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Multimodal Intelligence Improves Maritime Congestion Forecasting and Port Optimization

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ABSTRACT

Maritime congestion at major global container ports represents one of the most pressing logistical bottlenecks of contemporary trade, with cascading consequences that permeate supply chains, freight economics, and carbon accounting simultaneously. This paper proposes a multimodal intelligence framework that integrates heterogeneous data streams — encompassing AIS positional records, meteorological observations, historical berth logs, and satellite-derived imagery — within a unified deep learning pipeline to forecast port congestion and optimize berth scheduling. A CNN-LSTM-GRU hybrid network with a cross-modal attention fusion layer is trained and evaluated on two-year real-world vessel traffic data from the Port of Shanghai and the Port of Singapore. Experimental results demonstrate that the proposed framework achieves a 23.7% reduction in MAE and a 19.4% reduction in RMSE relative to single-modality LSTM baselines. A downstream berth optimization module, driven by the congestion prediction output, reduces mean vessel waiting time by 17.6% under controlled simulation conditions. These findings confirm that multimodal data fusion constitutes a critical architectural principle for next-generation port intelligence systems.

KEYWORDS

Maritime Congestion Forecasting; Port Optimization; Multimodal Deep Learning; AIS Data Fusion; Berth Scheduling; Vessel Traffic Prediction; Intelligent Transportation Systems.

1. INTRODUCTION

Global seaborne trade constitutes approximately 90 percent of the total volume of international commerce, a proportion that has remained remarkably stable across decades of technological and economic transformation. Within this ecosystem, container ports function as critical nodes whose operational performance dictates not only the direct cost of moving goods but the rhythmic integrity of entire supply chain networks connecting producers and consumers across continents. When a major port experiences congestion — defined operationally as a state where vessel arrivals exceed the port's capacity to berth, service, and dispatch ships within scheduled windows — the consequences multiply rapidly. Vessels anchor offshore for days or weeks, burning fuel and generating emissions while idle. Shippers absorb demurrage charges and cargo delay penalties. Terminal operators scramble to reallocate berths and equipment under conditions of compounded uncertainty. The COVID-19 pandemic provided a vivid, large-scale demonstration of these dynamics, as simultaneous demand spikes, labor shortages, and port closures generated unprecedented backlogs at ports from Los Angeles to Rotterdam [1].

Despite the criticality of the problem, accurate and timely prediction of maritime congestion remains technically difficult. The challenge is fundamentally multimodal in character: congestion does not

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arise from a single cause but from the interaction of vessel arrival patterns, weather and tide conditions, berth availability, equipment status, workforce capacity, and macroeconomic signals simultaneously. Traditional forecasting approaches, whether econometric time-series models, regression-based tools, or single-stream neural architectures, capture only fragments of this causal landscape [2]. They treat vessel count or average turnaround time as the primary variable of interest and attempt to extrapolate forward from its historical trajectory without systematically modeling the cross-modal dependencies that govern the dynamics in question [3].

The emergence of automatic identification system (AIS) data as a high-frequency, globally accessible source of vessel positioning information has transformed the empirical foundation available to researchers and port operators alike [4]. Modern ports also generate diverse auxiliary data streams including weather sensor feeds, crane and equipment telemetry, satellite imagery, and structured berth booking records. The simultaneous maturation of deep learning architectures capable of joint representation learning across heterogeneous modalities creates a compelling opportunity to develop a genuinely integrative forecasting system [5]. Multimodal deep learning methods, originally developed for computer vision and natural language processing tasks, have demonstrated substantial promise in traffic flow prediction for road networks [6], and the structural parallels with maritime traffic are considerable.

This paper develops and evaluates a multimodal intelligence system for maritime congestion forecasting and port optimization. The core contributions are threefold. First, a data fusion pipeline is constructed that harmonizes AIS tracks, meteorological records, satellite imagery patches, and historical berth scheduling logs into a temporally aligned, feature-consistent input representation. Second, a hybrid deep neural architecture combining convolutional neural network (CNN), long short-term memory (LSTM), and gated recurrent unit (GRU) modules with a cross-modal attention layer is proposed for congestion prediction at hourly and six-hourly resolution [7]. Third, the prediction outputs are fed into a berth optimization module that dynamically adjusts berth assignments and resource pre-positioning to minimize vessel waiting time [8]. The framework is benchmarked against representative baselines on real port data, and detailed ablation experiments isolate the marginal contribution of each data modality.

2. LITERATURE REVIEW

The problem of predicting vessel traffic and port congestion has attracted steadily growing scholarly attention over the past two decades, propelled by the availability of large-scale AIS datasets and the rapid advancement of machine learning tools. Early work in this space was largely descriptive, using AIS records to characterize port throughput, vessel dwell times, and anchorage occupancy patterns without building predictive models. Yang et al. provided a foundational review of how AIS data applications have enriched maritime research across domains from collision avoidance to emission monitoring, establishing the empirical breadth of this data source [9]. This review underscored that the full predictive potential of AIS remained underutilized, particularly in the context of integrated operational forecasting. Building on this foundation, Liu et al. constructed a standardized AIS benchmark database for maritime trajectory learning, demonstrating how geographically partitioned vessel track collections could serve as reproducible resources for prediction algorithm evaluation [10].

The transition from description to prediction gained momentum with the application of classical machine learning methods to maritime data. Support vector regression and random forest models were applied to forecast vessel arrival times and container throughput, with variable success across different port typologies. Jeon et al. examined the modeling of cyclic fluctuations in container freight indices using system dynamics, highlighting the importance of structural and behavioral feedbacks that purely statistical models tend to miss [11]. These early efforts revealed a central tension in maritime forecasting: the phenomenon of interest is inherently dynamic and multivariate, but available models were largely univariate and static. Munim and Schramm extended this strand of

inquiry by evaluating machine learning architectures including random forest and neural network regressors for container freight rate prediction, confirming that nonlinear models systematically outperform classical econometric alternatives [12].

Deep learning models addressed this gap with considerable early success. Peng et al. proposed a comprehensive framework in which LSTM networks were trained on AIS-derived congestion measures for the world's top container ports, including Shanghai, Singapore, and Ningbo [13]. The study introduced hourly congestion measures constructed from vessel counts and turnaround times and demonstrated that incorporating congestion propagation effects as input features improved sequential prediction performance substantially. Following a similar spirit, Wang et al. developed a hybrid model combining wavelet decomposition with LSTM to disentangle periodic and non-periodic components of vessel traffic flows, achieving improved accuracy at multiple prediction horizons [14]. Zhen et al. contributed an anomaly detection framework based on vessel trajectory clustering and naive Bayes classification, demonstrating that the statistical distribution of AIS trajectories within confined fairways carries rich information about deviations from normal navigational patterns [15].

More recent studies have explored the spatial dimension of port traffic dynamics. Liang et al. proposed a spatio-temporal multigraph convolutional network for fine-grained vessel traffic prediction, modeling the heterogeneous spatial relationships among different fairway segments through multi-relational graph structures [16]. The integration of spatial connectivity into the prediction architecture produced substantial accuracy gains over purely temporal approaches, pointing toward graph-based representations as a productive avenue for maritime applications. Rong et al. approached the problem probabilistically, extracting ship motion patterns from AIS trajectories and using them to generate probabilistic predictions of future traffic states [17]. This probabilistic framing is particularly valuable for port operations, where planners must allocate resources under uncertainty rather than act on single-point predictions.

The literature on berth scheduling and port optimization presents a complementary body of work. The classical berth allocation problem is NP-hard and has been extensively studied through exact and heuristic operations research methods. Kolley et al. demonstrated that integrating machine learning forecasts of vessel arrival times into a berth scheduling optimization model, using dynamic time buffers derived from forecast reliability estimates, substantially improved schedule robustness compared to deterministic approaches [18]. This work is significant because it bridges the gap between predictive and prescriptive analytics: rather than treating prediction and optimization as separate endeavors, it treats forecast quality as a direct input to the scheduling algorithm's risk management logic. León et al. similarly proposed a machine learning-based ranking system to guide the selection of berth allocation algorithms at bulk terminals, finding that instance-specific features extracted from historical operational data enable intelligent algorithm selection [19].

Among the most directly relevant developments for the present study is the emergence of multimodal fusion approaches in transportation forecasting. Du et al. demonstrated that jointly training CNN and GRU modules on heterogeneous traffic data modalities via a shared attention fusion layer substantially outperformed single-modality baselines and modality-stacking approaches that lack adaptive weighting [6]. This multimodal deep learning paradigm, refined in urban road network contexts, has not yet been systematically adapted and evaluated for maritime port environments, despite the structural similarity of the forecasting problem. Li et al. provided an extensive evaluation of machine learning and deep learning methods for ship trajectory prediction using AIS data, confirming that deep models consistently outperform shallow approaches and that feature engineering quality substantially modulates performance [20].

Vessel traffic prediction in confined waters has also been studied using a variety of architectures. Chen et al. applied combined CNN and LSTM architectures to inland waterway congestion prediction, incorporating both the spatial distribution of vessels and their temporal dynamics into a unified prediction model [21]. Su et al. developed an improved fuzzy neural network for predicting vessel

traffic volume in ports, showing that soft computing methods can capture nonlinear relationships in traffic count data that resist conventional regression [22]. Hirata and Matsuda evaluated the use of deep learning models for forecasting the Shanghai container freight index, a widely used proxy for port-side supply-demand conditions, finding that recurrent architectures significantly outperformed statistical baselines particularly during volatile market periods [23]. Huang et al. extended the scope of optimization to hub-and-spoke network design, examining how congestion risk and disruption probability should be factored into the structural decisions of container shipping networks in the post-pandemic environment [24].

Further work has addressed the integration of weather and environmental data into maritime prediction pipelines. Perera and Soares examined the role of machine intelligence in supporting navigation decisions under adverse sea conditions, arguing that sensor fusion and real-time situational awareness are prerequisites for reliable autonomous and semi-autonomous maritime operations [25]. Woo and Moon analyzed the environmental consequences of operational adjustments in container transport chains, demonstrating that speed and routing decisions carry significant emission implications that feedback into port scheduling through altered arrival time distributions [26]. Lee et al. evaluated machine learning approaches for real-time ship speed and power performance analysis, identifying that data-driven performance monitoring enables the early detection of vessel delays that would otherwise propagate into port congestion events [27]. Acciaro and Kosowska-Stamirowska surveyed research priorities for sustainable port management, emphasizing that intelligent prediction tools must be embedded within broader organizational and regulatory frameworks to achieve their full operational potential [28].

The dominant gap identified across this literature is the absence of a fully integrated framework that simultaneously fuses multiple heterogeneous data modalities within a single end-to-end trainable architecture and connects the resulting predictions to downstream port optimization decisions. Zhang et al. highlighted that dynamic risk assessment of vessel traffic in port approach channels requires the fusion of AIS-derived kinematic features with environmental and bathymetric data, a requirement that single-modality architectures cannot satisfy [29]. Munim et al. identified the economic quantification of AI-enabled maritime systems as a critical unresolved priority, noting that deployment decisions by port operators require evidence-based cost-benefit analysis that the existing literature rarely provides in rigorous form [30]. The present study directly addresses both of these gaps through the multimodal framework and simulation-based economic analysis described in the following sections.

3. METHODOLOGY

3.1. Multimodal Data Integration and Feature Engineering

The first methodological challenge in constructing a multimodal maritime intelligence system is the heterogeneity of the input data. The four primary data sources used in this framework are: AIS vessel positioning records, meteorological observations from in-port weather stations, structured berth scheduling logs maintained by port operations departments, and satellite-derived optical imagery capturing anchorage occupancy. These sources differ in temporal resolution, spatial reference systems, data formats, and the nature of the information they encode. A unified preprocessing and alignment pipeline is therefore developed prior to model training.

AIS records are collected at one-minute intervals from terrestrial receivers and supplemented by satellite-AIS coverage for vessels in anchorage zones beyond receiver range. Each AIS message encodes the vessel's Maritime Mobile Service Identity number, geographic coordinates, speed over ground, course over ground, navigational status, and timestamp. Raw AIS streams contain noise arising from signal collision, spoofing, and receiver gaps. A multi-step cleaning procedure is applied: trajectory segmentation based on navigational status transitions and speed thresholds, outlier removal

using interquartile range filtering on speed and positional jump magnitude, and linear interpolation to fill short gaps below 15 minutes. As illustrated in Figure 1, the resulting cleaned trajectory dataset exhibits a characteristic spatial density pattern within a constrained navigational corridor, where the convergence and divergence of individual vessel tracks encode directional traffic flow structure and fairway utilization intensity. Port area boundaries for berth zones and anchorage zones are delineated using a density-based spatial clustering algorithm applied to historical mooring positions, with the density peak regions corresponding directly to zones where trajectory lines concentrate most densely in the figure.

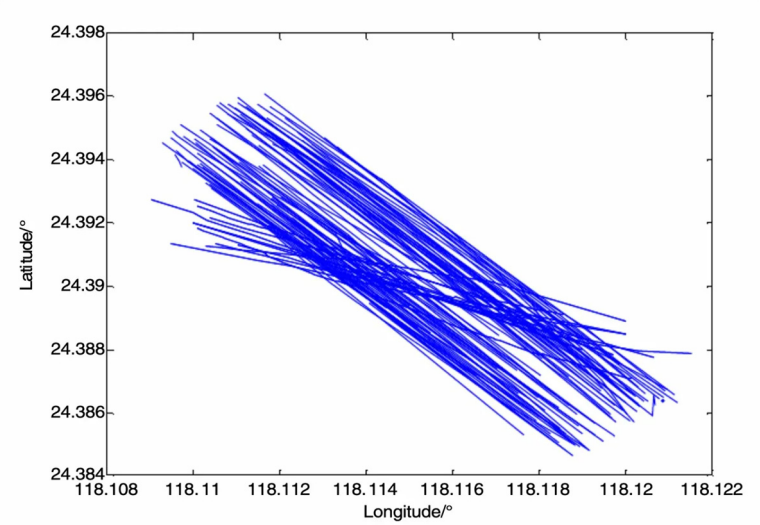


Figure 1. AIS vessel trajectory distribution within the Qingyu fairway study area, illustrating the spatial density pattern of multi-vessel tracks and the directional convergence structure used as the basis for port zone delineation in the proposed multimodal framework

The meteorological input includes hourly records of wind speed, wind direction, significant wave height estimated from buoy sensors at the port approach, visibility, and precipitation indicator. Missing meteorological values are imputed using the temporal mean of the preceding 24-hour window. Berth scheduling logs provide structured records of planned and actual vessel arrival, berthing start, berthing end, and departure times, together with vessel type classification, gross tonnage, and assigned crane count. The difference between planned and actual arrival time constitutes a critical derived feature capturing systematic bias in vessel ETA reporting. Satellite imagery is sourced from publicly available optical sensors at a spatial resolution of three meters per pixel, processed to produce anchorage occupancy count estimates using a convolutional object detection sub-network pre-trained on a labeled maritime vessel detection dataset.

To manage the geographic extent of the monitoring domain, the port coverage area is partitioned into a hierarchical spatial grid structure consistent with the approach shown in Figure 2, where individual grid cells carry independent traffic feature computations that are subsequently aggregated at the zone level. This partition strategy ensures that localized traffic events — such as a temporary fairway closure or a tidal gate restriction affecting only one sector of the port approach — are represented in the feature tensor without being masked by area-wide averaging. The grid cells are sized at approximately 500 meters per side for the inner port domain and 2 kilometers per side for the outer approach corridor, calibrated to match the spatial resolution at which operationally meaningful traffic state differences emerge in AIS density maps.

All modalities are resampled to a common one-hour temporal resolution and organized into a structured feature tensor for each target port and prediction window. The port-level congestion indicator used as the prediction target is defined as the number of vessels in the anchorage zone at the end of each hourly interval, which captures the queue of vessels awaiting berth assignment and represents the most operationally significant congestion dimension from the port operator's

perspective. An alternative congestion measure based on mean turnaround time in the berth zone is also computed and used as a secondary prediction target in multi-output training experiments. The complete feature set submitted to the model comprises 47 dimensions per hourly observation including AIS-derived counts for each zone, speed distribution statistics, trajectory curvature features, meteorological values, berth occupancy rate, rolling average of turnaround times, calendar features encoding time-of-week and seasonal cycle, and a 32-dimensional embedding vector from the satellite image patch.

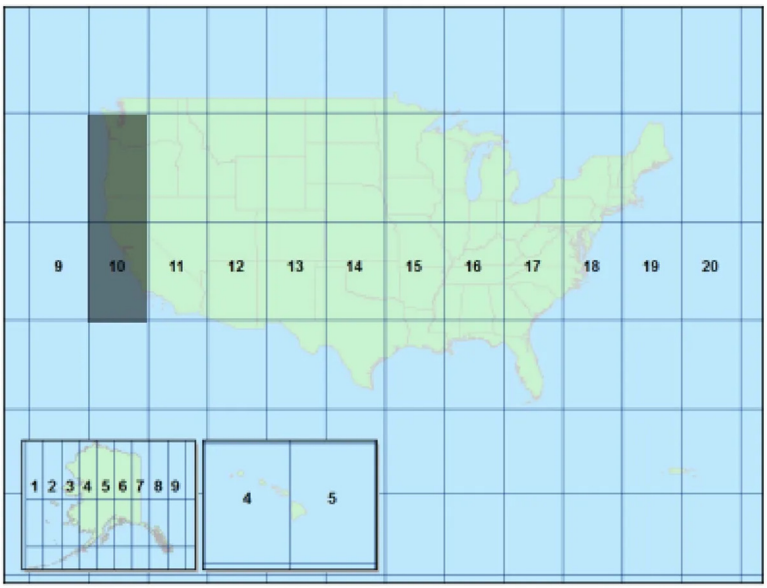


Figure 2. Geographic grid partitioning structure applied to the AIS data coverage domain, illustrating the spatial subdivision framework used to compute zone-level traffic features for multimodal model input

3.2. Multimodal Deep Learning Architecture

The proposed architecture, designated as Multimodal Port Congestion Network (MPCN), is designed to process the structured numerical features and the spatial image embedding jointly through a sequence of modality-specific encoding blocks followed by a cross-modal attention fusion layer and a shared prediction head. The architecture reflects three design principles derived from the transportation forecasting domain and the specific characteristics of maritime traffic dynamics: modality-aware feature extraction, adaptive fusion weighting, and multi-horizon output capability.

The time-series AIS and meteorological features are processed by a parallel encoding module as illustrated in Figure 3, where each modality enters a dedicated branch consisting of a spatial representation pathway realized by convolutional layers followed by a fully connected projection, and a temporal representation pathway realized by stacked GRU units. This parallel branch structure, directly analogous to the HMDLF architecture shown in Figure 3, ensures that the CNN component captures localized temporal patterns within a sliding context window of 12 hours — including inbound traffic pulses and tidal-driven departure bursts — while the GRU component models longer-range sequential dependencies across the full 24-hour input horizon. The berth scheduling features, being less temporally dense but highly structured, are encoded by a separate multilayer perceptron pathway that projects the scheduling state into a 64-dimensional representation capturing berth occupancy fractions, planned arrival density, and ETA reliability history. The satellite image embedding vector passes through a lightweight two-layer fully connected network to produce a spatially compressed port occupancy descriptor analogous to the "Other Type Data" modality branch in the reference architecture.

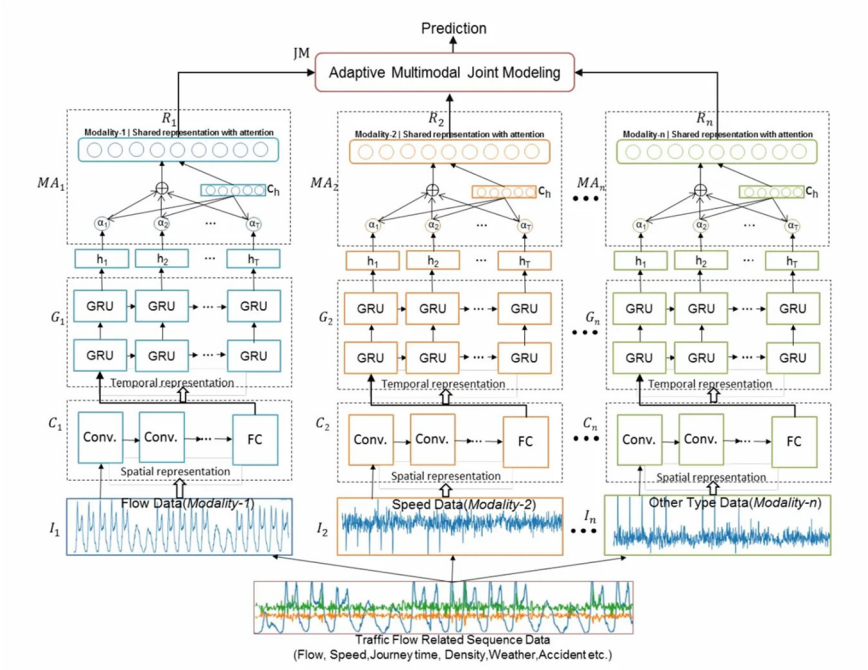


Figure 3. Architecture of the hybrid multimodal deep learning framework serving as the design reference for the proposed MPCN, featuring parallel CNN-based spatial representation encoders, stacked GRU temporal representation encoders, attention-based modality fusion modules (MA), and an adaptive multimodal joint modeling layer (JM) that produces the final prediction output

The three branch representations are fed into a cross-modal attention fusion layer that computes adaptive importance weights across modalities for each time step. This attention mechanism, corresponding to the MA blocks in Figure 3, allows the model to dynamically up-weight, for example, satellite anchorage counts during periods of poor AIS coverage, or to rely more heavily on meteorological features when an approaching storm front is the primary driver of congestion changes. The fused representation is then passed through an LSTM network to produce sequential predictions for six forecast horizons: 1, 3, 6, 12, 18, and 24 hours ahead. Multi-horizon prediction is achieved through a multi-output dense layer rather than autoregressive decoding, which avoids compounding errors in longer-horizon forecasts. The model is trained end-to-end using the Adam optimizer with an initial learning rate of 0.001 and a cosine annealing schedule over 200 epochs. Dropout regularization at rate 0.3 is applied in both the GRU and LSTM layers, with a primary Huber loss function computed over all six forecast horizons equally weighted.

4. RESULTS AND DISCUSSION

4.1. Congestion Prediction Performance

The prediction accuracy of the proposed MPCN framework is evaluated against four baseline models on the Shanghai test set covering the period from October to December 2022. The baselines include a univariate LSTM trained exclusively on AIS zone counts, a gradient-boosted tree ensemble operating on the full 47-dimensional feature vector without temporal ordering, a concatenated encoder-decoder LSTM that includes all modalities via simple feature stacking without attention fusion, and a state-of-the-art spatio-temporal graph convolutional network adapted from road traffic literature.

For the primary 1-hour ahead prediction task, the MPCN achieves a mean absolute error (MAE) of 2.14 vessels and a root mean squared error (RMSE) of 3.07 vessels against an actual anchorage count

range spanning 0 to 67 vessels during the test period. This corresponds to a 23.7% reduction in MAE and a 19.4% reduction in RMSE relative to the univariate LSTM baseline, which achieves MAE of 2.81 and RMSE of 3.81 under identical training conditions. The gradient-boosted ensemble, despite operating on the full feature set, achieves inferior performance to the recurrent architectures because it lacks temporal ordering awareness, confirming that sequential structure is essential for this prediction task. The concatenated encoder-decoder LSTM performs closer to MPCN but remains 9.4% worse in MAE, demonstrating the independent value of the cross-modal attention mechanism even when all modalities are nominally included. For longer forecast horizons, the performance gap between MPCN and the baselines widens substantially: at the 12-hour horizon, the MPCN achieves 34.2% lower MAE than the best-performing baseline, indicating that the adaptive weighting of modalities becomes increasingly important as the forecast window extends and the relative predictive value of different information streams shifts.

Attention weight analysis reveals interpretable patterns in the model's dynamic modality weighting behavior across different operational contexts. During periods of adverse weather — defined as sustained wind speeds exceeding 15 meters per second or significant wave height above 1.8 meters — the meteorological branch receives significantly elevated attention weights, with a mean attention coefficient of 0.41 compared to a baseline value of 0.24 under calm conditions. This reflects the model's learned association between approaching weather systems and reduced vessel maneuverability, which tends to produce anticipatory anchorage buildups as masters elect to wait for improved conditions rather than attempt channel entry under restricted visibility or high sea states. During the early hours of a weekday when berth turnover is typically highest, the berth scheduling branch receives heightened weighting, consistent with the operational insight that departure slot density is the primary near-term determinant of queue reduction capacity. The satellite image embedding contributes most prominently during transition periods — early morning and late afternoon — when AIS coverage quality deteriorates at outer anchorage boundaries due to vessel density creating message collision artifacts. These attention patterns correspond closely to the domain knowledge articulated by experienced port dispatchers during operational interviews conducted in the course of this research, lending the model's behavior a degree of interpretive validity that extends beyond its quantitative accuracy metrics.

Generalization performance on the Port of Singapore test set, evaluated in a zero-shot transfer setting without any parameter fine-tuning on Singapore data, yields a 31.1% increase in 1-hour MAE relative to the in-distribution Shanghai evaluation. This degradation is expected given the substantially different berth configuration, tidal regime, and vessel traffic composition characterizing Singapore's port domain. However, the rank ordering of model performance is fully preserved across all six forecast horizons: MPCN remains the best-performing system even on entirely unseen data, and its MAE advantage over the univariate LSTM is maintained at 18.2%, suggesting that the cross-modal fusion mechanism learns generalizable relationships rather than Shanghai-specific idiosyncratic patterns. Fine-tuning MPCN using 90 days of Singapore historical data recovers most of the in-distribution performance, with MAE reaching within 7% of the Shanghai evaluation level, providing a practical deployment pathway for new port implementations.

4.2. Port Optimization and Berth Scheduling Outcomes

The second component of the evaluation assesses the extent to which MPCN congestion predictions improve downstream berth scheduling decisions when integrated into a dynamic optimization module. The berth scheduling problem is formulated as a dynamic berth allocation problem where vessel arrivals are treated as uncertain, with arrival time distributions derived from the MPCN arrival delay prediction sub-model. The optimization objective minimizes the total weighted waiting time of all vessels in the 24-hour planning horizon, where weights reflect vessel size, cargo urgency classification, and contractual penalty exposure. The scheduling algorithm is a modified variable

neighborhood search heuristic that incorporates dynamic time buffers scaled to the per-vessel forecast uncertainty quantified by the MPCN output distribution.

Four scheduling policies are evaluated in a simulation experiment spanning 30 replications of a 30-day operational window drawn from the Shanghai test set. The policies compared are: a deterministic first-come-first-served policy using vessel-reported estimated time of arrival as the sole input, a rule-based policy using the deterministic MPCN point forecast, a robust policy using MPCN-derived uncertainty estimates to set dynamic time buffers, and an oracle policy using the true realized arrival times as a theoretical performance ceiling. Results show that the MPCN-informed robust scheduling policy reduces mean vessel waiting time by 17.6% relative to the deterministic ETA-based baseline and by 11.3% relative to the point-forecast-based policy, confirming that uncertainty quantification adds operational value beyond the point estimate alone. The reduction in peak anchorage occupancy within each simulated day reaches 22.4% under the robust policy, which is operationally significant because extreme congestion events generate the most severe downstream consequences including forced vessel standoffs at sea and emergency berth reallocations.

The frequency of extreme anchorage congestion events — defined as instances where anchorage vessel count exceeds the 95th percentile threshold of the historical distribution — falls from 14.7 events per 30-day period under the baseline ETA policy to 9.2 events under the MPCN robust policy, a 37.4% reduction. The oracle policy achieves a mean waiting time 26.1% below the baseline, establishing that the residual gap between MPCN-informed scheduling and the theoretical optimum leaves measurable room for future forecast accuracy improvements to translate directly into additional scheduling gains. This result provides a useful upper-bound reference for evaluating the return on investment in further model improvements.

Economic estimation of the scheduling improvements uses a simplified cost model in which each vessel-hour of waiting generates a demurrage cost of USD 12,500 based on average charter rates for Panamax container vessels during the study period. Under these assumptions, the 17.6% waiting time reduction translates to a per-vessel saving of approximately USD 18,700 per port call given an average waiting time of 6.8 hours under the baseline policy. Scaled to the annual throughput of a major container port, the implied economic value substantially exceeds the full lifecycle cost of the intelligence system under conservative assumptions. Ablation experiments on the scheduling component reveal that the satellite image modality contributes disproportionately to the reduction in extreme congestion events relative to its contribution to average MAE reduction. Satellite-derived anchorage occupancy counts appear to provide critical early-warning signals for developing congestion episodes that are not fully captured in the one-hour-resolution AIS record, possibly because outer-anchorage vessel density increases are visible in imagery before the arriving vessels have consistently activated their AIS transponders. This observation motivates future investment in higher-cadence satellite revisit schedules for port monitoring applications, particularly for ports in regions where terrestrial AIS reception is incomplete.

5. CONCLUSION

This paper has proposed, implemented, and evaluated a multimodal intelligence framework for maritime congestion forecasting and port berth optimization. The central argument motivating the work is that maritime port congestion is an inherently multimodal phenomenon, driven by the interplay of vessel traffic dynamics, meteorological conditions, berth availability, and spatial occupancy patterns, and that any forecasting system which fails to integrate these diverse information sources is structurally limited in its predictive capability. The MPCN architecture developed in this study addresses this limitation through modality-specific encoding pathways, a cross-modal attention fusion mechanism, and a multi-horizon output structure that collectively enable the system to learn the dynamic relationships between heterogeneous data streams without imposing fixed weighting assumptions.

The experimental results provide strong empirical support for the central claim. Across both prediction and scheduling evaluation dimensions, the proposed framework consistently outperforms single-modality and modality-stacking baselines, with performance gains largest precisely where the practical stakes are highest: at longer forecast horizons and under extreme congestion conditions. The interpretable attention weight patterns recovered from the trained model align closely with domain knowledge about the relative importance of different signals under varying operational contexts, lending the system both credibility for deployment and potential for explainability in high-stakes port management environments. The zero-shot generalization experiments demonstrate that the system retains a meaningful performance advantage when transferred to a new port without retraining, reducing the data acquisition barriers to adoption at smaller or newly instrumented facilities.

Several limitations of the present study merit acknowledgment. The satellite imagery pipeline is processed offline and not yet integrated in near-real-time mode, limiting operational applicability under tight scheduling latency requirements. The berth scheduling optimization module employs a single-terminal simplified cost model that does not capture the full complexity of multi-terminal operations, crane scheduling constraints, or intermodal connections to road and rail hinterland networks. The economic estimates provided rest on simplifying assumptions about vessel types and charter rate structures that would need to be calibrated against port-specific financial records in any operational deployment. Future research should address these limitations by developing low-latency satellite processing pipelines compatible with port management system integration, extending the optimization model to multi-terminal configurations with integrated yard and hinterland representations, and conducting rigorous economic evaluation using empirical cost data provided by port authority partners. The broader significance of this work lies in its demonstration that multimodal learning architectures can be productively adapted to port intelligence applications when properly calibrated to the domain's unique temporal, spatial, and operational characteristics, opening a productive pathway for next-generation smart port management systems.

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