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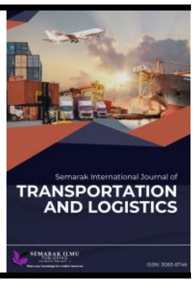

Evaluating the Efficiency Measurement of Malaysian Logistics Company

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ABSTRACT

Logistics plays a crucial role in the smooth flow of goods, data, money, technology, and individuals along the supply chain, which in turn affects the efficiency of commerce worldwide. Thus, a company's efficiency is very important. The purpose of this research is to find the efficiency score of 14 Malaysian logistic companies while enduring the Covid 19 pandemic in 2020. Data was gathered from corporate annual reports from 2010 to 2021. 14 Malaysian logistics organizations were chosen as decision making units (DMUs) for this study. The companies' performance was evaluated using the Data Envelopment Analysis (DEA) model, Super Efficiency for input orientation**.** The primary findings show that companies cope very well to be consistently fully efficient. Further analysis of the results was done using the Super Efficiency model to identify the company that can be ranked as the most efficient. Due to the pandemic and the variables used as inputs and outputs for the DEA model were precisely taken from the financial statements, limits strategic analysis. The outcomes of this research are useful to aid in the evaluation of resource use and have the possibility to be used in evaluating current policies in order to guarantee that logistics businesses are efficient and sustainable.

Keywords:
Data Envelopment Analysis (DEA); efficiency; logistic companies

1. Introduction

Logistics can be defined as a general strategic on how to handle procurement, movement, storage of raw materials, semi-finished products and finished goods, some associated information flows on how to transport finished goods to end customers in such an organization and its marketing channel [1,2,7,15,21,22]. Inbound logistics and outbound logistics are the two types of logistics activity. Both phrases allude to the movement and transit of items within the supply chain. Inbound logistics is concerned with receiving inventory such as raw materials and goods directly from manufacturers and suppliers to businesses, whereas outbound logistics is concerned with delivering and shipping finished goods and products to final customers, where order fulfilment processes include picking, packing, shipping, and delivery of packages.

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Malaysian logistics industry has been acknowledged worldwide recently. According to the World Bank Group of Logistics Performance Index (LPI), Malaysia is sitting at the 26th place in the Global Ranking 2023. Notwithstanding, Malaysia is lagged in the authorized country like Singapore. Singapore is ranked as the highest in 2023. However, Malaysia is in better ranking as compared to the other two neighboring countries where Indonesia is ranked 61st and Thailand is at the rank 34th [6]. This provides a clear insight that logistics sector in Malaysia is better than years before but there is room for improvement. The logistics industry has been pushed to boost their efficiency and productivity to achieve the prompt implementation so that they will be in the lead up to global value chain with the aid of new edge technology.

Ambiguity increases the likelihood of risk, as risk is a direct consequence of uncertainty. In logistics, risk arises from the unpredictability of future events, leading to unexpected disruptions that can cause operational and financial damage [11,12]. Among different delivery modes, such as air, sea, and road, courier delivery faces a higher degree of uncertainty and risk due to its reliance on rapid transit times, variable demand, and last-mile delivery challenges [13,14]. With the rapid growth of e-commerce, courier services have become a crucial component of international small and medium-sized package deliveries. However, uncertainty within supply chains, stemming from both external factors (e.g., fluctuating fuel prices, weather disruptions, and regulatory changes) and internal factors (e.g., inefficiencies in route planning and warehouse operations)—directly impacts the efficiency of logistics companies. Efficient logistics operations require robust risk management strategies, including predictive analytics, real-time tracking, and contingency planning, to mitigate these uncertainties and ensure smooth operations [9]. By effectively addressing risks through technology and strategic planning, logistics companies can enhance service reliability, reduce delays, and optimize resource utilization. This proactive approach is essential for maintaining competitiveness in the fast-evolving logistics landscape [10].

In early March 2020, the logistics sector was affected in the wake of pandemic spread in a different way. The outbreak of coronavirus named Covid-19 has disrupted almost all economic sectors [8]. Agriculture, oil gas and energy, tourism, retail, private healthcare and many more industries were severely affected by this pandemic. Due to this crisis, government of Malaysia imposed several restrictions such as travel restrictions, closed borders, large-scale quarantines, banned large scale gatherings and dining in restaurants and implemented partial lockdowns [16,17]. Therefore, several of society activities and business operations were forced to discontinue. The reason was because the business operation cannot be sustained, and the main effect was their sales went down and so did the profit. This pandemic affected the whole society where people were afraid to go out, especially in social areas such as shopping places and groceries stores. In fact, the virus of Covid-19 was transmitted through people's contact with each other and non-social distancing. Due to this circumstance, customers changed their view and preference to online shopping as it required less contact with people and reduced Covid-19 transmission.

In Malaysia, several retailers such as Senheng Electric, Tricubes Berhad and M Mall 202, have implemented technological innovations to enhance customer satisfaction, similar to Sam's Club's advancements. For example, Senheng Electric, Malaysia's largest consumer electronics retail chain, has integrated technology to improve the shopping experience. They introduced a fixed-price policy and a customer loyalty program, eliminating price bargaining and rewarding repeat customers. Additionally, they launched the senQ Digital Station, focusing on high-end electronic products, providing a premium shopping environment [18]. At the same time, Tricubes Berhad, a Malaysian technology company, specializes in biometric products and software solutions. They have developed identity authentication software and enterprise mobility solutions, enhancing customer interactions by streamlining processes like account openings through biometric verification [19]. Additionally, M

Mall O2O in Penang introduced virtual currency as a payment mode, allowing shoppers to use 'points' online in exchange for products and services within the mall. This innovative approach aimed to enhance the shopping experience by integrating online and offline transactions [20]. Enhancing productivity is vital for a company's success, and efficient logistics play a significant role in this aspect. Proper logistics management allows for more effective resource allocation, such as reorganizing warehouse storage to maximize space utilization and reduce storage costs. Amazon's investment in robotics-led warehouses exemplifies this approach, leading to significant cost reductions and faster delivery times. The company anticipates annual savings that could reach $10 billion by the end of the decade due to these efficiencies.

2. Background of Studies

This study aims to examine the technical efficiency of Malaysian logistics companies, with a specific focus on performance evaluation. Technical efficiency was selected over other efficiency measures, such as super efficiency, as the research assesses how effectively logistics firms operated over an 11-year period (2010–2021), by maximizing output while minimizing input, particularly in the face of labor shortages. The research methodology involves an extensive literature review of previous studies and an analysis of annual reports from Bursa Malaysia, focusing on selected logistics companies. The core findings of this paper are based on the Data Envelopment Analysis (DEA) and Super Efficiency Method, applied to 14 Decision-Making Units (DMUs). Efficiency evaluation typically involves calculating a productivity index, which serves as a benchmark for performance assessment and growth analysis. By leveraging productivity measurement, organizations can significantly enhance their sales and profitability, ensuring sustained competitiveness in the industry.

Evaluating the efficiency of Malaysian logistics companies using DEA alone does not provide insights into which company is the most efficient. However, incorporating the Super Efficiency DEA model allows for a more precise ranking, identifying the highest-performing companies. One of the primary challenges faced by logistics companies is the rising cost of transportation. To mitigate this, firms can optimize delivery routes by implementing route optimization software to identify the most efficient paths for deliveries or negotiate with carriers to establish strong relationships with transportation providers to secure better rates and cost savings.

3. Methodology

The study used secondary data that has been compiled in the yearly record from 2010 to 2021. As mentioned earlier, this study used a set of DMUs exploiting input and output data from 14 Malaysian logistics businesses from Bursa Malaysia as it is freely accessible to other users. Each DMU represents a logistics company. Table 1 summarises the variables used in this study with three (3) inputs and two (2) outputs.

Since the study was getting the yearly financial reports of the firms are readily available on the website of Bursa Malaysia, the list of logistics companies is chosen based on its criteria. Table 2 lists the 14 companies specializing on transportation and logistics services in Malaysia.

Table 1
The input and output variables of the study

INPUT	Current Asset	Cash and any other assets/resources that are expected to be consumed, used or converted to cash within one year
	Net Fixed Asset	Net value of fixed assets in company after discarding the depreciation of expenses, impairment expenses and liabilities that the entity used to procure fixed assets.
	Current Liabilities	Firms' short-term financial obligation that must be repaid within one year
OUTPUT	Operating Profit/Loss	Earnings Before Interest and Taxes (EBIT). It is also known as revenue left in company after removing operational direct and indirect expenses from sales revenue
	Revenue	Profit or income earned from the company by selling products and/or services measured over a set period

Table 2
List of Transportation and Logistics Services in the study

DMUs	Logistic Firms
DMU1	Ancom Logistics Berhad
DMU2	CJ Century Logistics Holdings Berhad
DMU3	Harbour-Link Group Berhad
DMU4	Lingkaran Trans Kota Holdings Berhad
DMU5	Malaysia Airports Holdings Berhad
DMU6	Malaysian Bulk Carriers Berhad
DMU7	MISC Berhad
DMU8	GD Express Carrier Berhad
DMU9	Sealink International Berhad
DMU10	See Hup Consolidated Berhad
DMU11	Suria Capital Holdings Berhad
DMU12	Tiong Nam Logistics Holdings Berhad
DMU13	Transocean Holding Berhad
DMU14	Perak Corporation

3.1 Data Envelopment Analysis (DEA)

There are several DEA model types to take into consideration, depending on the production potential and features of input or output data sets. The two main models are the free disposal hull model, the Banker, Charnes, and Cooper (BCC) model (1984), and the Charnes, Cooper, and Rhodes (CCR) (1978) model. The CCR model and the BCC model, both of which were designed to create weights without being fixed in advance and to accommodate positive inputs or outputs. The CCR model varies from the BCC model in that the former examines constant return to scale of activities, whilst the latter considers variable returns to scale of activities, hence mitigating the influence of economies of scale on operational efficiency. The fundamental version of the DEA model is stated mathematically as: for details of differences in these DEA models [23]. In this study the CCR model was chosen to evaluate the efficiency value. There were also selected results to elaborate more on DEA models, which are the slacks, lambdas, targets, returns and references.

The most likely method to be used to measure efficiency is based on ratios. Their handicap is that they reflect only a few of the factors having an impact on the overall efficiency of a productive unit. The efficiency rate of such a unit can then be generally expressed as:

$$\frac{Weighted\ sum\ of\ outputs}{Weighted\ sum\ of\ inputs} = \frac{\sum_{i=1}^{s} u_i y_{iq}}{\sum_{j=1}^{m} v_j x_{jq}}$$

Where,

V_j, j = 1,2,….,m, are weights assigned to j -th input,
U_i, I = 1,2,…..,s, are weights assigned to i -th output.

In DEA models, *n* productive units are considered, where each DMU takes *m* different inputs to produce *s* different outputs. The essence of DEA models in measuring the efficiency of productive unit DMU lies in maximizing its efficiency rate. Nevertheless, subject to the condition that the efficiency rate of any other units in the population must not be greater than 1. The tools used was deaR. The models must include all characteristics considered, i.e. the weights of all inputs and outputs must be greater than zero. Such a model is defined as a linear divisive programming model:

Maximize $\frac{\sum_i u_i y_{iq}}{\sum_j v_j x_{jq}}$
Subject to $\frac{\sum_i u_i y_{ik}}{\sum_j v_j x_{jk}}$ ≤ 1K = 1,2,……,n
$u_i \geq \in$ i = 1,2,……,s
$v_j \leq \in$ j = 1,2,……,m

3.2 Super Efficiency

Regarding the input-oriented scenario, the model yields an estimate of the incremental increase in a DMU's inputs that might occur without compromising its "efficient" standing in relation to the frontier established by the other DMUs. One may also consider the super-efficiency score to be a stability indicator. That is, the super-efficiency score offers a way to assess the degree to which changes in input data, for example, may happen without compromising the DMU's position as an efficient unit. As a result, the score produces a stability index. The tool that has been used is python function to measure the super efficiency.

The input-oriented super efficiency model under constant returns to scale is expressed as:

Super Radial-I-C :

$$\theta^* = \min_{\theta, \lambda, s^-, s^+} \quad \theta - \mathcal{E} e s^+$$

Subject to

$$\theta x_o = \sum_{j=1, \neq 0}^{n} \lambda j x j + s^-$$

$$\mathcal{Y}_o = \sum_{j=1, \neq o}^{n} \lambda j \mathcal{Y} j - s^+$$

3.3 Target

Step1: Setting the Target Efficiency Score (TES_o)

The Target Efficiency Score (TES_o) for a Decision-Making Unit (DMUo) is set by the decision or policy maker. Efficiency improvement projections are categorized into three types based on TES_o:

a) *$\theta = 1.000$ – Super-Efficient EDM Projection**
   - DMUs beyond the efficiency frontier fall into this category. These are units that have already achieved optimal efficiency but are projected to improve further.

b) *$1.000 > \theta > 0.900$ – Near-Efficient Projection**
   - DMUs close to the efficiency frontier but requiring minor improvements. These firms need small adjustments to reach full efficiency.

c) *$\theta < 0.900$ – Inefficient Projection**
   - DMUs that are significantly below the efficiency frontier. These units need substantial restructuring to enhance efficiency.

Step 2: Solving TES_0

The efficiency score is calculated as:

$$TES_0 = \frac{\theta^* + MP_0\ (1-\theta^*)\times\frac{\theta^*}{(1+\theta^*)}}{1-MP_0(1-\theta^*)\times\frac{\theta^*}{(1+\theta^*)}}$$

where:

- θ^* = Initial efficiency score of the DMU
- MP_o = Magnification Parameter, which adjusts the efficiency score based on expected performance improvements

The Magnification Parameter (MP_o) accounts for external factors influencing efficiency, such as technological advancements, resource allocation, or market conditions. A higher MP_o suggests a greater potential for efficiency improvement.

Step 3: Measuring Data Reduction or Change

To evaluate the percentage of change required to achieve the target efficiency, we use:

$$\frac{(Target\ Data - Actual\ Data)}{Actual\ Data} * 100 = \text{Percentage of change}$$

This calculation helps decision-makers determine how much input or output adjustments are required for a DMU to reach its target efficiency level.

4. Results and Discussion

4.1 Results of Efficiency and Super Efficiency Score

This study presents efficiency measurement formulations that incorporate both desirable and undesirable variables using Data Envelopment Analysis (DEA) and the Super Efficiency approach. DEA is employed to assess technical efficiency among the 14 Decision-Making Units (DMUs). To further distinguish the most efficient DMUs, the Super Efficiency DEA model is utilized, allowing for a more precise ranking of highly efficient units. This section provides a comprehensive understanding of both efficiency and super efficiency measurements applied in the study.

Table 3 and 4 show the results from DEA, which is the efficiency level of the 14 companies for year 2010 to 2021. Out of 14 DMUs, DMU 4 appears to be the only DMU that is fully efficient. One of the reasons for DMU 4 to achieve this, might be since the company has the highest return on equity over three years [4]. Over the previous three fiscal years, DMU 4, Lingkaran Trans Kota Holdings Bhd (Litrak) has been able to surpass competitors with a strong return on equity (ROE) to shareholders. The other DMUs including DMU 5, 6 and 11 exhibit a decreasing efficiency score between 2019 until 2021 and the lowest is DMU 9. One of the highlighted issues happening in these years was the Covid-19.

The Pandemic has negatively influenced the company's condition. Based on the table, the lowest average score recorded is year 2011 (54.5%). In 2011, the Vice-President and Country Head of Frost & Sullivan in Malaysia, highlighted that the Malaysian logistics industry was fragmented, with smaller service providers offering limited services. He noted that this fragmentation led to unhealthy price competition and inconsistent service quality [5].

Table 5 and Table 6 present the results of the Super Efficiency DEA analysis. While the standard efficiency model resolves efficiency issues for all competing Decision-Making Units (DMUs), it is possible for multiple DMUs to achieve a perfect efficiency score. In such cases, the Super Efficiency model provides further ranking to differentiate highly efficient units.

For instance, in 2010, five companies were identified as efficient. By applying the Super Efficiency model, the most efficient company for that year was determined to be DMU 5, followed by DMU 4, DMU 8, DMU 7, and DMU 3, in descending order of efficiency.

Table 3
The Efficiency Score, Rank and Average (2010-2015)

DMU/YEAR	2010 (%)	R	2011 (%)	R	2012 (%)	R	2013 (%)	R	2014 (%)	R	2015 (%)	R
1	61.40	12	69.90	4	70.10	8	1.00	1	57.00	8	70.70	9
2	94.60	9	48.60	9	1.00	1	89.40	8	1.00	1	1.00	1
3	1.00	1	35.10	10	79.10	7	1.00	1	88.20	7	76.60	8
4	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**
5	1.00	1	1.00	1	1.00	1	61.70	12	1.00	1	77.00	7
6	95.30	7	51.80	7	29.60	13	88.20	10	47.30	12	39.20	12
7	1.00	1	51.30	8	1.00	1	1.00	1	1.00	1	1.00	1
8	1.00	1	58.00	6	1.00	1	1.00	1	1.00	1	1.00	1
9	25.30	14	7.60	14	9.80	14	76.60	11	21.00	13	25.10	14
10	88.90	10	26.10	13	1.00	1	1.00	1	1.00	1	1.00	1
11	76.80	11	60.30	5	35.20	12	89.10	9	53.20	10	98.40	6
12	95.30	7	27.20	11	41.30	9	51.10	13	53.20	10	48.20	11
13	1.00	1	1.00	1	39.10	10	1.00	1	58.70	9	67.10	10
14	25.60	13	26.70	12	37.10	11	28.30	14	22.4	14	26.20	13
Average	83.1		54.5		67.2		84.6		71.5		73.5	

Table 4
The Efficiency Score, Rank and Average (2016-2021)

DMU/YEAR	2016 (%)	R	2017 (%)	R	2018 (%)	R	2019 (%)	R	2020 (%)	R	2021 (%)	R
1	1.00	1	57.3	9	86.2	11	90.4	12	94.0	9	48.5	11
2	87.50	10	93.4	7	1.00	1	1.00	1	1.00	1	1.00	1
3	1.00	1	79.7	8	1.00	1	1.00	1	1.00	1	70.0	8
4	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**	**1.00**	**1**
5	72.80	12	52.3	10	1.00	1	1.00	1	35.1	12	11.4	13
6	88.20	8	44.5	11	35.6	12	94.8	11	91.1	10	46.4	12
7	88.10	9	1.00	1	1.00	1	1.00	1	1.00	1	1.00	1
8	1.00	1	1.00	1	1.00	1	1.00	1	1.00	1	1.00	1
9	76.60	11	19.7	13	34.1	13	38.1	13	33.6	13	10.5	14
10	1.00	1	1.00	1	93.7	9	1.00	1	1.00	1	1.00	1
11	91.20	7	1.00	1	1.00	1	1.00	1	89.3	11	72.5	7
12	55.60	13	36.1	12	1.00	1	1.00	1	1.00	1	1.00	1
13	1.00	1	1.00	1	93.2	10	1.00	1	1.00	1	65.4	9
14	22.60	14	17.6	14	34.6	14	29.5	14	22.1	14	55.6	10
Average	84.5		71.5		84.1		89.5		83.2		71.1	

Table 5
The Super Efficiency Score for Year 2010 to 2015

DMU/YEAR	2010	R	2011	R	2012	R	2013	R	2014	R	2015	R
1	0.61	12	0.70	4	0.70	8	111.31	1	0.55	8	0.91	9
2	0.95	9	0.49	9	10.36	3	0.89	8	3.58	4	1.61	3
3	1.09	5	0.35	10	0.80	7	1.12	7	0.85	7	0.92	8
4	32.91	2	48.44	2	41.09	2	35.29	2	6.95	3	7.02	1
5	**127.71**	**1**	**655.51**	**1**	**0.23**	**6**	**0.62**	**12**	**0.36**	**6**	**0.81**	**7**
6	0.95	7	0.52	7	0.46	13	0.88	10	0.74	12	42.17	12
7	1.13	4	0.51	8	0.80	5	1.24	5	0.60	5	0.94	5
8	2.61	3	0.58	6	1.54	4	1.98	4	15.73	2	1.69	2
9	0.25	14	0.08	14	0.18	14	0.77	11	0.19	13	0.92	14
10	0.89	10	0.26	13	52.86	1	1.24	6	275.86	1	1.50	4
11	0.77	11	0.60	5	0.55	12	0.89	9	0.53	11	1.00	6
12	0.95	8	0.27	11	0.45	9	0.51	13	0.51	10	0.76	11
13	1.03	6	7.24	3	0.48	10	4.39	3	0.52	9	0.88	10
14	0.26	13	0.27	12	0.50	11	0.28	14	0.27	14	0.81	13

Table 6
The Super Efficiency Score for Year 2016-2021

DMU/ YEAR	2016	R	2017	R	2018	R	2019	R	2020	R	2021	R
1	111.31	1	0.78	9	0.98	11	0.90	9	0.94	9	0.49	11
2	0.87	10	0.97	7	1.01	6	1.10	5	1.16	6	30.39	1
3	1.07	6	0.92	8	1.18	3	1.26	4	1.29	5	0.69	8
4	35.29	2	37.46	1	1.86	2	1.69	2	1.59	3	1.24	4
5	**0.73**	**12**	**0.72**	**10**	**0.89**	**8**	**0.52**	**12**	**0.75**	**12**	**0.11**	**13**
6	0.88	8	3.29	11	0.76	12	0.95	8	1.11	10	0.44	12
7	0.88	9	0.94	6	0.97	7	0.67	11	0.89	8	0.51	6
8	1.98	4	2.20	3	1.75	4	1.42	3	1.15	7	1.91	3
9	0.77	11	0.94	13	0.73	13	0.38	13	0.30	13	0.11	14
10	1.24	5	1.24	5	0.99	9	1.01	6	1.59	4	1.13	5
11	0.91	7	1.32	4	1.27	5	1.04	7	0.97	11	0.72	7
12	0.56	13	0.58	12	2.53	1	1.99	1	2.07	2	2.19	2
13	4.39	3	3.17	2	0.98	10	0.75	10	3.85	1	0.65	9
14	0.23	14	10.67	14	0.80	14	0.29	14	0.27	14	0.55	10

Figure 1 illustrates the efficiency trends of 14 Decision-Making Units (DMUs) over an 11-year period. To measure company efficiency, five key variables were utilized. The fluctuations in the line graph indicate which companies-maintained efficiency and which experienced inefficiencies over time. The graph highlights that DMU 4 remained consistently efficient throughout the entire period, including before and during COVID-19, making it the most efficient company. DMU 8 initially displayed an efficient score, but in 2011, it experienced a sudden drop. However, it quickly recovered and maintained full efficiency until 2021.

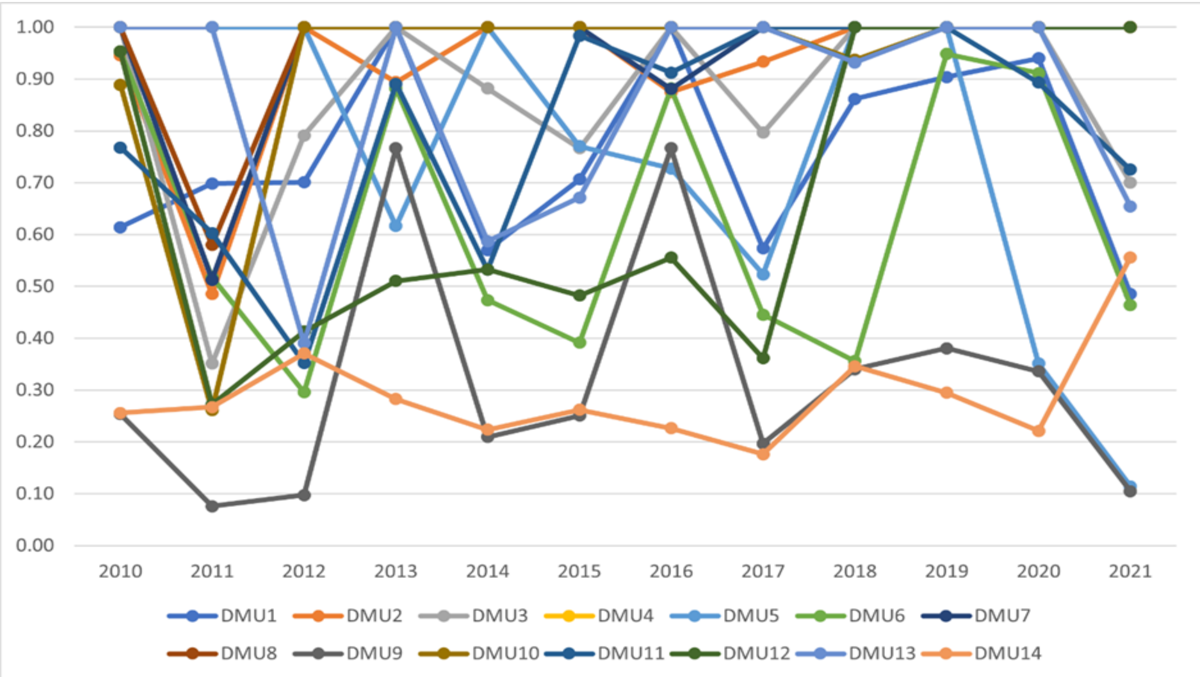

Fig. 1. The Line Graph of Efficiency For Each DMU

In contrast, DMU 9 started with poor efficiency, showing improvement in 2013, followed by fluctuations, a drop after 2013, an increase in 2016, and another decline in 2017. Although there were minor improvements in subsequent years, its efficiency significantly declined until 2021.

Similarly, DMU 10 started near efficiency, but in 2011, it experienced a sudden decline. However, it recovered strongly, achieving full efficiency for a period before experiencing another drop. Fortunately, it managed to sustain its efficiency until 2021. DMU 14 did not perform efficiently for most of the observed period. However, the data shows a fluctuating trend, and in 2021, the company exhibited a positive sign of improvement, outperforming other DMUs during the pandemic year. These findings emphasize the importance of identifying efficient and inefficient companies to enhance future performance and development. By understanding efficiency trends, companies can implement strategies to minimize waste, optimize resource utilization, and improve long-term sustainability.

4.2 Results of Efficiency and Super Efficiency Score

Finding out how effective the DMUs was the main objective of the original DEA models. Several studies under the headings of target setting and resource allocation have been conducted since it is crucial to understand whether or not the DMU projected onto the efficient frontier is acceptable and desirable for the decision makers (DMs) [3].

Based on Table 7, the scale direction with a value of zero for all three current assets, current liabilities and fixed asset exhibits that no change to the actual value of inputs is required as the expansion of desirable contraction of undesirable inputs becomes zero. This is due to the same value of actual and target data in 2021. For instance, DMU 2, 4, 7, 8, 10 and 12 are not required to increase or decrease their value of current assets, current liabilities and fixed asset since these DMU have achieved efficiency score of 100 percent.

Further analysis on the current assets, net fixed assets and liabilities, versus the target of a company was done. Figure 2 indicates the finding of Current Asset for 2021. The graph shows the actual and target current assets for 14 DMUs in 2021. Concurrently, the remaining observations must raise their current assets and so that the companies can reduce their targets. The results for DMU 5 and 9 show the highest change percentage (88.56 percent) and (89.49 percent) for current assets where DMU 5 and 9 need to reduce the actual current asset value because when the value for current assets is too high, it is not necessarily a good sign for the company. Looking at the net fixed assets in Figure 3 and Figure 4 on the current liabilities, the values need to be decreased as well.

Table 7
The Actual Data, Target Data and Data Changes (Bursa Malaysia, 2019)

YEAR	**ACTUAL DATA 2021 (RM)**			**TARGET DATA 2021 (RM)**			**DATA CHANGES (%)**		
VAR	Actual Current Asset	Actual Net Fixed Asset	Actual Current Liabilities	Target Current Asset	Target Net Fixed Asset	Target Current Liabilities	Current Asset	Net Fixed Asset	Current Liabilities
DMU 1	23,817,000	18,069,000	16,819,000	11,561,971	8,771,603	8,164,790	51.45	51.45	51.45
DMU 2	**15,024,000**	**428,227,000**	**215,189,000**	**15,024,000**	**428,227,000**	**215,189,000**	**0.00**	**0.00**	**0.00**
DMU 3	409,588,209	255,960,785	132,200,915	286,890,815	159,499,429	92,598,438	29.96	37.69	29.96
DMU 4	**707,285,000**	**1,393,000**	**231,403,000**	**707,285,000**	**1,393,000**	**231,403,000**	**0.00**	**0.00**	**0.00**
DMU 5	2,814,600	432,500,000	3,139,200	321,914	690,860	359,040	88.56	99.84	88.56
DMU 6	226,384,000	338,878,000	68,677,000	105,077,608	50,690,038	31,876,877	53.58	85.04	53.58
DMU 7	**12,826,000**	**1,889,000**	**12,427,000**	**12,826,000**	**1,889,000**	**12,427,000**	**0.00**	**0.00**	**0.00**
DMU 8	**381,776,337**	**121,947,502**	**76,338,818**	**381,776,337**	**121,947,502**	**76,338,818**	**0.00**	**0.00**	**0.00**
DMU 9	20,325,156	330,246,906	88,904,146	2,137,189	18,484,911	9,348,265	89.49	94.40	89.49
DMU 10	**44,743,661**	**8,531,318**	**44,743,661**	**44,743,661**	**8,531,318**	**44,743,661**	**0.00**	**0.00**	**0.00**
DMU 11	321,500,000	56,725,000	65,819,000	195,244,680	41,148,634	47,745,473	39.27	27.46	27.46
DMU 12	**495,002,000**	**1,072,293**	**445,230,000**	**495,002,000**	**1,072,293**	**445,230,000**	**0.00**	**0.00**	**0.00**
DMU 13	12,111,728	30,957,769	6,047,620	7,924,241	7,264,534	3,956,727	34.57	76.53	34.57
DMU 14	187,748,000	92,845,000	293,912,000	104,396,385	51,626,022	119,304,798	44.40	44.40	59.41

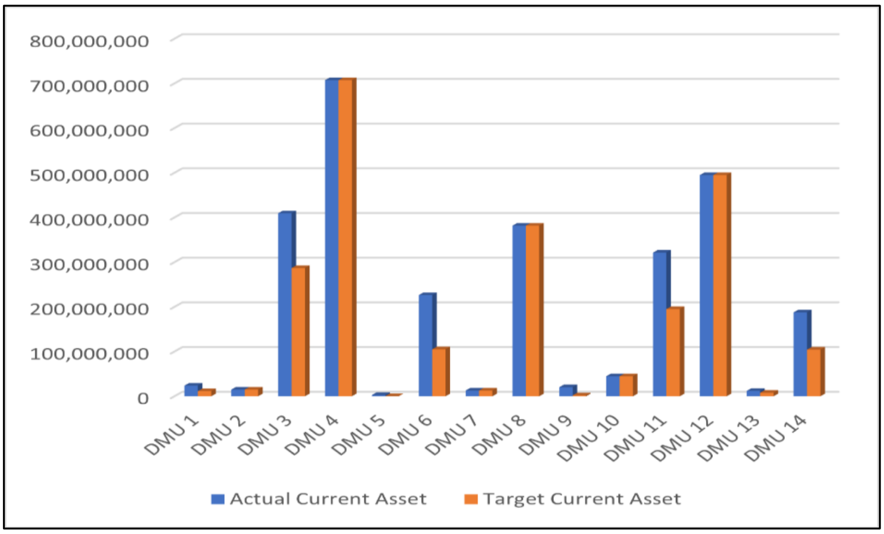

Fig. 2. The Actual and Target Current Asset 2021

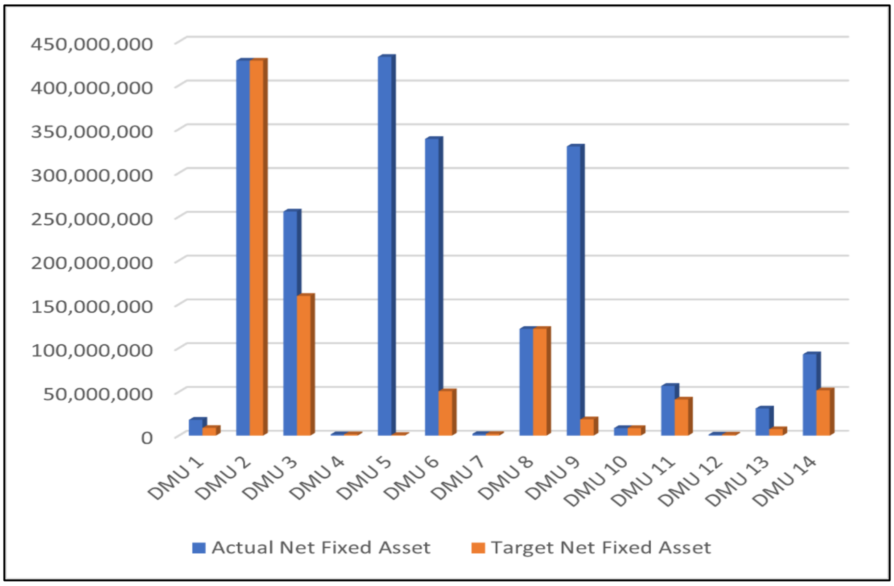

Fig. 3. The Actual and Target Net Fixed Asset 2021

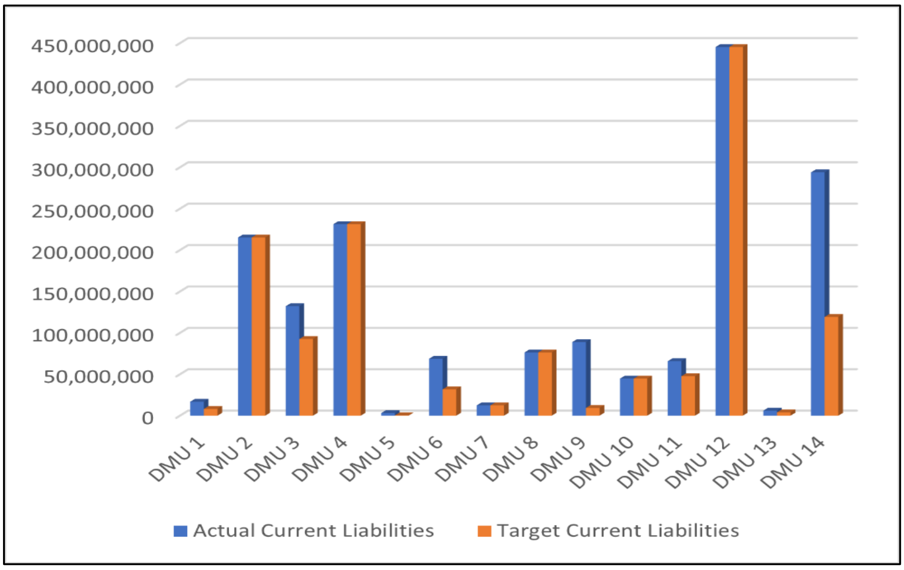

Fig. 4. The Actual and Target Current Liabilities 2021

5. Conclusion

In this paper, an evaluation on the efficiency scores of 14 Malaysian logistics companies was done and compared for their performance before, during, and after the COVID-19 pandemic. The empirical analysis of the Malaysian logistics sector is conducted using two approaches: Data Envelopment Analysis (DEA) and the Super Efficiency model, covering the period from 2010 to 2021.

The Super Efficiency model, with an input-oriented approach, is employed to assess company performance more precisely. Using these methods, the study presents the efficiency scores, super-efficiency rankings, and target scores to identify the strengths and weaknesses of each company. The findings of this study provide valuable insights for manufacturers and decision-makers by identifying the optimal levels of desirable inputs to be increased and the undesirable outputs to be reduced. This information serves as a strategic guideline for companies aiming to achieve full efficiency and enhance overall productivity. It also indicates that some companies consistently maintained high efficiency, while others experienced fluctuations due to external challenges, such as economic disruptions, labor shortages, and increased operational costs. By identifying efficient and inefficient companies, this research offers practical insights for logistics firms, manufacturers, and policymakers. Companies can leverage these results to optimize resource allocation, improve operational strategies, and enhance overall productivity. Additionally, the study highlights the importance of targeting desirable inputs and minimizing inefficiencies to remain competitive in a rapidly evolving logistics landscape.

Future studies could include a larger sample size by examining additional logistics companies across various regions and market segments to obtain a broader perspective on industry efficiency. At the same time, incorporating machine learning algorithms, artificial intelligence (AI), or hybrid efficiency models (e.g., DEA combined with Stochastic Frontier Analysis) can provide more accurate predictions of efficiency trends and performance improvements. With the rise of Industry 4.0, future research could explore how technological advancements, such as automated warehouses, blockchain, and IoT-based tracking systems, influence logistics efficiency.

Given the increasing focus on environmental sustainability, future studies could assess the role of green logistics practices in improving efficiency while reducing carbon footprints in supply chain operations. Similarly, analyzing long-term recovery trends after the pandemic and how logistics companies adapt to disruptions, changing customer demands, and global supply chain shifts can provide valuable insights for future resilience planning.

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