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Investigating Maritime Ports' Operational Performance Determinants: An Empirical Study of Operational Delays and Moroccan Container Terminal Productivity

Analyse des déterminants de la performance opérationnelle des ports maritimes : Une étude empirique des retards opérationnels et de la productivité des terminaux à conteneurs marocains

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Abstract:

This study investigates how operational delays influence container terminal productivity by quantifying their effect on Gross Crane Productivity (GCP) at Moroccan container terminals. Based on six months of calls data (April–September 2025), we used a simple linear regression based on a sample of 422 observations.The distribution of GCP shows a slight right skew, with a stable operating range of 28–35 moves per crane-hour, whereas delays are heavily right-skewed, mostly under 10 minutes with occasional long outliers. Ordinary Least Squares results reveal a significant negative association between delays and GCP ($\beta = -0.46$, $p < 0.001$), indicating that each additional minute of delay lowers productivity by about 0.46 moves per hour, delays account for roughly 20% of the variance in GCP ($R^2 = 0.20$). LOWESS analysis highlights a tolerance threshold near 10 minutes, after which productivity drops sharply due to congestion propagation and loss of synchronization between quay and yard operations. Over the study period, cumulative delays decreased by nearly half while average GCP improved by approximately 25%, suggesting learning effects, better planning, and enhanced coordination. Overall, the findings show how micro-level time losses affect terminal productivity and connect directly to the smart-port agenda, emphasizing that automation and digital connectivity yield the greatest benefits when supported by integrated scheduling and strong organizational readiness. The study recommends the development of predictive delay analytics (e.g., AIS combined with machine learning) and real-time, integrated equipment scheduling as key levers to sustain both operational efficiency and environmental performance.

Mots clés : Operational delays, Gross Crane Productivity (GCP), Automated container terminals, Integrated scheduling, Smart port performance.
JEL Classification : R41, L91, C21, C51
Type du papier : Empirical Research

Résumé :

Cette étude analyse l'influence des retards opérationnels sur la productivité des terminaux à conteneurs en quantifiant leur effet sur la Gross Crane Productivity (GCP) dans les terminaux marocains. À partir de six mois de données d'escales (avril–septembre 2025), nous avons appliqué une régression linéaire simple sur un échantillon de 422 observations. La distribution de la GCP présente une légère asymétrie à droite, avec une plage opérationnelle stable de 28 à 35 mouvements par grue et par heure, tandis que les retards sont fortement asymétriques, majoritairement inférieurs à 10 minutes avec quelques valeurs extrêmes prolongées.
Les résultats de l'estimation par moindres carrés ordinaires montrent une association négative significative entre les retards et la GCP ($\beta = -0.46$, $p < 0.001$), indiquant que chaque minute de retard supplémentaire réduit la productivité d'environ 0,46 mouvement par heure ; les retards expliquent environ 20 % de la variance de la GCP ($R^2 = 0.20$). L'analyse LOWESS met en évidence un seuil de tolérance autour de 10 minutes, au-delà duquel la productivité chute fortement en raison de la propagation de la congestion et de la perte de synchronisation entre les opérations quai et parc.
Sur la période étudiée, les retards cumulés ont diminué de près de moitié tandis que la GCP moyenne s'est améliorée d'environ 25 %, ce qui suggère des effets d'apprentissage, une meilleure planification et une coordination renforcée. Globalement, les résultats montrent comment les pertes de temps au niveau micro-opérationnel affectent la productivité terminale et s'inscrivent directement dans l'agenda du smart port, soulignant que l'automatisation et la connectivité numérique offrent leurs meilleurs bénéfices lorsqu'elles sont accompagnées d'une planification intégrée et d'une forte préparation organisationnelle.
L'étude recommande enfin le développement d'outils prédictifs d'analyse des retards (par exemple, AIS combiné à des techniques d'apprentissage automatique) ainsi que la mise en place d'une programmation intégrée et en temps réel des équipements comme leviers essentiels pour soutenir à la fois l'efficacité opérationnelle et la performance environnementale.

Keywords : Retards opérationnels, Productivité Brute des Grues (GCP), Terminaux à conteneurs automatisés, Planification intégrée, Performance smart port.
Classification JEL : R41, L91, C21, C51
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1. Introduction

As per (UNCTAD, 2021), The maritime sector constitutes the backbone of global trade, ensuring the transport of more than 80% of international goods by volume. It should be noted that the efficiency and performance of ports, as crucial logistical nodes, are essential determinants of economic success at both national and global levels (Haralambides, 2017 and Zhen, 2015).

(Lee & Song, 2023; Mishrif & Khan, 2023; Song et al., 2024) state that in the face of major post-pandemic challenges including COVID-19, digitalization, and decarbonization (CDD) the industry is experiencing unprecedented complexity that demands a radical transformation of port operations.

In order to address these challenges, the development of Automated Container Terminals (ACTs) has become a priority. Automation, one of the three fundamental pillars of automated container terminals, aims to enhance operational efficiency by reducing human intervention and minimizing congestion and turnaround time (Yen et al., 2023).

This evolution has led to an exponential growth in research publications since 2007 (Pallis et al., 2010, cited in Kishore et al., 2024) and to the emergence of a solid body of knowledge on operational optimization.

As per (Naeem et al., 2023), automation introduces new complexities, especially the critical issue of Integrated Scheduling of handling equipment: Quay Cranes (QCs), Automated Vehicles (AVs), and Yard Cranes (YCs).

Operational success in automated container terminals depends on avoiding interferences among these pieces of equipment (Naeem et al., 2023), as any disturbance in their coordination generates operational delays. These delays often stem from complex factors frequently neglected in theoretical models, such as insufficient buffer capacity beneath QCs or challenges in allocating yard storage locations for import containers (Naeem et al., 2023).

(Naeem et al., 2023) state that the impact of these delays directly affects the terminal's most critical productivity metric such as Gross Crane Productivity (GCP) which serves as the main indicator of efficiency at the ship-to-shore interface. Minimizing delays is therefore essential, as research recommends that scheduling objectives focus on minimizing equipment waiting time, an approach that reduces the vessel makespan while maximizing asset utilization.

Despite the centrality of GCP and operational delays, the field of smart port performance assessment is often described as fragmented and primitive, with insufficient research linking theory to practice (Molavi, 2020, cited in Paraskevas et al., 2024; Paraskevas et al., 2024). A major limitation of existing studies lies in the absence of an objective and scientific assessment framework capable of accurately identifying performance problems (Paraskevas et al., 2024), as analyses are often based on theoretical models or heterogeneous datasets.

Our study aims to fill this empirical and methodological research gap. The empirical contribution lies in conducting an in-depth analysis based on six months of operational data (April–September 2025) from Moroccan container terminals, providing an objective quantification of productivity losses in an emerging economy where studies are scarce (Alamoush et al., 2020, Paraskevas et al., 2024).

The methodological contribution is the combination of exploratory data analysis (EDA), LOWESS smoothing, and OLS regression to rigorously quantify the effect of operational delays.

The managerial contribution is the provision of actionable insights and recommendations for terminal planning and real-time operational monitoring, highlighting how delays can be mitigated to improve GCP.

Furthermore, the study contributes to the literature by focusing on an emerging economy (Moroccan context) an area where research remains scarce, as most studies focus on ports in

developed countries (Alamoush et al., 2020, cited in Paraskevas et al., 2024).
The structure of this article is as follows. Section 2 presents the Theoretical Framework, outlining the key concepts of port performance, GCP, and operational delays. Section 3 details the Research Methodology, including the nature of the operational data and the analytical techniques employed. Section 4 presents our Empirical Results, quantifying the impact of operational delays on GCP. Section 5 discusses the theoretical and managerial implications, and Section 6 concludes the article by identifying limitations and suggesting directions for the future research.

2. Literature review

2.1. Port Performance and Operational Efficiency

The maritime sector, responsible for transporting over 80% of global trade volume (UNCTAD, 2021), grants ports a crucial role as pillars of the global economy. Port performance efficiency is considered a fundamental determinant of success, directly linked to infrastructure design and the operational environment. Port performance evaluation has experienced exponential growth, with a notable emphasis on quantifying parameters since 2007 (Kishore et al., 2024). Traditional performance indicators, initially focused on internal operational efficiency, are evolving toward a broader approach integrating customer demand, reliability, and service quality (Brooks & Cullinane, 2006, cited in Hardianto et al., 2023).
With the rise of containerized trade volumes, Automated Container Terminals (ACTs) have drawn increasing research attention due to their potential to enhance terminal productivity and operational performance. Ports are increasingly urged to become Smart Ports by investing in technologies that promote more efficient operations via Information and Communication Technologies (ICT) and the Internet of Things (IoT).
Efficiency as a holistic concept: Modern port performance extends beyond mere technical efficiency. It is a multidimensional concept that must be assessed not only through economic indicators but also through social, environmental, and sustainability criteria. Recent research trends show a strong focus on sustainability, which has become the most relevant topic over the last five years (Kishore et al., 2024).
Evaluation methodology: Objective evaluation of port efficiency often relies on Data Envelopment Analysis (DEA), widely used in maritime transport due to its advantage as a non-parametric assessment providing objective measurements (Dewita, Yen, & Burke, 2018, cited in Yen et al., 2023). The DEA-Tobit model is frequently applied to assess the influence of external factors, such as smart port dimensions (Automation, Environment, Intelligence), on measured operational efficiency. Technical efficiency is often evaluated via resource utilization, fleet size, or fuel consumption to produce outputs such as throughput and revenue. Performance evaluation is thus essential for effective management, with managers relying on it for planning and resource optimization.

2.2. Operational Delays as a Determinant of Performance

Operational delays are a major source of efficiency loss, additional costs, and customer dissatisfaction in container terminals. The main objective of optimization studies is to minimize these delays.
In Automated Container Terminals (ACTs), where all equipment is automatically controlled, avoiding interference among each equipment pair is crucial to prevent disruption or cargo accumulation (backlog). Delays are a direct consequence of coordination failures. Literature highlights several interference and delay factors arising from the complexity of integrated scheduling among three main equipment types: Quay Cranes (QCs), Yard Cranes (YCs), and

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Automated Vehicles (AVs) (Naeem et al., 2023). Integrated scheduling remains a continuous and complex research domain (Naeem et al., 2023).

However, most studies have focused on scheduling a single equipment type, mainly AVs, assuming that scheduling of other equipment (e.g., QCs) is predetermined. Such simplifications render models inadequate when addressing real-world delays arising from complex interdependencies.

Neglected delay factors:

Storage allocation: The storage of import containers plays a crucial role in YC scheduling. Neglecting this factor affects operational time for both YCs and AVs. Incorporating storage allocation into handling equipment scheduling can yield more efficient solutions (Naeem et al., 2023).

Buffer capacity (BC): Buffer capacity beneath QCs is a major constraint that may generate interference, yet it is often ignored in integrated equipment scheduling studies. Performance analyses under different BC configurations provide critical insights for terminal performance assessment (Hu et al., 2013; Xinyan et al., 2014).

Tobit modeling: To evaluate the influence of external factors such as environmental conditions or smart port characteristics on efficiency, the Tobit regression model is used. Within this framework, operational delays or their determinants (e.g., level of digitalization, automation status, control systems) can be treated as independent variables to assess their impact on performance.

Thus, the literature justifies the causal link: interferences → operational delays → reduction in GCP, highlighting the need for empirical validation in emerging contexts, such as Moroccan terminals.

2.3. Gross Crane Productivity as a Key Performance Indicator

Gross Crane Productivity (GCP), measured in crane moves per hour, is one of the most direct and relevant terminal performance metrics, focusing on efficiency at the ship-to-shore interface. GCP is intrinsically linked to the fundamental management goal: minimizing the total time a vessel spends at berth.

Minimizing makespan: The most common scheduling objective is to reduce vessel makespan, as it represents a critical performance measure directly influencing vessel berthing time (Luo & Wu, 2020b, cited in Naeem et al., 2023).

Equipment-related KPIs: Equipment objectives, such as minimizing QC delay or AV waiting time, have received considerable attention (Yue et al., 2021).

Monitoring GCP enables managers to identify bottlenecks and optimize resource allocation, providing actionable insights for integrated planning and performance improvement (Hardianto et al., 2023; Al-Fatlawi & Motlak, 2023).

2.4. Operational Delays and Productivity

The relationship between operational delays and GCP is direct: effective delay management leads to immediate gains in productivity and asset utilization. In an automated terminal, any delay in equipment (e.g., an AV) can create a bottleneck, causing crane idleness and instant reduction in GCP.

Studies on buffer capacity and storage allocation show how terminal configurations influence GCP under real-world constraints (Hu et al., 2013; Xinyan et al., 2014; Roy et al., 2020). Collecting six months of operational microdata in Moroccan terminals enables quantification of delays and their direct impact on GCP, bridging theoretical scheduling challenges (interference, buffer capacity) with actual productivity outcomes and providing a strong empirical basis for recommendations on integrated scheduling and smart port practices.

Based on the above literature review, the research hypotheses are formulated as follows:

H1: *Operational delays have a negative impact on Gross Crane Productivity (GCP) in container terminals.*
H2: *Structural and technological conditions (e.g., automation, buffer capacity, storage allocation) moderate the relationship between operational delays and GCP.*

3. Methodology

3.1. Research Approach and Study Design

This research adopts a quantitative, empirical methodology grounded in the analysis of large-scale operational data. The aim is to provide an objective and scientific assessment of port efficiency, in contrast to prior studies relying on qualitative and subjective methods, which complicate comparability (Molavi et al., 2020).
The study draws on high-fidelity data collected from Moroccan container terminals over a consecutive six-month period (April–September 2025). This approach aligns with research trends prioritizing Big Data and predictive tools for resource management and operational efficiency (Dalaklis et al., 2023, Paternina-Arboleda et al., 2023).
Data and Source: The dataset comprises 422 ship calls during the six-month period, covering three shifts per day: morning (06:00–14:00), afternoon (14:00–22:00), and night (22:00–06:00). The data were obtained directly from Tanger Med 2 container terminal operational logs.
Unit of Analysis and Data Structure: Each observation corresponds to a single ship call per shift, with data aggregated at the call level. For each observation, operational variables include gross crane productivity (GCP), operational delays, and associated structural/technological factors.
Selection Criteria and Data Quality: Observations were included if they corresponded to standard handling operations at the terminal. Extreme or missing values were identified during Exploratory Data Analysis (EDA) and treated according to standard cleaning procedures, including removal or imputation, ensuring the robustness of subsequent regression models.
Study Design Justification: The dataset allows testing causal relationships at the micro (call) level, bridging theoretical models of interference, buffer capacity, and storage allocation with actual terminal productivity outcomes.

3.2. Definition and Operationalization of Variables

The study employs a causal modeling approach.
Dependent Variable: Gross Crane Productivity (GCP), measured in moves per STS-crane hour (moves/hour/crane). GCP reflects vessel berthing efficiency and overall terminal performance (Luo & Wu, 2020b; Naeem et al., 2023).
Independent Variable: Operational Delays, measured in minutes or hours, reflecting ship waiting times at berth or anchor. Delays are considered the empirical manifestation of coordination and interference issues (Naeem et al., 2023).
Moderating Variables: Structural and technological conditions (automation level, buffer capacity, storage allocation) are included as potential moderators of the relationship between delays and GCP.

3.3. Statistical Analysis and Analytical Framework

The methodology combines Exploratory Data Analysis (EDA) and inferential modeling using Python-based tools (Plotly, Pandas, Statsmodels, Seaborn).
Phase I: Exploratory Data Analysis (EDA).

- Information Exploration: Data cleaning, transformation, and consistency checks ensure suitability for analysis, as required for DEA-type analyses (Hsu et al., 2023).

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- Distribution Analysis: Kernel density estimates, histograms, and pairplots visualize dependent and independent variable distributions, highlighting outliers.
- Spatio-Temporal Analysis: Boxplots and line charts examine GCP and operational delays across months and shifts, identifying trends or seasonal effects.

Phase II: Inferential Analysis and Modeling

- Equation of Research: The basic regression model can be expressed as:

$$GCPi = \beta 0 + \beta 1 Delayi + \beta 2 Moderatori + \epsilon i$$

Where $\boldsymbol{i}$ is the ship call observation, $\boldsymbol{Delay}$ represents operational delays, and $\boldsymbol{Moderator}$ represents structural/technological conditions.

Correlation Analysis: Spearman and Pearson correlations quantify linear and non-linear relationships between operational delays and GCP.

Regression Modeling:

- OLS Regression: Used as the primary model to estimate the average effect of operational delays on GCP. Although simple and univariate, it allows interpretation of direct relationships.
- Quantile Regression: Employed to examine the effect of delays across the GCP distribution, addressing sensitivity to extreme values and differential impacts on high- vs. low-performing calls.

Justification of Approach: While the OLS univariate model provides a straightforward baseline, further robustness checks (quantile regression, sensitivity to extreme values) complement it and provide insights into heterogeneous effects across observations. The combination of EDA, correlation, OLS, and quantile regression ensures methodological rigor while maintaining transparency.

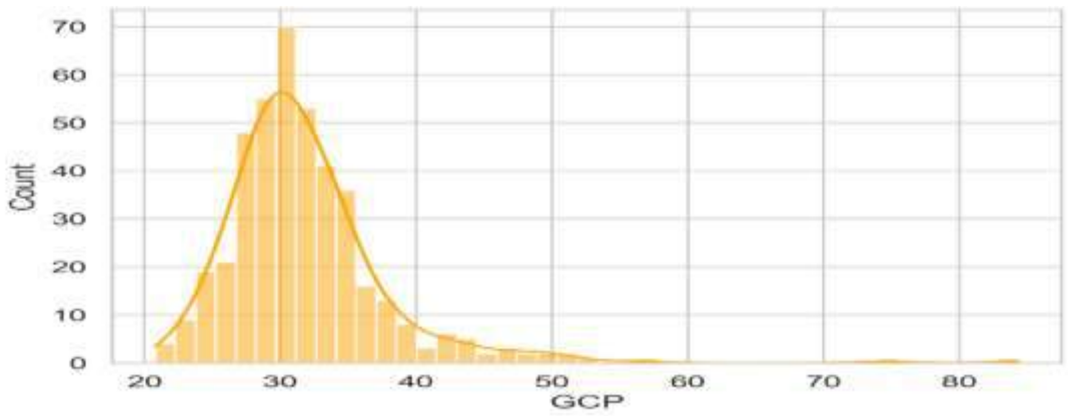
4. Results and Analysis

This section details the findings of the empirical analysis conducted on six months of operational data (April–September 2025) from Moroccan container terminals. The results are presented in three subsections covering performance trends, correlation assessment, and modeling of the causal impact of operational delays on Gross Crane Productivity (GCP).

4.1. Descriptive Analysis of Variables

Fig 1 present an Hitogram of GCP:

Figure 1. Histogram of GCP



Source: By our sides during data analysis, 2025.

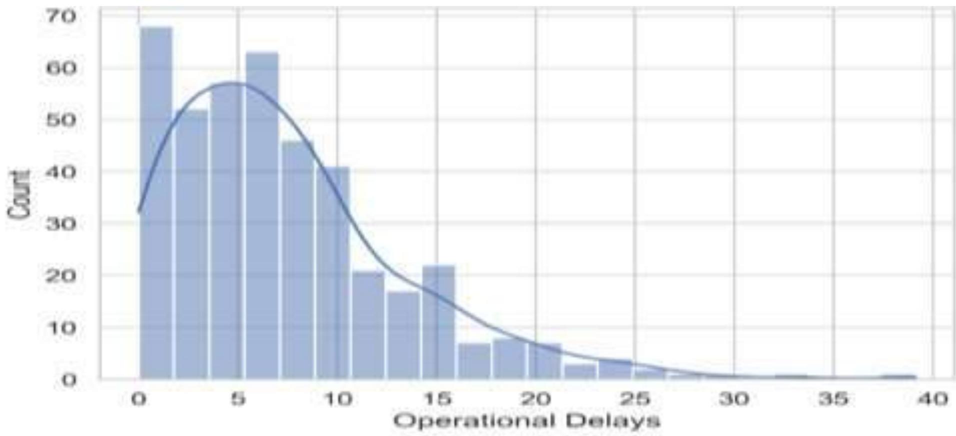
Figure 1 shows the empirical distribution of Gross Crane Productivity (GCP) observed at the container terminal over the analysis period. The density curve overlaid on the histogram reveals slight right skewness (positive skewness), indicating that most observations are concentrated around a central interval between 28 and 35 moves per crane-hour. This band represents the average performance level of quay cranes, reflecting sustained yet stable activity under normal operating conditions.

A few extreme values appear beyond 50 moves/hour, likely corresponding to exceptional high-productivity situations associated with favorable conditions such as optimal planning, low quay congestion, or a highly efficient handling team. Conversely, the low frequency of observations below 25 moves/hour reflects temporary slowdowns, often attributable to technical interruptions, vessel rotation, or adverse weather.

Overall, this distribution indicates moderate variability in crane performance typical of an automated or semi-automated terminal where operations are generally stable but sensitive to certain external factors. The descriptive analysis thus highlights controlled dispersion around the mean, confirming operational consistency at the terminal and providing a basis for analyzing the relationship between operational delays and crane productivity.

Fig 2 present an Histogram of Operational Delays:

Figure 2. Histogram of Operational Delays



Source: By our sides during data analysis, 2025.

Figure 2 presents the statistical distribution of operational delays over the study period. The density curve associated with the histogram reveals pronounced right skewness, showing a high concentration of observations at low delay values, mainly between 0 and 10 minutes. This pattern indicates that most port operations are completed within controlled timeframes, reflecting overall operational efficiency at the terminal.

However, the long right tail (delays exceeding 20–30 minutes) highlights occasional episodes of inefficiency likely associated with exceptional events: crane incidents, yard saturation, prolonged truck queues, or coordination constraints between quay and yard teams. Although rare, these extreme delays exert a disproportionate effect on overall performance especially on GCP by disrupting normal operational flow.

The strong dispersion observed in the upper part of the distribution also indicates non-negligible operational variability, suggesting that certain time windows or vessels face particular difficulties in maintaining the expected cadence. This descriptive analysis therefore reveals the coexistence of predominantly stable performance with localized peaks of inefficiency a key lever for improving cycle time management and optimizing port planning.

4.2. Monthly Performance Trends

Fig 3 present a Boxplot of GCP by month:

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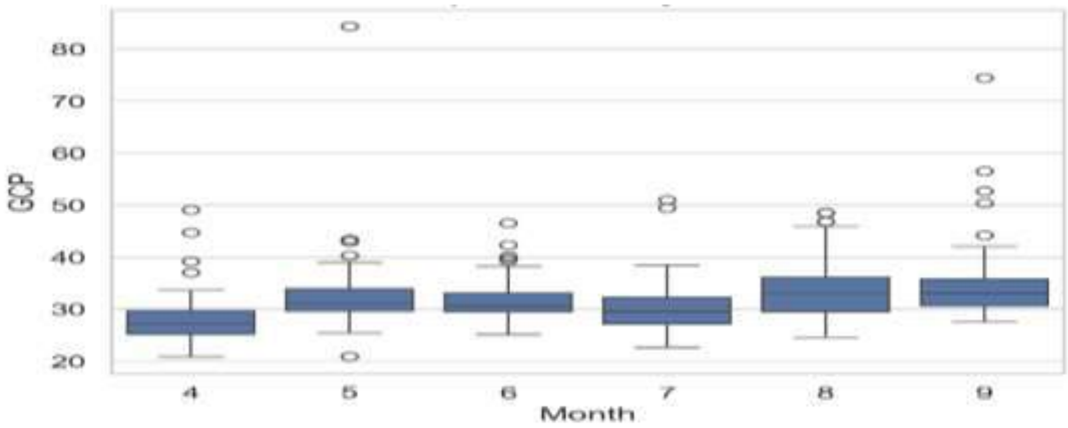
Figure 3. Boxplot of GCP by Month



Source: By our sides during data analysis, 2025.

Figure 3 displays monthly variation in GCP over the analysis period using boxplots. This visualization enables assessment of dispersion, the median, and potential outliers of GCP for each month from April to September.

Overall, there is a gradual upward trend in the monthly median GCP, indicating steady improvement in operational performance. This progression can be explained by several factors:

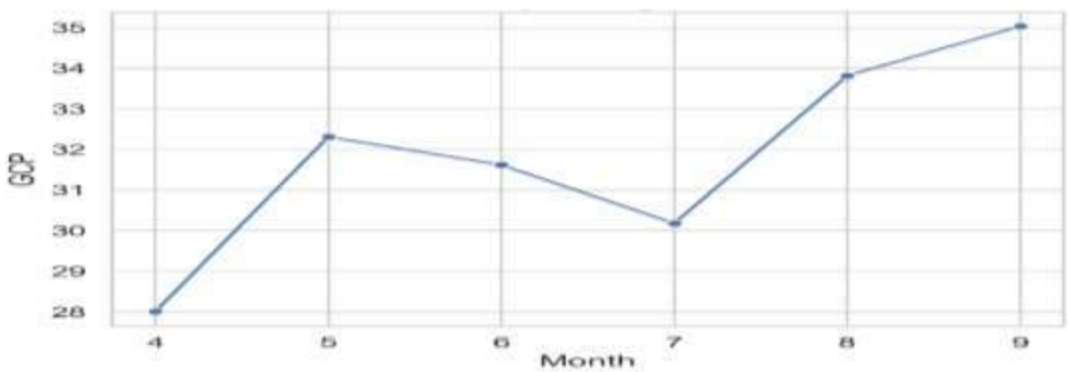
- Adjustments to work schedules and optimization of handling sequences after the initial weeks of observation.
- The learning curve of operators and technical teams, leading to better coordination among quay cranes, yard operations, and tractors.
- More favorable seasonal conditions in summer, often associated with increased fluidity in maritime operations.

Outliers observed in some months correspond to isolated instances of exceptional performance or, conversely, unexpected slowdowns. These isolated points reflect the dynamic and stochastic nature of port operations, where productivity varies with vessel size, handled volume, equipment availability, or stowage plan complexity.

Hence, the relatively stable dispersion and the progressive rise in the median suggest operational maturation at the terminal over the study period, trending toward greater stability in crane performance. This evolution confirms the effectiveness of internal measures adopted to improve productivity and mitigate operational contingencies.

Fig 4 present the monthly average of GCP:

Figure 4. Monthly Average GCP

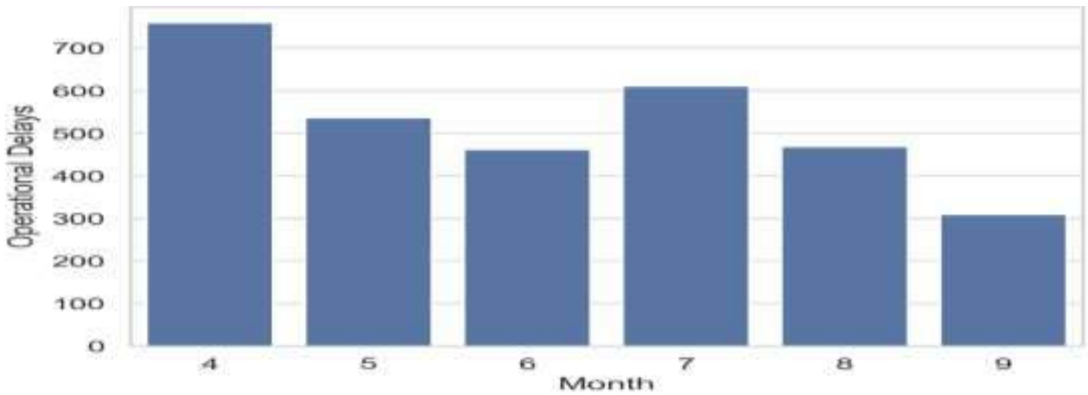


Source: By our sides during data analysis, 2025.

Figure 4 confirms the ascending trend seen in Figure 3. It depicts the evolution of average monthly GCP between April and September, during which GCP increases from about 28

moves/hour to nearly 35 moves/hour. This steady progression reflects continuous improvement in operational efficiency at the container terminal.
This roughly 25% rise in average productivity may be attributed to cumulative factors. On one hand, progressive refinements to internal processes such as vessel planning, allocation of human resources, and coordination between quay and yard areas have improved synchronization. On the other hand, accumulated operator experience and streamlined procedures reduced idle times and improved cycle throughput.
This positive trend may also reflect favorable seasonal conditions, notably meteorological stability in summer, which lowers the likelihood of wind- or swell-related interruptions. Optimization of call planning and improved preventive maintenance of equipment may also have played a significant role
Fig 5 present the monthly total operational delays:

Figure 5. Monthly Total Operational Delays



Source: By our sides during data analysis, 2025.

Figure 5 illustrates the monthly trend of cumulative operational delays from April to September. A progressive, continuous decline in total recorded delay minutes is observed, indicating notable improvement in the regularity and reliability of port operations.
April and July stand out with peaks exceeding 600 cumulative minutes, suggesting periods of high activity when the terminal likely faced organizational constraints and logistical bottlenecks. Such initial congestion may be attributed to sudden increases in maritime traffic, imperfect team coordination, or temporary equipment failures.
From August onward, the curve shows a clear downward trend, reaching the lowest cumulative delay level in September (below 300 minutes). This trajectory indicates stabilization of operations, likely stemming from better call planning, optimized resource allocation, and more responsive control of cranes and yard vehicles.
The significant late-period decline in delays attests to growing operational proficiency, reflecting effective corrective actions and continuous organizational learning. It also confirms the inverse correlation between delays and productivity highlighted in the following sections: as delays decrease, GCP tends to improve.
Fig 6 present the correlation Heatmap:

4.3. Correlation and Relationship Between Variables

Table 1. Correlation Matrix

Variables	Operational Delays	GCP
Operational Delays	1.00	-0.44
GCP	-0.44	1.00

Source: By our sides during data analysis, 2025.

Figure 6 presents the correlation matrix illustrating statistical relationships among the main

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variables under study, notably operational delays and GCP. The heatmap highlights the strength and direction of linear associations using a color gradient, where darker shades indicate stronger correlations.

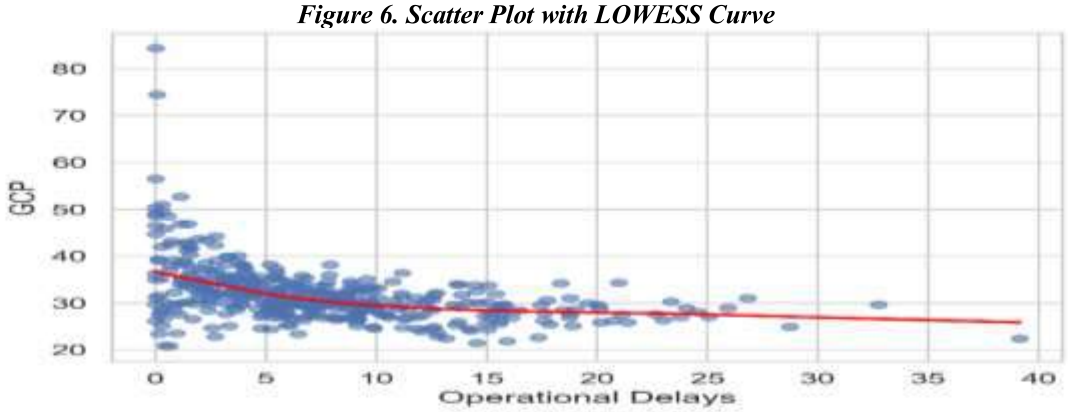
A moderate negative correlation is observed between operational delays and GCP (r = –0.44). This value indicates that as delays increase, GCP tends to decline proportionally. In other words, increases in handling or waiting time systematically reduce crane efficiency, confirming the inverse relationship posited in the research model.

Although moderate, this correlation is statistically significant, evidence of a real and consistent link between operational fluidity and mechanical performance of port equipment. It also suggests that terminal performance is influenced not only by cranes' technical capacities but also by organizational factors such as team coordination, container flow management, and movement planning.

Interpretively, this relationship underscores the direct dependence of productivity on execution time, confirming time as a key determinant of operational performance. These results thus provide empirical support for the main hypothesis that operational delays exert a significant negative impact on port productivity, paving the way for the detailed regression analysis presented below.

Fig 6 presents the Scatter Plot with LOWESS Curve:

Figure 6. Scatter Plot with LOWESS Curve



Source: By our sides during data analysis, 2025.

Figure 7 visually illustrates the empirical relationship between operational delays and GCP using a scatter plot with a non-parametric LOWESS smoothing curve. Each point represents an observation from the collected operational data, enabling visualization of the overall trend between these two key variables.

The downward-sloping LOWESS curve clearly indicates a negative relationship: as delays increase, GCP tends to fall. In the range between 0 and 10 minutes, the slope remains relatively flat, reflecting a moderate operational tolerance to minor cycle deviations. Beyond 10–12 minutes, however, the curve bends sharply, indicating a pronounced drop in crane performance. This non-linear pattern reveals that delays do not affect productivity uniformly: small delays can be absorbed without significant impact, but beyond a certain threshold they generate desynchronization, increased waiting between cranes and yard vehicles, and deterioration of the overall handling flow.

The graphical analysis thus confirms a declining performance effect once delays exceed a critical duration estimated here at around 10 minutes. These results corroborate the earlier correlation findings and provide strong visual support for the hypothesis that extended operational delays are a major impediment to crane productivity. In practice, this underscores the importance for terminal managers of rapidly identifying delay sources to maintain continuity and flow.

4.4. Regression Analysis and Model Validation

Table 2 present the OLS regression results for GCP vs. operational delays:

Table 2. OLS Regression Results for GCP vs. Operational Delays

Predictor	β (Coefficient)	Std. Error	95% CI	t-value	p-value
Constant (β_0)	35.18	0.61	[33.99, 36.38]	57.59	0.000
Operational Delays (β_1)	-0.46	0.06	[-0.57, -0.35]	-8.23	0.000

Source: By our sides during data analysis, 2025.

Model Statistics $R^2 = 0.20$, Adjusted $R^2 = 0.19$, F-statistic = 67.79 ($p < 0.000$), Observations (N) = 422

The OLS regression results confirm a statistically significant negative impact of operational delays on GCP. The slope coefficient $\beta_1 = -0.46$ ($p < 0.001$) indicates that each additional minute of delay leads on average to a 0.46 moves/hour decrease in crane productivity. This negative linear relationship reflects a direct, measurable inverse effect between the two variables: the more operations are delayed, the lower the handling rate.

The constant term $\beta_0 = 35.18$ ($p < 0.001$) corresponds to the expected average productivity in the absence of delay, estimated at about 35 moves/hour, the terminal's reference level under normal operational conditions. This reference, combined with the negative delay coefficient, allows interpretation of the regression slope as a sensitive performance indicator, revealing the average productivity loss per minute of operational slippage.

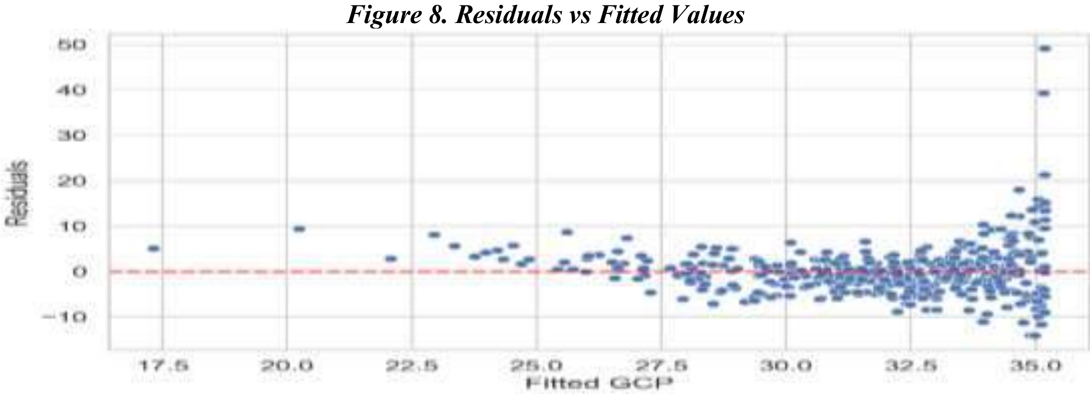
The $R^2 = 0.20$ (Adjusted $R^2 = 0.19$) indicates that delays alone explain 20% of the total variance in crane productivity. While this proportion may appear moderate, it is highly meaningful in a port context where numerous exogenous factors (weather, equipment availability, vessel size, call planning, etc.) simultaneously influence performance. The overall model fit ($F = 67.79$, $p < 0.001$) confirms robustness and validity, indicating that the estimated coefficients are not due to chance and that the model offers satisfactory explanatory power.

In practical terms, the delay coefficient (−0.46) implies that a 30-minute delay translates into roughly 14 lost moves/hour per crane, highlighting the operational relevance of even moderate schedule disruptions.

4.5. Diagnostic and Residual Analysis

Fig 8 present the residuals vs fitted values:

Figure 8. Residuals vs Fitted Values



Source: By our sides during data analysis, 2025.

Figure 8 shows the scatter of standardized residuals against fitted values from the regression model, used to test the fundamental assumption of homoscedasticity i.e., constant error variance across predicted values. This plot helps identify potential trends, clusters, or systematic structures in the residuals that would indicate a violation.

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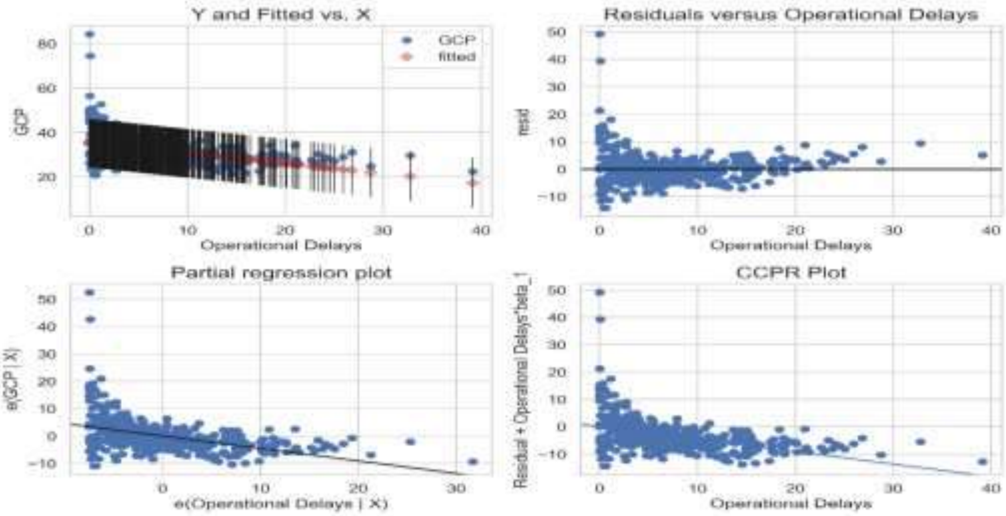
Here, residuals are randomly dispersed around the zero line without any discernible pattern. This absence of visible structure suggests no major bias due to functional misspecification and that errors are evenly distributed across predictions. The near-homogeneous spread indicates stable residual variance, confirming that the regression model adequately captures the relationship between operational delays and GCP.
A slight fan-out is visible at higher fitted values, suggesting mild heteroscedasticity a marginal increase in error variance when predicted productivity is higher. However, this deviation is limited and does not undermine overall model validity, especially since robust standard errors (HC3) were used to correct for such potential imbalance.
Fig 9 present the regression diagnostic Plots:

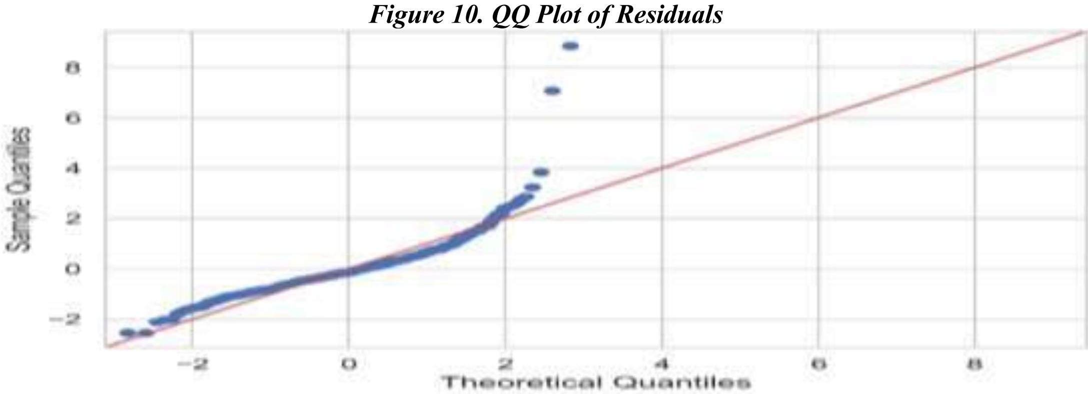
Figure 9. Regression Diagnostic Plots



Source: By our sides during data analysis, 2025.

Figure 9 brings together several essential diagnostic plots to assess the structural validity and robustness of the regression model estimating the effect of operational delays on GCP. These include the observed-vs-fitted scatter, the partial regression plot, and the CCPR (Component-Plus-Residual) plot, each providing complementary insight into fit quality and model adequacy. The partial regression plot displays the specific relationship between the independent variable (operational delays) and the dependent variable (GCP) after controlling for any other variables in the model.
A clear downward linear trend is observed, confirming that longer delays are associated with systematic reductions in crane productivity. This negative slope visually reflects the negative β_1 obtained in the OLS model, supporting internal consistency.
The CCPR curve complements this by checking stability and linearity. Points align, overall, along a descending line without trend breaks or excessive oscillation, indicating that the relationship between delays and productivity is essentially linear and not subject to misspecification. Moreover, the absence of abnormal patterns or clustered residuals suggests that no single observation unduly drives the overall fit, reducing the risk of outlier-induced bias.
Fig 10 present the QQ Plots of residuals:

Figure 10. QQ Plot of Residuals



Source: By our sides during data analysis, 2025.

Figure 10 presents the Quantile-Quantile (QQ) plot of the regression residuals, a classic tool to assess the normality of errors a key assumption for the validity of parametric tests in linear regression (coefficient t-tests and the overall F-test).

In the plot, empirical quantiles of standardized residuals are compared with theoretical normal quantiles. Most points align closely along the reference line, indicating that the empirical distribution of residuals closely follows a normal distribution.

This behavior confirms that the model largely satisfies the normality assumption, reinforcing the reliability of statistical inferences drawn from the regression coefficients.

Slight deviations at the extremes indicate the presence of tail outliers. Such deviations often unavoidable in real operational data do not signal a major departure from normality but rather the natural variability of field conditions (e.g., exceptional congestion episodes, sporadic mechanical interruptions, or unusual flow variations).

5. Discussion

The analysis of six months of operational data from Moroccan container terminals provides clear evidence that operational delays have a statistically significant negative impact on Gross Crane Productivity (GCP).

The regression results ($\beta_1 = -0.46$; $p < 0.001$) indicate that every additional minute of delay leads, on average, to a 0.46 moves/hour decrease in crane performance. This result underlines the crucial role of time in determining operational efficiency and confirms previous findings identifying waiting and turnaround times as major contributors to productivity losses caused by congestion (Peng et al., 2022).

The results also reveal a non-linear effect: minor delays do not immediately affect productivity, but once delays exceed roughly ten minutes, performance drops sharply. This suggests that crane systems operate within a limited buffer of tolerance, beyond that, synchronization between quay and yard operations deteriorates rapidly.

The pattern supports the congestion propagation mechanism discussed by Peng et al. (2022), where localized disruptions spread across the terminal network, amplifying inefficiencies among handling units.

The negative relationship between delays and productivity should be interpreted in light of the broader context of automation and integrated scheduling. As Naeem et al. (2023) noted, the efficiency gains of automated container terminals do not stem only from mechanization but also from the effective coordination of quay cranes, automated guided vehicles, and yard cranes.

The R^2 value of 0.20 found in this study indicates that about one-fifth of the variability in GCP is explained by delay duration, while the rest likely depends on factors such as coordination algorithms, yard congestion, or scheduling accuracy.

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Improving real-time synchronization and adopting intelligent task allocation systems could therefore yield further performance gains in line with integrated operation models (Naeem et al., 2023).

The monthly trend observed reinforces this interpretation. As the terminal refined its planning and coordination procedures, average delays were almost halved, while GCP increased by approximately 25%. This progression suggests that organizational learning, process optimization, and digital maturity play key roles in moderating the relationship between delays and productivity.

From the standpoint of modern logistics, these findings reaffirm the importance of automation, connectivity, and collaboration as the three main levers of operational performance. The notable decline in cumulative delays after August is consistent with Hardianto et al. (2023), who emphasized that operational efficiency and coordination across port actors are essential components of sustainable port performance.

Strengthened connectivity through digital links between cranes, yard vehicles, and planning systems facilitates early detection of potential bottlenecks. Similarly, closer collaboration among planning, maintenance, and vessel coordination teams enhances situational awareness and shortens reaction times when disruptions occur.

These developments show that improvements in time efficiency are not purely technical but also organizational in nature. The continuous rise in GCP at the Moroccan terminal parallels the evolution described by Yen et al. (2023) in their analysis of smart ports, where automation and environmental intelligence drive efficiency gains only when supported by capable management and integrated information systems. In this sense, the terminal's progress reflects a wider shift toward intelligent and adaptive port operations.

Yen et al. (2023) identified automation, environmental management, and digital intelligence as the three pillars of smart port performance, with automation providing the greatest efficiency improvements. The current results confirm this relationship within a developing-country context.

By reducing idle time and improving synchronization, automation contributes simultaneously to operational performance and environmental sustainability: shorter handling cycles mean lower energy use per container, while less idle time cuts auxiliary power consumption by cranes and yard tractors. These operational gains thus complement the decarbonization objectives central to smart-port development.

Nonetheless, the fact that 80% of GCP variation remains unexplained highlights the complex, multi-factor nature of port performance. Factors such as infrastructure capacity, ship size, equipment reliability, and workforce skills continue to play major roles.

This supports Hardianto et al. (2023)'s argument that port performance assessment must integrate operational, financial, and sustainability dimensions rather than rely solely on productivity indicators.

The study offers several practical lessons for port managers and policymakers:

First, the robust negative relationship between delays and productivity reinforces the need to make delay reduction a strategic objective. Predictive delay analytics using AIS data and machine learning models like LSTM (Peng et al., 2022) could allow managers to anticipate congestion and adjust schedules before disruptions occur.

Second, terminal operators should implement integrated scheduling platforms that dynamically reallocate cranes, vehicles, and human resources based on real-time operational data, as recommended by Naeem et al. (2023).

Finally, policymakers should view automation and environmental transition as mutually reinforcing, not competing, priorities. Investments in energy-efficient equipment and smart technologies, as highlighted by Yen et al. (2023), can simultaneously boost productivity and reduce environmental impact.

From a theoretical standpoint, this research bridges the gap between micro-level operational dynamics and macro-level port performance frameworks. It provides empirical confirmation that time efficiency acts as a key mediator linking automation capacity with overall productivity, extending the perspectives offered by Peng et al. (2022) and Yen et al. (2023).
Future studies should expand this model to include multiple terminals and examine how factors such as infrastructure quality, intelligent scheduling algorithms, and human–machine collaboration influence productivity.
The use of advanced forecasting techniques such as reinforcement learning or hybrid deep-learning models could further refine decision-support systems for next-generation smart ports, strengthening both operational reliability and sustainability outcomes.

6. Conclusion

This study provides clear, data-driven evidence that time losses are a primary constraint on quayside productivity. In the Moroccan terminals analyzed, every minute of operational delay measurably depresses GCP, with a nonlinear drop once delays exceed approximately 10 minutes. Beyond the headline coefficient ($\beta = -0.46$), two insights are particularly relevant for practice:

- First, delay management is not only a technical matter but an organizational one, as coordination quality among quay cranes, yard cranes, and transport vehicles determines how efficiently automation translates into throughput.
- Second, predictive and integrated control is decisive, since combining early-warning delay analytics with dynamic, real-time scheduling can prevent desynchronization, shorten cycle times, and reduce idle energy use.

The results also confirm that GCP sits at the intersection of the smart-port performance triad automation, connectivity, and sustainability. As delays declined during the study window, GCP improved accordingly, illustrating how digital maturity and continuous process learning compound efficiency gains.
However, the analysis also shows that a substantial share of GCP variance remains unexplained by delays alone, highlighting the influence of factors such as infrastructure capacity, vessel characteristics, equipment reliability, and workforce skill sets.
This introduces clear limitations. The study relies on a single-terminal dataset and focuses primarily on linear delay effects, which restricts generalizability and may overlook important threshold dynamics and heterogeneous impacts across operational conditions.
Additionally, the use of OLS imposes symmetry assumptions that may underrepresent tail risks periods of extreme congestion or exceptionally high performance.
Future research should address these limitations by extending the model across multiple terminals and by integrating moderating and mediating factors such as buffer capacity, yard allocation strategies, berth planning, or weather disruptions.
Methodologically, more advanced approaches offer promising avenues:

- Quantile regression, to capture how delays affect low-productivity versus high-productivity situations differently.
- Threshold or regime-switching models, to detect operational breakpoints (e.g., when delays surpass critical values).
- Reinforcement Learning and LSTM-based predictive control, to transition from reactive delay measurement toward proactive orchestration of cranes, vehicles, and yard assets.

Strategically, the findings reaffirm that reducing delays remains one of the most tractable and impactful pathways for enabling smarter, cleaner, and more resilient port operations.

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