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Benchmarking Regional Hub Port Efficiency: A DEA Window Analysis of the Port of Salalah and Peer Transshipment Hubs (2015-2024)

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ABSTRACT

This research examines the operational efficiency of the Port of Salalah (Oman) alongside three major competing transshipment hubs in the Indian Ocean and Gulf region which are Port of Singapore, Colombo Port (Sri Lanka) and the Port of Jebel Ali (UAE) over the period 2015-2024. Data Envelopment Analysis (DEA) window analysis, based on the CCR model, is applied under input and output-oriented specifications to overcome the limited discriminatory power that conventional cross-sectional DEA suffers due to small decision-making units. For input Berth length, quay length, number of cranes, vessel calls and geo index is used as inputs and annual transshipment throughput (TEU) is considered as output. For the analysis of the results six overlapping five-year windows were constructed to trace efficiency trends over the period. The results shows that Singapore and Jebel Ali maintained consistent high and stable efficiency scores across the study period, Salah has shown a favourable trend during the first three windows before declining from the fourth windows onwards, Colombo recorded the lowest and volatility scores among the ports.

1. Introduction.

Transshipment hubs position themselves in a distinctive position within the global maritime supply chain. Transshipment hubs have become central nodes in international maritime trade, providing the critical link between mainline and feeder shipping networks that keep global supply chains and port systems functioning efficiently (Notteboom and Rodrigue, 2005; Solesvik and Westhead, 2010b). The Port of Salalah occupies this distinctive position as positioned outside of Strait of Hormuz on the main East – West shipping corridor, Salalah was developed to capture this specific transshipment volumes moving between Asia, Europe and East Africa and get placed in the same competitive territory of hubs like Jabel Ali, Colombo and Singapore. Despite the location advantages of location, transshipment volumes at Salalah have fluctuated over the period (Martínez Moya et al., 2025; Ducruet and Notteboom, 2021). Much of the research remains descriptive, addressing the challenges of performance differences or governance arrangements without analysing or isolating the effect of operational efficiency metrics on the throughput (Hunjra and Sharma, 2024; Wu and Luo, 2021). This leave a genuine data driven analysis on Omani ports which this study is seeking to address. Based on which the main objective of the study is based on 1) to assess the operational efficiency of the Port of Salalah between 2015 and 2024 using DEA; (2) to identify the key operational efficiency determining factor of transshipment performance; and (3) to benchmark Salalah's operational effectiveness against selected regional transshipment ports. By incorporating this study de-

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sign the implementation and importance of hubs that can both accommodate large vessel calls and maintain operational productivity is elevated. Principal limitation of the study is the reliability of secondary data and the treatment of location as fixed also the pandemic shock (Millefiori et al., 2020; Verschuur, Koks and Hall, 2022f). By providing empirical evidence on the role of operational efficiency in the transshipment performance of one of the most strategically located Middle Eastern Port a topic still underexplored quantitively (Martínez Moya et al., 2025; Mdanat et al., 2024),the study aims to inform the port authorities, policy makers that seeks to strengthen completeness also looking into the performance levers that can be optimized to fully realized the benefits of strategic location that can contribute to Oman's national logistics strategy (Rahman et al., 2023b; Hamad, 2026).

2. Literature Review.

Maritime shipping plays a critical role in global trade as it is one the most cost-effective methods of transporting goods internationally. Ports play an important role as critical nodes in supply chain and directly effect a country's export potential and economic growth (Berkoz 1999; Ferrari 2011). The port sector contributes to a nation's economy by connecting countries to global trade system, creating new jobs and generating foreign currency. Therefore, an efficient port sector is vital for the development and economic growth of a country (Ferrari 2011; Berkoz 1999; Guoqiang et al., 2005; Oxford Economics 2013). Ports are one of the main infrastructures that are essential for linking land and sea transport which make it essential to assess their production and efficiency (Cullinane et al., 2007; Cullinane et al., 2010). Efficiency and productivity of ports can be affected by many financial and physical factors where changes in any factor may initiate extra challenges for port authorities. Hence, assessing the ports performance can serve as effective tool for evaluating ports operations to identify the areas of improvement (Cullinane et al., 2004).

Among the various methods that can be applied for efficiency assessment and performance evaluation, Data Envelopment Analysis (DEA) has become one of the most popular and widely used nonparametric approaches due to its simplicity and the fact that it does not require any prior knowledge on the functional relationship between inputs and outputs in the evaluation process. The application of DEA in port sector was initiated by the work of Roll and Hayuth (1993) where they used hypothetical data for 20 ports to demonstrate the applicability of DEA approach in evaluating port performance. In their study they considered labor force size, annual investment, facility uniformity, and cargo traffic as input variables and container throughput, service level, customer satisfaction, and ship calls as output variables. Even though this study was based on hypothetical data, it laid the foundation for subsequent empirical studies.

One of the first empirical applications was conducted by Martinez-Budria et al. (1999), who assessed the efficiency of 33 ports in Spain between 1993 and 1997. They classified ports into three groups according to a complexity criterion: low, medium and high complexity ports. Their result revealed that the high complexity ports showed an improvement in efficiency over time whereas the other two groups of ports did not show a similar pattern. Applying DEA approach in port studies expanded significantly in early 2000s. Tongzon (2001) assessed the efficiency of four Australian ports and twelve international container ports using DEA models specifically CCR and additive models. The input variables in this study were number of cranes, berths, labor, terminal area, and delay time, while cargo throughput and ship working rates were used as outputs. The results established that DEA approach could effectively identify sources of inefficiency and benchmark port performance. Itoh (2002) applied DEA window analysis to evaluate the efficiency of eight major container ports in Japan over the time period 1990-1999. This study highlighted the importance of dynamic performance assessment using DEA window analysis to capture the efficiency score trends over time.

Barros (2003) explored the efficiency of five Portuguese ports using DEA approach. This study evaluated the impact of regulatory procedures on port productivity and showed that existing regulatory mechanisms were insufficient to improve productive efficiency. Afterwards, Barros and Athanassiou (2004) extended DEA analysis to Portuguese and Greek ports and observed significant inefficiencies among several ports and suggested privatization as a possible strategy to improve the efficiency of these ports. Cullinane et al. (2004), employed DEA Window Analysis to assess the efficiency of leading international container ports between 1992 and 1999. The findings of their study demonstrated the advantages of using panel data to capture the trend in efficiency changes over time compared to traditional cross-sectional analyses.

Subsequent studies such as Cullinane et al. (2005), Barros (2006), Rios and Macada (2006), Cullinane and Wang (2006) and Al-Eraqi et al. (2008) applied DEA to various groups of ports and container terminals around the world and showed applicability and effectiveness of DEA models in evaluating efficiency of ports, identifying inefficiencies and providing benchmarking standards to support efficiency improvement for inefficient DMUs. For instance, Pjevčević et al. (2012) evaluated the efficiency of Serbian ports using window DEA analysis and detected underutilized infrastructure and insufficient throughput to be the major sources of inefficiency. Yuen et al. (2013) found that ownership structure and competitive conditions significantly influenced port efficiency in China, while Schøyen and Odeck (2013) concluded that Norwegian ports were technically efficient but suffered from limited scale efficiency.Han et al. (2010) employed DEA to compare the efficiency of Chinese ports with ports from five members of Association of South East Asian Nations (ASEAN). Their findings demonstrated that Chinese ports generally achieved higher efficiency levels comparted to the ASEAN ports included in the study. During the same period other studies such as Wu et al. (2010) utilized sensitivity analysis to assess the impact of each individual variable on efficiency of 77 international container ports. Their findings indicated that capital investment and the number of berths were the most influential variables affecting efficiency scores of ports.

Among the approaches to assess the efficiency of individual factors on the efficiency score some authors have used a combination of DEA and Tobit regression analysis. For example, Yuen et al. (2013) explored the effects of ownership structure and competition, and on the efficiency of 21 container terminals in China and neighboring countries employing a two stage DEA-regression analysis. Their findings showed that ownership structure significantly impacts terminal efficiency where the terminals with Chinese ownership performed generally better than the other terminals. It was also observed that both intra-port and inter-port competition can have a positive effect on container port efficiency, which shows the significance of market competition in performance improvement. Another study by Wan et al. (2014) investigated the impact of hinterland accessibility on the efficiency of US container ports using a two-stage DEA and Tobit regression method. The findings of this study uncovered that the provision of on-dock rail facilities was negatively associated with port efficiency; however, the effect of Class I rail services was inconclusive.

More recently Gamassa and Chen (2017) evaluated and compare the efficiency of main ports in East and West Africa over a seven-year period using DEA Window analysis. They used container throughput as the output and terminal area, quay length, number of berths, and number of cranes as input variables in their study. The finding of their study showed that the West African ports despite having larger infrastructure and throughput levels were generally less efficient compared to the East African ports. The study highlighted the effectiveness of DEA Window Analysis in benchmarking port performance and supporting port development strategies. Abdoulkarim et al. (2019) applied DEA approach to evaluate the competitiveness of five African dry ports (Mojo and Kality (Ethiopia), Mombasa (Kenya), Isaka (Tanzania), and Casablanca (Morocco)) considering Container throughput as the output variable and the variables such as dry port area, number of reach stackers, tractors, and forklifts were considered as inputs. Their findings showed great differences in efficiency among the ports under study, with Mombasa being the most efficient and Isaka as the least efficient port. DEA window analysis was employed by Seth and Feng (2020) to examine the efficiency of 15 U.S. container ports analysis, and the result found the Port of Los Angeles as the most efficient port.

Recent studies have continued to demonstrate the extensive application and effectiveness of DEA approach in evaluating the efficiency of ports across the world. Studies have applied a variety of conventional DEA models and their extensions to evaluate port efficiency, explore the changes in productivity over time, study the impact of various factors on efficiency, and identify sources of inefficiency. Applications include the evaluation of Asian container terminals (Munim, 2020), ports along the 21st Century Maritime Silk Road (Huang et al., 2020), Southeast Asian container ports (Nguyen et al., 2020), Vietnamese ports and container terminals (Kuo et al., 2020), major ports in Southern and Eastern Africa (Mwendapole et al., 2022).

Some of the most recent studies have expanded application of DEA approach beyond conventional efficiency measurement. Kammoun and Abdennadher (2023) evaluated the efficiency of the 30 major European ports over the period 2005-2018 applying a two-stage approach. The first stage of the study involved applying a DEA Window Analysis to determine port efficiency scores and in the second stage they applied bootstrap regression to study the influence of competition and environmental factors on efficiency. Nadarajan et al. (2023) combined fuzzy DEA models and liner shipping connectivity indicators to assess global seaport network efficiency under uncertainty. Atsunyo and Tetteh (2025) assessed the efficiency and productivity of major global ports, including Singapore, Rotterdam, Antwerp, and Durban. The study employed the DEA approach to evaluate efficiency of these ports and the Malmquist Productivity Index was used to investigate productivity changes over time. Similarly, Sulaimani (2026) further explored the relationship between liner shipping connectivity and port efficiency using a DEA-Malmquist Productivity Index framework. These developments demonstrate the growing trend of integrating external performance drivers and advanced DEA methodologies to obtain a broader understanding of port efficiency.

Collectively these studies highlight the continued importance of DEA methodology as a robust tool for measuring port efficiency, benchmarking performance, and identifying opportunities for operational improvement.

3. Methodology.

3.1. Data Envelopment Analysis (DEA).

Efficiency measurement is an essential tool to evaluate the performance of various types of organizations in various sectors such as shipping, transport, education, healthcare etc. Measuring and assessing how efficiently the organization utilizes their resources or inputs to produce output can help the managers and decision makers to identify best and worst performing units, improve their resource allocation and support further decision-making processes.

To measure efficiency various parametric approaches such as regression analysis and Stochastic Frontier Analysis (SFA) by Aigner, Lovell, and Schmidt (1977) as well as non - parametric techniques such as Data Envelopment Analysis (DEA) by Charnes, Cooper, and Rhodes (1978) have been developed. The main difference between these approaches is that the parametric approaches suppose a functional relationship between inputs and outputs and estimate efficiency based on statistical assumptions. In contrast, non-parametric methods do not require a predefined functional form and instead construct an efficiency frontier directly from the observed data and all units will be compared against the constructed frontier (Nguyen et al., 2016).

Among the efficiency measurement approaches DEA is one of the most well-known and papular performance measurement and decision-making approaches that has been widely applied in real-world managerial problems since it was first introduced Farrell (1957) and has grown significantly, leading to the development of various models that extend its methodology and applicability. DEA models evaluate the efficiency of a set of homogeneous decision-making units (DMU) which operate under similar conditions and use the same sets of inputs and outputs.

The main objective of DEA is to identify which DMUs operate efficiently compared to others and to benchmark inefficient units against efficient ones. This is achieved through linear programming techniques that calculate efficiency scores and determine whether units lie on or below the efficient frontier.

3.2. Input-oriented vs Output-oriented DEA models.

DEA models are classified into two subcategories of input-oriented and output-oriented models. The aim of the Input-oriented models is to minimize the resources (input) while satisfying at least the given level of output. In these models, a DMU is labelled as inefficient when at least one of its inputs can be decreased without requiring increasing any other input and without a decrease in any output.

On the other hand, output-oriented model aims to maximize the level of outputs without requiring an increase in input resources. In these models a DMU is labelled as inefficient if it is possible to increase any output without decreasing any other output or increasing any input (Cooper et al., 2007).

3.3. CCR Model.

3.3.1. Input-oriented CCR model.

In the CCR model, the envelopment form measures efficiency by comparing each DMU with a frontier which will be constructed by the most efficient DMUs while the multiplier form evaluates efficiency by finding the optimal combination of input and output weights. CCR model was introduced by (Charnes et al., 1978).

The envelopment form of the input-oriented CCR model for assessing the efficiency of h^{th} DMU (DMU_h) is formulated as following mathematical linear programming:

$$
\begin{aligned}
\min \quad & \theta_h \\
\text{s.t.} \quad & \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq \theta_h x_{ih}, \qquad i = 1, \dots, m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq y_{rh}, \qquad r = 1, \dots, s, \\
& \lambda_j \geq 0, \qquad j = 1, \dots, n.
\end{aligned}
\tag{1}
$$

And the multiplier form of input-oriented CCR model is formulated as below:

$$
\begin{aligned}
\max \quad & \theta_h = \sum_{r=1}^{s} u_r\, y_{rh} \\
\text{s.t.} \quad & \\
& \sum_{i=1}^{m} v_i\, x_{ih} = 1, \\
& \sum_{r=1}^{s} u_r\, y_{rj} - \sum_{i=1}^{m} v_i\, x_{ij} \leq 0, \qquad j = 1, \dots, n, \\
& u_r \geq 0, \qquad r = 1, \dots, s, \\
& v_i \geq 0, \qquad i = 1, \dots, m.
\end{aligned}
\tag{2}
$$

where

n = number of DMUs,

s = number of outputs,

m = number of inputs,

u_r = the assigned weight to output r,

v_i = the assigned weight to input i,

y_{rj} = amount of r^{th} output produced by j^{th} DMU,

x_{ij} = amount of i^{th} input used by j^{th} DMU.

In an input oriented CCR Model, a DMU is called efficient if $\theta_h^* = 1$. (θ^* is the optimal value of the objective function in model (1) and (2) and a DMU is called inefficient, if $0 < \theta_h^* < 1$. The score indicates the exact proportion to which input must be reduced to become efficient. For example, if a DMU has an efficiency score of 0.90, it could produce the exact same level of outputs using only 90 percent of its current inputs.

3.3.2. Output-oriented CCR model.

As mentioned before the aim in the output-oriented models is to maximize the level of output by utilizing the current level of input resources. The envelopment form of the output-oriented CCR model to evaluate the efficiency of DMU_h is formulated as the following mathematical programming:

$$
\begin{aligned}
\max \quad & \varphi_h \\
\text{s.t.} \quad & \\
& \sum_{j=1}^{n} \lambda_j x_{ij} \leq x_{ih}, \qquad i = 1, \dots, m, \\
& \sum_{j=1}^{n} \lambda_j y_{rj} \geq \varphi_h y_{rh}, \qquad r = 1, \dots, s, \\
& \lambda_j \geq 0, \qquad j = 1, \dots, n.
\end{aligned}
\tag{3}
$$

And the multiplier form of output-oriented CCR model given as follows:

$$
\begin{aligned}
\min \quad & \varphi_h = \sum_{i=1}^{m} v_i\, x_{ih} \\
\text{s.t.} \quad & \sum_{r=1}^{s} u_r\, y_{rh} = 1, \\
& \sum_{i=1}^{m} v_i\, x_{ij} - \sum_{r=1}^{s} u_r\, y_{rj} \geq 0, \qquad j = 1, \dots, n, \\
& u_r \geq 0, \qquad r = 1, \dots, s, \\
& v_i \geq 0, \qquad i = 1, \dots, m.
\end{aligned}
\tag{4}
$$

In an output oriented CCR Model, a DMU is called efficient if $\phi_h^* = 1$. (ϕ_h^* is the optimal value of the objective function in model (3) and (4). On the other hand, a DMU is called inefficient, if $\phi_h^* > 1$, which means the DMU can proportionally increase its outputs to reach the efficient level compared to its peers.

3.4. DEA Window Analysis.

Conventional DEA models assess the efficiency of DMUs in a single period, which can reduce the discriminatory power of the DEA model in cases where the number of DMUs or the sample size is limited. To tackle this issue, DEA window analysis which is an extension of the CCR model can be employed. One of the main advantages of window analysis is that it allows the assessment of DMUs' efficiency even when the number of DMUs is small by increasing the number of observations through expanding the data set over multiple time periods (Asmild et al., 2004). Instead of considering only one time periods, multiple time windows can be analyzed, and the same DMU can be observed as a distinct DMU over different periods of time. In this way, the number of DMUs will be increased significantly, the discriminatory power of the efficiency measurement will enhance, and the efficiency measurement results will become more reliable (Peykani et al., 2021).

Applying DEA window analysis provides a dynamic assessment of efficiency that enables researchers to assess trends, stability, and performance changes over time. Moreover, using this analysis each DMU can be compared not only with other DMUs operating in the same period, but also with its own performance across different time.

4. Case Study.

This study investigates the efficiency of four ports including Port of Salalah (Oman), Port of Singapore, Colombo port and Port of Jebel Ali (UAE) over the period of 2015- 2024. To evaluate the efficiency of these ports DEA window analysis has been utilized considering 4 input variables such ass berth length, quay length, number of cranes, vessel calls and Geo-index, while port throughput per year is considered as the output variable. Table 1 provides descriptive statistics of the selected input and output data over the period of 2015-2024.

Table 1: Descriptive statistics of ports (2015-2024).

	Inputs					Output
	Berths length	Quay length	Number of Cranes	Vessel Calls	Geo-Index	Transshipment TEU
Min	6	2197	18	780	87	2.45
Max	67	25000	240	42000	99	34.95
Mean	34.95	11946.75	111.55	12813.70	92.25	12.40
Standard Deviation	26.30	9297.02	81.08	15275.80	4.97	11.01

Source: Authors.

To evaluate the efficiency of ports effectively and provide reliable efficiency scores with the consideration of small sample size, the DEA window analysis method is employed. A five-year window length is selected for this study. Each port in each year is treated as a distinct DMU and is compared with itself alongside with all other DMUs within the selected window period. The six overlapping windows (2015-2019), (2016-2020), (2017-2021), (2018-2022), (2019-2023) and (2020-2024) allow the analysis to capture both short-term fluctuations and long-term performance trends. The efficiency evaluation results using the CCR input-oriented model are provided in Table 2.

Table 2 provides the efficiency scores for each DMU in each window using the input-oriented CCR model. The efficiency

Table 2: Efficiency scores using input-oriented CCR model.

Ports/year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Average
Salalah											
W-1	1	0.9781	0.9355	0.9468	0.9542						0.963
W-2		1	0.9625	0.9802	1	0.9471					0.978
W-3			0.9803	0.9922	1	0.9709	0.992				0.987
W-4				0.825	0.8315	0.8073	0.8248	1			0.858
W-5					0.8315	0.8073	0.8248	1	0.8436		0.861
W-6						0.8073	0.8248	1	0.8435	0.7686	0.849
Singapore											
W-1	0.9093	0.909	0.9556	0.9823	1						0.951
W-2		0.9099	0.9558	0.9823	1	1					0.97
W-3			0.9542	0.9823	1	1	1				0.987
W-4				0.9823	1	1	1	0.9928			0.995
W-5					1	1	1	0.9917	1		0.998
W-6						1	0.9914	0.9761	0.9793	1	0.989
Colombo											
W-1	0.7504	0.8142	0.8594	0.9311	0.9397						0.859
W-2		0.9099	0.9558	0.9823	1	1					0.97
W-3			0.8698	0.9394	0.9466	0.8851	0.9711				0.922
W-4				0.8216	0.8293	0.7655	0.8509	0.7844			0.81
W-5					0.8302	0.7668	0.8523	0.7858	0.7975		0.807
W-6						0.7628	0.8478	0.7811	0.7927	1	0.837
Jabel Ali											
W-1	1	0.9823	0.9952	0.9769	0.932						0.977
W-2		0.9933	1	0.9819	0.9373	0.962					0.975
W-3			1	0.9518	0.9679	0.9585	0.9511				0.966
W-4				1	0.9518	0.9679	0.9585	0.9511			0.966
W-5					0.968	0.98	0.9705	0.9631	1		0.976
W-6						0.9423	0.9328	0.9253	0.96	1	0.952

Source: Authors.

scores range between 0 and 1, where an efficiency score of 1 indicates an efficient DMU. In an input-oriented CCR model, this means that the DMU has used the resources (inputs) efficiently to produce outputs. On the other hand, an efficiency score of less than 1 indicates varying levels of inefficiency. For example, an efficiency score of 0.80 means that the DMU could reduce its input by 20% while maintaining the same level of output.

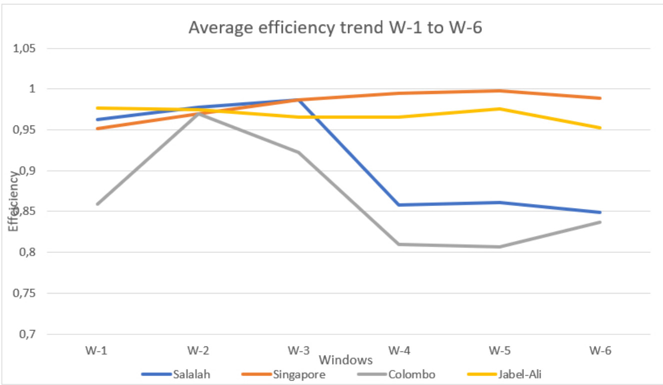
Among these four ports, Port of Singapore demonstrated a more consistent efficiency score throughout the study period, with an overall average of 0.982 across the six windows. Following the Port of Singapore, Port of Jebel Ali also showed a near-optimal efficiency score throughout the study period, ranging from an average of 0.952 to 0.977, with an overall average of 0.969 across all six windows.

Port of Salalah exhibited a moderate performance compared to the other ports, with more noticeable fluctuations over the study period. While the port recorded an increasing trend in efficiency scores across windows 1 to 3, its average efficiency score started to decline from window 4 to window 6. Overall, the port of Salalah has recorded an average efficiency score of 0.916 across all six windows.

Finally, among the four ports, Port of Colombo achieved the lowest efficiency scores compared to its peers in this study, with an average of 0.867 across all six time periods.

Figure 1 highlights the average efficiency score trend of the selected ports across different time windows. Among them, the port of Singapore and Jabel-Ali port have maintained higher efficiency scores and a more stable trend throughout all windows. In contrast, port of Salalah has demonstrated a visible decline in efficiency from W-3 onwards and port of Colombo has gone through the largest fluctuations and variability in the efficiency scores, whereas its efficiency has decreased noticeably during the 4^{th} and 5^{th} windows before slightly improving in window 6. Overall, the results indicate that the port of Singapore and Jabel Ali port have demonstrated more stable and efficient operations

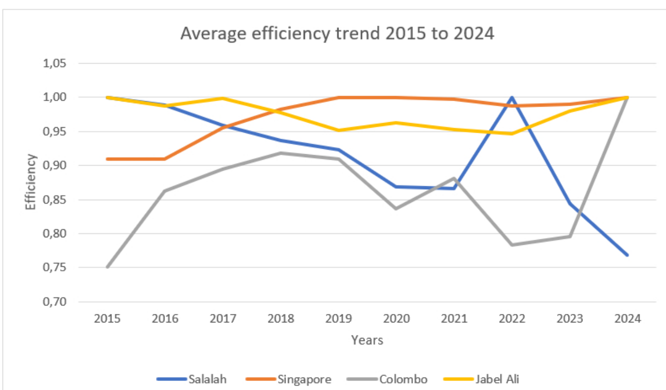
Figure 1: Average efficiency trend of ports across W-1 to W-6.



Source: Authors.

compared to port of Salalah and port of Colombo.

Figure 2: Average efficiency trend of ports from 2015 to 2024.



Source: Authors.

Figure 2 illustrates the average efficiency trends of the selected ports from 2015 to 2024 and visually supports the same findings presented in Table 2 and Figure 1.

In addition to applying the input-oriented CCR model, the efficiency scores of the selected ports are also evaluated using the output-oriented CCR model. The results obtained from the output-oriented window DEA analysis are presented in Table 3.

Table 3 provides the efficiency scores of ports using output-oriented CCR model. In contrast to the input-oriented model, these efficiency scores evaluate whether a DMU is able to assess the capability of each port to maximize its outputs while employing the existing level of input. In this model, an efficiency score of 1 show that the DMU under evaluation is operating efficiently, while a score greater than 1 indicates an inefficient DMU. For example, a score of 1.20 suggests that the port could proportionally increase its output by 20% using the same level of input to reach the efficient frontier. The results from the output-oriented model complement the outcomes of the input-oriented model and verify the relative efficiency ranking of the ports.

Table 3: Efficiency scores using output-oriented CCR model.

Ports/year	2015	2016	2017	2018	2019	2020	2021	2022	2023	2024	Average
Salalah W-1	1	1.0224	1.0689	1.0562	1.048						1.039
W-2		1	1.039	1.0202	1	1.0559					1.023
W-3			1.0201	1.0079	1	1.03	1.0081				1.013
W-4				1.2121	1.2026	1.2387	1.2124	1			1.173
W-5					1.2026	1.2387	1.2124	1	1.1854		1.168
W-6						1.2387	1.2124	1	1.1855	1.3011	1.188
Singapore W-1	1.0997	1.1001	1.0465	1.018	1						1.053
W-2		1.099	1.0462	1.018	1	1					1.033
W-3			1.048	1.018	1	1	1				1.013
W-4				1.018	1	1	1	1.0073			1.005
W-5					1	1	1	1.0084	1		1.002
W-6						1	1.0087	1.0245	1.0211	1	1.011
Colombo W-1	1.3326	1.2282	1.1636	1.074	1.0642						1.173
W-2		1.099	1.0462	1.018	1	1					1.033
W-3			1.1497	1.0645	1.0564	1.1298	1.0298				1.086
W-4				1.2171	1.2058	1.3063	1.1752	1.2749			1.236
W-5					1.2045	1.3041	1.1733	1.2726	1.2539		1.242
W-6						1.311	1.1795	1.2802	1.2615	1	1.206
Jabel Ali W-1	1	1.018	1.0048	1.0236	1.073						1.024
W-2		1.0067	1	1.0184	1.0669	1.0395					1.026
W-3			1	1.0506	1.0332	1.0433	1.0514				1.036
W-4				1	1.0506	1.0332	1.0433	1.0514			1.036
W-5					1.0331	1.0204	1.0304	1.0383	1		1.024
W-6						1.0612	1.072	1.0807	1.0417	1	1.051

Source: Authors.

5. Discussion.

5.1. Overview of the input-output profile.

The decision-making units (DMUs) show wide variations across the operational inputs as per the DEA model. Berth length ranges from 6 to 67 (mean 34.95, SD 26.30), quay length from 2,197 to 25,000 meters (mean 11,946.75, SD 9,297.02), crane numbers from 18 to 240 (mean 111.55, SD 81.08), and vessel calls from 780 to 42,000 (mean 12,813.70, SD 15,275.80). the geo – index which is the proxy for strategic location is relatively narrow and high across the sample (87–99, mean 92.25, SD 4.97), while transshipment output (TEU) ranges from 2.45 to 34.95 million (mean 12.40, SD 11.01). The fact that the locational variable is uniformly high and clustered tightly across the ports. This also highlights that the sampled ports are broadly comparable in terms of geographic advantage so the substantial differences in efficiency and productivity documented are plausible attributed to the differences in operational and management of location itself. This supports the study's main premise as the location advantage is held constant, operational efficiency becomes the differentiating factor to understand the transshipment performance. The window analysis results in Table 2 and 3 reveals a clear efficiency hierarchy among the four ports over 2015-2024. Singapore and Jebel Ali occupy the top slots; both showing average efficiency score to the frontier (0.982 and 0.969 respectively under the input-oriented model) and sustainably maintain the position across all six windows with very minimal variations. This stability is consistent with earlier findings that connect the node with strong institutional capacity, also continued infrastructure reinvestments. Singapore's case the scale advantage associated with its status as the world's largest transshipment hub. This highlights the Yuen et al.'s (2013) identification that competition tends to discipline port performance which directs to the fact that Singapore and Jabel

Ali operated in a highly competitive trade line which leave little room for slack in the resource utilization.

Salah's performance is instructive precisely due to its instability to maintain performance scores as witnessed the scores rose across the first windows (W-1 to W-3) which highlights that the capacity added in the early part of the decade was well matched with the growth throughput. From Window 4 onwards i.e. from 2018-2022 it witnessed an average efficiency fall and declining further in windows 5 and 6. Since the input-oriented model can interpret a falling score as an increase degree of input over provision relative to output, this pattern is consistent with a scenario in which Salalah's capacity expansion of additional berth length, quay length, or cranes which outpaced the throughput actually realized, which is supplemented by the global trade disruption of 2020-2021 and along with the intensified transshipment volumes competition in the later period. As the finding of this research Salalah's output oriented scores rose well above 1.0 in Window 4 through 6 reaching as high as 1.239, indicating that the existing input levels the port would need to raise substantially by approximately 17-19 percent on average to reach the efficient frontier which is benchmarked by the peers.

Colombo represents the weakest and most vulnerable ports among the four ports, with an average input – oriented efficiency score of 0.867 and swings between the windows. This volatility is broad consistent with findings of (Pjevčević et al., 2012) related to Serbian ports that underutilize infrastructure and inconsistent throughput growth. Colombo's partial recovery in Window 6 (2020-2024) suggested improvement in the recent years but still represents the weakest port among the four ports. When we investigate it from a bird's eye view it tells a consistent story (addressing RQ3) the ranking of the ports by efficiency is stable regardless of the orientation and the two models which was used for the analysis shows that the same underlying inefficiencies is expressed as excess input use or as shortfall in achievable output. For Salah, the results highlight the ports' competitive position while historically strong have weakened relative to the principal rivals in the second half of the study period. This raised a serious concern and a practical question for the port management whether the recent investments are matched by commercial strategies like shipping line agreements, connectivity improvements also pricing which can be used to convert the added capacity into throughput, rather than the investment outpacing the demand.

6. Conclusions.

The study has applied DEA windows analysis to benchmark the Port of Salah against three major competing transshipment hubs ie Singapore, Colombo and Jabel Ali over the period of 2015-2024 using input and output oriented CCR. The results indicate that a stable and consistent efficiency hierarchy ie Singapore and Jebel Ali have sustained high, stable efficiency throughout the decade while Salalah improved through the early study periods but experienced a marked decline in relative efficiency and Colombo has remained the least efficient and most volatile performed among the ports.

These findings have got direct relevance for Salalah's port authority as well as for Oman's overall logistics and diversification strategy, given the importance of transshipment gateway role. The evidence suggests that the recent capacity expansion at Salalah has not matched with the proportional increase in the throughput, which draws the conclusion that need to prioritize commercial and connectivity strategy along with the infrastructural investments if the port needs to reverse its declining trend and defend itself against the competing competitors.

This study is subject to some limitations that can suggest for future research. Firstly, the analysis is confined to only four physical and one composite input variable and a single throughput. It does not include financial or cost-based inputs which can refine the efficiency estimates. Secondly the DEA window analysis approach used here disseminates efficiency change into its technical change and scale efficiency components, by applying Malmquist Productivity Index alongside the window analysis as in Atsunyo and Tetteh (2025) have allowed the observed decline in Salalah to be attributed to the frontier shift versus catch up effects. Thirdly expanding the comparator set to include additional MENA ports would strengthen the robustness of Salalah's relative ranking among the peers.

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