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Data-Driven Assessment and Forecasting of Port Services Demand: A Case Study of Shahid Rajaee Port

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ABSTRACT

Ports play a vital role in maritime transport and international trade, and port services—as a critical component of the maritime supply chain—significantly influence overall port efficiency. Accordingly, accurately forecasting port service demand in relation to economic fluctuations, trade constraints, and infrastructural conditions is essential for operational planning and infrastructure development. This study aims to analyze various categories of port services and to forecast service demand, with a specific focus on Shahid Rajaee Port. For this purpose, real operational data—including maritime and land-side traffic information and key performance indicators—were collected, refined, and analyzed using regression, time-series and moving-average models. The results indicate that variables such as cargo handling volume, number of incoming vessels, duration of marine service operations, truck and rail flows, economic and political conditions have a decisive impact on port service demand. The findings of this research provide valuable guidance for managers in resource allocation, capacity development, congestion management, and enhancing port operations in line with sustainable development objectives.

1. Introduction

Ports, as key nodes within logistics networks and commercial transport systems, play a vital role in cargo flow, supply chain support, and the facilitation of international trade. With the continuous growth of cargo and passenger movements, the need to expand port infrastructure and provide diverse port services has become increasingly important. These services include a range of operational and support activities such as tugging, berthing, loading and unloading, warehousing, and customs-related services, each of which has a direct impact on the speed and quality of port performance. Despite their importance, port performance evaluations have often focused primarily on the volume of cargo handled, while port services have received comparatively less attention, an issue that can lead to an inaccurate understanding of a port's actual operational status and limit the ability to identify weaknesses and improvement opportunities. Moreover, the fundamental differences between goods and services further complicate the assessment and forecasting of port services. Goods are physical and measurable, whereas services are intangible, activity-based, and lack a standardized unit of measurement. This distinction necessitates more comprehensive and multi-dimensional analytical approaches for evaluating and forecasting port services.

In this study, focusing on Shahid Rajaee Port—the largest commercial port in Iran—a set of port service data has been extracted and analyzed using a data-driven modeling approach. This paper aims to provide a reliable picture of future port service behavior by presenting a clear conceptual framework, conducting detailed trend analysis, and applying quantitative forecasting models.

2. Research Background and Literature

The research related to forecasting port demand and analyzing maritime port services indicates that accurate modeling in this field requires a combination of economic, operational, and statistical approaches. A review of key studies shows that the literature can generally be categorized into economic and trade-based models, port operational models, and statistical and time-series models.

In the domain of economic approaches to port demand forecasting, classical studies such as the work of Miklius and Wu (1988) demonstrate that demand for port services is primarily a function of projected foreign trade and cargo volume. Their study forecasted demand for a new port through a multi-stage process involving national trade projection based on economic indicators, commodity-based demand estimation, and cargo allocation among ports using the PTA[1] model. In these models, national trade is first forecasted, then assigned to commodity groups, and finally allocated to individual ports.

In the study by Tongzon (1991), the future supply of shipping services was estimated through a model that examines the relationship between trade volume, global shipbuilding trends, and the physical limitations of the port. The model forecasts the number of future vessel trips as well as the characteristics of the incoming fleet. The findings indicate that the port's commercial demand plays the most significant role in determining the supply of shipping services, while the influence of global technological developments is assessed to be limited in the short term.

In the thesis by Joharianzadeh (2012), which is based on port operations models, future cargo volumes were forecasted using statistical methods such as trend analysis and regression. The forecasted cargo was then distributed among various ports using the PTA model, based on minimizing inter-port transportation costs, then an optimization model was employed for berth allocation. The results indicate that integrating cargo forecasting with berth allocation and vessel scheduling can reduce waiting times and lead to more efficient utilization of port capacity.

Joharianzadeh and Babazadeh (2012) reported in their article that the future demand of Kish Port was estimated using four approaches: historical trend analysis, macroeconomic indicators, induced demand arising from development projects, and the gravity model. Past data, regional capacities, and development plans were modeled under multiple scenarios. A comparison of scenario outputs with actual performance showed that the combined approach of historical trends and macroeconomic indicators produced the highest level of alignment and was identified as the most reliable estimation method.

Studies using statistical and data-driven approaches—such as those by Jugović, Hess, and Poletan Jugović (2011) and Lättilä and Hilmola (2012) demonstrate that statistical models including ARIMA [2], multivariate regression, and system dynamics perform strongly in long-term demand forecasting, particularly when uncertainties and structural changes are present in the data.

The study by Jugović et al. (2011) tested several time-series models—including linear trend, quadratic trend, moving average, and exponential smoothing—to forecast demand for the Port of Rijeka. Methods based on economic indicators were also examined to compare. The results showed that the linear-trend model yielded the lowest deviation from actual long-term data and was therefore identified as the most suitable method. In the study by Lättilä and Hilmola (2012), long-term port demand forecasting was conducted using a combination of multivariate regression, ARIMA, system dynamics, and Monte Carlo simulation. Instigators such as industrial production, GDP [3], and Russian oil exports were incorporated into the model, and multiple future scenarios were defined. The findings indicated that industrial production is the primary determinant of demand trends for Finnish ports, and that system-dynamics-based approaches provide greater accuracy in representing uncertainty.

In the field of machine learning, studies such as those by Sadaghi, Shivafar, and Rastad (2024) and Sadaghi and Shivafar (2024b) have shown that deep learning networks are capable of capturing nonlinear patterns present in port operations and can provide higher predictive accuracy compared to traditional models. In the study by Sadaghi and Shivafar (2024b), the demand for empty containers at Shahid Rajaee Port was forecasted using deep learning networks. Operational data from empty-container terminals, temporal patterns, and storage capacities were introduced into the model, and the nonlinear relationships among variables were extracted by the network. The results indicated a significant improvement in forecasting accuracy compared with conventional methods, enabling more optimal planning for the allocation and distribution of empty containers. Another study by Sadaghi and Shivafar (2024a) utilized operational data and simulation techniques to optimize container-handling processes at Shahid Rajaee Port. From this perspective, the study provides a practical framework for evaluating the efficiency and quality of port services based on statistical and operational data.

3. Methodology

For this study, data were extracted from the official statistics of the Ports and Maritime Organization (PMO), consisting of two main categories: traffic information (number of vessels, berth calls, truck and train movements) and operational data (cargo volume, vessel waiting time, berth utilization rate, and equipment capacities). These monthly data were obtained from the PMO portal and, assuming their accuracy, were used as the basis for the analysis. The dataset was consolidated in Excel, variable trends were plotted, and four analytical methods were applied: linear and nonlinear regression, descriptive–analytical assessment, moving-average analysis, and time-series forecasting.

[1] Port Traffic Allocations

[2] Autoregressive Integrated Moving Average

[3] Gross domestic product

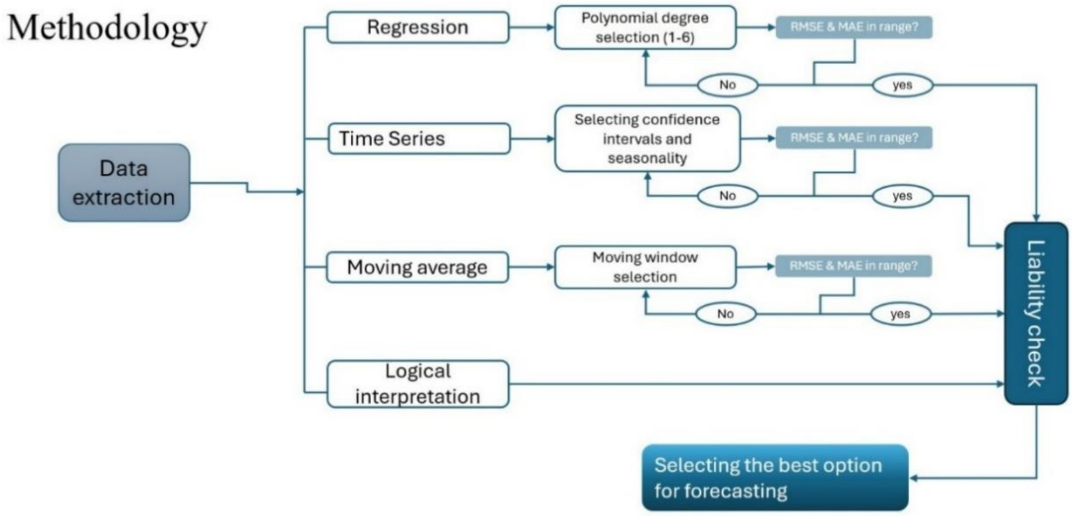

Figure 1. Methodology Diagram

In the regression analysis, polynomial equations of degrees 1 through 6 were fitted, and the model with the lowest RMSE[4] and MAE[5] was selected. It should also be noted that certain nonlinear functions—such as exponential, logarithmic, and trigonometric forms—are often unsuitable for empirical port data due to characteristics such as unbounded behavior, undefined domains, or periodic patterns, which may lead to unrealistic forecasts. For this reason, polynomial models generally provide more reliable results.

In the descriptive analytical assessment, upward or downward trends in the plotted data were interpreted in light of the port's economic, political, and operational conditions. In the moving-average method, an appropriate window was chosen to smooth short-term fluctuations and extract the underlying trend. Time-series forecasting was conducted using the Forecast Sheet tool in Excel, which allowed adjustment of confidence intervals and identification of potential seasonality to generate future estimates. Finally, the accuracy of the models was compared, and the most suitable forecasting method for each variable was selected (Figure 1).

4. The Port Under Study

The data used in this study were obtained from Shahid Rajaee Port (Figure 2), located in Iran, near the city of Bandar Abbas. Shahid Rajaee Port is the largest commercial port in the country, situated 15 kilometers west of Bandar Abbas along major international transit corridors, and handles more than one-third of Iran's maritime trade. The port is equipped with 30 gantry cranes, including Super Post-Panamax units, enabling it to accommodate seventh-generation container vessels. Its current annual handling capacity is 6 million TEU[6], which will increase to 8 million TEU upon completion of Phase 3 development.

5. Data Under Study (Rafati, 1403)

The extracted data is categorized into several fields which are shown in figure 3.

Figure 2. Aerial view of Shahid Rajaee Port

[4] Root Mean Square Error

[5] Mean Absolute Error

[6] Twenty-foot equivalent unit

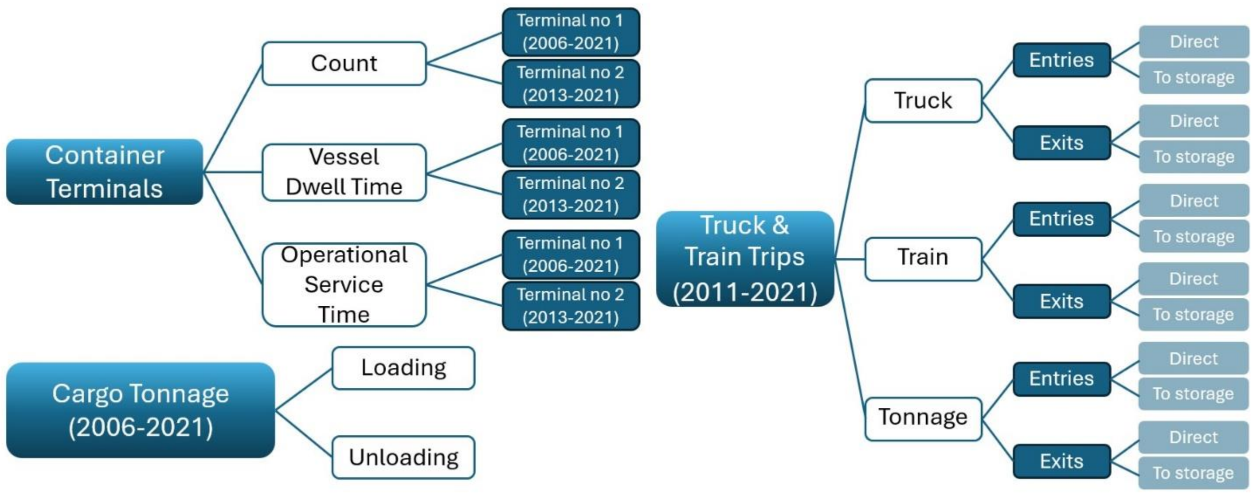

Figure 3. Extracted data categories

5.1. Container Vessel and Its Dwell and Service Times

The container terminals No. 1 and 2 of Shahid Rajaee Port, as the main hubs of container operations, play a significant role in Iran's maritime supply chain. Terminal No.1 has been operational since 1997, and Terminal No. 2 since 2013. Equipped with Super Post-Panamax cranes and modern infrastructure, Terminal No. 2 enables the accommodation of larger vessels and increases operational capacity, marking a major milestone in the port's development. In this analysis, the data are examined based on the number of arriving container vessels and the average dwell and service times. Accordingly, the results reflect the mean behavior of vessels and may differ for smaller or larger ships.

5.1.1. Temporal Pattern and Vessel Count in Terminal No. 1

As shown in Figure 4, in Terminal No. 1 the average vessel service time remained nearly constant throughout the statistical period, while the average dwell time increased significantly after 2013, coinciding with the intensification of sanctions and the commencement of operations at Terminal No. 2. During the same period, the number of vessels calling at Terminal No. 1 (Figure 5) declined, which can be attributed to the relocation of larger vessels to Terminal No. 2, the reduction in trade volumes caused by sanctions, decreased revenue and workforce among contractors, lower operational pressure and congestion, and limitations in equipment maintenance and spare parts supply. Consequently, after 2013 Terminal No. 1 experienced a reduction in vessel calls alongside a relative increase in dwell time, while service time remained almost unchanged.

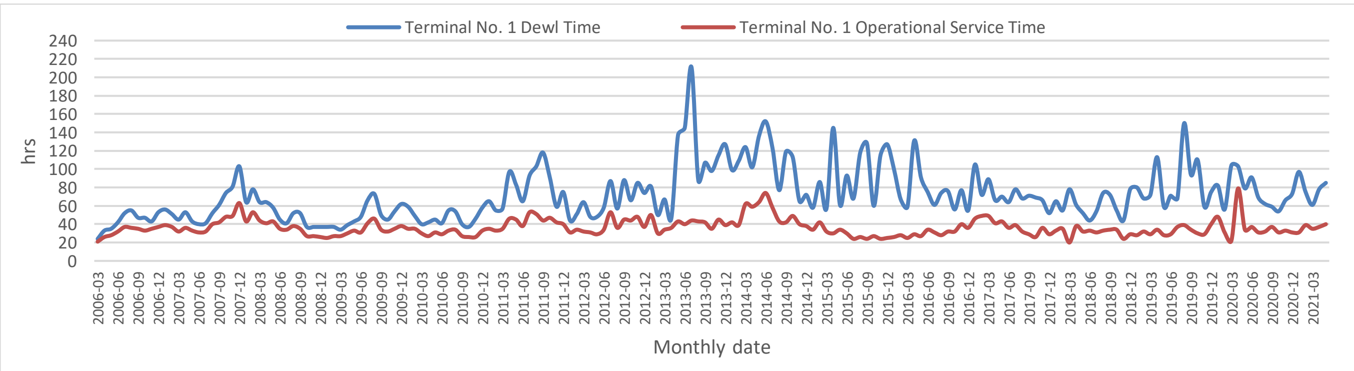

Figure 4. Vessel Dwell Time and Service Time at Container Terminal No. 1

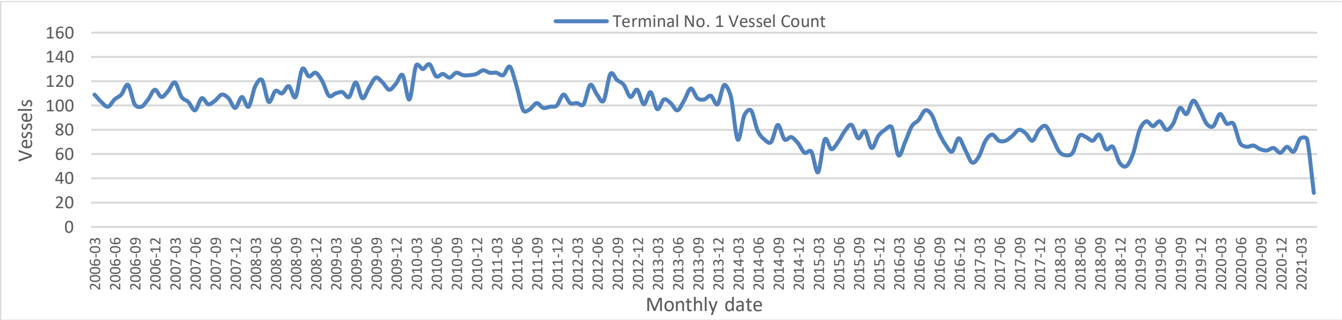

Figure 5. Vessel Count in Container Terminal No. 1

5.1.2. Temporal Pattern and Vessel Count in Terminal No. 2

Data for Terminal No. 2 begin in 2013 and show an upward trend in the number of arriving vessels (Figure 6), while the average service time remains nearly constant and the average dwell time exhibits fluctuations (Figure 7). Modern equipment such as high-capacity Super Post-Panamax cranes along with updated design and operational practices and improved management processes, have contributed to greater efficiency in berthing and cargo-handling operations, thus attracting a significant portion of container traffic. Consequently, Terminal No. 2 has gradually gained a prominent role in accommodating larger vessels and enhancing the port's overall operational capacity.

5.1.3. Forecasting the Number of Incoming Vessels to the Terminals

To forecast the number of vessels entering Terminals 1 and 2, a combination of linear and polynomial regression, moving-average analysis, and time-series models was applied, and the most suitable curves were selected based on RMSE and MAE indicators. In Terminal No. 1, although a third-degree polynomial provides a better fit over the historical dataset, simpler models and time-series forecasting (Figure 8) were found to be more realistic for future projections. For Terminal No. 2, the linear model (Figure 9) offers an appropriate representation of the trend. By integrating the results of the models and considering economic and political conditions, the number of incoming vessels for each terminal is estimated to be approximately 60 to 80 vessels per month over the next three years. This value is approximate and should be revised if underlying conditions change.

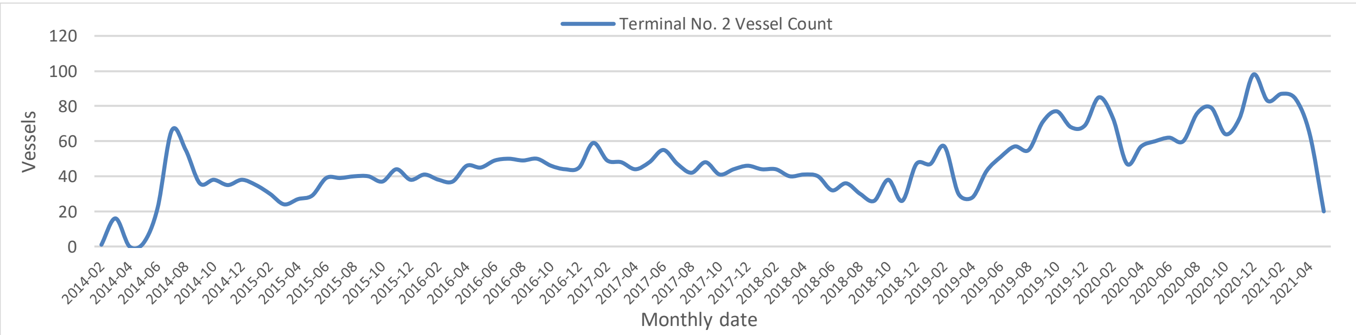

Figure 6. Vessel Count in Container Terminal No. 2

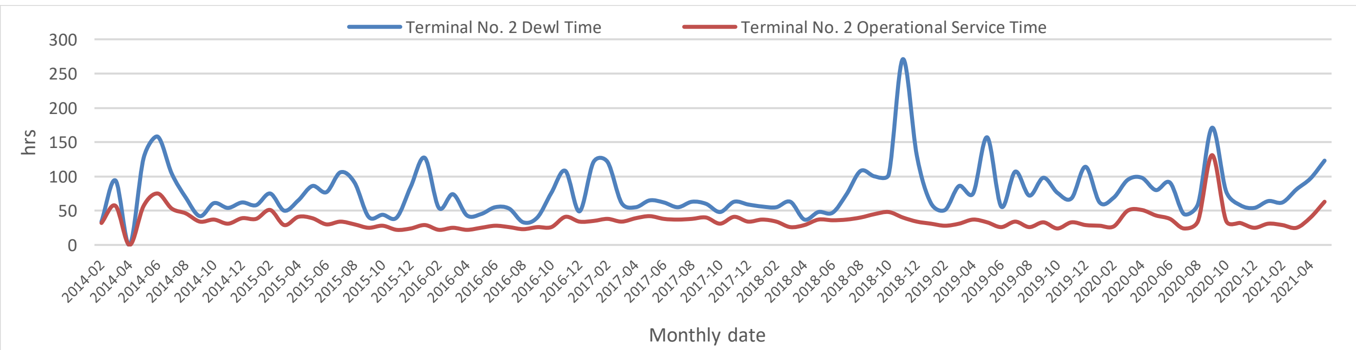

Figure 7. Vessel Dwell Time and Service Time at Container Terminal No. 2

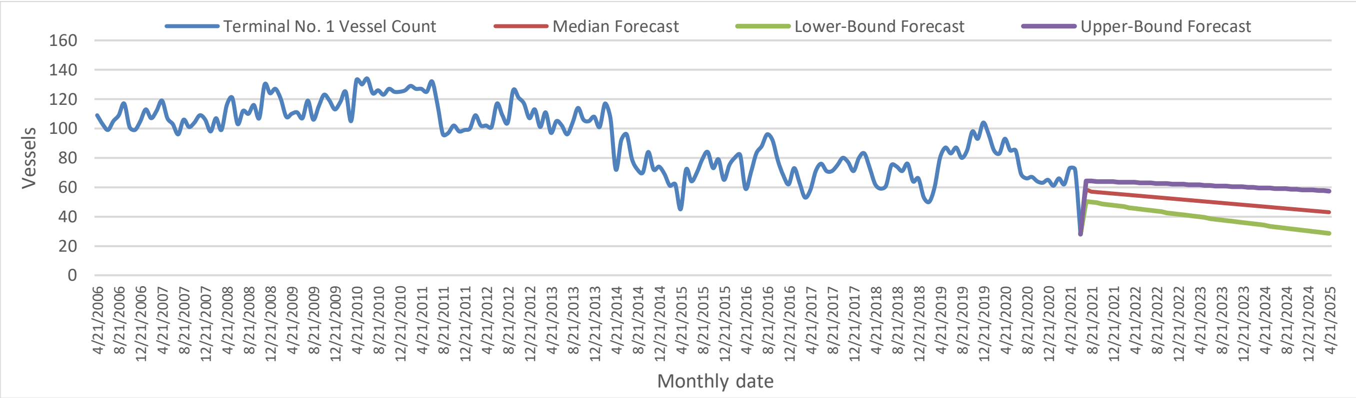

Figure 8. Three-Year Time-Series Forecast of Incoming Container Vessels at Terminal No. 1

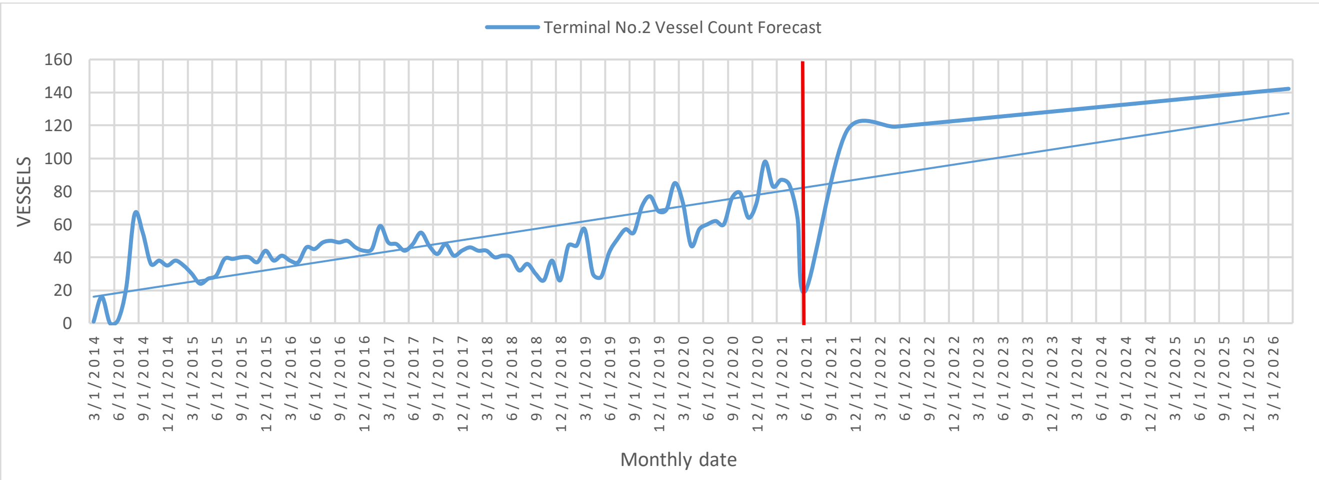

Figure 9. Regression Forecast of Incoming Container Vessels—Terminal No. 2

5.1.4. Forecasting the Average Vessel Dwell Time at Berth

To analyze and forecast the average vessel dwell time at each terminal, regression, moving-average analysis, and time-series modeling were employed. In Terminal No. 1, the 30-month moving average shows that dwell time increased by approximately 40% from 2011 to 2015, decreased by about 30% between 2015 and 2019, and then rose gradually by around 15% until 2021, reaching a relatively stable level thereafter. In Terminal No. 2, the 20-month moving average indicates an initial increase of about 60% up to 2018, followed by a 20% decline in 2020, and then stabilization. The time-series models (Figures 10 and 11) produced reasonable results consistent with the moving-average trends. Based on these findings, the average vessel dwell time for both terminals is estimated to be approximately 80 to 100 hours over the next three years.

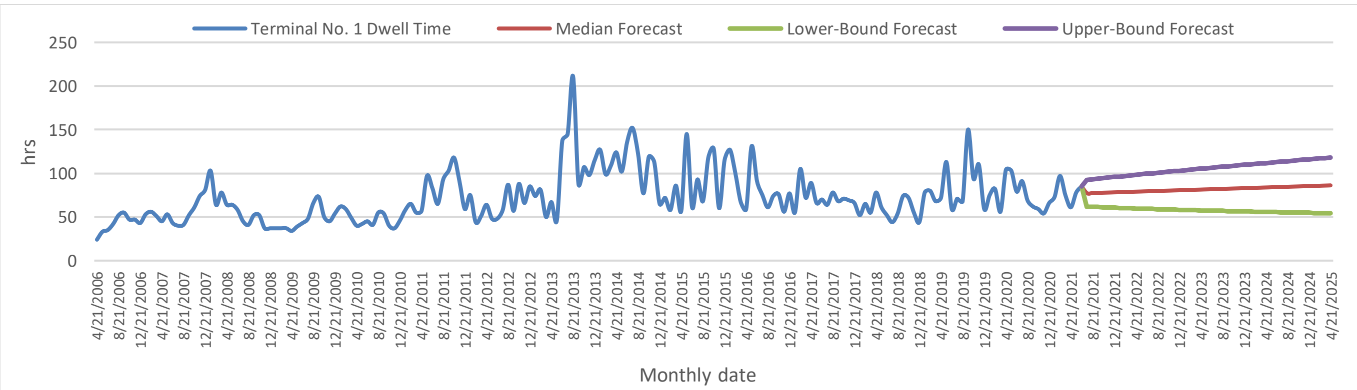

Figure 10. Three-Year Time-Series Forecast of Average Vessel Dwell Time—Terminal No. 1

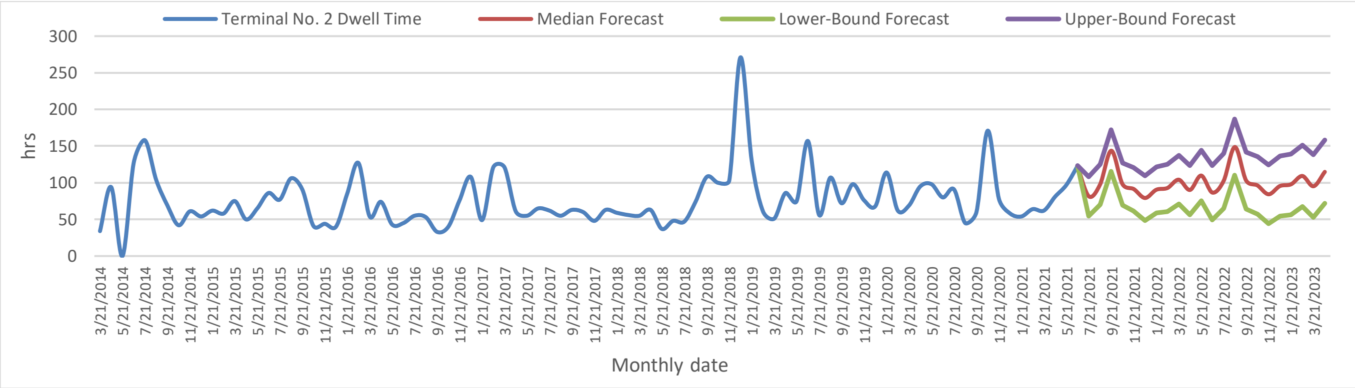

Figure 11. Three-Year Time-Series Forecast of Average Vessel Dwell Time—Terminal No. 2

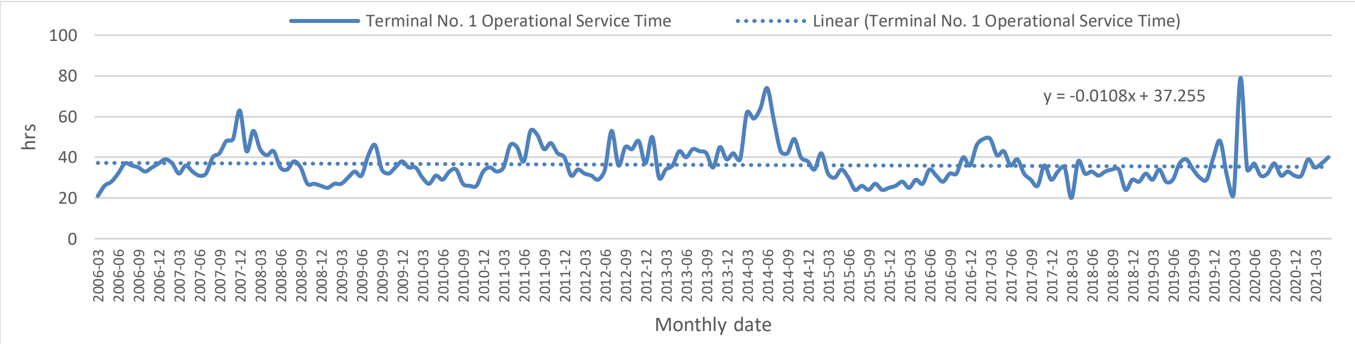

Figure 12. Average Vessel Service Time at Terminal No. 1

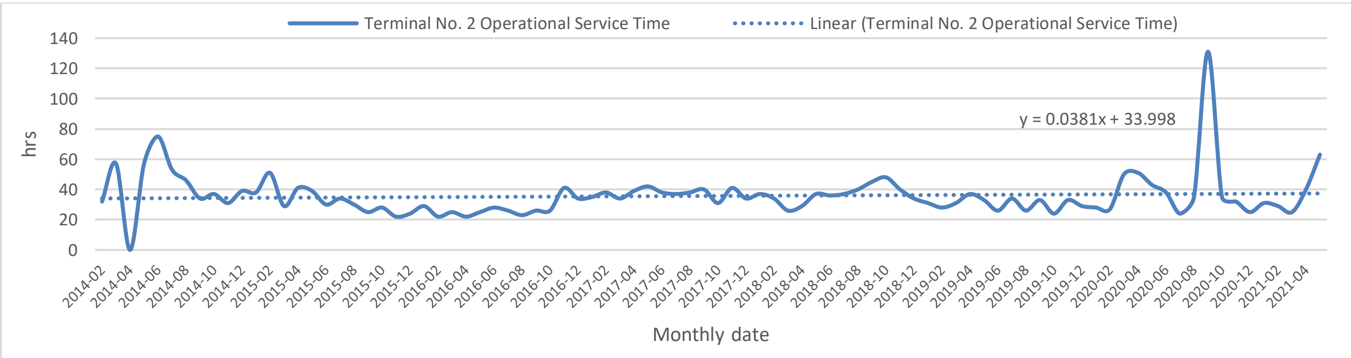

Figure 13. Average Vessel Service Time at Terminal No. 2

5.1.5. Forecasting the Average Vessel Service Time

The plots of average vessel service time in both terminals indicate a generally stable pattern with limited fluctuations. Polynomial regression analysis combined with RMSE and MAE evaluation shows that the linear (first-degree) model yields the lowest error in both terminals and is therefore suitable for approximate estimation. In Terminal No. 1 (Figure 12), despite fluctuations, the mean service time has remained nearly constant over the study period, reflecting relatively stable operational management, reasonably efficient equipment utilization, and a steady level of activity. A similar trend is observed in Terminal No. 2 (Figure 13), where service time fluctuates within a narrow and stable range. Based on this analysis, the average vessel service time in both terminals is projected to be approximately 30 to 40 hours over the next three years, provided that current operational and equipment conditions do not undergo major changes.

5.2. Truck and Wagon Movements and Cargo Tonnage

5.2.1. Truck Entries Forecasting

Incoming trucks to the port consist of two categories: direct-entry (ship-side) trucks and storage-entry trucks. At the beginning of the study period (2011), the number of trucks in both categories was nearly the same; however, since 2013, storage-entry traffic has sharply declined while direct-entry traffic has increased. This shift is attributed to improved port space utilization, higher warehousing costs, the mechanization of loading and unloading operations, changes in cargo characteristics (notably the rise of containerized and bulk cargo), and the growing share of time-sensitive goods. However, certain types of cargo—such as oversized or heavy items, shipments facing administrative delays, and some transit goods—still require mandatory entry into storage areas. The trend over recent years shows that storage-entry truck traffic has approached nearly zero, and future forecasts confirm this pattern; therefore, the need for major warehouse expansion is minimal. For direct-entry trucks, polynomial regression models were unsuitable and produced unrealistic results. Consequently, qualitative assessment, moving-average analysis (Figure 14), and time-series forecasting (Figure 15) were applied. Based on these methods and assuming current operational conditions remain unchanged, it can be said that over the next three years approximately 40,000 to 50,000 direct-entry trucks and 3,000 to 3,500 storage-entry trucks will arrive annually.

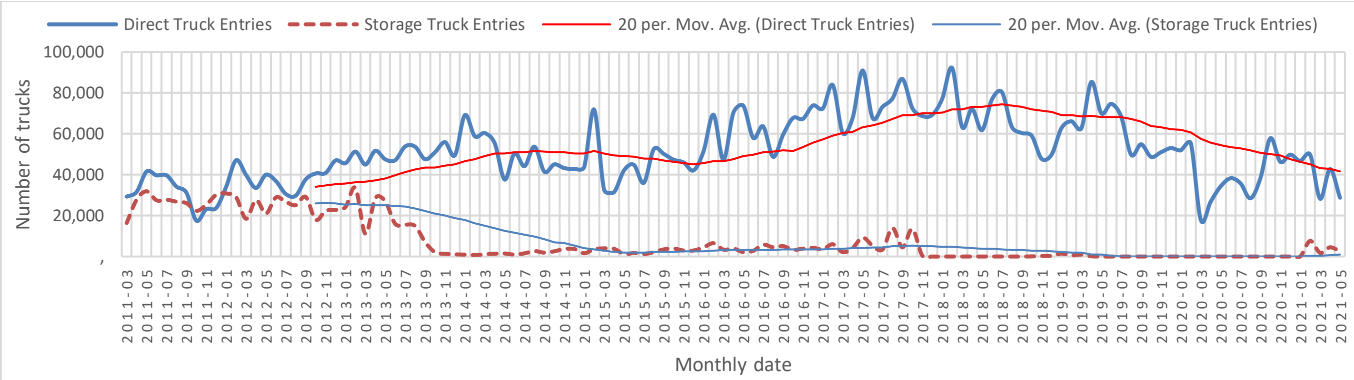

Figure 14. Incoming Truck Count with Fitted Moving-Average Curve

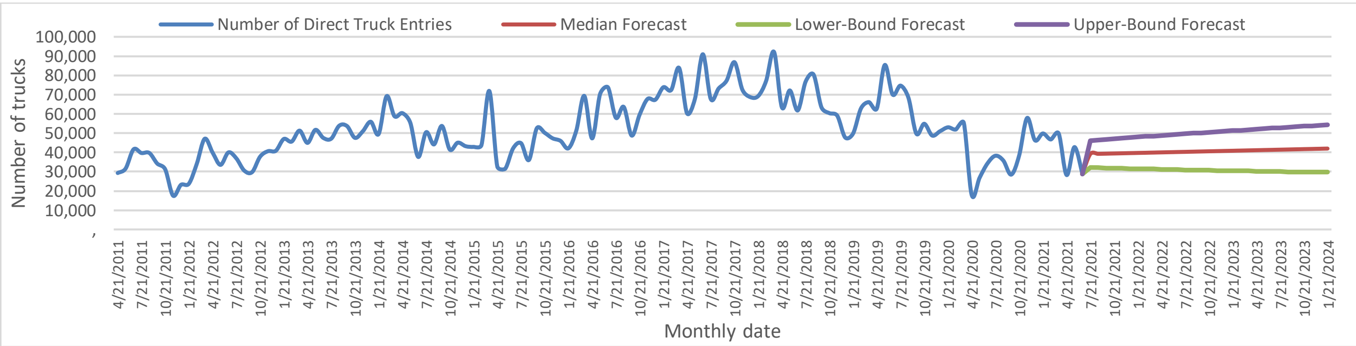

Figure 15. Three-Year Time-Series Forecast of Direct Entry Trucks

5.2.2. Trucks Exits and Forecasting

The pattern of outgoing trucks is similar to that of incoming traffic. Warehouse-based dispatches decreased to nearly zero by 2015, and after a period of decline (2015–2019), the total number of outgoing trucks began to rise from 2019 onward before stabilizing at a steady level. Using moving-average analysis (Figure 16) and time-series forecasting (Figure 17), it is estimated that over the next three years direct (ship-side) dispatches will range between 8,000 and 9,000 trucks per year, while warehouse-based dispatches will range from 1,500 to 2,000 trucks per year.

5.2.3. Incoming and Outgoing Wagons and Forecasting

Inbound rail transport to the port has nearly ceased in recent years, approaching zero (Figures 18 and 19). This decline is primarily due to the higher cost of rail transport, the complexity of loading and unloading processes, and the longer transit time associated with rail shipments. Although rail infrastructure is available, its practical utilization has significantly decreased. Based on this trend, the number of inbound wagons (both direct-entry and storage-entry) is projected to remain within the range of 0 to 200 units per year over the next three years. Similarly, the number of outgoing wagons has gradually declined and has almost reached zero. The influencing factors mirror those affecting inbound rail traffic, including economic and operational challenges associated with railway transport. Accordingly, future forecasts align with the inbound pattern, and the number of outbound wagons (direct and storage-based) is estimated to remain within 0 to 200 units per year.

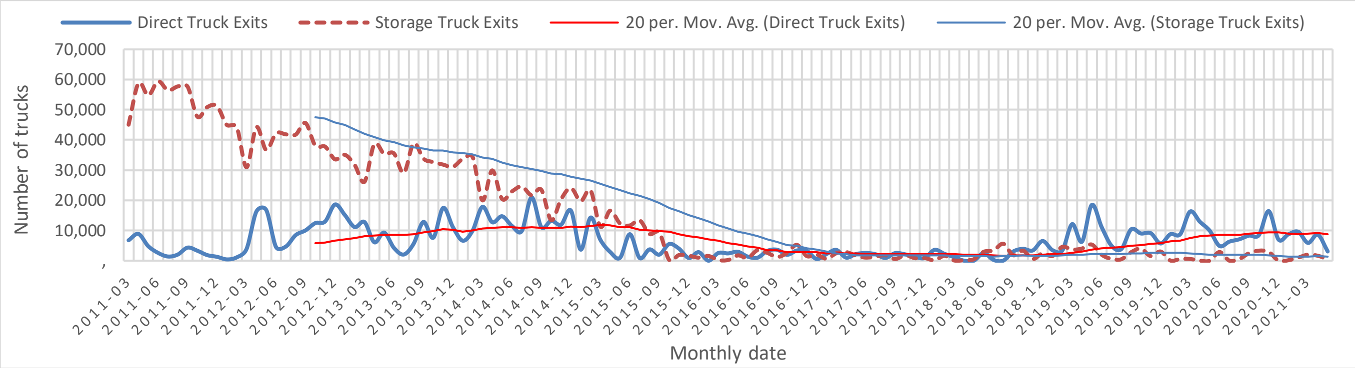

Figure 16. Outgoing Truck Count with Fitted Moving-Average Curve

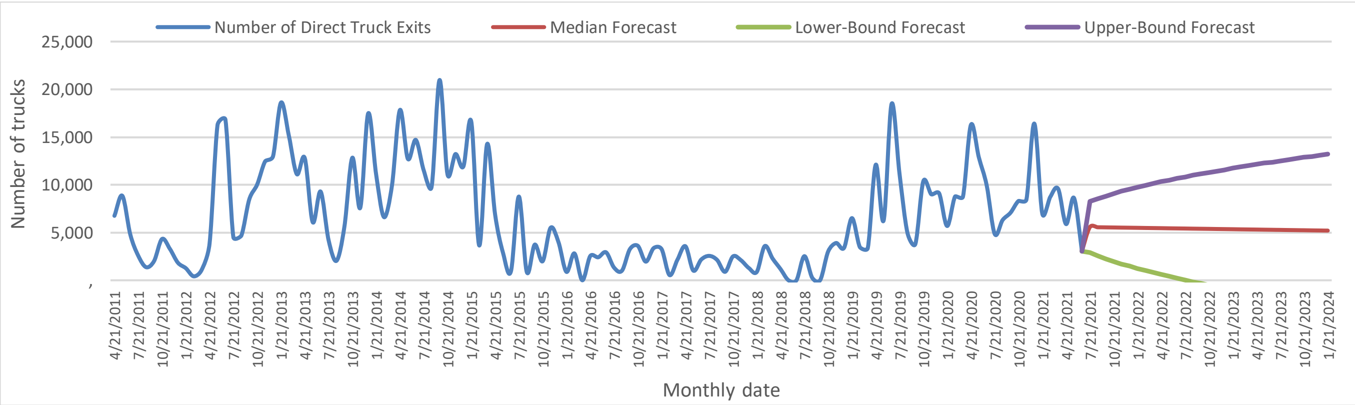

Figure 17. Three-Year Time-Series Forecast of Direct Exit Truck Numbers

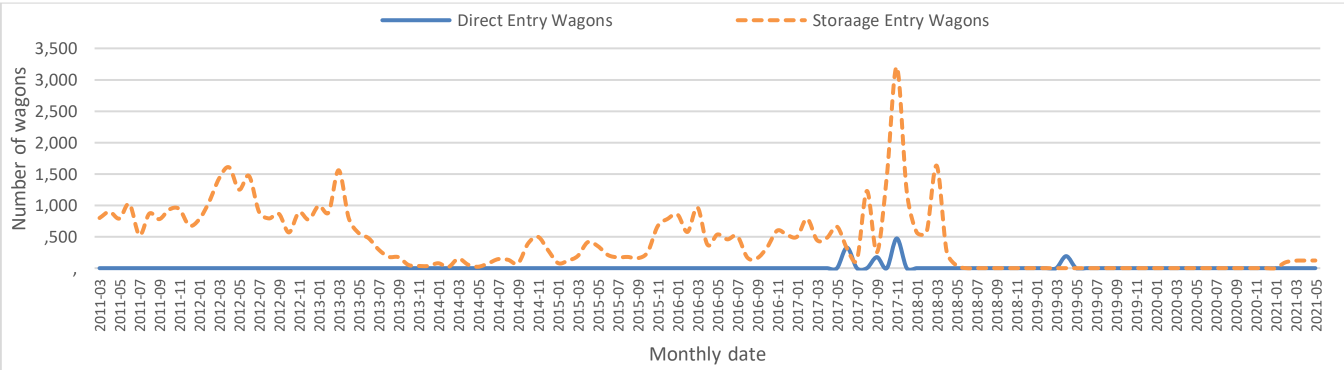

Figure 18. Number of Incoming Wagons to the Port

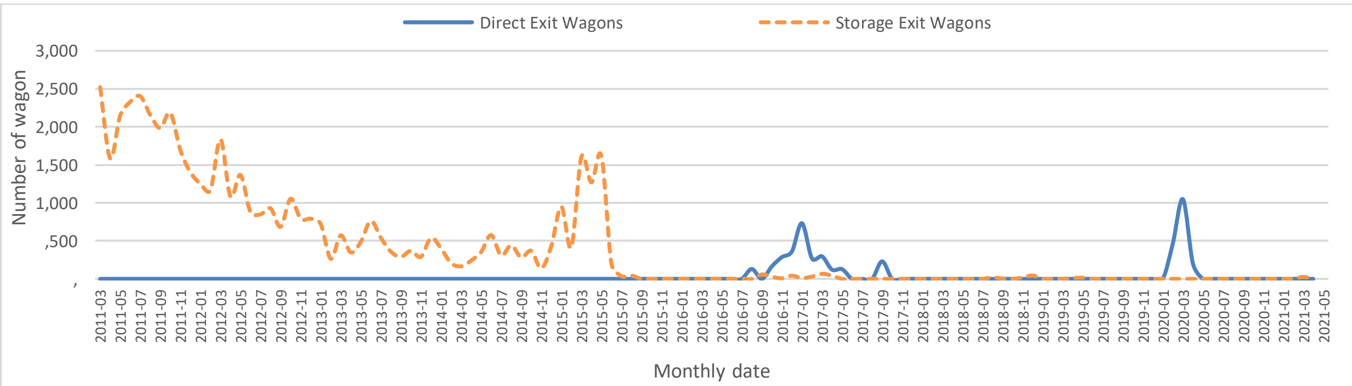

Figure 19. Number of Outgoing Wagons from the Port

5.2.4. Cargo Tonnage of Inbound and Outbound Shipments by Trucks and Wagons, and Forecasting

The inbound and outbound cargo tonnage of the port is primarily driven by truck operations, as the share of rail wagons is negligible; therefore, tonnage charts essentially reflect truck-traffic behavior. The inbound and outbound tonnage (both direct and to storage) follows a pattern similar to that of truck counts, confirming earlier trends. The moving-average analysis (Figures 20 and 21) shows that warehouse-related inbound and outbound tonnage has approached nearly zero in recent years, a condition that is expected the future. Direct outbound tonnage remains stable and is likely to continue this trend, while direct inbound tonnage despite fluctuations has become to a stable average over the past two years, making it a suitable basis for forecasting. Using moving-average analysis, time-series forecasting, and mean values from the final period, the three-year outlook suggests the following annual estimates:

- Direct inbound tonnage: approximately 2.5 to 3 million tons
- Inbound warehouse tonnage: 100,000 to 120,000 tons
- Direct outbound tonnage: approximately 1.5 to 1.7 million tons
- Outbound warehouse tonnage: about 190,000 to 200,000 tons

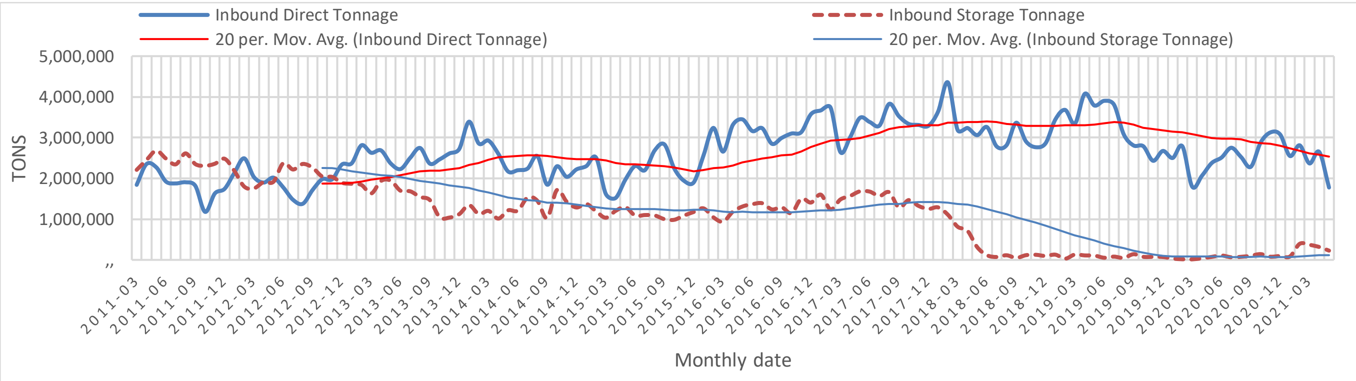

Figure 20. Inbound Cargo Tonnage by Trucks and Wagons with Fitted Moving-Average Curve

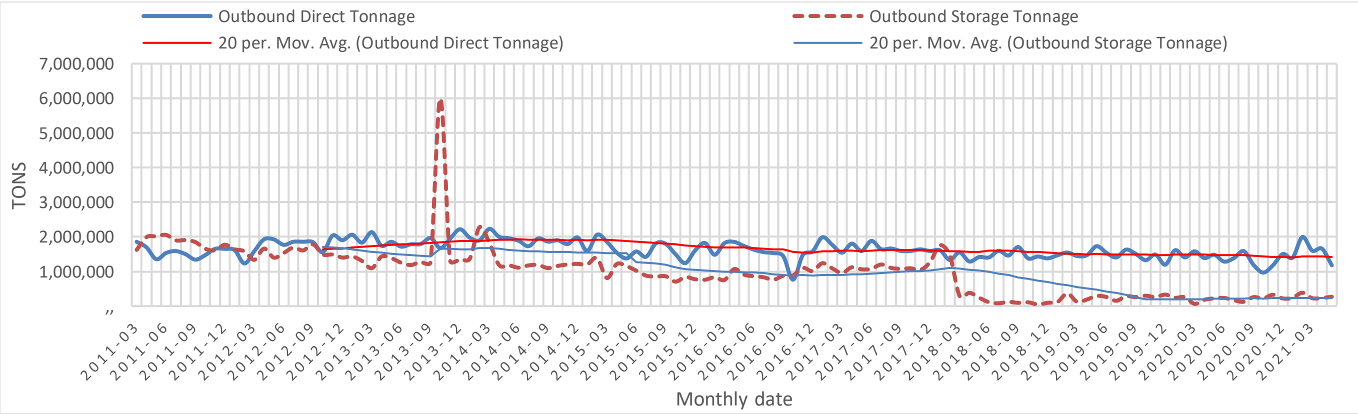

Figure 21. Outbound Cargo Tonnage by Trucks and Wagons with Fitted Moving-Average Curve

5.3. Total Port Cargo (Loading and Unloading)

5.3.1 Trend Analysis and Forecasting of Loading Tonnage

The port's loading data include the total volume of petroleum and non-petroleum commodities. The loading tonnage increased up to 2013, but with the imposition of sanctions by U.S. and EU—particularly those targeting oil and petrochemical exports—the trend shifted downward. Following the JCPOA agreement in 2015, a partial lifting of sanctions led to an increase in exports and a subsequent rise in loading tonnage. However, after the U.S. withdrawal from the JCPOA in 2018 and the reinstatement of sanctions, the downward trend resumed and continued through the end of the study period. Thus, fluctuations in this category are clearly driven by political and trade conditions. Based on error metrics (RMSE and MAE), the third-degree polynomial model (Figure 22) provided the best fit and was adopted for forecasting. The model output indicates that the forecast is reliable for approximately three years. Assuming current conditions remain unchanged, the loading tonnage over the next three years is estimated to be between

3.5 and 4 million tons per month. The 20-month moving-average curve shows a downward trend in the later months, suggesting that loading tonnage could fall below 3.5 million tons. In contrast, the time-series forecast (Figure 23) exhibits a slightly upward trend and suggests marginally higher values. Therefore, the actual amount is likely to fall somewhere between the ranges suggested by these three methods.

5.3.2. Trend Analysis and Forecasting of Unloading Tonnage

The unloading tonnage, representing the country's imports, exhibits a pattern similar to loading volumes and has been strongly influenced by economic conditions and trade restrictions. After an initial period of growth, a downward trend began in the mid-2010s, primarily driven by banking limitations, currency instability, and a decline in import volumes. In this section as well, based on RMSE and MAE metrics, the third-degree polynomial model (Figure 24) provided the best fit, and its three-year forecast aligns with the recent trend. Given the relative stabilization observed over the last three years, the unloading tonnage is estimated to range between 2 and 2.5 million tons per month over the next three years. The moving-average analysis confirms this range, while the time-series model (Figure 25) suggests slightly lower values. Therefore, a confident estimate for future unloading tonnage lies within 2 to 2.5 million tons per month.

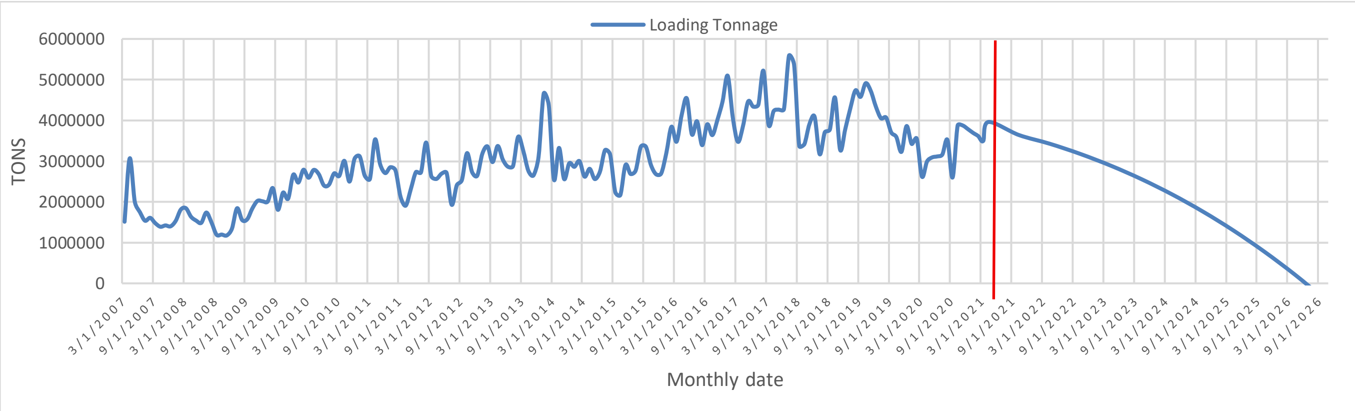

Figure 22. Forecast of Port Loading Tonnage (Values Are Reliable for Up to Three Years)

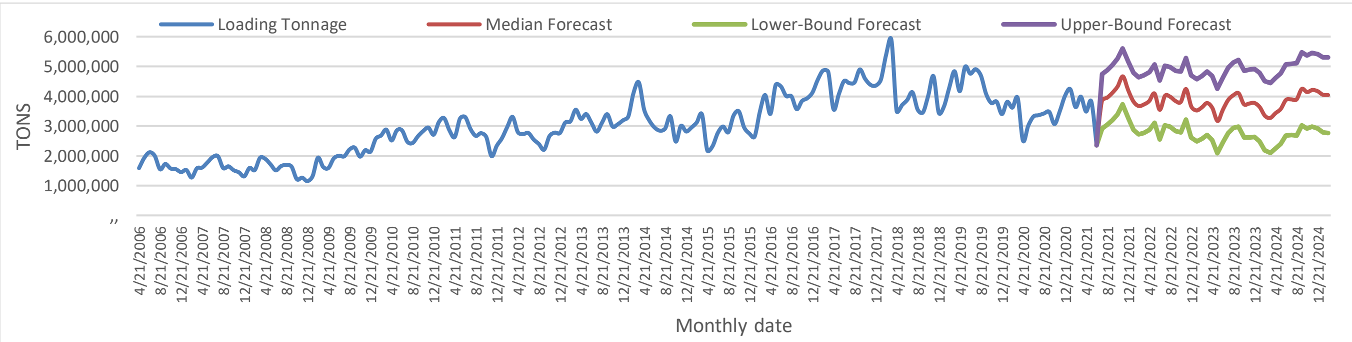

Figure 23. Three-Year Time-Series Forecast of Port Loading Tonnage

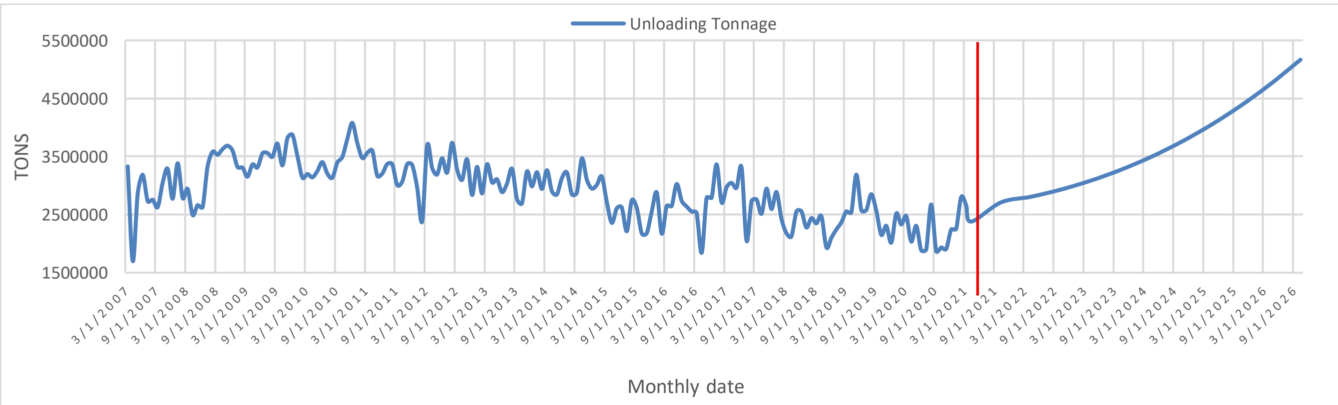

Figure 24. Forecast of Port Unloading Tonnage (Values Are Reliable for Up to Three Years)

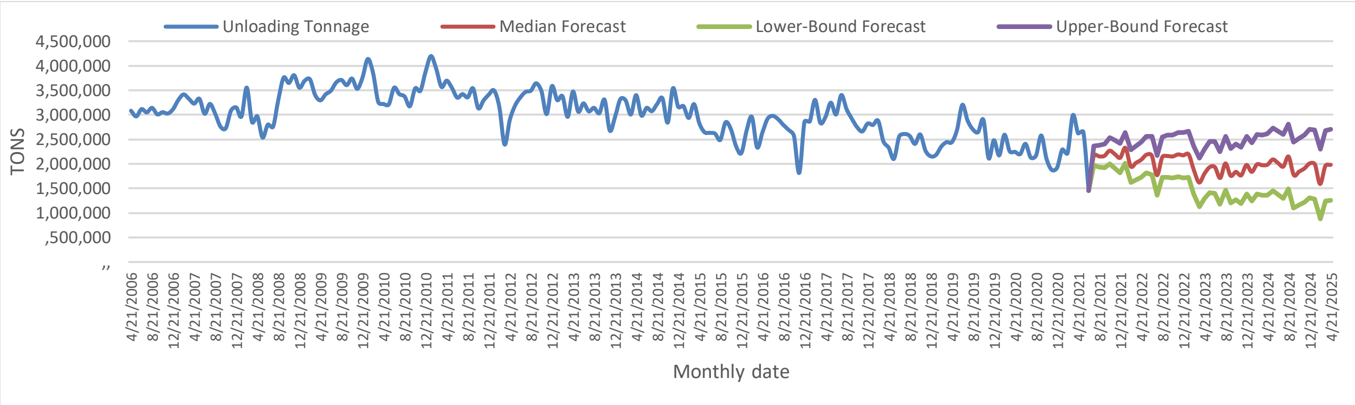

Figure 25. Three-Year Time-Series Forecast of Port Unloading Tonnage

6. Conclusion

This study provides a clear picture of the port's operational performance and demonstrates how operational fluctuations influence the efficiency of the maritime supply chain and the development of a marine-based economy. The findings offer a foundation for planning strategies aimed at enhancing productivity, reducing costs, and strengthening the port's role within a national sea economy.

a) Number of Vessels: The sharp decline in vessel calls at Terminal No. 1 following the 2013 sanctions indicates that external disruptions can significantly weaken trade flows. In contrast, Terminal No. 2 with its more modern equipment was able to retain a portion of the port's maritime trade capacity.

b) Vessel Dwell and Service Times: The increase in vessel dwell time at Terminal No. 1 after 2013, and at Terminal No. 2 after 2018, reflects higher operational costs and reduced productivity. The stability of service times (approximately 30 to 40 hours) in both terminals indicates a reliable level of operational efficiency within the maritime economy.

c) Incoming Trucks: The decline in warehouse-entry trucks since 2013 and the corresponding rise in direct (ship-side) operations signal a shift toward faster cargo circulation and improved alignment with optimized planning requirements.

d) Outgoing Trucks: The sharp reduction in outbound cargo from warehouses after 2015 followed by moderate recovery beginning in 2019 and subsequent stabilization suggests a restructuring of land-side distribution aimed at improving sea–land connectivity and reducing unnecessary delays.

e) Incoming and Outgoing Wagons: The significant decline in inbound wagons after 2018 and in outbound wagons after 2015 highlights reduced reliance on rail transport due to higher costs, operational complexity, and long transit times.

f) Cargo Tonnage via Trucks and Wagons: Cargo tonnage patterns are closely aligned with truck movement trends. The stable data observed from 2018 onward provide a reliable basis for future forecasting and maritime logistics planning.

g) Loading and Unloading Tonnage: The decline in unloading tonnage under economic pressures and sanctions, combined with the long-term upward trend in loading tonnage, reflects an increasing export-oriented role of the port within the broader marine-based economy.

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