EVALUATION ON THE FINANCIAL EFFICIENCY OF LISTED LOGISTICS COMPANIES IN MALAYSIA USING ENHANCED DATA ENVELOPMENT ANALYSIS MODEL WITH OPERATIONAL RISK

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By

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ABSTRACT

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Lee Pei Fun

Trade facilitation helps to improve the export and import performances which drive the economy of Malaysia. This interconnectedness is achievable with smooth logistics operations for the fulfilment of goods and services in the accurate amount and condition to the proper location at the exact time. Therefore, the logistics industry is a main driver that forms the bridge between the sourcing entity and the consumption point. As such, the financial efficiency of the logistics companies is important to ensure the continuous support to the economy of Malaysia. Data Envelopment Analysis (DEA) is a linear programming model which can be used to optimize the financial efficiency of the listed logistics companies in Malaysia. The efficiency is the ratio of the weighted sum of output to the weighted sum of input and can range from zero to one as the maximum efficiency is one. Logistics companies perform a series of operational activities to move goods and fulfil orders and are prone to operational risk. Therefore, operational risk is an important factor for the evaluation of efficiency of the listed logistics companies in Malaysia. Moreover, no study has measured the efficiency of the listed logistics companies in Malaysia with operational risk in the current DEA model. In view of the research gap, this research intends to propose an enhanced DEA model with operational risk to optimize the financial efficiency of the listed logistics companies in Malaysia. The listed logistics companies in Malaysia are assessed and compared between the existing and enhanced DEA models. The results of the enhanced DEA model show that 55.56% of the listed logistics companies are efficient. The efficient and inefficient listed logistics companies have been determined based on the optimal solution of enhanced DEA model. The efficient listed logistics companies are AIRPORT, COMPLET, GDEX, HUBLINE, ILB, MISC, MMCCORP, NATWIDE, POS, PDZ, PRKCORP, SEEHUP, SYSCORP, TNLOGIS and TOCEAN. The range of efficiency of the enhanced DEA model is from 0.6725 to 1.0000 while the average efficiency is 0.9600. This study has also determined the optimal weights of the output and input variables to the maximization of the efficiency of the listed logistics companies with the enhanced DEA model. The operational risk factor, which is the basic indicator approach (C_{BIA}) and the weighted average cost of capital (WACC) are the output and input which contribute the most to the efficiency of the listed logistics companies based on the enhanced DEA model. The enhanced DEA model also provides the reference sets for the inefficient listed logistics companies to perform potential improvements to increase the efficiency score to 1 to be categorized as efficient companies. The enhanced DEA model has a lower coefficient of variation, indicating that the enhanced DEA model outperforms the existing DEA model. The inefficient listed logistics companies can increase their sales by creating more values for customers and focusing on their target markets, reduce inventory cost by removing excessive inventories, minimize production cost by removing wastes, perform demand planning, restructure debt when appropriate, and improve their marketing strategy. The significance of this

study is to differentiate the efficient and inefficient listed logistics companies in Malaysia with the incorporation of operational risk factor into the DEA model. This is also a pioneer study in examining the efficiency of the listed logistics companies in Malaysia for the long-term.

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APPROVAL SHEET

This dissertation/thesis entitled "**<u>EVALUATION ON THE FINANCIAL EFFICIENCY OF LISTED LOGISTICS COMPANIES IN MALAYSIA USING ENHANCED DATA ENVELOPMENT ANALYSIS MODEL WITH OPERATIONAL RISK</u>**" was prepared by LEE PEI FUN and submitted as partial fulfillment of the requirements for the degree of Master of Science at Universiti Tunku Abdul Rahman.

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SUBMISSION OF FINAL YEAR PROJECT /DISSERTATION/THESIS

It is hereby certified that LEE PEI FUN (ID No: 20ADM06653) has completed this dissertation entitled "EVALUATION ON THE FINANCIAL EFFICIENCY OF LISTED LOGISTICS COMPANIES IN MALAYSIA USING ENHANCED DATA ENVELOPMENT ANALYSIS MODEL WITH OPERATIONAL RISK" under the supervision of Associate Professor Ts. Dr. Lam Weng Siew (Main Supervisor) from the Department of Physical and Mathematical Science, Faculty of Science, and Associate Professor Ts. Dr. Lam Weng Hoe (Co-Supervisor) from the Department of Physical and Mathematical Science, Faculty of Science.

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DECLARATION

I hereby declare that the dissertation is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

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CA	Current asset
C_{BIA}	Capital required for operational risk under the basic indicator approach
CL	Current liabilities
CoV	Coefficient of variation
CTR	Current ratio
DAR	Debt-to-asset ratio
DER	Debt-to-equity ratio
DEA	Data envelopment analysis
DMU	Decision making unit
EPS	Earnings per share
NP	Net profit
p	Number of the past three years where gross income is positive
ROA	Return on asset
ROE	Return on equity
TA	Total asset
TE	Total equity
TL	Total liabilities
TS	Total number of outstanding shares
WACC	Weighted average cost of capital
h_k	Relative efficiency of company k
t_r	Weight of output r
y_{rk}	Observed amount of rth output of company k
s	Number of outputs

w_i	Weight of input i
x_{ik}	Observed amount of ith input of company k
m	Number of inputs
ε	Small positive value
n	Number of companies
μ_k	Free variable of company k
t_1	Weight of earnings per share
t_2	Weight of return on asset
t_3	Weight of return on equity
t_4	Weight of the amount of capital for operational risk under the Basic Indicator Approach
$y_{EPS,k}$	Earnings per share of company k
$y_{ROA,k}$	Return on asset of company k
$y_{ROE,k}$	Return on equity of company k
$y_{C_{BIA},k}$	Amount of capital for operational risk under the Basic Indicator Approach of company k
w_1	Weight of current ratio
w_2	Weight of debt-to-asset ratio
w_3	Weight of debt-to-equity ratio
w_4	Weight of the weighted average cost of capital
$x_{CTR,k}$	Current ratio of company k
$x_{DAR,k}$	Debt-to-asset ratio of company k
$x_{DER,k}$	Debt-to-equity ratio of company k
$x_{WACC,k}$	Weighted average cost of capital of company k
GI_k	Positive yearly gross income of company k
α	15% as set by the Basel Committee on Banking

	Supervision
E	Market value of equity
D	Market value of debt
R_e	Cost of equity
R_d	Cost of debt
T	Corporate tax rate
R_f	Risk free rate
β	Beta
R_m	Expected return of the market
Y_{rh}	Target value of rth output of inefficient company h
α_g	Optimal coefficient of benchmark (efficient) company g
y_{rg}	Actual value of rth output of benchmark (efficient) company g
X_{ih}	Target value of ith input of inefficient company h
α_g	Optimal coefficient of benchmark (efficient) company g
x_{ig}	Actual value of ith input of benchmark (efficient) company g
σ	Standard deviation of the efficiency scores of the DMUs
μ	Mean of the efficiency scores of the DMUs

CHAPTER 1

INTRODUCTION

1.1 Introduction

Financial efficiency is a substantial concern to a company's management as a study on the financial efficiency provides a thorough understanding on the explanatory factors that affect the company's performance, which will help the company in controlling and managing its resources in the current and future operations and investments to generate higher results (Mansour and Moussawi, 2020; Kamel et al., 2021). Throughout the years, a company may expand, upsize, and grow to become global wherein high financial efficiency would strengthen its ability to perform in the competitive market. Many companies have sought to increase their synergies by forming strategic alliances, mergers and acquisition or perform divestitures to expand their market share to maintain or improve its financial efficiency for higher operational excellence (Borhan et al., 2014).

In fact, financial efficiency is a company's responsibility towards its shareholders for profit maximization. High financial efficiency may translate to the competency to transform resources to commit to greater growth and expansion opportunities (Agyabeng-Mensah and Tang, 2021). The analysis of financial efficiency helps to assess the economic health of a company among its peers. A study on the financial efficiency of a company can also determine the effectiveness of managerial decisions which will also identify the reasons for certain shortcomings. Moreover, an examination into the financial efficiency is a fundamental procedure to understand the results of a company's strategy implementation which then offer insights on strategy enhancement for potential improvements (Fisher et al., 2020). A study on financial efficiency involves the examination of the formal records from a company's balance sheet and income statement especially with the usage of financial ratios (Karimi and Barati, 2018; Al-Mana et al., 2020; Kedžo and Lukač, 2021). However, an official from the International Monetary Fund (IMF), Gopinath (2020) stated that the Great Lockdown had worse economic implications and all economies suffer from recession. Many companies also sustain drop in financial performances (Department of Statistics Malaysia, 2020; Shah et al., 2020; Organisation for Economic Co-operation and Development, 2020; Nguyen et al., 2021).

Malaysia has strong diplomatic ties with countries around the world which encourage export and import activities (Hong et al., 2019). With trade movement, the transition and storage of cargoes, services and information from the upstream to the downstream to meet consumer expectations for efficient and effective value creation require detailed designing, organization and management (Wang et al., 2021). This entire process is complex and require the collaborative efforts from an extensive line of stakeholders, particularly the logistics companies (Niu et al., 2022; Yin et al., 2023). The logistics industry is a key player in the domestic and global supply chains for the manufacturing, assembly, and distribution of raw, work in progress or finished materials, which would be indirectly contributing to the economy of a country (Kim et al., 2020). In Malaysia, the transport and storage sector under the logistics industry garnered a gross value added of about RM57.2 billion in 2019. The logistics industry is also categorized as a priority with several approaches such as the National Transport Policy 2019-2030 to drive the industry (Organisation for Economic Co-operation and Development, 2020a). Moreover, the government of Malaysia has acknowledged the importance of the logistics industry when the logistics companies were allowed to operate during the Movement Control Order despite strict restrictions throughout the nation (MIDA, 2021).

However, the logistics companies face many issues in terms of their financial efficiency. Besides the COVID-19 restrictions which hampers trade movement, the Fourth Industrial Revolution, which aims at digitization and automation such as smart warehouses and intelligent robotics, requires high financial commitment by the companies (Choi, 2021; Rahman et al., 2022). Moreover, since logistics companies are highly operational, there are high inventory, warehousing, transportation and other administration costs which add to the financial burden of the logistics companies (Banomyong et al., 2022). Karmaker et al. (2021) found that financial support from the authorities and business partners are important for survival in the industry during the pandemic. Miller and Saldanha (2016) noted an utmost concern that when a company faces financial distress, the management will likely make decisions to improve the company financially but at a cost which may be detrimental socially or environmentally. Having constant vital engagement with many other sectors to connect them with the various markets, the logistics industry needs to be assessed in terms of their financial efficiency (Al-Shboul, 2022).

Financial efficiency can be assessed with Data Envelopment Analysis (DEA) model which is able to evaluate decision making units (DMUs) with multiple inputs and outputs (Habib and Shahwan, 2020; Kedžo and Lukač, 2021; Akhtar et al., 2022; Kamel et al., 2022). Being a linear programming model, DEA model works on the basis of minimizing input utilization (cost) while maximizing output generation (benefit) (Costa et al., 2021; Mousa and Kamel, 2022). Therefore, the efficiency based on the DEA model is formulated as the weighted-sum of outputs to the weighted-sum of inputs where larger outputs and smaller inputs provide higher efficiency (Raval et al., 2020). The efficiency score classifies a DMU into being efficient or inefficient. An efficient DMU is a company which has an efficiency score of 1.0000, which means that the efficient DMU has utilized the least amount of input for the creation of the highest volume of output (Najafabadi et al., 2022). On the other hand, a DMU which is inefficient will have an efficiency score which is lower than 1.0000, which explains that the inefficient DMU is unable to use the lowest resources to generate the maximum outcomes (Tamatam et al., 2019; Martins et al., 2021). Meanwhile, a superiority of the DEA model lies in the benchmarking ability. The efficient DMUs will serve as the benchmarks to identify the inefficiencies and compute the potential improvements for the inefficient DMUs, which will be provided by the optimal solution of the DEA model (Gandhi and Sharma, 2018; Mozaffari et al., 2022). DEA is proven to be useful in the efficiency studies in many areas such as construction (Nahangi, Chen and McCabe, 2019; Qi et al., 2022), energy (Bhunia et al., 2021) and banking (Bod'a et al., 2020;

Henriques et al., 2020; Wasiaturrahma et al., 2020).

1.2 Problem Statement

Operational risk exists in the day-to-day activities of a company and is a widespread concern due to the impact on the financial efficiency (Cheng et al., 2018; Ebenezer et al., 2018; Gadzo et al., 2019). Operational risks exist within a business and are contributed by individuals, internal processes, systems, or externalities (CIMA, 2005; Pakhchanyan, 2016; Bain & Company, 2018; Ko et al., 2019; Deloitte, 2021). Operational risk in the logistics companies normally happens based on the decisions of the functions and priorities, such as human error, manpower shortage, demand uncertainty, supplier delay, accident, system error, improper internal control, capacity constraint, disaster, or third-party influence (Gurtu and Johny, 2021; Pham and Verbano, 2022). Even though some operational risk events are preventable, when an operational risk event happens, logistics companies usually suffer losses in revenue up to millions of dollars (Andrus, 2019; BERNAMA, 2019; International Finance Corporation, 2020; Boysen et al., 2021; Cheung et al., 2021; Everington, 2021; Lochan et al., 2021; Safety4Sea, 2021; Wills, 2021; Liu, 2022).

Gross income (GI) is a proxy for operational risk exposure. The Basel Committee on Banking Supervision (BCBS) has set GI as the risk indicator for operational risk after analyzing industry data (Basel Committee on Banking Supervision, 2001a; Peña et al., 2018a). Higher GI indicates higher complexity in business processes which are more prone to operational risks. BCBS proposed that every company shall hold a capital equal to a specific percentage, multiplied by the 3-year average of the positive GI of the company (Basel Committee on Banking Supervision, 2001b; Peña et al., 2018b; Bank for International Settlements, 2020b). Overall, operational risk events disrupt business operations and affect the financial efficiency of the logistics companies (Nguyen and Wang, 2018). The higher the operational risk, the weaker the financial efficiency of the logistics companies and vice versa as the companies will need to take corrective actions to rectify the damages caused by the operational risk events (Bai et al., 2022). Therefore, operational risk should be monitored and controlled for better efficiency among the logistics companies. BCBS proposed the basic indicator approach (BIA) under the Basel II Accord to calculate the capital required to hedge against operational risk (Bank for International Settlements, 2020a; Bank for International Settlements, 2020b). The capital required for hedging of operational risk is the average of at least 15% of the yearly gross income (GI) over the past 3 years (Couto and Bulhões, 2009; BCBS, 2010; Valová, 2011; Vasiliev et al., 2018; Siddika and Haron, 2020; Cristea, 2021). The adoption of the 3-year average GI mitigates the effects of volatility, particularly on capital requirements (Valová, 2011).

Despite the wide acceptance and adoption of BIA to prepare for operational risk events, no studies have adopted BIA into DEA model to optimize the financial efficiency of the logistics companies to prepare for operational risk events. Therefore, there is a need to analyze the operational risk capital requirement of logistics companies to determine if the logistics companies have been well prepared to embrace any unexpected events in their day-to-day business. This study optimizes the financial efficiency of listed logistics companies in Malaysia by proposing an enhanced Data Envelopment Analysis (DEA) model which incorporates operational risk capital requirement using BIA into the existing efficiency analysis of the listed logistics companies.

1.3 Research Questions

The research questions of this study include:

1. What is the efficiency of listed logistics companies in Malaysia with the existing DEA model?
2. What is the proposed enhanced data envelopment analysis model?
3. What is the efficiency of the listed logistics companies in Malaysia using the enhanced DEA model?
4. What is the potential improvement for the inefficient listed logistics companies to maximize the efficiency based on the enhanced DEA model?

1.4 Research Objectives

The main aim of this research is to propose an enhanced DEA model with operational risk factor to optimize the efficiency of the listed logistics companies in Malaysia. The main aim of this research can be achieved with the following objectives:

1. To determine the efficiency of listed logistics companies in Malaysia with the existing DEA model.
2. To propose an enhanced DEA model by integrating operational risk factor.
3. To optimize the efficiency of the listed logistics companies in Malaysia with the enhanced DEA model. The model performance is compared between the existing DEA model and the enhanced DEA model.
4. To determine the potential improvement for the inefficient listed logistics companies to maximize the efficiency based on the enhanced DEA model.

The flowchart of this study is shown in Figure 1.1 to illustrate the process flow of this research.

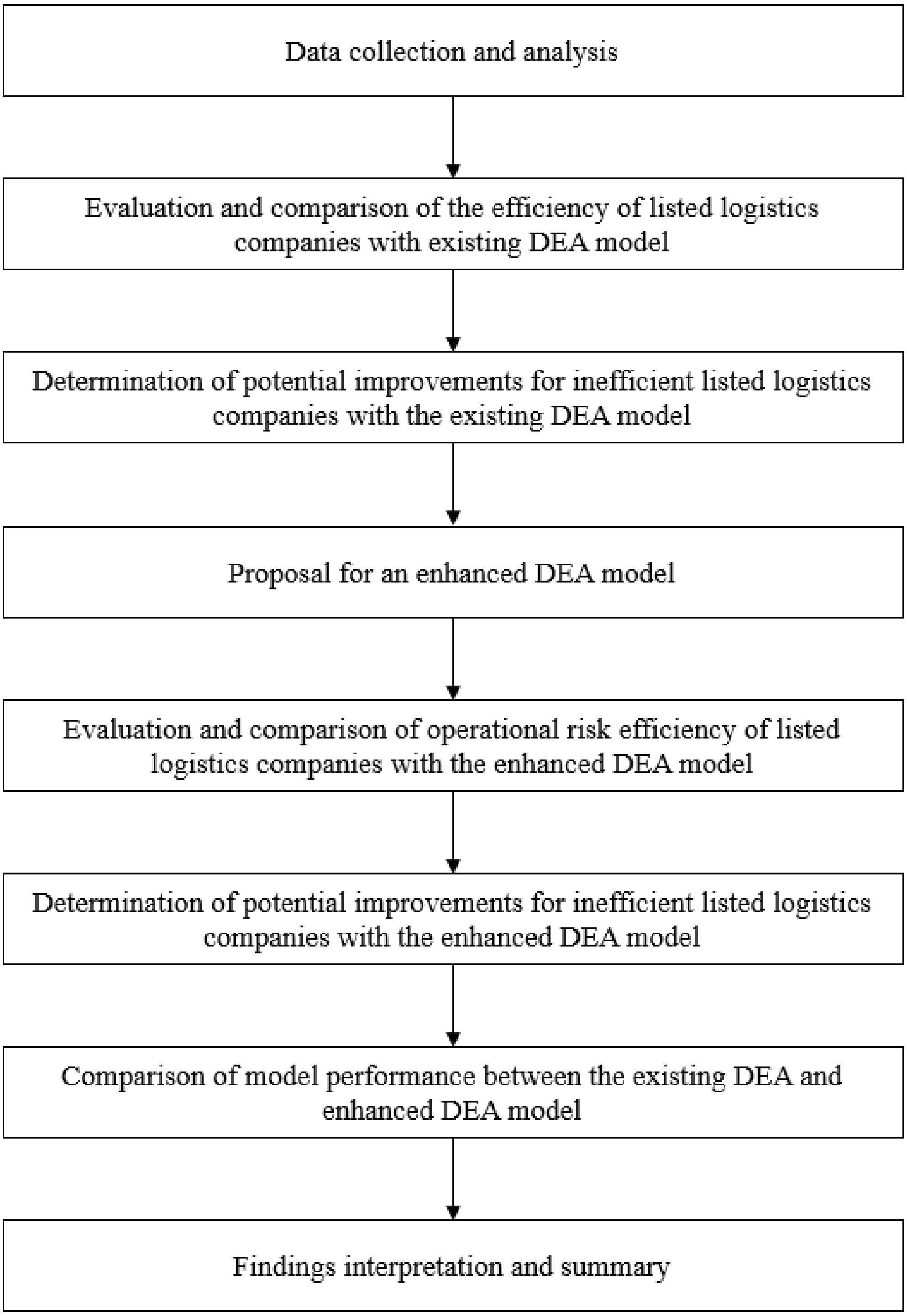

Figure 1.1: Research Flowchart

1.5 Significance of Research

This research adopts factual data from the financial statements in the

DEA model to optimize the efficiency of the listed logistics companies in Malaysia with the incorporation of operational risk capital requirement. Operational risk disrupts the daily business activities, which affects the financial efficiency of the companies. This research contributes to the development of the logistics companies as it helps the logistics companies to be aware of the operational risk, which is likely to occur out of the blue and cause high damage to the efficiency of the company. This is also a pioneer study to examine the long-term efficiency of the listed logistics companies in Malaysia.

The proposed enhanced DEA model, which includes operational risk, measures the relative efficiency of the listed logistics companies, and classify them into being efficient or inefficient. The efficiency or inefficiency of a listed logistics company is explained according to the efficiency score of the optimal solution of the DEA model. With this, the listed logistics companies may take action to continue operating at the optimum efficiency to maintain its performance or to improve its efficiency. As such, this proposed enhanced DEA model provides comprehensive understanding on the growth and development of the logistics companies in Malaysia, in terms of efficiency and operational risk.

The enhanced DEA model is also effective for benchmarking. The efficient listed logistics companies will be selected as the benchmarks for the inefficient listed logistics companies according to the optimal solution of the enhanced DEA model. Upon identification, the inefficiencies of the underperforming listed logistics companies can be improved based on the computation of the potential improvements to help the inefficient listed logistics companies to improve their efficiency levels. The enhanced DEA model provides the weights of the inputs and outputs for the determination of the importance of the inputs and outputs in maximizing the efficiency of the listed logistics companies. The potential improvements can then be computed by reducing the inputs and strengthening the outputs. Benchmarking is a part of continuous improvement which is imperative in strategic decision making for the sustainability of a company.

1.6 Organization of Dissertation

There are six chapters in total in this dissertation. The first chapter offers an introduction into the research involving the study of the efficiency of listed logistics companies in Malaysia with DEA. After a brief background description, the problem statement which highlights the need to incorporate operational risk capital is presented followed by the research objectives. The significance of study, which justifies the major contributions of this research is also stated in this chapter. The structure of the dissertation is the final subchapter.

The second chapter begins with a thorough explanation of DEA, followed by the evaluation of the efficiency using DEA model, the evaluation of efficiency in logistics companies using DEA model and the discussion on the literatures on operational risk.

The third chapter explains the data and methodology to examine the efficiency of listed logistics companies in Malaysia with the existing and the enhanced DEA models. Sub-topics under this chapter include data collection, existing DEA model to study the efficiency of the listed logistics companies, generation of the enhanced DEA model with operational risk, computation of potential improvements of inefficient companies and determination of model performance.

The fourth chapter discusses the findings and results of this research. This chapter starts with the results of the efficiency scores of the listed logistics companies with the existing DEA model, together with the optimal weights of the inputs and outputs and the potential improvements which can be achieved by the inefficient logistics companies.

The fifth chapter provides an interpretation of the enhanced DEA model, which assesses the efficiency of the listed logistics companies with operational risk. Results from the enhanced DEA model offers new insights into the efficiency scores of the listed logistics companies, optimal weights, and potential improvements. The model performances between the current and enhanced DEA model using the coefficient of variation (CoV) are also explained here.

The last chapter revolves around the summary of the entire dissertation. Important points such as objectives, results and significance are also highlighted in this chapter. The contributions of this research and future directions also make up this chapter.

CHAPTER 2

LITERATURE REVIEW

2.1 Introduction

This chapter presents the literatures of DEA as an optimization model for performance evaluation of the relative efficiency of DMUs. DEA is able to distinguish efficient and inefficient companies, determine the importance of each input and output criteria to the efficiency and also quantify potential improvements for the inefficient companies. The financial efficiency evaluation of decision-making units (DMUs) with DEA model will be reviewed in the Section 2.2, Section 2.3 discusses the efficiency evaluation of logistics companies with DEA. Finally, studies on the application of operational risk will be discussed in Section 2.4.

2.2 Evaluation of Financial Efficiency of Companies with Data Envelopment Analysis Model

Data envelopment analysis (DEA) is a mathematical programming model to deal with a huge number of variables with certain constraint limitations to evaluate the relative efficiency of decision-making units (DMUs). DMUs are entities such as companies, centres, universities, courts, countries or regions. The initial model of DEA is known as the Charnes, Cooper and Rhodes (CCR) model which determines the technical efficiency of the each DMU and identify the best practices as a DMU produces outputs from the inputs (Charnes et al., 1978; Khanna and Sharma, 2018; Krstić et al., 2022). A few years later, another standard model which is the Banker, Charnes and Cooper (BCC) model was introduced (Banker et al., 1984; Gardijan and Lukač, 2018; Smętek et al., 2022). The BCC model is able to overcome the limitation in CCR model whereby BCC model allows variable returns to scale (Malik et al., 2018). Variable return to scale can exist in two forms, namely increasing and decreasing returns to scale (Benicio and de Mello, 2015; Mohanta et al., 2021). Increasing returns to scale means that the increase in output is greater than the increase in input. For example, one unit increase in input will yield an increase of more than one unit in the output. Decreasing returns to scale happens when the increase in output is smaller than the increase in input. For example, an increase in one unit of input will lead to less than one unit increase in output. In short, there will be no proportional difference in outputs when there are changes to the inputs (Benicio and de Mello, 2015).

Efficiency in DEA is defined as the weighted sum of outputs over the weighted sum of inputs (Dalei and Joshi, 2022). Efficient DMUs will then receive the efficiency score of 1.0000 while inefficient DMUs shall obtain the efficiency score of less than 1.0000 (Gandhi and Sharma, 2018; Shabanpour et al., 2021).

A number of past studies on the study of efficiency applied financial ratios. The integration of financial ratios with DEA was proposed by Smith

(1990). This study noted that financial ratio analysis, which is univariate, is insufficient to examine the performance of a company because of the complexity in the business activities. In DEA, the efficiency, which is the ratio of the weighted outputs to the weighted inputs, is imposed into multiple dimensions instead of a two-dimensional activity as seen in a financial ratio. Moreover, this study emphasized the importance of slack variables wherein they quantify the potential improvements of each input or output for higher efficiency attainment (Mahmood, 1994). Another strength of DEA is also highlighted in this paper as the weights of the inputs and outputs reflect the relative importance of the respective input or output in assessing the financial efficiency of a company. This study served as the base for future DEA studies to include financial ratios (Diakoulaki et al., 1992; Lukač and Gardijan, 2017).

The study of financial ratios in DEA was applied in a study in banks in Taiwan (Yeh, 1996). In this study, Yeh (1996) successfully demonstrated that the combination of financial ratios in DEA can offer more meaningful insights. This paper had the aim of distinguishing peer groups into good and underperforming based on financial conditions. The average efficiency of the banks was around 0.9000 from 1981 to 1989. The results of this study found that banks with better efficiency scores also have better profitability, leverage and liquidity. This shows that this combination of financial ratios with DEA is able to categorize the efficiencies of decision-making units (DMUs) and reflect the actual financial performances of the DMUs. This paper concluded that this combination of financial ratio with DEA is able to be used as an early detection of inefficiencies in the performances of the DMUs.

Halkos and Salamouris (2004) applied DEA on Greek banking sector from 1997 to 1999. This paper also proposed the use of DEA as a complement to financial ratio analysis as DEA is superior to the traditional ratio analysis. Financial ratios were used because of its ability to permit comparisons among banks with various sizes. Moreover, the advantages of DEA were highlighted in this paper such that DEA is non-parametric. DEA considered a number of financial ratios and allowed the comparison of the efficiencies of the DMUs by translating all the financial ratios used into one relative efficiency. The financial ratios used as outputs for this study included return on asset (ROA), return on equity (ROE) and profit or loss per employee. This study noted that the efficiencies of the banks ranged from 0.41 to 1.00 and the average efficiency was up to 0.90. In the end, this paper computed the feasible improvement targets for the inefficient banks based on the optimal coefficients of the efficient banks in the reference sets as provided by the optimal solution of DEA.

De Souza et al. (2014) stated operational and financial matrices are standardized indicators to evaluate performances even in hospitals from 2008 to 2010. These matrices help the hospitals to optimize their resource allocations in several functional areas. DEA classifies the DMUs into being efficient or inefficient with regards to the input and output criteria, which can be of various units of measurements. The average efficiency score in this study ranged from 0.74 to 0.95.

In the paper by Li et al. (2014), The financial ratios used in this paper included profitability, liquidity, cash flow and capital structure ratios. The results conform to the actual situation whereby the less efficient companies posted higher risk of financial distress compared to the highly efficient companies. This study also noted that the efficiency scores of DEA can be combined with financial ratio.

DEA has also been widely accepted to evaluate the performances of financial institutions. Dhillon and Vachhrajani (2016) studied the financial performances of State Bank of India. The inputs were deposits and borrowings, and number of branches. The outputs were advance and investment, operating result, and profit per employees. This study also noted that about 50% to 60% of DMUs scored above the average efficiency scores.

Gardijan and Lukač (2018) adopted the financial ratios to evaluate the food and drink industry in 19 European countries. Financial ratios allow easy and direct comparison among the DMUs for the overall ranking. This study noted that the output-oriented BCC model is highly suitable for the evaluation of efficiency with financial ratios. This paper adopted financial ratios in liquidity, profitability, and leverage categories such as current ratios (CTR), DAR, ROA, and ROE. The profitability ratios are the outputs and are expected to the large for high efficiency. From the results, it is found that liquidity is the source of inefficiency in most of the companies.

Karimi and Barati (2018) assessed the performances of manufacturing companies listed in Iran. The manufacturing companies came from four industries, namely automotive, pharmaceutical, cement and petrochemical industries. This study employed financial ratios and categorized the ratios into various categories such as liquidity, leverage, profitability, and growth ratios. Under liquidity, the ratio chosen was current ratio (CTR). Leverage ratios used were DAR and DER. Profitability ratios, which were used as outputs, included EPS, ROA, and ROE.

Anounze and Bou-Hamad (2019) used DEA to analyse bank performances in the Middle East from 2008 to 2010. This study noted that financial data from the balance sheets are widely adopted as the inputs and outputs and proceeded to use an output-oriented BCC approach. The average efficiency score is approximately 88%. After that, this paper segregated the banks according to their countries and had successfully identified that banks in Algeria, Libya and Yemen performed better than the rest of the countries in the Middle East while banks in Jordan and Lebanon required improvements.

Ofori-Sasu (2019) used DEA to evaluate 25 banks in Ghana. This paper intended to study whether the banks were efficient with the current capital structure. With regards to using banking-specific financial ratios as the inputs and outputs, the percentage of efficiency was 40% while the average efficiency was 0.9069.

Kedžo and Lukač (2020) performed a study on the financial efficiency of food and drink manufacturers across the European Union from 2011 to 2015 using DEA. About 23% of the manufacturers were efficient from the results of this study. This study also pointed out that efficient manufacturers would have better liquidity, leverage and profitability. Among all the aspects of financial ratios, this study found that liquidity was the strongest cause of inefficiency based on the optimal solution of the DEA model.

Al-Mana et al. (2020) evaluated the financial efficiency of oil companies around the world from 2002 to 2016. This study noted the superiority of DEA in that it is non-parametric DEA is also comparative to distinguish efficiency against the best performers. This paper adopted a combination of financial indicators and ratios as the inputs and outputs. The results of the DEA efficiency scores of the oil companies are also similar to the actual situation in that international oil companies perform better than the national oil companies.

Meanwhile, a study was done to assess the efficiency of financial institutions in Iran from 2012 to 2017 with the use of financial ratios such as CTR, DAR, DER, ROA, ROE, and EPS. The authors were certain that financial ratios can be complemented with DEA to obtain real efficiency scores (Mohtashami and Ghiasvand, 2020).

Hospitals in Egypt was also analysed with DEA from 2014 to 2016 in the paper by Habib and Shahwan (2020). This paper noted that benchmarking in DEA helped in continuous improvement for inefficient DMUs. 33 hospitals were assessed between 2014 and 2016 in this paper. This study found that 16 out of 33 hospitals were efficient, yielding the percentage of efficient DMUs to be 48.48%.

Curtis et al. (2020) explored the efficiency of 12 wind farms in Greece in 2018. Financial indicators were used in this analysis. DEA complements the financial ratios to allow multiple aspects of measurement to increase the quality of efficiency assessment. This study noted that the wind farms require high assets and invested capital that determine the scale of operations. The percentage of efficiency was 33.33% and the average efficiency was 82.6%. This paper also proposed the benchmarks, optimal coefficients and the potential improvements for the inefficient wind farms.

Dahooie et al. (2021) proposed the use of DEA to evaluate the credit performance of loan applicants in a financial and credit institution in Iran from 2014 to 2017. Financial ratios used in this study were under the categories of liquidity, solvency, and profitability. DEA has been applied in identifying the importance of the input and output criteria to the maximization of the relative efficiency in this study.

Based on the study by Nurcan and Köksal (2021), Profitability ratios were classified as the outputs requiring maximization while the capital structure ratios and operational efficiency ratios were the inputs. DEA helps to provide information on the improvement of the financial ratios for greater financial achievement (Shetty et al., 2012; Li et al., 2014; Li et al., 2017).

Kamel et al. (2021) studied the financial efficiency of listed commercial banks in Egypt. The results showed that 4 out of 12 (33.33%) banks were efficient during the study period between 2017 and 2019. The efficient DMUs then made up the reference sets for the inefficient DMUs. Then, the efficiency change over the period of study was also assessed.

2.3 Efficiency Evaluation of Logistics Companies with Data Envelopment Analysis Model

According to Scheraga (2004) when analysing the performances of 38 airlines from America, Europe, Asia and the Middle East with DEA. This study adopted financial ratios such as operating ratio, CTR and net profit margin and found that 18 out of 38 (47.37%) of the airlines were efficient.

The railroad companies in North America have also been studied with financial ratios such as average collection period, cash flow per share, quick ratio, ROA and ROE. This study noted that the inputs and outputs should reflect the economic variables which are huge contributors to the strengths of the companies. Out of the 7 companies, 5 (71.43%) railway companies were efficient. These 5 (71.43%) companies were also above the average efficiency score of 87%. This paper has also noted that 4 out of 5 of the efficient railway companies were also the companies with best practices. Moreover, this paper has identified the efficient peer groups, which were the reference sets for the two inefficient companies and proceeded to compute the potential adjustments to facilitate the inefficient companies to become efficient (Malhotra et al., 2009).

Ablanedo-Rosas et al. (2010) studied 11 Chinese ports with financial ratio-based DEA model. This study noted that, based on Hollingsworth and Smith (2003), when financial ratios are adopted in DEA such as ROE, CTR, and quick ratio, the lowest efficiency score was around 0.5837, the percentage of efficiency was at 54.55% and the average efficiency was 0.8925. Besides, this paper also identified the reference set, optimal coefficients, and feasible targets for the inefficient ports.

Güner (2015) analysed seaports in Turkey in terms of infrastructure, superstructure, operating and financial efficiency. This study also noted that seaports had very high expenses which was one of the causes of inefficiency. The BCC model used found that the financial efficiency of the 13 seaports ranged from 7.78% to 100.00% with the average efficiency of 55.87%. Only 6 out of 13 (46.15%) of the seaports had above average efficiency. From this result, it is important to perform a thorough analysis on the financial efficiency of these entities.

DEA has also been applied to study the logistics performances in different regions China in 2009. From the optimal solution of the DEA model, the highest efficiency logistics performances were classified into one group and existed mostly in the East area (Tianjin, Hebei, Shanghai, and Shandong) in China while Anhui and Ningxia are in the Central and West area. Other West areas had lower efficiency due to slower economic development. Then, Shanghai appeared to have the highest efficiency while Tianjin was the second highest efficient region in logistics performances (Chen, 2018).

In the meantime, Venkadasalam et al. (2020) studied the efficiency of maritime and shipping lines in ASEAN region including Malaysia from 2011 to 2017 using DEA model. The input variables were equity, staff cost and fixed assets. The output variables included revenue, ROA and ROE. The minimum efficiency recorded was 0.661 while the maximum efficiency was 1.000. The average efficiency was up to 0.971. Out of the 45 companies, up to 12 companies (26.66%) were efficient with the scores of 1.000.

In a separate study, Hahn et al. (2021) adopted the DEA BCC model to study the supply chain performances from a financial market perspective from companies in 13 industries including aircraft, pharmaceutical, electronics, food products and construction materials in the United States from 2007 to 2015. This paper found that DEA was able to explain the financial crisis in 2009 as there was a dip in the results.

Li et al. (2022) evaluated the efficiency of 32 container terminal companies in China from 2017 to 2020. The results found that the efficiency of the terminals had huge variation especially when they were in regions of different levels of development. This paper has successfully identified the less efficient container terminal companies that require to manage its resources such as the employees, berthing facilities, and loading or unloading equipment for higher container throughput and the ability to handle greater cargo weight.

2.4 Operational Risk

The logistics companies perform many activities which carry value to the manufacturing industry but could be detrimental if the activities suffer from operational disruptions as these unexpected events could cause further chain reactions to other stakeholders. Due to fluctuations in supply and demand, the extensive global supply chain and declining product life cycles, the early detection and management of operational risk is inevitable. Most operational risk events come in shock and the impacts are unpredictable (Wee et al., 2012; Chand et al., 2014; Bellini, 2017; Ferreira and Dickason-Koekemoer, 2019).

One study has been done on the operational risk in Ancom Berhad Malaysia from 2012 to 2016. This study then concluded that operational risk had the strongest influence on the performance of this company. This study is also in accordance with Chew (2018) which found that operational risk had significant impact on the ROA and ROE in Complete Logistics Services Berhad.

Dziwok (2018) and Abdullah and Shahimi (2021) used the basic indicator approach (BIA) to analyse the minimum capital required for operational risk. The amount of capital under BIA is highly reliant on the gross income (GI) of the company. Operational risks tend to increase a company's operating cost or reduce the company's revenue, of which both are also detrimental to the performance of the company. BIA, which was proposed under Basel II, were based on actual risk profiles during the observation period. Thus, the adoption of BIA could help companies be better prepared in cases of the occurrence of operational risk events (Archer and Haron, 2007; Siddika and

Haron, 2020).

2.5 Summary

The adoption of financial ratios as the input and output criteria in DEA models have been proposed and applied to evaluate the efficiency of entities in the past studies. Most studies have also included the liquidity, leverage and profitability indicators and ratios. Based on this review, operational risk has not been considered and incorporated in DEA models, for the financial efficiency evaluation of logistics companies. Therefore, this study aims to close the research gap by incorporating operational risk capital requirement to evaluate the financial efficiency of the listed logistics companies in Malaysia with an enhanced DEA model.

CHAPTER 3

DATA AND METHODOLOGY

3.1 Introduction

This chapter aims to explains the method applied in this study and the use of DEA model for the evaluation of efficiency. This will be followed by a comprehensive instruction of the evaluation of the financial efficiency of the logistics companies using the existing DEA model. Subsequently, the proposed enhanced model will be explained before the potential improvements of inefficient logistics companies from DEA solutions is discussed. Lastly, this chapter will end with coefficient of variation (CoV) which is used to assess the performance of the enhanced DEA model.

3.2 Data

This research consists of all the 27 listed logistics companies under the Transportation & Logistics sector in Bursa Malaysia from 2010 to 2021 (Boussofiane, 1991; Golany and Roll, 1989; Bowlin, 1998; Cooper et al., 2002; Scheraga, 2004; Tan et al., 2018; Anouze and Bou-Hamad, 2019; Sharif et al., 2019; Tamatam et al., 2019; Gadepalli and Rayaprolu, 2020; Samuel et al., 2020; Agüero-Tobar et al., 2022; Hsu et al., 2022; Liu et al., 2022). Past studies have evaluated the logistics companies of various nature using DEA model. Yi and Yan (2018) assessed the logistics companies that offer transportation, warehousing, freight forwarding, and IT services using DEA in China. Thi (2019) evaluated a mixture of logistics companies such as railway, airline, ocean shipping, trucking, and freight forwarding in Vietnam using DEA model. Chen (2018) and Zheng (2020) also studied the logistics companies that provide transport, storage and postal services in China using DEA model. Lepchak and Voese (2020) studied the various transportation services and cargo handling in Brazil with DEA. Zhang et al. (2022) assessed the railway and waterway transportation systems using DEA model in China.

The period of study accommodates adequate business and product cycles for a sufficiently long period (Bowlin, 1999; Merendino et al., 2018; Tamatam et al., 2019; Yang and Wei, 2019). Cao and Yang (2009) performed an analysis on banks in Canada using DEA and the results showed that the efficiency of the banks was in accordance with economic and managerial events during the 10-year period. DEA is a non-parametric linear programming model for the maximization of the relative efficiency of the decision-making units (DMUs) (Sarkis, 2007).

All the financial data are studied and analysed from annual reports of the logistics companies from Bursa Malaysia and Bloomberg Terminal (Bursa, 2022; Bloomberg L. P., 2022). An annual report, being a regulated disclosure, contains factual, quantitative and audited financial data that represents explanations on a company’s business, financial outcomes and performances of operations (Lo et al., 2017). Information on the history, current and future organizational activities in an annual report are transparent, reliable and relevant (Pivac et al., 2017). Khatun et al. (2016) noted that investors typically use financial statements, particularly the income statement and balance sheets, in an annual report for investment decision making. Moreover, in Malaysia, Section 258 (1) of the Companies Act 2016 required that companies should release their financial statements while the Securities Commission Malaysia has also established the Audit Oversight Board to oversee the accuracy and quality of audited financial statements (Suruhanjaya Syarikat Malaysia, 2021; Securities Commission Malaysia, 2022). Therefore, data from financial statements in annual reports are important for the financial assessment of the companies (Lin et al., 2005). Table 3.1 lists the logistics companies used in this study.

Table 3.1 Listed Logistics Companies in Malaysia.

Logistics Companies	Abbreviations	Codes
Malaysia Airports Holdings Berhad	AIRPORT	5014
Boustead Heavy Industries Corporation Bhd	BHIC	8133
Bintulu Port Holdings Berhad	BIPORT	5032
CJ Century Logistics Holdings Berhad	CJCEN	7117
Complete Logistics Services Berhad	COMPLET	5136
Freight Management Holdings Berhad	FREIGHT	7210
G Capital Berhad	GCAP	7676
GD Express Carrier Berhad	GDEX	0078
Harbour-Link Group Berhad	HARBOUR	2062
Hubline Berhad	HUBLINE	7013

Logistics Companies	Abbreviations	Codes
Integrated Logistics Berhad	ILB	5614
Lingkaran Trans Kota Holdings Berhad	LITRAK	6645
Malaysian Bulk Carriers Berhad	MAYBULK	5077
MISC Berhad	MISC	3816
MMC Corporation Berhad	MMCCORP	2194
Nationwide Express Holdings Berhad	NATWIDE	9806
POS Malaysia Berhad	POS	4634
PDZ Holdings Berhad	PDZ	6254
Perak Corporation Berhad	PRKCORP	8346
Sealink International Berhad	SEALINK	5145
See Hup Consolidated Berhad	SEEHUP	7053
Suria Capital Holdings Berhad	SURIA	6521
Shin Yang Shipping Corporation Berhad	SYSCORP	5173
TAS Offshore Berhad	TAS	5149
TASCO Berhad	TASCO	5140
Tiong Nam Logistics Holdings Berhad	TNLOGIS	8397
Transocean Holdings Berhad	TOCEAN	7218

Financial ratios examine the relationships between two financial indicators in a financial statement. At times, financial ratios are used to evaluate the financial stability and growth potentials of companies. Financial ratios are also used for the comparison among companies within the similar industry or sector. Halkos and Salamouris (2004) and Oberholzer and Van der Westhuizen

(2004) utilized financial ratios with DEA and concluded that DEA could very well be used to complement financial ratio analysis to evaluate a company's performance as the efficiency measurement of DEA provides incremental information over financial ratio analysis alone (Feroz et al., 2003; Gümüş and Çelikkol, 2011). Rashid (2021) noted that the selection of financial ratios in a study should reflect a company's competitiveness. In fact, to perform a comprehensive study with financial ratios, liquidity, profitability and leverage ratios should be adopted (Horta et al., 2012; Ajlouni and Omari, 2013; Lee et al., 2018).

Therefore, the six (6) financial ratios are chosen to be applied as the inputs and outputs to evaluate the performances of listed logistics companies with DEA model. The inputs are current ratio (CTR), debt-to-asset ratio (DAR) and debt-to-equity ratio (DER). In existing literature, CTR, DAR and DER also act as inputs because of the minimization nature of these ratios (Ling et al., 2009; Morita and Avkiran, 2009; Dastgir et al., 2021; Khalili Araghi and Makvandi, 2012; Tehrani et al., 2012; Ajlouni and Omari, 2013; Jaradat, 2016; Karimi and Barati, 2018; Mohtashami and Ghiasvand, 2020; Ertuğrul and Öztaş, 2021; Štefko et al., 2021; Sumiri et al., 2021). The outputs are earnings per share (EPS), return on asset (ROA) and return on equity (ROE). From past studies, these three variables serve as the outputs as companies and its shareholders expect higher values of these variables to reflect higher performances (Fenyves et al., 2015; Karimi and Barati, 2018; Mehlawat et al., 2018; Merendino et al., 2018; Mohtashami and Ghiasvand, 2020; Moon and Min, 2020; Kamel et al., 2021; Kedžo and Lukač, 2021).

Current ratio (CTR) is a liquidity ratio to determine whether a company has sufficient current assets to cater to the current liabilities. The formula comes as a ratio of current assets to current liabilities, of which both of these indicators can be obtained from the balance sheet of a company's annual report. Current assets include short term investment, accounts receivables, inventories and cash on hand which could be converted into cash in a year. Current liabilities include accrued expenses and accounts payable which must be settled within a year (Karimi and Barati, 2018).

Debt-to-asset ratio (DAR) is a form of leverage ratio or long-term solvency ratio. This ratio reflects the sum of debt in response to the sum of assets within a company. It also tells how much assets are being financed by debt. Sum of debt and sum of assets in this ratio include both the short term and long term indicators which can be found in the balance sheet. The calculation of this ratio is total debt over total assets. It shows the financial stability of a company. As the ratio increases, the degree of leverage also rises, causing a spike in the investment risk because of greater default risk (Kedžo and Lukač, 2021).

Debt-to-equity ratio (DER) assesses the financial leverage of a company by dividing total debt by total equity as found in the balance sheet. This ratio measures the extent of financing with debt compared to shareholders' funds. This can also reflect the capital structure of a company as higher ratio indicates stronger preference of debt over equity and may be risky as it diminishes the abilities of shareholders' funds to cover outstanding liabilities in unexpected events (Malhotra et al., 2010; Karimi and Barati, 2018).

Earnings per share (EPS) is a profitability ratio used to gauge the amount a company generates for every share and is an indicator for corporate value. It determines the shareholder's profit from the overall company's profit. Higher ratio is a good sign for investors as they perceive higher profits compared to share prices and investors can receive higher profit distribution. This ratio involves net profit divided by number of outstanding shares (Al-Shammari and Salimi, 1998; Mostafa, 2009; Lu et al., 2019).

Return on asset (ROA) also measures profitability and this ratio has a positive relationship with efficiency to generate profit from assets. Higher ratio means greater efficiency in handling the balance sheets to create profit. It is a ratio of net profit to total asset. Total assets include current assets and fixed assets. The extractions of both indicators are from the income statement and balance sheet of a company's annual report (Joo et al., 2011; Shawtari et al., 2015; Venkadasalam et al., 2019; Habib and Shahwan, 2020).

Return on equity (ROE) is another profitability ratio which is the net profit created out of each unit of shareholder's equity and is therefore computed as net profit over total equity. This ratio is a revelation of the amount of profit produced from the funds invested in a company's stocks. The greater the ratio, the more efficient the company in generating profit (Campisi et al., 2019, Habib and Shahwan, 2020, Martins et al., 2021).

The formulas for the six (6) financial ratios used in this study are presented as follows:

$$CTR = \frac{CA}{CL}, \tag{3.1}$$

$$DAR = \frac{TL}{TA}, \tag{3.2}$$

$$DER = \frac{TL}{TE}, \tag{3.3}$$

$$EPS = \frac{NP}{TS}, \tag{3.4}$$

$$ROA = \frac{NP}{TA}, \tag{3.5}$$

$$ROE = \frac{NP}{TE}, \tag{3.6}$$

where

CTR refers to current ratio,

CA refers to current asset,

CL refers to current liabilities,

DAR refers to debt-to-asset ratio,

TL refers to total liabilities,

TA refers to total asset,

DER refers to debt-to-equity ratio,

TE refers to total equity,

EPS refers to earnings per share,

NP refers to net profit,

TS refers to total outstanding shares,

ROA refers to return on asset,

ROE refers to return on equity.

3.3 Data Envelopment Analysis

Data envelopment analysis (DEA) is a nonparametric method to quantify the relative efficiency of organizations known as decision making units (DMUs) (Charnes et al., 1978; Nahangi et al., 2019; Gadepalli and Rayaprolu, 2020; Smętek et al., 2022). DMUs are organizations or entities that convert multiple inputs to multiple outputs and the performances are to be assessed with DEA (Rahimpour et al., 2020). Since DEA is a non-parametric method, there will be no assumed frequency distribution, production, cost or profit function that relate inputs to outputs, which is the characteristic of DEA (Mohanta et al., 2021). DEA has been very successful in assessing performances and evaluating efficiency (Khoshroo et al., 2021; Młynarski et al., 2021; Amin and Boamah, 2022; Hsu et al., 2022).

DEA is a linear programming (LP) model which computes the efficiency scores of the DMUs. LP is used for optimization when a goal involves maximizing the benefits or minimizing the costs, known as the objective function, subject to linear constraints. The LP scenario includes an objective function, decision variables, alternatives, and constraints (Mirasol-Cavero and

Ocampo, 2021). LP model then optimizes the objective function while fulfilling all the linear constraints to derive the optimal solution. Decision variables in DEA consists of inputs and outputs. Inputs are resources to be transformed into outputs. Outputs are desirable results which reflect productivity and value creation. Therefore, larger output is generally welcomed while smaller inputs are mostly favoured (Costa et al., 2021).

When a DMU is efficient, the DMU then attains the maximum efficiency score of 1. Otherwise, the efficiency score of the DMU shall range from 0 to less than 1 (Martins et al., 2021). DEA also stipulates the improvements that ineffective DMUs could benchmark to follow to raise the efficiency level because of DEA's ability to analyse every DMU separately and compare with other DMUs (Mousavi et al., 2019; Henriques, 2020; Mousa and Kamel, 2022). Efficiency can be written as the weighted-sum of output over the weighted-sum of input (Gandhi and Sharma, 2018; Shabanpour et al., 2021, Dalei and Joshi, 2022). Therefore, efficiency score is formed from minimizing inputs and maximizing outputs (Mirmozaffari et al., 2021). A DMU is considered efficient when it is able to reduce its inputs to create certain outputs or increase its outputs with similar inputs (Martín-Gamboa and Iribarren, 2021). Since the efficiency score is limited to the range of 0 and 1, an efficient DMU will have a score of 1 as this DMU is efficient in consuming its resources to generate maximum outcomes. On the other hand, when a DMU scores less than 1, the DMU is inefficient and have not allocated its resources well to reach its expected outcomes (Akhtar et al., 2021).

The fractional programming model of DEA is shown below (Chandel et al., 2017; Ferro et al., 2018; Li et al., 2021; An et al., 2022):

$$\text{Maximize } h_k = \frac{\sum_{r=1}^{s} t_r y_{rk} - \mu_k}{\sum_{i=1}^{m} w_i x_{ik}} \tag{3.7}$$

subject to

$$\frac{\sum_{r=1}^{s} t_r y_{rk} - \mu_k}{\sum_{i=1}^{m} w_i x_{ik}} \leq 1, k = 1,2,3, \ldots, n, \tag{3.8}$$

$$t_r \geq \varepsilon, r = 1,2,3, \ldots, s \tag{3.9}$$

$$w_i \geq \varepsilon, i = 1,2,3, \ldots, m \tag{3.10}$$

where

h_k refers to the relative efficiency of company k,

t_r refers to the weight of output r,

y_{rk} refers to the observed amount of rth output of company k,

s refers to the number of outputs,

w_i refers to the weight of input i,

x_{ik} refers to the observed amount of ith input of company k,

m refers to the number of inputs,

ε refers to small positive value,

n refers to the number of companies,

μ_k refers to free variable of company k.

The objective function of DEA model is to maximize the relative efficiency of DMUs Equation (3.7). μ_k, which is the free variable is used to allows the variable returns to scale (VRS). $\mu_k = 0$ indicates constant returns to scale, $\mu_k > 0$ signifies increasing returns to scale while $\mu_k < 0$ shows decreasing returns to scale (Miranda et al., 2017; Shabanpour et al., 2019). The constraint in Equation (3.8) shows that the relative efficiency can only exist from 0 to 1. The output weights and input weights are represented by t_r and w_i respectively. The model above will then be transformed into the linear programming form as follows (Chandel et al., 2017; Belgin, 2019; Pham et al., 2021; An et al., 2022; Hesampour, 2022):

$$\text{Maximize } h_k = \sum_{r=1}^{s} t_r y_{rk} - \mu_k, \tag{3.11}$$

subject to

$$-\sum_{r=1}^{s} t_r y_{rk} + \sum_{i=1}^{m} w_i x_{ik} + \mu_k \geq 0, k = 1,2,3, \dots, n, \tag{3.12}$$

$$\sum_{i=1}^{m} w_i x_{ik} = 1, \tag{3.13}$$

$$t_r \geq \varepsilon, r = 1,2,3, \dots, s \tag{3.14}$$

$$w_i \geq \varepsilon, i = 1,2,3, \dots, m \tag{3.15}$$

where

h_k refers to the relative efficiency of company k,

t_r refers to the weight of output r,

y_{rk} refers to the observed amount of rth output of company k,

s refers to the number of outputs,

w_i refers to the weight of input i,

x_{ik} refers to the observed amount of ith input of company k,

m refers to the number of inputs,

ε refers to small positive value,

n refers to the number of companies,

μ_k refers to free variable of company k.

The above formulation is linear with the objective function as defined in Equation (3.11). This is an output-oriented model which aims to maximize the weighted-sum of outputs. Equation (3.12) is the rearranged linear form of Equation (3.8) as DEA is a linear programming model. Equation (3.12) ensures that the efficiency score is in the range of [0,1]. Equation (3.13) is to fix the weighted sum of inputs and scaled to 1. t_r and w_i are the output and input weights.

From the linear programming model of DEA above, the variables in the weighted-sum of outputs and weighted-sum of inputs are presented in Equation (3.16) and Equation (3.17) respectively in this study. The weighted sum of outputs involves the weights given to the 3 outputs, which are EPS, ROA and ROE. The weighted sum of inputs is formed from the 3 outputs which are CTR, DAR and DER.

$$\sum_{r=1}^{3} t_r y_{rk} = t_1 y_{EPS,k} + t_2 y_{ROA,k} + t_3 y_{ROE,k} \quad (3.16)$$

$$\sum_{i=1}^{3} w_i x_{ik} = w_1 x_{CTR,k} + w_2 x_{DAR,k} + w_3 y_{DER,k} \quad (3.17)$$

where

t_1 refers to the weight of earnings per share,

t_2 refers to the weight of return on asset,

t_3 refers to the weight of return on equity,

$y_{EPS,k}$ refers to the earnings per share of company k,

$y_{ROA,k}$ refers to the return on asset of company k,

$y_{ROE,k}$ refers to the return on equity of company k,

w_1 refers to the weight of current ratio,

w_2 refers to the weight of debt-to-asset ratio,

w_3 refers to the weight of debt-to-equity ratio,

$x_{CTR,k}$ refers to the current ratio of company k,

$x_{DAR,k}$ refers to the debt-to-asset ratio of company k,

$x_{DER,k}$ refers to the debt-to-equity ratio of company k.

In this study, the computational work of DEA is performed using LINGO software (Alizadeh et al., 2019; Chen et al., 2019; Shah and Ahmad, 2020; Gazori-Nishabori et al., 2021; Dohale et al., 2022).

3.4 Proposed Enhanced Data Envelopment Analysis Model

Operational risk makes up a huge part of a company's risk exposure and would lead to great financial loss for the company as it will bring down the company's revenue but cause a rise in the operational cost. Operational risk involves uncontrolled internal or external events in daily operations that lead to financial loss (Ferreira and Dickason-Koekemoer, 2019). Mostly, losses from operational risk events are difficult to quantify, with some events such as miscommunication and data entry error occurring at higher frequency but with lower severity (Xu et al., 2021). Even though most internal operational risk events are confidential, some events which are disclosed will cause severe impact to the reputation of the company and might increase the liquidity and leverage risk of the company.

BCBS has implemented a directive on the minimum capital requirement for operational risk in which a company should have a certain level of capital adequacy to minimize the impact of operational risk events. The basic indicator approach (BIA) developed by BCBS is based on the annual gross income (GI) of a company. In this approach, companies are required to hold a minimum amount of capital equivalent to the average over the past 3 years of a constant percentage of positive yearly GI, where the percentage is denoted by alpha. When the GI is zero or non-positive, the GI figure of the year shall be excluded from calculation in the capital requirement according to BIA (Valová, 2011).

According to BCBS, the capital charge to be at least 15% of the average yearly GI over the past 3 years, thereby setting alpha to be 15% (Basel Committee on Banking Supervision, 2002; Couto and Bulhões, 2009; Basel Committee on Banking Supervision, 2010). BIA has been widely adopted since 2008 (Ismail and Sulaiman, 2007; Xie et al., 2011; Vasiliev et al., 2018; Sidika and Haron, 2020; Cristea, 2021). Cooper et al. (2007) stated that measurement unit of inputs and outputs do not have to reflect congruency (Liang et al., 2006; Halkos and Tzeremes, 2012; Venkadasalam et al., 2019; Lang, 2020; Zhang and Koutmos, 2021).

Despite the wide acceptance and adoption of BIA to prepare for operational risk events, no studies have adopted BIA into DEA model to evaluate the efficiency of logistics companies to consider the operational risk. Since the capital required for operational risk has to be at least 15% of the average yearly GI for the past 3 years, and that DEA works under the principle to conserve inputs and maximizes outputs, BIA can be incorporated into DEA as an output variable. The capital required for operational risk as indicated under BIA is computed as follows Equation (3.18) (Ismail and Sulaiman, 2007; Valová, 2011; El Arif and Hinti, 2014; Hasan et al., 2020).

$$C_{BIA} = \frac{\sum_{k=1}^{p}(GI_k \cdot \alpha)}{p} \tag{3.18}$$

where

C_{BIA} refers to the capital required for operational risk under the basic indicator approach,

p refers to the number of the past three years where gross income is positive,

GI_k refers to the positive yearly gross income of company k,

α equals to 15% as set by the Basel Committee on Banking Supervision.

Meanwhile, the weighted average cost of capital (WACC) involves a combination of cost that a company incurs to finance its assets. Basically, assets are financed from debts and equities, therefore, it is the cost of debt and cost of equity. The main aim to obtain cost of capital is to investigate a company's ability to continue with their operational activities. Shareholders expect that their capital could be used efficiently in the operational activities to maximize their profits through value incrementation of the company. WACC also signifies the minimum return that a company shall earn from its assets and operations

(Mohamad and Saad, 2012).

Lower WACC is mostly preferred because the company is not incurring much cost for the company's financing. It also translates to efficient operational activities and lower operational risk. Higher WACC reflects higher operational risk as the company is incurring high cost in the day-to-day operation. High WACC also indicates that the company is spending excessively in the operational activities to create value. Therefore, WACC is positively related to operational risk but negatively related to a company's value (Sattar, 2015; Ibrahim et al., 2021; Mali and Lim, 2021).

Operational risk events may bring down the actual return of a company and may lead to non-fulfilment of the required return (KPMG, 2016). At the same time, when operational risk events happen, a company may require more funds to overcome the operational risk event and return to normalcy, thus increasing the cost of capital and hence WACC because of greater risks. In cases where a company is identified with fraudulent activities or legal violation, the interests and trusts of the shareholders and debtors may be affected and will eventually pose a higher volatility in the company's equity, causing higher and unstable WACC.

Since lower WACC signifies lower risks and increases company value, WACC shall serve as an input variable (Oberholzer, 2014; Oberholzer et al., 2017; Shah and Masood, 2017). The formula for WACC is as follows:

$$WACC = \left[\frac{E}{E+D} x R_e\right] + \left[\frac{D}{E+D} x R_d x(1-T)\right] \tag{3.19}$$

$$R_e = R_f + \beta(R_m - R_f) \tag{3.20}$$

where

WACC refers to the weighted cost of capital,

E refers to the market value of equity,

D refers to the market value of debt,

R_e refers to the cost of equity,

R_d refers to the cost of debt,

T refers to the corporate tax rate,

R_f refers to the risk-free rate,

β refers to beta,

R_m refers to the expected return of the market.

The fractional programming of the proposed enhanced DEA model is shown below:

$$\text{Maximize } h_k = \frac{\sum_{r=1}^{s} t_r y_{rk} - \mu_k}{\sum_{i=1}^{m} w_i x_{ik}} \tag{3.21}$$

subject to

$$\frac{\sum_{r=1}^{s} t_r y_{rk} - \mu_k}{\sum_{i=1}^{m} w_i x_{ik}} \leq 1, k = 1,2,3, \dots, n, \tag{3.22}$$

$$t_r \geq \begin{cases} \varepsilon, if\ r = 1,2,3, \dots, s, where\ r \neq C_{BIA}; \\ \alpha, if\ r = C_{BIA}. \end{cases} \tag{3.23}$$

$$w_i \geq \varepsilon, i = 1,2,3, \dots, m \tag{3.24}$$

where

h_k refers to the relative efficiency of company k,

t_r refers to the weight of output r,

y_{rk} refers to the observed amount of rth output of company k,

s refers to the number of outputs,

w_i refers to the weight of input i,

x_{ik} refers to the observed amount of ith input of company k,

m refers to the number of inputs,

ε refers to small positive value,

n refers to the number of companies,

μ_k refers to free variable of company k,

α refers to the fixed percentage of 15% as set by BCBS,

C_{BIA} refers to the sth output that represents capital required for operational risk under the basic indicator approach.

The enhanced DEA model begins with an objective function to maximize the relative efficiency of the listed logistics companies according to Equation (3.21). Constraint (3.22) ensures that the maximum relative efficiency is 1. t_r is the output weight determined in the DEA model for all outputs except for C_{BIA}. Since BCBS has set α to be at least 15%, therefore, the weight for C_{BIA} is constrained to be at least 15% as seen in Equation (3.23). w_i is the input weight as determined by the DEA model Equation (3.24). This linear programming the enhanced DEA model is shown below (Mohanta et al., 2021; Agüero-Tobar et al., 2022):

$$\text{Maximize } h_k = \sum_{r=1}^{s} t_r y_{rk} - \mu_k, \tag{3.25}$$

subject to

$$-\sum_{r=1}^{s} t_r y_{rk} + \sum_{i=1}^{m} w_i x_{ik} + \mu_k \geq 0, j = 1,2,3, \dots, n, \tag{3.26}$$

$$\sum_{i=1}^{m} w_i x_{ik} = 1, \tag{3.27}$$

$$t_r \geq \begin{cases} \varepsilon, if\ r = 1,2,3, \dots, s, where\ r \neq C_{BIA}; \\ \qquad\qquad \alpha, if\ r = C_{BIA}. \end{cases} \tag{3.28}$$

$$w_i \geq \varepsilon, i = 1,2,3, \dots, m \tag{3.29}$$

where

h_k refers to the relative efficiency of company k,

t_r refers to the weight of output r,

y_{rk} refers to the observed amount of rth output of company k,

s refers to the number of outputs,

w_i refers to the weight of input i,

x_{ij} refers to the observed amount of ith input of company k,

m refers to the number of inputs,

ε refers to small positive value,

n refers to the number of companies,

μ_k refers to free variable of company k,

α refers to the fixed percentage of 15% as set by BCBS,

C_{BIA} refers to the sth output that represents the basic indicator approach.

The linear programming of the enhanced DEA model shows that this is output oriented which aims at maximizing the relative efficiency of the listed logistics companies Equation (3.25). This is subjected to the efficiency to be from 0 to 1 Constraint (3.26). Constraint (3.27) scales the inputs to 1 (Raval et al., 2020; Mohanta et al., 2021). t_r and w_i specify the output and input weights. The output weight of C_{BIA} set to be at least 0.15 as seen in Equation (3.28).

The variables for output and input in the enhanced DEA model are constructed in Equation (3.30) and Equation (3.31) respectively. The output variables include EPS, ROA, ROE and C_{BIA}. The inputs include CTR, DAR, DER and WACC for the enhanced DEA model.

$$\sum_{r=1}^{4} t_r y_{rk} = t_1 y_{EPS,k} + t_2 y_{ROA,k} + t_3 y_{ROE,k} + t_4 y_{C_{BIA},k} \tag{3.30}$$

$$\sum_{i=1}^{4} w_i x_{ik} = w_1 x_{CTR,k} + w_2 x_{DAR,k} + w_3 x_{DER,k} + w_4 x_{WACC,k} \tag{3.31}$$

where

t_1 refers to the weight of earnings per share,

t_2 refers to the weight of return on asset,

t_3 refers to the weight of return on equity,

t_4 refers to the weight of the amount of capital for operational risk under the Basic Indicator Approach,

$y_{EPS,k}$ refers to the earnings per share of company k,

$y_{ROA,k}$ refers to the return on asset of company k,

$y_{ROE,k}$ refers to the return on equity of company k,

$y_{C_{BIA},k}$ refers to the amount of capital for operational risk under the Basic Indicator Approach of company k,

w_1 refers to the weight of current ratio,

w_2 refers to the weight of debt-to-asset ratio,

w_3 refers to the weight of debt-to-equity ratio,

w_4 refers to the weight of weighted average cost of capital,

$x_{CTR,k}$ refers to the current ratio of company k,

$x_{DAR,k}$ refers to the debt-to-asset ratio of company k,

$x_{DER,k}$ refers to the debt-to-equity ratio of company k,

$x_{WACC,k}$ refers to the weighted average cost of capital of company k.

The computational work of linear programming DEA model above is then performed using LINGO (Alizadeh et al., 2019; Shah and Ahmad, 2020; Gazori-Nishabori et al., 2021).

3.5 Potential Improvements

An important contribution of DEA is the ability to quantify potential improvements for inefficient DMUs with benchmarking techniques. This process provides managerial implications whereby actions can be taken to improve the efficiency of the DMUs for higher organizational performances. The optimal solution of DEA provides the efficiency scores of each DMU and benchmarking information for the inefficient DMUs for continuous improvements, best practices and future goal settings (Piran et al., 2021; Morinibu and Morita, 2022; Mozaffari et al., 2022).

The benchmarking process starts with the identification of the efficient DMUs, which are also known as the best performing DMUs that have obtained the efficiency score of 1.0000 (Mousa and Kamel, 2022). The optimal solution of DEA identifies the best performing DMUs which can be used as benchmarks for the inefficient DMUs, which will then form a reference set. Each inefficient DMU shall have a reference set for benchmarking to improve the sources of inefficiency. The reference set shall contain the corresponding benchmarks and the respective optimal coefficients. The optimal coefficients reflect the weights of each benchmark in the reference set (Rayeni and Saljooghi, 2010; Alam et al., 2022).

After that, new target values of the output and input variables of the inefficient DMUs can be determined from the benchmarks and the respective optimal coefficients. The target value of a variable is computed from the summation of the multiplication of the optimal coefficients of the benchmarks and the actual values of the variable of the benchmarks (Halkos and Salamouris, 2004; Ng et al., 2019). Since lower inputs and higher outputs are preferred, target values detail the amount that an inefficient DMU should reduce in inputs and increase in outputs (Raith et al., 2018). Moreover, the relative efficiency of a DMU is the weighted sum of outputs over the weighted sum of inputs. Therefore, increase in outputs or reduction in inputs shall contribute to the rise in the relative efficiency of the DMU (Kamel et al., 2021).

The target values for the output variables of inefficient DMUs can be computed as follows (Halkos and Salamouris, 2004; Ng et al., 2019; Puyenbroeck et al., 2021):

$$Y_{rh} = \sum_{g=1}^{n} \alpha_g y_{rg}\, , r = 1,2,3, \dots s \tag{3.32}$$

where

Y_{rh} refers to the target value of rth output of inefficient company h,

α_g refers to the optimal coefficient of benchmark (efficient) company g,

y_{rg} refers to the actual value of rth output of benchmark (efficient) company g.

The computation of the target values of the input variables of the inefficient DMUs is as follows (Halkos and Salamouris, 2004; Ng et al., 2019; Puyenbroeck et al., 2021):

$$X_{ih} = \sum_{g=1}^{n} \alpha_g x_{ig}, i = 1,2,3, \ldots m \qquad (3.33)$$

where

X_{ih} refers to the target value of ith input of inefficient company h,

α_g refers to the optimal coefficient of benchmark (efficient) company g,

x_{ig} refers to the actual value of ith input of benchmark (efficient) company g.

3.6 Model Performance Measurement

The performance of a model could be determined using coefficient of variation (CoV). CoV is denoted by standard deviation over mean to measure the variability of the efficiency scores with regards to the mean. Smaller value of CoV indicates smaller variation, thus reflects higher consistency, which is more preferred (Hur et al., 2022). Lower CoV better reflects the actual performances of the companies in terms of relative efficiency because DEA measures the relative efficiency of the companies (Singh and Ali, 2023). Therefore, smaller value of CoV indicates higher performance of the model. Past studies have also adopted CoV to measure the variability of the efficiency of DEA models (Bal et al., 2008; Czarnecki et al., 2010; Galagedera and Silvapulle, 2002; Watkins et al., 2014; Kang et al., 2017; Singh and Ali, 2023).

$$CoV = \frac{\sigma}{\mu} \, x \, 100\% \tag{3.34}$$

where

CoV refers to the coefficient of variation,

σ refers to the standard deviation of the efficiency scores of the DMUs,

μ refers to the mean of the efficiency scores of the DMUs.

Smaller CoV shows low variation in a model and a higher consistency, which is more preferred.

CHAPTER 4

RESULTS AND DISCUSSION ON THE EXISTING DATA ENVELOPMENT ANALYSIS MODEL

4.1 Introduction

This chapter presents and discusses the results of the financial efficiency of the listed logistics companies in Malaysia with the existing DEA model. This chapter shall begin with the efficiency evaluation of the listed logistics companies based on the existing DEA model and further categorize the companies based on their respective efficiency scores. After that, this chapter shall continue with the presentation of the optimal weights of the outputs and inputs used in this study. The optimal weights reflect the extent of the contribution of the outputs and inputs in maximizing the relative efficiency of the listed logistics companies. The next section shall deal with the reference sets for the inefficient companies based on the optimal solution of DEA. The reference sets are made up of efficient logistics companies with the respective optimal coefficients which have the potential to facilitate the inefficient companies to move towards maximum efficiency. Then, potential improvements of the inefficient companies will be displayed to quantify the increase or decrease in inputs and outputs which are suggested to the inefficient companies in order to be efficient.

4.2 Efficiency Evaluation based on the Existing DEA Model

Table 4.1 tabulates the efficiency of the listed logistics companies based on the existing DEA model as presented in Section 3.3.

Table 4.1: Efficiency of Listed Logistics Companies based on Existing DEA Model

Companies	Efficiency	Categorization
AIRPORT	0.6627	Inefficient
BHIC	0.8437	Inefficient
BIPORT	0.5663	Inefficient
CJCEN	0.7786	Inefficient
COMPLET	1.0000	Efficient
FREIGHT	0.7874	Inefficient
GCAP	0.6419	Inefficient
GDEX	1.0000	Efficient
HARBOUR	0.7924	Inefficient
HUBLINE	1.0000	Efficient
ILB	1.0000	Efficient
LITRAK	0.4685	Inefficient
MAYBULK	0.8436	Inefficient
MISC	0.9945	Inefficient
MMCCORP	0.7160	Inefficient
NATWIDE	1.0000	Efficient

Companies	Efficiency	Categorization
POS	1.0000	Efficient
PDZ	1.0000	Efficient
PRKCORP	1.0000	Efficient
SEALINK	0.9913	Inefficient
SEEHUP	0.8553	Inefficient
SURIA	0.9583	Inefficient
SYSCORP	1.0000	Efficient
TAS	0.6250	Inefficient
TASCO	0.7985	Inefficient
TNLOGIS	0.8280	Inefficient
TOCEAN	1.0000	Efficient
Average	0.8575	

The relative efficiency of the listed logistics companies is presented in Table 4.1. Companies with efficiency score of 1.0000 are efficient companies which have maximized the usage of its inputs to generate the outputs. From Table 4.1, 10 out of 27 listed logistics companies are identified as efficient companies. These 9 efficient companies are COMPLET, GDEX, HUBLINE, ILB, NATWIDE, POS, PDZ, PRKCORP, SYSCORP and TOCEAN as their efficiency scores reflect 1.00000. From the results, it can also be implied that 37.04% of the listed logistics companies are efficient. The results of this study align with past studies on efficiencies whereby about 20% to 60% of DMUs are efficient (Chen et al., 2008; Gandhi and Sharma, 2018; Anouze and Bou-

Hamad, 2019; Habib and Shahwan, 2020; Kamel et al., 2021). On the other hand, companies obtaining scores lower than 1.00000 gives an implication that the companies are inefficient in managing their resources to create expected results.

From Table 4.1, it can also be seen that 17 out of 27 (or 62.96%) listed logistics companies display efficiency scores of less than 1.0000. These inefficient listed logistics companies are AIRPORT, BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, MISC, MMCCORP, SEALINK, SEEHUP, SURIA, TAS, TASCO and TNLOGIS. These inefficient listed logistics companies would now be arranged in descending order with regards to the efficiency score and are presented as follows: MISC (0.9945), SEALINK (0.9913), SURIA (0.9583), SEEHUP (0.8553), BHIC (0.8437), MAYBULK (0.8436), TNLOGIS (0.8280), TASCO (0.7985), HARBOUR (0.7924), FREIGHT (0.7874), CJCEN (0.7786), MMCCORP (0.7160), AIRPORT (0.6627), GCAP (0.6419), TAS (0.6250), BIPORT (0.5663) and LITRAK (0.4685) (Güner, 2015; Amin and Hajjami, 2021; Kamel et al., 2021).

The average efficiency score of this study is 0.5587 and there are 6 out of 13 (46.15%) companies which score above the average efficiency. This has been in accordance with several past literatures (Dhillon and Vachhrajani, 2016; Curtis et al., 2020).

4.3 Optimal Weights for Inputs and Outputs

The optimal weights for inputs and outputs for the listed logistics companies are tabulated in Table 4.2. The optimal weights reflect the influence of each input and output when measuring the maximum efficiency of the listed logistics companies. Therefore, the objective function of the DEA model, which is to maximize the relative efficiency, is attributed to the input and output weights in Table 4.2.

Table 4.2: Optimal Output and Input Weights based on Existing DEA Model

Companies	EPS	ROA	ROE	CTR	DAR	DER
AIRPORT	0.9977	0.0012	0.0012	0.2021	0.7979	0.0001
BHIC	0.9985	0.0007	0.0007	0.3107	0.6893	0.0001
BIPORT	0.9970	0.0015	0.0015	0.0322	0.9677	0.0001
CJCEN	0.7837	0.2154	0.0009	0.0325	0.9675	0.0000
COMPLET	0.7713	0.2283	0.0004	0.0826	0.0001	0.9174
FREIGHT	0.7837	0.2154	0.0009	0.0325	0.9675	0.0000
GCAP	0.9425	0.0571	0.0004	0.0001	0.0001	0.9999
GDEX	0.0045	0.9909	0.0045	0.0000	0.0000	0.9999
HARBOUR	0.7837	0.2154	0.0009	0.0325	0.9675	0.0000
HUBLINE	0.9988	0.0006	0.0006	0.3106	0.6893	0.0001
ILB	0.9471	0.0526	0.0003	0.0000	0.0469	0.9531
LITRAK	0.9349	0.0016	0.0635	0.2021	0.7978	0.0001
MAYBULK	0.8526	0.0009	0.1465	0.0323	0.9676	0.0000
MISC	0.9988	0.0006	0.0006	0.3619	0.0001	0.6380

Companies	EPS	ROA	ROE	CTR	DAR	DER
MMCCORP	0.9982	0.0009	0.0009	0.3107	0.6892	0.0001
NATWIDE	0.0040	0.9920	0.0040	0.0000	0.0000	0.9999
POS	0.8989	0.1003	0.0008	0.2020	0.7979	0.0001
PDZ	0.0055	0.9890	0.0055	0.0000	0.1050	0.8949
PRKCORP	0.8991	0.0997	0.0012	0.2020	0.7979	0.0001
SEALINK	0.3333	0.3333	0.3333	0.8070	0.0001	0.1929
SEEHUP	0.9352	0.0009	0.0640	0.2021	0.7979	0.0001
SURIA	0.9983	0.0009	0.0009	0.0322	0.9678	0.0000
SYSCORP	0.9985	0.0008	0.0008	0.2021	0.7979	0.0001
TAS	0.8991	0.0998	0.0011	0.2020	0.7979	0.0001
TASCO	0.8989	0.1002	0.0009	0.2020	0.7979	0.0001
TNLOGIS	0.9494	0.0005	0.0500	0.8124	0.0001	0.1875
TOCEAN	0.9985	0.0008	0.0008	0.2021	0.7979	0.0001
Average (%)	0.8004	0.1741	0.0254	0.1855	0.5632	0.2513

Table 4.2 presents the optimal weights of outputs and inputs to maximize the relative efficiency of the listed logistics companies in Malaysia. For AIRPORT, EPS contributes the most to the outputs, which accounts to 0.9977 of the total output weights. ROA and ROE have the similar influence of 0.0012 to the outputs of AIRPORT respectively. In terms of inputs for AIRPORT, DAR (0.7979) is the greatest contributor, followed by CTR (0.2021) and DER (0.0001). DER has a very low influence on the overall inputs for AIRPORT. In terms of the average output weights, EPS is still the highest contributor with a

weight of 0.8004. This is followed by ROA (0.1741) and ROE (0.0254). Among the inputs, DAR has the greatest influence to maximize the efficiency of the listed logistics companies in Malaysia, with a weight of 0.5632. The second most important input is DER, which is at 0.2513 while CTR contributes the least to the input factors at only 0.1855 (Ong and Kamil, 2010).

4.4 Reference Sets

As mentioned in Chapter 3.5, DEA is able to quantify the improvement values for the inefficient logistics companies based on the optimal coefficients of the efficient logistics companies. All the efficient logistics companies with the scores of 1 make up the reference set for the inefficient logistics companies. The optimal coefficients which are used to compute the potential improvements are obtained from the optimal solution of the DEA model. Moreover, the more the appearance of an efficient logistics company as the reference for the inefficient logistics company, the higher the performance in the overall efficiency of that company (Halkos and Salamouris, 2004). Table 4.3 presents the reference set for the inefficient logistics companies.

Table 4.3: Reference Set for Inefficient Logistics Companies based on Existing DEA Model

Inefficient Companies	Efficiency Scores	Reference Set of Efficient Companies (Optimal Coefficients, α_g)			
AIRPORT	0.6627	PRKCORP (0.0354)	SYSCORP (0.6764)	TOCEAN (0.2882)	
BHIC	0.8437	HUBLINE (0.8431)	PRKCORP (0.0115)	SYSCORP (0.1454)	
BIPORT	0.5663	COMPLET (0.2479)	PRKCORP (0.0611)	TOCEAN (0.6910)	
CJCEN	0.7786	COMPLET (0.0356)	POS (0.0014)	PRKCORP (0.0181)	TOCEAN (0.9448)
FREIGHT	0.7874	COMPLET (0.2215)	POS (0.0024)	PRKCORP (0.0136)	TOCEAN (0.7625)
GCAP	0.6419	GDEX (0.1981)	NATWIDE (0.7968)	PRKCORP (0.0051)	
HARBOUR	0.7924	COMPLET (0.0914)	POS (0.0021)	PRKCORP (0.0159)	TOCEAN (0.8907)
LITRAK	0.4685	POS (0.0040)	PRKCORP (0.0557)	SYSCORP (0.0978)	TOCEAN (0.8425)
MAYBULK	0.8436	COMPLET (0.3871)	POS (0.0026)	PRKCORP (0.0069)	TOCEAN (0.6035)

Inefficient Companies	Efficiency Scores	Reference Set of Efficient Companies (Optimal Coefficients, α_g)			
MISC	0.9945	PRKCORP (0.0608)	SYSCORP (0.1757)	TOCEAN (0.7635)	
MMCCORP	0.7160	HUBLINE (0.6058)	PRKCORP (0.0270)	SYSCORP (0.3672)	
SEALINK	0.9913	HUBLINE (0.1194)	SYSCORP (0.8806)		
SEEHUP	0.8553	POS (0.0005)	PRKCORP (0.0055)	SYSCORP (0.5180)	TOCEAN (0.4760)
SURIA	0.9583	COMPLET (0.9045)	PRKCORP (0.0207)	TOCEAN (0.0748)	
TAS	0.6250	POS (0.0010)	PRKCORP (0.0051)	SYSCORP (0.1133)	TOCEAN (0.8806)
TASCO	0.7985	POS (0.0015)	PRKCORP (0.0315)	SYSCORP (0.2434)	TOCEAN (0.7237)
TNLOGIS	0.8280	HUBLINE (0.4807)	POS (0.0003)	PRKCORP (0.0166)	SYSCORP (0.5024)

From the optimal solution of the DEA model, COMPLET, GDEX, HUBLINE, ILB, NATWIDE, POS, PDZ, PRKCORP, SYSCORP and TOCEAN have obtained maximum efficiency of 1.0000. Besides computing the efficiency scores, DEA is also able to propose a reference set formed from the efficient logistics companies. From Table 4.3, PRKCORP, TOCEAN and SYSCORP are the top 3 efficient companies which are used as benchmarks for the inefficient logistics companies as they appear for 16, 12 and 10 times respectively.

AIRPORT obtains an efficiency score of 0.6627. The reference set to represent AIRPORT are PRKCORP, SYSCORP and TOCEAN. SYSCORP reflects the highest optimal coefficient of 0.6764, followed by TOCEAN with the coefficient of 0.2882 and PRKCORP with 0.0354. Secondly, BHIC, which obtains an efficiency score of 0.8437, can benchmark HUBLINE, PRKCORP and SYSCORP. A higher weightage is offered by HUBLINE (0.8431) while SYSCORP and PRKCORP offer intensities of 0.1454 and 0.0115 in terms of the optimal coefficients which will be used for the determination of potential improvements.

Thirdly, BIPORT has an efficiency of 0.5663. The reference set for BIPORT is made up of COMPLET, PRKCORP and TOCEAN. Among them, TOCEAN has the greatest weight of 0.6910, followed by COMPLET (0.2479) and PRKCORP (0.0611). This implies that TOCEAN contributes the most to the target value of BIPORT. Fourthly, COMPLET, POS, PRKCORP and TOCEAN make up the reference set for CJCEN, which has an efficiency score of 0.7786. Based on the optimal solution of DEA, TOCEAN contributes an outstanding weight of 0.9448 to the potential improvement of CJCEN. COMPLET, PRKCORP and POS contribute 0.0356, 0.0181 and 0.0014 respectively to enhance CJCEN's efficiency.

The fifth inefficient logistics company is FREIGHT with an efficiency of 0.7874. TOCEAN is still the highest contributor to the target value of FREIGHT, with a weight of 0.7625. This is followed by COMPLET (0.2215), PRKCORP (0.0136) and POS (0.0024). The sixth inefficient logistics company is GCAP. GCAP has an efficiency of 0.6419. As such, amelioration is highly needed for GCAP and the company can benchmark NATWIDE (0.7968), GDEX (0.1981) and PRKCORP (0.0051) for the setting of new target value.

At the same time, HARBOUR is also inefficient with a score of only 0.7941. Four efficient logistics companies, namely TOCEAN (0.8907), COMPLET (0.0914), PRKCORP (0.0159) and POS (0.0021) make up the reference set for HARBOUR. The weight of TOCEAN among the companies in the reference set is very high, signalling a huge importance for HARBOUR when considering potential improvements.

Meanwhile, LITRAK has the lowest efficiency score of 0.4685. TOCEAN (0.8425) still carries the most weight among the referred companies. SYSCORP and PRKCORP carry 0.0978 and 0.0557 importance respectively. POS has the least influence on the target value of LITRAK, with a weight of only 0.0040. Consequently, MAYBULK, with a score of 0.8436, can benchmark TOCEAN (0.6035), COMPLET (0.3871), PRKCORP (0.0069) and POS

(0.0026).

MISC has an efficiency score of 0.9945, which is close to the maximum efficiency. However, MISC can still benchmark on three (3) out of nine (9) of the efficient listed logistics companies to maximize its efficiency. In descending order from the greatest influence to the lowest influence, the reference set is made up of TOCEAN (0.7635), SYSCORP (0.1757) and PRKCORP (0.0608). Next, MMCCORP has an efficiency of 0.7160 and is categorized as inefficient. HUBLINE (0.6058), SYSCORP (0.3672) and PRKCORP (0.0270) form the reference set for MMCCORP in which the influence of HUBLINE on the improvement of MMCCORP is the greatest.

Among the inefficient logistics companies, SEALINK is close to attain full efficiency with the score of 0.9913. Based on the optimal solution, this gap can be filled if SEALINK takes HUBLINE and SYSCORP as benchmarks based on the optimal solution of DEA. More focus can be placed on SYSCORP because of its contribution weight of 0.8806 while HUBLINE's influence is only 0.1194. At the same time, SEEHUP's score is 0.8553, which is also inefficient. POS, PRKCORP, SYSCORP and TOCEAN are the benchmarks for SEEHUP. SYSCORP and TOCEAN contribute higher weights to the improvement of SEEHUP, at values of 0.5180 and 0.4760 respectively. PRKCORP and POS have lower weights of 0.0055 and 0.0005 respectively to help SEEHUP better position itself.

In the meantime, SURIA has an efficiency score of 0.9583, which is classified as inefficient. COMPLET, PRKCORP and TOCEAN are the three companies that make up the reference set of SURIA. Among them, COMPLET offers the greatest importance, which amounts to 0.9045, followed by TOCEAN (0.0748) and PRKCORP (0.0207). The next inefficient logistics company is TAS, which scored only 0.6250, which is also below the average efficiency level. A large proportion of the reference set is covered by TOCEAN (0.8806) while SYSCORP, PRKCORP and POS contribute 0.1133, 0.0051 and 0.0010 respectively.

Similarly, TASCO only managed to obtain an efficiency score of 0.7985 and could benchmark four efficient logistics companies, which are POS, PRKCORP, SYSCORP and TOCEAN. The highest contributor to the potential improvement of TASCO is TOCEAN, at 0.7237. SYSCORP, PRKCORP and POS have weights of 0.2434, 0.0315 and 0.0015 respectively. Lastly, TNLOGIS scored 0.8280 for its efficiency, which is a little below the average efficiency. For improvement, TNLOGIS can benchmark SYSCORP, HUBLINE, PRKCORP and POS with the optimal coefficients of 0.5024, 0.4807, 0.0166 and 0.0003 respectively.

Figure 4.1 then provides a summary of the number of efficient listed logistics companies in the reference sets of the inefficient listed logistics companies.

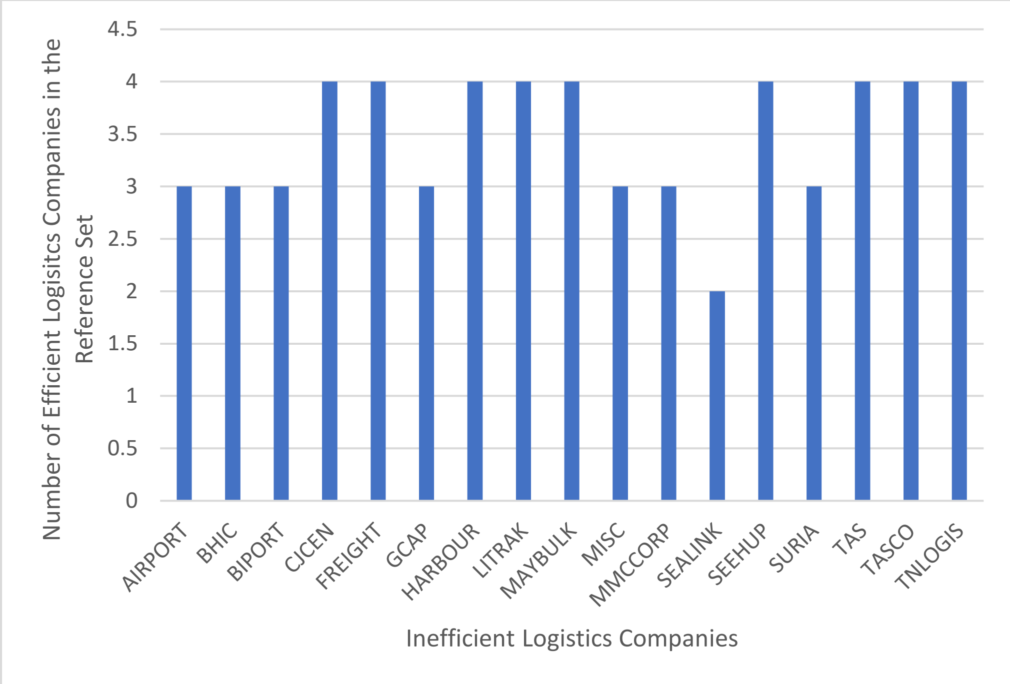

Figure 4.1: Number of Efficient Companies in the Reference Set based on the Existing DEA Model.

From Figure 4.1, SEALINK have two efficient logistics companies in their reference sets respectively. AIRPORT, BHIC, BIPORT, GCAP, MISC, MMCCORP and SURIA have three efficient logistics companies as their benchmarks. There are 9 inefficient logistics companies which need to benchmark four efficient logistics companies for improvements, they are CJCEN, FREIGHT, HARBOUR, LITRAK, MAYBULK, SEEHUP, TAS, TASCO and TNLOGIS.

4.5 Potential Improvements

After identifying the reference sets for all the inefficient logistics companies in Section 4.4, the potential improvements of the inefficient logistics companies can then take place so that they can achieve maximum efficiency in their performances. The potential improvement is determined after deducting the actual values from the target values which are presented in Table 4.4.

Table 4.4: Potential Improvements for Inefficient Logistics Companies based on Existing DEA Model

Company	Outputs / Inputs	Actual Values	Target Values	Potential Improvements (Target Values - Actual Values)
AIRPORT	EPS	0.2197	0.2197	0.0000
	ROA	0.0225	0.0468	0.0243
	ROE	0.0517	0.1175	0.0658
	CTR	1.7832	1.1818	-0.6015
	DAR	0.5651	0.3745	-0.1906
	DER	1.3526	0.6411	-0.7115
BHIC	EPS	0.0690	0.0691	0.0000
	ROA	0.0192	0.0209	0.0017
	ROE	0.0414	0.0489	0.0075
	CTR	0.9947	0.8393	-0.1554
	DAR	0.5779	0.4876	-0.0903
	DER	1.8922	1.5561	-0.3362
BIPORT	EPS	0.3648	0.3648	0.0000
	ROA	0.0689	0.0815	0.0126
	ROE	0.1501	0.1998	0.0497

Company	Outputs / Inputs	Actual Values	Target Values	Potential Improvements (Target Values - Actual Values)
	CTR	3.2174	1.8220	-1.3953
	DAR	0.5415	0.3066	-0.2348
	DER	1.2977	0.4879	-0.8099
CJCEN	EPS	0.1121	0.1121	0.0000
	ROA	0.0456	0.0456	0.0000
	ROE	0.0739	0.0950	0.0211
	CTR	1.8669	1.4535	-0.4134
	DAR	0.3959	0.3083	-0.0877
	DER	0.6771	0.4891	-0.1879
FREIGHT	EPS	0.1018	0.1018	0.0000
	ROA	0.0633	0.0633	0.0000
	ROE	0.1023	0.1154	0.0131
	CTR	2.1968	1.7299	-0.4670
	DAR	0.3794	0.2988	-0.0806
	DER	0.6125	0.4636	-0.1489
GCAP	EPS	0.0362	0.0362	0.0000
	ROA	1.1417	1.1417	0.0000
	ROE	0.0650	1.7672	1.7023
	CTR	13.9511	3.9352	-10.0158
	DAR	5.2244	0.3772	-4.8473
	DER	0.5446	0.3501	-0.1945
HARBOUR	EPS	0.1041	0.1041	0.0000

Company	Outputs / Inputs	Actual Values	Target Values	Potential Improvements (Target Values - Actual Values)
	ROA	0.0550	0.0550	0.0000
	ROE	0.0907	0.1070	0.0162
	CTR	1.9375	1.5353	-0.4022
	DAR	0.3852	0.3053	-0.0800
	DER	0.6587	0.4811	-0.1776
LITRAK	EPS	0.3192	0.3192	0.0000
	ROA	0.0753	0.1146	0.0394
	ROE	0.2539	0.2539	0.0000
	CTR	3.0011	1.4064	-1.5947
	DAR	0.6972	0.3267	-0.3705
	DER	2.9152	0.5375	-2.3777
MAYBULK	EPS	0.0771	0.0771	0.0000
	ROA	0.0668	0.0681	0.0013
	ROE	0.1121	0.1121	0.0000
	CTR	2.3389	1.9731	-0.3658
	DAR	0.3433	0.2896	-0.0537
	DER	0.7257	0.4389	-0.2868
MISC	EPS	0.3483	0.3483	0.0000
	ROA	0.0329	0.0691	0.0362
	ROE	0.0493	0.1839	0.1346
	CTR	1.3925	1.3849	-0.0076
	DAR	0.3443	0.3342	-0.0101

Company	Outputs / Inputs	Actual Values	Target Values	Potential Improvements (Target Values - Actual Values)
	DER	0.5575	0.5545	-0.0030
MMCCORP	EPS	0.1616	0.1616	0.0000
	ROA	0.0167	0.0374	0.0206
	ROE	0.0461	0.0936	0.0475
	CTR	1.2849	0.9200	-0.3649
	DAR	0.6481	0.4640	-0.1841
	DER	2.0432	1.3185	-0.7246
SEALINK	EPS	0.0122	0.0286	0.0165
	ROA	0.0067	0.0129	0.0063
	ROE	0.0136	0.0208	0.0071
	CTR	1.0091	1.0004	-0.0088
	DAR	0.4391	0.4094	-0.0297
	DER	0.8154	0.8083	-0.0071
SEEHUP	EPS	0.0517	0.0517	0.0000
	ROA	0.0224	0.0225	0.0001
	ROE	0.0428	0.0428	0.0000
	CTR	1.4082	1.2045	-0.2038
	DAR	0.4141	0.3542	-0.0599
	DER	0.7605	0.5910	-0.1695
SURIA	EPS	0.1925	0.1925	0.0000
	ROA	0.0439	0.0762	0.0323
	ROE	0.0620	0.1308	0.0687

Company	Outputs / Inputs	Actual Values	Target Values	Potential Improvements (Target Values - Actual Values)
	CTR	2.8923	2.7717	-0.1206
	DAR	0.2793	0.2676	-0.0116
	DER	0.4018	0.3813	-0.0205
TAS	EPS	0.0405	0.0405	0.0000
	ROA	0.0266	0.0266	0.0000
	ROE	0.0450	0.0493	0.0042
	CTR	2.1528	1.3457	-0.8071
	DAR	0.5080	0.3175	-0.1904
	DER	1.5783	0.5086	-1.0697
TASCO	EPS	0.1886	0.1886	0.0000
	ROA	0.0597	0.0597	0.0000
	ROE	0.1032	0.1346	0.0314
	CTR	1.6644	1.3290	-0.3354
	DAR	0.4191	0.3347	-0.0844
	DER	0.8357	0.5513	-0.2845
TNLOGIS	EPS	0.1087	0.1087	0.0000
	ROA	0.0302	0.0309	0.0008
	ROE	0.0708	0.0708	0.0000
	CTR	1.1303	0.9358	-0.1945
	DAR	0.5834	0.4496	-0.1338
	DER	1.4325	1.1860	-0.2465

The potential improvement of an inefficient logistics company, as seen in Table 4.4, is determined based on the differences between the target values and actual values of the outputs and inputs. The optimal coefficients of the efficient companies in the reference set of the inefficient logistics company are used to determine the target values of the outputs and inputs of the inefficient logistics company. The determine of the target value of an output or input is the sum of the product of the actual values of the output or input and the optimal coefficients of the efficient logistics companies in the reference set as presented in the. Equations (3.32) and (3.33).

An example using AIRPORT is illustrated. From Table 4.3, the reference set for AIRPORT includes PRKCORP (0.0354), SYSCORP (0.6764) and TOCEAN (0.2882). Therefore, AIRPORT has to benchmark these three (3) companies by considering the optimal coefficients of the efficient companies in the reference set. The computation for the target values of the outputs and inputs for AIRPORT is then determined as shown below.

$$\begin{bmatrix} EPS \\ ROA \\ ROE \\ CTR \\ DAR \\ DER \end{bmatrix} = 0.0354 \text{ x} \begin{bmatrix} 5.5148 \\ 1.0030 \\ 2.8171 \\ 2.4758 \\ 0.5062 \\ 1.0867 \end{bmatrix} + 0.6764 \text{ x} \begin{bmatrix} 0.0323 \\ 0.0135 \\ 0.0214 \\ 1.0297 \\ 0.3967 \\ 0.6856 \end{bmatrix} + 0.2882 \text{ x} \begin{bmatrix} 0.0095 \\ 0.0075 \\ 0.0116 \\ 1.3798 \\ 0.3061 \\ 0.4819 \end{bmatrix}$$

$$\begin{bmatrix} EPS \\ ROA \\ ROE \\ CTR \\ DAR \\ DER \end{bmatrix} = \begin{bmatrix} 0.2197 \\ 0.0468 \\ 0.1175 \\ 1.1818 \\ 0.3745 \\ 0.6411 \end{bmatrix}$$

In order to achieve 1.000 efficiency and classified as efficient company, AIRPORT should focus on the target values computed with the actual values of the outputs and inputs and optimal coefficients of the efficient logistics companies in the reference set. Then, the target values are obtained, and it can be observed that the target values of EPS, ROA and ROE are 0.2197, 0.0468 and 0.1175 respectively. As seen from Table 4.4, this means that AIRPORT can maintain its EPS at the current value of 0.2197 but is recommended to improve the ROA and ROE by increasing them by 0.0243 and 0.0658 respectively. At the same time, AIRPORT should reduce its CTR by 0.6015 to reach the target value of 1.1818. For DAR, AIRPORT should achieve the target value of 0.3745 by a reduction of 0.1906. To reach the target value of 0.6411 for DER, AIRPORT should bring the value down by 0.7115.

Another example would be LITRAK due to its very low efficiency of only 0.4685. From Table 4.3, the reference set for LITRAK includes POS, PRKCORP, SYSCORP and TOCEAN. The optimal coefficients for POS, PRKCORP, SYSCORP and TOCEAN for the improvement of LITRAK are 0.0040, 0.0557, 0.0978 and 0.8425 respectively. Therefore, the target values of LITRAK are calculated as follows:

$$\begin{bmatrix} EPS \\ ROA \\ ROE \\ CTR \\ DAR \\ DER \end{bmatrix} = 0.0040 \text{ x} \begin{bmatrix} 0.1416 \\ 12.8936 \\ 21.4690 \\ 1.3051 \\ 0.4601 \\ 0.9685 \end{bmatrix} + 0.0557 \text{ x} \begin{bmatrix} 5.5148 \\ 1.0030 \\ 2.8171 \\ 2.4758 \\ 0.5062 \\ 1.0867 \end{bmatrix} + 0.0978 \text{ x} \begin{bmatrix} 0.0323 \\ 0.0135 \\ 0.0214 \\ 1.0297 \\ 0.3967 \\ 0.6856 \end{bmatrix}$$

$$+ 0.8425 \text{ x} \begin{bmatrix} 0.0095 \\ 0.0075 \\ 0.0116 \\ 1.3798 \\ 0.3061 \\ 0.4819 \end{bmatrix}$$

$$\begin{bmatrix} EPS \\ ROA \\ ROE \\ CTR \\ DAR \\ DER \end{bmatrix} = \begin{bmatrix} 0.3192 \\ 0.1146 \\ 0.2539 \\ 1.4064 \\ 0.3267 \\ 0.5375 \end{bmatrix}$$

The target values of EPS, ROA and ROE are 0.3192, 0.1146 and 0.2539 respectively for LITRAK. EPS and ROE for GCAP can be maintained at the current values of 0.3192 and 0.2539 respectively. However, ROA of LITRAK has to increase by 0.0394 to attain the target value. In the meantime, for the inputs, CTR, DAR and DER have to be reduced by 1.5947, 0.3705 and 2.3777 to reach the target values of 1.4064, 0.3267 and 0.5375 respectively in order for LITRAK to maximize its efficiency.

For BHIC, it can be observed that EPS can maintain its value at 0.0691. All the other two outputs and three inputs have to be adjusted to achieve full efficiency. As outputs, ROA and ROE of BHIC need to increase from 0.0192 and 0.0414 to 0.0209 and 0.0489 respectively to reach 1.000 efficiency. Since inputs should be reduced for greater efficiency, CTR, DAR and DER have to be decreased by 01554, 0.0903 and 0.3362 respectively to move towards the target values.

EPS of BIPORT is optimal and at its target value of 0.3648. However, BIPORT has to increase its ROA and ROE by 0.0126 and 0.0497 to reach the target values of 0.0815 and 0.1998 respectively. BIPORT may improve its efficiency by also considering bringing down its CTR to 1.8220 since there is a gap of 1.3953. DAR of BIPORT may also be reduced by 0.2348 to reach 0.3066. Since the DER of BIPORT is very high, it is also recommended to lower its DER by 0.8099 to attain the target value of 0.4879.

For CJCEN, its EPS and ROA shall remain constant at 0.1121 and 0.0456 while an increase of 0.0211 in its ROE is forecasted to aid in improving its efficiency. All the inputs of CJCEN, namely CTR, DAR and DER should be reduced by 0.4134, 0.0877 and 0.1879 to reach 1.4535, 0.3083 and 0.4891 respectively.

Meanwhile, the EPS and ROA of FREIGHT are at its optimal levels. FREIGHT can improve its ROE to reach 0.1154 from the initial value of 0.1023. CTR, DAR and DER of FREIGHT are suggested to be reduced by 0.4670, 0.0806 and 0.1489 to achieve the target values of 1.7299, 0.2988 and 0.4636 respectively.

At the same time, GCAP can keep its EPS and ROA at 0.0362 and 1.1417 respectively. ROE should be increased by 1.7023 to reach 1.7672. It is important to note that GCAP has a very high CTR value of 13.9511 and this value should be lowered to 3.9352 to improve its efficiency. DAR and DER should be reduced by 4.8473 and 0.1945 respectively.

HARBOUR can maintain its EPS and ROA but is recommended to enhance its ROE from 0.0907 to 0.1070 by filling the gap of 0.0162. Reductions of 0.4022, 0.0800 and 0.1776 are proposed so that HARBOUR can reach 1.5353, 0.3053 and 0.4811 for CTR, DAR and DER respectively.

EPS and ROE of LITRAK can remain at 0.3192 and 0.2539 respectively. ROA can rise from 0.0753 to 0.1146 by filling the gap of 0.0394. Acting as inputs, the CTR, DAR and DER of LITRAK are higher than the optimum values. Therefore, CTR, DAR and DER of LITRAK can be reduced from 3.0011, 0.6972 and 2.9152 to 1.4064, 0.3267 and 0.5375 respectively.

As for MAYBULK, two out of the three outputs, which are EPS and ROE shall remain the same at 0.0771 and 0.1121. ROA should increase from 0.0668 to 0.0681. Reductions in all the inputs are required to attain maximum efficiency. CTR, DAR and DER of MAYBULK should reduce by 0.3658, 0.0537 and 0.2868 to 1.9731, 0.2896 and 0.4389 respectively to reach their target values.

All the variables of MISC are recommended to undergo improvements except for EPS which could remain at 0.3483. For the remaining outputs, the ROA and ROE could increase from 0.0329 and 0.0493 to 0.0691 and 0.1839 respectively. As for the outputs, CTR, DAR and DER can be reduced by 0.0076, 0.0101 and 0.0030 to 1.3849, 0.3342 and 0.5545 respectively.

The EPS for MMCCORP can also remain at 0.1616. ROA and ROE of

MMCCORP can be increased by 0.0206 and 0.0475 to reach 0.0374 and 0.0936 respectively. CTR, DAR and DER should be reduced from 1.2849, 0.6481 and 2.0432 to obtain the target values of 0.9200, 0.4640 and 1.3185 respectively.

SEALINK is also another listed logistics company which is inefficient based on the optimal solution of the DEA model. All the outputs and inputs require amelioration. The initial values of EPS, ROA and ROE are 0.0122, 0.0067 and 0.0136. However, EPS, ROA and ROE are suggested to increase by 0.0165, 0.0063 and 0.0071 to attain 0.0286, 0.0129 and 0.0208 respectively. CTR, DAR and DER should be reduced by 0.0088, 0.0297 and 0.0071 to reach 1.0004, 0.4094 and 0.8083 respectively.

EPS and ROE of SEEHUP can be maintained at 0.0517 and 0.0428 respectively. It is recommended that SEEHUP increases its ROA by 0.0001 to reach 0.0225 to improve its efficiency. At the same time, CTR, DAR and DER can be reduced by 0.2038, 0.0599 and 0.1695 to reach 1.2045, 0.3542 and 0.5910 respectively.

For SURIA, its EPS can be kept at 0.1925. ROA and ROE can be increased from 0.0439 and 0.0620 to 0.0762 and 0.1308 respectively. CTR, DAR and DER can also be lowered from the actual values of 2.8923, 0.2793 and 0.4018 to the target values of 2.7717, 0.2676 and 0.3813 respectively.

For TAS, both EPS and ROA are recommended to remain at its current values of 0.0405 and 0.0266 respectively. ROE is suggested to increase by

0.0042 from the initial value of 0.0450. Reducing CTR, DAR and DER by 0.8071, 0.1904 and 1.0697 to 1.3457, 0.3175 and 0.5086 could help TAS achieve higher efficiency.

EPS and ROA of TASCO can remain at 0.1886 and 0.0597 respectively. ROE can be improved by 0.0314 to reach the target value of 0.1346 from its initial value of 0.1032. The target values of CTR, DAR and DER are 1.3290, 0.3347 and 0.5513 respectively. To reach these target values, the potential improvements which TASCO could take is to reduce CTR, DAR and DER by 0.3354, 0.0844 and 0.2845 respectively.

Lastly, for TNLOGIS, its EPS and ROE require no potential improvement as they could remain at 0.1087 and 0.0708 respectively. ROA can be increased by 0.0008 to attain 0.0309. For the outputs, CTR, DAR and DER can be reduced by 0.1945, 0.1338 and 0.2465 to achieve the target values of 0.9358, 0.4496 and 1.1860 respectively.

4.6 Summary

In summary, this chapter has identified the efficient and inefficient listed logistics companies by comparing the respective efficiency scores using DEA model. The listed logistics companies which attained maximum efficiency with the score of 1.0000 are COMPLET, GDEX, HUBLINE, ILB, NATWIDE, POS, PDZ, PRKCORP, SYSCORP and TOCEAN. The inefficient companies are AIRPORT, BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK,

MAYBULK, MISC, MMCCORP, SEALINK, SEEHUP, SURIA, TAS, TASCO and TNLOGIS because their efficiency scores are less than 1.0000. The average efficiency attained by the logistics industry is 0.8575 with 13 out of 27 companies scoring above the average efficiency.

CHAPTER 5

RESULTS AND DISCUSSION ON THE ENHANCED DATA ENVELOPMENT ANALYSIS MODEL

5.1 Introduction

This chapter centers on the results from the proposed enhanced DEA model as presented in Chapter 3.4. This enhanced DEA model can also perform benchmarking to improve the efficiency of the inefficient listed logistics companies. Benchmarking using the enhanced DEA model helps to identify the reference sets and quantify the incremental improvement of an output and the subtractive amount of an input so that the inefficient listed logistics companies can reduce their gaps with the efficient listed logistics companies. After that, the performances of the enhanced DEA model and the existing DEA is compared for the validity of the enhanced DEA model.

5.2 Efficiency Evaluation based on the Enhanced DEA model

The efficiency of the listed logistics companies based on the enhanced DEA model, is presented in Table 5.1. In another words, Table 5.1 summarizes the maximum efficiency of the listed logistics companies when operational risk factor is considered.

Table 5.1: Efficiency of Listed Logistics Companies based on the Enhanced DEA Model

Companies	Efficiency	Categorization
AIRPORT	1.0000	Efficient
BHIC	0.9649	Inefficient
BIPORT	0.9737	Inefficient
CJCEN	0.8889	Inefficient
COMPLET	1.0000	Efficient
FREIGHT	0.9400	Inefficient
GCAP	0.9026	Inefficient
GDEX	1.0000	Efficient
HARBOUR	0.9860	Inefficient
HUBLINE	1.0000	Efficient
ILB	1.0000	Efficient
LITRAK	0.8875	Inefficient
MAYBULK	0.8497	Inefficient
MISC	1.0000	Efficient
MMCCORP	1.0000	Efficient
NATWIDE	1.0000	Efficient
POS	1.0000	Efficient
PDZ	1.0000	Efficient
PRKCORP	1.0000	Efficient
SEALINK	0.9906	Inefficient
SEEHUP	1.0000	Efficient
SURIA	0.9666	Inefficient
SYSCORP	1.0000	Efficient
TAS	0.6725	Inefficient
TASCO	0.8966	Inefficient
TNLOGIS	1.0000	Efficient
TOCEAN	1.0000	Efficient
Average	0.9600	

Based on Table 5.1 where the efficiency of the listed logistics companies is optimized with the enhanced DEA model, there are fifteen (15) efficient companies as they have received the efficiency of 1.0000. These efficient companies are AIRPORT, COMPLET, GDEX, HUBLINE, ILB, MISC, MMCCORP, NATWIDE, POS, PDZ, PRKCORP, SEEHUP, SYSCORP, TNLOGIS and TOCEAN. These 15 efficient companies have capitalized fully on its resources for the most substantial outcomes. According to this enhanced DEA model that maximizes the efficiency of the listed logistics companies with the incorporation of operational risk, 55.56% of the listed logistics companies are efficient. This indicates that a considerable number of the listed logistics companies are aware of the importance of operational risk and have taken measures to prepare for operational risk events especially from the financial perspective. The percentage of efficiency concurs with the past studies by Gandhi and Sharma (2018), Anouze and Bou-Hamad (2019), Habib and Shahwan (2020) and Kamel et al. (2021).

On the other hand, there are twelve (12) listed logistics companies which show inefficiency because their efficiencies are less than 1.0000. BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, SEALINK, SURIA, TAS and TASCO are inefficient in making full use of their resources for the greatest output creation. Inefficient management of operational risk could pose a threat to a company's business activities and lead to financial and reputational damages. In descending orders, the inefficient listed logistics companies are SEALINK (0.9906), HARBOUR (0.9860), BIPORT (0.9737),

SURIA (0.9666), BHIC (0.9649), FREIGHT (0.9400), GCAP (0.9026), TASCO (0.8966), CJCEN (0.8889), LITRAK (0.8875), MAYBULK (0.8497) and TAS (0.6725).

Among the inefficient listed logistics companies, SEALINK (0.9906) is the closest to obtaining the efficiency of 1.0000. However, TAS, with an efficiency of 0.6725, is the least efficient listed logistics company. The range of efficiency of the enhanced DEA model is therefore, 0.6725 to 1.0000, which is in accordance with the studies by Lee et al. (2017) and Van et al. (2022). The average efficiency score of the efficiency of the listed logistics companies when taking operational risk into consideration is 0.9600. This result is supported by the study of Chen et al. (2008) whereby the average efficiency is above 0.9300 and Karimi and Barati (2017) whereby the average efficiency score is 0.9674. Meanwhile, there are twenty (20) (74.07%) listed logistics companies which have managed to obtain above the average efficiency, they are AIRPORT, COMPLET, GDEX, HUBLINE, ILB, MISC, MMCCORP, NATWIDE, POS, PDZ, PRKCORP, SEEHUP, SYSCORP, TNLOGIS, TOCEAN, SEALINK, HARBOUR, BIPORT, SURIA and BHIC (Hsu et al., 2022).

5.3 Optimal Weights for Inputs and Outputs

Table 5.2 presents the contributions of the output and input variables to the maximization of the efficiency of the listed logistics companies according to the enhanced DEA model. The higher the weight of the variable, the greater the contribution of the variable to the maximization of the efficiency of the listed logistics companies using this enhanced DEA model.

Table 5.2: Optimal Output and Input Weights based on Enhanced DEA Model

Companies	EPS	ROA	ROE	C_{BIA}	CTR	DAR	DER	WACC
AIRPORT	0.0002	0.0002	0.0282	0.9715	0.0000	0.0000	0.0105	0.9895
BHIC	0.2523	0.0372	0.0002	0.7103	0.0917	0.0000	0.0000	0.9082
BIPORT	0.0196	0.0529	0.0002	0.9274	0.0000	0.0325	0.0037	0.9638
CJCEN	0.0006	0.0006	0.0759	0.9228	0.0035	0.1357	0.0000	0.8608
COMPLET	0.1987	0.0134	0.0971	0.6908	0.0058	0.0000	0.1058	0.8885
FREIGHT	0.0006	0.0006	0.1047	0.8941	0.0038	0.0000	0.0578	0.9384
GCAP	0.0005	0.1784	0.0005	0.8205	0.0000	0.0000	0.0255	0.9745
GDEX	0.0003	0.1248	0.0003	0.8745	0.0054	0.0010	0.1410	0.8526
HARBOUR	0.0006	0.1690	0.0006	0.8298	0.0039	0.0000	0.0588	0.9373
HUBLINE	0.0007	0.0007	0.0007	0.9980	0.8074	0.0001	0.1924	0.0001
ILB	0.0006	0.0006	0.1106	0.8882	0.0040	0.0000	0.0592	0.9368
LITRAK	0.0362	0.0002	0.0584	0.9052	0.0000	0.0000	0.0000	1.0000
MAYBULK	0.3509	0.0004	0.0564	0.5924	0.0323	0.9676	0.0000	0.0000
MISC	0.0281	0.0002	0.0002	0.9715	0.0000	0.0000	0.0122	0.9878

Companies	EPS	ROA	ROE	C_{BIA}	CTR	DAR	DER	WACC
MMCCORP	0.0002	0.0002	0.0292	0.9705	0.0000	0.0000	0.0106	0.9894
NATWIDE	0.0006	0.0006	0.1309	0.8680	0.0055	0.0000	0.1013	0.8932
POS	0.0176	0.0509	0.0002	0.9313	0.0000	0.0000	0.0122	0.9878
PDZ	0.0007	0.0007	0.0007	0.9980	0.0373	0.8205	0.1422	0.0000
PRKCORP	0.0176	0.0510	0.0002	0.9312	0.0000	0.0000	0.0122	0.9878
SEALINK	0.0007	0.0007	0.0007	0.9980	0.8074	0.0001	0.1924	0.0001
SEEHUP	0.0281	0.0002	0.0002	0.9716	0.0000	0.0000	0.0122	0.9878
SURIA	0.2732	0.0005	0.0005	0.7259	0.0053	0.2573	0.0000	0.7374
SYSCORP	0.1187	0.0003	0.0003	0.8807	0.0132	0.0678	0.0000	0.9190
TAS	0.0007	0.0007	0.0007	0.9980	0.0027	0.1182	0.0000	0.8791
TASCO	0.1179	0.1081	0.0005	0.7735	0.0032	0.1286	0.0000	0.8682
TNLOGIS	0.0963	0.0003	0.0375	0.8660	0.0132	0.0678	0.0000	0.9189
TOCEAN	0.0007	0.0007	0.0007	0.9980	0.0042	0.0000	0.0649	0.9309
Average	0.0579	0.0294	0.0273	0.8855	0.0685	0.0962	0.0450	0.7903

The optimal control of the outputs and inputs provide an indicator on the importance of the respective outputs and inputs towards the maximization of the efficiency of the listed logistics companies in Malaysia. For example, GDEX, which is an efficient listed logistics company, has a C_{BIA} output weight of 0.8745, which is the highest weight among all the outputs. This means that in terms of outputs, C_{BIA} contributes the most to the efficiency of GDEX. This is followed by ROA with a weightage of 0.1248, EPS with a weight of 0.0003 and ROE with a weight of 0.0003. The most prevalent input for GDEX is WACC, which accounts for 0.8526 of the overall input weight, therefore, WACC plays an important role in facilitating GDEX to achieve the highest efficiency. DER contributes 0.1410 of the total input weight. CTR contributes a relative low weight of 0.0054 to the efficiency of GDEX. DAR has an input weight of 0.0010 (Ong and Kamil, 2010).

Meanwhile, from Table 5.2, it can be noted that the overall efficiency of the listed logistics companies in Malaysia is largely driven by BIA with an average weightage of 0.8855, among the output variables. EPS, ROA and ROE each contribute 0.0579, 0.0294 and 0.0273 to the overall efficiency of the listed logistics companies. Among the input variables, WACC is the leading variable with an average weight of 0.7903, signalling a high contribution towards the maximization of the efficiency of the listed logistics companies in Malaysia. DAR (0.0962) is the second most important variable in the overall efficiency of the listed logistics companies in Malaysia based on the enhanced DEA model. CTR has an average weight of 0.0685 while DER is the lowest contributor with an average weight of 0.0450.

5.4 Reference Sets

A powerful feature in the enhanced DEA model is the benchmarking capability. For benchmarking, reference sets are identified for the inefficient listed logistics companies. Reference sets are made up of efficient listed logistics companies which serve as the benchmarks because they have superior efficiency than the inefficient listed logistics companies. Therefore, the listed logistics companies which make up the reference sets are the companies with the efficiency of 1.0000. The optimal solution of the enhanced DEA model also provides the optimal coefficients of the benchmarked companies for the calculation of the new target values for the inefficient listed logistics companies. The reference sets which made up of the benchmarks and the optimal coefficients for the inefficient listed logistics companies are shown in Table 5.3.

Table 5.3: Reference Set for Inefficient Logistics Companies based on Enhanced DEA Model

Inefficient Companies	Efficiency Scores	Reference Set of Efficient Companies (Optimal Coefficients, α_g)					
		HUBLINE	MMCCORP	POS	PRKCORP	TNLOGIS	
BHIC	0.9649	(0.5682)	(0.1476)	(0.0001)	(0.0025)	(0.2816)	
		MISC	MMCCORP	POS	PRKCORP	SEEHUP	TNLOGIS
BIPORT	0.9737	(0.1580)	(0.1239)	(0.0001)	(0.0406)	(0.1368)	(0.5405)
		ILB	MISC	POS	SEEHUP		
CJCEN	0.8889	(0.0894)	(0.5247)	(0.0019)	(0.3840)		
		ILB	MISC	POS	SEEHUP		
FREIGHT	0.9400	(0.2039)	(0.4376)	(0.0025)	(0.3560)		
		ILB	POS	SEEHUP			
GCAP	0.9026	(0.7071)	(0.0857)	(0.2072)			
		ILB	MISC	POS	SEEHUP		
HARBOUR	0.9860	(0.1507)	(0.2119)	(0.0021)	(0.6353)		
LITRAK	0.8875	MMCCORP	POS	PRKCORP	TNLOGIS		

Inefficient Companies	Efficiency Scores	Reference Set of Efficient Companies (Optimal Coefficients, α_g)				
		(0.1478)	(0.0039)	(0.0375)	(0.8108)	
		COMPLET	MISC	POS	PRKCORP	TOCEAN
MAYBULK	0.8497	(0.4004)	(0.1028)	(0.0032)	(0.0003)	(0.4933)
		HUBLINE	SYSCORP			
SEALINK	0.9906	(0.1194)	(0.8806)			
		COMPLET	ILB	MISC	PRKCORP	
SURIA	0.9666	(0.8525)	(0.0336)	(0.0992)	(0.0147)	
		ILB	MISC	SEEHUP		
TAS	0.6725	(0.0379)	(0.6720)	(0.2901)		
		ILB	MISC	POS	PRKCORP	SEEHUP
TASCO	0.8966	(0.0334)	(0.3635)	(0.0022)	(0.0049)	(0.5960)

Based on the enhanced DEA model, BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, SEALINK, SURIA, TAS and TASCO are inefficient because their efficiency scores are below 1.0000, which means that they have not fully utilized their resources for the transformation into the greatest yields. On the other hand, AIRPORT, COMPLET, GDEX, HUBLINE, ILB, MISC, MMCCORP, NATWIDE, POS, PDZ, PRKCORP, SEEHUP, SYSCORP, TNLOGIS and TOCEAN are efficient with the incorporation of operational risk factor. This shows that these efficient listed logistics companies are superior to the inefficient listed logistics companies because efficient companies have successfully maximized their yields from proper management of resources.

Despite being efficient, AIRPORT, GDEX, NATWIDE and PDZ are not in the reference sets of any inefficient listed logistics companies based on Table 5.3. The inefficient listed logistics companies do not benchmark against AIRPORT, GDEX, NATWIDE and PDZ for the calculation of new target values when considering operational risk. Therefore, only eleven (11) efficient listed logistics companies serve as the benchmarks in the corresponding reference sets of the inefficient listed logistics companies. They are COMPLET, HUBLINE, ILB, MISC, MMCCORP, POS, PRKCORP, SEEHUP, SYSCORP, TNLOGIS and TOCEAN.

Firstly, with an efficiency of 0.9649, BHIC is inefficient. To improve its efficiency, BHIC can set new target values for its output and input variables based on the optimal coefficients of the benchmarks in the reference set. The reference set of BHIC is made up of HUBLINE, MMCCORP, POS, PRKCORP and TNLOGIS with the optimal coefficients of 0.5682, 0.1476, 0.0001, 0.0025 and 0.2816 respectively. BHIC can then improve based on the best practices of the benchmarked companies to improve and reach their new target values for higher efficiency. Secondly, BIPORT has an efficiency of 0.9737. There are six (6) efficient logistics companies, which are MISC, MMCCORP, POS, PRKCORP, SEEHUP and TNLOGIS which form the reference set for BIPORT for the calculation of new target value for potential improvement. The most important benchmark is TNLOGIS with a weight of 0.5405, followed by MISC (0.1580), SEEHUP (0.1368), MMCCORP (0.1239), PRKCORP (0.0406) and POS (0.0001).

Thirdly, CJCEN is also an inefficient listed logistics company with an efficiency of 0.8889. Its reference set consists of ILB, MISC, POS and SEEHUP. MISC has the highest optimal coefficient of 0.5247. SEEHUP, ILB and POS have the optimal coefficients of 0.3840, 0.0894 and 0.0019 respectively. Fourthly, the efficiency of FREIGHT is 0.9400, which also implies that FREIGHT is less efficient. ILB, MISC, POS and SEEHUP are also the benchmarks for FREIGHT. In the order of the highest weightage to the least weightage, MISC contributes most with the optimal coefficient of 0.4376, followed by SEEHUP (0.3560), ILB (0.2039) and POS (0.0025).

Meanwhile, GCAP’s efficiency is 0.9026 and GCAP could benchmark ILB, POS and SEEHUP for potential improvement. The optimal coefficients for ILB, SEEHUP and POS are 0.7071, 0.2072 and 0.0857. At the same time, HARBOUR is inefficient with the efficiency of 0.9860. There are four (4) benchmarks for HARBOUR, which are ILB, MISC, POS and SEEHUP. The highest contributor to facilitate in the formation of new target value to increase the efficiency of HARBOUR is SEEHUP with a weight of 0.6353. MISC, ILB and POS contribute 0.2119, 0.1507 and 0.0021 to the target values of HARBOUR.

LITRAK has an efficiency of 0.8875. The reference set of LITRAK consists of MMCCORP, POS, PRKCORP and TNLOGIS. To increase its efficiency, LITRAK should take note of the optimal coefficients of TNLOGIS (0.8108), MMCCORP (0.1478), PRKCORP (0.0375) and POS (0.0039). Next, MAYBULK is also inefficient because its efficiency is only 0.8497. COMPLET, MISC, POS, PRKCORP and TOCEAN are the five benchmarks for MAYBULK. TOCEAN and COMPLET have weights of 0.4933 and 0.4004 to the calculation of the target values of MAYBULK. MISC, POS and PRKCORP each contribute 0.1028, 0.0032 and 0.0003 to the target values of MAYBULK.

Among the inefficient listed logistics companies, SEALINK is the closest to becoming efficient. There are only two (2) listed logistics companies which are the benchmarks for SEALINK, they are HUBLINE and SYSCORP. The weight of SYSCORP (0.8806) is very high, indicating that SYSCORP is very important in determining the target values for SEALINK. HUBLINE has a weight of 0.1194, which also helps in contributing to the target values of SEALINK. Consequently, SURIA has an efficiency of 0.9666 and is also inefficient. The four (4) benchmarks for SURIA are COMPLET, ILB, MISC and

PRKCORP. COMPLET has a very high optimal coefficient weight of 0.8525, followed by MISC (0.9992), ILB (0.0336) and PRKCORP (0.0147) in the calculation of the target values for SURIA.

TAS has the lowest efficiency of 0.6725. TAS can take proactive measures to improve its efficiency so that TAS can continue to provide excellent services to drive the economy of Malaysia. The reference set for TAS include ILB, MISC and SEEHUP. MISC has the highest optimal coefficient of 0.6720, followed by SEEHUP (0.2901) and ILB (0.0379). Finally, TASCO has an efficiency of 0.8966. There are five (5) efficient logistics companies which make up the reference set for TASCO, they are SEEHUP (0.5960), MISC (0.3935), ILB (0.0334), PRKCORP (0.0049) and POS (0.0022).

Figure 5.1 shows the summary of the number of efficient listed logistics companies which serve as benchmarks in the reference sets of the twelve (12) inefficient listed logistics companies in Malaysia based on the enhanced DEA model.

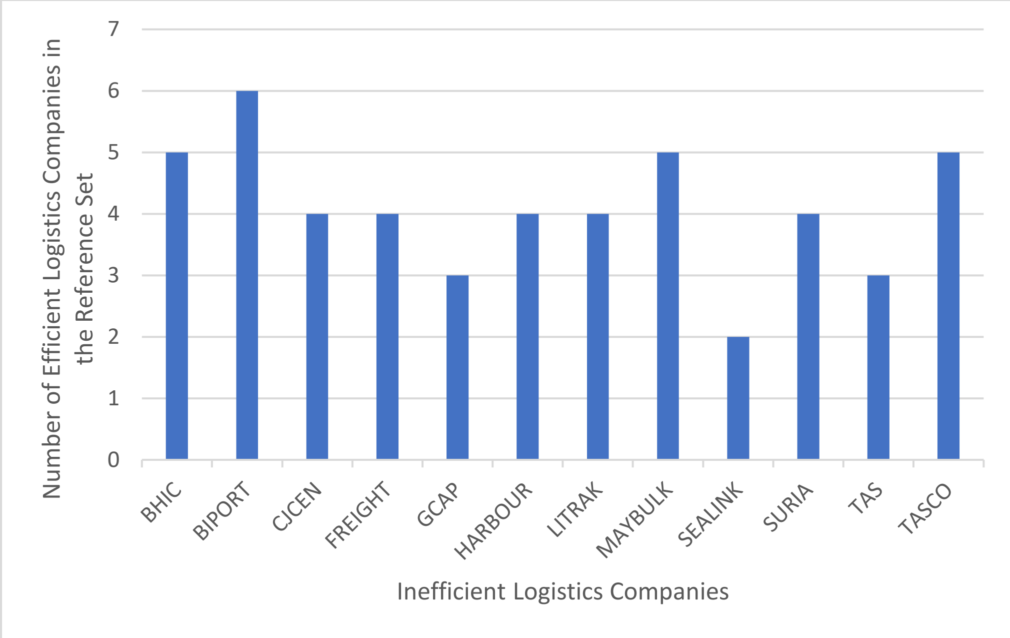

Figure 5.1: Number of Efficient Companies in the Reference Set based on the Enhanced DEA Model.

The number of efficient listed logistics companies which form the reference set of each inefficient listed logistics company is shown in Figure 5.1. There are twelve (12) inefficient listed logistics companies and eleven (11) efficient listed logistics companies which serve as benchmarks for the corresponding inefficient companies respectively because AIRPORT, GDEX, NATWIDE and PDZ have not become the benchmarks for any inefficient listed logistics company. From Figure 5.1, BIPORT has the most benchmarks in its reference set, which consists of six (6) efficient listed logistics companies. BHIC, MAYBULK and TASCO have five (5) efficient listed logistics companies in their reference set respectively. CJCEN, FREIGHT, HARBOUR, LITRAK and SURIA have four (4) benchmarks in the reference set respectively. GCAP and TAS can benchmark two (2) efficient listed logistics companies for improvement. SEALINK, which is very close to being efficient, only has to benchmark one (1) efficient listed logistics company for improvement.

5.5 Potential Improvements

Upon the identification of the reference set which consists of the benchmarks and optimal coefficients, the target values of the output and input variables of the inefficient listed logistics companies can be calculated. The difference between the target value and the actual value reflects the potential improvement which could facilitate the inefficient listed logistics company to increase its efficiency. The potential improvements of the twelve (12) inefficient listed logistics companies based on the enhanced DEA model are shown in Table 5.4.

Table 5.4: Potential Improvements for Inefficient Logistics Companies based on Enhanced DEA Model

Companies	Outputs / Inputs	Actual Values	Target Values	Potential Improvements
BHIC	EPS	0.0690	0.0691	0.0000
	ROA	0.0192	0.0192	0.0000
	ROE	0.0414	0.0441	0.0027
	C_{BIA}	0.0545	0.0544	0.0000
	CTR	0.9947	0.9598	-0.0349
	DAR	0.5779	0.5471	-0.0308
	DER	1.8922	1.6809	-0.2113

Companies	Outputs / Inputs	Actual Values	Target Values	Potential Improvements
	WACC	0.0733	0.0707	-0.0026
BIPORT	EPS	0.3648	0.3648	0.0000
	ROA	0.0689	0.0689	0.0000
	ROE	0.1501	0.1746	0.0245
	C_{BIA}	0.1102	0.1102	0.0000
	CTR	3.2174	1.2836	-1.9338
	DAR	0.5415	0.5273	-0.0142
	DER	1.2977	1.2638	-0.0339
	WACC	0.0602	0.0586	-0.0016
CJCEN	EPS	0.1121	0.1146	0.0025
	ROA	0.0456	0.0464	0.0008
	ROE	0.0739	0.0872	0.0133
	C_{BIA}	0.0116	0.1769	0.1653
	CTR	1.8669	1.6568	-0.2101
	DAR	0.3959	0.3228	-0.0731
	DER	0.6771	0.3979	-0.2792
	WACC	0.0772	0.0612	-0.0160
FREIGHT	EPS	0.1018	0.1932	0.0914
	ROA	0.0633	0.0641	0.0008
	ROE	0.1023	0.1023	0.0000
	C_{BIA}	0.0160	0.1710	0.1550
	CTR	2.1968	2.1162	-0.0807
	DAR	0.3794	0.3513	-0.0281

Companies	Outputs / Inputs	Actual Values	Target Values	Potential Improvements
	DER	0.6125	0.5900	-0.0225
	WACC	0.0731	0.0704	-0.0027
GCAP	EPS	0.0362	0.0991	0.0629
	ROA	1.1417	1.1417	0.0000
	ROE	0.0650	1.8885	1.8235
	C_{BIA}	0.0049	0.0166	0.0117
	CTR	13.9511	3.8790	-10.0721
	DAR	5.2244	0.3059	-4.9185
	DER	0.5446	0.4934	-0.0513
	WACC	0.0775	0.0702	-0.0073
HARBOUR	EPS	0.1041	0.1232	0.0191
	ROA	0.0550	0.0550	0.0000
	ROE	0.0907	0.0911	0.0003
	C_{BIA}	0.0122	0.0899	0.0777
	CTR	1.9375	1.9331	-0.0044
	DAR	0.3852	0.3755	-0.0097
	DER	0.6587	0.6572	-0.0015
	WACC	0.0657	0.0655	-0.0001
LITRAK	EPS	0.3192	0.3192	0.0000
	ROA	0.0753	0.1150	0.0398
	ROE	0.2539	0.2539	0.0000
	C_{BIA}	0.0608	0.0608	0.0000
	CTR	3.0011	1.2042	-1.7969

Companies	Outputs / Inputs	Actual Values	Target Values	Potential Improvements
	DAR	0.6972	0.5896	-0.1076
	DER	2.9152	1.5080	-1.4072
	WACC	0.0603	0.0535	-0.0068
MAYBULK	EPS	0.0771	0.0771	0.0000
	ROA	0.0668	0.0730	0.0062
	ROE	0.1121	0.1121	0.0000
	C_{BIA}	0.0425	0.0425	0.0000
	CTR	2.3389	1.9873	-0.3516
	DAR	0.3433	0.2917	-0.0516
	DER	0.7257	0.4414	-0.2843
	WACC	0.0997	0.0801	-0.0195
SEALINK	EPS	0.0122	0.0286	0.0165
	ROA	0.0067	0.0129	0.0063
	ROE	0.0136	0.0208	0.0071
	C_{BIA}	0.0034	0.0081	0.0048
	CTR	1.0091	1.0004	-0.0088
	DAR	0.4391	0.4094	-0.0297
	DER	0.8154	0.8083	-0.0071
	WACC	0.0719	0.0682	-0.0037
SURIA	EPS	0.1925	0.1925	0.0000
	ROA	0.0439	0.0712	0.0274
	ROE	0.0620	0.1157	0.0537
	C_{BIA}	0.0159	0.0404	0.0245

Companies	Outputs / Inputs	Actual Values	Target Values	Potential Improvements
	CTR	2.8923	2.8063	-0.0861
	DAR	0.2793	0.2710	-0.0083
	DER	0.4018	0.3875	-0.0143
	WACC	0.0848	0.0822	-0.0025
TAS	EPS	0.0405	0.2532	0.2127
	ROA	0.0266	0.0303	0.0037
	ROE	0.0450	0.0477	0.0026
	C_{BIA}	0.0018	0.2577	0.2559
	CTR	2.1528	1.5306	-0.6222
	DAR	0.5080	0.3612	-0.1468
	DER	1.5783	0.6088	-0.9695
	WACC	0.1028	0.0731	-0.0297
TASCO	EPS	0.1886	0.1886	0.0000
	ROA	0.0597	0.0597	0.0000
	ROE	0.1032	0.1058	0.0026
	C_{BIA}	0.0160	0.1463	0.1303
	CTR	1.6644	1.5248	-0.1396
	DAR	0.4191	0.3840	-0.0351
	DER	0.8357	0.6753	-0.1604
	WACC	0.0734	0.0672	-0.0062

Table 5.4 explains the potential improvement for the inefficient listed

logistics companies based on the enhanced DEA model. Table 5.4 is obtained from the benchmarking capability of the enhanced DEA model to facilitate the improvements of the inefficient listed logistics companies. The potential improvement is calculated based on the difference between the target value and the actual value so that the inefficient listed logistics companies can increase their efficiency. The target value is calculated by taking the sum of the product of the actual value of the output or input of the benchmarked companies and the optimal coefficient of the corresponding benchmark companies in the reference set.

The computation of the target value is explained using TAS, which has the least efficiency of 0.6725. From Table 5.3, the benchmarks for TAS are made up of ILB (0.0379), MISC (0.6720) and SEEHUP (0.2901). Therefore, TAS has to consider the optimal coefficients of these three (3) benchmarks and the respective output or input variables of these benchmarks for the computation of the target values. The calculation of the target values of the outputs and inputs for TAS is shown below.

$$\begin{bmatrix} EPS \\ ROA \\ ROE \\ C_{BIA} \\ CTR \\ DAR \\ DER \\ WACC \end{bmatrix} = 0.0379 \text{ x } \begin{bmatrix} 0.1079 \\ 0.0454 \\ 0.0562 \\ 0.0021 \\ 4.9151 \\ 0.2555 \\ 0.3575 \\ 0.0703 \end{bmatrix} + 0.6720 \text{ x } \begin{bmatrix} 0.3483 \\ 0.0329 \\ 0.0493 \\ 0.3769 \\ 1.3925 \\ 0.3443 \\ 0.5575 \\ 0.0789 \end{bmatrix} + 0.2901 \text{ x } \begin{bmatrix} 0.0517 \\ 0.0224 \\ 0.0428 \\ 0.0149 \\ 1.4082 \\ 0.4141 \\ 0.7605 \\ 0.0598 \end{bmatrix}$$

$$\begin{bmatrix} EPS \\ ROA \\ ROE \\ C_{BIA} \\ CTR \\ DAR \\ DER \\ WACC \end{bmatrix} = \begin{bmatrix} 0.2532 \\ 0.0303 \\ 0.0477 \\ 0.2577 \\ 1.5306 \\ 0.3612 \\ 0.6088 \\ 0.0731 \end{bmatrix}$$

The target values of TAS can be calculated with the method above. Being the least efficient listed logistics company, TAS has to take necessary amendments on its outputs and inputs to increase its efficiency. From the enhanced DEA model, it is suggested that all the outputs of TAS should be increased while all the inputs should be reduced. EPS, ROA, ROE and C_{BIA} of TAS should increase by 0.2127, 0.0037, 0.0026 and 0.2559 to reach the target values of 0.2532, 0.0303, 0.0477 and 0.2577 respectively. In terms of inputs, TAS should decrease its CTR, DAR, DER and WACC by 0.6222, 0.1468, 0.9695 and 0.0297 to reach the target values of 1.5306, 0.3612, 0.6088 and 0.0731 respectively.

The enhanced DEA model has also rated BHIC as inefficient with the efficiency of 0.9649. Therefore, amelioration should be performed on the outputs and inputs of BHIC to increase its efficiency. For the outputs, BHIC can maintain its EPS, ROA and C_{BIA} at their respective values of 0.0691, 0.0192 and 0.0544. ROE can be increased from 0.0414 to 0.0441, signalling an increase of 0.0027. The inputs, namely CTR, DAR, DER and WACC should be reduced by 0.0349, 0.0308, 0.2113 and 0.0026 so that the target values of 0.9598, 0.5471, 1.6809 and 0.0707 can be attained respectively.

BIPORT has an efficiency of 0.9737. For efficiency improvement, among the outputs, BIPORT can increase its ROE from 0.1501 to 0.1746, with a potential improvement of 0.0245. The remaining outputs, which are EPS, ROA and C_{BIA} are at their optimal levels of 0.3648, 0.0689 and 0.1102 respectively and are adequate to contribute to the efficiency of BIPORT. Due to the high initial CTR value, BIPORT could reduce its CTR by 1.9338 to reach the target value of 1.2836. DAR of BIPORT can be reduced by 0.0142 from 0.5415 to 0.5273. The initial DER value of BIPORT is 1.2977 and it is recommended that this value be reduced by 0.0339 to 1.2638. WACC of BIPORT requires a small reduction of 0.0016 from 0.0602 to 0.0586.

CJCEN has an efficiency score of 0.8889, which is below the average efficiency. All the outputs and inputs require amelioration. EPS, ROA, ROE and C_{BIA} can be increased from 0.1121, 0.0456, 0.0739 and 0.0116 to 0.1146, 0.0464, 0.0872 and 0.1769, which means that potential improvements of 0.0025, 0.0008, 0.0133 and 0.1653 can be taken respectively. For CTR, DAR, DER and WACC, the respective values can be reduced from 1.8669, 0.3959, 0.6771 and 0.0772 to 1.6568, 0.3228, 0.3979 and 0.0612, suggesting potential improvements of -0.2101, -0.0731, -0.2792 and -0.0160.

FREIGHT has an efficiency of 0.9400 and is also inefficient. ROE can be maintained at 0.1023 according to the optimal solution of the enhanced DEA model. The other three outputs, which are EPS, ROA and C_{BIA}, however, require improvements of 0.0914, 0.0008 and 0.1550 to attain the target values of 0.1932, 0.0641 and 0.1710 respectively. For the inputs, CTR, DAR, DER and WACC can be reduced by 0.0807, 0.0281, 0.0225 and 0.0027 from 2.1968, 0.3794, 0.6125 and 0.0731 to 2.1162, 0.3513, 0.5900 and 0.0704 respectively.

Next, GCAP is also inefficient and is below the average efficiency. The optimal solution of the enhanced DEA model proposes that among the outputs, EPS, ROE and C_{BIA} can be increased from 0.0362, 0.0650 and 0.0049 to 0.0991, 1.8885 and 0.0166 to increase the efficiency of GCAP. GCAP has a very high CTR value of 13.9511, which can be reduced by 10.0721 to reach the target value of 3.8790. GCAP also has a high DAR value of 5.2244. A reduction of 4.9185 can be performed to bring DAR down to 0.3059. DER and WACC can also be reduced by 0.0513 and 0.0073 respectively.

HARBOUR has an efficiency of 0.9860. To increase its efficiency, HARBOUR can improve its EPS, ROE and C_{BIA} by 0.0191, 0.0003 and 0.0777 to reach the target values of 0.1232, 0.0911 and 0.0899. ROA is at a suitable level to contribute to the efficiency of HARBOUR, therefore, can remain at 0.0550. CTR, DAR, DER and WACC can be brought down by 0.0044, 0.0097, 0.0015 and 0.0001 to reach the target values of 1.9331, 0.3755, 0.6572 and 0.6555 respectively.

Another inefficient company is LITRAK, with the efficiency of 0.8875 and is also below the average efficiency. Among the outputs, only ROA requires a potential improvement of 0.0398 to reach the target value of 0.1150. EPS, ROE and C_{BIA} can remain at 0.3192, 0.2539 and 0.0608 respectively. Among the inputs, LITRAK's CTR, DAR, DER and WACC can also be decreased from

3.0011, 0.6972, 2.9152 and 0.0603 to 1.2042, 0.5896, 1.5080 and 0.0535 respectively. This means that there will be potential improvements of -1.7969, -0.1076, -1.4072 and -0.0068 for CTR, DAR, DER and WACC.

At the same time, MAYBULK is having an efficiency of 0.8497. To be on the efficient frontier, ROA can be increased from 0.0668 to 0.0730, signalling a potential improvement of 0.0062. EPS, ROE and C_{BIA} are sufficient at the values of 0.0771, 0.1121 and 0.0425 respectively. CTR, DAR, DER and WACC can be reduced from 2.3389, 0.3433, 0.7257 and 0.0997 to 1.9873, 0.2917, 0.4414 and 0.0801 respectively, each showing improvements of -0.3516, -0.0516, -0.2843 and -0.0195.

SEALINK is also inefficient and requires amelioration. EPS, ROA, ROE and C_{BIA} can increase from 0.0122, 0.0067, 0.0136 and 0.0034 to 0.0286, 0.0129, 0.0208 and 0.0081 with potential improvements of 0.0165, 0.0063, 0.0071 and 0.0048 respectively. Higher efficiency may be achieved by SEALINK if SEALINK lowers its CTR, DAR, DER and WACC by 0.0088, 0.0297, 0.0071 and 0.0037 respectively.

SURIA has an efficiency of 0.9666. Its EPS can be kept constant at 0.1925 according to the optimal solution of the enhanced DEA model. For higher efficiency, SURIA can increase its ROA, ROE and C_{BIA} by 0.0274, 0.0537 and 0.0245 to arrive at the target values of 0.0712, 0.1157 and 0.0404. For the inputs, CTR, DAR, DER and WACC can be decreased by 0.0861, 0.0083, 0.0143 and 0.0025 from the initial values of 2.8923, 0.2793, 0.4018 and

0.0848 to 2.8063, 0.2710, 0.3875 and 0.0822.

Meanwhile, TAS has the lowest efficiency of 0.6725. Therefore, TAS needs to improve in order to gain higher efficiency and position itself strategically in the market. EPS, ROA, ROE and C_{BIA} can be increased from 0.0405, 0.0266, 0.0450 and 0.0018 to 0.2532, 0.0303, 0.0407 and 0.2577, with the improvements of 0.2127, 0.0037, 0.0026 and 0.2559 respectively. CTR, DAR, DER and WACC are high and should be reduced for better efficiency. CTR, DAR, DER and WACC can be reduced by 0.6222, 0.1468, 0.9695 and 0.0297 to reach 1.5306, 0.3612, 0.6088 and 0.0731 respectively.

Lastly, TASCO, which has an efficiency of 0.8966, is also inefficient. Among the outputs, EPS and ROA can remain at 0.1886 and 0.0597 respectively. However, ROE and C_{BIA} requires improvements of 0.0026 and 0.1303 from their initial values of 0.1032 and 0.0160 to the target values of 0.1058 and 0.1463 respectively. On the other hand, for the inputs, CTR, DAR, DER and WACC could be reduced from 1.6644, 0.4191, 0.8357 and 0.0734 to 1.5248, 0.3840, 0.6753 and 0.0672 respectively.

Based on these results, the listed logistics companies can take measures to improve their performances by increasing their outputs or reducing their inputs. CJCEN, FREIGHT, GCAP, HARBOUR, SEALINK, and TAS should increase their EPS respectively. The EPS of these companies can be increased by improving a company’s net profit through the rise in sales volume. Sales can be improved by enhancing the value of the products and services offered by understanding the customers' expectations. Meanwhile, focusing on the target market for a company's product and services could also increase the customer base, which helps to generate sales (Lin and Bowman, 2022). To increase profit through sales, these logistics companies should perform the seven rights with great commitment to fulfill the exact order with the requested amount in the most excellent quality to the correct location and designated receiver by the stipulated time at the best price (Hsiao et al., 2017; Sosik et al., 2019). This will increase customers' confidence and attract more orders with higher customer retention rate.

At the same time, seven companies, including CJCEN, FREIGHT, LITRAK, MAYBULK, SEALINK, SURIA, and TAS, require amelioration for ROA. ROA can be managed by increasing net profits or reducing total assets. Asset cost is an important element to consider when managing ROA. Inventory cost contributes to the total asset cost which is included in the ROA calculation. Therefore, the logistics companies should monitor their inventory levels and ensure that the inventories are adequate for their operations. The cost of holding excessive inventories which do not contribute to the sales and operations of the company could be high and would reduce the ROA of the company. These logistics companies could purchase and store only the suitable amount of inventories to reduce the purchasing cost, inventory storage cost, and insurance cost for the inventories. Proper management of the adequate number of inventories could also reduce obsoletion, which will then improve the ROA of the company (Nasution, 2020). The logistics companies should also increase their inventory turnover rates to improve net profits, which could also increase

ROA (Alnaim and Kouaib, 2023).

Subsequently, BHIC, BIPORT, CJCEN, GCAP, HARBOUR, SEALINK, SURIA, TAS, and TASCO should improve their ROE based on the enhanced DEA model. These companies can choose to increase their profit margins by minimizing production or operation costs. The logistics companies can practice *kaizen*, which is to perform continuous improvement. The companies can perform lean six sigma to reduce non-value-added processes (Acero et al., 2019). These non-value-added processes can exist in surplus of inventories, lengthy transportation procedures, idle time, redundant movement, overproduction, improper space utilization, and damaged products. By identifying these categories of non-value-added activities, the companies can come up with improvement processes such as proper storage procedures, work ergonomics, training, and setting up rules for health and safety (Adeodo et al., 2023). By performing continuous improvements, the companies can reduce their cost of operation and improve their profits to enhance their ROE. Next, CJCEN, FREIGHT, GCAP, HARBOUR, SEALINK, SURIA, TAS, and TASCO need to improve their C_{BIA}. These companies should increase their capital for operational risk based on C_{BIA} so that possible operational risk losses may be covered by the capital. The Basel Committee on Banking Supervision recommended that companies could purchase insurances for operational risk, however, the ratio of the insurance and C_{BIA} should only be up to 20% (Chorafas, 2004).

All the inefficient listed logistics companies including BHIC, BIPORT,

CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, SEALINK, SURIA, TAS, and TASCO have high CTR and should reduce their CTR values. These companies can manage their inventories well to manage their current ratios. By performing demand planning and forecasting, the companies can have adequate inventories to fulfill orders while removing surpluses (Christensen et al., 2021). Using historical data and enterprise resource planning software, the short-term future demand of the companies can be predicted with higher accuracy to allow only sufficient inventories to be kept (Tanava et al., 2020; Wang and Yun, 2020). This will reduce surpluses in buffer stocks and the cost to hold inventories, thus removing excess current assets. This will then decrease the CTR of the companies.

High DAR may expose a company to greater risk in leverage. Thus, BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, SEALINK, SURIA, TAS, and TASCO need to reduce their DAR. If the interest rate of the debts is high, these companies can choose to refinance or restructure their debts to bring down the cost of debt, which will reduce the DAR (Bedendo and Siming, 2018). Meanwhile, all the inefficient logistics companies should also reduce their DER. These logistics companies can increase their revenue by improving their marketing strategy (Juga et al., 2008; Hong and Nguyen, 2020). There are several ways of positioning, for example, positioning by service quality, service pricing, product quality, or product pricing. Moreover, by positioning the companies in the relevant market segments, the companies can attract and engage with highly interested customers (Paridaens and Notteboom, 2022). These companies could identify their strengths in the industry so that they could highlight their offerings to create better company awareness and image. To reduce the WACC of all the inefficient logistics companies, the companies can review their mixtures of debt and equity. Since debt is usually cheaper than equity and is tax-deductible, the companies can switch expensive equity with cheaper debts (Breitschopf and Alexander-Haw, 2022). However, these companies should keep debts at a considerable level (Sikveland et al., 2022). The companies can also choose to refinance its debt if the current market rate is lower than the existing interest rate.

5.6 Efficiency Comparison between Existing DEA and Enhanced DEA Models

Table 5.5 compares the efficiency of the listed logistics companies in Malaysia between the existing and enhanced DEA models.

Table 5.5: Efficiency Comparison between Existing DEA and Enhanced DEA Models

Companies	Efficiency (Existing DEA Model)	Efficiency (Enhanced DEA Model)
AIRPORT	0.6627	1.0000
BHIC	0.8437	0.9649
BIPORT	0.5663	0.9737
CJCEN	0.7786	0.8889

Companies	Efficiency (Existing DEA Model)	Efficiency (Enhanced DEA Model)
COMPLET	1.0000	1.0000
FREIGHT	0.7874	0.9400
GCAP	0.6419	0.9026
GDEX	1.0000	1.0000
HARBOUR	0.7924	0.9860
HUBLINE	1.0000	1.0000
ILB	1.0000	1.0000
LITRAK	0.4685	0.8875
MAYBULK	0.8436	0.8497
MISC	0.9945	1.0000
MMCCORP	0.7160	1.0000
NATWIDE	1.0000	1.0000
POS	1.0000	1.0000
PDZ	1.0000	1.0000
PRKCORP	1.0000	1.0000
SEALINK	0.9913	0.9906
SEEHUP	0.8553	1.0000
SURIA	0.9583	0.9666
SYSCORP	1.0000	1.0000
TAS	0.6250	0.6725
TASCO	0.7985	0.8966
TNLOGIS	0.8280	1.0000
TOCEAN	1.0000	1.0000

Companies	Efficiency (Existing DEA Model)	Efficiency (Enhanced DEA Model)
Average	0.8575	0.9600

Table 5.5 compares the efficiency of the listed logistics companies between the existing and the enhanced DEA models. The objective function of DEA involves maximizing the relative efficiency of the listed logistics companies. Based on the existing DEA model, ten (10) listed logistics companies including COMPLET, GDEX, HUBLINE, ILB, NATWIDE, POS, PDZ, PRKCORP, SYSCORP and TOCEAN are found to be efficient with the efficiency of 1.0000. The remaining 17 companies, which are AIRPORT, BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, MISC, MMCCORP, SEALINK, SEEHUP, SURIA, TAS, TASCO and TNLOGIS are inefficient because their efficiency is less than 1.0000 based on the existing DEA model.

The enhanced DEA model found that fifteen (15) listed logistics companies are efficient with the efficiency of 1.0000. They are AIRPORT, COMPLET, GDEX, HUBLINE, ILB, MISC, MMCCORP, NATWIDE, POS, PDZ, PRKCORP, SEEHUP, SYSCORP, TNLOGIS and TOCEAN. Inefficiencies have been detected in BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, SEALINK, SURIA, TAS and TASCO due to the efficiency of below 1.0000.

Table 5.6 summarizes the efficiency of the listed logistics companies based on the existing and the enhanced DEA models.

Table 5.6: Summary of Efficiency based on the Existing DEA and Enhanced DEA Models

	Existing DEA Model	Enhanced DEA Model
Minimum efficiency	0.4685	0.6725
Maximum efficiency	1.0000	1.0000
Average efficiency	0.8575	0.9600
Number of efficient companies	10	15
Percentage of efficient companies (%)	37.04	55.56

A summary between the existing and the enhanced DEA models is shown in Table 5.6. The existing DEA model concludes that 10 out of 27 listed logistics companies are efficient, which accounts for 37.04% of the total number of listed logistics companies. On the other hand, the enhanced DEA model yields a result that shows 15 out of 27 listed logistics companies as efficient, which reflects that 55.56% of the listed logistics companies are efficient when considering operational risk. The existing DEA model has an average efficiency of 0.8575 while the enhanced DEA model has a greater average efficiency of 0.9600 (Chen et al., 2008; Mohanta et al., 2021; Hesampour et al, 2022; Hsu et al., 2022).

Meanwhile, the minimum and maximum efficiency of the listed logistics companies also vary between the existing and the enhanced DEA model. The existing DEA model has a range of efficiency between 0.4685 and 1.0000 (Qi et al., 2022). The enhanced DEA model has efficiencies from 0.6725 to 1.0000 (Młynarski et al., 2021; Najafabadi et al., 2022; Van et al., 2022).

The comparison of the existing and the enhanced DEA model shows the impact of the integration of operational risk in the enhanced DEA model. This will better reflect the operational risk in the enhanced DEA model in the evaluation of the financial efficiency of the listed logistics companies. The enhanced model can facilitate the management of operational risk in the listed logistics companies. Based on the optimal solution of the enhanced DEA model, the inefficient listed logistics companies could identify the suitable operational risk hedging strategy to minimize the adverse effects of operational risk.

5.7 Model Performance Comparison

The model performance between the existing and the enhanced DEA models to optimize the efficiency of the listed logistics companies is tabulated in Table 5.7. This comparison is performed using the coefficient of variation (CoV), which is the quotient of standard deviation and mean (Hur et al., 2022).

Table 5.7: Model Performance between the Existing DEA and Enhanced DEA Models

	Existing DEA Model	Enhanced DEA Model
Average efficiency	0.8575	0.9600
Standard deviation among efficiencies	0.1599	0.0730
CoV (%)	18.65	7.61

From Table 5.7, the enhanced DEA model has a higher average efficiency of 0.9600 compared to the existing DEA model with only 0.8575. The standard deviation among the efficiency scores in the enhanced DEA model is 0.0730, which is also lower than the existing DEA model (0.1599). With lower standard deviation and higher average efficiency, the enhanced DEA model then shows a lower CoV of 7.61% compared to the existing DEA model with a CoV of 18.65%. Lower CoV better reflects the actual performances of the companies in terms of relative efficiency because DEA measures the relative efficiency of the companies (Singh and Ali, 2023). Therefore, the enhanced DEA model outperforms the existing DEA model because of a lower CoV.

5.8 Summary

This chapter has presented the results from the optimization of the efficiency of the listed logistics companies with the enhanced DEA model. The enhanced DEA model considers operational risk factor. From this model, the listed logistics companies which are efficient are AIRPORT, COMPLET,

GDEX, HUBLINE, ILB, MISC, MMCCORP, NATWIDE, POS, PDZ, PRKCORP, SEEHUP, SYSCORP, TNLOGIS and TOCEAN because of the attainment of the efficiency score of 1.0000. However, the remaining 12 listed logistics companies, which are BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, SEALINK, SURIA, TAS and TASCO are inefficient as their efficiency scores are below 1.0000. Based on this enhanced DEA model, the average efficiency score of the listed logistics companies is 0.9600.

The maximum efficiency of the listed logistics companies is mainly contributed by BIA with a corresponding average output weight of 0.8855. EPS, ROA and ROE also contribute 0.0579, 0.0294 and 0.0273 to the maximization of the efficiency of the listed logistics companies, in terms of outputs. On the other hand, in terms of the inputs, WACC shows a heavy weightage of 0.7903 as compared to DAR (0.0962), CTR (0.0685) and DER (0.0450).

This enhanced DEA model provides reference sets for the inefficient listed logistics companies. The reference sets are made up of the efficient listed logistics companies together with their respective optimal coefficients. This allows the inefficient listed logistics companies to benchmark the best performing companies for improvements. The recommended potential improvements based on the enhanced DEA model are then obtained by observing the differences between the actual and target values of the variables.

Lastly, the percentage of efficiency between the existing and the enhanced DEA models also vary. In the existing DEA model, 10 out of 27 companies (37.04%) are efficient while in the enhanced DEA model, 15 out of 27 companies (55.56%) are efficient. The average efficient in the existing DEA model (0.8575) is also lower than the enhanced DEA model (0.9600). The existing DEA model, however, has a higher standard of deviation (0.1599) compared to the enhanced DEA model (0.0730). Therefore, this results in the enhanced DEA model having a lower CoV of 7.61% compared to the existing DEA model which has a CoV of 18.65%. As such, the enhanced DEA model outperforms the existing DEA model in maximizing the efficiency of the listed logistics companies.

CHAPTER 6

CONCLUSION

6.1 Introduction

This chapter revisits the objectives of the study and relates the objectives to the results obtained from the optimal solution of the existing and enhanced DEA models. Subsequently, this section also discusses the significance of study with highlighted contributions in the academic and industry. Based on the implications of this study, the final section suggests future research.

6.2 Summary of Research Findings

This study determines the efficiency of the listed logistics companies in Malaysia using the DEA model. Based on the existing DEA model, empirical results found that 10 companies, which include COMPLET, GDEX, HUBLINE, ILB, NATWIDE, POS, PDZ, PRKCORP, SYSCORP and TOCEAN, are fully efficient with the efficiency score of 1.0000. However, the remaining 17 companies, which are AIRPORT, BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, MISC, MMCCORP, SEALINK, SEEHUP, SURIA, TAS, TASCO and TNLOGIS are inefficient because their efficiency scores are less than 1.0000. The results obtained from the existing DEA model shows that the first objective has been achieved.

The novelty of this study lies in the enhancement of the existing DEA model. This study proposes the incorporation of an operational risk factor to evaluate the efficiency of the listed logistics companies in Malaysia to fill the gap in current literature. Operational risk reduces the financial efficiency of the logistics companies, therefore the need to incorporate operational risk factor could improve the measurement of the financial efficiency of the logistics companies. Section 3.4 presents and explains this model that incorporates the operational risk factor into the DEA model. Thus, the second objective has been accomplished.

The enhanced DEA model, with the incorporation of operational risk factor, is applied to evaluate the efficiency of the listed logistics companies. This enhanced model identifies AIRPORT, COMPLET, GDEX, HUBLINE, ILB, MISC, MMCCORP, NATWIDE, POS, PDZ, PRKCORP, SEEHUP, SYSCORP, TNLOGIS and TOCEAN as the efficient companies with the efficiency score of 1.0000. These efficient listed logistics companies have performed well in their financial efficiency with operational risk management. On the other hand, inefficiency has been detected in BHIC, BIPORT, CJCEN, FREIGHT, GCAP, HARBOUR, LITRAK, MAYBULK, SEALINK, SURIA, TAS and TASCO. These inefficient logistics companies have scored the efficiency of less than 1.0000.

Meanwhile, the existing DEA model has a coefficient of variation of 18.65% while the enhanced DEA model has the coefficient of variation of

7.61%. Having lower coefficient of variation, the enhanced DEA model outperforms the existing DEA model. These results based on the enhanced DEA model reflects the attainment of the third objective.

DEA allows for benchmarking to compute the potential improvements for the inefficient listed logistics companies. The potential improvements, which involve reducing the inputs or increasing the outputs, could lead the inefficient logistics companies to improve their efficiency. Inefficient companies would be assigned with a reference set consisting of the efficient companies with the optimal coefficients respectively to be used to calculate the potential improvements. Therefore, the last objective has also been fulfilled.

6.3 Research Contributions

This study allows a comprehensive understanding on the efficiency of the listed logistics companies in Malaysia. Inefficiency could be an early detection of financial deterioration to the companies. Understanding the efficiency of the listed logistics companies could also serve as a preventive measure for future degradation of the company. The main contribution of this study is to evaluate the efficiency of the listed logistics companies by proposing an enhanced DEA model. This study has also acknowledged the importance of managing operational risk in the logistics companies and has incorporated operational risk factor in the assessment of the financial efficiency.

The enhanced DEA model has also been successful to differentiate the efficient listed logistics companies from the inefficient logistics companies by maximizing the relative efficiency. The listed logistics companies with the efficiency score of 1.0000 are efficient while the listed logistics companies with efficiency score below 1.0000 are inefficient. The proposal of the development of the enhanced DEA model adds to the contribution of literature in dealing with efficiency. Moreover, this provides insights to the management and investors regarding the performance of the companies.

The strength of the enhanced DEA model lies in the ability to provide benchmarking. The efficient listed logistics companies act as benchmarks for the inefficient listed logistics companies. With the optimal coefficients of the respective benchmarks in the reference set as provided by the optimal solution of the DEA model, the inefficient listed logistics companies can move towards achieving the feasible targets.

The results of the enhanced DEA model stimulate the intention to change and improve for the betterment of the companies and the economy of Malaysia. The enhanced DEA model identifies sources of inefficiency for potential improvements. The inefficient listed logistics companies can take actions to rectify the weaknesses in their financial efficiency and operational risk management. The inefficient listed logistics companies can reduce the usage of inputs or increase the generation of outputs for higher efficiency.

The novel contribution of this study also includes the evaluation of the listed logistics companies with the enhanced DEA model which includes operational risk factor. This is a pioneer study in assessing the long-term efficiency of the listed logistics companies in Malaysia with factual financial data for a comprehensive and reliable understanding on the development of the logistics industry in Malaysia.

6.4 Research Limitations

This study has some limitations. Firstly, it is applicable to the listed logistics companies because these listed logistics companies provide financial data for transparency and analysis in this study. Secondly, according to BCBS, BIA requires the 3-year average GI of a company multiplied by a specified percentage. Therefore, newly listed companies can be evaluated from the third year only.

6.5 Recommendations for Future Research

The logistics industry provides value added activities which increases the competitive power of the manufacturers and distributors. Since the logistics industry helps to drive the economy of the country, the logistics industry is evaluated for the financial efficiency with operational risk factor. However, other industries such as the digital and technology sector, healthcare industry, financial services industry and energy sectors could also examine their efficiency based on the enhanced DEA model so that they can review their operations to increase their strengths in this competitive business environment.

The enhanced DEA model can also be applied to other countries to measure the efficiency of the companies. Financial efficiency is also important to the companies in other countries because strong financial positions could help the companies to sustain, grow and expand for better performance. Therefore, the enhanced DEA model, with the incorporation of operational risk factor, can also evaluate the efficiency of companies in other countries.

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LIST OF PUBLICATIONS

Journals

1. Lee, P. F., Lam, W. S. and Lam, W. H. Performance evaluation of the efficiency of logistics companies with Data Envelopment Analysis model. *Mathematics*, 11(3), pp. 1-15. (Web of Science SCIE Q1 / Scopus Q1)

2. Lee, P. F., Lam, W. S. and Lam, W. H., 2021. Evaluation and improvement of the efficiency of logistics companies with Data Envelopment Analysis model. *Engineering Journal*, 25(6), pp. 45-54. (Web of Science ESCI / Scopus Q3)

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3. Lee, P. F., Lam, W. S. and Lam, W. H., 2022. Optimizing the Financial Efficiency of Logistics Companies with Data Envelopment Analysis Model. *Proceedings of the 8th International Conference on Computational Science and Technology*, 28-29 August 2021, Labuan, Malaysia. Lecture Notes in Electrical Engineering 835, pp. 1-12. (Web of Science / Scopus)

4. Lee, P. F., Lam, W. S. and Lam, W. H. (Accepted). Analysis on the

Efficiency of Logistics Companies in Malaysia using Data Envelopment Analysis Model. *8th International Conference on Mechanical, Manufacturing, and Plant Engineering (ICMMPE 2022)*, 24 November 2022, Kuala Lumpur, Malaysia. Advances in Material Science and Engineering, Lecture Notes in Mechanical Engineering. (Web of Science / Scopus)

LIST OF AWARDS

Best Paper Presentation

1. Analysis on the Efficiency of Logistics Companies in Malaysia using Data Envelopment Analysis Model. The 8th International Conference on Mechanical, Manufacturing, and Plant Engineering (ICMMPE 2022), Berjaya Times Square Hotel, Kuala Lumpur, Malaysia, 24 November 2022.

APPENDICES

APPENDIX A

FINANCIAL DATA OF THE LISTED LOGISTICS COMPANIES

COMPANY	CTR	DAR	DER	EPS	ROA	ROE
AIRPORT	1.7832	0.5651	1.3526	0.2197	0.0225	0.0517
BHIC	0.9947	0.5779	1.8922	0.0690	0.0192	0.0414
BIPORT	3.2174	0.5415	1.2977	0.3648	0.0689	0.1501
CJCEN	1.8669	0.3959	0.6771	0.1121	0.0456	0.0739
COMPLET	2.8935	0.2590	0.3568	0.0857	0.0606	0.0791
FREIGHT	2.1968	0.3794	0.6125	0.1018	0.0633	0.1023
GCAP	13.9511	5.2244	0.5446	0.0362	1.1417	0.0650
GDEX	6.3880	0.3179	0.3849	0.0157	5.7194	7.3153
HARBOUR	1.9375	0.3852	0.6587	0.1041	0.0550	0.0907
HUBLINE	0.7842	0.5030	1.7126	0.0013	0.0088	0.0160
ILB	4.9151	0.2555	0.3575	0.1079	0.0454	0.0562
LITRAK	3.0011	0.6972	2.9152	0.3192	0.0753	0.2539
MAYBULK	2.3389	0.3433	0.7257	0.0771	0.0668	0.1121
MISC	1.3925	0.3443	0.5575	0.3483	0.0329	0.0493
MMCCORP	1.2849	0.6481	2.0432	0.1616	0.0167	0.0461
NATWIDE	3.3349	0.3911	0.3367	0.0059	0.0046	0.3812
POS	1.3051	0.4601	0.9685	0.1416	12.8936	21.4690
PDZ	3.1735	0.2467	0.3537	0.0011	0.0065	0.0086
PRKCORP	2.4758	0.5062	1.0867	5.5148	1.0030	2.8171
SEALINK	1.0091	0.4391	0.8154	0.0122	0.0067	0.0136
SEEHUP	1.4082	0.4141	0.7605	0.0517	0.0224	0.0428
SURIA	2.8923	0.2793	0.4018	0.1925	0.0439	0.0620
SYSCORP	1.0297	0.3967	0.6856	0.0323	0.0135	0.0214
TAS	2.1528	0.5080	1.5783	0.0405	0.0266	0.0450
TASCO	1.6644	0.4191	0.8357	0.1886	0.0597	0.1032
TNLOGIS	1.1303	0.5834	1.4325	0.1087	0.0302	0.0708
TOCEAN	1.3798	0.3061	0.4819	0.0095	0.0076	0.0116

APPENDIX B

COMPANY'S OPERATIONAL RISK FACTOR AND WEIGHTED AVERAGE COST OF CAPITAL

COMPANY	C_{BIA}	WACC
AIRPORT	0.5212	0.0781
BHIC	0.0545	0.0733
BIPORT	0.1102	0.0602
CJCEN	0.0116	0.0772
COMPLET	0.0032	0.0834
FREIGHT	0.0160	0.0731
GCAP	0.0049	0.0775
GDEX	0.0298	0.0999
HARBOUR	0.0122	0.0657
HUBLINE	0.0041	0.0828
ILB	0.0021	0.0703
LITRAK	0.0608	0.0603
MAYBULK	0.0425	0.0997
MISC	0.3769	0.0789
MMCCORP	0.3253	0.0605
NATWIDE	0.0027	0.0833
POS	0.1406	0.0949
PDZ	0.0014	0.1348
PRKCORP	0.0136	0.0628
SEALINK	0.0034	0.0719
SEEHUP	0.0149	0.0598
SURIA	0.0159	0.0848
SYSCORP	0.0087	0.0663
TAS	0.0018	0.1028
TASCO	0.0160	0.0734
TNLOGIS	0.0144	0.0516
TOCEAN	0.0041	0.0777