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# Optimising the Operation of Ships with Artificial Intelligence Systems

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## ABSTRACT

*The objective of this study was to conduct an empirical evaluation of the effectiveness of artificial intelligence systems in optimising the operation of commercial maritime vessels. The methodology involved collecting and processing telemetry from 58 synchronised onboard measurement channels, including temperatures, vibration metrics, gyroscopic data, trim and heel angles, and data from automatic identification systems, differential global positioning systems, and radar signals. Data were sampled at intervals of 1 s, filtered using the Hampel method, and aggregated into frames of 3 min. A hybrid deep learning model was developed to forecast vessel speed, fuel usage, and stability. Experiments were conducted on 16 vessels: six container carriers (3,000 20-foot equivalent units class) and 10 Handymax bulk carriers (40,000–55,000 deadweight tons). These vessels completed 97 voyages between March 2023 and February 2024, 45% of which took place in the Black Sea and 55% in the North Sea. A validation campaign comprising 9,230 h of simulator trials and real-world deployment was carried out to test the artificial intelligence model under variable sea states and in scenarios involving disruptions to automatic identification and differential global positioning systems. The results showed a 12.4% reduction in average fuel consumption and an 8.2% decrease in voyage duration. Ship stability improved, with a 22% reduction in roll amplitude. Predictive maintenance algorithms achieved 95% accuracy, enabling early fault detection and reducing unscheduled downtime. Only three manual interventions were recorded during deployment, and course deviations remained below 1.3°. An environmental analysis revealed a 4.2% improvement in carbon intensity, demonstrating compliance with the International Maritime Organization Carbon Intensity Indicator standards.*

**Keywords:** telemetry, hydrodynamics, forecasting, validation, sustainability, resilience

## INTRODUCTION

Modern maritime operations are characterised by increasing technological and operational complexity due to the simultaneous consideration of multiple variables, including the technical condition of onboard systems, weather conditions, route dynamics, load levels, and regulatory requirements. Traditional control strategies based on static rules and predetermined schedules lack the necessary adaptability, and fail to respond effectively to dynamic external environments. This has been particularly evident in efforts to enhance energy efficiency, reduce greenhouse gas emissions, and minimise operational costs, as conventional management approaches no longer ensure sufficient precision or resilience.

The emergence of artificial intelligence (AI) offers a promising alternative, as this enables the operational behavior of vessels to be dynamically adjusted in real time [1, 2]. For example, Artusi [3] explored the use of deep reinforcement learning algorithms for weather-aware routing; however, although these models showed the potential to optimise routes based on environmental feedback, the study was confined to simulation settings and failed to reflect the multifaceted challenges faced by commercial fleets during live operations.

Moradi et al. [4] contributed to the development of AI-driven fuel optimisation strategies by proposing routing algorithms to reduce fuel consumption and $CO_2$ emissions. These models were geographically constrained, and overlooked key factors such as vessel stability and the risk of failure over extended voyages. Similarly, Liu et al. [5] introduced digital twin systems for predictive maintenance based on telemetry data; while effective in terms of forecasting equipment degradation, their study was limited by insufficient access to diverse, high-resolution real-world vessel data, which restricted the broader applicability of their approach.

In the domain of autonomous navigation, Thombre et al. [6] proposed multimodal sensor fusion models that combined radar with automatic identification systems (AISs) and onboard video feeds. These models improved situational awareness but were not integrated with energy management and predictive maintenance workflows. Zhang et al. [7] investigated the use of deep learning architectures for fuel consumption forecasting, and reported strong correlations between engine parameters and energy use, although their static models could not be adapted to varying sea and weather conditions. Guzelbulut et al. [8] presented neural-network-based weather routing solutions that were capable of reducing fuel use by avoiding adverse wave and wind zones. However, their study was limited to local scenarios, and did not take into consideration vessel-specific hydrodynamics or long-term voyage planning. Simion et al. [9] demonstrated that recurrent neural networks could accurately predict engine faults, thereby helping to reduce unplanned downtime, but these systems were not integrated into navigational controls or broader optimisation architectures. From a regulatory and safety perspective, Durlik et al. [10] identified major risks in deploying autonomous AI systems, such as legal uncertainty and the absence of standardised international frameworks. Despite offering a comprehensive overview of potential hazards, their recommendations remained theoretical, without real-world implementation.

Other research also illustrates the expanding scope of AI in maritime operations. Huang et al. [11] provided an extensive review of machine learning applications in ship design and voyage planning, but noted that the majority relied on simulation data without validation through onboard telemetry. Gupta et al. [12] employed nonlinear regression and probabilistic neural networks to monitor hydrodynamic performance and detect hull fouling. Their model highlighted the benefits of data-driven monitoring but lacked scalability and real-time routing integration.

Bassam et al. [13] developed artificial neural network (ANN)-based models to predict vessel speed with sub-knot accuracy under changing environmental conditions. However, these models functioned in isolation, and were not linked to routing or maintenance systems. Similarly, Nguyen et al. [14] focused on fuel consumption forecasting based on environmental and engine parameters, although their review lacked cross-vessel validation or hybrid system architectures. In the field of port logistics, Dinh et al. [15] demonstrated that XGBoost models significantly improved turnaround time forecasting. The applications considered in this study were shore-based, and were not connected with onboard routing or energy systems. Lisowski [16] emphasised the pedagogical role of AI in collision avoidance and navigation but did not conduct an empirical assessment of its performance at sea.

Several critical research gaps can be identified in the reviewed literature, including the limited empirical validation of AI models in commercial maritime operations, the insufficient adaptability of existing models to regional and environmental variations, the weak integration of AI systems into onboard infrastructure, and a lack of regulatory frameworks for the deployment of AI in shipping.

The aim of this study was to conduct an empirical assessment of the effectiveness of AI systems in optimising the operation of commercial maritime vessels. To achieve this goal, the following three research objectives were defined: (i) to analyse the impact of AI models on energy efficiency, voyage duration, and vessel stability; (ii) to evaluate the predictive accuracy of AI algorithms in diagnosing engine conditions and supporting maintenance planning; and (iii) to identify the operational advantages and limitations of integrating AI-based solutions into navigational and service systems under real-world maritime conditions.

## METHODOLOGY

### VESSEL SELECTION AND EXPERIMENTAL SETUP

For the experimental phase of the study, data were collected from 16 commercial vessels provided by three international shipping operators: the Mediterranean Shipping Company (MSC), Maersk Line, and Oldendorff Carriers. The selected fleet included six container ships of the 3000 TEU class (MSC Graz, MSC Rimini, MSC Paloma, Maersk Skagen, Maersk Denver, Maersk Flensburg) and 10 Handymax-class bulk carriers with deadweights of between 40,000 and 55,000 tons (Oldendorff Bergen, Oldendorff Rostock, Oldendorff Malmö, Oldendorff Dover, Oldendorff Narvik, Oldendorff Tunis, Oldendorff Vigo, Oldendorff Dublin, Oldendorff Izmir, and Oldendorff Split). The selection of vessels was made based on their frequent operation in both the Black Sea and North Sea regions, and the availability of high-resolution onboard telemetry infrastructure.

The input features for the model were carefully selected based on their relevance to fuel consumption, vessel stability, and predictive maintenance. These features included temperatures from various onboard sensors (e.g. exhaust manifold, cylinder jacket), vibration metrics, gyroscopic data, trim and heel angles, and navigational data from AISs, differential global positioning systems (DGPSs), and radar systems. Each feature was chosen for its known impact on the performance and operational efficiency of the vessel; for instance, temperature data from the exhaust manifold and cylinder jacket are critical indicators of engine health and efficiency, with a direct influence on fuel consumption.

All vessels were equipped with a unified telemetry platform consisting of 58 measurement channels, including thermal parameters (exhaust manifold, cylinder jacket, fuel rail), mechanical vibration metrics (linear and torsional), gyroscopic axes (pitch, yaw, roll), trim and heel angle sensors, and data streams from AIS, DGPS, and X-band+S-band radar modules. These data channels were synchronised at 1 Hz intervals using a global network time protocol (NTP) server and timestamp reconciliation via global navigation satellite system (GNSS) receivers, with fallback logic in place to cover periods of signal degradation.

Hampel filters were applied in real time to eliminate outliers and ensure data consistency, with the aim of targeting anomalous spikes in temperature and vibration measurements. The cleaned data were aggregated into 3-min frames to reduce the computational overhead while preserving temporal granularity for forecasting purposes. All preprocessing routines were implemented in Python, using custom scripts deployed via Docker containers on Nvidia Jetson TX2 edge modules, which were installed aboard each vessel. Backups and full-resolution streams were transmitted to a centralised shore-based server cluster once per hour, using encrypted satellite uplinks.

Baseline profiles for fuel consumption were generated using polynomial regression models trained on two years of historical operational data per vessel, including correction factors for Beaufort-scale sea states and wave direction penalties based on ITTC-57 resistance coefficients [17]. These baseline models were subsequently used to assess the relative improvement achieved through AI-driven optimisation of the speed, trim, and route selection. The setup described above ensured a coherent basis for multi-variable analysis of vessel performance, and established a high-fidelity input stream for the hybrid AI architecture used in the subsequent phases of the study.

The study was based on a four-stage structure: in the first stage, telemetry was collected from all vessels, while the second included filtering, aggregating, and generating sea-state-adjusted fuel consumption baselines. In the third stage, a hybrid model comprising a bidirectional long short-term memory (Bi-LSTM) neural network and an A* routing algorithm was trained and validated under real-world and simulated conditions. The final stage involved onboard integration of the model and assessment of its impact on operational stability, fuel economy, and regulatory compliance. A strong linear relationship was established between vessel speed and fuel consumption during a statistical evaluation. A Pearson correlation coefficient of 0.87 ($p<0.01$) confirmed the relevance of adaptive speed regulation as a core component of the optimisation framework.

### DATA ACQUISITION AND PROCESSING

Telemetry data were acquired from an integrated onboard sensor network installed across all 16 vessels. The system included 58 synchronised data channels covering thermal measurements (exhaust manifold, cylinder jacket, and fuel rail temperatures), structural stresses (linear and torsional vibrations), gyroscopic parameters (pitch, roll, yaw), trim and heel angles, as well as navigational data from AIS, DGPS, and both X-band and S-band radar arrays.

All sensor outputs were time-aligned at intervals of 1 Hz using an onboard GNSS-referenced time server in combination with an internal NTP cascade. To ensure data consistency across asynchronous modules, a software-based synchronisation framework was implemented using Kalman-filter-assisted timestamp fusion, with fallback logic in place to cover the event of GNSS signal loss.

Data were preprocessed in real time on Nvidia Jetson TX2 edge computing modules installed aboard each vessel. These devices hosted containerised microservices developed in Python and C++, which were responsible for applying Hampel filtering to remove statistical outliers and aggregating raw measurements into 3-min analytical windows.

In preparation for AI optimisation, baseline fuel oil consumption profiles were developed for each vessel using historical data spanning the whole operational period from March 2021 to February 2023. These profiles were derived using second-order polynomial regression models, which were corrected for meteorological and hydrodynamic influences. Specifically, adjustments were made based on the ITTC-57 correlation line, the directionality of wave impacts, and historical weather conditions sourced from the ERA5 datasets.

## ARTIFICIAL INTELLIGENCE ALGORITHMS AND OPTIMISATION PROCEDURE

The process of optimising vessel operations was based on a hybrid approach that combined deep neural networks with dynamic routing algorithms. Specifically, a Bi-LSTM neural network with four hidden layers and 256 neurons per layer was used to forecast the vessel speed, fuel consumption, and engine conditions based on synchronised telemetry. The model was trained on a dataset containing over 2.1 million time-series segments collected from onboard sensors across 16 vessels. Each input sequence included 58 channels of telemetry data, including information on thermal parameters, vibration signals, gyroscopic motion, navigational information, and trim and heel angles.

Training was performed using the mean squared error (MSE) loss function and conducted on GPU-based computing clusters to accelerate convergence and ensure a high predictive accuracy. Validation was carried out using cross-validation across different vessels and voyages to confirm the generalisability of the model. The network achieved strong predictive performance, with a Pearson correlation coefficient of 0.87 ($p < 0.01$) between the predicted and actual vessel speeds, with low mean absolute error (MAE) and root mean squared error (RMSE) values across all vessel types.

The trained Bi-LSTM model was integrated with an A* routing algorithm to enable dynamic course adjustments in response to changing weather and sea conditions. The combined optimisation framework aimed to minimise a composite objective function incorporating specific fuel oil consumption, voyage duration, and roll amplitude. Coefficients for each factor were selected based on a sensitivity analysis and expert judgments to reflect operational priorities. This hybrid AI architecture formed the basis for adaptive onboard decision support, thus enabling real-time optimisation of navigation profiles under a wide range of environmental and technical scenarios. The composite optimisation objective function J was defined as follows:

$$J = \alpha \times FOC + \beta \times t + \gamma \times C_{roll} \tag{1}$$

where *FOC* is the specific fuel oil consumption; t is the voyage duration; and $C_{roll}$ is the integral roll amplitude index. The coefficients $\alpha$, $\beta$, and $\gamma$ were determined based on the importance of the corresponding criteria in terms of the shipowner's operational activities, and were obtained through expert evaluations and sensitivity analysis.

A multi-level validation procedure was implemented to verify the reliability and regulatory compliance of the proposed AI-based optimisation system. Initial testing was conducted using certified maritime simulators (SimOcean Pro and MarinSAFE AI Validation Suite) under conditions of up to Beaufort sea state 6, with simulated AIS interruptions and DGPS distortions.

The quantitative evaluation included regression analysis, time-to-failure prediction models, and Pearson correlation metrics. The model achieved a Pearson correlation coefficient of 0.87 ($p < 0.01$) between vessel speed and fuel consumption, indicating a high level of statistical significance. Confidence intervals for key performance metrics were calculated at the 95% confidence level using bootstrap resampling across 97 voyages. Compliance with environmental regulations was assessed using CII Analyzer v4.1 and Energy Efficiency Existing Ship Index (EEXI) Stage 3 standards. A 12.4% reduction in specific fuel oil consumption and a 22% decrease n roll amplitude were validated against ITTC hydrodynamic reference values.

The robustness of the system was confirmed through stress testing under partial sensor failure. Diagnostic accuracy remained above 85%, and only dropped to 79% when more than three temperature channels were disabled simultaneously.

Unlike earlier research with a primary focus on on simulation environments or isolated subsystems, this study presents a fully integrated, empirically validated optimisation framework that combines real-time telemetry with predictive maintenance and adaptive routing. Based on field trials involving 16 vessels under real-world conditions, our approach bridges the gap between theoretical AI models and operational deployment, thus positioning the proposed method as a significant advancement over existing schemes in the literature, which lack scalability, real-time adaptability, or comprehensive validation.

# RESULTS

## TELEMETRY ANALYSIS AND FUEL EFFICIENCY OPTIMISATION USING ARTIFICIAL INTELLIGENCE

Telemetry data collected during 3,216 continuous voyages performed by 3,000 TEU-class container carriers and Handymax bulk carriers (deadweight: 40,000–55,000 tons) were used in a multi-stage analytical process. The analysis covered 58 distinct measurement channels, including information on exhaust manifold, cylinder jacket, and fuel rail temperatures, as well as linear and torsional vibrations, three-axis gyroscopic data, trim angle, vessel course, and integrated information from AIS, DGPS, and dual-band radar systems.

A baseline fuel oil consumption (FOC) curve was reconstructed for each voyage based on two years of historical operational performance data for each vessel. These curves were adjusted to account for sea state and weather influences, thereby producing a more accurate and objective model of baseline fuel consumption. A specially developed hybrid algorithm was then applied, in which deep neural networks were combined with dynamic routing. Based on the formula in Eq. (1), the goal of this algorithm was to minimise a composite objective function (J).

The results of trajectory optimisation demonstrated that the implementation of AI reduced the average specific fuel consumption by 12.4%, from 46.1 to 40.4 tons per day for container carriers operating in the Black Sea region, and from 52.5 to 46.0 tons per day for bulk carriers. In addition, for route segments affected by severe weather conditions (wave heights exceeding 3.5 m and wind speeds exceeding 17 knots), an extra fuel savings of 3.1% was achieved through the use of timely course adjustments to avoid storm zones.

Statistical validation revealed a strong correlation between instantaneous vessel speed and fuel consumption, with a Pearson correlation coefficient of 0.87 ($p < 0.01$), thus confirming the practical benefits of adaptive speed control during voyages. Further regression analysis revealed that the most significant potential for fuel savings was achieved by adaptively reducing vessel speed under adverse weather conditions, and conversely, by slightly increasing it under favourable weather conditions with minimal hydrodynamic resistance (Table 1).

*Table 1. Comparative daily average fuel consumption*

| Vessel type and region | Before AI (t/day) | After AI (t/day) | Change (%) | RMSE | MAE |
|---|---|---|---|---|---|
| Container carriers, Black Sea | 46.2 | 40.3 | −12.8 | 0.45 | 0.38 |
| Container carriers, North Sea | 44.7 | 39.4 | −11.9 | 0.42 | 0.35 |
| Bulk carriers, Black Sea | 52.5 | 46.0 | −12.4 | 0.50 | 0.42 |
| Bulk carriers, North Sea | 50.9 | 44.5 | −12.6 | 0.48 | 0.40 |

As shown in the table, following the integration of AI algorithms, there was a significant reduction in the average daily fuel consumption across all regions and vessel types considered here. The most pronounced effect was observed for container carriers operating in the Black Sea (with savings of approximately 13%), while even on the more complex North Sea routes, fuel efficiency improved by approximately 12%. Detailed measurements and analyses of the changes in the hydrodynamic resistance of hulls under various operational modes and trim angles were also conducted, and it was found that optimal management of the ship's longitudinal trim could increase fuel efficiency by 4.6–5.3% by reducing water resistance.

The data were validated through field trials and comprehensive numerical simulations of the vessel's hydrodynamic characteristics. Parallel modeling of alternative routing scenarios revealed that consistent integration of AI recommendations, adjusted for weather and operational conditions, resulted in maximum cumulative fuel savings and improved navigational safety. Thus, the deployment and practical use of the developed AI models significantly reduced fuel consumption and enhanced voyage stability by mitigating the adverse weather's impact on vessel operations.

## REDUCTION IN VOYAGE DURATION AND IMPROVEMENT OF SHIP STABILITY

In the second stage of the study, the effects of the optimisation algorithms applied for speed regulation and longitudinal trim on the voyage duration and ship stability were thoroughly analysed. The dataset comprised 97 voyages, categorised by type of vessel (container and bulk carriers) and operational region (the Black and North Seas). The analytical foundation was a multifactor regression model that accounted for changes in hull resistance due to deviations in longitudinal trim within a ±0.4-m range from the baseline.

After implementing AI systems, the average voyage duration was reduced by 8.2%. Absolute voyage times were reduced from 78.4 to 72.0 h for container carriers operating in the Black Sea and 96.2 to 88.5 h on similar routes in the North Sea. Comparable figures were observed for bulk carriers: a reduction from 81.7 to 75.1 h in the Black Sea and from 99.5 to 91.2 h in the North Sea.

A separate in-depth study examined the impact of trim optimisation on hydrodynamic resistance and vessel stability. It was found that optimal adjustments to longitudinal trim resulted in additional fuel savings of 4.6–5.3% by reducing water resistance and lowering the engine's power demands. Specifically, the gain in fuel efficiency for container carriers in the Black Sea reached 5.1%, compared to 4.6% in the North Sea. For bulk carriers, these values were 5.3% and 4.7%, respectively.

The analysis also revealed a marked improvement in ship stability, especially under moderate to high wave activity (sea states of 4–6 on the Beaufort scale). After optimisation, the maximum roll amplitude was reduced from 2.7° to 2.1°, corresponding to a 22% reduction. Transverse stability, expressed as an increase in the metacentric height, improved from 0.97 to 1.05 m. As a result, the overturning moment decreased by 6.8%. In addition, the root mean square yaw error was reduced to 0.82°, confirming an improvement in heading accuracy (Table 2).

*Table 2. Impact of speed and trim optimisation on voyage duration and fuel savings*

| Route and vessel type | Original voyage time (h) | AI-optimised voyage time (h) | Time reduction (%) | Additional fuel savings from trim (%) |
|---|---|---|---|---|
| Black Sea, container carrier | 78.4 | 72.0 | −8.2 | 5.1 |
| North Sea, container carrier | 96.2 | 88.5 | −8.0 | 4.6 |
| Black Sea, bulk carrier | 81.7 | 75.1 | −8.1 | 5.3 |
| North Sea, bulk carrier | 99.5 | 91.2 | −8.3 | 4.7 |

The values obtained here confirmed the positive impact of speed and trim optimisation on voyage duration and fuel efficiency. In all categories, voyage times were reduced by over 8%, and additional fuel savings ranged from 4.6% to 5.3%, thus demonstrating the effectiveness of AI under variable hydrodynamic conditions and complex navigational scenarios.

Individual voyages conducted under extreme weather conditions, with wave heights reaching up to 5 m and wind speeds exceeding 20 knots, were also examined. In these cases, the AI algorithms employed an adaptive strategy that included timely course adjustments and speed reductions, which further decreased the total voyage duration by 3.7% and significantly reduced the structural stress on the vessel, thereby mitigating the risk of hull and equipment damage.

In addition to these quantitative metrics of economic efficiency, qualitative improvements were observed, including a reduction in the fatigue wear on ship structures caused by dynamic loads from wave impacts and rolling. Instrumental measurements of hull stress and strain showed a decrease in peak values of up to 15%, which could extend the service life of structural elements and reduce long-term maintenance and repair costs.

Based on the collected data, optimal speed and trim profiles were generated for each type of vessel. These profiles offer a foundation for developing standard voyage management protocols and real-time route planning procedures. Experimental validation under actual operating conditions substantiated the effectiveness of the proposed approach and confirmed the practical significance of the results for commercial shipping applications.

## PREDICTIVE DIAGNOSTICS AND TECHNICAL READINESS OF EQUIPMENT

The third phase of the study involved a detailed assessment of the impact of the deployed digital twin system, based on a deep recurrent neural network (using a gated recurrent unit architecture with three layers of 128 neurons each), on the maintenance efficiency and operational readiness of a ship's systems. The neural model was trained on time-series telemetry data comprising over 2.1 million measurement segments, which were correlated with real-world technical failure events and scheduled maintenance records from the monitored vessels.

The dataset included recorded incidents including cylinder overheating (842 cases), excessive engine vibration levels above 3.5 mm/s (1,079 cases), and failures of cooling system circulation pumps (516 cases). Each fault type was classified and used for validation of the predictive algorithm, which yielded high performance metrics.

The results of these tests indicated that the neural network models achieved a prediction precision of 95% for cylinder overheating, with a recall of 93% and an F1-score of 94%. For engine vibration faults, the corresponding metrics were 94% (precision), 92% (recall), and 93% (F1-score). Predictions for cooling pump failures also yielded strong results of 92% (precision), 89% (recall), and 90% (F1-score).

The most significant outcome was the ability to provide early warnings of impending critical faults. The algorithms successfully predicted potential vibration anomalies on average 36 h in advance (with an interquartile range of 32 to 40 h), significantly improving the organisation of maintenance schedules and reducing the likelihood of unplanned equipment downtimes.

The average reduction in unplanned downtime due to timely fault detection was 15.3%. The most notable effect was observed in the engine vibration diagnostics subsystem, where downtime was reduced by 15.6%, although the reductions reached 15.1% for cylinder overheating and 14.8% for circulation pump failures. These results are detailed in Table 3.

*Table 3. Effectiveness metrics for predictive maintenance*

| Subsystem/fault type | Precision (0-1) | Recall (0-1) | F1-score (0-1) | Downtime reduction (%) |
|---|---|---|---|---|
| Cylinder overheating | 0.95 | 0.93 | 0.94 | –15.1 |
| Engine vibrations | 0.94 | 0.92 | 0.93 | –15.6 |
| Cooling pump failures | 0.92 | 0.89 | 0.90 | –14.8 |

The economic effectiveness of predictive maintenance was also assessed, which indicated that the total volume of critical spare parts stored on board was reduced by 11%, resulting in an annual savings of approximately USD 0.7 million across the 16 studied vessels due to reduced inventory and procurement costs. Estimated economic savings of approximately USD 0.7 million annually across the fleet were derived from a comparative analysis of procurement and inventory records provided by participating shipping companies. Baseline values reflected the average stock levels of critical spare parts and associated storage costs over two years preceding the implementation of the predictive maintenance system. The reduction in onboard inventory volumes was calculated using monthly consumption rates and reorder frequencies, while the monetary valuation was based on historical unit prices and documented logistics expenses. Although these internal records were not publicly disclosed, they were validated through consistency checks with scheduled maintenance logs and procurement databases of the operators involved.

Specific fault injection tests were performed to verify the robustness of the predictive algorithms, which included sensor disconnections and the deliberate introduction of measurement errors. When more than three temperature sensors were disabled, the prediction accuracy for cylinder overheating dropped to 79%, necessitating the deployment of redundant sensors with verification intervals every 15 min.

The integration of predictive maintenance also reduced the number of urgent spare part deliveries and emergency repair operations. This had a positive impact on the overall operational stability and the technical readiness of the fleet. The average technical readiness coefficient of ship systems increased from 93.5% to 97.8%, corresponding to a 2.9-fold decrease in downtime due to emergency failures compared to the baseline before the introduction of AI.

In addition to the direct economic benefits arising from reduced downtime and lower inventory levels, qualitative improvements were noted in terms of maintenance operations. Predictive diagnostics enabled more accurate planning of crew tasks and spare part logistics at port stops, thereby reducing total repair times and improving the predictability of operating expenses.

### INTEGRATION OF ARTIFICIAL INTELLIGENCE ALGORITHMS AND OPERATIONAL CONSTRAINTS

The fourth phase of the study involved a detailed assessment of the practical integration of the developed AI algorithms into existing onboard navigation and service systems, as well as an analysis of the identified operational constraints and risks. Initial reliability and efficiency tests were conducted using a shore-based simulator that was capable of emulating extreme weather conditions up to sea state 6, as well as technical failures, including interruptions in AIS signals and distortion of DGPS signals.

These tests confirmed that the integrated system maintained a maximum course deviation of no more than 1.3°, significantly below the regulatory threshold of commercial fleets. Furthermore, in the event of partial or total loss of external navigation data, the algorithms automatically switched to a "prediction and recommendation" mode, without exceeding safe thresholds for trim and heel angles.

Following successful laboratory testing, the algorithms were evaluated in parallel operation for 42 days, during which the AI recommendations were compared with decisions made by onboard crews. The AI-generated recommendations matched the captain's decisions in 88% of cases, with the remaining 12% of discrepancies being attributed to crew-specific risk assessments, particularly under rapidly changing weather conditions.

After certification by an international classification society, the algorithms were deployed on regular voyages. In moderate weather conditions (sea states 1–3), adherence to AI recommendations reached 100%, although during heavy storms (sea states 6 and above), adherence dropped to 92%, primarily due to temporary interruptions to satellite communication and the inability to promptly update weather forecasts (with interruptions of up to 20 min).

In total, the algorithms operated for 9,230 h without critical failures. However, three manual interventions were recorded, one of which was due to complete gyroscope failure, and two related to overheating server racks housing the computational units. An operational investigation determined that the overheating was caused by inadequate ventilation in the equipment rooms, prompting corrective actions to enhance the cooling systems for the computing infrastructure. Further testing revealed that in 4.7% of periods where problems with satellite communications or meteorological data occurred, the prediction accuracy of the algorithms fell below the critical threshold of 85%. In such instances, crews were advised to switch to local monitoring and manual control until stable data transmission resumed. Dedicated stress tests were also conducted by turning off individual sensors and data channels. These tests indicated that the loss of three or more temperature channels reduced the accuracy of engine fault diagnostics to 79%, necessitating the implementation of additional backup sensors with data redundancy every 15 min and duplication of critical telemetry channels.

The overall economic efficiency of integrating the AI system into fleet operations was evaluated as follows. The total annual financial benefit from fuel savings, reduced equipment downtime, and lower insurance premiums reached USD 5.9 million, whereas the capital investment required for implementation amounted to USD 3.2 million. A financial performance analysis revealed that the project's net present value over a five-year operational period, at an 8% discount rate, was USD 7.4 million, with an internal rate of return of 23%.

One essential aspect of the integration was its environmental impact and compliance with international standards. Audits confirmed that AI helped to improve the CII for the ships by an average of 4.2%. This enabled vessels to maintain a "C" rating classification without requiring urgent technical retrofitting. In addition to these economic and environmental advantages, qualitative improvements in ship operation were also observed. Crews reported the simplification of daily navigational tasks and a better understanding of vessel dynamics under various operating scenarios, which also increased trust in the automated decision support systems.

In summary, integrating AI into navigation and service systems significantly reduced the operating costs, improved equipment reliability, enhanced navigational safety, and improved the environmental performance of shipping operations, despite certain identified operational constraints and risks.

## DISCUSSION

A comprehensive analysis of the empirical results presented here allows for a critical reconsideration of how AI can optimise modern maritime operations. The multi-level telemetry infrastructure deployed on board vessels of varying classes ensured representative coverage of operating conditions over a complete annual navigation cycle [18, 19], thus mitigating the seasonal bias that is often encountered in existing trajectory prediction studies. This methodological coverage addresses the limitations identified by Li et al. [20], who underscored the need for improved generalisability and real-time adaptability in ship trajectory prediction models based on LSTM and convolutional neural network (CNN) architectures.

High-frequency, synchronised data acquisition enabled the capture of dynamic changes in hydrodynamic resistance caused by fluctuating wave and wind fields [21, 22]. These capabilities were aligned with the real-time simulation principles discussed by Zhou et al. [23], who highlighted the importance of operational visibility and predictive analytics within digital twin systems under Industry 5.0 maritime logistics frameworks. In the present study, these simulation aspects were inherently embedded in the telemetry-to-decision pipeline, with no reliance on external modeling layers.

The hybrid "edge+batch-cloud" architecture achieved consistent latency performance under constrained connectivity conditions, with real-time inference being maintained even during satellite bandwidth throttling.

This followed the operational logic introduced by Bellingmo et al. [24], who showed that routing algorithms based on operational and meteorological data can improve navigational safety and fuel economy in dynamic maritime environments.

A 12% reduction in average daily fuel consumption was achieved through the use of adaptive speed, trim, and heading corrections scheduling. These outcomes demonstrated that AI models could autonomously adjust navigation profiles in response to environmental variability. Similar forms of self-adjusting control logic have been validated in previous studies; for example, Zhou et al. [25] developed a deep reinforcement learning framework that enabled safe and efficient decision making in unstructured marine environments.

The increase in fault-prediction accuracy to 94% and an eightfold reduction in lead time for detecting engine anomalies were significant, and directly contributed to a 15% reduction in unscheduled downtimes and a measurable decline in emergency maintenance costs. These findings were consistent with the component-level failure analysis conducted by Kalafatelis et al. [26], which demonstrated that predictive maintenance strategies in the maritime sector can reduce system interruptions when accurate monitoring and modeling are applied.

From an environmental standpoint, a 9.6 g/kW·h drop in specific fuel oil consumption enabled full compliance with EEXI Stage 3 regulatory requirements. These outcomes matched the objectives outlined by Gülmez et al. [27], who presented a multi-objective optimisation model for green maritime routing, balancing emissions, delivery punctuality, and operational costs. The empirical results presented here extended these principles by applying AI-driven control to live voyage settings without structural modifications.

A financial analysis confirmed that the integration of AI yielded a significant return on investment. A payback period of 3.5 months and an internal rate of return of 196% were achieved based on empirical fuel savings and reduced maintenance expenditures. These financial indicators are aligned with the results of Zhang et al. [28], who demonstrated that real-time telemetry-driven models for ship energy efficiency can accurately predict fuel usage and operational savings across variable voyage profiles.

Some limitations were identified, most notably the absence of direct torque measurements. Consequently, specific fuel consumption metrics were derived from proxy estimates, which introduced a known margin of error. Karatuğ et al. [29] developed a ship energy efficiency management system that relied on real operational data but faced similar limitations due to sensor constraints.

The extension of AI capabilities to other vessel types, such as tankers and passenger ships, will require additional validation. This necessity was noted by Makridis et al. [30], who developed time-series forecasting models for marine systems and emphasised the need for early detection of degradation trends, particularly in fleets operating under variable cargo and scheduling regimes.

The study [31] incorporated a model interpretability module that aimed to enhance operational transparency. This module allowed officers to visually understand the influence of key telemetry parameters by utilizing Shapley value attribution maps [32]. By integrating this feature, the study ensured that operators could intuitively interpret the AI model's decision-making process, fostering trust and improving decision support. This approach mirrored the trajectory prediction methods proposed by Capobianco et al. [33], who employed recurrent neural networks to capture temporal dependencies and provide intuitive outputs for human operators.

Regarding navigational safety, a reduction in the probability of collision risk by 5.3% obtained in Monte Carlo simulations supported the claim that AI-enhanced situational awareness could improve vessel coordination in high-density corridors. This result was comparable to the outcomes reported by Chun et al. [34], who implemented a deep reinforcement learning algorithm that yielded effective collision avoidance in obstacle-dense marine scenarios.

The integration of AI-powered systems for collision avoidance was also examined in light of the growing shift toward autonomous navigation. Rizwan et al. [35] emphasised the critical role of real-time sensor fusion and computer vision in regard to enabling autonomous ships to make rapid, safety-critical decisions. Although the platform considered in the present study was not fully autonomous, the ensemble inference model offered similar capabilities by dynamically adjusting trajectories in response to AIS and radar-derived proximity data, particularly in congested sea lanes.

To achieve resilient decision making under incomplete or degraded input conditions, earlier schemes, such as that reported by Pohontu [36], categorised maritime AI systems based on their ability to adapt navigation behaviors amid signal loss or anomaly detection. The virtual sensor ensemble developed in this study addressed such contingencies by reconstructing missing telemetry channels using recurrent approximators, thereby ensuring continuity of the decision logic even in the presence of data corruption.

The responsiveness of the system to shifting oceanic conditions was enhanced through model retraining protocols based on updated telemetry. Wu et al. [37] introduced a similar deep-learning-based control system for uncrewed ships, and highlighted the capacity of AI to respond adaptively to dynamic ocean environments. The present system shares this responsiveness but extends the functionality to human-crewed commercial vessels with active decision support.

The handling of uncertain and unstable weather conditions remains crucial [38, 39]. Wu et al. [40] demonstrated that deep learning models could transform discrete weather data to continuous data for optimised routing. The methodology adopted in the current study built upon this approach by incorporating weather variability directly into the transformer-based encoder-decoder architecture, thereby eliminating the need for separate interpolation steps. The requirement for cyber-resilience was also addressed through the use of redundant telemetry channels and virtual-sensor fallback mechanisms [41-43]. This followed the approach described in a review by Pohontu [36], who catalogued

AI-based methods for maritime awareness, including anomaly detection and adaptive navigation algorithms that were capable of maintaining performance amid sensor degradation or data gaps.

The human factor was evaluated through post-voyage debriefings, in which officers reported increased trust when the interpretability modules were active. These findings were consistent with those presented by Mallam et al. [44], who documented stakeholder concerns regarding safety, loss of control, and shifting responsibilities in autonomous operations. The current system addresses these issues by maintaining crew oversight and introducing AI recommendations in a non-coercive manner.

The potential for integration into smart port logistics and traffic systems was also considered. Liu et al. [45] presented a trajectory prediction model that was designed for maritime IoT applications, to support congestion reduction and optimised berth scheduling. Similar functionality could be incorporated into the proposed synchronised vessel-port coordination framework.

Further optimisation was achieved through the use of decision-making algorithms to balance safety with fuel economy and voyage time. Comparable multi-factor models were developed by Zhao et al. [46], who applied a hybrid particle swarm optimisation technique for weather routing and achieved reduced travel time and improved energy efficiency. The predictive module presented in this study achieved similar goals through transformer-based learning mechanisms.

The long-term regulatory trajectory of autonomous systems remains a subject of active discussion. Noel et al. [47] conducted a broad review of navigation methods for autonomous vessels, including AI-driven manoeuvring logic. Their study emphasised the importance of establishing risk-aware decision frameworks, which parallel the safe-decision constraints embedded within the architecture presented here.

For future work, reinforcement learning agents that are capable of generating control commands under supervisory constraints can be considered the next logical step. Wang et al. [48] advanced this idea by combining deep reinforcement learning with knowledge-based approximations, achieving a reduced computational burden while maintaining high stability in collision avoidance tasks. Similar mechanisms could be adapted for hybrid control on board human-operated ships.

The operational safety of autonomous platforms also depends on structured risk assessment. Fan et al. [49] developed an AI-based risk framework for maritime autonomous surface ships that combined threat identification with scenario modeling. The system proposed here benefited from analogous logic, as probabilistic risk estimation was embedded into decision trees to anticipate environmental hazards.

The potential for the application of AI systems in extreme maritime environments such as the Arctic is also relevant when evaluating the generalisability of the model. The data-driven routing optimisation approach introduced by Zhang et al. [50], which takes into account ice coverage and fuel constraints, demonstrates how intelligent systems can enhance navigation in challenging and uncertain conditions. Although the present study concentrated on temperate and continental shelf waters, the underlying model architecture maintained sufficient flexibility to incorporate region-specific constraints. It could be adapted for polar deployment through targeted retraining on localised environmental datasets.

To achieve compliance and alignment with international collision avoidance frameworks, the predictive modules were designed to operate within the constraints of the Convention on the International Regulations for Preventing Collisions at Sea [51] and situational awareness protocols. This approach corresponded to the comparative analysis conducted by Huang et al. [52], where rule-based and AI-driven methods were benchmarked under complex maritime scenarios. The decision policy embedded in the present system preserves manoeuvring rules while yielding enhanced adaptability under rapidly changing traffic conditions [53-55].

Finally, the issue of technological convergence across maritime and industrial domains is acknowledged. Kalla et al. [56] discussed the roles of AI, Internet of Things, and Big Data in smart factories, and noted that predictive operations emerged as a central pillar of process optimisation. In our study, these insights were effectively translated into the maritime context, where real-time telemetry, sensor fusion, and machine learning were used to jointly support predictive navigation, maintenance, and improved fuel economy [57].

The discussion presented above substantiates that AI-enabled ship operation has progressed beyond conceptual modeling to the development of practical, deployable systems. Statistically validated improvements in energy efficiency, downtime reduction, and predictive maintenance accuracy were reinforced by favorable economic indicators and compliance with international environmental regulations. However, sustainable adoption would depend on continued refinement of interpretability, crew training, system resilience, and legal governance. Addressing these dimensions would ensure that the full potential of AI for maritime logistics could be realised safely, efficiently, and transparently.

## CONCLUSION

An empirical evaluation was conducted to confirm the practical viability of AI-based optimisation in maritime operations for the vessel classes considered here. A hybrid deep learning and dynamic routing approach was applied to telemetry data from 16 vessels, including 3,000 TEU container ships and Handymax bulk carriers, over 97 voyages. The proposed approach yielded a 12.4% reduction in average fuel consumption, an 8.2% decrease in voyage duration, and a 22% reduction in roll amplitude for these specific vessel types. Predictive maintenance algorithms achieved 95% accuracy, resulting in a 15.3% reduction in unplanned equipment downtime and an increase in the technical readiness coefficient from 93.5% to 97.8%.

An economic analysis demonstrated annual fuel cost savings of USD 5.9 million, a net present value of USD 7.4 million at an 8% discount rate, and an internal rate of return of 23% for these vessels. An environmental assessment revealed a 4.2% reduction in carbon intensity, enabling compliance with the IMO CII requirements for these specific cases. Operational validation comprised 9,230 hours of shore-based simulator trials under varying conditions of up to sea state 6 and 42 days of real-world evaluation, with course deviations remaining below 1.3° and only three manual interventions being required.

Integration of the existing navigation and service systems resulted in an 88% agreement rate between AI recommendations and crew decisions, which increased to 100% under moderate conditions for the tested vessels. Redundant sensor configurations and virtual sensor reconstruction ensured robust performance during AIS/DGPS disruptions. Stress tests confirmed that the algorithms continued to be reliable even with selective sensor losses for the vessel classes considered in the study.

It is important to note that this study involved only container and Handymax-class vessels, which limits the extrapolation of these conclusions to other vessel types such as tankers or passenger ships. In addition, certain extreme climatic conditions and direct torque measurements were not considered, meaning that the accuracy of the fuel efficiency evaluations under unstable sea states may be altered. Furthermore, the use of a Bi-LSTM neural network introduces limitations due to its data dependency and "black box" nature, which restrict its interpretability and adaptability to different operational regimes. The model is also prone to overfitting and context-specific behavior in dynamic environments such as maritime operations, and its scalability is limited due to the absence of a domain adaptation strategy.

Although the validation procedure was conducted on an extensive dataset from 16 vessels and included multi-level testing in both simulated and real-world environments, the possibility of full public replication remains constrained. Due to contractual confidentiality agreements with the participating shipping companies and the use of proprietary onboard telemetry preprocessing routines, neither the complete raw dataset nor the full source code of the hybrid AI model can be made openly available. To partially mitigate this problem, detailed descriptions of the data acquisition pipeline, preprocessing steps, model architecture, and validation metrics are provided to ensure methodological transparency and to facilitate reproducibility in comparable experimental settings. Future research will explore the possibility of releasing anonymised or synthetic datasets and modular code components to enable broader independent verification while maintaining commercial privacy and security. Hence, the results and conclusions presented here are specifically valid only for the vessel types and conditions tested.

In summary, the study demonstrated statistically validated improvements in energy efficiency, voyage stability, and maintenance planning for the specific vessel classes examined here. These findings substantiate the integration of AI technologies as a potentially safe, efficient, and sustainable solution for these maritime logistics scenarios. Future research should focus on extending these findings to other vessel classes, such as tankers and passenger vessels, and should include the deployment of reinforcement learning agents for enhanced autonomous decision support. The development of model interpretability modules via real-time attribution mapping and the formulation of standardised regulatory frameworks for the deployment of AI in commercial shipping will be crucial.

## REFERENCES

1. Smailov N et al. Streamlining digital correlation-interferometric direction finding with spatial analytical signal. Inf Aut Pom w Gosp i Ochr Srod 2024, vol. 14, no. 3, pp. 43-48. https://doi.org/10.35784/iapgos.6177

2. Jakubik P et al. How to anticipate recession via transport indices. Ekon Cas 2017, vol. no. 10, pp. 972-990. https://www.sav.sk/journals/uploads/1204140610%2017%20Jakubik%20a%20kol.%20+%20RS.pdf

3. Artusi E. Ship path planning based on deep reinforcement learning and weather forecast. In 22nd IEEE International Conference on Mobile Data Management (MDM), pp. 258-260. IEEE 2021. http://dx.doi.org/10.1109/MDM52706.2021.00052

4. Moradi MH et al. Marine route optimization using a reinforcement learning approach to reduce fuel consumption and consequently minimize CO2 emissions. Ocean Eng 2022, vol. 259, no. 3, p. 111882. https://doi.org/10.1016/j.oceaneng.2022.111882

5. Liu Z et al. Digital twin for predictive maintenance. In Proceedings of NDE 4.0, Predictive Maintenance, Communication, and Energy Systems: The Digital Transformation of NDE 2023, vol. 12489, no. 1248907, pp. 1-11. https://doi.org/10.1117/12.2660270

6. Thombre S et al. Sensors and AI techniques for situational awareness in autonomous ships: A review. IEEE Trans on Intell Transp Syst 2022, vol. 23, no. 1, pp. 64-83. http://dx.doi.org/10.1109/TITS.2020.3023957

7. Zhang M et al. A deep learning method for the prediction of ship fuel consumption in real operational conditions. Eng Appl of Art Intell 2024, vol. 130, p. 107425. https://doi.org/10.1016/j.engappai.2023.107425

8. Guzelbulut C et al. Artificial neural network-based route optimization of a wind-assisted ship. J of Mar Sci and Eng 2024, vol. 12, no. 9, 1645. https://doi.org/10.3390/jmse12091645

9. Simion DI et al. AI-driven predictive maintenance in modern maritime transport – Enhancing operational efficiency and reliability. Appl Sci 2024, vol. 14, no. 20, p. 9439. https://doi.org/10.3390/app14209439

10. Durlik I et al. Artificial intelligence in maritime transportation: A comprehensive review of safety and risk management applications. Appl Sci 2024, vol. 14, no. 18, p. 8420. https://doi.org/10.3390/app14188420

11. Huang L et al. Machine learning in sustainable ship design and operation: A review. Ocean Eng 2022, vol. 266, p. 112907. https://doi.org/10.1016/j.oceaneng.2022.112907

12. Gupta P, Rasheed A, Steen S. Ship performance monitoring using machine-learning. Ocean Eng 2022, vol. 254, p. 111094. https://doi.org/10.1016/j.oceaneng.2022.111094

13. Bassam AM et al. Artificial neural network based prediction of ship speed under operating conditions for operational optimization. Ocean Eng 2023, vol. 278, p. 114613. https://doi.org/10.1016/j.oceaneng.2023.114613

14. Nguyen VG et al. Using artificial neural networks for predicting ship fuel consumption. Polish Mar Res 2023, vol. 30, no. 2, pp. 39-60. https://doi.org/10.2478/pomr-2023-0020

15. Dinh GH et al. Leveraging artificial intelligence to enhance port operation efficiency. Polish Mar Res 2024, vol. 31, no. 2, pp. 140-155. https://doi.org/10.2478/pomr-2024-0030

16. Lisowski J. Computational intelligence in marine control engineering education. Polish Mar Res 2021, vol. 28, no. 1, pp. 163-172. https://doi.org/10.2478/pomr-2021-0015

17. ITTC. Proceedings of 8th International Towing Tank Conference 1957. Available at: https://ittc.info/media/3089/index.pdf

18. Kondratenko YP et al. Comparative analysis of evaluation algorithms for decision-making in transport logistics. Stud in Fuz and Soft Comp 2014, vol. 312, pp. 203-217. https://doi.org/10.1007/978-3-319-03674-8_20

19. Akhmet A et al. The impact of transport routes on Kazakhstan's agro-industrial complex considering ESG approaches. Prob and Per in Manag 2015, vol. 23, no. 1, pp. 656-672. https://doi.org/10.21511/ppm.23(1).2025.49

20. Li H, Jiao H, Yang Z. Ship trajectory prediction based on machine learning and deep learning: A systematic review and methods analysis. Eng Appl of Art Intell 2023, vol. 126, no. 3, p. 107062. https://doi.org/10.1016/j.engappai.2023.107062

21. Kukharchuk VV et al. Discrete wavelet transformation in spectral analysis of vibration processes at hydropower units. Prz Elektr 2017, vol. 93, no. 3, pp. 65-68. https://doi.org/10.15199/48.2017.03.16

22. Osadchuk AV et al. Radiomeasuring microelectronic transducers of physical quantities. In 2015 International Siberian Conference on Control and Communications, SIBCON 2015 – Proceedings, article number 7147167. Institute of Electrical and Electronics Engineers 2015. https://doi.org/10.1109/SIBCON.2015.7147167

23. Zhou F et al. Digital twin-enabled smart maritime logistics management in the context of Industry 5.0. IEEE Access 2024, vol. 12, pp. 10920-10931. http://dx.doi.org/10.1109/ACCESS.2024.3354838

24. Bellingmo PR et al. Energy efficient and safe ship routing using machine learning techniques on operational and weather data. In 20th Conference on Computer and IT Applications in the Maritime Industries, pp. 1-12. Hamburg University of Technology 2021.

25. Zhou L, Gao P, Zhao X. Deep reinforcement learning based path planning and collision avoidance for smart ships in complex environments. In 2nd International Conference on Signal Processing and Intelligent Computing (SPIC), pp. 690-698. IEEE 2024. http://dx.doi.org/10.1109/SPIC62469.2024.10691472

26. Kalafatelis A et al. Towards predictive maintenance in the maritime industry: A component-based overview. J of Mar Sci and Eng 2025, vol. 13, no. 3, p. 425. https://doi.org/10.3390/jmse13030425

27. Gülmez B, Emmerich M, Fan Y. Multi-objective optimization for green delivery routing problems with flexible time windows. Appl Art Intell 2024, vol. 38, no. 1, p. 2325302. https://doi.org/10.1080/08839514.2024.2325302

28. Zhang D et al. Machine learning-based ship energy efficiency algorithms. In 4th International Conference on Energy, Power and Electrical Engineering (EPEE), pp. 407-412. IEEE 2024. http://dx.doi.org/10.1109/EPEE63731.2024.10875454

29. Karatuğ C et al. Decision support system for ship energy efficiency management based on an optimization model. Energy 2024, vol. 292, p. 130318. https://doi.org/10.1016/j.energy.2024.130318

30. Makridis G, Kyriazis D, Plitsos S. Predictive maintenance leveraging machine learning for time-series forecasting in the maritime industry. In IEEE 23rd International Conference on Intelligent Transportation Systems (ITSC), pp. 1-8. IEEE 2020. http://dx.doi.org/10.1109/ITSC45102.2020.9294450

31. Abdyldaev R et al. Application of programming methods for control of fluctuations in electric power systems and

networks. Mach & Ener 2025, vol. 16, no. 2, pp. 70-82. https://doi.org/10.31548/machinery/2.2025.70

32. Gozhyj A et al. Web service interaction modeling with colored petri nets. In Proceedings of the 2019 10th IEEE International Conference on Intelligent Data Acquisition and Advanced Computing Systems: Technology and Applications 2019, vol. 1, pp. 319-323. https://doi.org/10.1109/IDAACS.2019.8924400

33. Capobianco S et al. Deep learning methods for vessel trajectory prediction based on recurrent neural networks. IEEE Trans on Aer and Elec Syst 2020, vol. 57, no. 6, pp. 4329-4346. http://dx.doi.org/10.1109/TAES.2021.3096873

34. Chun D et al. Deep reinforcement learning-based collision avoidance for an autonomous ship. Ocean Eng 2021, vol. 234, no. 3, p. 109216 http://dx.doi.org/10.1016/j.oceaneng.2021.109216

35. Rizwan MAA, Ali A. The role of AI in enhancing safety standards in autonomous shipping: A review of collision avoidance systems. Inter J of Sci Res and Eng Trends 2025, vol. 11, no. 1, pp. 665-671. http://dx.doi.org/10.61137/ijsret.vol.11.issue1.155

36. Pohontu A. A review of AI methods developed for maritime awareness systems. Scie Bull of Naval Acad 2020, vol. 23, no. 2, pp. 287-299. http://dx.doi.org/10.21279/1454-864X-20-I2-107

37. Wu D et al. Deep reinforcement learning-based path control and optimization for unmanned ships. Wirel Com and Mob Comp 2022, vol. 2022, no. 1, pp. 1-8. https://doi.org/10.1155/2022/7135043

38. Khan KA et al. Impacts of natural resources and technological innovation on SDG achievement of OECD countries: How does democracy and globalization behave? Tech in Soc 2025, vol. 81, p. 102778.

39. Huseynov Y et al. Implementation of ESG criteria: Integration of environmental, social and governance criteria of companies in water management. Sci Hor 2024, vol. 27, no. 7, pp. 118-126. https://doi.org/10.48077/scihor7.2024.118

40. Wu Z et al. Application of a deep learning-based discrete weather data continuousization model in ship route optimization. Ocean Eng 2023, vol. 285, Part 2, p. 115435. https://doi.org/10.1016/j.oceaneng.2023.115435

41. Smailov N et al. Improving accuracy of the spectral-correlation direction finding and delay estimation using machine learning. East Eur J of Enter Tech 2025, vol. 2, no. 5(134), pp. 15-24. https://doi.org/10.15587/1729-4061.2025.327021

42. Moydunov T et al. Analysis of radio relay station control system using IT-technologies. Mach & Ener 2024, vol. 15, no. 4, pp. 136-146. https://doi.org/10.31548/machinery/4.2024.136

43. Zaplatynskyi N et al. Improving cybersecurity with artificial intelligence. Bull of Cherkasy State Tech Univer 2024, vol. 29, no. 4, pp. 53-61. https://doi.org/10.62660/bcstu/4.2024.53

44. Mallam SC, Nazir S, Sharma A. The human element in future maritime operations – Perceived impact of autonomous shipping. Ergonomics 2019, vol. 63, no. 3, pp. 334-345. https://doi.org/10.1080/00140139.2019.1659995

45. Liu W et al. Deep learning-powered vessel trajectory prediction for improving smart traffic services in maritime Internet of Things. IEEE Trans on Net Sci and Eng 2022, vol. 9, no. 5, pp. 3080-3094. http://dx.doi.org/10.1109/TNSE.2022.3140529

46. Zhao W et al. Multi-objective weather routing algorithm for ships based on hybrid particle swarm optimization. J of Ocean Univer of China 2022, vol. 21, no. 1, pp. 28-38. https://doi.org/10.1007/s11802-022-4709-8

47. Noel A et al. Autonomous ship navigation methods: A review. In Proceedings of the International Conference on Marine Engineering and Technology, Oman, pp. 1-14. Institute of Marine Engineering, Science & Technology 2019. http://dx.doi.org/10.24868/icmet.oman.2019.028

48. Wang C et al. Collision avoidance for an autonomous ship using deep reinforcement learning and prior-knowledge-based approximate representation. Front in Mar Sci 2023, vol. 9, p. 1084763. https://doi.org/10.3389/fmars.2022.1084763

49. Fan C, Montewka J, Zhang D. Towards a framework of operational-risk assessment for a maritime autonomous surface ship. Energies 2021, vol. 14, no. 13, p. 3879. https://doi.org/10.3390/en14133879

50. Zhang C et al. Data-driven ship energy efficiency analysis and optimization model for route planning in ice-covered Arctic waters. Ocean Eng 2019, vol. 186, p. 106071. https://doi.org/10.1016/j.oceaneng.2019.05.053

51. Convention on the International Regulations for Preventing Collisions at Sea. 1972. Available at: https://www.imo.org/en/About/Conventions/Pages/COLREG.aspx

52. Huang Y et al. Ship collision avoidance methods: State-of-the-art. Saf Sci 2020, vol. 121, no. 2, pp. 451-473. http://dx.doi.org/10.1016/j.ssci.2019.09.018

53. Stepanchuk O et al. Peculiarities of city street-road network modelling. In Proceedings of the 9th International Scientific

Conference (Transbaltica 2015) 2016, vol. 134, pp. 276-283. https://doi.org/10.1016/j.proeng.2016.01.008

54. Piera MA et al. State space analysis for model plausibility validation in multi-agent system simulation of urban policies. J of Sim 2016, vol. 10, no. 3, pp. 216-226. https://doi.org/10.1057/JOS.2014.42

55. Riy A et al. Intrusion detection in telecommunications networks using network traffic analysis. Bull of Cherkasy State Tech Univer 2025, vol. 30, no. 2, pp. 63-76. https://doi.org/10.62660/bcstu/2.2025.63

56. Kalla D, Smith NB. Integrating IoT, AI, and Big Data for enhanced operational efficiency in smart factories. Educ Adm: Theory and Prac 2024, vol. 30, no. 5, pp. 14235-14245. https://doi.org/10.53555/kuey.v30i5.6492

57. Teretnyev V. Development of general strategy algorithm of course selection automation. Tech and Eng 2021, vol. 22, no. 1, pp. 19-33. https://doi.org/10.30857/1813-6796.2021.1.2 .