INTEGRATED EFFICIENCY AND PRODUCTIVITY ANALYSIS OF CONTAINER TERMINALS: A COMPREHENSIVE FRAMEWORK USING DEA, SBM, MPI, AND PREDICTIVE MODELING

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ABSTRACT

Container terminals are critical nodes in the global supply chain, connecting maritime and inland transport systems. This study evaluates the efficiency and productivity of eight Malaysian container terminals over a 15-year period (2003–2018) using an integrated framework of Data Envelopment Analysis (DEA), Slack-Based Model (SBM), Malmquist Productivity Index (MPI), and Machine Learning (ML) techniques. It benchmarks performance, diagnoses inefficiencies, tracks productivity trends, and predicts future efficiency. DEA and SBM reveal disparities, with high-performing terminals near the efficiency frontier and underperformers showing resource slack and throughput shortfalls. MPI highlights the role of innovation in driving long-term competitiveness, while predictive modeling using ML provides actionable insights for proactive planning. This study bridges traditional efficiency analysis with modern predictive tools, offering recommendations to optimize terminal operations and sustain competitiveness.

Keywords: efficiency; productivity; container terminal; Malaysia; optimization
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1.0 INTRODUCTION

Container terminals serve as vital nodes in the global supply chain, facilitating the seamless transfer of goods between maritime and inland transport networks (Zaghdoud et al., 2012; Wilmsmeier et al., 2013). With over 80% of global trade conducted via maritime shipping, the performance of container terminals is critical to the cost-efficiency, timeliness, and reliability of international trade (UNCTAD, 2021). As globalization and e-commerce continue to fuel increasing shipping volumes (Lee & Cullinane, 2016), terminals face growing demands to accommodate larger vessels process higher throughput, and meet stringent operational deadlines (Li et al., 2017; Song et al., 2020).

Historically, terminal performance improvements have been driven by infrastructure expansion and manual optimization (Rashidi & Tsang, 2013;Zhang et al., 2013). However, the complexity of modern terminal operations

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necessitates more sophisticated analytical tools to evaluate and enhance performance (Castilla-Rodríguez et al., 2020; Sharma & Yu, 2010). Efficient resource utilization, such as optimal crane operations, berth allocation, and yard stacking, can significantly reduce turnaround times and operational costs (Elwany et al., 2013; Yıldırım et al., 2020). In contrast, inefficiencies lead to delays, congestion, and financial losses, threatening competitiveness in the global market (Notteboom & Rodrigue, 2005).

Despite substantial investments in terminal infrastructure, significant disparities persist between high-performing and underperforming terminals (Raghuram et al., 2017). While some terminals set global benchmarks for efficiency, others struggle with underutilized resources, technological gaps, and outdated processes (Sharma & Yu, 2009; Sharma & Yu, 2010). The challenge lies in accurately diagnosing inefficiencies, benchmarking performance, and adopting targeted solutions to address operational bottlenecks (Li et al., 2020; Witte et al., 2012). Traditional evaluation tools such as Data Envelopment Analysis (DEA) and Slack-Based Model (SBM) have been widely applied in port studies, offering critical insights into relative efficiency and resource wastage (Mokhtar et al., 2016; Tone & Tsutsui, 2014).

DEA is a popular technique for measuring the relative efficiency of decision-making units (DMUs) by comparing their inputs (e.g., berth length, crane efficiency) and outputs (e.g., container throughput). It identifies top-performing terminals and highlights inefficiencies among others (Banker et al., 1984). However, while DEA provides an overall efficiency score, it does not quantify the specific input or output slack contributing to inefficiencies (Cooper et al., 2006). SBM addresses this limitation by explicitly measuring input excesses and output shortfalls, offering a more granular perspective on resource utilization (Tone, 2001). By leveraging SBM, terminal operators can pinpoint areas for improvement, such as reducing idle resources or optimizing cargo handling (Tone & Tsutsui, 2009).

Efficiency analysis often requires consideration of changes over time, which is where the Malmquist Productivity Index (MPI) proves valuable (Caves et al., 1982; Odeck & Schøyen, 2020). The MPI decomposes productivity changes into operational efficiency improvements and technological advancements, providing a dynamic perspective on terminal performance (Färe et al., 1994; Simar & Wilson, 1999). However, traditional DEA and MPI analyses are retrospective, focusing on historical performance and lacking predictive capabilities (Emrouznejad & Yang, 2018).

With the increasing availability of operational data, Machine Learning (ML) has emerged as a promising approach for forecasting terminal performance (Li et al., 2019). Techniques such as the Random Forest Regressor can leverage historical data to uncover complex nonlinear relationships between inputs and outputs, providing actionable predictions for future efficiency trends (Friedman, 2001; Zhang et al., 2018). Predictive modeling complements traditional benchmarking methods, enabling terminal operators to proactively address inefficiencies and plan for future demands (Sharma et al., 2020).

Table 1. Comparison Table for Analysis

Tool	Best For	Focus	Limitations
DEA	Benchmarking DMUs	Cross-sectional efficiency	No temporal or slack analysis
SBM	Identifying specific inefficiencies	Input-output slacks	Data-intensive
Malmquist Index	Analyzing productivity changes over time	Temporal trends	Requires panel data
Machine Learning	Predicting and modeling efficiency in complex scenarios	Dynamic prediction	Black-box; requires large datasets

Table 1 outlines the strengths and limitations of four key tools namely the DEA, SBM, MPI, and ML used for evaluating and enhancing efficiency and productivity. Each tool serves distinct purposes, making them suitable for specific types of analysis. DEA is ideal for benchmarking DMUs by assessing their cross-sectional efficiency. However, it does not account for temporal changes or slack analysis, which limits its utility for more detailed performance evaluations (Cooper et al., 2006). SBM extends DEA by identifying specific inefficiencies, focusing on input-output slack such as excess resource utilization or output shortfalls. Despite its granular insights, SBM is data-intensive, requiring high-quality input and output data for accurate results (Tone, 2001).

The MPI excels in analyzing productivity changes over time by capturing temporal trends and distinguishing between operational efficiency and technological advancements (Färe et al., 1994). However, it requires panel data, which may not always be available or complete for all DMUs. Lastly, ML is a powerful tool for predicting and modeling efficiency in complex scenarios (Chen et al., 2019). It is particularly useful for dynamic predictions and integrating external variables like trade volumes or weather conditions.

In the context of terminal efficiency and productivity, a combined approach is recommended. DEA or SBM should be used for benchmarking performance and identifying inefficiencies, providing a foundational understanding of resource utilization and output shortfalls. The Malmquist Index can then be applied to track productivity changes over time, capturing the impact of technological advancements and operational improvements. If forecasting future trends or examining the effects of external factors like trade volumes is critical, ML can complement these methods by providing predictive insights. This integrated approach ensures a comprehensive analysis of terminal performance, addressing both current inefficiencies and future opportunities for improvement. This study, hence, integrates DEA, SBM, MPI, and predictive modeling into a unified framework to comprehensively evaluate and forecast the efficiency of container terminals.

In Malaysia, container terminals serve as crucial enablers of international trade and national logistics development, particularly given the country's strategic location along the Strait of Malacca, one of the world's busiest shipping lanes. Despite substantial investments through port privatization and modernization such as Westports, Northport, Port of Tanjung Pelepas, wide performance disparities persist across terminals, ranging from technologically advanced hubs to underperforming mid-tier facilities. Past studies have often focused on global or regional analyses, overlooking the operational heterogeneity and institutional challenges unique to Malaysian ports, such as fluctuating trade volumes, public-private ownership structures, and varied adoption levels of automation and digitalization (Mokhtar et al., 2013; Mokhtar & Shah, 2013a; 2013b; Mokhtar et al., 2016).

Following that, this study aims to fill in the gap by providing a systematic, data-driven evaluation of eight major Malaysian container terminals over a 15-year period, using an integrated framework of DEA, SBM, MPI, and machine learning. First, benchmark efficiency is assessed using Data Envelopment Analysis (DEA) to evaluate the relative performance of terminals, establish efficiency benchmarks, and identify underperforming terminals. The Slack-Based Measure (SBM) extends this analysis by quantifying input slack and output shortfalls, providing a detailed understanding of resource inefficiencies. Second, to track temporal productivity, the Malmquist Productivity Index (MPI) is applied to measure productivity changes over time. This approach decomposes improvements into operational efficiency gains and technological advancements, offering insights into whether productivity gains stem from better resource utilization or innovations in infrastructure and processes. Third, inefficiencies are analyzed by leveraging SBM to identify specific operational shortcomings, such as underutilized berth capacity or crane productivity shortfalls, and deliver actionable recommendations for improvement. Finally, to predict future trends, a Random Forest Regressor is employed to forecast DEA efficiency scores by incorporating historical data and external factors. This predictive modeling supports long-term operational planning and enables data-driven decision-making to anticipate and mitigate future inefficiencies.

This paper is organized into the following sections: Section 2 delves into the Literature Review, providing a comprehensive foundation for the study. Section 3 outlines the Methodology employed in this research. Section 4 presents the Results and Discussion, offering an in-depth analysis of the findings. Finally, Section 5 concludes the study by summarizing key insights and offering practical recommendations.

2.0 REVIEW OF ANALYTICAL APPROACHES

Efficiency and productivity in container terminals are crucial for global trade, driving significant academic interest. This review explores key methodologies namely DEA, SBM, MPI, and ML by highlighting their strengths, limitations, and the value of integrated frameworks to bridge existing gaps.

2.1 Data Envelopment Analysis (DEA)

DEA evaluates the relative efficiency of DMUs using inputs (e.g., berth length, crane productivity) and outputs (e.g., throughput) to establish an efficiency frontier (Charnes et al., 1978). It remains a widely utilized method for benchmarking the relative efficiency of DMUs in container terminals. Recent advancements have enhanced DEA's capabilities, particularly in dynamic and real-time scenarios (Ray, 2004). For example, hybrid models combining DEA with predictive analytics have been developed to classify and predict DMU efficiency based on historical performance data (Chen et al., 2019; Cullinane et al., 2006). Additionally, the incorporation of real-time data streams into DEA frameworks has enabled more responsive benchmarking, allowing for immediate adjustments to operational strategies. Studies such as Wu et al. (2021) highlight the potential of integrating DEA with dynamic analytics to anticipate efficiency trends and improve resource allocation. Nonetheless, while widely applied (Cullinane et al., 2005; Barros, 2003), DEA is limited by its assumption of proportional input-output changes and inability to diagnose specific inefficiencies, necessitating complementary methods like SBM (Jahanshahloo et al., 2005; Zhu, 2014).

2.2 Slack-Based Model (SBM)

SBM extends DEA by measuring slack in inputs and outputs, pinpointing inefficiencies such as underutilized yard space (Tone, 2001). Recent advancements have focused on addressing dynamic inefficiencies in real time. For instance, advanced models have been used to identify patterns in resource utilization, enabling the proactive reduction of input slacks (Zhang et al., 2024). Furthermore, the application of dynamic modeling to SBM has enhanced its capability to recommend real-time adjustments in terminal operations, such as berth and crane scheduling. Castilla-Rodríguez et al. (2020), on the other hand, demonstrated how combining SBM with IoT-enabled real-time data can optimize terminal operations by minimizing excess resource utilization and maximizing throughput efficiency, while studies by Song and Cullinane (2007); and Wu and Goh (2010) reveal SBM's diagnostic value in operational contexts but acknowledge its data-intensive nature and sensitivity to outliers (Cook et al., 2014).

2.3 Malmquist Productivity Index (MPI)

MPI analyzes productivity changes by decomposing trends into Efficiency Change (EC) and Technological Change (TC) (Caves et al., 1982; Färe et al., 1994). While valuable for tracking temporal dynamics, its reliance on panel data and inability to incorporate external factors, such as economic shifts, limit broader applicability (Balk, 2001; Coelli et al., 2005). Recent advancements have expanded MPI's utility by incorporating predictive capabilities and dynamic analyses. For instance, advanced techniques have been applied to model temporal changes in productivity, enabling forecasts of EC and TC trends (Fan & Guo, 2018; Grifell-Tatjé & Lovell, 1995). Additionally, the integration of MPI with digital twin technologies and advanced analytics has enabled terminals to simulate various scenarios, identifying potential bottlenecks and the impact of technological innovations on productivity. Studies like Heilig and Voß (2017) emphasize the importance of combining MPI with real-time data analytics to dynamically adjust operational strategies and sustain competitiveness in rapidly evolving maritime environments.

2.4 Machine Learning (ML)

Apart from previous analytical approaches, recent advancements in Machine Learning (ML) have significantly transformed port and terminal management, particularly in addressing dynamic and real-time scenarios. ML techniques have become instrumental in enhancing operational efficiency, predicting port throughput, optimizing resource allocation, and enabling proactive decision-making.

2.4.1 Predictive Modeling and Throughput Forecasting

Predictive modeling has been a prominent application of ML in port management, especially for forecasting container throughput (Cheon, 2010). Techniques such as Random Forest, Gradient Boosting, and Neural Networks have demonstrated their ability to accurately predict throughput by analyzing historical data and external variables, including trade volumes, weather conditions, and economic indicators (Li et al., 2019; Wang et al., 2020). For instance, Yu et al. (2020) integrated ML algorithms with traditional econometric models to enhance the accuracy of throughput predictions, providing real-time insights that enable terminal operators to anticipate demand fluctuations and adjust operations accordingly.

2.5 Integrated Frameworks

Integrating DEA, SBM, MPI, and ML combines their strengths: DEA and SBM benchmark performance, MPI tracks temporal trends, and ML forecasts future efficiency. This approach enables multidimensional analysis, actionable insights, and proactive planning (Chen et al., 2019; Wu et al., 2021). By addressing individual limitations, such as DEA's static focus or ML's interpretability challenges, integrated frameworks provide a robust toolkit for diagnosing inefficiencies, optimizing resources, and preparing for dynamic operational demands. This study contributes to the field by integrating DEA, SBM, MPI, and machine learning into a framework that provides a multidimensional analysis of efficiency and productivity. The inclusion of predictive modeling enhances forward-looking capabilities, enabling data-driven decision-making and resource optimization. By offering tailored insights for Malaysian ports, the study addresses geographical gaps and provides actionable recommendations to improve competitiveness and sustainability in maritime logistics.

3.0 METHODOLOGY

This study adopts an integrated methodology to evaluate and forecast the efficiency of container terminals using DEA, SBM, MPI, and ML. The following sections describe the data collection, the mathematical formulation of each analytical method, and the integration of these tools.

3.1 Data Collection and Preparation

The dataset used in this study comprises operational and performance metrics from 8 container terminals over a 15-year period (2003 to 2018). Operational data were retrieved directly from the terminals involved in the study. The selected timeframe coincides with significant operational transformations in the maritime industry:

- **2003–2008**: Characterized by growth in trade volumes, increased competition among ports, and the early adoption of digital solutions in terminal operations (Notteboom & Rodrigue, 2005; Davis, 2007; UNCTAD, 2007).
- **2008–2012**: Reflects the industry's response to the global financial crisis, including cost-cutting measures, consolidation among shipping lines, and slower investment in infrastructure (Wilmsmeier et al., 2013).
- **2013–2018**: Represents a recovery period marked by renewed investments in automation, digitalization, and sustainability initiatives, as well as the growing impact of e-commerce on global trade flows (Heilig & Voß, 2017).

This segmentation allows for the analysis of how terminals adapted to distinct phases of industry transformation.

The following Tables (Table 2 and 3) summarize the list of DMUs (container terminals of ports in Malaysia), inputs, as well as outputs. To ensure comparability, all input (x_i) and output variables (y_r) were normalized using Min-Max scaling.

$$x' = \frac{x - x_{min}}{x_{max} - x_{min}} \tag{1}$$

where x is the original value, x_{min} and x_{max} are the minimum and maximum values of the variable, respectively. The resulting normalized data enabled unbiased efficiency comparisons across terminals. Additionally, missing or inconsistent data were addressed through interpolation and cross-referencing with industry reports to ensure a robust and reliable dataset.

Table 2. List of DMUs

List of DMUs	i.	AW
	ii.	BN
	iii.	CP
	iv.	DJ
	v.	EPP
	vi.	FK
	vii.	GB
	viii.	IS

In general, there are seven main federal ports in Peninsular Malaysia administered by the Federal Government through their respective port authorities under the Ministry of Transport. These include Penang Port, Port Klang, Johor Port, Kuantan Port, Kemaman Port, the Port of Tanjung Pelepas, and Bintulu Port. As shown in Table 2, the analysis includes eight container terminals, comprising seven federal ports and one state-administered port. However, for confidentiality reasons, the specific port abbreviations used in the analysis cannot be disclosed.

Table 3. List of Inputs and Outputs

List of Inputs	a)	Total terminal area in m^2
	b)	Maximum draft in meter
	c)	Berth length in meter
	d)	Quay crane Index
	e)	Yard stacking index
	f)	Number of gate lanes
	g)	Ground slots (TGS)
	h)	Average QC moves per hour
	i)	Average stacking height of yard equipment
	j)	Average dwell time in yard
List of Outputs	Terminal throughput	

3.2 Benchmarking with DEA and SBM

DEA was used to establish an efficiency frontier by comparing the input-output combinations across DMUs of each terminal (k) (Charnes et al., 1978). The DEA model employed a variable return to scale (VRS) assumption to reflect the operational realities of terminals of different sizes and capacities (Banker et al., 1984). Efficiency scores were calculated for each terminal, with scores closer to 1 indicating high relative efficiency and lower scores reflecting inefficiency.

$\max_{\theta,\lambda} \theta$ subject to;

$$\sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ik}, \qquad i = 1,2,\ldots..m \qquad (2)$$

$$\sum_{j=1}^{n} \lambda_j y_{rj} \leq y_{rk}, \qquad r = 1,2,\ldots..m \qquad (3)$$

$$\sum_{j=1}^{n} \lambda_j = 1, \qquad \lambda_j \geq 0 \qquad (4)$$

where λ_j are weights assigned to DMUs, θ represents the efficiency score, and x_{ij} and y_{rj} are the inputs and outputs, respectively.

Building on the DEA results, the SBM was applied to diagnose inefficiencies more granularly. SBM explicitly measured input slack (e.g., underutilized berth space) and output shortfalls (e.g., low throughput), providing actionable insights for resource optimization (Cullinane et al., 2005; Lozano & Villa, 2004). The integration of DEA and SBM allowed for the identification of efficient terminals and the pinpointing of specific operational inefficiencies in underperforming terminals (Cooper et al., 2011; Lin & Tseng, 2007).

3.2.1 Slack-Based Model (SBM)

SBM extends DEA by explicitly incorporating slack in inputs and outputs. The SBM efficiency score (ρ) is given by:

$$\rho = \frac{1-\frac{1}{m}\sum_{i=1}^{m} s_i^- / x_{ik}}{1+\frac{1}{s}\sum_{r=1}^{s} s_r^+ / y_{rk}} \tag{5}$$

where:

- s_i^- is the slack in input i,
- s_r^+ is the slack in output r,
- m and s are the total number of inputs and outputs, respectively.

This formulation highlights inefficiencies by measuring input excess and output shortfalls, providing granular insights into operational bottlenecks.

3.3 Temporal Analysis with MPI

To track changes in terminal productivity over time, the MPI was employed. MPI decomposes productivity into two components (Balk, 2001; Kumar & Gulati, 2008):

i. Efficiency Change (EC): Reflecting improvements in operational performance.
ii. Technological Change (TC): Capturing the effects of innovations and infrastructure upgrades.

MPI is calculated as:

$$MPI = \sqrt{\frac{D_t^t(x_{t+1,}y_{t+1})D_{t+1}^{t+1}(x_{t+1,}y_{t+1})}{D_t^t(x_{t,}y_t)D_{t+1}^{t+1}(x_{t,}y_t)}} \tag{6}$$

where:

- $D_t^t(x_{t,}y_t)$ is the efficiency of the DMU at time t using technology available at t,
- $D_{t+1}^{t+1}(x_{t+1,}y_{t+1})$ represents efficiency at time $t+1$ using the technology available at $t+1$.

The index is decomposed as:

$$MPI = EC \times TC \tag{7}$$

where:

$$EC = \frac{D_t^t(x_{t+1,}y_{t+1})}{D_t^t(x_{t,}y_t)}, \qquad TC = \sqrt{\frac{D_{t+1}^{t+1}(x_{t+1,}y_{t+1})}{D_t^t(x_{t+1,}y_{t+1})}} \tag{8}$$

MPI scores were calculated for each terminal and year, highlighting trends in productivity and identifying periods of significant operational or technological advancements (Wu & Ma, 2015). By combining MPI with SBM results, this study explored whether improvements in productivity were driven by better resource utilization or the adoption of new technologies.

The analysis for DEA, SBM and MPI are conducted using MaxDEA software. Its flexibility in modeling multiple decision-making units (DMUs) and decomposing productivity changes into efficiency and technological components makes it suitable for longitudinal performance assessment of container terminals.

3.4 Forecasting with Machine Learning

To complement the retrospective analyses provided by DEA, SBM, and MPI, this study employed ML to predict future terminal efficiency. A Random Forest Regressor was selected due to its robustness and ability to handle nonlinear relationships between inputs and outputs (Breiman, 2001). The Random Forest model was chosen for this study due to its reliability, simplicity, and ability to handle structured data commonly used in terminal operations. Compared to models like XGBoost or Gradient Boosting, Random Forest offers a built-in feature for identifying key operational drivers of terminal efficiency and is less dependent on complex hyperparameter tuning, making it easier to implement without the risk of over-optimization. Even though XGBoost and Gradient Boosting are effective for complex relationships, they are more prone to overfitting on small or imbalanced datasets, making them less suitable for generalizable insights across diverse terminals.

Due to this, Random Forest's method of averaging predictions from multiple decision trees reduces overfitting risks and ensures stable performance, even with noisy data. The model in this study is trained on historical DEA efficiency scores, using operational inputs and external factors (for example, trade volumes, weather conditions) as features (Peng et al., 2018). The training process minimizes the mean squared error (MSE):

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (9)$$

where:

- y_i are the actual DEA scores
- $\hat{y}_i$ are the predicted scores
- n is the number of observations

The model's predictive performance was then validated using metrics such as R^2 and Mean Absolute Error (MAE) on a separate test set. The integration of ML into the methodology enabled the forecasting of DEA efficiency scores for each terminal, providing actionable insights for long-term operational planning (Wu & Zhuang (2019). Furthermore, feature importance analysis from the Random Forest model identified the key variables influencing terminal efficiency, offering additional guidance for resource allocation and infrastructure development. The ML analyses were conducted using MATLAB for model training, validation, and interpretability.

3.5 Integration of Methodology

The combined application of DEA, SBM, MPI, and ML provided a comprehensive framework for evaluating and improving terminal performance. DEA and SBM established benchmarks and diagnosed inefficiencies, MPI tracked productivity trends over time, and ML forecasted future efficiency levels. This integrated approach ensured that the study addressed both current inefficiencies and future planning needs.

By leveraging the strengths of these tools, the methodology not only identified underperforming terminals but also offered tailored recommendations for improvement. For example, terminals with high input slack identified by SBM were further analyzed using MPI to determine whether their inefficiencies were improving or persisting over time. ML predictions for these terminals then guided proactive planning efforts, such as infrastructure investments or process optimizations.

4.0 RESULTS AND DISCUSSION

The analysis of container terminals using DEA, SBM, MPI, and predictive modeling reveals significant disparities in performance, offering a comprehensive understanding of operational strengths and inefficiencies. By evaluating current efficiency, diagnosing inefficiencies, assessing temporal productivity trends, and forecasting future performance, this study highlights critical opportunities and challenges for optimizing terminal operations.

4.1 Efficiency Benchmarking with DEA

The DEA demonstrates that certain terminals, such as AW, CP, EPP and BN, consistently operate near the efficiency frontier, reflecting their ability to allocate resources effectively and maintain high throughput (Table 4). These terminals exhibit efficiency scores exceeding 0.90 across most years, underscoring their operational stability. In contrast, terminals such as IS and DJ persistently show DEA lower scores, indicating systemic inefficiencies and misalignment between resource capacity and throughput demands. These findings emphasize the critical need for targeted interventions in underperforming terminals. For example, IS's inefficiencies may stem from limited infrastructure investments or outdated operational processes, echoing challenges faced by mid-tier ports such as Mombasa, where inefficiencies arise from inadequate equipment and congested yard spaces (Hope & Willis, 2004; Notteboom & Rodrigue, 2009). The disparities in DEA scores also highlight the competitive edge of high-performing terminals, which leverage advanced technologies to sustain their efficiency.

Table 4. The DEA, SBM and ML Results

Container Terminal	DEA Efficiency	SBM Efficiency	Predicted DEA Efficiency (ML)
AW03	1	-3.86744	0.999297
BN03	0.919496	0.890855	0.920644
CP03	1	0.90585	1
DJ03	0.897684	0.954399	0.897737
EPP03	1	1	1
FK03	0.907959	-2.22134	0.908741
GB03	1	1	1
IS03	0	0	0
AW04	0.755525	0.865509	0.757408
BN04	0.942904	0.97128	0.943406
CP04	1	-0.84522	0.992763
DJ04	0.96374	0.991957	0.961126
EPP04	1	0.999996	1
FK04	1	0.999977	0.999956
GB04	0.986301	-4.54	0.986507
IS04	0	0	0
AW05	0.883083	0.999256	0.884663
BN05	1	0.954448	1
CP05	1	0.900638	1
DJ05	1	0.999894	0.996249
EPP05	1	1	1
FK05	1	0.980425	1
GB05	0.510051	-3.877	0.511182
IS05	0	0	0
AW06	0.91711	0.925836	0.917703
BN06	0.993279	0.910653	0.993525
CP06	1	0.915337	0.998492
DJ06	1	0.999997	0.9991
EPP06	0.991863	0.954123	0.992767
FK06	1	0.999983	0.999904
GB06	0.688238	-4.15	0.688236
IS06	0	0	0
AW07	1	0.285725	0.993559
BN07	1	0.922018	0.999673
CP07	1	0.968495	0.999449
DJ07	1	0.999994	0.996785
EPP07	1	0.898478	0.998904
FK07	1	0.999905	1
GB07	0.867776	-3.18	0.866632
IS07	0.68072	0.98845	0.682252
AW08	1	0.996331	0.984496
BN08	0.938736	0.759451	0.938358

CP08	1	0.904575	0.997531
DJ08	1	1	0.998152
EPP08	0.805093	0.909493	0.80656
FK08	0.995776	0.963796	0.996828
GB08	1	1	0.99935
IS08	0.821688	-12.824	0.822303
AW09	0.800066	0.947207	0.798761
BN09	0.879994	0.947603	0.882139
CP09	1	0.886427	0.999437
DJ09	0.903815	0.039138	0.904923
EPP09	0.809565	0.985731	0.809961
FK09	0.930828	0.9837	0.931623
GB09	1	-0.09155	0.999928
IS09	1	0.999998	1
AW10	1	0.999999	0.978692
BN10	1	-0.08426	0.997659
CP10	1	0.920208	0.999166
DJ10	0.937419	0.97704	0.937495
EPP10	0.901375	0.92411	0.900537
FK10	1	1	1
GB10	0.866039	-0.08687	0.866071
IS10	0.917548	0.999996	0.918053
AW11	0.865747	0.135491	0.877556
BN11	0.961462	0.951042	0.959964
CP11	0.887068	-6.864	0.891287
DJ11	0.997067	0.912562	0.996067
EPP11	0.836513	0.975523	0.836924
FK11	0.975717	0.669547	0.975654
GB11	1	1	1
IS11	1	0.999999	1
AW12	0.949902	0.903663	0.953233
BN12	0.929041	0.358736	0.929575
CP12	0.910312	-1.15877	0.911824
DJ12	0.961906	0.930668	0.961683
EPP12	0.811159	0.93977	0.812571
FK12	1	0.999756	0.999814
GB12	0.706445	0.369003	0.706969
IS12	1	0.997414	0.999856
AW13	0.943037	0.909751	0.946506
BN13	0.824309	0.843561	0.824361
CP13	0.900923	-0.091811	0.903529
DJ13	0.909029	0.93952	0.909974
EPP13	0.861245	0.896154	0.86068
FK13	0.929809	0.982918	0.929977

GB13	0.730802	0.942222	0.731457
IS13	1	0.993779	0.999817
AW14	0.983356	0.939843	0.979395
BN14	0.736698	0.78752	0.742269
CP14	1	0.999998	0.991066
DJ14	0.95163	0.908778	0.951634
EPP14	0.880728	0.988796	0.879394
FK14	0.964313	0.417616	0.964307
GB14	0.789321	0.956192	0.792191
IS14	1	1	0.998992
AW15	1	0.973908	0.988226
BN15	0.8109	0.804678	0.811796
CP15	1	0.977157	1.000537
DJ15	0.850184	0.753888	0.851358
EPP15	0.916661	0.967027	0.917304
FK15	0.958637	0.999998	0.958706
GB15	0.744738	0.759247	0.746566
IS15	0.910695	0.982338	0.910599
AW16	1	0.999999	0.985019
BN16	0.841959	0.841382	0.840899
CP16	0.937769	0.964921	0.938982
DJ16	0.878316	0.950513	0.878793
EPP16	1	0.8855	0.997298
FK16	0.963262	-0.93423	0.963306
GB16	0.794777	0.967652	0.794553
IS16	0.896153	0.979825	0.894801
AW17	0.907491	0.919118	0.910119
BN17	0.858614	0.842359	0.859413
CP17	0.921865	0.963386	0.922411
DJ17	0.956566	-6.17042	0.955106
EPP17	1	0.999983	0.999265
FK17	1	0.999995	0.999845
GB17	0.886665	0.982282	0.885732
IS17	0.885544	0.953816	0.885059
AW18	0.957667	0.934543	0.956594
BN18	0.801373	0.960368	0.805772
CP18	1	1	0.995354
DJ18	1	-2.65545	0.997756
EPP18	0.991172	0.995628	0.99123
FK18	1	-3.15057	1
GB18	1	1	0.998193
IS18	0.938227	0.999998	0.943895

4.2 Diagnosing Inefficiencies through SBM

The SBM further elucidates the granular aspects of inefficiency, identifying significant input slack and output shortfalls in underperforming terminals (Table 4). Slack variables, which measure the excess inputs or output deficits for inefficient DMUs, are typically non-negative in standard formulations, reflecting the extent of inefficiency. However, in this study, certain adjustments to the model's constraints result in slack variables exhibiting negative values. Terminals such as IS and DJ exhibit severe inefficiencies, with SBM scores reaching as low as -12. This reflects high levels of idle resources, such as unused berth capacity and crane underutilization. Conversely, terminals such as CP and AW show minimal slack, indicating optimized resource deployment and effective operational management. The SBM analysis reveals systemic misalignments in resource allocation in underperforming terminals, necessitating a strategic overhaul of processes. For instance, the Port of Rotterdam's success in minimizing slack through automated yard operations and dynamic crane scheduling, underscore the importance of operational innovation in addressing inefficiencies (Van der Lugt et al., 2017). The critical implication of SBM findings is the need for data-driven interventions tailored to specific inefficiencies, ensuring resource utilization aligns with operational objectives.

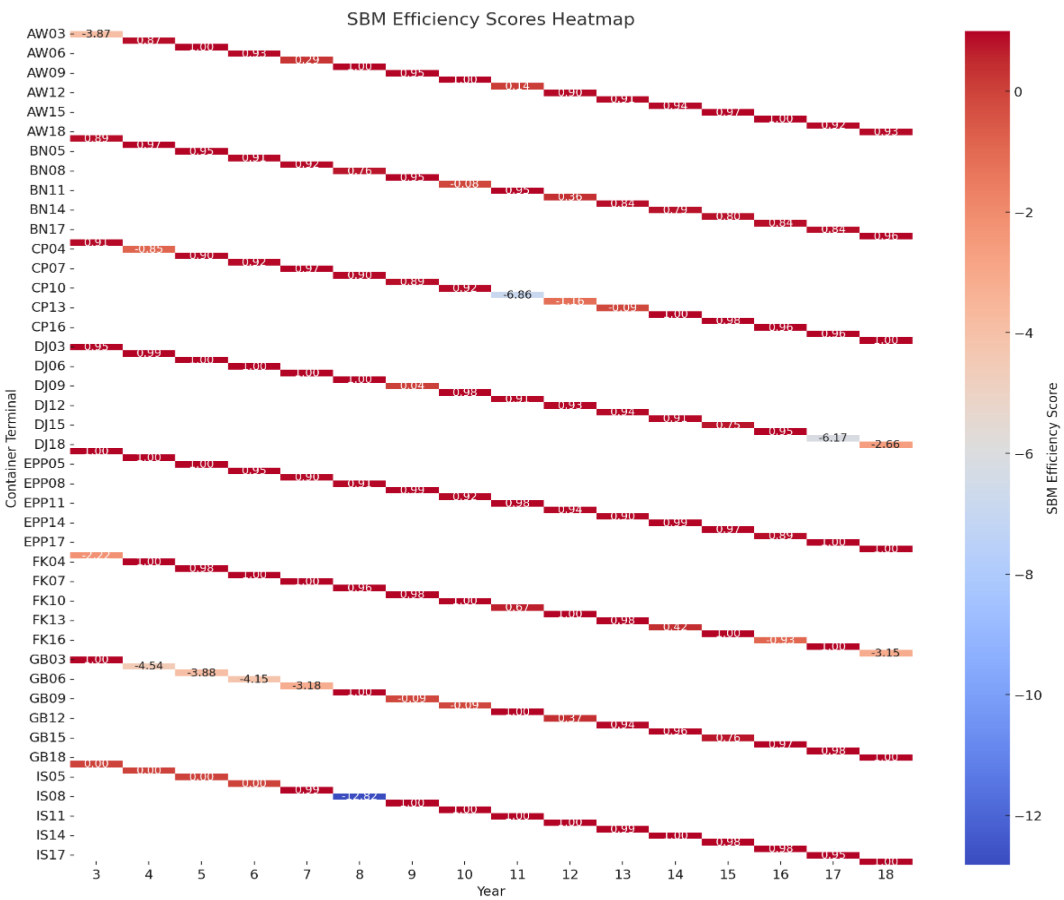

Figure 1. SBM Efficiencies Scores

Figure 1 visualizes SBM Efficiency Scores for container terminals from 2003–2018, highlighting inefficiencies through input slack (e.g., unused resources) and output shortfalls (e.g., insufficient throughput). The heatmap ranges from red (efficient) to blue (inefficient), clearly distinguishing high-performing and underperforming terminals.

High performers like AW, CP, and BN maintain stable red hues, reflecting strong operations, resource optimization, and advanced infrastructure. Conversely, DJ and IS consistently show dark blue shading, indicating inefficiencies such as outdated systems and poor resource allocation. Moderate performers, including GB, and EPP, exhibit lighter shades, signifying occasional inefficiencies from temporary disruptions or capacity constraints. Some terminals, like IS, show tremendous improvements over time, transitioning from severe inefficiency (-12) to less inefficiency (0.999) by the end of the period. However, persistent challenges underline the need for systemic reforms, including automation, process reengineering, and infrastructure upgrades.

The heatmap reveals performance clusters, enabling tailored strategies. High performers should sustain innovation and share best practices, while moderate performers could benefit from targeted optimizations like real-time analytics. Chronic underperformers require comprehensive reforms to close performance gaps and enhance competitiveness. This visualization underscores the importance of sustained investments, proactive monitoring, and data-driven strategies to improve efficiency and resilience in the maritime sector.

4.3 MPI Analysis

Moving on, the MPI provides insights into temporal productivity trends, decomposing performance into EC and TC (Table 5). Terminals such as CP and EPP demonstrate consistent MPI values exceeding 1.0, driven by operational improvements (EC > 1.0) and technological advancements (TC > 1.0). These trends reflect ongoing investments in infrastructure and innovation, enabling sustained productivity growth. The analysis of terminal performance highlights distinct patterns in efficiency and TC across facilities. High-performing terminals like CP and EPP consistently demonstrate above-average EC and TC, reflecting strong operational strategies and successful innovation. CP, with its high TC peak of 1.26, exemplifies the benefits of sustained investments in advanced systems, while EPP's significant technological advancements underscore the potential of innovative solutions to drive growth. These terminals can serve as benchmarks, emphasizing the importance of consistent technology adoption and scalable solutions to maintain competitiveness. Conversely, mid-performers such as AW and BN exhibit stability with near-average EC and TC values but need transformative strategies, such as automation and digital transformation, to push performance beyond current thresholds.

Underperforming terminals like DJ and IS face significant challenges, with below-average EC and TC values reflecting inefficiencies and technological stagnation. IS, in particular, struggles with inconsistency and a lack of modern practices, requiring targeted investments in advanced technologies like automated crane systems and predictive analytics to enhance performance. Terminals with moderate performance, such as FK and GB, show potential for growth through addressing operational bottlenecks and leveraging technology to stabilize performance and reduce variability.

The findings suggest that while operational efficiencies can temporarily sustain performance, long-term competitiveness requires consistent technological upgrades. The implications are particularly critical for terminals with declining TC trends, as they risk falling behind global standards without significant investments in automation and digital transformation.

Table 5. Summary of EC and TC Breakdown

Base Terminal	**Average EC**	**EC Variability**	**Minimum EC**	**Maximum EC**	**Average TC**	**TC Variability**	**Minimum TC**	**Maximum TC**
AW	0.970609	0.272859	0.212376	1.249896	0.970609	0.272859	0.212376	1.249896
BN	0.999127	0.072252	0.893716	1.152255	0.999127	0.072252	0.893716	1.152255
CP	1.028939	0.118776	0.783026	1.263702	1.028939	0.118776	0.783026	1.263702
DJ	0.92847	0.256332	0.092264	1.08909	0.92847	0.256332	0.092264	1.08909
EPP	1.075829	0.258023	0.696537	1.923465	1.075829	0.258023	0.696537	1.923465
FK	1.064278	0.226754	0.795091	1.832793	1.064278	0.226754	0.795091	1.832793
GB	1.067877	0.137163	0.855825	1.349351	1.067877	0.137163	0.855825	1.349351
IS			0.910689	inf			0.910689	inf

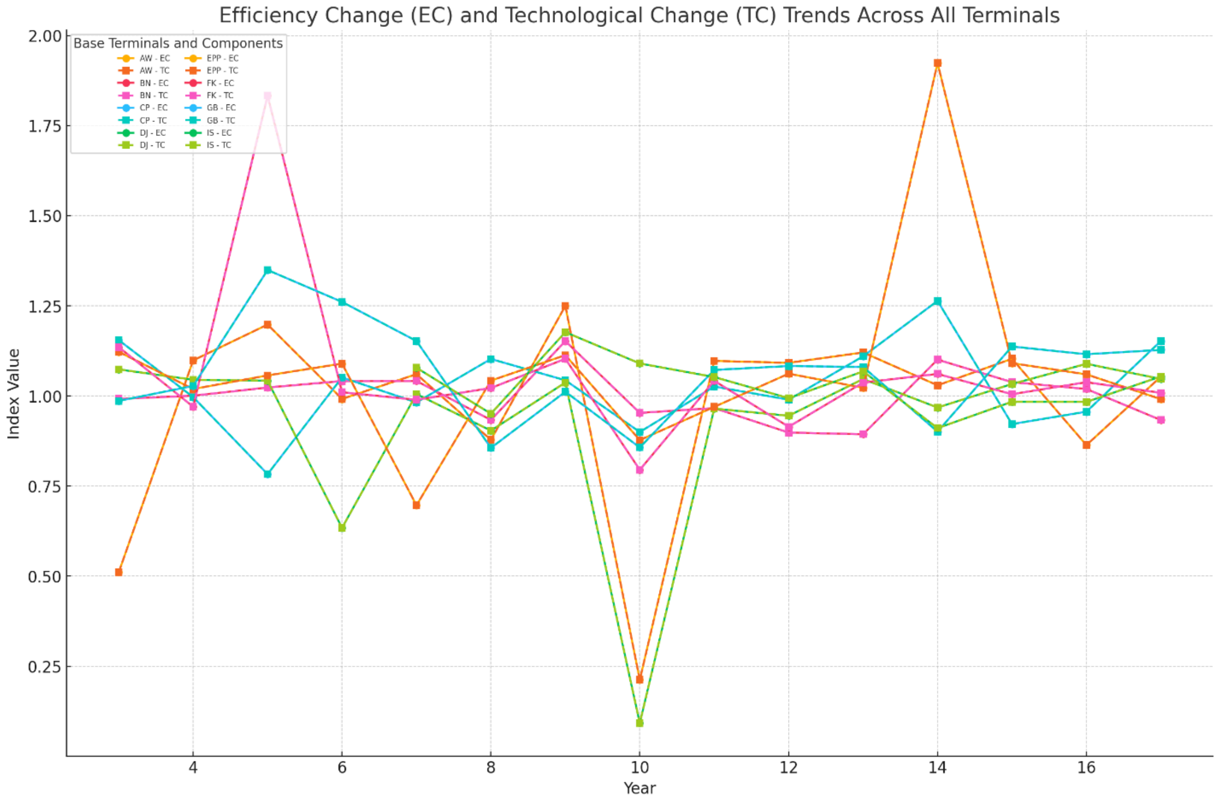

Figure 2. EC and TC Trends Across All Terminals

Figure 2 offers a more granular view by breaking down EC and TC trends for individual terminals. This visualization highlights the variability in performance across terminals, reflecting disparities in their ability to manage resources and adopt new technologies. High-performing terminals like CP and EPP exhibit stable and consistently positive EC and TC trends, demonstrating their capacity for sustained operational improvements and effective integration of technological innovations. In contrast, terminals like DJ and IS show significant fluctuations and periodic declines in both EC and TC, reflecting their struggle to maintain consistent performance. For example, DJ experiences sharp dips in both metrics around year 10, suggesting external disruptions or inefficiencies in adapting to changing operational demands.

The variability across terminals further emphasizes the need for tailored strategies to address unique challenges. Terminals like CP, which demonstrate consistent upward trends in both EC and TC, likely benefit from robust operational and technological strategies that ensure sustained productivity growth. On the other hand, underperforming terminals like DJ and IS require focused interventions, such as modernizing outdated infrastructure, adopting automation technologies, and improving workforce training to stabilize their performance.

Key periods, such as the systemic decline in EC and TC around year 10, indicate potential global or regional disruptions that impacted multiple terminals. These disruptions could stem from global trade slowdowns, supply chain bottlenecks, or failures to maintain critical infrastructure. Such challenges highlight the importance of proactive planning and scenario forecasting to mitigate the impact of similar events in the future. The trends in TC also underscore the importance of consistent investment in innovation. While some terminals exhibit episodic technological advancements, the lack of sustained innovation in others reveals gaps in long-term planning. Terminals must adopt a continuous approach to modernization, leveraging automated systems, advanced analytics, and digital technologies to enhance productivity and maintain competitiveness. High-performing terminals can further consolidate their leadership by sharing best practices with underperforming counterparts, fostering a more cohesive and competitive industry landscape.

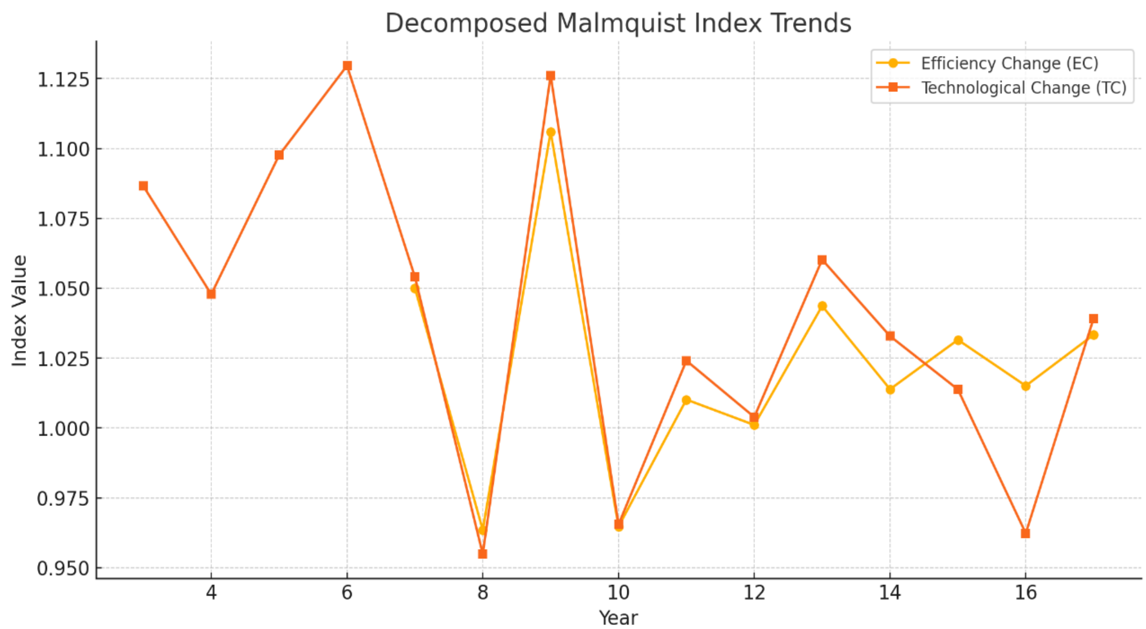

Figure 3. Decomposed Malmquist Trends

Additionally, Figure 3 illustrates the decomposed MPI trends, focusing on the aggregate EC and TC values across all terminals. The EC line reflects the changes in operational efficiency over the years. Periodic peaks, such as those observed around year 6 and year 14, signify moments of improved operational efficiency, likely driven by effective resource management, process optimization, or external factors such as favorable market conditions. Conversely, the dips in EC, particularly around year 8, point to periods of inefficiency that may have been caused by operational disruptions, bottlenecks, or external challenges like trade volume fluctuations.

The TC line, representing the impact of infrastructure and technological advancements, follows a similar trajectory to EC but displays slightly sharper fluctuations. This suggests that technological innovation tends to occur in episodic bursts rather than as a consistent trend. For instance, the spikes in TC around years 6 and 14 likely correspond to significant investments in new equipment, automation, or terminal operating systems. However, the dip around year 10 reveals a stagnation in technological progress, which could be attributed to financial constraints, delays in implementing upgrades, or misaligned investment strategies. The close alignment between EC and TC trends underscores the interdependence of operational efficiency and technological advancement in driving productivity.

In summary, these figures highlight the dynamic interplay between operational efficiency and technological innovation in shaping terminal productivity. The alignment between EC and TC trends underscores their mutual importance, while the variability across terminals emphasizes the need for customized strategies to address performance gaps. To sustain productivity growth, terminals must prioritize both operational excellence and continuous innovation, ensuring they remain resilient and competitive in a rapidly evolving global trade environment.

4.4 Predictive Modeling of DEA Efficiency

The ML offers a forward-looking perspective, highlighting potential areas of improvement and future performance trends. The Random Forest model predicted DEA efficiency scores with high accuracy, demonstrating its robustness in forecasting terminal performance (Table 4). For high-performing terminals such as AW and CP, predictive insights align closely with observed trends, reinforcing their operational stability. However, predictions for underperforming terminals such as IS and DJ remained consistently low, underscoring the entrenched nature of their inefficiencies. Feature importance analysis identified key predictors of efficiency, such as berth length and crane productivity, emphasizing the critical role of infrastructure and resource management in driving performance. The predictive model provides actionable insights, enabling terminal operators to prioritize investments and mitigate inefficiencies proactively. For instance, predictive modeling has been instrumental at the Port of Los Angeles, where similar tools have optimized berth allocation and reduced vessel turnaround times, offering a roadmap for underperforming terminals (Lee et al., 2021; Lam & van de Voorde, 2019).

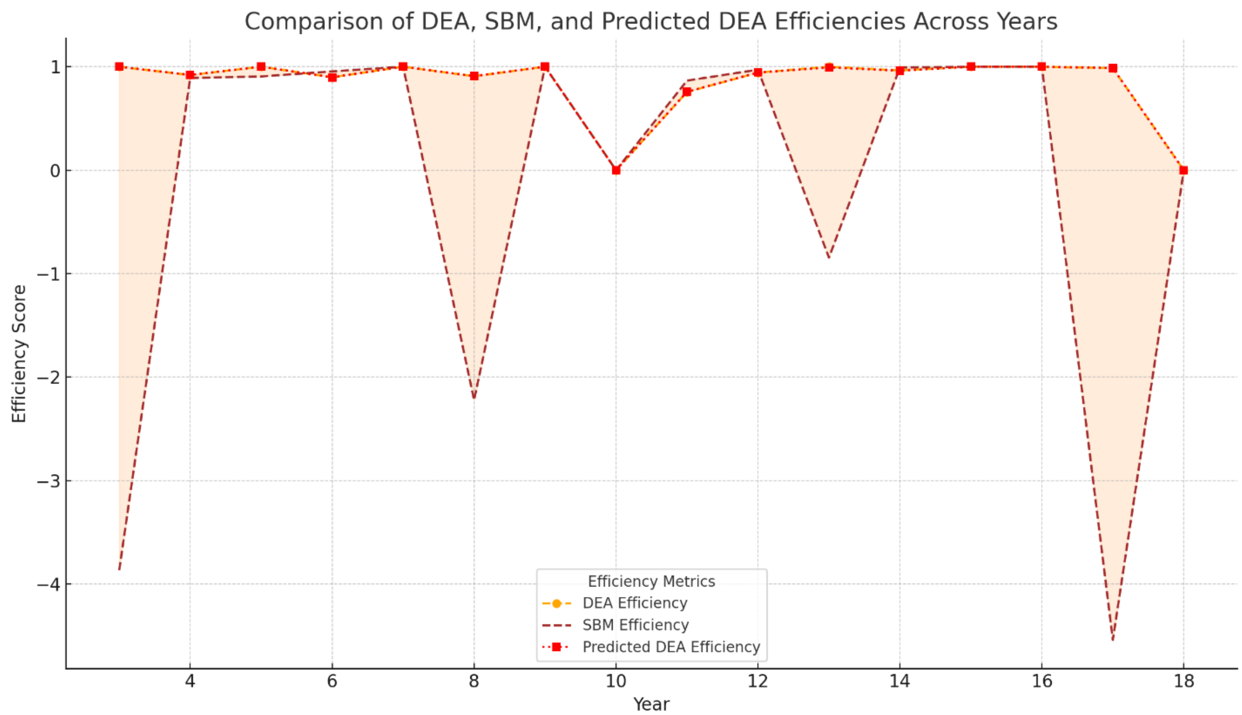

Figure 4. Comparison between DEA, SBM, and Predicted DEA Efficiencies

Figure 4 visualizes DEA Efficiency, SBM Efficiency, and Predicted DEA Efficiency scores over time, capturing the evolution of container terminal performance. The stability of DEA efficiency scores near zero indicates consistent underperformance relative to the efficiency frontier, reflecting a lack of significant operational improvements. This stagnation is likely due to outdated infrastructure, inefficient processes, or external challenges, as seen in mid-tier ports where resource constraints and bottlenecks limit performance (Raballand et al., 2012; Udo & Akpan, 2011).

SBM efficiency scores reveal greater variability, with consistently negative values highlighting persistent inefficiencies, such as underutilized resources and low throughput. Early sharp declines suggest severe operational challenges, while partial recoveries reflect incremental improvements like better crane scheduling. However, deeply embedded inefficiencies persist, similar to the Port of Mombasa's struggles with yard congestion and infrastructure gaps (Hope & Willis, 2004). The variability among terminals underscores the need for tailored interventions.

The predicted DEA scores align closely with actual DEA trends, validating the model's accuracy. Predictive insights suggest terminal efficiency will remain stagnant without significant operational changes. Key factors influencing efficiency, including crane productivity, berth length, and yard capacity, emphasize the importance of infrastructure upgrades and resource optimization (Brooks & Pallis, 2012).

4.5 Critical Discussion and Implications

The alignment between DEA, SBM, and MPI metrics underscores the interconnected nature of operational efficiency and productivity growth. Terminals such as CP and AW exemplify how optimized resource utilization and continuous technological investments can sustain high performance. These findings resonate with trends observed at globally recognized ports like Singapore and Shanghai, where automation and process optimization drive long-term efficiency (Lam & Yap, 2011; Rodrigue & Notteboom, 2020; Wang & Cullinane, 2015). Conversely, underperforming terminals like IS and DJ exhibited inefficiencies similar to those observed in mid-tier African ports, such as Mombasa, where resource constraints and infrastructure limitations impede performance (Hope & Willis, 2004). The persistence of low

DEA and SBM scores in these terminals reflects structural inefficiencies that require strategic interventions, such as targeted investments in automation, infrastructure modernization, and workforce training.

MPI trends further emphasize the critical role of technological innovation in sustaining competitiveness. Terminals with positive TC trends are better positioned to adapt to evolving demands, while those with stagnant or declining TC scores risk obsolescence. These findings highlight the dual necessity of operational efficiency and technological advancement. Real-world examples, such as the Port of Qingdao's successful implementation of automated guided vehicles, provide a blueprint for underperforming terminals to enhance their MPI metrics and remain competitive in a rapidly evolving industry (Heilig & Voß, 2017; UNCTAD, 2021).

Predictive modeling reinforces the importance of proactive planning in mitigating inefficiencies. By forecasting future trends, terminal operators can allocate resources effectively, prioritize investments, and address potential bottlenecks before they impact operations (Nazri et al., 2024). This forward-looking approach is particularly critical for mid-performing terminals, where strategic decisions can significantly influence future performance. The successful application of predictive tools in ports like Los Angeles underscores their potential to transform operational planning and resource allocation, offering valuable lessons for terminals across performance tiers (Becker et al., 2018; Notteboom & Rodrigue, 2017).

5.0 CONCLUSION

This study evaluated the efficiency and productivity of eight Malaysian container terminals over 15 years (2003–2018) using DEA, SBM, MPI, and ML methodologies. The findings offer robust empirical insights into both static and dynamic efficiency, slack utilization, and predictive modeling within the port sector.

The DEA results demonstrate that certain terminals particularly AW, CP, EPP, and BN consistently operate near the efficiency frontier, reflecting effective resource allocation and strong throughput performance. These terminals frequently record efficiency scores exceeding 0.90 across most years, indicating operational stability and strategic resilience. In contrast, terminals such as IS and DJ consistently show lower DEA scores, highlighting persistent operational bottlenecks and suboptimal resource use.

SBM analysis further reveals deeper inefficiencies, especially in IS and DJ, where efficiency scores dropped as low as -12. Such extreme slack values point to significant idle resources, including underutilized berth length and crane capacity. On the other hand, terminals like CP and AW exhibit minimal slack, confirming their optimized resource deployment and disciplined operational management.

The MPI results underscore the dual influence of operational improvements and technological progress on terminal productivity. Terminals such as CP and EPP consistently report MPI scores exceeding 1.0, driven by both efficiency change and technical change. These outcomes reflect sustained investments in digitalization and physical infrastructure. In contrast, mid-performing terminals like AW and BN show stable yet unremarkable MPI scores, suggesting the need for transformative strategies such as automation, green technologies, and integrated IT systems to break through their current performance plateaus.

In parallel, the integration of ML techniques specifically Random Forest regression enabled accurate prediction of DEA scores. Predictive insights closely mirrored observed trends for high-performing terminals such as AW and CP, affirming their operational consistency. However, predicted scores remained consistently low for underperformers such as IS and DJ, reinforcing the systemic nature of their inefficiencies. Feature importance analysis highlighted berth length and crane productivity as primary efficiency drivers, underscoring the critical role of infrastructure and asset utilization in shaping terminal performance.

Collectively, this study demonstrates the value of a multi-method evaluation framework that combines frontier-based efficiency measurement, longitudinal productivity tracking, and data-driven forecasting. The insights generated can inform port authorities and terminal operators in prioritizing investments, optimizing operations, and designing policies that foster long-term performance improvements. Future research may explore the incorporation of qualitative enablers such as governance quality, regulatory frameworks, ESG indicators, and region-wide benchmarking to extend the utility of this approach.

5.1 Recommendations and Way Forward

To improve terminal operations and align with broader sustainability goals, this study offers the following actionable recommendations for ports such as:

a) Implement automation: Automating key processes such as crane operations, berth scheduling, and yard management can significantly enhance operational efficiency. Automation not only reduces human error but also accelerates cargo handling, thereby improving turnaround times. High-performing terminals globally, such as those in Rotterdam and Singapore, have demonstrated the transformative impact of automation on efficiency and competitiveness.

b) Enhance crane productivity: Investing in modern cranes with higher handling capacities and integrating real-time monitoring systems can optimize crane productivity. Predictive maintenance systems should be adopted to minimize downtime and ensure continuous operations, thereby reducing delays and associated costs.

c) Integrate predictive tools into daily operations: Predictive analytics should be incorporated into operational decision-making processes to forecast demand, allocate resources efficiently, and mitigate potential bottlenecks. For example, leveraging predictive models to anticipate peak periods can help terminals preemptively adjust operations and reduce congestion.

d) Focus on sustainability and emission reduction: Efficiency improvements should be aligned with environmental objectives to reduce emissions and support global sustainability goals. For instance, optimizing vessel turnaround times and reducing idle times at berths can lower fuel consumption and associated greenhouse gas emissions. Investments in green technologies, such as electrified cranes and alternative fuels, should be prioritized to enhance sustainability.

e) Adopt industry best practices: Learning from global benchmarks, such as the digital twin technology used at the Port of Rotterdam or advanced congestion management at the Port of Los Angeles, can guide the development of innovative solutions tailored to local contexts.

These recommendations not only address the operational inefficiencies identified in this study but also contribute to broader environmental and sustainability goals by promoting resource efficiency and reducing emissions. By adopting these strategies, Malaysian container terminals can enhance their competitiveness and resilience in a rapidly evolving global maritime industry.

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DECLARATION OF GENERATIVE AI AND AI-ASSISTED TECHNOLOGIES IN THE WRITING PROCESS

In the course of preparing this manuscript, the authors employed Bing Copilot, Gemini, and Perplexity.ai to augment the effectiveness of the written material. Despite this assistance, the authors carefully reviewed and refined the content, retaining full responsibility for the publication’s integrity.

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