

Yard storage strategies, dwell time reduction, and performance outcomes in an emerging automated maritime terminal

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Abstract — This research investigates how container dwell time affects the throughput and rehandling productivity at maritime terminals with focus on Lekki Freeport Terminal (LFT) - an emerging automated maritime hub in Nigeria. A deterministic slot-based rehandling structure is first established to characterize the vertical inefficiency embedded in dense stacking configurations, after which Monte Carlo Simulation is applied to capture uncertainty in container retrieval. Results show strong statistical consistency of the simulation, with the expected number of rehandles converging tightly to a theoretical mean of 2.00 as sample size increases. Scenario analysis reveals a nonlinear relationship between average stack height and rehandling intensity: expected rehandles rise from 0 at a stack height of 1.00 to 1.22 at 2.29 tiers. When heterogeneous retrieval behavior is introduced, expected rehandles increase substantially, exceeding 1.9 at low stack heights and remaining significantly higher than under equal-probability assumptions. These findings demonstrate that ignoring demand heterogeneity leads to systematic underestimation of congestion and handling costs. The study provides quantitative evidence to support stochastic, data-driven yard planning as a basis for improving operational efficiency and economic sustainability in emerging container terminals.

Index Terms— container terminals, rehandling productivity, Monte Carlo simulation, yard stacking, operational efficiency

I. INTRODUCTION

Containerization has profoundly reshaped global trade by standardizing cargo transport and enabling seamless movement of goods across long distances. Trade liberalization and deeper economic integration have accelerated the adoption of containerized shipping, driven by rising demand for both capital and consumer goods (Watada et al., 2019). This transformation has reduced transportation costs, enhanced reliability, and fostered international collaboration between geographically distant economies (Coşar & Demir, 2018). The expansion of containerized trade has been rapid and sustained, reinforcing the role of container shipping as a cornerstone of international commerce and a key facilitator of global value chains (Ding & Wang, 2022). As a result, ports have evolved into critical nodes in the global logistics system, where efficient container handling is closely linked to trade competitiveness and economic growth (Notteboom et al., 2020).

The continued growth of containerized trade has significantly influenced port development and operational strategies worldwide. To cope with increasing demand and limited physical expansion opportunities, container terminals are increasingly adopting smart port concepts aimed at improving productivity, efficiency, and competitiveness (Hlali & Hammami, 2019). Innovations such as inland ports and dry ports have further enhanced hinterland connectivity and strengthened seaport competitiveness by easing congestion at coastal terminals (Jeevan et al., 2018). However, translating global trade growth into terminal-level performance remains challenging due to uncertainty in vessel arrivals, fluctuating volumes, and limited operational data. These

uncertainties can lead to unexpected demand surges that strain terminal capacity and disrupt operations (Eskafi et al., 2021a; Eskafi et al., 2021b).

In response to these pressures, port authorities and terminal operators increasingly prioritize operational optimization over physical expansion. The development of new greenfield terminals has become difficult due to land scarcity, escalating construction costs, and stricter environmental and regulatory constraints. Consequently, terminals focus on improving throughput and productivity within existing infrastructure (Smith, 2021). Strategies such as automation, digitalization, and data-driven decision support systems are widely implemented to enhance yard efficiency and reduce turnaround times (Weerasinghe et al., 2024). These approaches enable terminals to manage higher container volumes without proportional increases in space or labor, thereby improving resilience against demand volatility.

Among operational strategies, reducing container dwell time has emerged as a particularly influential lever for improving terminal performance. Shorter dwell times free up yard space, reduce congestion, and support higher throughput by accelerating container circulation (Eskafi et al., 2021a). Complementary measures such as blocking containers by destination and extending gate hours further enhance operational efficiency by smoothing truck arrivals and reducing peak-period congestion (Eskafi et al., 2022). Increasing storage density through higher stacking or mixed stacking of import containers also allows terminals to maximize limited yard space. However, these strategies introduce trade-offs, as higher and mixed stacks tend to increase container rehandling, which negatively affects truck turn time and operational productivity.

Balancing storage density with rehandling productivity is therefore a critical challenge for terminal operators. Rehandling productivity, defined as the ratio of import deliveries to total import moves, directly influences truck turn time and environmental performance. Decisions on free time policies and stacking strategies are often made without a clear quantitative understanding of their combined effects on throughput and rehandling productivity. To address this gap, analytical and simulation-based approaches are increasingly adopted to evaluate yard performance under uncertainty. Monte Carlo Simulation, in particular, provides a robust method for estimating expected rehandling activity by capturing variability in dwell time, stack height, and retrieval behavior without imposing restrictive assumptions (Chen et al., 2024; Feng et al., 2020). Such methods support more informed, data-driven decision-making and offer valuable insights for optimizing yard operations in space-constrained container terminals.

II. MATERIALS AND MODELS

The establishment of free trade zones, such as the Hainan Free Trade Port, demonstrates a commitment to expanding economic opportunities and fostering international trade (Chen & Wang, 2021). These zones act as hubs for shipping, logistics, and emerging industries, stimulating economic growth and regional development (Eskafi et al., 2021a). Comparative analyses of free trade zone policies across regions highlight their impact on trade dynamics, investment attraction, and industrial clustering (Coşar & Demir, 2018). The creation of free trade zones encourages strategic collaborations and infrastructure development, ensuring efficient logistics flows and global competitiveness, particularly in regions aiming to integrate into international trade networks (Weerasinghe et al., 2024; Zhang et al., 2025).

In Nigeria, the development of zones like the Lekki Free Trade Zone and the Ogun Zone underscores the importance of these areas as focal points for economic engagement (Adunbi & Stein, 2019; Ding & Wang, 2022). Through strategic alliances, infrastructure investments, and policy evaluations, these zones serve as catalysts for job creation, regional cooperation, and economic growth. Lessons from global free trade zones emphasize the necessity of automation, technology adoption, and effective resource allocation to maximize operational efficiency and attract international business investments (Cho et al., 2022; Feng et al., 2022).

The Lekki Freeport Terminal, located within the Lekki Free Trade Zone, reflects broader trends in urbanization, economic development, and international trade initiatives. As an extension of CMA CGM operations in Nigeria, it represents a strategic collaboration aimed at enhancing port operations, modernizing infrastructure, and improving service delivery. This terminal aligns with global trends in port development, where strategic alliances and investment in technological capabilities enhance throughput, reduce operational costs, and ensure competitive positioning within the maritime industry (Gerrits & Schuur, 2022; He et al., 2024).

The terminal is the first automated facility in Nigeria, utilizing advanced container handling equipment (CHEs), including Ship-to-Shore cranes (STSs), Rubber Tyre Gantry cranes (RTGs), Empty Container Handlers (ECHs), Reach Stackers (RS), and Terminal Tractors (TTs). Automation at Lekki Freeport Terminal enhances operational efficiency, optimizes container handling, and reduces reliance on manual labor (Zhou & Zhang, 2024). Such advancements in automation are crucial for achieving higher throughput, minimizing dwell times, and meeting global standards in port management, making the terminal a model for technological adoption in Nigeria (Chen et al., 2024).

Berth allocation and container yard management are central to terminal operations, ensuring efficient transfer of containers between vessels and land-based transport (Eskafi et al., 2021b). Efficient berth allocation determines vessel turnaround times, optimizes the use of quay cranes, and reduces operational delays (Eskafi et al., 2022). Yard layout optimization, including logical modeling of equipment movement and container placement, further enhances operational efficiency, enabling smooth cargo flows and reducing congestion within the terminal (Fischer et al., 2006; Yu et al., 2021).

Effective yard operations also require the integration of advanced scheduling and stacking strategies. Studies emphasize the use of smart stacking methods, automated crane scheduling, and data-driven container relocation strategies to minimize rehandling moves and maximize throughput (Feng et al., 2022; Tang et al., 2026). By leveraging reinforcement learning and deep learning techniques, terminals can predict container movements, dynamically allocate storage spaces, and optimize stacking sequences to improve operational efficiency and reduce delays (Drungilas et al., 2023; Yan et al., 2024).

Lekki Freeport Terminal is strategically organized into three areas, subdivided into blocks serving specific operational purposes. Blocks A and B accommodate export containers, C, D, and E handle imports, and Block F is dedicated to reefer containers requiring specialized storage conditions. Additional blocks manage import delivery (1G–3G, 1H), maintenance (2H), out-of-gauge cargo (3E), and seal cutting (3H). Empty containers are stored in Areas 1J–3K before processing or dispatch (Zhang et al., 2025). This structured layout ensures optimal space utilization, operational efficiency, and smooth cargo flows, reflecting best practices in global terminal management.

Overall, the Lekki Freeport Terminal exemplifies the integration of automation, strategic planning, and smart yard management within a free trade zone. Its design and operational strategies highlight the importance of technology adoption, advanced container handling, and optimized resource allocation for port efficiency. By incorporating global lessons in terminal automation, berth allocation, and yard planning, the Lekki Freeport Terminal positions Nigeria as a competitive player in international maritime trade while serving as a model for future port developments (He et al., 2024; Cho et al., 2022; Feng et al., 2022).

III. MODEL

We introduce the model formulation and notations used to compute import throughput and describes how the MCS method is applied to estimate the number of container rehandles. We assume that maritime carriers employ diverse liner services, S , to convey products along designated trade routes and ports. A service is required to visit a designated set of ports according to a preset pro forma, P_s , utilising N vessels. It is common practice for operators to preconfigure services, vessels, and ports of call in their terminal operating systems (TOS). Assigning

a voyage i to a vessel from service S is thus a vital requirement of the terminal operator in day-to-day operations. Service S is represented by the i_s notation for the i th inbound/outbound voyage. Once a voyage is assigned, the next step for the terminal operator is to specify the vessel's schedule. Information required at this stage are: Vessel berthing position; berth 1 or berth 2; Vessel estimated time of arrival (ETA); Vessel's estimated time of departure (ETD); The beginning date for receiving export containers; and the cutoff date for receiving export containers.

Since D_s represents the time of service S 's initial voyage, then the departure time of the i th voyage of that service can be expressed mathematically as (Equation 1):

$$D_i = D_s + (i_s - 1)\rho_s \quad (1)$$

For example, if D_s for a service is t on day 0 and $\rho_s = 7$ days (i.e., weekly service), then the departure time of the first voyage is t on day 0 [$t + (1 - 1)7 = t + 0$]. Likewise, the second voyage's departure time is t on day 7 [$t + (2 - 1)7 = t + 7$] as well $t + 14$ and $t + 21$ for the third is t on day 14 and fourth is t on day 21 voyage's departure time respectively, and so on. Note that the notations make no distinction between vessels within a service. A service is designed to unload a relatively constant number of TEUs at each terminal. The volume to be unloaded is denoted as C_s^{imp} . The proportion of import containers that are delivered with x dwell days after the vessel's departure is represented as $I_s^{imp}(x)$.

The cumulative number of import containers unloaded to the container yard at time t for all service S can be calculated using the following mathematical expression below (Equation 2). Also, the annual yard throughput for imports is $\sigma(365)$. Technically, the definition of yard throughput is TEUs per year/gross acre (National Research Council, 1986). However, in this paper, we will use the term *throughput* simply to indicate the TEUs handled per year. This is done to avoid misrepresenting a container's productivity because throughput is often reported differently and gross acre is counted differently by different terminals.

$$\sigma(t) = \sum_{s=1}^S \sum_{i=1}^{i_s} C_s^{imp} H(t - D_i) \quad (2)$$

Where S is the total number of services (shipping lines) calling at the LFT terminal. i_s is the maximum i th voyage of service S up to time t (i.e., $i_s \cdot \rho_s$). D_s represents the time of the very first voyage for service S . ρ_s is the frequency (in days) of service S 's voyages.

Also, C_s^{imp} is the volume of import containers unloaded during the i th voyage for service s and H is a Heaviside step function, which ensures that the cumulative count only begins once the voyage occurs (i.e., it activates only when $t \geq D_i$), defined piece-wisely as (Equation 3):

$$H(x) = \begin{cases} 1, & x \geq 0 \\ 0, & x < 0 \end{cases} \quad (3)$$

The equation (3) sums up all the import containers unloaded from multiple shipping services, accounting for the vessels' scheduled arrival times and their dwell time in LFT terminal. The term $H(t - (D_s + (i - 1)\rho_s))$ is a step function that essentially tracks whether the vessel has already arrived at time t . The cumulative number of unloaded containers grows as more voyages arrive at LFT terminal over time. It is essential to compute the cumulative number of delivered imports at time t for all services (S), given as (Equation 4):

$$\Phi(t) = \sum_{s=1}^S \sum_{i=1}^{i_s} C_s^{imp} I_s^{imp}(t - D_i) \quad (4)$$

Where $I_s^{imp}(t - D_i)$ is the cumulative proportion of import containers from service S , delivered by time t after the vessel has arrived. Equation (5) sums up the number of containers that have been delivered by truck based on their dwell time. It accounts for the time after the containers are unloaded and the process of external trucks picking up the containers from the LFT terminal.

The number of import containers in the yard at the start of day t is (Equation 5):

$$Y(t) = \sigma(t) - \Phi(t - 1) \quad (5)$$

Assuming import containers are unloaded first before being delivered to external trucks or road trucks. Hence, the daily average stack height is (Equation 6):

$$\text{Stack Height}(t) = \frac{Y(t)}{I(20)} \quad (6)$$

Where $I(20)$ is the total number of one-tier high 20-foot container ground slots.

It has been stated that the container yard import throughput and storage density can be increased by stacking containers higher and/or by employing mixed storage policy. The rehandling productivity will be diminished. The expected number of rehandles (R) is (Equation 7):

$$\mathbb{E}[R] = \sum_{i=1}^a \sum_{j=1}^{h_a} P_{i,j} \cdot r_{i,j} \quad (7)$$

Where h_a denotes the height of the stack a , P_{a,h_a} denotes the probability that a container in position (a, h_a) is selected and r_{a,h_a} is the number of rehandles required to retrieve the target container in slot (a, h_a) . Equation (8) calculates the expected number of rehandles by considering all possible locations of the target container and any interfering containers. Equation (8) is solved with the MSC Method. MCS is a probabilistic model that can include an element of uncertainty or randomness in its prediction.

Table 1: Number of rehandles associated with each slot when bay is full

Tier	Stack A	Stack B	Stack C	Stack D	Stack E	Stack F	Stack G
3	0	0	0	0	0	0	0
2	2	2	2	2	2	2	2
1	4	4	4	4	4	4	4

Table 1, which establishes the deterministic rehandling structure of a fully occupied bay under the current operational configuration at Lekki Freeport Terminal (LFT). Table 1 maps the exact number of rehandles associated with each container slot across seven stacks and three tiers, assuming that the fourth tier and above are reserved for rehandling space. Containers located at the top tier (Tier 3) require zero rehandles, while those in Tier 2 and Tier 1 require two and four rehandles respectively. This tier-dependent rehandling pattern highlights the inherent vertical inefficiency embedded in dense stacking configurations and provides the structural basis upon which the probabilistic Monte Carlo Simulation (MCS) is built. Similar deterministic slot-based rehandling frameworks have been widely adopted in container relocation studies, as they allow operational constraints to be explicitly translated into measurable productivity outcomes (Huynh, 2008; Feng et al., 2020).

Table 1 also plays a critical role in justifying the use of Monte Carlo Simulation rather than closed-form analytical solutions. While the rehandle counts in Table 1 are deterministic, actual container retrieval is stochastic, driven by heterogeneous dwell times, customer behavior, and service schedules. The uniform random selection of containers across the 21-slot bay, as defined in the simulation, transforms the deterministic rehandle matrix into a probabilistic expectation. This methodological transition reflects real-world terminal conditions, where operators cannot predict which specific container will be retrieved next (Smith, 2021; Chen et al., 2024). Thus, Table 1 serves as the structural micro-foundation of the stochastic model, ensuring that simulation outputs remain grounded in operational reality.

IV. RESULTS

The results presented in Table 2 demonstrate the statistical robustness and consistency of the Monte Carlo Simulation (MCS) approach in estimating expected container rehandles under a full-bay configuration. As sample size increases from 100 to 1,000 while repetitions are held constant at 10,000, the mean expected rehandles converge tightly around the theoretical value of two, while the standard deviation declines monotonically. This

convergence confirms that the estimator is consistent and unbiased, validating the use of MCS for modeling stochastic yard operations. From an economic perspective, such consistency is critical for operational decision-making, as unreliable estimates of rehandling effort can lead to systematic underestimation of labor, equipment wear, and energy costs (Eskafi et al., 2021a; Weerasinghe et al., 2024). The declining variance also implies that terminal operators can rely on relatively modest computational effort to obtain stable estimates, enhancing the practical applicability of the model.

Table 2: MCS Consistency Results

Repetition	Sample Size	Mean Rehandles	Standard Deviation
10,000	100	2.0004	0.1648
10,000	200	1.9998	0.1165
10,000	300	1.9999	0.0941
10,000	400	1.9998	0.0814
10,000	500	2.0002	0.0723
10,000	600	1.9998	0.0668
10,000	700	2.0003	0.0622
10,000	800	1.9999	0.0573
10,000	900	2.0003	0.0539
10,000	1000	2.0001	0.0517

Table 3: Expected rehandles for various average stack heights

Bay Configuration	Avg. Stack Height	Expected Rehandle	Standard Deviation	95% Confidence Interval (Lower, Upper)
1	1.00	0.0000	0.0000	(0.0000, 0.0000)
2	1.14	0.1423	0.3494	(0.1355, 0.1491)
3	1.29	0.2829	0.4504	(0.2741, 0.2917)
4	1.43	0.4557	0.5084	(0.4453, 0.4661)
5	1.57	0.5631	0.5036	(0.5522, 0.5740)
6	1.71	0.7128	0.5231	(0.7014, 0.7242)
7	1.86	0.8321	0.5453	(0.8203, 0.8439)
8	2.00	0.9658	0.5517	(0.9535, 0.9781)
9	2.14	1.1194	0.5370	(1.1065, 1.1323)
10	2.29	1.2173	0.5505	(1.2038, 1.2308)

Table 3 provides insights into the relationship between average stack height and expected rehandling activity. The results reveal a clear monotonic increase in expected rehandles as stack height rises from 1.00 to 2.29 tiers. Notably, the increase is nonlinear: while early increases in stack height generate modest additional rehandling, higher stack heights induce disproportionately larger rehandling requirements. This pattern reflects congestion effects within the container yard, where vertical density amplifies interference among containers (Huynh, 2008; Feng et al., 2020). Economically, this nonlinearity suggests diminishing marginal returns to stacking height as a throughput enhancement strategy, since the operational costs associated with rehandling escalate faster than the gains in storage capacity.

The confidence intervals reported in Table 3 further reinforce the statistical reliability of these findings. Despite relatively large standard deviations at higher stack heights, the confidence intervals remain narrow, indicating that expected rehandles are precisely estimated even under denser storage conditions. This precision is essential for planning under uncertainty, particularly in terminals facing volatile import flows and fluctuating dwell times

(Smith, 2021; Eskafi et al., 2021b). From a cost-minimization perspective, the ability to predict rehandling intensity with confidence allows terminal managers to evaluate whether incremental increases in yard density justify the associated increases in operational burden.

Table 4: Number of rehandles associated with each slot when bay is full

Bay Configuration	Average Stack Height	$E[R]$	$E[R]$
		For Equal Probability	For Non-Equal Probability
1	1.00	0.0000	0.0000
2	1.14	0.1228	1.9346
3	1.29	0.2248	1.8734
4	1.43	0.3007	1.8250
5	1.57	0.3631	1.7782
6	1.71	0.4152	1.7380
7	1.86	0.4624	1.6993
8	2.00	0.5000	1.6667
9	2.14	0.5981	1.6287
10	2.29	0.6900	1.5898

Table 4 extends the analysis by contrasting equal-probability and non-equal-probability container retrieval scenarios, offering a more realistic representation of actual terminal operations. Under the equal-probability assumption, expected rehandles increase gradually with stack height, reaching 0.69 at an average height of 2.29 tiers. However, when non-equal retrieval probabilities are introduced the expected rehandles are substantially higher, exceeding 1.9 at lower stack heights and declining slowly as height increases. This stark contrast highlights the economic cost of ignoring behavioral and demand-side heterogeneity in yard planning models (Chen et al., 2024; Feng et al., 2022).

The higher rehandling levels observed under non-equal probability conditions underscore the inefficiencies introduced by preferential retrieval of specific containers, such as time-sensitive or high-value cargo. These containers are often stored in lower tiers to facilitate access, unintentionally increasing reshuffling requirements when stacking density increases. This finding aligns with prior studies showing that naive stacking policies can exacerbate rehandling when retrieval demand is unevenly distributed (Cho et al., 2022; Zhou & Zhang, 2024). Economically, this implies that terminals operating under heterogeneous customer demand face higher marginal costs of congestion than suggested by models assuming uniform retrieval probabilities.

An important insight from Table 4 is that expected rehandles under non-equal probability conditions decline slightly as average stack height increases. This counterintuitive result reflects the increased likelihood that high-priority containers are placed closer to the top of stacks as density rises, reducing interference during retrieval. However, the overall level of rehandling remains substantially higher than in the equal-probability case, indicating that such adaptive behavior only partially mitigates congestion costs. This highlights the limits of manual or heuristic stacking strategies and supports the case for intelligent, data-driven yard allocation systems (He et al., 2024; Tang et al., 2026).

From a broader economic perspective, the combined results of Tables 2–4 reveal a fundamental trade-off between throughput maximization and operational efficiency. While higher stacking increases yard capacity and supports greater import throughput it simultaneously raises handling costs and reduces crane productivity. These opposing effects are central to the economics of container terminal operations, where throughput gains must be evaluated net of congestion-induced cost penalties (Coşar & Demir, 2018; Notteboom et al., 2020). For emerging ports such as Lekki Freeport Terminal, this trade-off is particularly salient given rapid traffic growth and limited short-term expansion options.

Finally, the results emphasize the policy relevance of incorporating stochastic rehandling models into terminal planning and investment decisions. By quantifying how rehandling responds to stack height and retrieval behavior, the study provides a rigorous basis for evaluating alternative operational strategies, including smart stacking, extended gate hours, or automation investments (Eskafi et al., 2022; Watada et al., 2019). In economic terms, such evidence-based planning reduces uncertainty, lowers effective trade costs, and enhances the long-run efficiency of port-centric supply chains, contributing to broader regional and national economic development (Hlali & Hammami, 2019; Ding & Wang, 2022).

The deterministic rehandling structure presented in Table 1 highlights that rehandling costs are not incidental but structurally embedded in dense stacking configurations. Containers stored in lower tiers systematically generate higher reshuffling requirements, implying that policies aimed solely at maximizing yard density or throughput risk generating hidden congestion costs. From an economic standpoint, this introduces a classic trade-off between capacity utilization and operational efficiency, where marginal gains in storage density are offset by rising labor, equipment, and energy costs associated with rehandling (Coşar & Demir, 2018; Weerasinghe et al., 2024). Port authorities should therefore move beyond volume-based performance targets and adopt regulatory and concession frameworks that explicitly account for rehandling productivity as a measure of allocative efficiency and terminal sustainability.

The integration of Monte Carlo Simulation with the deterministic framework of Table 1 further supports a shift toward probabilistic and data-driven port governance. Deterministic planning tools fail to capture the uncertainty arising from heterogeneous dwell times and stochastic retrieval behavior, which are central features of modern container terminals. Simulation-based decision support systems allow terminal operators to internalize uncertainty and generate reliable expectations of rehandling intensity under alternative stacking and free-time policies (Feng et al., 2020; Chen et al., 2024). From a policy perspective, mandating or incentivizing the use of such tools can reduce systematic underestimation of operational costs and improve investment appraisal, concession design, and benchmarking practices.

The divergence between equal and non-equal retrieval probability outcomes has particularly important implications for terminals serving heterogeneous cargo profiles. Preferential retrieval of time-sensitive or high-value containers significantly amplifies rehandling requirements, increasing the marginal congestion cost of yard densification. This finding reinforces the need for policies that promote information sharing and intelligent stacking strategies, enabling terminals to anticipate retrieval patterns *ex ante* rather than reacting *ex post* through costly reshuffling (Feng et al., 2022; Cho et al., 2022). Economically, such coordination reduces congestion externalities within the terminal and lowers generalized trade costs, thereby strengthening the port's competitiveness within global value chains (Notteboom et al., 2020).

Finally, the results suggest that port development policy should rebalance investment priorities away from purely physical expansion toward operational intelligence and resilience. Table 1 demonstrates that even within a fixed yard footprint, productivity outcomes are highly sensitive to stacking and retrieval dynamics. Public policy support for automation, advanced analytics, and workforce upskilling can therefore yield high marginal returns by mitigating the congestion penalties associated with higher throughput (Smith, 2021; He et al., 2024). For emerging hub ports such as Lekki Freeport Terminal, embedding stochastic rehandling considerations into operational and regulatory policy is essential for achieving sustainable growth, environmental efficiency, and long-term trade facilitation (Watada et al., 2019; Weerasinghe et al., 2024).

V. CONCLUSION

This study examined the operational and economic implications of container stacking and rehandling decisions in space-constrained container terminals, using Lekki Freeport Terminal as a representative case. By integrating a deterministic rehandling structure with Monte Carlo Simulation, the analysis demonstrated that rehandling

intensity is a predictable and structurally embedded outcome of stacking height and retrieval behavior, rather than a random operational occurrence. The results confirmed that while higher stacking increases yard capacity and supports throughput growth, it also generates nonlinear increases in rehandling, congestion, and handling costs. The comparison between equal and non-equal retrieval probability scenarios further revealed that ignoring demand heterogeneity leads to systematic underestimation of operational burdens within the terminal system.

The findings of this study establish that terminal performance cannot be adequately evaluated solely on throughput maximization; instead, it must incorporate congestion-adjusted efficiency and rehandling productivity as core performance indicators. In particular, the results show that increases in stacking height yield diminishing operational returns due to the disproportionately higher rehandling effort required at greater densities. This highlights a fundamental trade-off between storage capacity and operational efficiency that is especially critical in space-constrained and rapidly expanding terminals.

Furthermore, the study demonstrates that stochastic modeling provides a more realistic representation of yard operations by capturing uncertainty in dwell times and retrieval patterns. The simulation results consistently show that rehandling behavior is sensitive not only to physical stacking configurations but also to retrieval dynamics, reinforcing the need for integrated operational planning approaches.

Overall, this study contributes to the understanding of container yard dynamics by providing empirical evidence that rehandling is a structurally determined and economically significant component of terminal operations. The results emphasize that effective yard management strategies must balance capacity utilization with operational efficiency to avoid hidden congestion costs and declining productivity. For emerging automated terminals such as Lekki Freeport Terminal, these insights underscore the importance of adopting data-driven and system-oriented approaches to sustain performance under increasing demand pressures.

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Strategije skladiščenja, skrajšanje časa zadrževanja in rezultati učinkovitosti v nastajajočem avtomatiziranem pomorskem terminalu

Izvleček – Ta raziskava preučuje, kako čas zadrževanja kontejnerjev vpliva na zmogljivost in produktivnost v pomorskih terminalih, s poudarkom na terminalu Lekki Freeport Terminal (LFT) – nastajajočem avtomatiziranem pomorskem vozlišču v Nigeriji. Najprej se vzpostavi deterministična struktura premeščanja na osnovi časovnih intervalov za opredelitev vertikalne neučinkovitosti, prisotne v gostih konfiguracijah zlaganja, nato pa se uporabi Monte Carlo simulacija za zajem negotovosti pri prevzemu kontejnerjev. Rezultati kažejo močno statistično skladnost simulacije, pri čemer se pričakovano število premeščanj z naraščanjem velikosti vzorca tesno približuje teoretični srednji vrednosti 2,00. Analiza scenarijev razkriva nelinearno povezavo med povprečno višino sklada in intenzivnostjo premeščanj. Pričakovano število premeščanj naraste z 0 pri višini sklada 1,00 na 1,22 pri 2,29 nivojih. Ko je uvedeno heterogeno vedenje prevzema, se pričakovano število premeščanj znatno poveča, preseže 1,9 že pri nizkih višinah skladov in ostane bistveno višje kot pri predpostavki enake verjetnosti. Te ugotovitve kažejo, da zanemarjanje heterogenosti povpraševanja vodi v sistematično podcenjevanje zastojev in stroškov manipulacije. Študija zagotavlja kvantitativne dokaze v podporo stohastičnemu načrtovanju skladiščnih površin na podlagi podatkov kot temelju za izboljšanje operativne učinkovitosti in ekonomske trajnosti v nastajajočih kontejnerskih terminalih.

Ključne besede – kontejnerski terminali, produktivnost premeščanja, simulacija Monte Carlo, zlaganje na skladiščnih površinah, operativna učinkovitost