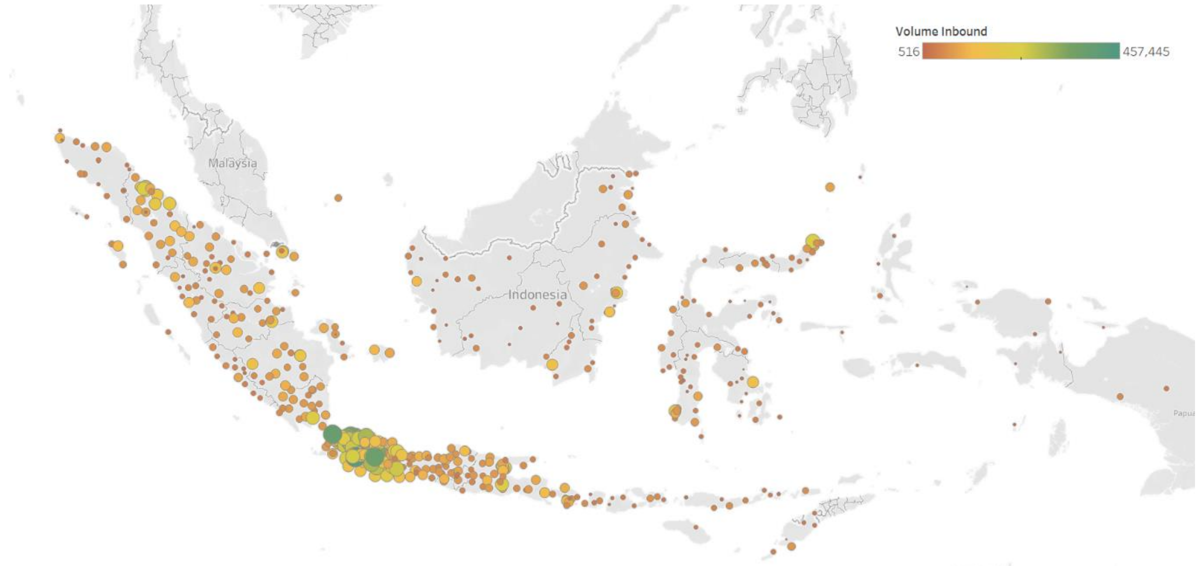


Fig. 1: Distribution of Inbound Volume per Station of the logistic company

In this research, we will discuss the case studies from one of the Indonesian logistics companies that provide parcel delivery services for online shopping. Figure 1 shows the distribution of the number of parcels received by the station from the company being studied. The green color indicates a high volume of inbound parcels. It can be observed from the figure that parcel delivery is concentrated in the Java region, specifically in West Java and Jakarta. There may be discrepancies among stations' performance, leading to the need to group stations with similar characteristics.

The disparities in delivery performance between regions will affect the overall quality of the service. To understand the reasons for these performance differences, it is necessary to conduct further research to identify the factors that influence the performance of last-mile stations. The performance of last-mile stations can be evaluated by comparing the efficiency of different stations relative to one another.

One method that can be used to evaluate the efficiency of last-mile stations as part of the service industry is Data Envelopment Analysis (DEA). DEA is a non-parametric method used to analyze the efficiency of multiple inputs and outputs from each domain, also known as Decision Making Units (DMUs)[12)]. In this context, we can utilize DEA to measure the efficiency of the last-mile stations by treating them as DMUs. This approach allows us to assess the efficiency of the last-mile stations.

In DEA analysis, it is necessary to assume that the DMUs are homogenous. However, as previously noted, the heterogeneity of last-mile stations is unavoidable. To overcome heterogeneity, the step that can be taken is by grouping the last-mile stations with the same characteristics as cluster analysis (CA). All DMUs cannot be assumed to be homogeneous because it will limit the results of the DEA analysis, even if heterogeneity in the sample will increase the discriminatory power of DEA results[13)].

The characteristics of a relatively efficient DMU need to be identified to determine what variables affect the efficiency and cluster differences of the last-mile delivery station. By knowing these characteristics, companies can then identify how to increase efficiency to influence the service quality of the last-mile delivery stations. Identification of the characteristics of this relatively efficient station can use classification modeling with a Decision Tree (DT). Previous studies have combined DT and DEA in analyzing the characteristics of the DMU[13,14)].

Based on the background, the research questions that emerge are: how to measure the efficiency of last-mile delivery stations and classify their efficiency? In light of these questions, this study aims to analyze the efficiency of last-mile delivery stations and investigate the modeling of their efficiency classification. We aim to develop a reliable framework for evaluating the efficiency of the last-mile process.

2. Theoretical review

2.1. Data Envelopment Analysis (DEA)

DEA is a non-parametric method that can be used to assess the efficiency of various Decision Making Units (DMUs) with multiple inputs and outputs[12)]. It is a mathematical technique that can be applied to a range of industries, such as the service sector (e.g., hospitals, universities, schools, banks)[15,16,17,18)]. DEA utilizes programming methods that can handle a large number of variables and constraints, and allows for flexibility in the selection of inputs and outputs[19)].

One of the non-radial DEA models is the Slacks-Based Measure (SBM) Model. This model was first introduced by Tone (2001). The SBM model is designed to meet the following two requirements[20)].

- The size does not change with the unit of measurement for each input and output item (Unit Invariant)
- The size is monotonous according to each input and output slack (Monotone)

In estimating the efficiency of the DMU(x_o, y_o), the formulation of the fractional program λ, s^-, and s^+ is shown in equation (1).

$$(SBM) \quad \rho = \frac{1 - \frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{io}}{1 - \frac{1}{\delta}\sum_{r=1}^{\delta} s_r^+ / y_{io}} \qquad (1)$$
$$subject\ to \quad x_o = X\lambda + s^-$$
$$y_o = Y\lambda - s^+$$
$$\lambda \geq 0, s^- \geq 0, s^+ \geq 0$$

where ρ is the value of efficiency and the value of X≥0. The first SBM requirement, namely Unit Invariant, can be proven from the value of the objective function ρ because the numerator and denominator are measured in the same unit for each item.

2.2. Cluster analysis

One of the algorithms for cluster analysis is the k-means method. K-means is a straightforward and effective algorithm for finding clusters[21,22]. The algorithm for k-means is as follows:

- Stage 1: Determine the number of clusters k, based on the results of calculations or business decisions.
- Stage 2: Randomly assigns k as much data to the center of the initial cluster.
- Stage 3: Find the nearest cluster center for each data set. So, each data is grouped based on its nearest center to become a data set with data clusters or groups $C_1, C_2, \dots, C_k$.
- Stage 4: For each cluster k, find the center or centroid and vary the location for each cluster center to the center.
- Stage 5: Repeat stages 3-5 until convergent.

The determination of the closest distance in Stage 3 usually uses the Euclidean distance. The cluster center at stage 4 is found in the following stages. For example, there are n data $(a_1, b_1, c_1), (a_2, b_2, c_2), \dots, (a_n, b_n, c_n)$, so that the center or centroid of the data is located at point $\left(\sum \frac{a_i}{n}, \sum \frac{b_i}{n}, \sum \frac{c_i}{n}\right)$.

2.3. Decision tree

The decision tree classification method involves constructing a decision tree, a collection of decision nodes linked by branches, extending downward from the root (root node) to ending at the leaf nodes. Algorithms start from the root node, which is usually placed at the top of the decision tree diagram, and attributes are tested on the decision nodes, with each possible result producing a branch[21].

In general, two decision tree algorithms are often used, namely Classification and Regression Trees (CART) and the C4.5 algorithm. The CART was first introduced by Breiman in 1984. The decision tree for the CART is binary, containing two branches for each decision node.

The Gini index is used in the CART method. Equation 2 shows the calculation of the Gini value.

$$Gini(D) = 1 - \sum_{i=1}^{m} p_i^2 \qquad (2)$$

where m is the number of classes, p_i is the probability that the tuples in data D are in class C_i and are estimated $|C_{i,D}|/|D|$. The Gini index considers the binary separation for each attribute.

3. Research methods

3.1. Data collection and pre-processing

This study will discuss the efficiency of the last-mile delivery station from a shipping company in Indonesia. The data period is October to December 2020. The calculation of efficiency using DEA has two variables: input and output. Table 1 shows the input and output variables used in this study. The data used in this study are from 599 stations spread throughout Indonesia. The data used shows the performance of each station. The performance variable of each station is seen from the delivery lead time[23] and the service performance[24].

The Inbound Volume was selected as the input variable because it reflects the demand from each station. The total courier and employee salary variables are factors that can be controlled by the company in operations and therefore act as supporting variables to the demand. The performance of each station is shown through measures of productivity, on-time volume, and volume of full parcels. It is assumed that the volume of inbound goods should be proportional to the volume of goods sent on time and in full. In addition, a station's productivity is likely to increase with a higher number of couriers and higher salaries. Therefore, there is a relationship between the input and output variables.

Table 1. Research Variables

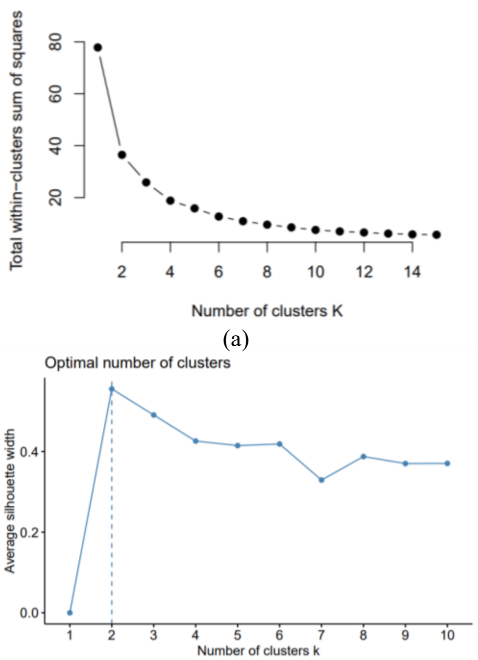
Variable Type	Variable Name	Definition
Input	Total courier	Number of couriers per Last-mile Delivery Station
	Inbound Volume	The total number of parcels inbound to the station
	Employee salary	The average cost to pay employees, all station coordinators, contract-based riders, and freelance riders
Output	Productivity	Total number of parcels sent to customers each day
	Ontime volume	Total number of parcels delivered on time (N-0 inbound)
	Volume in-full parcels	Total parcels without complaints from customers

Data pre-processing was necessary before data processing. This pre-processing stage consisted of data cleaning and selection. The data cleansing and selection phase is carried out by deleting data that have missing values because the stations have closed or moved places in the data observation period, which October-December 2020. Initially, the data on the number of stations were 766 stations decreased to 599 stations due to data cleaning.

3.2. Cluster analysis

Conducting cluster analysis as a preliminary step not only makes each group more homogeneous, but it can also help to identify outliers[25]. Therefore, cluster analysis is carried out first to apply DEA for each formed cluster.

The first step in cluster analysis is to determine the number of clusters. Figure 1 shows the results of determining the optimum number of clusters of the 599 DMU stations using the Elbow method. The line graph in Figure 2 (a) on the number of clusters 2 tends to be steady-state, so it can be concluded that the optimum number of clusters is 2.



(a)

(b)

Fig. 2: Determination of the Number of Clusters (a) Elbow, (b) Silhouette

Using the k-means clustering method, there are 2 clusters formed, namely Cluster I and II. Cluster I consist of stations with high inbound volume and the number of couriers, so this cluster is called the Leader cluster. On the other hand, cluster II consists of stations with an inbound volume and a relatively lower number of couriers called the Majority cluster. The number of DMUs from each cluster and examples of its members are shown in Table 2.

There is no method to find the best clustering[26]. This cluster analysis aims to ensure the homogeneity of the observations because one of the assumptions that must be met in the analysis using DEA is the assumption of homogeneity. To check whether the 2 clusters formed were homogeneous, homogeneity testing was carried out using Levene's test. The hypothesis in this test is as follows.

H_0: Both populations are homogeneous

H_1: The two populations are not homogeneous

Table 3 shows the results of the test statistics from homogeneity testing using Levene's test. With a significant level of 0.05, the decision taken is to reject H_0 for the variable number of couriers and inbound volume. It means that the two populations (i.e., the Leader and Majority clusters) are not homogeneous, as can be seen from the difference in the number of couriers and inbound volume of the two clusters.

Table 2. k-Means Clustering DMU

	Cluster I (Leader)	**Cluster II (Majority)**
Number of DMUs	133	466
Member	SUB-GYN	BDO-BJR
	BDO-ASM	BDO-GJT
	SUB-BA2	BDO-MGR
	BDO-TSM	BDO-KRN
	JKT-AYR	KNO-KIS
	etc.	etc.

Table 3. Levene's Test

Variable	**F**	**Sig.**
Number of Couriers	163.44	0.000
Inbound Volume	46.38	0.000
Employee Salary	1.93	0.165

3.3. Calculation of relative efficiency with DEA

The calculation of the efficiency value using DEA on the last-mile station data as DMU is carried out for each cluster that has been formed from the previous section. The DEA method used in this analysis is SBM. The efficiency value that becomes the output of DEA ranges from 0 to 1.

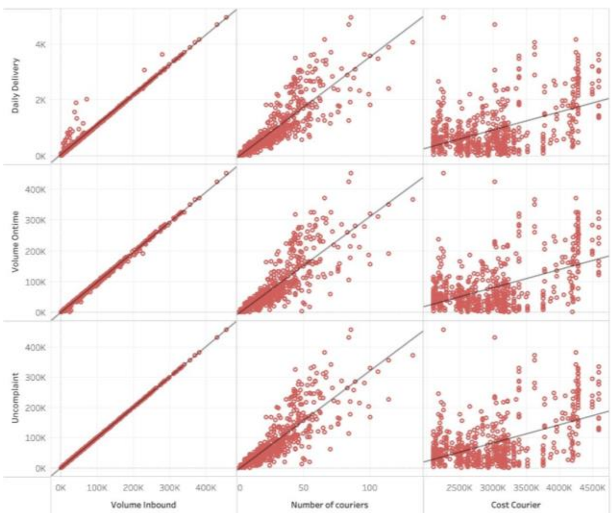


Fig. 3: Scatter plot of Input and Output Variables

Fig 4: Number of Couriers and Relative Efficiency Value on Leader Cluster

Fig 5: Number of Couriers and Relative Efficiency Value in Modest Cluster

The analysis was started by visually examining the relationship between input and output variables using a scatter plot to test for isotonicity. The scatter plot, shown in Figure 3, plots the input variables on the x-axis and the output variables on the y-axis. From the plot, it can be seen that there is a positive trend between the input and output variables. This positive correlation indicates that as the inputs increase, the outputs also tend to increase, which is consistent with the underlying economic principles of production and resource allocation. It suggests that the assumption of isotonicity is likely to be satisfied, and the SBM DEA model will likely produce reliable and meaningful efficiency scores.

In this research, the variable returns to scale (VRS) assumption is used, which posits that the relationship between inputs and outputs may change as the scale of production changes. It means that the proportionality between inputs and outputs may not be constant as the scale of production changes.

As described in the previous section, three input and three output variables are used to determine these relative efficiency values. Table 4 shows the relative efficiency values of each cluster using the DEA method. The average efficiency value for the Leader cluster is 0.90, and for the Majority cluster is 0.76. The average efficiency value in the Leader cluster is higher than that of the Majority. As many as 71% of the DMUs in the Leader cluster are said to be efficient DMUs; namely, the efficiency value is higher than 0.85, while in the Majority cluster is only 29%.

Table 4. Relative Efficiency of each Cluster

Cluster	Average Relative Efficiency	Efficiency Category	
		Inefficient (<0.85)	Efficient (≥0.85)
Cluster I	0.90	39 (29%)	94 (71%)
Cluster II	0.76	330 (71%)	136 (29%)
		369 (62%)	230 (38%)

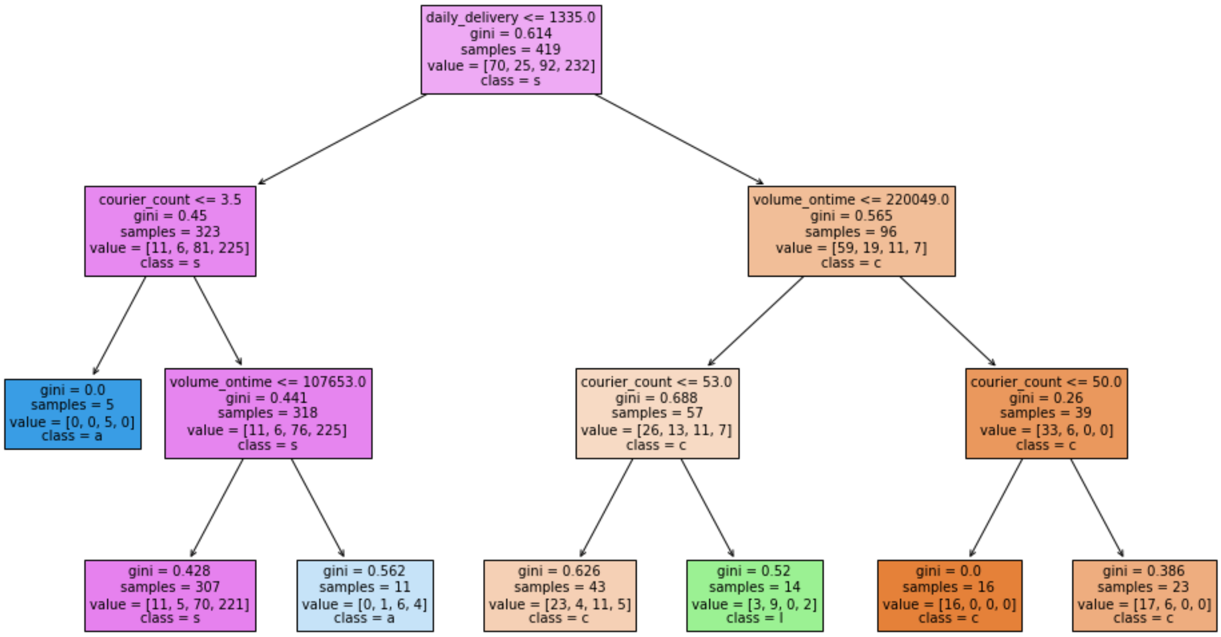


Fig 6: Decision Tree from Last-Mile Delivery Station

One of the classification methods used to determine the relationship between independent and dependent variables is a decision tree[27]. In this section, modeling will be carried out using a decision tree that can describe the relative efficiency category of the input and output variables of the DEA model.

This modeling will require a target variable which is the efficiency category. In this study, the categories used were two categories for each cluster, namely efficient and inefficient DMUs. The efficiency category, which is the target variable in this decision tree modeling, is represented as follows (Table 5).

- **Class 1**: a relatively efficient DMU from the Leader cluster
- **Class 2**: the relatively inefficient DMU of the Leader cluster
- **Class 3**: relatively efficient DMU of the Majority cluster
- **Class 4**: the relatively inefficient DMU of the Majority cluster

Table 5. Class Classification

Cluster	**Efficiency**	
	Efficient	**Inefficient**
Leader	Class 1	Class 2
Majority	Class 3	Class 4

The decision tree modeling used in this research is CART because all input and output variables used as attributes are numerical data. The ratio between data used as training and testing data is 70:30. Table 6 shows the results of the classification using CART. The accuracy of this modeling is 0.62 (Table 7).

Table 6. Confusion Matrix

Class		**Predictions**			
		1	**2**	**3**	**4**
Actual	**1**	13	4	2	5
	2	7	4	1	2
	3	6	0	5	33
	4	3	4	2	89

Table 7. CART Model performance

Category	**precision**	**recall**	**f1-score**	**support**
1	0.45	0.54	0.49	24
2	0.33	0.29	0.31	14
3	0.50	0.11	0.19	44
4	0.69	0.91	0.78	98

4. Research results and discussion

4.1. Efficiency analysis

The location of the stations, which are geographically dispersed over many points, makes it difficult to measure their performance. One measure of performance that can be used is the value of its efficiency. By looking at the efficiency, the company can find out which stations require immediate attention. The purpose of paying attention to the performance of each station is for a more effective process that can lower operating costs.

Cluster analysis was performed before efficiency analysis. The cluster analysis results show that the stations are divided into 2 clusters, namely the Leader and Majority clusters. In this study, three input variables are used: the number of couriers, the volume of packages that enter the station (inbound volume), and employee salaries.

The number of couriers is used as an input variable because the courier carries out the delivery process. It means that the higher the number of couriers, the more goods can be sent. The second input variable is the inbound volume because this package can be considered the "raw material" of the delivery process. The third input variable is employee salary or courier salary. The fees used to pay couriers and employees are different for each station because the UMR (Regional Minimum Salary) is different for each region. Hence it affects the operational costs for each station.

The results of the calculation of the efficiency value are shown in Table 4. A deeper analysis needs to be done from the resulting values to determine what variables affect the efficiency value. Figure 4 shows the efficiency values and input variables for the Leader cluster for 20 stations with the total inbound volume. Figure 5 shows the efficiency values and input variables for the Majority cluster for 20 stations with the total inbound volume. The orange line shows the efficiency value of each station. There is a tendency that if the number of couriers is low, the efficiency value will be higher. It is likewise for the variable courier salary (courier cost). It means that the efficiency value can be increased by reducing the value of the input variable.

The calculation results of this efficiency value can be used to show the performance of each station by identifying stations with low efficiency. For example, in Figure 4, one of the lowest efficiency values is that of BDO-MJA or Majalaya stations, with an efficiency of 0.77. The number of couriers at this station is 106, which is relatively high compared to other stations with inbound volumes that are not significantly different.

4.2. Decision Tree Modeling

The formation of a classification model can help predict whether a station is efficient based on the results of previous efficiency analyses. The target variables used were categorized from cluster analysis and DEA as analyzed from the data processing section. The cluster analysis results show that 2 clusters classify stations with a large enough input variable, called the Leader cluster. The second cluster is those stations with insufficient input variables, called Majority clusters. An efficiency analysis using DEA is carried out for each cluster to show a relatively efficient or inefficient station. Table 5 shows the class classifications that are the target variables in this modeling.

Figure 6 shows a decision tree from CART modeling for station efficiency data. Variables that affect class are daily deliveries, the number of couriers, and on-time parcel volume. The variable that is the starting point of this decision tree is the number of daily deliveries. If the number of daily deliveries is less than 1,335 parcels per day, then the classification is in Class 3 and 4, or this is the classification for the Majority cluster. If the number of daily deliveries is more than 1,335 parcels per day, then the classification is entered into Class 1 and 2, or it can be said that this is the classification for the Leader cluster.

In the second branch for the classification on the left side of the chart (purple and blue), the following variable for determining the station's efficiency is the number of couriers. If the number of couriers is less than 3, then the classification goes to Class 3 or DMU that is relatively efficient from the Majority cluster. It shows that with daily delivery of 1,335 packages per day, the station must be efficient if the number of couriers ranges between 3-4. If the number of couriers exceeds 3, the following criterion is the volume of goods sent on time (on-time volume). If the on-time volume is less than 107,653 packages, then the station is classified as Class 4. If the on-time volume is more than 107,653 packages, then the station is classified as Class 3.

In contrast to the second tree branch for the classification of the right side of the chart (orange and green colors), the criterion after the number of daily deliveries is the on-time volume variable. The third criterion is the variable number of couriers. If a station is less than 222,049 and the number of couriers is more than 53, then the station is classified as Class 2 or DMU that is relatively inefficient from the Leader cluster. In addition to these criteria, the station will be classified as Class 1.

The DT model in this study is a predictive approach that combines the results of the DEA and CA methods. DT uses the results as predictors to identify which factors significantly impact the efficiency of last-mile delivery stations, which are the decision-making units (DMUs) under examination in this study. This approach is similar to that used in prior research by Lee (2010), which also used DT to identify factors affecting the efficiency of DMUs.

5. Conclusions

This study employs two approaches to evaluate the efficiency of stations: DEA-CA and the Decision Tree prediction model. The DT model is used as an alternative method to DEA-CA. Additionally, DT can be utilized to determine which factors significantly impact the efficiency of the decision-making unit (DMU) under examination, which in this case, is the last-mile delivery station.

To address the issue of heterogeneity, cluster analysis was first conducted before conducting the DEA analysis. DEA was then applied to each cluster to evaluate efficiency. In this analysis, of the 133 stations in the Leader cluster, 94 were found to be relatively efficient when the efficiency threshold was set at 0.85. Similarly, out of the 466 stations in the Majority cluster, 136 were relatively efficient under the same threshold.

In addition to developing a framework for measuring efficiency, this research may also identify specific variables that impact efficiency and can be immediately implemented in operations. The DT model can be used to identify which variables have the most significant impact on station efficiency for each cluster. The daily delivery or inbound volume for each station was found to be the primary variable that determines which stations fall into the Leader or Majority cluster. After separating the clusters based on inbound volume, the second criterion for stations in the Majority cluster was the number of couriers and time volume, while the second criterion for stations in the Leader cluster was time volume followed by the number of couriers.

A limitation of this study is that it is based on data from a single logistics company in Indonesia, collected from October to December 2020. This narrow scope may limit the generalizability of the findings to other companies or contexts.

Future research may add variables related to the efficiency of last-mile delivery stations, such as population density. Also, other costs that may be associated with the last-mile process besides driver salaries, such as fuel, maintenance and repair costs for delivery vehicles, insurance, taxes and fees. Other potential expenses could include the cost of packing materials and shipping supplies, storage and warehouse fees, and the cost of any technology or software used to manage the delivery process. There may also be costs associated with returns and lost or damaged packages. In addition, the accuracy of the decision tree modeling in this study can still be improved by modeling other classifications since CART does not always create high predictive accuracy modeling[28)].

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