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Performance Evaluation Using Input-Oriented DEA Envelopment Model: A Case Study of Warehousing, Expedition, and Courier Companies in Indonesia

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ABSTRACT
In order to gather information on business decisions and to evaluate the economy and efficiency of current operations, companies require performance evaluation. In the absence of standards or benchmarks for assessment, performance evaluation plays a crucial role in enhancing the business's operational procedures. Data envelopment analysis (DEA) is a tool for measuring performance. The objectives of this study are to measure the efficiency of warehousing, expedition, and courier companies using the input-oriented DEA envelopment model; to analyze the DEA efficiency scores of each decision-making unit (DMU); to identify the efficient and inefficient status of each DMU; and to provide recommendations for development strategies to improve the efficiency of these companies. The results of the study indicate that the inefficient DMU has a presentation of 60%. This value is 20% greater than the efficient DMU (40%). Based on the fluctuation of DEA efficiency score distribution in each DMU, there are 6 DMU efficiency groups. These are Group 1 (ES = 1, Very Efficient), Group 2 (ES = 0.90 - 0.99, Highly Efficient), Group 3 (ES = 0.80 - 0.89, Quite Efficient), Group 4 (ES = 0.60 - 0.79, Less Efficient), Group 5 (ES = 0.41 - 0.59, Inefficient), and Group 6 (ES = 0 - 0.40, Very Inefficient). Group 1 ranks first with the largest percentage (40%). The second and third ranks are Group 3 (30%) and Group 4 (20%). The fourth rank is Group 2 (1%). This study does not have DMU with 2 efficient categories, namely: Group 5 and Group 6.

INTRODUCTION

The logistics sector has rapidly evolved into a significant trend in tandem with the growth of digital technology 4.0. In the contemporary digital era, logistics plays a function that goes beyond simply storing and transporting items; rather, it utilizes high-tech adaptive systems to provide quick, effective, and efficient services. The swift growth of digital logistics, or e-commerce, has pushed its auxiliary sectors—particularly shipping and warehousing—to become technological services. Warehousing and shipping are key elements in supporting the e-commerce industry supply chain. Growth in these sectors is also an important indicator of increasing economic growth in Indonesia. Therefore, to support the measurement of economic growth, up-to-date and complete data is needed along with the changing times. Technological advancements have led to a growth in online trading and e-commerce, which in turn has fueled the emergence of warehousing companies that store and transport items via couriers and expeditions. This is due to the many demands from business owners to distribute their goods to customers. At the moment, Indonesia's adventure business is expanding quickly, in high demand, and facing fierce competition. While couriers concentrate primarily on quick, small-scale local deliveries, the expedition acts as a middleman between senders (suppliers or manufacturers) and recipients on a bigger scale. There are an estimated 15,848 warehouse, expedition, and courier companies dispersed across Indonesia, indicating the significance of transportation, particularly in the warehousing, expedition, and courier service industries, in propelling the country's economy [1]. Due to the sector's significant importance, numerous initiatives are required to enhance business performance.

Companies need performance evaluation to assess the economy and efficiency of ongoing operations and to collect data on business decisions. Performance evaluation can be used to improve the company's operating processes, and its role becomes very important if standards or benchmarks are not presented for evaluation. Performance can be measured using data envelopment analysis (DEA) [2], [3]. Data envelopment analysis (DEA) is a mathematical technique that was first presented by Charnes and Cooper. The foundation of DEA is linear programming. This approach has been used in a variety of contexts, including supply chain management, manufacturing engineering optimization, healthcare services, project selection, and safety enhancement. The efficacy of a group of decision-making units (DMUs) with various inputs and outputs can be assessed using this method. This performance will be used as a standard by which to compare and assess the DMUs' respective performances. In order to determine the weights of each input and output, DEA permits each DMU to define a set of weights that, in the best-case scenario, constitute a unit [4], [3].

This definition states that comparative performance evaluation compares the performance of a group of identical entities in a methodical manner. They are referred to as DMUs, or decision-making units. DMUs are made up of departments, businesses, communities, and other organizations. Since they convert the same collection of resources into the same set of services and/or goods, they are regarded as homogenous. DEA is a method based on mathematical programming. Therefore, DEA is concerned with piecewise boundary estimation and DMU comparison under real multiple input and output conditions. There are variations between benchmarking and DEA. Benchmarking addresses both statistical average performance and engineering basics. DEA evaluates the efficacy (particularly efficiency) of the best practice DMUs that are being examined. In order to handle a multifaceted performance picture, DEA makes the fewest a priori assumptions necessary. In the sequence of uneven optimization designs, DEA provides a comprehensive structure. Their performance-related work processes are interpreted using it [5, 3].

Efficiency is often measured using techniques like data envelope analysis. The degree to which different units or organizations have implemented efficient resource usage will be measured with great effectiveness using this methodology. Since the goal is to maximize output by making efficient use of inputs, the input-oriented DEA envelopment model is frequently used. The effectiveness of businesses or organizations in using resources can be assessed and compared thanks to data envelopment analysis, or DEA. This approach makes it possible to determine which departments or businesses are more effective at generating the intended results. DEA can also be used to assess a company's efficiency by taking into account a number of pertinent input and output parameters [6, 7]. In the case study research on warehousing, expedition, and courier companies, these inputs consist of the average number of workers, average monthly wages, use of information technology, and average warehouse volume. Outputs consist of income scale and average warehouse rates.

In order to improve efficiency, this study focuses on how to assess the performance of Indonesian courier, warehouse, and expedition organizations. The study's goals areo (i) identify the efficient and inefficient status of each decision-making unit (DMU); (ii) analyze the DEA efficiency scores of each DMU; (iii) measure the efficiency of warehousing, expedition, and courier companies using the input-oriented DEA Envelopment Model approach; and (iv) offer suggestions for development strategies to increase the efficiency of managing warehousing, expedition, and courier companies.

MATERIALS AND METHODS

Performance Evaluation. In today's corporate setting, issues requiring efficiency analysis to aid in decision-making are highly relevant. In the words of Farel [8,] "It is important to know to what extent a particular industry can increase its production only by increasing its efficiency." Thus, in addition to acquiring these estimations, a number of tools were created to give managers the proper assistance in their endeavors. Because they are primarily focused on making sound business decisions, operational research and its numerous subfields are expanding quickly in light of this situation. Multi-criteria decision approaches (MCDM) have been applied in a number of prior research studies to real-world challenges [9], [10], [11], and in relation to the public's access to such approaches [12]. Data Envelopment Analysis (DEA) stands out among them as a potent instrument with numerous applications [13]. DEA aims to determine the relative efficiency of two or more production units that generate goods and/or services (outputs) using different inputs. Nevertheless, because the commutations are made between very dissimilar things, some of the quality of the suggested analysis will be lost when the production units to be examined are highly heterogeneous [14].

The evaluation of organizational performance in the context of implementing improvement plans that set management goals is a broad application of data envelopment analysis, or DEA. At the time of the performance review, managers often set unrealistically low targets or set goals without any evidence that they can be achieved. By using DEA for benchmarking, it is ensured that the evaluation is based on realistic objectives and best practices. Setting goals is a common step in management planning for progress. Managers and supervisors set goals throughout time, and performance is assessed ex post in reference to those goals as part of the monitoring and control process. Goals are usually set as a consequence of stakeholder interactions, taking into account policies, past performance knowledge, and other elements [15].

Data envelopment analysis (DEA) is a technique that solves a linear programming problem to assess the effectiveness and performance of a homogenous group of decision-making units (DMUs). By employing varying resources (inputs) to generate varying effects (outputs), the DEA model assesses the relative effectiveness of a group of DMUs. Many additional scholars have since developed the DEA model, which was first proposed by Charnes, Cooper, and Rhodes in 1978. A generalization of Farell's (1957) idea of single-input, single-output efficiency, this model is frequently referred to as the Charnes, Cooper, and Rhodes (CCR) model. Constant returns to scale are assumed by CCR models while defining the production possibility set. Banker, Charnes, and Cooper put out the idea of generalizing it (1984). In the Banker, Charnes, and Cooper (BCC) model, variable returns to scale are taken into account. Choosing the best model for a given situation requires decision-makers to determine whether to assume constant or variable returns to scale. The units that express the efficient frontier as described by the model are given efficiency ratings of 1 in both the CCR and BCC models. With efficiency scores below 1, the other inefficient units are not competitive. Inefficient DMUs can be ranked using the efficiency score; however, efficient DMUs cannot be ranked because of their maximum score being the same. Because of this, a number of models and techniques have been put forth in the past to enable the ranking of initially effective units. Since the aforementioned groundbreaking studies, numerous researchers have advanced the DEA theory. Cooper et al., 1999, Seiford, 1996, Seiford and Thrall, 1990, and other articles provide further details on developments in the theory and its application [16].

Input-Oriented DEA Envelopment Model. Data Envelopment Analysis (DEA), a linear programming technique, is used to measure performance in integrated models. A number of performance metrics make use of input and output parameters. It is necessary to minimize expenses, labor, materials, and other inputs. Output, which encompasses manufactured goods, sales, and revenues, is one element that requires optimization. DEA is used once inputs and outputs have been chosen and categorized. The DEA uses decision-making units (DMUs) to represent all corporate entities, processes, and activities in the estimate. An inefficient DMU can be raised to the efficient DMU criterion level using one of two techniques. Two primary approaches can be used to meet these criteria: activities that reduce input relative to maximizing output at the current level and activities that increase output relative to reducing input at the current levels. These techniques can be applied to the criteria in any scenario. Equations 1 through 4 display the DEA model's linear programming formula. The output criteria of the model are set at the present level and are intended to reduce input.

$$\theta^* = \min \theta \quad . \quad (1)$$

subjected to the following restrictions:

$$\sum_{j=1}^{n} Xij\,\lambda j \leq \theta\, Xio\,, \qquad i = 1, \dots, m \quad . \quad (2)$$

$$\sum_{j=1}^{n} Yrj\,\lambda j \geq Yro\,, r = 1, \dots, s \quad (3)$$

$$\sum_{j=1}^{n} \lambda j = 1 \quad (4)$$

$$\lambda j \geq 0 \quad j = 1, \dots, n$$

Among the n DMUs that were discussed is DMU0. The symbols Xi0 and Yr0 stand for r-input and r-output, respectively, for DMU0. By using λj to represent the unknown weight, where j = 1,..., n, the DMU number can be determined. The efficacy value is represented by the symbol θ, which is the solution variable. The following equation shows that if $\theta = 1$, the solution is feasible. When θ^* is at its peak, it is less than 1. When $\theta^* = 1$, DMU0 is at the optimal criteria limit, meaning that a proportional reduction in the current input level is not possible. If DMU0 is on the edge and θ^* is less than 1, the input can be reduced by the same percentage as θ^*. Thus, a greater amount of output can be produced with less input [17], [18]. Data Envelopment Analysis compares the output generated to the input used to assess the efficiency of DMUs. This method finds units that are efficient and examines the causes of inefficiencies in other units. Industry, education, and the public sector are just a few of the sectors that use both traditional and advanced DEA models. The DEA-solver program makes it simple to calculate efficiency and pinpoint areas in need of improvement. DEA was used in many case studies with the goal of improving resource management to help businesses compete in the public and private sectors and attain maximum operational efficiency [19].

Research Methodology. The Input-Oriented DEA Envelopment Model is used in this study to analyze efficiency based on pertinent inputs and outputs pertaining to Indonesian courier, warehouse, and expedition industries. This study's methodology consists of the following steps: (i) determining input and output variables; (ii) identifying Decision-Making Units (DMUs); (iii) applying the Input-Oriented DEA Envelopment Model; (iv) analyzing DEA efficiency scores; (v) grouping DMUs according to DEA efficiency scores; and (vi) suggesting development strategies for DEA efficiency groups. A more thorough explanation of each stage is provided in Table 1.

Table 1. Research methodology stages

Steps	**Deskripsi**
Determining input and output variables	The input variables consist of the average number of workers, the average monthly wage, the use of information technology, and the average warehouse volume. The output variables consist of income scale and average warehouse rate.
Identifying Decision-Making Units (DMUs)	Based on the company type and region/area of the courier, warehousing, and expedition companies, Decision-Making Units (DMUs) are determined. Ten DMUs are identified in this study, including DMU_A, DMU_B, DMU_C, DMU_D, DMU_E, DMU_F, DMU_G, DMU_H, DMU_I, and DMU_J.
Applying the Input-Oriented DEA Envelopment Model	An input-oriented DEA envelopment model, which minimizes inputs to maximize output, is used in this study.
Analyzing DEA efficiency scores	Whereas inefficiency is indicated by a score below one, complete efficiency is shown by a score of one.
Grouping DMUs according to DEA efficiency scores	In this study, there are 6 DMU Efficiency Groups based on the DEA efficiency score range. The DMU Efficiency Groups include: Group 1 (ES = 1, Very Efficient), Group 2 (ES = 0.90 - 0.99, Highly Efficient), Group 3 (ES = 0.80 - 0.89, Quite Efficient), Group 4 (ES = 0.60 - 0.79, Less efficient), Group 5 (ES = 0.41 - 0.59, Inefficient), and Group 6 (ES = 0 - 0.40, Very Inefficient).
Suggesting development strategies for DEA efficiency groups	Various company development strategies, such as how to maintain performance, document best practices, benchmark externally, identify small gaps, optimize input output, conduct internal efficiency audits, and build new management or work systems. Other strategies include logistics processes, cost structures, productivity, HR competencies, and technological competencies.

Research Gap. Although DEA has been widely used to evaluate efficiency in a number of industrial sectors, such as banking, education, and hospitals, its use in DEA research in the logistics sector—specifically in Indonesia's courier, warehousing, and expedition subsectors—remains limited, despite DEA's increasing significance in the digital and e-commerce era. In addition, a variety of additional factors include: (i) Few studies using the input-oriented DEA approach to evaluate the efficacy of logistics companies using microdata (average workers, wages, IT usage, warehouse volume, warehouse rates, and revenue); (ii) Few studies linking DMU development strategies to DEA efficiency outcomes (especially in low-efficiency groups so that they can be fixed); and (iii) The absence of an integrative approach that considers variations in operational areas and types of companies as classification factors in decision making.

Research Originality. This study's novel values include: (i) applying the input-oriented DEA model specifically to logistics companies in Indonesia, which hasn't been thoroughly examined in the country's literature; (ii) using eight specific variables based on microdata, which involve aspects of warehouse capacity and information technology as input/output elements in efficiency analysis; (iii) using DEA not only for efficiency assessment but also for grouping and formulating development strategies based on efficiency scores, making this study both diagnostic and strategic; and (iv) using a case study-based approach with the MS Excel Solver, which makes this model simple to replicate for the purposes of evaluating internal company policies or strategies.

RESULTS AND DISCUSSIONS

Results

Decision-Making Units (DMUs) and Input-Output Variables. A case study on Indonesian warehousing, expedition, and courier companies is used in this research. Six categories of data are used in its implementation: (i) company type, (ii) company region, (iii) average number of employees, (iv) average monthly wages, (v) information technology use, (vi) average warehouse volume, (vii) income scale (less than 2 billion rupiah), and (viii) average warehouse rates [1]. Using these data, decision-making units (DMUs) and input-output variables can be identified in Table 2 and Table 3.

Table 2. Decision-making units (DMUs)

No.	Company Type	Region	DMUs
1	Warehousing	Sumatera	DMU_A
2	Warehousing	Jawa Bali	DMU_B
3	Warehousing	Kalimantan	DMU_C
4	Warehousing	Sulawesi	DMU_D
5	Warehousing	Nusa Tenggara, Maluku, Papua	DMU_E
6	Expedition - Courier	Sumatera	DMU_F
7	Expedition - Courier	Jawa Bali	DMU_G
8	Expedition - Courier	Kalimantan	DMU_H
9	Expedition - Courier	Sulawesi	DMU_I
10	Expedition - Courier	Nusa Tenggara, Maluku, Papua	DMU_J

There are 2 types of companies (warehousing and expedition-courier), 5 regions (Sumatra, Jawa-Bali, Kalimantan, Sulawesi, and Nusa Tenggara-Maluku-Papua), and 10 DMUs. Input variables consist of X1, X2, X3, and X4. Output variables consist of Y1 and Y2. Input and output data are presented in Table 4.

Table 3. Input and output variables

Input - Output	Explanation	Unit	Variable
Input	Average Number of Workers	person	X1
	Average Monthly Wages	Rp	X2
	Use of Information Technology (IT)	%	X3
	Average Warehouse Volume	m^3/year	X4
Output	Revenue Scale (< 2 Billion)	%	Y1
	Average Warehouse Rates	Rp/m^3/day	Y2

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Table 4. Input and output data

No.	DMUs	X1	X2	X3	X4	Y1	Y2
1	DMU_A	7	3,255,352	48.81	11,234	51.94	79,620
2	DMU_B	11	4,102,288	51.66	15,322	39.32	96,787
3	DMU_C	7	3,636,182	32.88	5,691	67.63	69,012
4	DMU_D	7	3,525,755	57.34	7,809	58.52	73,234
5	DMU_E	6	2,098,528	33.91	3,123	79.42	77,409
6	DMU_F	6	3,470,536	82.75	11,234	64.13	79,620
7	DMU_G	6.75	3,746,700	82.92	15,322	60.76	96,787
8	DMU_H	6.75	3,676,705	84.38	5,691	61.1	69,012
9	DMU_I	4.5	3,265,700	57.34	7,809	69.31	73,234
10	DMU_J	5	2,198,532	81.5	3,123	76.25	77,409

Microsoft Excel Worksheet - MS Excel Solver. A Microsoft Excel worksheet is prepared to compile input and output data. MS Excel Solver is run to obtain the results of efficiency scores for each DMU. The calculation of efficiency scores implements the Input-Oriented DEA Envelopment Model. Table 5 presents the calculation process.

Table 5. Microsoft Excel Worksheet - MS Excel Solver

No.	DMU	X1	X2	X3	X4	Y1	Y2	λ
1	DMU_A	7	3,255,352	48.81	11,234	51.94	79,620	0
2	DMU_B	11	4,102,288	51.66	15,322	39.32	96,787	0
3	DMU_C	7	3,636,182	32.88	5,691	67.63	69,012	0
4	DMU_D	7	3,525,755	57.34	7,809	58.52	73,234	0
5	DMU_E	6	2,098,528	33.91	3,123	79.42	77,409	0
6	DMU_F	6	3,470,536	82.75	11,234	64.13	79,620	0
7	DMU_G	6.75	3,746,700	82.92	15,322	60.76	96,787	0
8	DMU_H	6.75	3,676,705	84.38	5,691	61.1	69,012	0
9	DMU_I	4.5	3,265,700	57.34	7,809	69.31	73,234	0
10	DMU_J	5	2,198,532	81.5	3,123	76.25	77,409	1

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	Reference		**DMU under**	**10**	**Efficiency**
Constraints	**Set**		**Evaluation**		**1.0000**
Input - X1	5	≤	5		
Input - X1	2,198,532	≤	2,198,532		

Input - X1	82	≤	82		
Input - X1	3,123	≤	3,123		
Output – Y1	76	≥	76		
Output – Y2	77,409	≥	77,409		
$\sum\lambda$	1				

DEA Efficiency Score Analysis. An efficient DMU is defined as having an efficiency score of one. Conversely, a DMU that is inefficient has a score below 0.99. Table 6 displays the DMU status analysis based on these parameters. DMU's presentation is 60% (6/10 x 100%), which is inefficient. This figure is 20% higher than the 40% efficient DMU.

Table 6. DEA efficiency score analysis

No.	DMU	Skor Efisiensi	Status	No.	DMU	Skor Efisiensi	Status
1	DMU_E	1.0000	Efficient	1	DMU_G	0.9378	Inefficient
2	DMU_C	1.0000	Efficient	2	DMU_F	0.8446	Inefficient
3	DMU_I	1.0000	Efficient	3	DMU_A	0.8407	Inefficient
4	DMU_J	1.0000	Efficient	4	DMU_B	0.8207	Inefficient
				5	DMU_D	0.7536	Inefficient
				6	DMU_H	0.6848	Inefficient

DMU Grouping Based on DEA Efficiency Score. Figure 1 shows the distribution of DEA efficiency score fluctuations for each DMU. DMU grouping can be carried out based on the distribution's fluctuations. According to the range of DEA efficiency scores, there are six DMU efficiency groups in this study. Group 1 is Very Efficient (ES = 1), Group 2 is Highly Efficient (ES = 0.90 - 0.99), Group 3 is Quite Efficient (ES = 0.80 - 0.89), Group 4 is Less Efficient (ES = 0.60 - 0.79), Group 5 is Inefficient (ES = 0.41 - 0.59), and Group 6 is Very Inefficient (ES = 0 - 0.40). Table 7 provides an explanation of each DMU Efficiency Group.

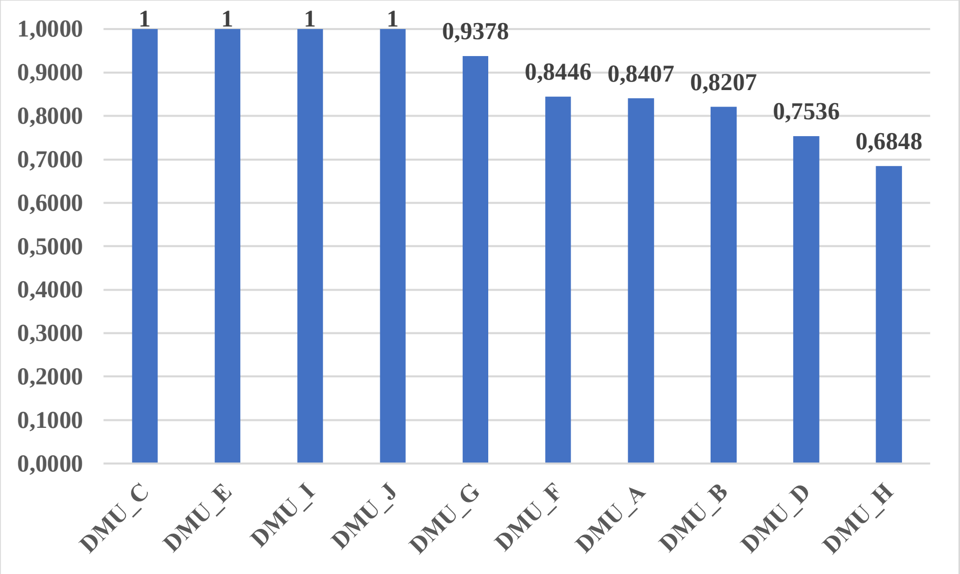

Figure 1. Fluctuation in DEA efficiency score distribution

Figure 1 shows the distribution of DEA efficiency score fluctuations for each DMU. DMU grouping can be carried out based on the distribution's fluctuations. According to the range of DEA efficiency scores, there are six DMU efficiency groups in this study. Group 1 is Very Efficient (ES = 1), Group 2 is Highly Efficient (ES = 0.90 - 0.99), Group 3 is Quite Efficient (ES = 0.80 - 0.89), Group 4 is Less Efficient (ES = 0.60 - 0.79), Group 5 is Inefficient (ES = 0.41 - 0.59), and Group 6 is Very Inefficient (ES = 0 - 0.40). Table 7 provides an explanation of each DMU Efficiency Group.

Table 7. DMU Grouping Based on DEA Efficiency Score

Group	Efficiency Score Range	DMU	Efficient Category	Explanation
1	1	DMU_C DMU_E DMU_I DMU_J	Very Efficient	Businesses that are on the efficiency frontier can serve as models for others.
2	0.90 - 0.99	DMU_G	Highly Efficient	They are nearly effective and could be improved.
3	0.80 - 0.89	DMU_F DMU_A DMU_B	Quite Efficient	Although there are a few inefficiencies, they can still be fixed.
4	0.60 – 0.79	DMU_D DMU_H	Less Efficient	Relatively poor performance while using input-output.
5	0.41 – 0.59	--	Inefficient	Since it is far from the efficiency frontier, it requires a great deal of work.
6	0 – 0.40	--	Very Inefficient	A comprehensive assessment is required because of the significant resource waste.

Figure 2 shows the Efficiency Group's percentage composition. Group 1 (highly efficient) has the highest proportion (40%) and is ranked top. The four DMU types in this group are DMU_C, DMU_E, DMU_I, and DMU_J. Group 3 (Quite Efficient) has a 30% presentation (DMU_F, DMU_A, and DMU_B), while Group 4 (Less Efficient) has a 20% presentation (DMU_D and DMU_H), placing them in second and third place. Group 2 (Highly Efficient) comes in at number four with a 1% (DMU_G) rate. Two efficient categories—Group 5 (Inefficient) and Group 6 (Very Inefficient)—do not have DMU in this study.

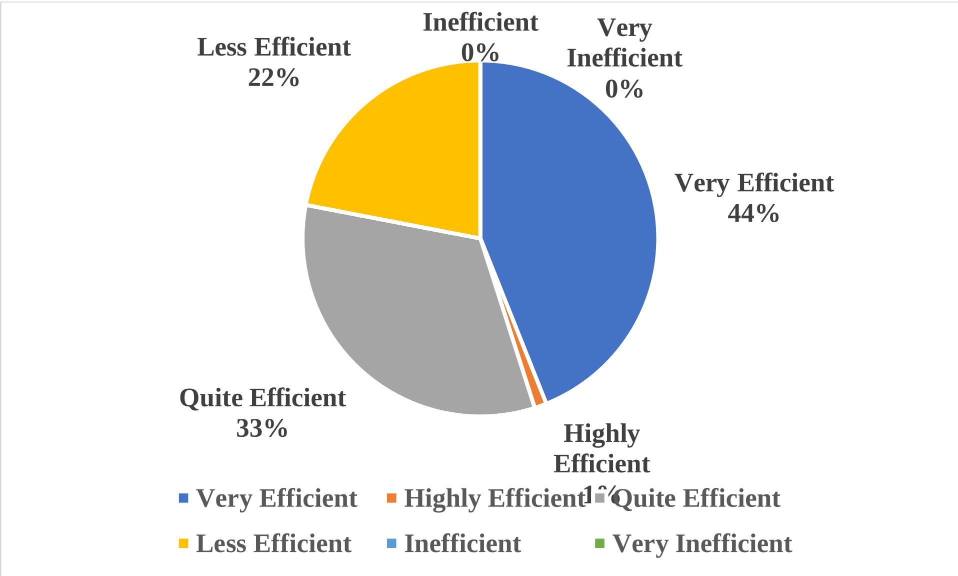

Figure 2. Percentage composition in the efficiency group

Discussions

Factors Causing Efficient and Inefficient DMU. The efficiency of a Decision Making Unit (DMU) in the warehousing, expedition, and courier sector in Indonesia is supported by a combination of the use of advanced information technology—from Warehouse Management System, Internet of Things for temperature/position sensors, sorting automation, to big data analytics that minimize errors and idle time—, determining the right scale of operations so that the ratio of warehouse capacity-demand, number of workers, and capital intensity are at the optimum point, increasing productivity through structured training, performance incentives, and job rotation that reduce downtime, controlling operational costs through utility tariff negotiations, preventive maintenance, and output-based wage schemes, strategic locations near ports, airports, or distribution centers that cut lead-time and haulage costs, and service diversification—fulfillment, cross-docking, cold-storage, same-day delivery—that increase revenue per square meter of the warehouse. DMUs become inefficient when there is input redundancy—excessive labor, idle warehouse space, equipment investment beyond needs—, delayed technology adoption (manual systems, separate spreadsheets, lack of real-time tracking), weak market demand due to remote locations or narrow sales networks, disproportionate business scale that causes fixed costs to squeeze margins, weak operational management—as seen in high truck waiting times, unergonomic warehouse layouts, and missed cycle counts—, and low human resource quality due to minimal training, high turnover, and lack of a culture of continuous improvement, all of which cause inputs (wages, warehouse space, working hours) to increase without a commensurate increase in revenue or service rates.

DEA Efficiency Groups Development Strategy. The development strategy to improve the performance of DEA efficiency groups in warehousing, expedition, and courier companies in Indonesia is explained. Companies in Group 1 (Very Efficient) have achieved maximum efficiency and operate on the efficiency frontier. They should maintain optimal performance by continuously monitoring key operational indicators. In addition, it is important to document and disseminate the best practices they implement, as well as actively participate in external benchmarking activities to remain adaptive to market and technology dynamics. Businesses in Group 2 are highly efficient, if not flawless. Small sources of slack, such as too much input or a lack of specific outputs, must be found. Processes that still have gaps can be optimized to reach their highest possible levels of efficiency. Techniques like using automation systems or boosting output without adding input may be the best course of action. Although Group 3's performance is really good (Quite Efficient), there is still a lot of space for improvement. It is advised to carry out a thorough internal efficiency audit in order to pinpoint operational procedures that are not functioning at their best. In order to boost efficiency, the business must also reassess its logistical plan, carefully implement digital technologies, and enhance human resource development and training. Business units in Group 4 (Less Efficient) are beginning to exhibit input-output imbalances. As a result, it is advised to assess the resource performance and cost structure. Businesses must examine inefficient procedures and enhance supply chain and logistics management solutions. Efficiency can also be increased by investing in the right IT equipment and raising employee proficiency. The output of Group 5 (Inefficient) is not yet comparable, and there is a significant reliance on input. Businesses are urged to completely restructure their operational procedures in order to increase efficiency. This includes rethinking workflows and cutting back on non-value-added tasks. Management and employees must also receive extensive training in order to comprehend the concepts of efficiency and use digital technology in day-to-day operations. Companies in Group 6 (Highly Inefficient) are the least efficient, with high levels of resource waste and output far below optimal potential. The main recommendation is to undertake a complete organizational transformation. This includes evaluating business strategies, improving organizational structures, and possibly replacing ineffective management systems. Companies should also consider adopting modern logistics systems and automation technologies to drastically accelerate efficiency improvements.

CONCLUSION

The study's findings show that ineffective DMUs have a presentation of 60% and efficient DMUs 40%. In accordance with the DEA efficiency score range, DMU has six efficiency groups: Group 1 (ES = 1, Very Efficient); Group 2 (ES = 0.90 - 0.99, Highly Efficient); Group 3 (ES = 0.80 - 0.89, Quite Efficient); Group 4 (ES = 0.60 - 0.79, Less Efficient); Group 5 (ES = 0.41 - 0.59, Inefficient); and Group 6 (ES = 0 - 0.40, Very Inefficient). According to the DMU Efficiency Group's percentage composition, Group 1 (highly efficient DMU) has the highest proportion (40%) and is ranked first. There are four different varieties of DMU in this group: DMU_C, DMU_E, DMU_I, and DMU_J. Group 3 (Quite Efficient) holds the second and third positions with a 30% presentation (DMU_F, DMU_A, and DMU_B), while Group 4 (Less Efficient) has a 20% presentation (DMU_D and DMU_H). Group 2 (Highly Efficient), with a 1% percentage (DMU_G), comes in at number four. DMU with two efficient categories—Group 5 (Inefficient) and Group 6 (Very Inefficient)—is absent from this study.

The following are the development strategies to enhance the performance of DEA efficiency groups in Indonesian courier, storage, and expedition companies: (i) Group 1 (maintaining performance, recording best practices, and participating in external benchmarking); (ii) Group 2 (identifying minor gaps to be filled and optimizing output without increasing input); (iii) Group 3 (conducting internal efficiency audits and concentrating on under-optimal logistics processes); (iv) Group 4 (conducting internal efficiency audits and concentrating on under-optimal logistics processes); (v) Group 5 (assessing cost structures and productivity and enhancing HR or technology competencies); and (vi) Group 6 (a comprehensive transformation is required, and new management or new work systems are built for total efficiency).

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