Article

Machine-Learning-Based Prediction of Port-Channel Traffic Demand and Capacity Adaptability Assessment - A Case Study of the Core Port Area of Ningbo-Zhoushan Port

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Abstract: The sustained growth of port throughput and the increasing size of vessels have rendered the relationship between channel traffic demand and navigational capacity progressively complex. Assessing channel development requirements solely on the basis of cargo throughput growth fails to capture shifts in vessel-type composition, temporal traffic clustering, or the disproportionate channel resources consumed by large vessels. Taking the core port area of Ningbo-Zhoushan Port as the study area, this paper investigates port-channel traffic-demand forecasting and capacity adaptability by integrating port statistics, publicly available Automatic Identification System (AIS) data, and channel-operation records. First, changes in port transport demand from 2015 to 2025 are analyzed, and hourly vessel traffic flows are reconstructed from AIS records. Second, a short-term traffic-demand forecasting framework comprising Autoregressive Integrated Moving Average (ARIMA), Support Vector Regression (SVR), Random Forest (RF), and Extreme Gradient Boosting (XGBoost) is established. On this basis, differences in channel-resource occupation among vessel types are considered, actual vessel calls are converted into equivalent traffic demand, and channel operating conditions are evaluated using the volume-to-capacity ratio. The results indicate that cargo throughput at Ningbo-Zhoushan Port increased from 890 million tonnes in 2015 to 1.432 billion tonnes in 2025, with a compound annual growth rate of approximately 4.87%. Growth in port throughput and vessel calls does not occur proportionally; vessel upsizing exerts a dual effect of reducing transport vessel calls while increasing the channel resources occupied per vessel. Annual traffic flow through the Xiazhimen Channel is approximately 50,000 vessel transits and is already approaching saturation. Following the commissioning of the 300,000-dwt Tiaozhoumen Channel at the end of 2025, the core port area formed two primary 300,000-dwt channels, and the passage capacity for ultra-large vessels is expected to increase by more than 50%. The study concludes that port-channel planning should transition from throughput extrapolation toward AIS-based, vessel-type-specific traffic-demand forecasting, with particular attention to changes in the peak-period volume-to-capacity ratio.

Keywords: port channel; automatic identification system; machine learning; traffic demand forecasting; navigational capacity; capacity adaptability

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1. Introduction

Navigation channels constitute critical maritime infrastructure that underpins safe, efficient, and orderly vessel movement within port waters. Their functional performance—measured in terms of throughput capacity, navigational reliability, and resilience to operational disruptions—directly governs the temporal efficiency and logistical continuity of vessel arrivals, departures, and transits. In recent years, sustained growth in national and regional trade volumes has driven continuous expansion in port cargo handling volumes. Concurrently, fleet modernization trends have accelerated the deployment of ultra-large container vessels, very large crude carriers, and capesize bulk carriers, all of which exhibit significantly higher deadweight tonnages and dimensional profiles than previous generations [1]. As a consequence, conventional demand-forecasting approaches—particularly those relying solely on historical cargo-throughput growth rates as proxies for channel utilization—have increasingly demonstrated structural inadequacies, failing to capture the nonlinear, multi-scale dynamics inherent in contemporary maritime traffic systems.

Cargo throughput serves as a widely adopted macroeconomic indicator of port production scale and regional economic integration; however, it is fundamentally decoupled from the physical parameters governing channel usage. Vessel upsizing leads to substantial gains in unit freight-carrying efficiency, thereby reducing the absolute number of vessel calls required to move equivalent cargo volumes. Yet this reduction in call frequency is counterbalanced by several operational intensifiers: larger vessels necessitate wider lateral safety margins, extended longitudinal separation distances, longer transit durations through constrained waterways, heightened sensitivity to hydrodynamic interactions, and stricter environmental and meteorological constraints during navigation. Consequently, the relationship among cargo volume, vessel count, and channel occupancy is neither linear nor static—it is mediated by vessel size distribution, traffic composition heterogeneity, scheduling practices, tidal windows, pilotage protocols, and real-time traffic management interventions. Empirical analyses consistently indicate that treating throughput as a direct surrogate for navigational load introduces systematic bias in capacity planning models.

The widespread adoption of Automatic Identification System (AIS) technology has enabled high-resolution, spatiotemporally granular observation of vessel movements across major shipping corridors and port approaches. This rich observational dataset supports rigorous empirical modeling of traffic demand patterns beyond aggregate statistics. Recent methodological advances include time-series forecasting frameworks leveraging autoregressive integrated moving average structures, hybrid deep learning architectures incorporating attention mechanisms and stacked long short-term memory networks for capturing sequential dependencies in vessel trajectories, and physics-informed machine learning models that integrate navigational constraints with data-driven prediction. Studies conducted using AIS data from key Chinese port complexes have successfully reconstructed short-term traffic flows, identified congestion precursors, and quantified spatial-temporal variability in vessel dwell times and maneuvering intensity. Internationally, ensemble methods such as Random Forest and support vector machines, alongside convolutional and graph neural networks, have been applied to predict vessel states—including position, speed, heading, and maneuver type—with growing fidelity. While these techniques demonstrate strong capability in modeling complex, nonlinear traffic behaviors, their integration into strategic port infrastructure planning remains limited, particularly regarding dynamic alignment between forecasted demand trajectories and engineered capacity thresholds [2].

Channel capacity assessment traditionally emphasizes deterministic or probabilistic modeling of vessel interaction parameters, including minimum safe passing distances, speed-dependent stopping envelopes, vessel-type-specific maneuverability envelopes, and traffic flow equilibrium conditions under varying organizational configurations such as one-way versus two-way traffic, segregated lanes, or dynamic routing. Theoretical foundations often draw upon ship-following theory, queuing theory, and stochastic process models to quantify maximum sustainable flow rates under defined safety criteria [3]. From a port development planning perspective, isolated projections of future traffic volume—or static snapshots of current capacity—offer insufficient decision support. What is critically needed is a forward-looking, time-resolved mismatch analysis: identifying the precise temporal horizon at which projected traffic demand exceeds the operational envelope of existing infrastructure, accounting for both nominal design capacity and real-world degradation factors such as sedimentation, aging aids-to-navigation, or evolving regulatory safety standards. To address this gap, this study establishes an integrated analytical framework that synergistically couples machine-learning-based vessel traffic demand forecasting with context-sensitive channel capacity evaluation. Using the core port area of Ningbo-Zhoushan Port as a representative case, the research systematically examines the interdependencies among regional transport demand drivers, observed and projected vessel traffic characteristics, and the functional adaptability of navigational infrastructure—specifically evaluating how modifications to the Tiaozhoumen Channel's geometric and hydrodynamic configuration influence its ability to sustainably accommodate anticipated traffic growth while maintaining prescribed safety and efficiency benchmarks.

2. Study Area and Data

2.1. Study Area

Ningbo-Zhoushan Port constitutes one of the most strategically significant comprehensive hub ports in China, serving as a critical node in the national maritime logistics network and facilitating large-scale international trade. Its operational scope encompasses diverse cargo categories, including containerized goods, bulk iron ore, crude oil, refined petroleum products, coal, and other dry and liquid bulk commodities. The port's vessel traffic exhibits notable heterogeneity, characterized by a high frequency of ultra-large container vessels (ULCVs), very large crude carriers (VLCCs), and capesize bulk carriers, all of which necessitate deep-water berths and highly engineered navigation channels. This structural dependency on deep-water infrastructure imposes stringent requirements on hydrographic surveying, real-time tidal monitoring, and dynamic channel maintenance. Between 2015 and 2025, the port demonstrated sustained growth in cargo throughput, rising from 890 million metric tons to 1.432 billion metric tons—an absolute increase of 542 million tons. This represents a cumulative growth of 60.9% over the decade, corresponding to a compound annual growth rate of approximately 4.87%, reflecting both expanding domestic industrial demand and enhanced global supply chain integration [2] (As shown in Table 1) (As shown in Figure 1).

Table 1. Cargo Throughput of Ningbo-Zhoushan Port, 2015–2025

Year	Throughput / 108 t	Year	Throughput / 108 t
2015	8.9	2021	12.24
2016	9.22	2022	12.61
2017	10.1	2023	13.24
2018	10.8	2024	13.77
2019	11.2	2025	14.32
2020	11.7	-	-

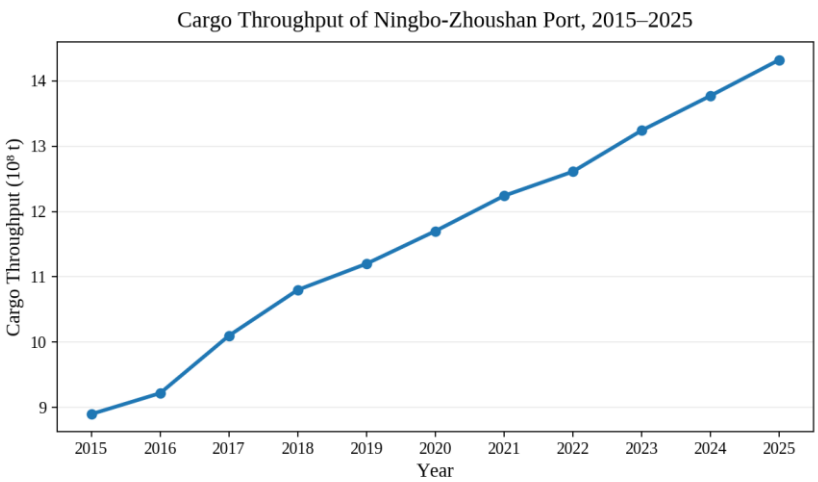

Figure 1. Changes in Cargo Throughput of Ningbo-Zhoushan Port, 2015–2025

2.2. AIS Data and Samples

The AIS data are sourced from a publicly accessible shipping dataset aligned with the Belt and Road Initiative, hosted on the Peking University Open Research Data Platform [4]. This dataset comprises global automatic identification system records collected over a continuous three-month period—specifically from July through September 2016—and includes spatiotemporal metadata for commercial vessels operating across international maritime routes. Its structured format supports rigorous spatial filtering, enabling precise extraction of vessel trajectories within the designated study area: the navigable waters adjacent to Ningbo-Zhoushan Port and the broader Zhoushan Archipelago. Prior to analysis, comprehensive data preprocessing was conducted to ensure integrity and analytical validity. This included detection and removal of geospatial outliers arising from sensor malfunction or signal interference, elimination of redundant or duplicated AIS messages caused by broadcast repetition, chronological sorting of trajectory points per vessel to reconstruct coherent movement sequences, and interpolation-based handling of short-duration gaps in positional reporting. A virtual cross-sectional line was then defined orthogonally across the primary navigation channel of interest; vessel passage events were identified algorithmically when successive trajectory points straddled this section, thereby confirming unidirectional transit. Traffic demand is subsequently quantified at an hourly resolution.

$Q_t = N_t$ (1)

where Q_t denotes the hourly channel traffic demand at time t, and N_t represents the total count of distinct vessels whose trajectories intersect the virtual cross-section during that hour [1]. The temporal span of 92 days yields a theoretical maximum of 2,208 non-overlapping hourly observations, offering robust statistical coverage for model training, validation, and hyperparameter tuning in conventional supervised machine learning frameworks. This sample size exceeds typical minimum thresholds required for stable convergence in regression and classification algorithms, particularly when feature engineering incorporates temporal lags, moving averages, and vessel-type stratification. Furthermore, the high-frequency nature of AIS reporting—often sub-minute intervals—ensures sufficient point density along each trajectory to support accurate passage detection and reduce misclassification due to sparse sampling.

3. Methodology

3.1. Equivalent Traffic Demand

Vessels of varying dimensions and operational characteristics impose heterogeneous demands on navigational infrastructure, particularly in constrained waterways such as narrow channels, locks, or port approach routes. A simple count of vessel calls fails to capture the differential strain exerted by vessel size, draft, maneuvering requirements, and required separation distances [5]. For instance, a very large crude carrier (VLCC) may occupy channel space for several minutes and necessitate extended traffic separation intervals, whereas a small coastal feeder vessel transits rapidly with minimal impact on overall throughput capacity. Consequently, treating all vessels uniformly distorts assessments of congestion risk, infrastructure utilization efficiency, and long-term capacity planning. To address this limitation, a standardized vessel-type conversion framework is adopted, wherein each vessel class is assigned a dimensionless coefficient reflecting its relative channel resource consumption compared to a baseline reference vessel—typically a standard Panamax container ship or equivalent medium-sized cargo vessel.

$Q_te = \sum_{k=1}K\ \alpha_k N_{kt}$ (2)

where Q_te denotes the aggregated equivalent traffic volume during time period t; N_{kt} represents the observed count of vessels belonging to type k (e.g., bulk carriers, tankers, container ships, Ro-Ro vessels) within that same period; and α_k is the empirically calibrated channel-resource-occupation conversion coefficient specific to vessel type k, derived from hydrodynamic simulation, historical transit time analysis, and AIS-based trajectory clustering. This formulation enables dynamic monitoring of traffic pressure not only through changes in total vessel numbers but also through shifts in fleet composition—such as increasing proportions of ultra-large container vessels or LNG carriers—which carry disproportionate implications for safety margins, pilotage demand, and environmental risk exposure in sensitive maritime zones [4].

3.2. Traffic-Demand Forecasting

The model input variables mainly include historical traffic flow, vessel-type composition, and time attributes, as shown in Table 2. The forecasting target is vessel traffic volume in the next hour [6]. To enhance predictive robustness, temporal lags are carefully selected to capture diurnal and weekly periodicity, while vessel-type composition variables—such as proportions of container ships, bulk carriers, and tankers—are normalized to reflect structural shifts in port throughput demand. Time attributes incorporate both cyclical representations (e.g., sine-cosine encoding of hour and weekday) and categorical indicators to preserve non-linear temporal dependencies without introducing discontinuities at period boundaries.

Table 2. Main Variables for Traffic-Demand Forecasting

Type	Variable	Meaning
Historical traffic	Qt-1	Traffic volume in the previous 1 h
Historical traffic	Qt-3	Traffic volume in the previous 3 h
Historical traffic	MA6	Average traffic volume over the previous 6 h
Vessel composition	P_L	Proportion of large vessels
Vessel composition	L_avg	Average vessel length
Operating state	V_avg	Average sailing speed
Time attribute	Hour	Hour of day
Time attribute	Weekday	Day of week

$\hat{Q}_{t+1} = f(Q_{t-1}, Q_{t-3}, MA_6, P\_L, L\_avg, V\_avg, Hour, Weekday)$ (3)

Four types of models are selected: ARIMA, SVR, Random Forest, and XGBoost. ARIMA serves as the conventional time-series benchmark, while the other models are used to identify nonlinear relationships among multiple variables [7]. Samples are divided chronologically into contiguous segments, with 70% allocated for training, 15% for validation, and 15% for testing, ensuring temporal integrity and preventing forward-looking bias that may arise from non-sequential partitioning strategies. This chronological segmentation aligns with best practices in maritime traffic forecasting, where temporal causality must be strictly preserved to maintain model interpretability and operational reliability under real-world deployment conditions.

$MAE = (1/n) \sum_{i=1}^{n} |yi - \hat{y}i|$ (4)

$RMSE = \sqrt{[(1/n) \sum_{i=1}^{n} (yi - \hat{y}i)^2]}$ (5)

$MAPE = (100\%/n) \sum_{i=1}^{n} |(yi - \hat{y}i)/yi|$ (6)

The relative performance of the different models should be determined from test-set results rather than by assuming in advance that one model is optimal. Because the publicly available AIS data used in this study have not yet undergone unified cleaning and model computation, this paper does not report forecasting-accuracy results for ARIMA, SVR, Random Forest, or XGBoost [8]. Instead, existing empirical research on Ningbo-Zhoushan Port is used as a reference for the applicability of AIS-based short-term traffic forecasting methods. Such methodological triangulation supports evidence-informed model selection and underscores the importance of domain-specific validation when adapting general-purpose machine learning techniques to maritime infrastructure management contexts.

To further illustrate the applicability of AIS data to short-term traffic-demand forecasting for port channels, an existing empirical study of Ningbo-Zhoushan Port is referenced. That work utilized AIS data from the waters of Ningbo-Zhoushan Port collected between June and December 2020 to forecast short-term vessel flow at inbound-channel cross-sections. The results showed that the MAPE values of the grey-theory model, the ARIMA model, and the disaggregate model based on LSTM and historical-trajectory matching were 72.00%, 45.54%, and 19.96%, respectively (Figure 5). Compared with conventional aggregate forecasting methods, the disaggregate method based on individual AIS vessel-trajectory information can more fully reflect vessel operating states and inbound behavior and can characterize short-term traffic-flow variation more accurately. This indicates that relying solely on historical traffic-flow sequences has certain limitations, and that AIS features such as vessel trajectories, vessel-type composition, and operating states should be incorporated into forecasting models. Such integration enables richer representation of maritime behavioral patterns, including speed variations, course adjustments, and anchorage decisions, thereby improving responsiveness to dynamic navigational constraints and port operational rhythms (As shown in Figure 2).

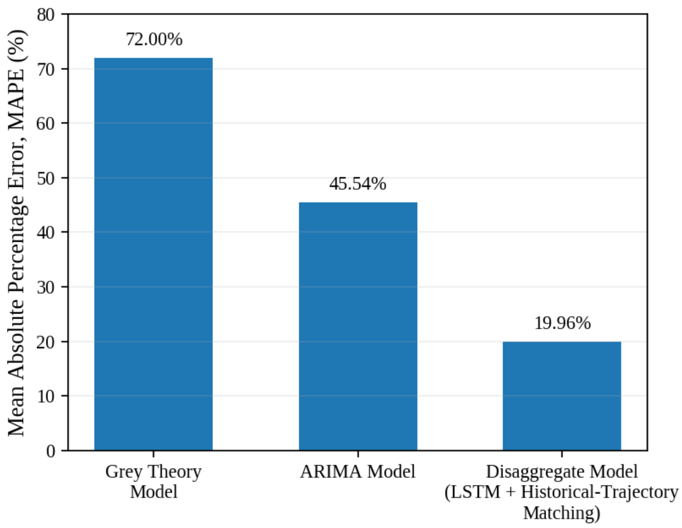

Figure 5. Comparison of MAPE for Existing Short-Term Vessel-Traffic-Flow Forecasting Methods

At Ningbo-Zhoushan Port

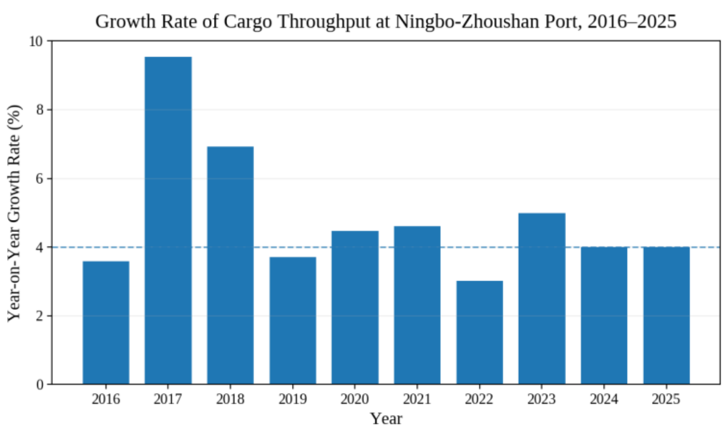

Figure 2. Growth Rate of Cargo Throughput at Ningbo-Zhoushan Port, 2016–2025

Note: Compiled from the empirical results of Cai Jiacheng et al. [3] based on AIS data from Ningbo-Zhoushan Port from June to December 2020; a lower MAPE indicates a smaller forecasting error.

3.3. Capacity Adaptability

Channel navigational capacity represents the maximum number of vessels that can safely and efficiently pass through a given waterway segment within a specified time unit under prevailing operational constraints. It is not a fixed physical constant but a dynamic parameter jointly influenced by multiple interdependent factors, including the minimum required safety spacing between vessels, the configuration and segregation of traffic flow directions (e.g., one-way versus two-way navigation), ambient natural conditions such as wind speed, visibility, wave height, current velocity, and tidal range, as well as the effectiveness of traffic organization measures—including vessel traffic services (VTS), routing schemes, pilotage requirements, and real-time regulatory interventions [9]. These variables collectively determine how theoretical throughput potential is reduced or modulated in practice.

$C_t = C_0\ \beta_s\ \beta\_d\ \beta\_w\ \beta\_m$ (7)

Here, C_0 denotes the baseline theoretical navigational capacity derived under idealized assumptions—namely, uniform vessel dimensions, identical speeds, perfect visibility, calm hydro-meteorological conditions, and unimpeded bidirectional flow without regulatory constraints [10]. The dimensionless correction coefficients βs, β_d, β_w, and β_m quantitatively reflect the cumulative degradation effect of non-ideal conditions: βs accounts for heterogeneity in vessel size, maneuverability, and speed profiles; β_d captures efficiency losses due to directional interactions or asymmetric traffic volume distribution; β_w integrates the impact of adverse weather and hydrological variability; and β_m embodies the net influence of traffic management infrastructure, procedural rigor, and human–system interaction quality. Channel adaptability is then rigorously evaluated using the ratio of equivalent traffic demand to practical capacity:

$VCR_t = Q_te / C_t$ (8)

In this study, a Vessel Capacity Ratio (VCR) threshold of ≤ 0.60 signifies robust capacity reserve, implying sufficient margin for unexpected surges, maintenance variations, or incident response; a range of 0.60–0.80 indicates basic functional adaptation, where routine operations remain feasible but with limited flexibility; values between 0.80 and 1.00 denote high-load operation, necessitating close monitoring and proactive mitigation strategies to prevent congestion escalation; while VCR > 1.00 unequivocally signals structural insufficiency, requiring either demand management, infrastructure enhancement, or operational optimization. This four-tier classification serves primarily as a comparative planning tool and must be empirically validated and contextually adjusted—through field observation, simulation calibration, and stakeholder consultation—for accurate application in specific engineering design and management scenarios.

4. Changes in Traffic Demand and Channel Capacity

4.1. Port Transport Demand Continues to Grow

From 2015 to 2025, cargo throughput at Ningbo-Zhoushan Port exhibited a sustained upward trajectory, reflecting the port's continued integration into global supply chains and its role as a critical node in China's maritime logistics infrastructure. While the compound annual growth rate fluctuated across sub-periods, the overall trend remained consistently positive. Specifically, the year-on-year growth rates in 2017 and 2018 reached approximately 9.54% and 6.93%, respectively—levels indicative of robust expansion during that phase. Following 2019, growth moderated and stabilized, with most years registering increases within the 3%–5% range, consistent with maturing infrastructure utilization and structural adjustments in trade composition. Official statistics indicate throughput volumes of 1.324 billion tonnes in 2023, 1.377 billion tonnes in 2024, and 1.432 billion tonnes in 2025. This progression demonstrates a transition from earlier-phase volume acceleration toward a more mature operational state characterized by steady, high-volume throughput under increasingly optimized resource allocation.

Given the observed consistency in recent throughput growth—predominantly clustering between 3% and 5%—a baseline annual growth assumption of 4% is adopted for analytical modeling purposes. To ensure methodological rigor and assess system resilience, two additional demand scenarios are introduced: a conservative low-growth scenario assuming a 2% annual increase, and an elevated high-growth scenario assuming 6% annual growth [11]. These three scenarios collectively enable a comprehensive evaluation of how varying demand intensities influence navigational channel capacity utilization, safety margins, scheduling efficiency, and long-term infrastructure adaptability. The selection of these thresholds is grounded in empirical throughput trends, macroeconomic indicators related to international trade, and projected shifts in regional industrial output and export orientation.

It should be noted that growth in total cargo throughput cannot be directly equated with proportional growth in vessel call frequency. Vessel demand is a function not only of freight volume but also of fleet composition, vessel size optimization strategies, and operational efficiency parameters. If total port freight volume is denoted as T, the average effective carrying capacity per vessel as L, and the average load factor (i.e., ratio of actual cargo carried to maximum capacity) as λ, then the approximate number of required vessel calls N can be expressed as the quotient of total volume divided by the product of capacity and utilization efficiency.

$N = T / (L\lambda)$ (9)

For example, a 10% increase in freight demand coupled with an 8% improvement in average vessel carrying capacity yields only about a 1.85% rise in the total number of vessel calls, assuming constant load factors and no changes in routing or transshipment patterns [11, 12]. This illustrates how fleet modernization and vessel upsizing serve as key moderating factors in port traffic intensity. However, larger vessels impose stricter navigational requirements—including greater minimum under-keel clearance, wider lateral separation distances, and enhanced maneuvering corridors—which collectively elevate the spatial and temporal demands placed on navigation channels. Consequently, evaluating channel adequacy requires multi-dimensional analysis beyond simple vessel count metrics, incorporating hydrodynamic constraints, tidal windows, pilotage complexity, and real-time traffic density.

4.2. Capacity Pressure on the Existing Channel

The Xiazhimen Channel has long served as the principal navigational corridor for large-tonnage vessels entering and departing the core operational zone of Ningbo-Zhoushan Port, one of China's busiest and most strategically significant port complexes. Publicly accessible maritime traffic statistics indicate that the channel accommodates approximately 50,000 vessel transits annually, a figure that reflects sustained high utilization and signals approaching functional saturation under current infrastructure constraints. This volume represents cumulative movement across all vessel categories, including container ships, bulk carriers, and tankers, and is derived from official port authority monitoring systems and vessel traffic service (VTS) logs. The channel's design capacity was established based on hydrodynamic modeling, navigational safety margins, and regulatory separation standards, all of which are now being tested by growing throughput demands.

Q◎_d = 50,000 / 365 ≈ 137 vessel transits/d (10)

The above result represents only the annual average and cannot adequately reflect the actual operational stress experienced during periods of heightened activity. Vessel arrivals display pronounced temporal clustering, particularly during daylight hours and favorable meteorological windows, while large vessels remain subject to strict tidal scheduling requirements and coordinated traffic management protocols enforced by the local maritime safety administration. Consequently, channel-capacity assessment must extend beyond aggregate annual metrics; it requires rigorous analysis of peak-hour equivalent demand, incorporating vessel size distribution, minimum safe separation intervals, and dynamic traffic flow harmonization parameters to ensure navigational safety and system resilience.

VCR_peak = Q_peake / C_peak (11)

4.3. Effects of the Tiaozhoumen Channel Widening

In December 2025, the Tiaozhoumen Channel—designed to accommodate vessels with a deadweight tonnage of up to 300,000 metric tons—commenced operational service. Following the completion of its infrastructure enhancement, the channel extends approximately 48 kilometers in length and supports safe navigation for 200,000-dwt container ships under all tidal conditions. For 300,000-dwt oil tankers, navigational access is feasible during favorable tidal windows, subject to real-time hydrodynamic monitoring and traffic management protocols. Together with the Xiazhimen Channel, the Tiaozhoumen Channel now constitutes one of two primary deep-water access routes enabling entry and exit of ultra-large vessels into the core port area. This dual-channel configuration enhances spatial redundancy, improves scheduling flexibility, improves scheduling flexibility, and strengthens resilience against localized events such as adverse weather or maintenance closures. The design parameters reflect rigorous hydrographic surveying, sediment transport modeling, and vessel maneuverability simulations conducted over a multi-year planning horizon. Furthermore, integrated navigation aids—including differential GPS beacons, AIS-based traffic surveillance, and dynamic under-keel clearance calculation systems—have been deployed to ensure compliance with international maritime safety standards (As shown in Table 3) (As shown in Figure 3).

Table 3. Changes in Navigational Conditions for Large Vessels in the Core Port Area

Indicator	Before expansion	After expansion
Main route for large vessels	Mainly Xiazhimen	Xiazhimen + Tiaozhoumen
Tiaozhoumen channel class	150,000 dwt	300,000 dwt
200,000-dwt container ships	Restricted navigation	All-tide navigation
300,000-dwt oil tankers	Restricted navigation	Tidal-window navigation
Passage capacity for ultra-large vessels	Baseline	Increase of more than 50%

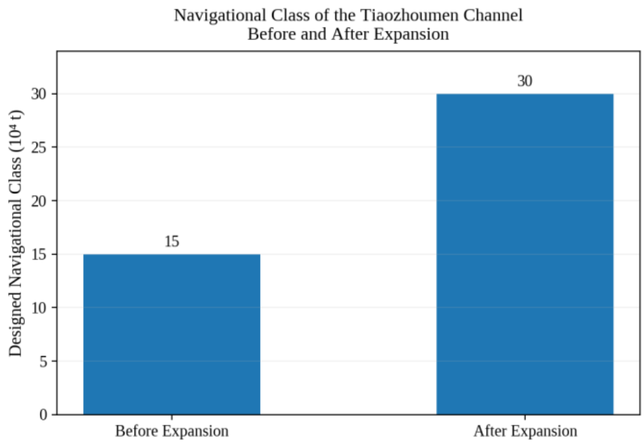

Figure 3. Changes in the Navigational Class of the Tiaozhoumen Channel Before and After Expansion

It should be noted that upgrading the designated navigational class of the Tiaozhoumen Channel from 150,000 dwt to 300,000 dwt does not imply a proportional doubling of overall port-area navigational capacity. Actual throughput capability is governed by multiple interdependent factors, including minimum safe vessel separation distances, bidirectional versus unidirectional traffic flow configurations, tidal amplitude and timing constraints, prevailing meteorological conditions, and the sophistication of vessel traffic service (VTS) coordination mechanisms. The widely cited figure of 'more than 50% increase' pertains exclusively to the theoretical passage frequency of ultra-large vessels within the core port zone, not to aggregate cargo handling volume or total vessel movements across all size categories. Empirical data indicate that Ningbo-Zhoushan Port's total cargo throughput rose by approximately 4% in 2025 relative to 2024—a figure consistent with broader trends in global maritime trade growth and port utilization efficiency. In the near term, activation of the enhanced Tiaozhoumen Channel serves to better align infrastructure capability with evolving fleet composition, reduce bottlenecks during peak arrival windows, and provide additional operational headroom for contingency routing and emergency response coordination [13, 14].

5. Scenario Analysis and Discussion

Long-term port transport demand is influenced by a complex interplay of macroeconomic, industrial, maritime, and technological factors—including hinterland economic performance, regional industrial transformation, global shipping market dynamics, trends in vessel size optimization, port infrastructure utilization efficiency, and evolving international trade patterns—rendering precise long-term forecasting inherently uncertain. Given that throughput at Ningbo-Zhoushan Port has exhibited a sustained medium-to-low growth trajectory since 2019—characterized by structural stabilization rather than rapid expansion—the 2025 throughput figure of 1.432 billion tonnes is adopted as the calibrated base period for scenario construction. To reflect plausible future development pathways, three distinct yet internally consistent growth trajectories are formulated: a conservative low-growth scenario assuming an annual compound growth rate of 2%, a moderate baseline scenario at 4%, and an optimistic high-growth scenario at 6%. These rates are derived from historical trend analysis, regional GDP projections, national logistics development plans, and sectoral demand modeling for key export-oriented industries such as petrochemicals, electronics, and advanced manufacturing, all aligned with China's broader high-quality development strategy (As shown in Figure 4).

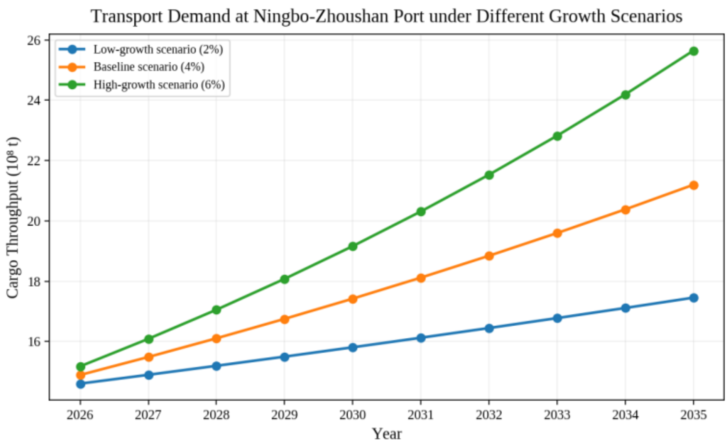

Figure 4. Changes in Transport Demand at Ningbo-Zhoushan Port under Different Growth Scenarios

The divergence among the three scenarios remains relatively modest during the initial years of the projection horizon but exhibits pronounced cumulative amplification as the forecast extends forward in time. By 2030, the modeled throughput demand under the low-, baseline-, and high-growth assumptions reaches approximately 1.581 billion tonnes, 1.742 billion tonnes, and 1.916 billion tonnes respectively; by 2035, these values further widen to 1.746 billion tonnes, 2.120 billion tonnes, and 2.564 billion tonnes. This non-linear widening effect underscores how seemingly minor differences in annual growth assumptions—on the order of just 2 percentage points—compound exponentially over multi-decade planning horizons, ultimately yielding significantly divergent infrastructure implications. Consequently, long-term port capacity planning must move beyond deterministic single-point forecasts and instead adopt a robust, scenario-based analytical framework that explicitly evaluates system adaptability, resilience thresholds, and marginal capacity margins across multiple plausible futures [15]. Such an approach supports evidence-informed decision-making for phased investment, operational flexibility design, and adaptive governance mechanisms.

It is essential to clarify that Figure 4 illustrates macro-level freight throughput demand scenarios—not direct projections of vessel traffic volume or call frequency. Actual vessel traffic demand will be modulated not only by cargo volume changes but also by ongoing fleet modernization trends, particularly the widespread adoption of larger container ships, bulk carriers, and LNG vessels. While increased vessel carrying capacity per voyage reduces the required number of vessel calls to handle equivalent cargo tonnage, it simultaneously intensifies spatial and temporal demands on navigational infrastructure: larger vessels require wider safety margins, longer stopping distances, extended transit times through constrained waterways, and more stringent tidal and weather windows. The net impact on channel utilization pressure therefore hinges on the dynamic balance between the quantitative reduction in vessel movements and the qualitative increase in per-vessel resource consumption [16]. This dual-effect mechanism necessitates integrated modeling that jointly considers cargo throughput, fleet composition evolution, vessel maneuvering characteristics, and hydrodynamic constraints within the port's navigational environment.

The application of machine learning in this study serves a fundamentally strategic purpose: it leverages high-frequency Automatic Identification System (AIS) data—not merely to improve statistical accuracy relative to traditional time-series models—but to uncover latent, nonlinear dependencies among historical traffic states (e.g., speed distribution, density clustering, queuing behavior), dynamic vessel-type mix (including shifts toward ultra-large container vessels and specialized bulk carriers), and time-sensitive attributes (e.g., diurnal cycles, tidal phases, seasonal variations, weekday–weekend differentials). This enables granular estimation of peak-hour vessel concentration ratios (VCR_peak), which function as a real-time operational stress indicator. When VCR_peak consistently exceeds 0.80 over consecutive tidal cycles or operational periods, it signals emerging congestion risk and triggers proactive review of traffic organization protocols, berth allocation strategies, and pilotage scheduling [1, 9]. Sustained VCR_peak values approaching unity indicate that the current navigational infrastructure has reached functional saturation, warranting comprehensive evaluation of capacity enhancement options. For Ningbo-Zhoushan Port, following the commissioning of the Tiaozhoumen Channel, strategic emphasis should transition from isolated physical augmentation of individual routes toward intelligent, system-wide coordination across the dual-channel network. Capacity optimization can be achieved through differentiated vessel routing policies (e.g., assigning large deep-draft vessels preferentially to the new channel), mandatory arrival and departure slot reservation systems, precise synchronization of vessel movements with optimal tidal windows, and enhanced integration of Vessel Traffic Service (VTS) decision-support tools for dynamic traffic flow regulation.

6. Conclusions

(1) Between 2015 and 2025, cargo throughput at Ningbo-Zhoushan Port rose steadily from 890 million metric tons to 1.432 billion metric tons, reflecting a compound annual growth rate of approximately 4.87%. This sustained upward trajectory confirms that port

transport demand remains in a robust expansion phase, underpinned by regional industrial development, international trade integration, and evolving logistics network configurations. The growth is not merely linear but exhibits structural acceleration during periods aligned with major infrastructure commissioning and policy-driven trade facilitation initiatives, suggesting that throughput trends are increasingly shaped by both macroeconomic forces and targeted operational interventions.

(2) It is critically important to recognize that increases in cargo throughput do not translate proportionally into increases in vessel traffic volume. Vessel upsizing—particularly the growing deployment of very large ore carriers, ultra-large container ships, and capesize bulk carriers—has led to a measurable decoupling between freight tonnage and vessel call frequency. While fewer vessels handle more cargo per voyage, each such vessel occupies significantly greater navigational space, requires longer transit times through constrained waterways, and imposes higher demands on pilotage, tug assistance, and real-time traffic management systems. Consequently, evaluating channel demand solely on raw vessel counts risks substantial underestimation of resource pressure; instead, vessel-type-specific equivalent traffic volume—calibrated using displacement, draft, maneuvering envelope, and typical transit duration—provides a far more accurate, operationally grounded metric for capacity assessment and bottleneck identification.

(3) Short-term traffic forecasting for port navigation channels must be anchored in high-resolution, temporally granular data sources. Hourly Automatic Identification System (AIS) records offer the necessary fidelity to capture diurnal patterns, tidal influences, weather-related disruptions, and weekday–weekend variability. Effective forecasting models should integrate not only historical traffic flow sequences but also dynamic covariates—including vessel type distribution, seasonal loading profiles, departure/arrival time windows, and prevailing meteorological conditions. Empirical model selection—through rigorous cross-validation across ARIMA, support vector regression (SVR), Random Forest, XGBoost, and hybrid ensemble architectures—is essential; theoretical complexity does not guarantee superior predictive performance, and overfitting remains a persistent risk when insufficient out-of-sample testing is conducted.

(4) Current traffic volumes in the Xiazhimen Channel have reached levels approaching its designed operational capacity, resulting in elevated congestion indices, extended waiting times during peak tidal windows, and increased reliance on dynamic scheduling protocols. Following the commissioning of the Tiaozhoumen Channel—designed to accommodate vessels up to 300,000 deadweight tons—the core port area now operates a dual-channel configuration. This structural reconfiguration has enhanced passage capacity for ultra-large vessels by more than 50%, substantially improving short-term adaptability to surge demand, reducing average transit delays, and enabling more resilient response to unplanned disruptions such as adverse weather or emergency berthing requirements.

(5) Strategic port-channel planning must evolve beyond traditional annual throughput projections toward a dynamic equilibrium framework that explicitly aligns temporal peaks in traffic demand with time-varying capacity availability. Integrating machine-learning-derived hourly traffic forecasts with empirically validated, context-sensitive channel capacity models—accounting for tidal state, visibility, vessel interaction rules, and traffic separation schemes—enables precise identification of critical threshold periods. Such analysis supports proactive traffic organization adjustments—including staggered arrival slots, priority routing protocols, and adaptive speed limits—and informs evidence-based decisions regarding future infrastructure enhancements or operational optimization measures.

This study relies on publicly accessible AIS datasets, which inherently introduce temporal limitations: the most recent available observations predate the full operational integration of the Tiaozhoumen Channel. To strengthen empirical validation, future work should acquire continuous, high-fidelity AIS data spanning 2024–2026 and conduct comparative analyses of key performance indicators—including total vessel transits, average waiting durations, queue formation frequency, and volume-to-capacity ratios—

before and after the establishment of the dual-channel system. Such longitudinal evaluation would yield actionable insights into the real-world efficacy of the new navigational infrastructure, clarify residual bottlenecks, and refine predictive models for next-generation port capacity planning.

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