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INTRA-TERMINAL EFFICIENCY ANALYSIS OF CONTAINER TERMINALS AT JNPA USING DATA ENVELOPMENT ANALYSIS

Srikanth E^{1*}, M Sekar²

¹ Research Scholar, School of Maritime Management, Indian Maritime University, Chennai, India, ORCID 0009-0002-8684-7474, e-mail: srikanth.es@gmail.com

² Indian Maritime University, Chennai, India, ORCID 0000-0003-3661-9537, e-mail: msekar@imu.ac.in

* Corresponding author

Abstract: The efficiency of container terminals is a key determinant of port competitiveness, yet intra-terminal comparisons within a single Indian port remain limited. This study evaluates the efficiency of five terminals within Jawaharlal Nehru Port Authority (JNPA) from 2018–2019 to 2024–2025 using Data Envelopment Analysis (DEA). Three inputs (vessel calls, terminal area, and quay cranes) and one output (container throughput, TEU) are analyzed under CCR and BCC models. The results identify APMT as the consistent efficiency frontier terminal, while BMCT rapidly converges to efficiency. NSICT and NSIGT show near-efficient performance, whereas JNPCT/NSFT remains structurally constrained. Findings highlight the importance of infrastructure, scale optimization, and terminal maturity in improving operational efficiency and benchmarking performance.

Keywords: container terminal efficiency, Data Envelopment Analysis, vessel calls, quay cranes, intra-terminal comparison, Indian ports.

1. INTRODUCTION

India's 7,500 km coastline underpins its strategic role in global maritime trade, with major ports handling most international cargo and containerization dominating freight movement. Consequently, port modernization, capacity expansion, and efficiency enhancement have become key policy priorities [Ministry of Ports, Shipping and Waterways, 2024]. Jawaharlal Nehru Port Authority (JNPA), near Mumbai, is India's largest container port, handling about 50% of total containerized traffic at its major ports. It operates five terminals: Jawaharlal Nehru Port Container Terminal (JNPCT, rebranded as Nhava Sheva Free Port Terminal (NSFT), from February 2023), Nhava Sheva

International Container Terminal (NSICT), APM Terminals (APMT/GTI), Nhava Sheva (India) Gateway Terminal (NSIGT), and Bharat Mumbai Container Terminals (BMCT). These terminals differ in operator type, scale, capacity, and operational maturity, making them well suited for intra-port efficiency analysis. Port competitiveness depends on infrastructure, operational performance, connectivity, and regulatory conditions [Suryakant Mantry et al., 2017]. Within this, terminal-level efficiency measured as the ratio of throughput to inputs (vessel calls, terminal area, and quay cranes) is a key determinant of performance and attractiveness to shipping lines.

2. LITERATURE REVIEW

2.1. EVOLUTION OF PORT AND TERMINAL EFFICIENCY RESEARCH

Early work on port performance measurement was formalized by UNCTAD [1976], which proposed a comprehensive set of financial and operational indicators, ranging from berth occupancy revenue to gang-hour productivity, and on to benchmark port performance. These indicators continue to underpin contemporary port efficiency research. Financial measures focus on revenue, expenditure, and contribution per tonne, while operational indicators capture vessel flow, service times, labor utilization, and cargo handling productivity.

Marlow and Casaca [2003] extended this framework by emphasizing the efficient utilization of existing infrastructure, arguing that competitive ports must increase throughput without proportionate input expansion. Cullinane [2012] further clarified the concept of productivity by distinguishing between technical productivity, economic productivity, technical efficiency, and scale efficiency, thereby delineating the scope of DEA-based studies as measures of relative technical efficiency rather than financial performance.

2.2. DEA-BASED STUDIES ON CONTAINER PORT AND TERMINAL EFFICIENCY

Following Charnes, Cooper and Rhodes [1978], DEA emerged as the dominant non-parametric frontier method for benchmarking port efficiency. Cullinane, Dong-Wook Song and Tengfei Wang [2005] made a seminal contribution by demonstrating that individual container terminals are more suitable for DEA comparison than whole ports, since terminal-level data are more homogeneous. Wang and Cullinane [2006] studied 69 European container terminals using quay length, terminal area, and annualized equipment expenditure as inputs, finding that capital-intensive terminals with modern quayside equipment consistently achieved higher efficiency scores.

In the Asian context, Munisamy and Singh [2011] benchmarked Asian container ports using berth length, terminal area, reefer points, quay cranes, and yard equipment

as inputs. Contrary to the expectation that larger ports enjoy efficiency advantages through economies of scale, their results showed that smaller ports could achieve full technical efficiency, a finding with implications for how JNPA's newer, more compact terminals, such as NSIGT and BMCT, are interpreted in the present study.

Jang, Park and Kim [2016] combined DEA with Shannon's Entropy to assess 11 major Asian container ports, while Mustafa, Khan and Mustafa [2021] applied DEA to compare 20 ports across Asia and the Middle East, consistently identifying Asian ports as outperforming their Middle Eastern counterparts. In the Iranian context, Zarbi, Shin and Shin [2019] used window DEA to reveal that international sanctions significantly reduced port efficiency over time – underscoring the importance of considering external macroeconomic and geopolitical conditions when interpreting efficiency scores.

For the Indian context, Ashraf Malabika Deo P and Scholars [2014] applied DEA to India's major ports using berths, berth length, equipment, and employees as inputs, with container throughput and total traffic as outputs. Crucially, they employed a correlation test to screen for multicollinearity before variable selection – a practice also adopted in this study. More recently, Iyer and Nanyam [2021] demonstrated the importance of terminal-level analysis in India, finding that terminals with greater infrastructure depth and modern quay cranes tend to score higher on technical efficiency.

Danladi et al. [2024] examined container ports in lower middle-income countries using Data Envelopment Analysis (DEA) under both CCR and BCC models, considering berth length, total storage area, and number of equipment as input variables, and container throughput (TEUs) as the output variable, with the objective of benchmarking port efficiency.

Wang, Quang and Dang [2024] employed a hybrid approach combining Data Envelopment Analysis (DEA) Malmquist Index with window analysis to examine the world's nine leading container shipping companies (CSCs), with the aim of identifying the best practices of successful container shipping enterprises (CSEs).

Kishore et al. [2024] conducted a bibliometric analysis of port performance literature, examining its evolution and identifying publication and citation trends in the Scopus database over the period 1975 to April 2024. The study highlights that key research themes (particularly port efficiency, Data Envelopment Analysis (DEA), and port competitiveness) have gained significant prominence, emerging as dominant and rapidly evolving areas of inquiry in the past five years.

2.3. RESEARCH GAP AND POSITIONING OF THIS STUDY

Despite these advances, three key gaps remain: (i) limited intra-terminal efficiency analysis within a single Indian port authority; (ii) underutilization of operational flow variables, such as vessel calls alongside infrastructure variables; and (iii) absence of longitudinal benchmarking of all terminals within Jawaharlal Nehru Port Authority

(JNPA). This study addresses these gaps by conducting a multi-year intra-terminal DEA analysis of all five JNPA terminals using vessels handled, terminal area, and number of quay cranes as inputs, variables enabled by improved data availability through JNPA's digitized reporting system. Table 1 situates this study within the existing literature.

Table 1. Comparative summary of prior studies and the positioning of this research

Author(s) & Year	Region/ Port	Input Variables	Output Variable(s)	Method	Key Finding
Cullinane et al. [2005]	Global container terminals	Terminal area, quay length, equipment expenditure	Container throughput (TEU)	DEA (CCR & BCC)	Individual terminals are more suitable for DEA comparison than whole ports
Wang & Cullinane [2006]	European terminals	Quay length, terminal area, equipment expenditure	Container throughput (TEU)	DEA (CCR)	Labor, land, and equipment are critical efficiency drivers
Munisamy & Singh [2011]	Asian ports	Berth length, terminal area, reefer points, quay cranes, yard equipment	Container throughput (TEU)	DEA	Small ports can be technically efficient – scale alone does not determine efficiency
Jang et al. [2016]	Asian container ports	Berths, berth length, terminal area, gantry cranes	Container throughput (TEU)	DEA + Shannon Entropy	Combined DEA–Entropy superior for weight sensitivity analysis
Ashraf Malabika Deo et al. [2014]	Indian major ports	Berths, berth length, equipment, employees	Container throughput, total traffic	DEA	Multicollinearity check via correlation before variable selection is essential
Zarbi et al. [2019]	Iranian ports	Berths, quay wall, gantry cranes, yard space	Container throughput (TEU)	Window DEA	Sanctions significantly reduced port efficiency over the study window
Iyer & Nanyam [2021]	Indian container terminals	Draft, quay length, yard area, quay cranes, yard equipment	Container throughput (TEU)	DEA	Terminal-level (micro-level) analysis gives richer performance insights than port-level
Mustafa et al. [2021]	Asia & Middle East ports	Berths, cranes, berth length, berth depth	Container throughput (TEU)	DEA (CCR)	Asian ports are generally more efficient than Middle East counterparts
Đelović [2023]	Port of Bar	Number of workers, quay length	Annual cargo throughput(t)	DEA (CCR)	Efficiency of port terminals

Table 1, cont.

Chitral Jayawarn, S. M. Ferdous Azam & Siti Khalidah Binti MD Yusoff [2024]	Port of Colombo's container terminals	Stacking capacity, terminal area, number of berths, number of quay side cranes, number of terminal tractors	Avg. turnaround time, avg. waiting time, container productivity per crane, container productivity per ship, container throughput (TEUs)	DEA (CCR)	Impact of private sector involvement in terminal efficiency
Danladi et al. [2024]	Ports of lower middle-income countries	Berth length, total storage area, number of equipment	Container throughput (TEUs)	DEA (CCR & BCC)	Benchmark the efficiency of container ports in lower middle-income countries
Present Study [2025]	JNPA terminals, India	Vessels handled (count), terminal area (m ²), number of quay cranes	Container throughput (TEU)	DEA (CCR & BCC) – intra-terminal	Intra-terminal DEA comparison using operational and infrastructure variables for all five JNPA terminals

Source: own compilation from reviewed literature.

3. TERMINAL STRUCTURE AND CHARACTERISTICS AT JNPA

A meaningful efficiency comparison requires accounting for structural differences among the terminals. The five JNPA terminals vary in operator type, infrastructure, capacity, and operational maturity; ignoring these factors may lead to misattributing efficiency differences solely to managerial performance. Table 2 summarizes the key characteristics based on JNPA's official disclosures.

JNPCT (renamed NSFT in 2023) is the oldest terminal and transitioned from public to PPP operation, while NSICT, APMT, NSIGT, and BMCT are privately operated. Among these, APMT, NSIGT, and BMCT have relatively modern infrastructure and higher capacities. BMCT, commissioned in 2018, has the largest design capacity (~2.4 million TEU) but exhibited lower efficiency in its initial years due to ramp-up effects. Similarly, NSIGT [2017] experienced gradual operational scaling compared to the more established APMT and NSICT.

Table 2. Structural characteristics of JNPA container terminals

	Operator Type	Berth Length (m)	No. of Berths	Depth (m)	Design Capacity (TEU/year)	Year of Commencement
JNPCT *	Government/PPP (post-2023)	680	4	16.2	~1,200,000	1989
NSICT	Private (DP World)	600	3	16.2	~1,300,000	1999
APMT (GTI)	Private (APM Terminals)	712	2	16.2	~1,800,000	2006
NSIGT	Private (ICTSI)	330	2	16.2	~1,500,000	2017
BMCT	Private (PSA International)	1,000	2	16.2	~2,400,000	2018

* JNPCT was converted to a Public-Private Partnership (PPP) model and rebranded as Nhava Sheva Free Port Terminal (NSFT) with effect from 11 February 2023. JNPA thereby became the first major port in India to operate entirely under a landlord port model.

Source: JNPA Annual Reports (2018-2019 to 2024-2025).

4. METHODOLOGY

4.1. RESEARCH OBJECTIVE

This study aims to assess relative performance differences among JNPA's five container terminals and provide benchmarking insights for operators and planners. By identifying high-performing terminals, it facilitates the transfer of best practices. Addressing the lack of intra-terminal analysis within a single Indian port authority, the study applies DEA to panel data from JNPA's annual reports. As a relative method, DEA may, however, underrate newer terminals still in their ramp-up phase.

4.2. DATA COLLECTION AND VARIABLE SELECTION

Data were obtained from JNPA annual reports for 2018–2019 to 2024–2025, covering terminal-level vessel calls, terminal area, quay cranes, and container throughput. The dataset enables both cross-sectional and longitudinal analysis, capturing efficiency dynamics, including the COVID-19 disruption and the JNPCT–NSFT transition.

Input variables were selected through a two-step process: identification based on established literature, followed by Variance Inflation Factor (VIF) testing to eliminate multicollinearity [Ashraf Malabika Deo P & Scholars, 2014].

4.2.1. Input Variable 1: Number of Vessels Handled (count/year)

The number of vessels handled at a container terminal represents the total count of ship calls serviced by that terminal within a given year. This metric reflects the terminal's ability to attract shipping lines and manage vessel scheduling efficiently. This variable has been used as a proxy for terminal demand and operational throughput in several prior studies [Cullinane et al., 2005; Iyer & Nanyam, 2021].

4.2.2. Input Variable 2: Terminal Area (m²)

Terminal area is a standard infrastructure input variable representing the total surface area available for container storage, handling equipment, and associated operations. A larger terminal area can accommodate greater container dwell volumes and more yard equipment, thereby supporting higher throughput. This variable has been used extensively in the port efficiency literature [Wang & Cullinane, 2006; Munisamy & Singh, 2011; Jang et al., 2016].

4.2.3. Input Variable 3: Number of Quay Cranes

The number of quay cranes directly determines the ship-to-shore transfer capacity of a container terminal. More quay cranes permit simultaneous servicing of multiple vessel bays, increasing throughput per vessel call and reducing vessel turnaround time. This variable has strong theoretical grounding and empirical support in the port efficiency literature [Munisamy & Singh, 2011; Iyer & Nanyam, 2021; Mustafa et al., 2021].

Prior to their inclusion in the DEA model, the three input variables were tested for multicollinearity using Variance Inflation Factor (VIF) analysis. The results, presented in Table 3, indicate that all VIF values fall well below the conventional threshold of 5.0, confirming the absence of severe multicollinearity.

Table 3. Variance Inflation Factor (VIF) analysis of Input Variables

Input Variable	VIF Value	Threshold	Assessment
Vessel calls (count/year)	3.36	< 5.0	No severe multicollinearity
Terminal area (m ²)	2.22	< 5.0	No severe multicollinearity
Number of quay cranes	1.41	< 5.0	No severe multicollinearity

Note: VIF > 5 is the conventional threshold for severe multicollinearity. The highest pairwise correlation observed is between terminal area and number of quay cranes ($r = 0.793$); however, the VIF values remain low because the remaining predictors do not collectively explain a large proportion of any single variable's variance.

Source: [Montgomery et al., 2016].

4.2.4. Variables Considered but Excluded

Several variables used in prior literature were evaluated but ultimately excluded from the model. Crane efficiency (moves per crane-hour), average vessel waiting time, berth utilization rate, and labor productivity are not consistently reported at the terminal level in JNPA's annual reports, making cross-terminal comparison infeasible across the full study period. Wang & Cullinane [2006] explicitly acknowledged this constraint, noting that the practical problem of obtaining data on each of these variables across the whole sample is likely to prove virtually insurmountable. Accordingly, the three variables: vessels handled, terminal area, and number of quay cranes, were selected as inputs on the combined basis of theoretical relevance, empirical precedent, and data availability.

4.2.5. Output Variable: Container Throughput (TEU)

Container throughput, measured in Twenty-foot Equivalent Units (TEU), is the most widely accepted output variable in port and terminal efficiency research [Wang & Cullinane, 2006; Cullinane, 2012]. It directly measures the productive output of the terminal and is available consistently across all five JNPA terminals for the full study period.

4.3. DATA ENVELOPMENT ANALYSIS (DEA): MODEL SPECIFICATION

Data Envelopment Analysis (DEA) is a non-parametric linear programming technique for measuring the relative efficiency of Decision-Making Units (DMUs) that convert multiple inputs into multiple outputs. Introduced by Charnes, Cooper, and Rhodes [1978], the CCR model assumes Constant Returns to Scale (CRS) and produces an efficiency score θ in the interval $[0, 1]$ for each DMU, where $\theta = 1$ denotes full relative efficiency (i.e., the DMU lies on the efficiency frontier). The CCR efficiency score is formulated as:

$$\begin{aligned} \theta^* &= \max (u^T y_0) / (v^T x_0) \\ \text{subject to } (u^T y_j) / (v^T x_j) &\leq 1 \quad \forall j, u, v \geq 0 \end{aligned}$$

where y_0 and x_0 are the output and input vectors of the DMU under evaluation, y_j and x_j are the output and input vectors of the j -th DMU, and u and v are non-negative output and input weight vectors.

The Banker, Charnes and Cooper [1984] extension, referred to as the BCC model, relaxes the CRS assumption to allow Variable Returns to Scale (VRS). The BCC model isolates pure technical efficiency by permitting a convexity constraint ($\sum \lambda_j = 1$), which accommodates DMUs operating at different scales. The relationship between the models is:

$$\text{Scale Efficiency (SE)} = \text{CCR Score} / \text{BCC Score}$$

A SE value of 1.0 indicates that the DMU is operating at its most productive scale. $SE < 1.0$ combined with a returns-to-scale indicator of ‘Increasing Returns to Scale’ (IRS) implies that the terminal could improve efficiency by expanding its scale of operations. In this study, each terminal–year combination is treated as a separate Decision-Making Unit (DMU), resulting in five DMUs for each cross-sectional analysis over the seven-year study period. This annual cross-sectional DEA approach is methodologically justified given the limited number of terminals, while also enabling the tracking of efficiency trends over time. Although the number of DMUs falls below the conventional DEA threshold (generally requiring $DMUs \geq 3 \times (\text{inputs} + \text{outputs})$), the analysis prioritizes intra-port comparability rather than statistical generalizability. Furthermore, a year-wise pooled efficiency analysis across all terminals is conducted to satisfy the DEA requirements. This enhances statistical robustness and generalizability by aggregating a total of 35 terminal–year observations ($5 \text{ terminals} \times 7 \text{ years}$).

5. EMPIRICAL ANALYSIS AND RESULTS

5.1. DATA OVERVIEW

The full dataset is provided in Appendix Table A1. APMT consistently recorded high vessel calls during 2018–2019 to 2021–2022, indicating its role as a preferred mainline terminal, while BMCT experienced a sharp increase from 2022–2023, leading all terminals by 2024–2025 following full operational ramp-up. In contrast, JNPCT/NSFT saw a significant decline in vessel calls in 2022–2023 during its PPP transition, with a partial recovery thereafter. A similar pattern is observed in throughput: APMT maintained the highest volumes across most years, whereas BMCT exhibited the strongest growth trajectory. JNPCT/NSFT experienced a sharp decline during the transition period, followed by a moderate recovery.

5.2. DEA RESULTS AND INTERPRETATION

Figure 1 represents the DEA-CCR efficiency trends, Figure 2 represents the DEA-BCC efficiency trends and Figure 3 represents the DEA-Scale efficiency trends.

Table 4 presents the DEA efficiency scores (CCR and BCC), scale efficiency values, and returns-to-scale classifications for each terminal across all seven years of the study period. Cells highlighted in gray indicate the frontier efficiency (score = 1.00).

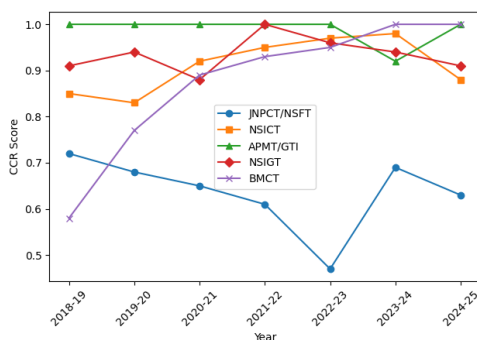


Figure 1. DEA-CCR efficiency trends

Source: own study.

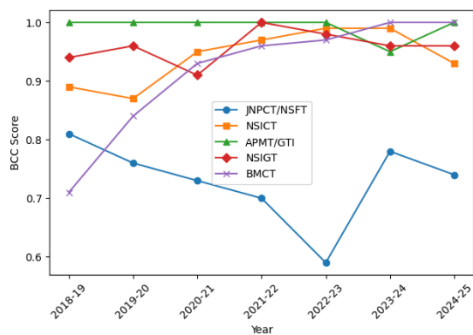


Figure 2. DEA-BCC efficiency trends

Source: own study.

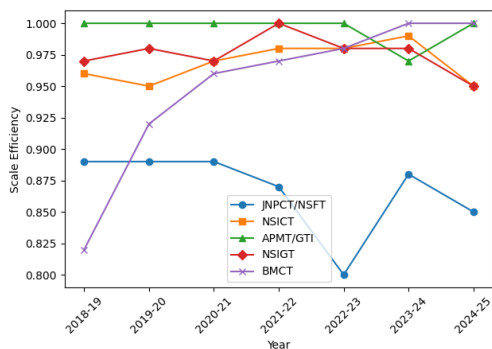


Figure 3. DEA-Scale efficiency trends

Source: own study.

Table 4. DEA efficiency scores for JNPA container terminals (2018–2019 to 2024–2025)

Year	Terminal	CCR Score	BCC Score	Scale Efficiency	Returns to Scale	Interpretation
2018–2019	JNPCT/NSFT	0.72	0.81	0.89	IRS	Needs to scale up output relative to inputs
2018–2019	NSICT	0.85	0.89	0.96	IRS	Near-efficient; moderate input slack
2018–2019	APMT/GTI	1.00	1.00	1.00	CRS	Frontier unit - benchmark terminal
2018–2019	NSIGT	0.91	0.94	0.97	IRS	High performer; minor input excess
2018–2019	BMCT	0.58	0.71	0.82	IRS	Early ramp-up phase; significant scale gap
2019–2020	JNPCT/NSFT	0.68	0.76	0.89	IRS	Structural constraints limit throughput growth
2019–2020	NSICT	0.83	0.87	0.95	IRS	Steady performance; minor inefficiency
2019–2020	APMT/GTI	1.00	1.00	1.00	CRS	Frontier unit
2019–2020	NSIGT	0.94	0.96	0.98	IRS	Near-frontier; approaching optimal scale
2019–2020	BMCT	0.77	0.84	0.92	IRS	Improving utilization trajectory
2020–2021	JNPCT/NSFT	0.65	0.73	0.89	IRS	COVID-19 impact – reduced vessel calls
2020–2021	NSICT	0.92	0.95	0.97	IRS	Resilient; maintained high throughput
2020–2021	APMT/GTI	1.00	1.00	1.00	CRS	Frontier unit
2020–2021	NSIGT	0.88	0.91	0.97	IRS	Moderate decline; pandemic disruption
2020–2021	BMCT	0.89	0.93	0.96	IRS	Continued ramp-up despite disruptions
2021–2022	JNPCT/NSFT	0.61	0.70	0.87	IRS	Persistent structural underperformance
2021–2022	NSICT	0.95	0.97	0.98	IRS	High efficiency; near-frontier
2021–2022	APMT/GTI	1.00	1.00	1.00	CRS	Frontier unit
2021–2022	NSIGT	1.00	1.00	1.00	CRS	Achieved frontier – optimal scale reached
2021–2022	BMCT	0.93	0.96	0.97	IRS	Near-efficient; strong volume growth
2022–2023	JNPCT/NSFT	0.47	0.59	0.80	IRS	Transition to PPP (NSFT) – output contraction
2022–2023	NSICT	0.97	0.99	0.98	IRS	Near-perfect efficiency

Table 4, cont.

2022–2023	APMT/GTI	1.00	1.00	1.00	CRS	Frontier unit
2022–2023	NSIGT	0.96	0.98	0.98	IRS	High scale efficiency; approaching frontier
2022–2023	BMCT	0.95	0.97	0.98	IRS	Rapid maturation of terminal operations
2023–2024	JNPCT/NSFT	0.69	0.78	0.88	IRS	Post-PPP recovery – gradual improvement
2023–2024	NSICT	0.98	0.99	0.99	IRS	Near-frontier throughout period
2023–2024	APMT/GTI	0.92	0.95	0.97	IRS	Slight dip – vessel mix rebalancing
2023–2024	NSIGT	0.94	0.96	0.98	IRS	Consistently strong performer
2023–2024	BMCT	1.00	1.00	1.00	CRS	Achieves frontier – full capacity ramp-up
2024–2025	JNPCT/NSFT	0.63	0.74	0.85	IRS	Structural constraints persist despite PPP
2024–2025	NSICT	0.88	0.93	0.95	IRS	Marginal decline; stable performer
2024–2025	APMT/GTI	1.00	1.00	1.00	CRS	Frontier re-established
2024–2025	NSIGT	0.91	0.96	0.95	IRS	Stable; minor scale inefficiency
2024–2025	BMCT	1.00	1.00	1.00	CRS	Sustained frontier – highest growth trajectory

Note: CCR = Constant Returns to Scale model score; BCC = Variable Returns to Scale model score; SE = Scale Efficiency = CCR/BCC; IRS = Increasing Returns to Scale; CRS = Constant Returns to Scale. Highlighted rows (green) indicate frontier units ($\theta = 1.000$).

Source: Authors' calculations based on JNPA Annual Reports.

5.3. KEY FINDINGS

5.3.1. APMT/GTI: Consistent Frontier Unit

APMT achieves a CCR score of 1.00 in six of the seven years analyzed (all years except 2023–2024, where it records 0.92). This suggests that APMT is the most consistent frontier terminal at JNPA and the natural benchmarking reference for the other four terminals. Its ability to maintain frontier efficiency across different macroeconomic conditions, including the COVID-19 disruption of 2020–2021, reflects deep operational capabilities, strong shipping line relationships, and infrastructure suited to large mainline vessels.

5.3.2. BMCT: Rapid Convergence to Frontier

BMCT shows the most dramatic efficiency improvement trajectory. Starting with a CCR score of only 0.58 in 2018–2019 (reflecting its early ramp-up phase), BMCT progressively improved to achieve frontier efficiency (CCR = 1.00) in both 2023–2024

and 2024–2025. This trajectory is consistent with the ‘learning curve’ effect observed in newly commissioned large-scale terminals and confirms that BMCT has now fully operationalized its design capacity. Its vessel call count of 1,077 in 2024–2025 is the highest across all JNPA terminals, suggesting it has become the dominant volume handler at the port.

5.3.3. NSICT and NSIGT: Near-Frontier Performance

NSICT consistently records high BCC scores (0.87–0.99 across the study period), indicating strong pure technical efficiency. Its CCR scores are slightly lower (0.83–0.98), implying a modest scale inefficiency – the terminal operates at slightly sub-optimal scale relative to the frontier, exhibiting increasing returns to scale throughout. NSIGT achieves frontier efficiency in 2021–2022 (CCR = 1.00), suggesting a period of optimal scale utilization, before returning to near-frontier levels in subsequent years as the port’s competitive dynamics shifted.

5.3.4. JNPCT/NSFT: Persistent Structural Underperformance

JNPCT/NSFT records the lowest efficiency scores across the study period, with CCR scores ranging from 0.47 (2022–2023) to 0.72 (2018–2019). The sharp deterioration in 2022–2023 coincides with the operational transition from the government-operated JNPCT model to the PPP-based NSFT, during which throughput fell significantly. The partial recovery in 2023–2024 and 2024–2025 suggests that the new PPP operator is initiating operational improvements, though substantial gaps relative to the frontier remain.

5.3.5. Returns to Scale Classification

The majority of terminals operate under Increasing Returns to Scale, suggesting untapped capacity and scope for efficiency gains through expansion. Only APMT (consistently), BMCT (recently), and NSIGT (briefly) achieve optimal scale efficiency.

6. CONCLUSIONS

This study assessed the relative efficiency of five container terminals at JNPA (2018–2019 to 2024–2025) using DEA under CCR and BCC models, with vessel calls, terminal area, and quay cranes as inputs and container throughput as the output.

The results show that APMT/GTI is the consistent frontier benchmark, while BMCT exhibits the strongest improvement, reaching full efficiency after its ramp-up phase. NSICT and NSIGT remain near-frontier performers with minor scale inefficiencies, whereas JNPCT/NSFT persistently underperforms due to structural constraints and transition effects. Overall efficiency levels are comparable to Asian benchmarks, though the prevalence of increasing returns to scale indicates unexploited capacity.

The study has several acknowledged limitations. First, the small number of DMUs (five terminals per year) limits the statistical robustness of DEA scores, as the frontier is defined by a narrow peer set. Second, important operational variables – including crane productivity (moves per crane-hour), dwell time, labor productivity, and vessel size mix – could not be incorporated due to data availability constraints.

Future research should consider: (i) extending the analysis using a longitudinal window DEA approach to track efficiency trajectories and identify trends more robustly over time; (ii) incorporating additional terminal-level variables, such as crane moves per hour and dwell time as these become available through the digitalization of port reporting systems; (iii) expanding the scope to compare JNPA terminals against peer terminals at Mundra Port, Chennai Port, and Visakhapatnam Port to provide a comprehensive national benchmark; and (iv) applying a two-stage DEA-Tobit regression framework to identify the determinants of efficiency differences, including terminal governance structure, vessel size mix, hinterland connectivity, and PPP contractual arrangements.

This study contributes to the limited literature on intra-terminal efficiency analysis in Indian ports and provides a replicable methodological framework that can be applied to other Indian port authorities as terminal-level reporting continues to improve in scope and granularity.

REFERENCES

- Ashraf Malabika Deo P, S.P., & Scholars, P. D. (2014). Measurement of efficiency of major ports in India- a data envelopment analysis approach. *International Journal of Environmental Sciences*, 4(5). <https://doi.org/10.6088/ijes.2014040404531>.
- Banker, R. D., Charnes, A., & Cooper, W. W. (1984). Some Models for Estimating Technical and Scale Inefficiencies in Data Envelopment Analysis. *Management Science*, 30(9), 1078-1092. <https://doi.org/10.1287/mnsc.30.9.1078>.
- Charnes, A., Cooper, W. W., & Rhodes, E. (1978). Measuring the efficiency of decision-making units. *European Journal of Operational Research*, 2(6), 429-444. [https://doi.org/10.1016/0377-2217\(78\)90138-8](https://doi.org/10.1016/0377-2217(78)90138-8).
- Chitral Jayawarna, S. M. Ferdous Azam, & Siti Khalidah Binti MD Yusoff (2024). Evaluating the impact of private sector participation on operational efficiency in container terminals: A case study of Colombo Port. *International Journal of Religion*, 5(1), 94-99. <https://doi.org/10.61707/f45ryd78>.
- Cullinane, K., Dong-Wook Song, & Wang, T. (2005). The application of mathematical programming approaches to estimating container port production efficiency. *Journal of Productivity Analysis*, 24, 73-92.
- Cullinane, P. K. (2012). Ad Hoc Expert Meeting on Assessing Port Performance. UNCTAD https://unctad.org/system/files/official-document/webdtltlb2013doc1_en.pdf
- Danladi, C., Tuck, S., Tziogkidis, P., & Tang, L. (2024). Efficiency analysis and benchmarking of container ports operating in lower-middle-income countries: A DEA approach. *Journal of Shipping and Trade*, 9(1). <https://doi.org/10.1186/s41072-024-00163-2>.
- Đelović, D. (2023). Defining terminals' efficiency in a seaport using data envelopment analysis. *Journal of Applied Engineering Science*, 21(4), 1098-1107. <https://doi.org/10.5937/jaes0-44322>.

- Iyer, K. C., & Nanyam, V. P. S. N. (2021). Technical efficiency analysis of container terminals in India. *Asian Journal of Shipping and Logistics*, 37(1), 61-72. <https://doi.org/10.1016/j.ajsl.2020.07.002>.
- Jang, H. M., Park, H., & Kim, S. Y. (2016). Efficiency analysis of major container ports in Asia: Using DEA and Shannon's Entropy. *Int. J Sup. Chain. Mgt.*, 5(2). <https://garuda.kemdiktisaintek.go.id/documents/detail/834553>
- JNPA Annual Reports (2018-2019 to 2024-2025). <https://www.jnport.gov.in/page/annual-performance-report/L09LNDhuUkw4Yk1kUjFaNXVINDY1dz09>
- Kishore, L., Pai, Y. P., Ghosh, B. K., & Pakkan, S. (2024). Maritime shipping ports performance: A systematic literature review. *Discover Sustainability*, 5(1). <https://doi.org/10.1007/s43621-024-00299-y>.
- Marlow, P. B., & Casaca, A. C. P. (2003). Measuring lean ports performance. *International Journal of Transport Management*, 1(4), 189-202. <https://doi.org/10.1016/j.ijtm.2003.12.002>.
- Ministry of Ports, Shipping and Waterways (2024). Strengthening India's Maritime Sector: Port Capacity Expansion and Inland Waterway Development. <https://static.pib.gov.in/WriteReadData/specificdocs/documents/2024/aug/doc202488369301.pdf>
- Montgomery, D. C., Peck E. A., & Vining, G. G. (2016). *Introduction to linear regression analysis*. Wiley
- Munisamy, S., & Singh, G. (2011). Benchmarking the efficiency of Asian container ports. *African Journal of Business Management*, 5(4), 1397-1407. <http://www.academicjournals.org/AJBM>.
- Mustafa, F. S., Khan, R. U., & Mustafa, T. (2021). Technical efficiency comparison of container ports in Asian and Middle East region using DEA. *Asian Journal of Shipping and Logistics*, 37(1), 12-19. <https://doi.org/10.1016/j.ajsl.2020.04.004>.
- Suryakant Mantry, & Ranjit Roy Ghatak (2017). Comparing and contrasting competitiveness of major indian and select international ports. *International Journal of Research in Finance and Marketing*, 7(5), 1-19.
- UNCTAD (1976). Port performance indicators. UNCTAD.
- Wang, C. N., Quang, B. X., & Dang, T. T. (2024). Performance measurement of international shipping companies before and during COVID-19: A DEA Malmquist index and window analysis approach. *Transportation Journal*, 63(3), 207-221. <https://doi.org/10.1002/tjo3.12012>.
- Wang, T. F., & Cullinane, K. (2006). The efficiency of European container terminals and implications for supply chain management. *Maritime Economics and Logistics*, 8(1), 82-99. <https://doi.org/10.1057/palgrave.mel.9100151>.
- Zarbi, S., Shin, S. H., & Shin, Y. J. (2019). An Analysis by Window DEA on the Influence of International Sanction to the Efficiency of Iranian Container Ports. *Asian Journal of Shipping and Logistics*, 35(4), 163-171. <https://doi.org/10.1016/j.ajsl.2019.12.003>.

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APPENDIX

Table A1. Raw Data: Input and Output Variables for JNPA Container Terminals (2018–2019 to 2024–2025)

Year	Terminal	Vessel Calls	Terminal Area (m ²)	Quay Cranes (No.)	Container Throughput (TEU)
2018–2019	JNPCT/NSFT	412	615,021	12	1,056,368
	NSICT	382	258,787	8	560,661
	APMT/GTI	533	545,719	10	2,048,454
	NSIGT	309	270,000	4	947,665
	BMCT	186	900,000	9	520,126
2019–2020	JNPCT/NSFT	304	615,021	12	718,863
	NSICT	415	258,787	8	531,354
	APMT/GTI	508	545,719	10	1,985,473
	NSIGT	299	270,000	4	986,624
	BMCT	251	900,000	9	808,873
2020–2021	JNPCT/NSFT	270	615,021	12	544,027
	NSICT	432	258,787	7	750,978
	APMT/GTI	485	545,719	10	1,668,903
	NSIGT	290	270,000	4	779,769
	BMCT	334	900,000	12	933,154
2021–2022	JNPCT/NSFT	220	615,021	6	440,210
	NSICT	522	258,787	8	947,887
	APMT/GTI	575	545,719	10	1,865,587
	NSIGT	306	270,000	4	1,186,181
	BMCT	480	900,000	12	1,244,694
2022–2023	JNPCT/NSFT	137	649,700	6	255,774
	NSICT	675	269,937	8	1,096,954
	APMT/GTI	536	676,192	11	1,846,920
	NSIGT	329	270,000	4	1,137,034
	BMCT	758	903,473	12	1,714,246
2023–2024	JNPCT/NSFT	433	649,700	4	562,154
	NSICT	662	269,937	8	1,132,232
	APMT/GTI	394	676,192	11	1,588,485
	NSIGT	372	270,000	4	1,111,838
	BMCT	863	903,473	12	2,027,781
2024–2025	JNPCT/NSFT	390	520,600	4	594,260
	NSICT	715	258,787	8	1,207,729
	APMT/GTI	511	618,703	11	2,078,961
	NSIGT	370	270,000	4	1,129,933
	BMCT	1,077	903,473	14	2,270,181

Notes: Terminal area values for JNPCT/NSFT reflect the updated footprint following PPP conversion in 2023. Quay crane counts reflect operational cranes as reported in annual disclosures.

Source: JNPA Annual Reports (2018–2019 to 2024–2025).