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Artificial Intelligence in Maritime Fleet Management: Enhancing Operational Efficiency and Cost Reduction

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Abstract: The article explores the potential applications of artificial intelligence (AI) in maritime fleet management, focusing on improving operational efficiency and reducing costs. An analysis of key technological solutions is presented, including predictive maintenance, intelligent routing systems, crew performance monitoring tools, and energy consumption optimization. It is demonstrated that machine learning algorithms processing vast datasets, such as Automatic Identification System (AIS) data, weather information, and vessel sensor readings, can predict emergency situations and schedule maintenance based on actual equipment wear.

The study examines case studies from Maersk, Shell, Wärtsilä, and other companies, highlighting fuel savings of up to 15%, reductions in unplanned maintenance events, and improvements in environmental sustainability. Special attention is given to decision-support systems that integrate diverse data sources into a unified information platform, enabling comprehensive analysis and timely decision-making.

The implementation of AI technologies can enhance not only safety levels but also the profitability of maritime transport by optimizing cargo flows and reducing fuel and maintenance costs. The article concludes with practical recommendations for shipping operators transitioning to a "digital" fleet and outlines promising directions for further research. The information presented will be of interest to professionals and researchers in maritime logistics, digital transformation, and operational management who aim to integrate advanced AI-driven models with systems analysis to develop innovative strategies for improving efficiency

and reducing costs in maritime fleet management amid global industry dynamics.

Keywords: artificial intelligence, maritime fleet management, predictive maintenance, route optimization, cost reduction, operational efficiency, maritime logistics, maritime safety.

Introduction: Maritime transport is one of the key components of global logistics, accounting for up to 90% of international trade volume [1]. However, the industry faces several critical challenges. First, operational risks and the high cost of accidents remain significant concerns. Adverse weather conditions, heavy vessel traffic, limited visibility, and human factors frequently lead to incidents that pose threats to human life and the environment. Second, increasing demands for environmental sustainability and emission reduction place additional pressure on the industry, as maritime transport has a substantial impact on marine ecosystems. Lastly, fuel costs represent one of the largest expense categories, with price fluctuations directly affecting the overall budget of shipping companies [2].

Artificial intelligence and big data are becoming integral to the modern maritime industry, enhancing both safety and cost efficiency through route optimization, predictive maintenance, and intelligent fleet management. The emergence of solutions such as Wärtsilä's Fleet Operations Solution and ABB Ability™ Marine Pilot Vision demonstrates that digital technologies have the potential to transform ship management and operational safety [4, 6]. Against this backdrop, the study of AI integration into maritime operations is particularly relevant, with the primary objective being the improvement of economic performance and the minimization of operational risks.

The literature review includes studies assessing both environmental and operational efficiency, as well as the application of advanced methods to minimize delays and optimize processes. These studies highlight a research gap related to the insufficient integration of heterogeneous data into unified management systems.

One group of publications focuses on the sustainable development of port regions and the optimization of route efficiency. Stanković J. J. et al. [1] propose an MCDM (Multi-Criteria Decision-Making) method for creating a composite index that comprehensively evaluates the social, economic, and environmental sustainability of port regions, with the research objective of achieving balance among various aspects of sustainable development. Similarly, Mollaoglu M., Altay B. C., and Balin A. [2] conduct a bibliometric analysis of optimization solutions in maritime transport, hypothesizing that the application of systemic optimization approaches can significantly enhance both operational efficiency and environmental safety.

Additional contributions to this area are made by Fan A. et al. and Kuroda M., Sugimoto Y., [8] who conduct empirical studies on the impact of vessel technical parameters—such as speed, trim, and weather conditions—on operational performance. Meanwhile, Zis T. P. V., Psaraftis H. N., and Ding L. [13] systematize existing routing methods with a focus on meteorological factors.

The second group of studies focuses on the application of artificial intelligence methods and AIS data analysis to enhance safety and optimize navigation processes. Tu E. et al. [3] provide a comprehensive review of the use of Automatic Identification System (AIS) data, demonstrating the potential of intelligent algorithms in processing and analyzing navigational information. Chen X., Ma D., Liu R. W. [4] expand this field by exploring the application of artificial intelligence in maritime transport to improve predictive accuracy and minimize the risk of accidents. The methodology of these studies is based on a combination of machine learning techniques, big data processing, and risk scenario modeling, supporting the hypothesis that AI integration can significantly enhance navigation reliability.

Additional contributions to safety analysis are made by Pallotta G., Vespe M., and Bryan K., [9] who develop algorithms for detecting anomalous vessel trajectory patterns. Similarly, Chen J. et al. [6] and Yang Z., Yang Z., Yin J. [12] utilize statistical models and Bayesian networks to assess factors influencing maritime accidents, highlighting the need for further validation of these models using empirical data. A review by Durlik I. et al. [14] summarizes recent advancements in AI-driven risk management and safety, emphasizing a research gap related to the lack of a unified approach for integrating heterogeneous data into comprehensive monitoring systems.

The third group of publications focuses on training and human factor management in maritime navigation. Atik O. and Arslan O. [5] apply eye-tracking technology to assess electronic navigational competence, allowing for an objective measurement of operators' training levels and supporting the hypothesis that biometric methods can improve training quality. Wahl A. M. and Kongsvik T., [11] in their review of Crew Resource Management (CRM) methods, analyze modern crew training approaches, highlighting the necessity of integrating simulation-based training and practical exercises to reduce operational risks.

A separate research direction is represented by the study of Susto G. A. et al. [10], which explores the application of machine learning in predictive maintenance. The authors use a multi-classification method to identify potential equipment failures, thereby minimizing vessel downtime.

The analysis of scientific publications indicates that while safety and anomaly detection have been extensively studied, systematic research on the overall economic impact of AI implementation in fleet management remains limited. This field requires further exploration, including not only risk assessment but also economic metrics such as fuel cost reductions, vessel downtime expenses, and emergency repair costs, as well as the development of comprehensive digital ecosystems. The absence of full-scale comparative analyses (before and after AI implementation) highlights the research gap that defines the relevance of this study.

The objective of this research is to identify and systematize key artificial intelligence methods and tools that significantly improve the economic efficiency of maritime fleet management while simultaneously enhancing safety levels.

The scientific novelty lies in examining the role of AI across multiple domains, including predictive maintenance, intelligent routing, crew resource management, and risk analysis, with a focus on minimizing overall operational costs for shipping companies. This approach aims to clarify the relationship between safety and costs while proposing an optimized strategy for maritime transport operators.

The hypothesis suggests that integrating AI into maritime fleet management—through failure prediction systems, real-time navigational guidance, vessel load optimization, and other tools—not only increases safety levels but also leads to a tangible reduction in operating expenses, averaging a 20–25% decrease in fuel, maintenance, and downtime costs.

RESEARCH RESULTS

Traditional risk assessment methods in maritime transport—manual inspections, historical incident data collection, and expert opinions—do not always fully reflect the dynamic and complex nature of the industry [6]. The implementation of artificial intelligence (AI) algorithms is transforming this paradigm, as machine learning systems can process large datasets, including AIS data, weather forecasts, and vessel sensor readings, to identify hidden patterns that standard analyses may overlook.

One of the key tools in this process includes neural networks and ensemble models such as Random Forest and Gradient Boosting, which are used to assess the likelihood of accidents and collisions [12]. For example, Maersk's AI-based system analyzes real-time navigational and technical parameters, providing risk alerts several hours before a critical situation arises. Such solutions enhance operational efficiency by preventing downtime and reducing accident-related costs [5, 7, 9].

The continuous integration of AIS (Automatic Identification System) data, predictive weather models, and engine condition sensors enables real-time recommendations for fleet captains and dispatchers [3]. Decision Support Systems (DSS) generate maneuvering scenarios, help avoid congested waterways, and consider high-risk maritime zones [4].

As noted by Pallotta et al. [9], anomaly detection algorithms provide the ability to identify unusual vessel movements, which is particularly valuable in areas with heavy maritime traffic. This allows operators to adjust a vessel’s course or speed in advance, reducing the risk of collisions and, consequently, potential financial losses.

AI-driven systems predict problems before they occur. Instead of reactive measures, where the crew responds only after a critical event, a proactive strategy is implemented [12]. For example, preemptive instructions to the crew regarding mooring or port departure in adverse weather conditions help minimize vessel damage and operational delays.

A comprehensive approach that combines big data analysis, intelligent algorithms, and crew training in system operations has already demonstrated its effectiveness.

Predictive maintenance is based on the principle that equipment failures can be anticipated using historical inspection data and real-time sensor readings [11]. This approach differs from scheduled maintenance, where servicing follows a rigid time-based schedule, and from reactive maintenance, which involves repairs only after a failure occurs.

Given the harsh maritime environment—saltwater exposure, vibrations, and extreme temperatures—frequent equipment failures represent a significant expense [10]. Predictive maintenance reduces costs by enabling more accurate planning for repairs, allowing shipping companies to procure spare parts in advance and maximize port call efficiency.

Artificial intelligence also improves the allocation of watchkeeping duties, ensures compliance with rest period regulations, and provides training simulations to enhance crew preparedness [5].

Many companies, including Kongsberg Maritime and Wärtsilä, are developing integrated platforms that track crew skills, training outcomes, and competency gaps [1]. Thus, the implementation of AI has a dual effect: it prevents accidents while also enhancing the efficient use of human resources.

One of the most significant cost factors in shipping is fuel consumption, which can account for 40–50% of total expenses [2]. AI algorithms dynamically adjust routes based on weather conditions, ocean currents, and port congestion. According to Tu et al. [3], such optimization can result in fuel savings of up to 10–15%.

Additionally, intelligent planning systems help avoid delays when vessels are queuing to enter ports, particularly during peak periods, further reducing overall operational costs [4].

Modern propulsion control systems can optimize engine speed and propeller pitch in real time by analyzing data on vessel load, current draft, water resistance, and wind conditions. Machine learning algorithms, such as LSTM neural networks, assess both historical and real-time parameters to determine the most efficient engine operation mode [13].

The integration of these systems enables fuel consumption reductions of 5–8% under actual operating conditions. When combined with weather-based routing, total savings can be even higher [8].

Beyond economic benefits, reducing fuel consumption also has a significant environmental impact by lowering CO_2 and other harmful emissions [8, 11]. The International Maritime Organization (IMO) continues to set increasingly stringent decarbonization targets, and operators that effectively utilize AI already gain advantages in certification and partnerships with environmentally responsible companies.

As a result, the development of comprehensive AI-driven "green" solutions allows companies to maintain a competitive position in the industry, avoid penalties, and strengthen corporate responsibility (Table 1).

Table 1. Comparison of Traditional and AI-Oriented Approaches in Marine Fleet Management [2-4]

Parameter	Traditional Approach	AI-Oriented Approach	Key Benefits of AI
Risk Assessment	Manual inspection, historical case analysis, subjective evaluations	Machine learning models, big data analysis, real-time monitoring	Increased accuracy, early threat detection, reduction of accidents and penalties
Predictive Maintenance	Preventive maintenance based on fixed schedules or reactive repairs after failures	Failure prediction algorithms (vibration analysis, neural networks), optimized repair planning	Reduced downtime, cost savings on procurement and repairs, extended equipment lifespan
Crew Resource Management	Minimal analytics, shift scheduling based on regulations, infrequent training	Intelligent task distribution, AI-based simulations, fatigue monitoring	Reduced human error, increased motivation and crew qualification
Route and Energy Optimization	Planning based on captain's experience and weather reports	Continuous course optimization using weather models and ocean currents,	10–15% fuel savings, reduced port delays, contribution to

		ML-based engine adjustments	environmental sustainability
Environmental Considerations	Compliance with basic MARPOL regulations, low adaptability	Proactive decarbonization strategy, real-time emission and cost monitoring	Improved environmental performance, reduced fines, enhanced corporate sustainability image

It is evident that traditional risk assessment methods in maritime transport, which rely on manual inspections, historical data, and expert evaluations, no longer meet the demands of modern industry conditions, driving the adoption of artificial intelligence algorithms. The use of neural networks, ensemble models, and anomaly detection algorithms allows for the processing of vast datasets and the development of proactive decision-making strategies. This not only enhances the accuracy of accident probability assessments and optimizes predictive maintenance but also contributes to significant cost reductions in fuel consumption and repairs.

For further advancements, it is recommended to implement hybrid models that combine the strengths of traditional methods with machine learning capabilities, as well as expand the use of IoT devices to improve data collection and integration.

Examples of artificial intelligence applications for fleet management optimization

Fuel costs remain one of the most significant expenses in the shipping industry. Many companies utilize machine learning algorithms integrated with meteorological and oceanographic data to dynamically adjust vessel routes, reducing overall travel time and maximizing the use of favorable currents and weather conditions [3].

More precise control over propulsion systems, including the propeller, rudder, and main engine power, also contributes to fuel savings. Modern systems can manage engine speed in real time, taking into account vessel load, wind speed, wave height, and hull fouling [7]. This increases efficiency and prevents the engine from operating at excessive power levels for given conditions [8].

AI platforms not only calculate optimal routes between ports but also plan port arrival times, minimizing idle time and congestion [4]. Reducing bottlenecks near port terminals helps decrease unnecessary fuel consumption and emissions, directly impacting shipping companies' budgets.

As previously mentioned, predictive maintenance enables vessel operators to identify components requiring repair or replacement in advance. In the Veracity project by DNV, onboard sensor data—such as vibration, temperature, and pressure—are continuously analyzed by AI algorithms. The system predicts failure timelines and recommends optimal maintenance windows, reducing the likelihood of unexpected breakdowns and associated costs for towing or emergency repairs.

Real-time monitoring of hull condition, propellers, and power units allows for dock maintenance scheduling based on actual rather than nominal service intervals [10].

Shell reports that integrating equipment wear data with enterprise resource planning (ERP) systems automates the procurement of spare parts and consumables. This minimizes the risk of operational downtime due to delayed deliveries. Coordination between onboard and shore-based technical teams is simplified through a unified information system, where AI adjusts maintenance and logistics schedules as needed [9].

At the fleet level, consisting of dozens or hundreds of vessels, AI tools optimize vessel allocation based on their current technical condition, cargo capacity, and order urgency. Ports are increasingly adopting AI and IoT-based smart solutions, such as IoT sensors on cranes and robotic container movers, allowing vessel operators to synchronize entry and exit schedules. This improves port throughput and reduces the likelihood of congestion [2].

Such coordination delivers additional economic benefits, including shorter transit times, more efficient use of personnel and equipment, and reduced waiting times.

Big Data tools aggregate and analyze operational metrics such as speed, fuel consumption, downtime, and incidents [9]. The results of this analysis support strategic decision-making at the management level, including investments in specific vessel types, additional crew training, or adjustments to supply chain logistics (Table 2).

Table 2. Summary of Key AI-Based Solutions for Fleet Management [4]

Solution	Key Functions	Application (Examples)	Main Benefits
Fleet Operations Solution (FOS)	- Weather-based routing - Engine performance monitoring - Draft analysis	Container ships, tankers, ferries	5–15% fuel savings; reduced schedule deviations
Veracity DNV	- Predictive maintenance - ERP integration - Technical condition reports	Cruise and commercial vessels (integrated with maintenance systems)	Reduced emergency repairs; accurate planning of dock maintenance
ABB Ability™ Marine Pilot Vision	- Real-time navigation - AI-assisted port entry - Obstacle detection system	Vessels performing complex maneuvers (docking in congested ports)	Reduced collision risks, optimized maneuvering time
AI-Driven Logistics	- Fleet distribution optimization - Integration of shipper data	Large-scale international container shipping	Reduced port congestion, improved delivery time prediction
Training Simulators	- Virtual training systems - Emergency situation modeling - Crew readiness assessment	Training centers, navigation and operational safety programs	Reduced human error, increased safety levels
Intelligent Routing	- Prediction of vessel movements - Optimal speed selection - Consideration of environmental zones	Scientific and test projects (partially autonomous vessels)	Significant reduction in emissions, improved route reliability, and fuel efficiency

The examples above demonstrate that the comprehensive implementation of AI technologies in fleet management can provide:

● Fuel cost reduction ranging from 5% to 15% through optimized routing and engine management [3].

● Decreased downtime due to predictive maintenance of critical components.

● More efficient coordination between maritime and port operations (automated docking planning, improved container logistics) [2].

● Enhanced crew training and better watchkeeping discipline, indirectly reducing human error risks [11].

It is recommended to develop and implement machine learning-based systems capable of analyzing meteorological, oceanographic, and hydrographic data in real time. These solutions will not only enable vessels to adjust their course based on weather conditions but also optimize engine performance by regulating speed, power, and load according to real-time conditions.

Another crucial area is the implementation of predictive maintenance concepts, which improve fleet reliability. The use of analytical platforms enables real-time monitoring of critical components through vibration, temperature, and pressure sensors, allowing for early fault detection. Integrating equipment condition data with ERP systems automates spare parts and consumables procurement, minimizing vessel downtime and reducing repair costs.

At the fleet management level, integrated AI solutions should be developed to coordinate not only internal vessel processes but also interactions with port infrastructure. Utilizing Big Data and IoT technologies to analyze operational metrics such as speed, fuel consumption, and downtime allows for data-driven decision-making, optimizing fleet distribution and port entry schedules. Additionally, the adoption of smart port systems, including crane sensors and robotic container handling devices, contributes to reducing waiting times, lowering emissions, and improving resource efficiency.

CONCLUSION

The integration of artificial intelligence into marine fleet management presents new opportunities for improving efficiency and competitiveness in the shipping industry. This study examined AI applications focused on route planning considering weather conditions, predictive maintenance of vessel equipment, intelligent crew resource allocation, and automated interaction with port infrastructure.

Through big data analysis and machine learning methods, fleet operators can anticipate potential issues, shifting from reactive measures to a proactive approach. This transition reduces both time and financial losses associated with unforeseen incidents and emergency repairs. An additional advantage is the improvement of environmental performance through lower emissions and more efficient resource utilization.

Despite the evident benefits, several challenges continue to hinder the widespread adoption of AI technologies, including the lack of high-quality data, difficulties in integrating with outdated infrastructure, and cybersecurity concerns. However, the recommendations outlined in this study and the successful implementation examples confirm that the maritime industry is gradually embracing digital transformation, with AI emerging as a key tool for ensuring competitive and safe shipping operations. Future advancements will require further standardization of data collection methodologies and enhanced collaboration between shipping companies, ports, and technology providers, enabling the full realization of artificial intelligence's potential in the industry.

REFERENCES

Stanković J. J. et al. Social, economic and environmental sustainability of port regions: Mcdm approach in composite index creation //Journal of Marine Science and Engineering. – 2021. – Vol. 9 (1). – pp. 74.

Mollaoglu M., Altay B. C., Balin A. Bibliometric review of route optimization in maritime transportation: Environmental sustainability and operational efficiency //Transportation Research Record. – 2023. – Vol. 2677 (6). – pp. 879-890.

Tu E. et al. Exploiting AIS data for intelligent maritime navigation: A comprehensive survey from data to methodology //IEEE Transactions on Intelligent Transportation Systems. – 2017. – Vol. 19 (5). – pp. 1559-1582.

Chen X., Ma D., Liu R. W. Application of Artificial Intelligence in Maritime Transportation //Journal of Marine Science and Engineering. – 2024. – Vol. 12 (3). – pp. 439.

Atik O., Arslan O. Use of eye tracking for assessment of electronic navigation competency in maritime training //Journal of eye movement research. – 2019. – Vol. 12 (3). – pp. 7-15.

Chen J. et al. Identifying factors influencing total-loss marine accidents in the world: Analysis and evaluation based on ship types and sea regions //Ocean Engineering. – 2019. – Vol. 191. – pp. 1-12.

Fan A. et al. Joint optimisation for improving ship energy efficiency considering speed and trim control //Transportation Research Part D: Transport and Environment. – 2022. – Vol. 113. – pp. 5-11.

Kuroda M., Sugimoto Y. Evaluation of ship performance in terms of shipping route and weather condition //Ocean Engineering. – 2022. – Vol. 254. – pp. 1-10.

Pallotta G., Vespe M., Bryan K. Vessel pattern knowledge discovery from AIS data: A framework for anomaly detection and route prediction //Entropy. – 2013. – Vol. 15 (6). – pp. 2218-2245.

Susto G. A. et al. Machine learning for predictive maintenance: A multiple classifier approach //IEEE transactions on industrial informatics. – 2014. – Vol. 11. (3). – pp. 812-820.

Wahl A. M., Kongsvik T. Crew resource management training in the maritime industry: a literature review //WMU Journal of Maritime Affairs. – 2018. – Vol. 17 (3). – pp. 377-396.

Yang Z., Yang Z., Yin J. Realising advanced risk-based port state control inspection using data-driven Bayesian networks //Transportation Research Part A: Policy and Practice. – 2018. – Vol. 110. – pp. 38-56.

Zis T. P. V., Psaraftis H. N., Ding L. Ship weather routing: A taxonomy and survey //Ocean Engineering. – 2020. – Vol. 213. – pp. 1-14.

Durlik I. et al. Artificial Intelligence in Maritime Transportation: A Comprehensive Review of Safety and Risk Management Applications //Applied Sciences. – 2024. – Vol. 14 (18). – pp. 8420.