

Review

Smart Routing for Sustainable Shipping: A Review of Trajectory Optimization Approaches in Waterborne Transport

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Abstract

Smart routing has emerged as a critical enabler of sustainable shipping, addressing the growing demand for energy-efficient, safe, and adaptive vessel navigation in both maritime and inland waterborne transport. This review examines the current landscape of trajectory optimization approaches by analyzing selected peer-reviewed studies and categorizing them into six thematic areas: AI/ML-based prediction, optimization and path planning algorithms, data-driven methods using AIS and GIS, weather routing and environmental modeling, digital platforms and decision support systems, and hybrid or rule-based frameworks for autonomous navigation. The analysis highlights recent advances in deep learning for trajectory forecasting, multi-objective and heuristic optimization techniques, and the use of real-time environmental data in routing decisions. Supplemental review using Scopus-based topic mapping confirms the centrality of integrated digital strategies, high-performance computing, and physics-informed modeling in emerging research. Despite notable progress, the field remains fragmented, with limited real-time integration, underexplored regulatory alignment, and a lack of explainable AI applications. The review concludes by outlining future directions, including the development of hybrid and interpretable optimization frameworks, and expanding research tailored to inland navigation with its distinct operational challenges. These insights aim to support the design of next-generation navigation systems that are robust, intelligent, and environmentally compliant.

Keywords: energy efficiency; smart routing; trajectory optimization; sustainable shipping; maritime navigation; artificial intelligence; autonomous vessels



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1. Introduction

The global maritime industry is undergoing a profound transformation, driven by the dual imperatives of digitalization and sustainability. As shipping remains the backbone of international trade, accounting for over 80% of global goods transportation by volume, the sector faces growing pressure to reduce fuel consumption, cut greenhouse gas emissions, and improve operational efficiency. In this context, trajectory optimization has emerged

as a critical enabler of smart routing—the intelligent, data-driven selection of optimal navigational paths that balance energy efficiency, safety, and environmental impact.

Advanced artificial intelligence (AI) and machine learning (ML) approaches are increasingly applied in transportation research, including optimization problems such as the traveling salesman problem and network optimization. However, these methods depend strongly on methodological conditions, such as data quality, distributional assumptions, and problem formulation. Without a proper definition of the optimization task, repetitive learning models may be created that lack interpretability or generalizability. Therefore, while AI/ML models offer powerful predictive and adaptive capabilities, it remains vastly important to combine them with traditional model-building approaches (e.g., operations research, control theory, and statistical modeling), which provide robustness and reliability in practical maritime navigation contexts [1,2]. These strategies are being deployed in both maritime and inland waterway domains, enhancing vessel performance through adaptive routing, predictive analytics, and decision support systems (DSSs). With the increasing availability of Automatic Identification System (AIS) data, high-resolution environmental forecasts, and on-board sensor networks, modern routing systems are capable of making dynamic, context-aware navigational decisions in real time.

Recent years have witnessed a surge in academic and industrial interest in optimizing vessel trajectories to support climate-resilient, autonomous, and digitalized shipping operations [3–6]. Research has expanded from traditional shortest-path algorithms to include deep learning-based trajectory prediction, multi-objective optimization, weather-aware routing, and COLREGs-compliant autonomous navigation. In parallel, digital platforms and smart port infrastructure are playing an increasingly important role in enabling integrated, collaborative decision-making across the maritime logistics chain.

Despite this progress, the literature remains fragmented across disciplines and application domains, making it difficult to obtain a consolidated view of the state of the art. To address this gap, the present paper provides a comprehensive and structured review of existing approaches to trajectory optimization in waterborne transport, with a particular focus on their contribution to smart routing and sustainable shipping.

The main objectives of this review are:

- To classify and analyze the current body of research based on methods, technologies, and digital strategies for vessel trajectory optimization;
- To identify key challenges, research gaps, and limitations in current trajectory optimization approaches for waterborne transport;
- To outline emerging trends and future research directions toward greener and more intelligent maritime navigation.

The remainder of the paper is organized as follows:

Section 2 outlines the methodology used for literature selection and categorization. Section 3 presents the thematic classification of the reviewed papers into six major research groups. Section 4 supplements the core review with a Scopus-based analysis of trajectory optimization research in waterborne transport. Section 5 outlines key challenges and future research directions. Section 6 provides an integrative discussion of findings across categories and supplemental sources. Section 7 concludes the paper by summarizing the main insights, identifying research gaps, and providing recommendations for future work.

Key Concepts and Definitions

In maritime navigation research, the following interrelated yet distinct concepts are frequently used: trajectory prediction, trajectory optimization, path planning, and smart routing. Although these concepts are closely connected, their objectives, methods, and

outputs differ significantly. Clarifying these definitions is essential to understanding the scope and structure of this review.

Trajectory prediction refers to forecasting a vessel's future positions based on historical movement data, environmental conditions, and operational parameters. These prediction models use machine learning, statistical methods, and sensor data integration to estimate likely paths of vessels. These techniques are primarily used for the following: collision avoidance, traffic flow analysis, and ETA prediction.

Trajectory optimization involves selecting the best possible route from multiple alternatives by minimizing or maximizing specific objectives such as fuel consumption, CO₂ emissions, travel time, safety, and comfort. Optimization methods include deterministic algorithms, metaheuristic algorithms, and multi-objective frameworks that balance cost, safety, and sustainability.

Path planning refers to generating feasible navigational paths between defined origins and destinations while considering physical constraints such as bathymetry, obstacles, currents, and restricted areas. Path planning techniques often combine the following: environmental models (e.g., wind, waves, and currents); geographic information system (GIS)-based spatial data; and safety compliance rules (e.g., COLREGs). While trajectory optimization focuses on optimality, path planning focuses on feasibility and safety.

Smart routing represents the integration of prediction, optimization, and planning into a comprehensive digital framework. Smart routing systems combine real-time environmental data, AI-based prediction models, optimization engines, and digital decision-support platforms (e.g., smart ports and autonomous navigation systems). Smart routing aims to enable energy-efficient, safe, and sustainable maritime transport by aligning operational decisions with environmental regulations and emerging autonomous shipping technologies.

This review focuses on trajectory optimization as the core topic, while also covering prediction, path planning, and smart routing because these domains are inherently interconnected in modern digital navigation ecosystems.

Figure 1 illustrates the conceptual relationships among the four key domains analyzed in this review: trajectory prediction, trajectory optimization, path planning, and smart routing. Trajectory prediction provides input data for forecasting vessel positions. Trajectory optimization selects the best possible route under multi-objective criteria such as fuel efficiency, emissions, and safety. Path planning ensures navigational feasibility across three operational levels: strategic pre-departure route planning, tactical collision avoidance during transit, and local maneuvering in ports and inland waterways. Smart routing integrates these domains into a unified decision-support framework for sustainable and autonomous vessel navigation. This integrated perspective justifies including all six thematic research areas in this paper.

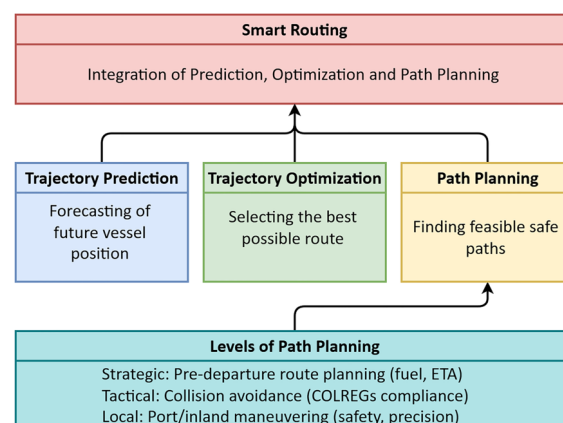


Figure 1. Conceptual Framework of Intelligent Maritime Navigation.

2. Methodology

This literature review was conducted using a structured approach to identify, select, and analyze relevant scientific contributions addressing trajectory optimization in waterborne transport. The goal was to capture the current state of research and technological developments that support smart routing and sustainable shipping objectives. The methodology consisted of four main stages: literature search, screening and selection, categorization, and synthesis.

2.1. Literature Search

An extensive literature search was carried out using a combination of academic databases and digital libraries, including:

- Scopus
- Web of Science
- IEEE Xplore
- ScienceDirect
- MDPI
- SpringerLink
- Google Scholar

The search was conducted using a combination of keywords and Boolean operators, such as:

("ship trajectory optimization" OR "vessel routing" OR "maritime path planning") AND ("AI" OR "machine learning" OR "AIS data" OR "weather routing" OR "smart shipping" OR "sustainability")

The time window was limited to publications from 2010 to 2025, with a focus on the most recent and impactful studies (particularly from 2019 onwards). Both journal articles and conference proceedings were considered. Only publications in English were included.

2.2. Screening and Selection Criteria

The initial search returned over 500 results. These were filtered using the following inclusion criteria:

- Direct relevance to trajectory optimization, path planning, or route prediction for maritime or inland waterborne transport
- Clear contribution to smart routing, sustainability, or digitalization
- Use of technical or methodological frameworks (e.g., algorithms, models, systems)
- Peer-reviewed or reputable conference papers

Studies focusing exclusively on land-based or air transportation were excluded. After duplicate removal and relevance screening based on abstracts and keywords, a total of 93 papers were selected for full-text analysis.

2.3. Categorization and Thematic Grouping

Each selected paper was analyzed in detail to identify its core contribution, methodology, and application domain. Based on this content analysis, the papers were grouped into six thematic categories reflecting the dominant research trends:

1. AI/ML-Based Ship Trajectory Prediction and Forecasting
2. Trajectory Optimization and Path Planning Algorithms
3. Data-Driven and Big Data Approaches Using AIS/Geographic Information System (GIS)
4. Weather Routing and Environmental Optimization
5. Digital Platforms, Smart Ports, and Decision Support Systems
6. Hybrid, Rule-Based, and COLREGs-Oriented Systems for Autonomous or Safe Navigation

This classification enables a structured comparison of approaches, technologies, and use cases across the maritime digitalization landscape.

2.4. Review Synthesis

For each category, the most prominent algorithms, technologies, evaluation metrics, and application scenarios were extracted. The review also aimed to identify overlaps between categories, gaps in current research, and opportunities for future developments, particularly in the context of integrated, intelligent, and sustainable maritime transport systems.

3. Literature Review

The field of vessel trajectory optimization and intelligent routing is rapidly evolving. It combines advances in machine learning, mathematical optimization, big data analytics, and digital decision support systems. Following the conceptual framework introduced in Figure 1, the reviewed literature is organized into six categories. Each subsection begins with a synthesis of current trends and introduces studies, followed by a structured discussion of studies grouped by approach. Each subsection concludes with key insights relevant to sustainable and intelligent navigation.

Before presenting the six thematic categories, it is important to recognize that these domains are inherently interconnected and overlapping. For instance, many AI/ML-based trajectory prediction models (Section 3.1) depend on AIS and GIS data processing techniques (Section 3.3), and numerous weather routing studies (Section 3.4) use optimization algorithms (Section 3.2). Similarly, digital platforms and decision support systems (Section 3.5) often integrate prediction, optimization, and planning functions into unified frameworks. While the categories are presented separately in this review for clarity, they function together as multidisciplinary components of smart routing ecosystems in practice. This overlap underscores the growing trend toward integrated digital strategies in maritime navigation research.

Trajectory optimization is the core of this review. However, prediction models and digital platforms are included where directly relevant to optimization implementation.

3.1. AI/ML-Based Ship Trajectory Prediction and Forecasting

Machine learning (ML) and deep learning (DL) models are increasingly being used to forecast vessel positions based on AIS data and environmental factors. Accurate predictions improve collision avoidance, traffic flow management, and ETA estimation, all of which are critical for smart routing frameworks.

This category includes studies that utilize artificial intelligence and machine learning techniques—such as Long Short-Term Memory (LSTM) networks, Transformer models, and hybrid deep learning frameworks—for predicting vessel movement. These methods aim to enhance navigational safety, traffic control, and fuel efficiency by providing accurate short- and long-term trajectory forecasts.

Recent advances in artificial intelligence and machine learning have significantly (1) improved vessel trajectory prediction, (2) enhanced maritime transportation safety and intelligence, and (3) increased operational efficiency. These developments underscore the importance of data-driven methods as a foundation for smart routing and sustainable waterborne transport [7]. A bidirectional data-driven method that utilizes AIS spatio-temporal data has been shown to increase prediction accuracy and reduce errors, thereby supporting smart routing and improving maritime safety, although it does not discuss alternative technologies or methods [8]. A broad evaluation of trajectory prediction approaches—including regression models, artificial neural networks, Kalman

filters, random forests, and deep learning architectures such as Convolutional Neural Networks (CNNs), Recurrent Neural Networks (RNNs), LSTMs, and Gated Recurrent Units (GRUs)—demonstrates their potential in improving navigational efficiency and reducing maritime traffic risks [9]. Transformer-based AI algorithms applied to AIS data have outperformed traditional LSTM models in trajectory prediction accuracy, thus enhancing maritime traffic safety and efficiency by enabling more precise forecasting [10]. Further improvements are achieved through the use of dual spatial–temporal attention networks that incorporate multi-attribute information and dynamic interactions, significantly increasing prediction accuracy in support of smart routing and sustainability goals [11].

3.1.1. Prediction Approaches

A comparison of twelve trajectory prediction techniques, including five machine learning models (e.g., Kalman Filter, Random Forest) and seven deep learning frameworks (e.g., LSTM, Transformer), illustrates their effectiveness in improving maritime transport safety and operational [12]. Similarly, an in-depth analysis of five classical ML methods and eight deep learning models underscores the role of intelligent trajectory forecasting, particularly in applications involving unmanned ships [13]. One proposed Dynamic Spatial-Temporal Refinement Network (DSTNet) enhances prediction accuracy through improved interaction modeling, though it does not address broader optimization strategies or sustainability impacts [14]. Another approach, combining a Whale Optimization Algorithm with an Attention-BiLSTM network, enhances prediction precision and applicability in maritime surveillance and collision avoidance scenarios [15]. Temporal Convolutional Networks, CNNs, and Convolutional Long Short-Term Memory (ConvLSTM)-based models have also demonstrated increased robustness and accuracy, supporting the development of predictive routing tools even though they lack broader strategic integration [16].

Hybrid architectures such as CNN-GRU with attention mechanisms have proven effective in processing AIS data for accurate trajectory estimation, contributing to optimization efforts at the tactical level [17]. Transformer-based deep learning models continue to demonstrate strong performance in modeling complex vessel behaviors, facilitating improved route planning and traffic management [18]. LSTM networks remain a popular and effective choice in maritime Internet of Things (IoT) applications, particularly for collision avoidance and proactive surveillance systems [19]. Multimodal prediction models that integrate satellite AIS and environmental data offer enhanced reliability and predictive power, contributing to smarter vessel operations and sustainable maritime services [20].

A multi-gated attention encoder–decoder network applied to AIS data has demonstrated improved accuracy and efficiency in ship trajectory prediction. However, the study does not explicitly address broader methods or digital strategies for trajectory optimization in waterborne transport [21]. A Density-Based Spatial Clustering of Applications with Noise (DBSCAN)-based LSTM model has been proposed to enhance prediction accuracy in maritime traffic control. While effective in this context, it lacks coverage of trajectory optimization frameworks or strategic digital integration [22]. A deep learning framework built on a GRU architecture improves computational efficiency and predictive accuracy, offering enhanced vessel navigation based on AIS-derived insights [23]. The integration of data denoising and Bi-LSTM models for AIS-based prediction has shown promise in improving navigation planning and collision avoidance, thereby contributing to smart routing and maritime traffic management [24]. The use of a spatio-temporal multigraph convolutional network (STMGCN), combined with mobile edge computing, has shown high accuracy and robustness in vessel position prediction, supporting intelligent traffic safety solutions within maritime IoT environments [25].

A diffusion probability model employing a temporal-social encoding network and LSTM decoder enables accurate prediction in congested maritime areas by balancing trajectory determinacy and diversity—crucial for effective smart routing [26]. A CNN-LSTM-SE hybrid model focuses on AIS data preprocessing, temporal dependencies, and spatial feature extraction, ultimately improving navigational efficiency and contributing to sustainability and safety at sea [27]. A framework integrating Graph Attention Neural Networks and Bidirectional GRUs has been developed to address the complexity of dense maritime traffic, enhancing prediction accuracy but without detailing holistic optimization methodologies [28].

Context-aware LSTM models with a custom enviro-MSE loss function have been introduced to improve prediction in complex maritime environments, thereby enhancing situational awareness and supporting sustainable routing strategies [29]. Another study leverages LSTM networks optimized by a modified firefly algorithm to improve trajectory forecasting accuracy. This advancement contributes to better-informed routing decisions aligned with smart and sustainable shipping practices [1]. Causal Language Modeling and the H3 spatial indexing technique have been utilized to improve trajectory prediction performance. While the study enhances routing accuracy and efficiency, it does not cover broader strategies for trajectory optimization [30].

3.1.2. Forecasting Approaches

Sequence-to-sequence architectures using RNNs have also shown high accuracy in forecasting future trajectories, enabling more informed routing decisions based on historical AIS data [31]. Another contribution combines AIS data with adaptive learning, motion modeling, and particle filtering techniques. This approach enables timely risk detection and informed decision-making, directly supporting smart routing and sustainable shipping goals [32]. Improvements in autonomous route generation have been demonstrated using an optimized LSTM algorithm trained on large AIS datasets. The method enhances trajectory optimization through effective clustering and route classification [33]. A ConvLSTM-based sequence-to-sequence model captures both temporal and spatial features, increasing trajectory prediction accuracy and contributing to safer, higher-quality navigation—though its impact is more indirect regarding smart routing objectives [34].

An intelligent, data-driven framework based on LSTM learning supports accurate vessel movement forecasting and proactive collision avoidance, both essential components of smart and sustainable maritime operations [35]. The ShipTrack-TVAE model, which combines Variational Autoencoders with Transformer architectures, enhances prediction accuracy and incorporates collision avoidance logic, although it does not elaborate on broader optimization strategies [36]. A divide-and-conquer framework employing Temporal Convolutional Networks and Multi-Layer Perceptrons boosts prediction accuracy, indirectly supporting smarter routing through more reliable navigational decisions [37]. High-precision forecasting has also been achieved using a model based on a multi-head attention mechanism and bidirectional gate recurrent unit (MHA-BiGRU), which leverages AIS data and advanced processing techniques to improve navigational safety and minimize collision risks in waterborne environments [38].

A novel deep learning architecture has been proposed for vessel destination estimation using AIS data. By applying a differentiated data-driven approach, this model improves accuracy and efficiency in maritime surveillance, thereby supporting trajectory optimization, smart routing, and sustainable shipping goals [39]. An innovative trajectory prediction technique combining AIS data, data encoding, and an attention-based LSTM architecture demonstrates enhanced navigational safety and efficiency through improved prediction accuracy [40]. Another method utilizes bidirectional LSTM networks

combined with source/destination clustering, achieving high accuracy for both straight and curved trajectories. This contributes to improved maritime safety and more efficient routing decisions [41]. Encoder–decoder deep learning models applied to AIS data have shown effectiveness in forecasting vessel positions, aiding in collision avoidance and traffic management—key elements of smart routing in maritime transport [42]. Trajectory prediction using historical AIS data is also explored through a regression-based approach. The use of interpolation, similarity queries, and a least-squares support vector machine (LSSVM) optimized via Particle Swarm Optimization enhances shipping management and navigation safety [43].

A hybrid approach integrating clustering techniques with sequence-to-sequence deep learning models has also proven effective, offering gains in computational efficiency and prediction accuracy—both critical for maritime safety and operational effectiveness [44]. Finally, a neural network architecture combining grey forecasting with LSTM modeling has shown improved accuracy in vessel trajectory prediction. However, it lacks a broader discussion of optimization frameworks or sustainability-oriented applications [45].

To synthesize the performance and characteristics of the most frequently applied AI/ML-based trajectory prediction methods, Table 1 provides a comparative overview. It highlights each model’s typical application domain, reported prediction accuracy, strengths, and limitations as discussed in the reviewed studies. In addition to performance metrics, we also consider the computational complexity and training data requirements of the different models, since these factors strongly influence their practical deployment on vessels or in operational platforms.

Table 1. Comparative Summary of Common AI/ML-Based Ship Trajectory Prediction Methods.

Method/Model	Typical Use Case	Reported Accuracy (RMSE/MAE)	Strengths	Limitations	Computational Complexity
LSTM [7,9,19]	AIS-based short/long-term prediction	RMSE: ~0.02–0.15 (varies by dataset)	Handles temporal sequences well; good generalization	Limited interpretability; slower training	Medium
Transformer [10,18,36]	High-density traffic and long sequences	MAE: ~0.01–0.10	Captures long-term dependencies; high accuracy	High computational cost; complex model tuning	High
CNN-GRU [17]	Tactical-level prediction using AIS data	RMSE: ~0.02–0.10	Good spatio-temporal feature fusion; efficient	Less suited for long-term dependencies	Medium
Bi-LSTM with Attention [15,24,40]	Real-time collision avoidance	RMSE: ~0.01–0.12	Improved focus on critical segments; higher precision	May overfit with limited AIS data	Medium
ConvLSTM [16,34]	Spatio-temporal forecasting	RMSE: ~0.03–0.09	Captures spatial and temporal context simultaneously	Slower inference compared to vanilla LSTM	High

Table 1. Cont.

Method/Model	Typical Use Case	Reported Accuracy (RMSE/MAE)	Strengths	Limitations	Computational Complexity
GRU + Graph Attention Net [25,28]	Dense maritime traffic areas	MAE: ~0.01–0.07	Incorporates vessel interactions; robust in congestion	Complex architecture; explainability still limited	Medium
Hybrid (CNN-LSTM) [27,41,44]	Route planning and AIS data integration	RMSE: ~0.02–0.08	Combines spatial and temporal modeling effectively	Model complexity; needs tuning per use case	High
SocialVAE + Transformer [26,36]	Prediction in congested waterways	MAE: ~0.01–0.05	Probabilistic modeling; captures uncertainty/diversity	High training time; requires large datasets	High
Statistical Models (Kalman, SVM) [9,12,43]	Baseline or explainable prediction	MAE: ~0.05–0.25	Lightweight; interpretable	Less accurate on non-linear or noisy data	Low

The complexity and data requirement levels (High/Medium/Low) are based on reported implementations in maritime and related transportation studies, providing practical guidance for method selection.

This structured summary facilitates the identification of trade-offs between interpretability, computational demands, and prediction performance in maritime navigation contexts. For example, while deep learning architectures such as Transformers may achieve the highest accuracy, they often require large-scale training datasets and high computational capacity, which may limit real-time onboard deployment. In contrast, simpler models like standard LSTM variants are less resource-intensive, making them more practical for certain maritime applications despite lower accuracy.

Key study clusters:

- Transformer-based prediction models outperform LSTM in long-term dependency modeling, enabling highly accurate forecasts. Dual-path spatial-temporal attention networks integrate multi-attribute information to improve prediction accuracy by over 15%.
- LSTM and Bi-LSTM remain dominant, achieving RMSE values between 0.02 and 0.15 for AIS-driven predictions. These models improve vessel ETA estimates, supporting traffic safety.
- CNN-GRU hybrids, ConvLSTM, and CNN-LSTM-SE improve spatio-temporal feature extraction, enhancing prediction robustness under complex maritime dynamics.
- Graph Attention Networks handle congested waterways, while diffusion probability encoders balance prediction determinacy and diversity. Variational Autoencoder-Transformer hybrids (ShipTrack-TVAE) achieve up to 20% better accuracy in dense maritime environments.

AI-driven prediction techniques enable high-precision forecasts. However, challenges remain in terms of interpretability and real-time deployment, particularly on vessels with limited onboard computing capabilities. Integrating them into smart routing systems requires improved explainable AI (XAI) frameworks.

Recent research outside the maritime domain demonstrates the broad applicability of AI/ML forecasting approaches in transportation and logistics. For instance, Jebbor et al. [46] used machine learning to predict supply chain disruptions in the textile industry, proving that predictive modeling can identify operational risks in complex logistics networks. Similarly, Jebbor et al. [47] examined the use of artificial intelligence to predict disruptions in the automotive supply chain, highlighting the ability of data-driven forecasting to increase the resilience of transportation systems. While these studies are not maritime-specific, their findings underscore the transferability of AI-based predictive frameworks, supporting the notion that advances in other logistics domains can inform trajectory prediction in shipping.

3.2. Trajectory Optimization and Path Planning Algorithms

Trajectory optimization involves selecting the best route given constraints such as fuel use, emissions, ETA, and safety. Methods range from deterministic algorithms to metaheuristics and hybrid optimization frameworks.

This group comprises research focusing on optimization techniques like A*, Particle Swarm Optimization (PSO), Genetic Algorithms, and Model Predictive Control. These methods are designed to generate energy-efficient, safe, and collision-free routes, often incorporating dynamic constraints and vessel motion models.

3.2.1. Trajectory Optimization

PSO has been applied to vessel trajectory optimization to enhance energy efficiency and reduce CO₂ emissions. This approach integrates advanced motion control methods, including adaptive neural networks and asymmetric barrier Lyapunov functions, to ensure both safety and sustainability in maritime operations [48]. Current methods for trajectory optimization in waterborne transport include A* algorithm, artificial potential field, RRT, and reinforcement learning. These technologies enhance navigation safety, reduce fuel consumption, and improve efficiency, contributing to smart routing and sustainable shipping objectives [49]. An Efficient and Safe Path planning (ESP) method based on GIS data has been proposed. By emphasizing fuel consumption, trajectory smoothness, and real-time obstacle avoidance, it contributes directly to the development of intelligent and sustainable maritime navigation systems [50]. A Mixed-Integer Linear Programming (MILP)-based optimization method has also been introduced, combining historical data with predictive modeling of multiple vessel trajectories. This method enhances safety and efficiency, particularly by minimizing close-quarter navigation risks in congested port areas [51]. Dynamic programming combined with high-resolution ocean models has been used to generate optimal trajectories for underwater vehicles, accounting for time-varying ocean currents. This enables efficient navigation in complex environments, thereby supporting smart routing and sustainability objectives [52].

3.2.2. Path Planning Algorithms

One real-time optimization approach utilizes current ocean velocity measurements instead of forecast data to plan energy-efficient routes. This method improves computational efficiency while aligning with broader environmental goals in sustainable shipping [53]. Alternative methods such as Dijkstra's algorithm, Markov chain analysis, and game-theoretic modeling have been applied to maritime route optimization. These strategies account for spatial constraints, probabilistic transitions, and inter-stakeholder cooperation to reduce costs and improve route efficiency [54]. A practical example of vessel routing optimization employs the two-phase sweep algorithm within a spreadsheet-based environment (Microsoft Excel). While highlighting the limitations of manual planning, this method demonstrates potential cost and time savings in offshore marine operations [55]. Another

dual-optimization strategy integrates Particle Swarm Optimization for route planning with a steepest descent algorithm for power generation scheduling. This configuration minimizes propulsion energy demand and emissions, contributing to smarter navigation and improved environmental compliance [2]. Finally, a hybrid approach combining model-based and data-driven methods—including analytical cost functions and deep neural networks (DNN)—has been proposed to address trajectory optimization in uncertain conditions. This framework enhances routing efficiency while maintaining flexibility for real-world variability [56].

Path planning and trajectory optimization are applied in maritime navigation across different operational contexts, each with its own objectives, constraints, and algorithmic requirements.

Pre-departure strategic route planning focuses on global or regional routing between ports. It optimizes for fuel consumption, emissions, and ETA under known environmental conditions.

Collision avoidance through tactical path adjustment ensures real-time safety during transit by dynamically adjusting routes to avoid other vessels, drifting objects, or ice. This is typically done using control frameworks that comply with COLREGs.

Local maneuvering in ports and inland waterways requires precise navigation in narrow, shallow, and congested areas, where maneuverability and traffic constraints are primary considerations.

As shown in Figure 1, path planning problems occur at different operational levels—strategic, tactical, and local. This distinction clarifies how different problem contexts require specialized algorithms and optimization strategies.

Table 2 summarizes the strengths and weaknesses of the most frequently applied methods, including deterministic algorithms (A, Dijkstra), metaheuristics (GA, PSO), control-based approaches (MPC), machine learning methods (RL), and hybrid frameworks. This comparative perspective complements the detailed discussion of individual studies provided in the following subsections.

Table 2. Comparative Analysis of Trajectory Optimization and Path Planning Methods.

Method/Approach	Main Advantages	Main Limitations	Typical Applications
A*/Dijkstra [49,54]	Finds optimal paths, efficient for simple maps	Sensitive to dynamic conditions; limited for real-time replanning	Pre-departure strategic route planning
Genetic Algorithms [50]	Good for multi-objective optimization, handles nonlinearities	Requires tuning; slower convergence on large datasets	Energy-efficient routing under variable weather
Particle Swarm Optimization [2,48]	Fast convergence, balances fuel savings and collision avoidance	Can get trapped in local optima; requires careful initialization	Weather-aware, fuel-efficient navigation
Model Predictive Control [52]	Enables real-time trajectory adjustments, integrates COLREGs	Computationally demanding; dependent on accurate forecasts	Collision avoidance, dynamic traffic
Reinforcement Learning [51,55]	Learn adaptive navigation strategies from experience	Requires large training datasets; interpretability issues	Autonomous MASS control, inland waterways

Table 2. *Cont.*

Method/Approach	Main Advantages	Main Limitations	Typical Applications
Potential Field Methods [53]	Simple, fast, effective for avoiding obstacles	Prone to local minimum; not robust in congested traffic	Tactical collision avoidance
Hybrid Frameworks [56]	Combine prediction, optimization, and decision-support	Higher system complexity; integration challenges	Smart routing in digital twin ecosystems

Key study clusters:

- Algorithms like A*, Dijkstra, and MILP provide globally optimal solutions, especially useful in constrained waters such as port entries.
- PSO minimizes fuel use and CO₂ emissions while ensuring safe navigation. Genetic Algorithms (GA) support multi-objective optimization, reducing voyage costs and energy demand.
- Real-time speed re-optimization using MPC achieves significant fuel savings and emission reductions.
- Combining deep neural networks with analytical cost functions provides adaptive performance under uncertain weather and traffic conditions.

Optimization frameworks are shifting toward real-time, multi-objective decision-making systems that form the core enabler of autonomous maritime navigation.

By evaluating both the methodological contributions and their practical trade-offs, this review goes beyond a descriptive listing of methods and provides comparative insights into the suitability of different approaches for strategic, tactical, and local navigation contexts. This structured analysis addresses the ongoing need for decision-support guidance in selecting trajectory optimization techniques for sustainable and intelligent maritime transport.

3.3. Data-Driven and Big Data Approaches Using AIS/GIS

Big-data analytics harnesses AIS and GIS datasets to enable trajectory clustering, network modeling, and traffic pattern prediction. These techniques underpin intelligent routing strategies and predictive monitoring.

Studies in this category leverage AIS and GIS data for trajectory mining, clustering, network modeling, and traffic behavior analysis. These data-intensive approaches enable route planning based on empirical vessel movement patterns and environmental context.

3.3.1. Data-Driven Approaches

A methodology combining historical vessel tracking data with the A* search algorithm has been proposed to generate optimal route recommendations. This approach reduces operational costs and emissions while enhancing the overall efficiency of maritime transport, supporting both smart routing and sustainable shipping objectives [3]. Route optimization techniques are categorized into three main types: those based on meteorological data, fuel consumption models, and waypoint databases. Algorithms such as dynamic programming and machine learning are analyzed for their roles in improving routing performance and promoting environmental sustainability [57]. State-of-the-art algorithmic strategies for maritime trajectory data mining are reviewed with a focus on trajectory forecasting, activity recognition, and clustering. These techniques contribute to smart routing by optimizing vessel movement patterns and improving operational efficiency [58]. To improve navigation accuracy, an adaptive waypoint extraction model (ANPG) and an enhanced kernel

density estimation technique (KDE-T) have been introduced. These tools support smart routing by refining digital maritime traffic networks and ultimately contribute to more sustainable shipping practices [59]. A polynomial approximation-based route planning algorithm has been developed, incorporating Douglas–Peucker compression and HDBSCAN clustering. This method enhances route similarity detection and trajectory optimization, thereby supporting efficient and sustainable vessel operations [60].

3.3.2. Big Data Approaches

An online multi-dimensional AIS trajectory simplification algorithm is presented to optimize path data by preserving spatial-temporal integrity—position, direction, and speed. The result is more effective data management and improved support for smart routing decisions [61]. Recent advances in intelligent ship positioning and sensing technologies are reviewed with emphasis on trajectory-based maritime route network construction. These innovations facilitate intelligent navigation, anomaly detection, and route planning within a sustainable operational framework [62]. A suite of AIS-driven algorithms for trajectory segmentation, waypoint detection, and clustering has been shown to reduce route generation time by over 17%, improving navigability and supporting sustainability objectives through smart routing [63]. Lattice-based DBSCAN clustering combined with kernel density estimation is used for maritime traffic forecasting. This methodology enables knowledge-driven trajectory optimization by accurately predicting vessel movements and improving strategic routing decisions [64]. Key technologies for analyzing ship trajectories include standard association models, historical pattern mining, anomaly detection, and deep learning prediction methods. Together, these tools enhance routing efficiency, optimize decision-making, and uncover new opportunities in sustainable maritime logistics [65].

Deep learning and network-based approaches are also being leveraged to optimize vessel routes by constructing maritime traffic networks from AIS data. These methods improve route prediction accuracy while contributing to ecological impact reduction, cost savings, and navigational safety [66]. AIS-based optimization techniques have been applied to inland waterway transport using the MPDP algorithm for compression, OPTICS for clustering, and A* for connectivity analysis. This integrated method improves routing efficiency and reduces congestion, promoting sustainability in inland shipping systems [67]. Finally, historical AIS-derived ship tracks combined with the ant colony optimization algorithm have been used to enhance traffic safety and routing efficiency—particularly in complex navigation zones such as the Three Gorges dam—thereby supporting smart routing practices [68].

While AIS data forms the backbone of many trajectory prediction and optimization models, its practical application is constrained by several limitations. Signal loss can occur in high-traffic areas, regions with poor satellite coverage, or during adverse weather, leading to data gaps that reduce model accuracy. Privacy concerns also arise when AIS transmissions reveal sensitive commercial routes or vessel activities. Potential solutions include integrating AIS with complementary data sources such as radar, satellite imagery, or terrestrial tracking systems to ensure redundancy. Data anonymization and encryption can mitigate privacy risks, while interpolation and machine learning-based gap-filling techniques can address missing data, thereby improving the reliability of AIS-based navigation models.

Key study clusters:

- Advanced clustering techniques like DBSCAN and HDBSCAN improve the detection of commonly used routes, while adaptive waypoint extraction enhances traffic mapping accuracy.

- AIS-driven maritime traffic network models predict congestion and improve route connectivity, allowing for strategic avoidance of bottlenecks.
- Combining AIS data with predictive models accelerates real-time decision-making for traffic control and routing.

AIS/GIS-based data-driven methods form the backbone of intelligent navigation systems but face persistent challenges with signal loss, data sparsity, and privacy concerns. Solutions include the integration of multiple sensors, such as radar and satellite data, as well as ML-based gap-filling.

3.4. Weather Routing and Environmental Optimization

Weather routing refers to the process of selecting vessel routes that account for real-time or forecasted meteorological and oceanographic conditions such as wind, waves, currents, and ice. The goal is to improve fuel efficiency, voyage safety, and regulatory compliance while minimizing environmental impact. Current research in this area can be broadly grouped into three interrelated directions:

1. Route Planning involves static or pre-departure optimization methods, which generate initial routes based on climatological data or forecast conditions available before sailing. Methods include deterministic algorithms (e.g., Dijkstra, A*), isochrone techniques, and dynamic programming. These approaches optimize for expected voyage duration, fuel use, or emissions under baseline weather assumptions.
2. Weather-Dependent Routing is an adaptive routing method that dynamically updates planned trajectories using near-real-time meteorological and oceanographic forecasts. These approaches employ stochastic optimization, genetic algorithms, reinforcement learning, and scenario-based methods to adjust routes during a voyage. They are designed to handle uncertainties in changing environmental conditions, improving resilience and energy efficiency.
3. Environmental Speed Optimization is a specific subset of weather routing strategies in which the vessel's speed profile is adjusted along a fixed or semi-fixed route to minimize fuel consumption, emissions, or hull stresses under environmental constraints. Unlike route planning, which focuses on spatial trajectory, speed optimization focuses on temporal adjustments and power management.

A wide range of algorithms has been applied across these categories, including genetic algorithms, dynamic programming, multi-objective evolutionary optimization, and reinforcement learning. For example [69], GA-based weather routing has achieved 3–5% fuel savings by adapting routes and speeds to rolling meteorological updates, while dynamic programming combined with high-resolution ocean models has improved efficiency in current-dominated waters.

It is important to clarify that supporting tools such as prognostic weather charts and vessel performance graphs are not optimization methods themselves but serve as input data and visualization aids in weather routing systems. Similarly, spectral wave models (e.g., WAVEWATCH III, SWAN) [70], which provide frequency-direction sea-state spectra used by optimization algorithms to assess added resistance and seakeeping performance.

3.4.1. Adaptive Weather-Dependent Routing

Current research trends in route optimization highlight three key directions: route planning, weather-dependent routing, and environmental speed optimization. These approaches collectively improve operational efficiency and reduce ecological impact, thereby aligning with the principles of smart routing and sustainable shipping [4]. Stochastic optimization techniques—such as Markov decision processes and scenario-based optimization—have been proposed to improve trajectory planning under uncertainty. These methods

contribute to enhanced fuel efficiency, navigational safety, and temporal reliability, especially in the context of climate variability [71]. Weather routing has emerged as a central strategy for trajectory optimization. By integrating reliable meteorological forecasts with AI algorithms, this approach helps reduce both travel time and fuel consumption, supporting decarbonization efforts and sustainable maritime navigation [5]. Genetic algorithms have been effectively applied to dynamic trajectory optimization using rolling meteorological data. These algorithms improve route and speed decisions, achieving fuel savings of over 3.5% and contributing to energy-efficient shipping operations [69]. Another study employs a genetic algorithm for trajectory optimization, utilizing a weather routing tool that accounts for hull and propeller fouling and ocean currents, enhancing fuel efficiency and supporting smart routing and sustainable shipping objectives through improved route selection [72].

3.4.2. Environmental Speed Optimization (As a Subset of Weather Routing)

A combination of prognostic weather charts, vessel performance graphs, and spectral wave models (e.g., WAVEWATCH III, SWAN) has been used to optimize ship trajectories. These methods contribute to time-efficient, safe, and comfortable voyages while supporting sustainability goals [70]. Recent developments in weather routing optimization include systems that continuously monitor fuel consumption and adapt routing to real-time sea and weather conditions. These technologies directly support smart routing and energy savings through dynamic course adjustments [73]. Voyage optimization solutions leveraging Dijkstra's algorithm and Kwon's resistance modeling aim to minimize total travel time, fuel usage, and greenhouse gas emissions. These tools offer real-time support to crews, promoting more sustainable decision-making during navigation [74]. The Time Boundary Semicircles (TBS) algorithm has been developed to use real-time weather inputs for speed reduction and waypoint optimization. This method improves route efficiency while lowering CO₂ emissions and overall energy consumption [6]. Finally, a range of modeling and optimization algorithms for ship weather routing is explored, with a focus on minimizing emissions and fuel usage. These methods are vital for enabling efficient, climate-conscious waterborne transport systems [75].

Key study clusters:

- GA-based weather routing achieves 3–5% fuel savings while accounting for changing sea conditions [67,68].
- Models incorporating probabilistic weather scenarios [65] enhance safety under uncertainty.
- Time Boundary Semicircles (TBS) [72] and continuous environmental updates [70] allow real-time trajectory adjustments.

Overall, weather routing research demonstrates quantifiable benefits for sustainable shipping by enabling dynamic adaptation to environmental variability, reducing fuel consumption, and improving voyage safety. Future work should focus on integrating weather routing with digital platforms and emission compliance frameworks, ensuring that optimized trajectories not only minimize operational costs but also align with IMO decarbonization goals.

3.5. Digital Platforms, Smart Ports, and Decision Support Systems

Digitalization integrates optimization algorithms, prediction models, and sensor data into collaborative platforms supporting dynamic route selection and fleet coordination.

This group addresses the broader digital ecosystem supporting smart routing, including smart port infrastructure, e-navigation platforms, data integration frameworks, and decision support systems. These technologies facilitate real-time monitoring, intermodal coordination, and policy compliance in sustainable maritime operations.

3.5.1. Smart Ports, E-Navigation Platforms, and Data Integration

AI is increasingly applied in maritime route planning to optimize vessel trajectories. By enabling data-driven path selection, these technologies enhance fuel efficiency and reduce emissions, thereby contributing to smart routing and supporting sustainability through improved operational and environmental performance [76]. Intelligent shipping solutions have also been developed to support trajectory prediction under varying climate conditions and vessel types. These approaches emphasize data security and multi-source integration, advancing smart routing by improving operational efficiency and reducing ecological impact [77]. Advanced data-sharing infrastructures—such as the Maritime Single Window, Port Community Systems, and blockchain-based smart containers—are enhancing route optimization through better data visibility. These platforms facilitate smart routing and sustainable maritime transport via integrated, real-time coordination across the logistics chain [78]. Emerging digital technologies, including AI, automation, and maritime data analytics, are being deployed to address efficiency bottlenecks, reduce emissions, and improve decision-making across shipping and port operations. These advancements play a vital role in achieving sustainable waterborne transport [79]. A methodological framework combining maritime domain knowledge with autonomous maneuvering models has been proposed for customized route design. Using historical big data, this system improves safety and reliability—particularly in high-density corridors such as Singapore-Rotterdam—while advancing sustainability and smart routing goals [80].

3.5.2. Decision Support Systems and AI-Driven Route Optimization

Some studies take a broader perspective, focusing on digitalization, automation, and technologies like AI, blockchain, and big data without delving into specific methods for trajectory optimization. Nonetheless, they highlight the strategic role of digital transformation in achieving sustainable maritime logistics [81]. Developments in Big Data, IoT, and AI have also enhanced port operations management by streamlining technical, procedural, and operational tasks. These improvements contribute to smart routing and sustainable shipping and reflect the evolving influence of Industry 4.0 in maritime transport [82]. Tools such as Very High Frequency (VHF)-AIS, integrated with geographic information services and real-time data analytics, are used to forecast vessel speeds and optimize routing decisions. These systems support energy-efficient, context-aware navigation aligned with sustainability objectives [83]. Optimizing maritime routes through digital strategies and technological innovations is a recurring theme in the recent literature. Such approaches help reduce emissions, increase routing efficiency, and ensure regulatory compliance within global environmental frameworks [84]. AI-based applications like intelligent berthing systems and visual energy consumption management are also being leveraged to support sustainable routing. These tools enhance operational efficiency and reduce environmental impact in waterborne transport [85]. Some contributions do not directly examine trajectory optimization technologies but instead focus on the broader effects of digitalization in shipping. These works emphasize cost-effectiveness, competitiveness, and strategic planning among maritime stakeholders [86].

3.5.3. Cybernetic Decisions

Trajectory optimization is crucial for both deep sea vessel navigation and inland water vessels to ensure safety and efficiency in transport [87,88]. For unmanned ships, multi-objective optimization techniques can generate trajectory solutions optimized for distance and smoothness, enhancing control in real-world applications [89]. The development of a new generation of waterborne transportation systems emphasizes green, intelligent, and resilient features, integrating digital ecological infrastructures and resilient operation

services within a cyber-physical system framework [90]. Autonomous navigation decision-making for inland waterways involves constructing a digital traffic environment model and developing collision risk identification models based on trajectory derivation, contributing to navigation safety and efficiency [91]. A hybrid route planning approach using an enhanced particulate swarm algorithm and Chaos Genetic Algorithm is proposed for function optimization in cruise liners without a man, demonstrating improved performance compared to traditional methods [92]. Voyage optimization, also known as weather routing, has been extensively investigated and commercial solutions have been launched to find the shortest path for voyage planning, reducing operating costs and fuel consumption [3,93].

3.5.4. Decision Support System

Trajectory optimization is crucial for safe ship navigation, and decision support systems play a vital role in this process [87,94]. The use of electronic navigational charts and information on water area parameters and moving targets is essential for trajectory optimization [94]. In the context of inland water vessels, trajectory optimization ensures safe passage through bridges and efficient vessel locking [87]. For MASS, an improved approach for trajectory planning based on a trajectory library has been proposed, demonstrating potential in inland waters [95]. Unmanned ships' autonomous navigation and water traffic systems benefit from multi-objective non-linear trajectory planning methods, considering trajectory distance, smoothness, and safety constraints [89].

Decision support models have been implemented for river transportation planning and scheduling, involving simulation-driven optimization models for cargo flow operations [96]. While most ocean shipping companies plan fleet schedules manually, the development of optimization-based decision support systems, such as TurboRouter, has shown the importance of user-system interaction in system design [97].

Key study clusters:

- Port Community Systems and the Maritime Single Window streamline decision-making and enable predictive scheduling.
- Blockchain-based systems ensure trusted, real-time exchange of routing and performance data across stakeholders.
- AI-powered dashboards combine ETA predictions, optimization engines, and environmental compliance into unified interfaces.

Digital platforms and smart port infrastructures enable integrated fleet-wide decision support but require standardized data exchange protocols and cybersecurity frameworks for full interoperability.

3.6. Hybrid and Rule-Based Systems with COLREGs Considerations

This category includes studies that integrate algorithmic optimization with rule-based navigation logic. Some of these studies explicitly implement COLREGs-compliant collision avoidance rules to ensure that autonomous or semi-autonomous vessels respect international regulations on give-way, stand-on behavior, and safe passing distances. For instance, studies [98–100] incorporate COLREGs rules into model predictive control and particle swarm optimization frameworks to guarantee compliance with regulations in mixed-traffic environments. Other contributions, though labeled as rule-based, apply hybrid control strategies (e.g., potential fields, A*, or heuristic safety margins) that indirectly relate to COLREGs, though they do not explicitly implement the rules. We distinguish between these two subgroups to reflect their different levels of regulatory alignment.

3.6.1. COLREGs-Oriented and Hybrid Control Frameworks

AI, GIS, and decision support systems are being integrated for trajectory optimization in unmanned shipping. This combination enhances navigational safety and operational efficiency by reducing human error and enabling more accurate path planning, ultimately supporting smart routing and sustainability goals [101]. A two-layer maritime route network modeling method has been developed using ship trajectory data, clustering techniques, and spatial computing to define waypoint regions. This approach improves autonomous navigation by increasing safety and routing precision, contributing to sustainable shipping practices [102]. A decision support system employing Multi-Objective Particle Swarm Optimization (MOPSO) and Multi-Criteria Decision Making (MCDM) methods has been introduced to optimize trajectories in autonomous vessel operations. This system minimizes safety violations, abrupt speed changes, and path deviations, directly supporting smart routing [103]. Model Predictive Contouring Control (MPCC), combined with COLREGs-compliant logic, has been applied to trajectory optimization for autonomous surface vessels. This strategy ensures safe navigation in mixed-traffic environments, promoting both intelligent routing and environmental compliance [98].

3.6.2. Data-Driven, GIS, and Learning-Oriented Methods for Autonomous Navigation

The Potential Energy-based A* (PE-A*) algorithm enhances global route planning and local collision avoidance through the use of potential energy fields. It also enables integration of criteria such as fuel consumption and time efficiency—both essential for sustainable maritime operations [104]. An enhanced A* algorithm, combined with a multi-target artificial potential field model, supports ship trajectory planning by improving obstacle avoidance and maneuvering safety. The method contributes to smart routing by enabling precise and safe navigation [105]. A hybrid technique utilizing electronic navigational charts (ENCs) and trapezoidal mesh modeling supports ship trajectory optimization. It incorporates a three-dimensional ship domain for enhanced safety assessment and decision support in complex maritime environments [94]. AIS-based trajectory optimization has also been addressed using naive Bayesian algorithms. This method improves route accuracy and navigational safety by enabling intelligent prediction and real-time adjustment of ship trajectories [106]. For Maritime Autonomous Surface Ships (MASS) operating in inland waters, an improved trajectory planning method based on precompiled trajectory libraries and efficient optimization routines has been proposed. It enhances computational performance and path feasibility, furthering the objectives of smart and sustainable navigation [95].

Key study clusters:

- Potential Energy-based A*, multi-target artificial potential fields, and MPCC improve safety in mixed-traffic environments.
- Multi-objective PSO combined with Multi-Criteria Decision Making optimizes trade-offs between emissions, safety, and voyage time.
- Pre-compiled trajectory libraries improve path feasibility for MASS navigating restricted inland waterways.

Autonomous routing frameworks demonstrate significant potential but require XAI, standardization, and regulatory alignment to enable large-scale adoption.

4. Supplementary Insights and New Trends in Trajectory Optimization Research

While Section 3 presented a structured review of the existing literature, this section complements those findings using a Scopus-based bibliometric analysis to identify research clusters, emerging themes, and technology integration trends.

To enhance the completeness and relevance of the literature review, a supplemental topic mapping was performed using the Scopus database, focusing on the keyword “Trajectory Optimization in Waterborne Transport”. The concept map (see Figure 2) visually highlights the key thematic clusters and emerging areas associated with the topic.

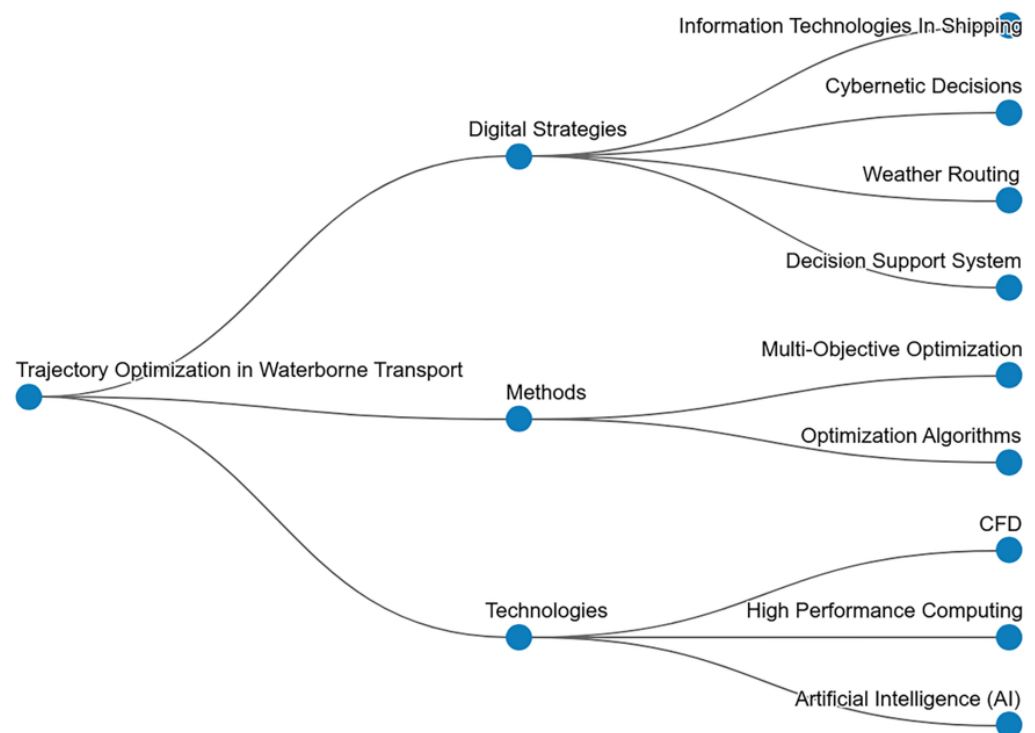


Figure 2. Concept map of trajectory optimization in waterborne transport.

As shown in the map, the field is organized around three major dimensions:

1. Digital Strategies, including:
 - Information Technologies in Shipping
 - Cybernetic Decisions
 - Weather Routing
 - Decision Support Systems
2. Methods, including:
 - Multi-Objective Optimization
 - Optimization Algorithms
3. Technologies, including:
 - Artificial Intelligence
 - High Performance Computing
 - Computational Fluid Dynamics

These clusters confirmed and enriched the previously thematic structure. They also validated the importance of combining AI-based forecasting, optimization methodologies, and digital decision support systems to enable sustainable and intelligent ship routing.

Additional relevant articles identified through this Scopus-based exploration were incorporated into the final review sample, ensuring broader coverage of recent scientific trends and multidisciplinary approaches.

Figure 2 presents a concept map of trajectory optimization in waterborne transport, highlighting the interrelationships between digital strategies, methods, and technologies. The clusters reveal three main thematic dimensions: (1) Digital Strategies, which include information technologies in shipping, cybernetic decisions, and weather routing; (2) Methods,

such as multi-objective optimization and algorithmic approaches; and (3) Technologies, including artificial intelligence, high-performance computing, and computational fluid dynamics. The proximity of these clusters reflects the high degree of integration between computational advancements and operational strategies in the literature, with AI serving as a central connector across themes. This suggests that future research will increasingly merge data-driven forecasting with optimization frameworks, reinforcing the multidisciplinary nature of smart routing research.

To complement the thematic classification and Scopus-based concept mapping, a co-occurrence analysis of terms was conducted using VOSviewer version 1.6.20. The visualization (Figure 3) is based on terms extracted from the titles and abstracts of all reviewed publications. The overlay network shows the frequency and interconnection of key concepts, where dominant terms such as optimization, problem, path, prediction, ship trajectory, and artificial intelligence are prominently positioned in the graph. The results (Figure 3) reveal three dominant clusters: Digital Strategies, Methods, and Technologies (Figure 2). These clusters confirm the six thematic categories defined in Section 3, demonstrating that modern research integrates prediction, optimization, and routing strategies within shared digital ecosystems.

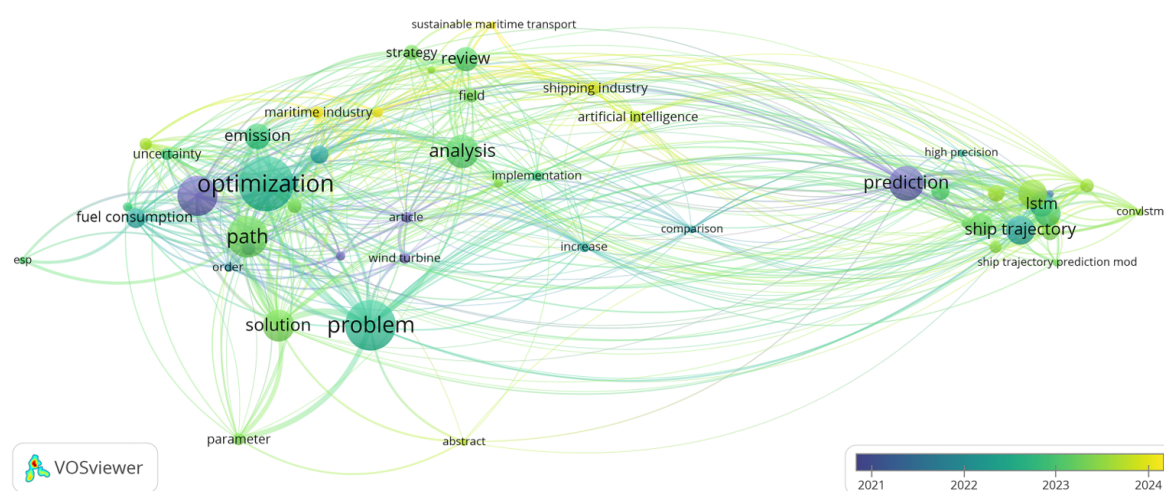


Figure 3. Overlay visualization of term co-occurrence from article titles and abstracts.

The color gradient represents the average publication year, with terms in yellow and green (e.g., LSTM, convLSTM, high-precision) reflecting emerging trends from 2022 to 2024. Meanwhile, foundational terms such as optimization, fuel consumption, and path planning appear in darker shades, reflecting their earlier and sustained presence. This visualization validates the relevance of the six thematic groups defined in Section 3 and supplemental topic mapping in Section 4 and highlights the ongoing shift toward data-driven prediction models, AI integration, and emission-aware routing in maritime transport research.

Figure 3 illustrates the co-occurrence network of terms derived from the reviewed literature. The network reveals key terms such as “optimization”, “path”, “prediction”, and “ship trajectory” as dominant nodes, positioned centrally due to their high connectivity. The color gradient indicates temporal trends, with yellow and green tones corresponding to emerging concepts from 2022 to 2024, including “LSTM”, “convLSTM”, and “high precision”. Darker shades denote established concepts, such as “fuel consumption” and “path planning”, which have remained relevant over time. The network structure indicates a shift toward AI integration and emission-aware routing, suggesting that emerging technologies are increasingly being applied to solve long-standing efficiency and sustainability challenges in maritime navigation.

Trajectory optimization in waterborne transport involves ensuring safe navigation, efficient transport, and minimizing operational costs [87,107,108]. Multi-objective optimization techniques are crucial for generating trajectory solutions optimized for distance, smoothness, and safety, especially for unmanned vessels [89]. The use of mathematical optimization procedures and driver assistance systems is essential for effective trajectory optimization [87,109]. Efficient trajectory planning is vital for reducing environmental impact, congestion, and operational costs in waterway networks [107,109]. In the context of Arctic shipping, trajectory optimization methods consider ice navigation, power optimization, and spatiotemporal constraints to improve transport efficiency and reduce emissions [108]. Optimal control models are utilized for generating reference paths for ships, prioritizing navigational efficiency and safety considerations [88]. The application of meta-heuristic algorithms such as differential evolution and genetic algorithms can assist in optimizing ship trajectories [92,109]. Obstacle avoidance and time optimal control methods are crucial for planning safe and efficient movement trajectories of unmanned surface vehicles in local waters [110]. Global optimization algorithms such as Genetic Algorithms are used for finding the optimal trajectory of ships, considering various environmental and operational constraints [111].

4.1. Implemented Methods

Trajectory optimization in waterborne transport involves various methods to ensure safe and efficient vessel navigation [87–89,93,95,107,108,111–113]. Different optimization techniques are used, such as genetic algorithms, dynamic programming, and hybrid algorithms, to consider factors like distance, smoothness, speed, and steering angles [88,89,93,108,112]. Efforts are made to reduce operational costs, congestion, and emissions through the use of optimal paths and control models [88,107,108,113]. The proposed algorithms and models aim to provide rapid, feasible, and economical path information for vessels, especially in restricted waters [88,93,95,107]. These methods have been shown to achieve reductions in the number of turning points, average turning angles, and fuel costs, contributing to improved transport efficiency and environmental impact [88,89,93,108,113].

4.1.1. Multi-Objective Optimization

Multi-objective optimization is crucial for generating trajectory solutions optimized for both distance and smoothness in unmanned vessels' autonomous navigation and water traffic systems [89]. An improved genetic algorithm is proposed for multi-objective non-linear trajectory planning, considering trajectory distance, smoothness, safety characteristics, speed, and steering angles [89]. A three-dimensional graph model is suggested for multi-objective route optimization in water areas with drifting ice objects, aiming to find a set of Pareto-optimal solutions [114]. The paper introduces a method for transforming the unconstrained waterweeds algorithm into a constrained algorithm for trajectory optimization, addressing oscillation and aerodynamic heating problems during the reentry process [115].

4.1.2. Optimization Algorithms

Multi-objective optimization techniques are essential for generating trajectory solutions optimized for both distance and smoothness, improving control of unmanned vessels [89]. Hybrid route planning approaches, such as the Complex Waters Based on Chaos Genetic Algorithm (CWCGA), have been designed for ship trajectory tracking, demonstrating improved performance compared to traditional methods [92]. Optimization algorithms have been developed for multi-disciplinary aircraft trajectory optimization, focusing on minimizing total flight time, fuel burned, and emissions, with satisfactory

accuracy compared to commercial optimizers [116]. Methods have been devised to generate path-search graphs based on ship-trajectory data and determine optimal routes using dynamic programming, resulting in estimated fuel savings of approximately 7.8% for various ship types and maritime zones [93].

4.2. Implemented Technologies

Trajectory optimization is crucial for both deep sea vessel navigation and inland water vessels to ensure safety, efficiency, and resource optimization [87,109]. For unmanned ships, multi-objective optimization techniques can generate trajectory solutions optimized for distance and smoothness, enhancing control in real-world applications [89]. The development of new and effective methods for ship routing in ice and open water is essential for reducing emissions and improving transport efficiency, particularly in the context of Arctic shipping [108]. Trajectory planning is a fundamental function of MASS, and an improved approach for trajectory planning of inland MASS has been proposed, demonstrating potential in restricted waters [95]. A ship path planning model based on optimal control has been proposed to provide reference paths for ships, prioritizing navigational efficiency and safety considerations [88]. Voyage optimization, also known as weather routing, has been extensively investigated and commercial solutions have been launched to find the shortest path for voyage planning, helping to reduce the operating costs of the ship [93].

4.2.1. Artificial Intelligence

AI is applied in maritime navigation for autonomous navigation, pattern recognition, weather forecasting, fuel consumption optimization, condition monitoring, enhancing safety, efficiency, and performance in maritime transport [117].

AI for Well Trajectory Optimization: AI-driven approaches, such as the Artificial Intelligence Well Trajectory Builder (AIWT), use advanced AI techniques like Genetic Algorithms for simultaneous multi-objective optimization of well paths, demonstrating significant efficiency improvements and reduced planning time [118].

Vessel Traffic Services (VTS) and XAI: There is a strong demand for VTS using AI techniques, and the application of XAI techniques in VTS is an important development direction, particularly in intelligent prediction and perception in water transportation [119].

Vessel Trajectory Prediction: The use of AI, including deep learning, for vessel trajectory prediction is essential for maritime transportation safety, intelligence, and efficiency, with a focus on data sources, methodologies, and performance evaluation [7].

4.2.2. Role of Enabling Technologies

Technologies like CFD and HPC are supporting enablers for simulating environmental dynamics and accelerating optimization algorithms. While not central to this review, they represent complementary advances and are discussed briefly in Appendix A for completeness.

4.3. Implemented Digital Strategies

Trajectory optimization is crucial for deep sea vessel navigation, inland water vessels, and MASS to ensure safety and efficiency [87–89,95,108].

Multi-objective optimization techniques, such as genetic algorithms, are proposed for unmanned ships' autonomous navigation, considering factors like trajectory distance, smoothness, and safety constraints [89].

For Arctic shipping, a hybrid algorithm is developed to optimize ship trajectory, shaft power, and movement mode, considering various constraints and reducing emissions [108].

Voyage optimization, also known as weather routing, is essential for reducing operating costs and fuel consumption in maritime transport [93].

The use of mathematical optimization algorithms, such as genetic algorithms and particle swarm optimization, is explored for ship trajectory planning [92,109,120].

Rapid digitization and automation in maritime operations provide opportunities for trajectory optimization and risk reduction through multiagent trajectory optimization methods [51].

4.3.1. Information Technologies in Shipping

The shipping industry is undergoing digital transformation, with a focus on autonomous vessel-port management systems and the use of information technology (IT) for route optimization, intelligent sensors, and geographic information systems (GIS) [121]. Trajectory optimization is crucial for safe and efficient navigation in waterborne transport. It involves the use of optimization algorithms, dynamic programming, and mathematical models to plan vessel routes, considering factors such as energy efficiency, safety, and environmental impact [3,73,87,88,93,109,122]. Information technologies play a significant role in optimizing vessel trajectories by providing real-time position, navigation, and timing (PNT) data, weather condition variation monitoring, and route selection based on ongoing sea and weather conditions [73,87,123]. Digital strategies and information technologies contribute to green, energy-efficient, and safe navigation by enabling the analysis and planning of vessel and fleet performance, as well as the implementation of energy-saving technology options [122,123]. Challenges in trajectory optimization include accurately estimating fuel costs and validating routes within an acceptable computational time. However, methods such as dynamic programming and the use of high-resolution maps can address these challenges and lead to fuel savings [73,93].

4.3.2. Weather Routing

Optimization of trajectories is crucial for both deep sea vessel navigation and inland water vessels to ensure safe passage, efficient loading, and resource-efficient transport of goods and passengers [87]. A study on voyage optimization for ships, also known as weather routing, has shown that accurately estimating fuel costs and validating routes within an acceptable computational time remain challenging [93]. Academic research has focused on ship routing optimization through pathfinding algorithms that consider meteo-oceanographic forecasts, such as wind, wave, and current predictions [124].

The implementation of Trajectory-Based Operations in air traffic management enables airlines to fly along optimized waypoint-less trajectories, significantly increasing the sustainability of the air transport system [125]. A novel optimization algorithm, HADAD, has been developed for weather routing, conducting a global exploration using an A* search on a hexagonal grid with higher-order neighbors, enhancing directional flexibility and overcoming limitations of traditional graph searches that constrain vessel movements [126].

Weather ship routing has become a recognized measure to target safe, sustainable, and economical ship activities, with a focus on optimizing travel time considering wave action and reducing fuel consumption [124]. A study on the comparison of routing optimization algorithms for minimum fuel consumption in the North Atlantic has highlighted the pros and cons of different algorithms, such as modified Isochrone and Isopone methods, dynamic programming, three-dimensional dynamic programming, and Dijkstra's algorithm [127].

4.4. Contributions to Smart Routing and Sustainable Shipping

Table 3 contains a summary of the current methods' contribution. Dijkstra Algorithm is modified to dynamically account for changing ship positions and weather conditions, aiming to minimize seakeeping performance and add resistance indices for safe and fuel-efficient navigation [128].

Table 3. Contributions to Smart Routing and Sustainable Shipping.

Method/Technology	Description	Contribution
Dijkstra Algorithm [128]	Dynamic route optimization considering weather and ship position	Fuel efficiency, safety
A* Search Algorithm [3]	Optimal route recommendations using historical data	Cost savings, efficiency
Model Predictive Control [129]	Real-time speed re-optimization based on dynamic conditions	Energy reduction, emissions control
Evolutionary Algorithms [130–132]	Multi-objective route optimization	Fuel savings, emission reduction
High Performance Computing (HPC) [133]	Efficient computation for real-time optimization	Real-time application, efficiency
On-Board Decision Support Systems [128]	Real-time decision-making integration	Dynamic adjustments, safety
Trajectory Libraries [3,51,95]	Pre-generated trajectory units for optimal sequence planning	Efficiency in restricted waters
Generative Models [51]	Predicting future trajectories for risk reduction	Safety, optimal planning
Weather Routing [93,132]	Optimization based on weather forecasts and hydrodynamic simulations	Fuel efficiency, safety, comfort

A Search Algorithm is utilized for optimal route recommendations based on historical vessel tracking data, leading to shorter routes and cost savings [3].

Model Predictive Control re-optimizes speed planning using real-time data on water depth, speed, and expected delays, achieving energy reductions [129].

Evolutionary Algorithms are used to create multiple locally optimal routes, with parallel genetic algorithms optimizing the final route [130].

Multi-Objective Evolutionary Algorithms address complex optimization problems by considering multiple objectives like fuel consumption, emissions, and voyage duration [131,132].

High-Performance Computing technologies, such as CUDA and OpenMP, are employed to handle the computational intensity of multi-objective optimization problems, enabling real-time or near-real-time applications [133].

Historical trajectory data is leveraged to predict future vessel movements and optimize routes, enhancing efficiency and reducing risks [3,51].

Weather Routing: Incorporates sophisticated weather forecasts and hydrodynamic simulations to optimize routes based on criteria like ETA, fuel consumption, and safety [93,132].

On-Board Decision Support Systems: Integration of optimization algorithms into on-board systems to assist in real-time decision-making for route adjustments based on dynamic conditions [128].

In practical applications, the effectiveness of optimization methods varies depending on operational context, data availability, and environmental conditions. For example, weather routing tools based on genetic algorithms have demonstrated average fuel savings

of 3–5% in transoceanic voyages, whereas MILP-based optimization methods have been effective in congested port approaches by reducing close-quarter navigation incidents by over 20%. AI-based trajectory prediction models such as LSTM and Transformer architectures have improved Estimated Time of Arrival accuracy by up to 15% compared to traditional statistical models, facilitating better coordination with port operations. However, these benefits come at the cost of increased computational requirements, which may limit real-time deployment on smaller vessels. Such case-driven insights underline the importance of selecting an optimization strategy that balances computational feasibility with operational impact.

Trajectory Libraries: Use of pre-generated trajectory units collected in a library, which are then optimized to find the best sequence for navigation in restricted waters [95].

Generative Models: Predict multiple possible future trajectories based on historical data, aiding in risk reduction and optimal route planning [51].

4.4.1. Fuel Efficiency and Emission Reduction

Optimization methods like MPC and evolutionary algorithms contribute to significant fuel savings and emission reductions by optimizing speed and route planning [93,129,131].

Weather routing and real-time re-optimization based on updated weather forecasts further enhance fuel efficiency [125].

4.4.2. Safety and Comfort

Algorithms consider seakeeping performance and added resistance to ensure safe and comfortable navigation, reducing the risk of accidents and improving crew and passenger comfort [128,132].

4.4.3. Economic Benefits

Shorter and more efficient routes lead to cost savings for the maritime industry, enhancing overall operational efficiency [3,130].

4.4.4. Environmental Sustainability

Multi-objective optimization models address environmental goals by minimizing CO₂ emissions and considering the broader impact on sustainability [134].

These methods and technologies collectively contribute to achieving smart routing and sustainable shipping by optimizing fuel consumption, reducing emissions, enhancing safety, and improving overall operational efficiency.

4.5. New Trends in Scientific Research

The bibliometric analysis highlights several ongoing shifts in trajectory optimization research:

- Increased integration of AI with digital platforms for predictive route optimization.
- Growing interest in real-time adaptive routing through edge and cloud-based systems.
- Expansion of hybrid multi-objective optimization frameworks combining emissions, ETA, cost, and safety considerations.
- Stronger emphasis on policy-aware smart routing, including IMO emissions reduction goals.

5. Open Challenges and Future Directions

As demonstrated by the literature reviewed in this study, the development of smart routing technologies for sustainable shipping is a multifaceted challenge that spans beyond algorithmic efficiency to encompass issues of interoperability, real-time adaptability,

explainability, and regulatory alignment. While notable progress has been made in trajectory prediction and optimization, current approaches often remain isolated in scope. For example, many weather-routing models are still developed as stand-alone prototypes without integration into digital port community systems or fleet management platforms. Similarly, AI-based trajectory prediction frameworks frequently operate on historical AIS data but are rarely linked to environmental policy frameworks such as Emission Control Area compliance or IMO decarbonization goals. CFD-based optimization methods also tend to focus on hydrodynamic accuracy without connection to decision-support systems or real-time operational use. These gaps highlight the challenge of moving from technically promising methods to holistic smart routing solutions embedded within broader digital infrastructures and regulatory contexts. To advance the state of the art, future research must focus on developing intelligent, adaptive, and interpretable systems capable of operating reliably across diverse maritime environments. In this section, we outline several key research directions and emerging trends that are expected to shape the next generation of trajectory optimization technologies in waterborne transport.

5.1. Emerging Trends

Multiple emerging trends are poised to significantly reshape ship trajectory optimization methods. These developments not only enhance the potential for more efficient and adaptive route planning but also introduce new layers of complexity to existing challenges. The impact spans both technological dimensions—such as AI-driven navigation, advanced sensor integration, and autonomous vessel systems—and operational aspects, including dynamic weather routing, environmental regulations, and evolving global shipping logistics.

- **Ship Route Optimization Using Machine Learning Techniques.** The consistent interest in optimizing ship routes using machine learning techniques highlights the ongoing importance of improving efficiency and reducing costs in maritime transport. This theme encompasses various approaches, including dynamic programming, genetic algorithms, and neural networks, to enhance route planning and decision-making processes for ships [135–137].
- **Autonomous Underwater Vehicle (AUV) Path Planning.** The development of path planning algorithms for autonomous underwater vehicles (AUVs) remains a consistent area of research. This theme focuses on optimizing the trajectories of AUVs to navigate complex underwater environments, considering factors such as ocean currents, obstacles, and energy efficiency [138–140].
- **Vessel Trajectory Prediction Using AIS Data.** The prediction of vessel trajectories using AIS data is a critical area of research for improving maritime traffic management and safety. This theme involves the use of machine learning models, such as LSTM and ConvLSTM, to predict the future positions of vessels based on historical AIS data [141,142].
- **Optimization Techniques for Multimodal Transport.** The novel theme of optimizing multimodal transport routes, particularly in the context of green and sustainable logistics, is emerging as a significant area of interest. This theme explores the optimization of transport routes that involve multiple modes of transportation, such as road, rail, and waterways, with a focus on reducing environmental impact and improving efficiency [143].
- **Trajectory Optimization for Connected and Automated Vehicles.** The optimization of trajectories for connected and automated vehicles (CAVs) is a novel and rapidly growing area of research. This theme addresses the challenges of planning optimal

paths for CAVs, considering factors such as limited computing capacity, dynamic environments, and the need for real-time decision-making [144–146].

5.2. Future Research Directions

Based on the comprehensive analysis of existing literature and emerging trends, several promising directions for future research in vessel trajectory optimization and smart routing can be identified:

- **Integrated Hybrid Models for Multi-Factor Optimization.** There is a growing need to develop hybrid models that integrate multiple optimization criteria, such as fuel consumption, emission levels, navigational safety, time reliability, and economic cost. Future studies should focus on multi-objective and multi-modal frameworks that dynamically balance these often-conflicting objectives, especially under uncertain environmental and traffic conditions [56,68,71,103].
- **Real-Time Adaptive Routing with Edge and Cloud Computing.** Despite advances in predictive modeling, the deployment of real-time adaptive routing systems remains limited. Future work should leverage edge computing and cloud-based decision platforms to enable continuous monitoring, context-aware adjustments, and seamless coordination between vessels, ports, and fleet operators [25,73,78,83].
- **Explainable and Trustworthy AI in Maritime Navigation.** As AI-based methods increasingly influence critical routing decisions, ensuring transparency, explainability, and trustworthiness becomes essential. Research into XAI for maritime applications can improve user confidence, facilitate regulatory acceptance, and support human–AI collaboration, particularly in autonomous or semi-autonomous navigation systems [32,39,60,65].
- **Trajectory Optimization for Inland and Riverine Transport.** The majority of existing studies focus on deep-sea or coastal navigation. Inland waterways, however, present unique challenges such as narrow passages, complex traffic patterns, and local regulatory constraints. Future research should explore context-specific optimization models and datasets tailored to inland and mixed-use transport corridors [5,67,86,95].
- **Integration with Environmental and Policy Frameworks.** Trajectory optimization research should increasingly align with international environmental regulations (e.g., International Maritime Organization (IMO) GHG Strategy, EU Fit for 55) and support sustainability reporting. This includes designing routing systems that explicitly account for carbon intensity indicators, emission compliance zones, and energy efficiency targets [5,69,76,84].
- **Explainable AI for Safety-Critical Maritime Applications.** As vessel trajectory optimization relies on black-box AI systems, the need for interpretable models becomes more urgent, especially in safety-critical and regulatory-sensitive contexts. Future research should explore the integration of XAI techniques—such as SHapley Additive exPlanations (SHAP), Local Interpretable Model-agnostic Explanations (LIME), attention visualizations, and saliency mapping—into deep learning frameworks used for ship trajectory prediction. In particular, developing explainable extensions of LSTM, GRU, or Transformer-based models could support greater transparency in decision-making processes, facilitate model validation by maritime authorities, and enable human–AI collaboration on the bridge. Such advancements will be essential for regulatory acceptance and operational trust in autonomous and AI-augmented navigation systems [119].
- **A promising yet under-explored area is inland navigation,** which differs from open-sea navigation in several important ways. Inland waterways are characterized by narrow and shallow passages, locks and bridges, high traffic density with various vessel types,

and the strong influence of riverine hydrology, such as currents, floods, and fog. These conditions necessitate specialized approaches to trajectory prediction, path planning, and weather routing that differ from those used in the deep sea. For instance, inland trajectory forecasting requires higher-resolution AIS/GIS data, and path planning must consider regulatory constraints on traffic separation and passage through locks. Inland weather routing focuses less on ocean swell and more on localized meteorological factors, such as fog and ice formation. Therefore, future studies should develop models tailored to inland conditions to ensure that optimization methods address the specific challenges of riverine and canal-based transport.

These directions aim to foster the development of next-generation smart routing systems that are robust, sustainable, scalable, and interoperable, ensuring their relevance in both current and future maritime transport ecosystems.

6. Discussion

This review has revealed a broad and rapidly evolving landscape of methods, technologies, and strategies for vessel trajectory optimization, each contributing uniquely to the advancement of smart routing and sustainable shipping. The analysis of 93 publications grouped into six thematic categories highlights the multidisciplinary nature of the field, with significant contributions from artificial intelligence, operations research, control theory, environmental modeling, and maritime systems engineering.

Among the categories, AI/ML-based trajectory prediction stands out for its widespread application and rapid advancement. Deep learning techniques—particularly LSTM, Transformer, and hybrid models—have achieved remarkable accuracy in predicting vessel trajectories using AIS data [7,10,18,36]. However, many of these models still lack interpretability and are seldom linked directly to decision-support or routing frameworks, limiting their operational applicability [32,39,65].

While some studies have acknowledged the importance of transparency in deep learning models, few have implemented formal XAI methods in the context of maritime trajectory prediction. For example, recent work [119] has explored the potential of explainable AI techniques in VTS systems, focusing on interpretable prediction and perception. However, their application to AIS-based trajectory models remains limited and largely experimental. The integration of SHAP or attention heatmaps in models such as Transformer or ConvLSTM remains underexplored, despite their potential to enhance trust and explainability in routing decisions. This underscores the need for further research into interpretable learning architectures that can be deployed in real-time, safety-critical maritime operations.

A comparative summary of commonly applied AI/ML-based trajectory prediction models (see Table 1 in Section 3.1) reveals important trade-offs between prediction accuracy, model complexity, and interpretability. While Transformer-based and hybrid models offer superior accuracy, they require extensive training data and computational resources, making them less practical for real-time deployment on vessels with limited onboard computing capacity. In contrast, LSTM and Bi-LSTM architectures strike a balance between performance and usability, though their black-box nature remains a limitation in safety-critical environments. Statistical models and simpler neural networks provide more interpretable outputs but often underperform on non-linear, high-variance AIS datasets. These findings underscore the need for model selection frameworks that consider operational constraints, explainability requirements, and data availability in different maritime contexts.

Trajectory optimization and path planning algorithms offer a diverse toolbox of heuristics, metaheuristics, and deterministic methods (e.g., A*, PSO, MILP), which are well-established in offline and tactical routing [48,51,56]. Yet, few studies address real-time adap-

tation or the integration of these techniques with predictive models and environmental data streams, a gap that remains crucial for dynamic and resilient maritime navigation [25,53].

Data-driven approaches using AIS and GIS provide valuable insights into vessel behavior, traffic patterns, and route networks [3,58,62]. These studies excel in trajectory mining, clustering, and behavioral modeling but often operate independently of optimization logic, missing the opportunity for end-to-end integration with routing systems [59,63,67].

In the domain of weather routing and environmental optimization, there is a strong emphasis on fuel savings and emissions reduction through climate-aware route planning [5,69,73,75]. Nevertheless, few models explicitly quantify trade-offs between environmental impact, travel time, and safety, nor do they integrate directly with policy targets such as IMO's carbon intensity indicators [76,84].

The role of digital platforms and decision support systems is critical in enabling operational deployment. These systems support interoperability and coordination but are still in early stages of connecting real-time data with optimization algorithms, especially in the context of port-to-port integration and fleet-wide decision-making [78,79,82].

Hybrid and rule-based systems for autonomous navigation highlight the growing relevance of COLREGs compliance, onboard automation, and human-machine collaboration [94,98,103]. These studies point toward the convergence of trajectory planning and autonomy, but challenges remain in standardization, explainability, and regulatory certification [60,95].

In addition to the primary review, the supplemental exploration (Section 4) based on Scopus concept mapping reinforces the centrality of three dimensions in contemporary trajectory optimization research: methods, technologies, and digital strategies. The clustering of themes such as multi-objective optimization, weather routing, computational fluid dynamics (CFD), AI, and cybernetic decision-making suggests growing convergence between data-driven forecasting, physics-based modeling, and energy-efficient navigation frameworks [87–89,92,93,107–111]. Notably, the supplemental literature highlights emerging directions, such as:

- The integration of high-performance computing for solving complex optimization tasks in near-real time [133],
- The use of CFD-based models for holistic hull–propeller–engine optimization [147],
- And the development of trajectory libraries and generative models for constrained and autonomous operations [148].

While the core literature in Sections 3.1–3.6 primarily covers applied methods and system-level implementations, the supplemental review in Section 4 emphasizes foundational optimization theory, simulation capabilities, and design-oriented trajectory generation. These two perspectives are highly complementary: practical deployment requires not only robust AI systems and platforms but also validated models that consider ship dynamics, environmental physics, and computational feasibility.

Overall, the synthesis of primary and supplemental findings underscores the need for cross-domain integration—combining AI-based trajectory forecasting, high-fidelity physical modeling, and scalable optimization engines within decision-centric digital ecosystems. Such integration is essential for developing the next generation of maritime navigation systems that are accurate, interpretable, energy-aware, and regulation-compliant across both open-sea and inland waterway contexts.

Additionally, environmental policy impacts and cross-domain sensing approaches have been identified as relevant to trajectory optimization and sustainable navigation. For example, evaluating the impact of Emission Control Area policy on sulfur emissions in major U.S. ports using a difference-in-differences model demonstrates how regulatory measures can drive operational changes in shipping [149]. Similarly, comparative analyses

of traffic flow prediction methods leveraging denoising schemes and artificial neural networks [150] highlight transferable methodologies that could enhance maritime traffic forecasting accuracy when applied to AIS datasets.

Interoperability and Standardization as a Deployment Bottleneck

Despite recent advancements in vessel trajectory optimization technologies, one of the critical obstacles to large-scale adoption is the lack of interoperability between routing systems, data platforms, and maritime infrastructure components. This fragmentation stems from the absence of universally adopted data standards, inconsistent implementation of digital protocols across regions, and varying levels of technological maturity among stakeholders [151].

At the core of interoperability efforts are several ongoing international standardization initiatives [152]. The IMO promotes the e-Navigation strategy, which aims to harmonize electronic navigational tools and data exchange across ship and shore platforms [153]. Similarly, the International Association of Marine Aids to Navigation and Lighthouse Authorities (IALA) has introduced the S-200 framework, which supports the exchange of route plans, vessel intentions, and dynamic navigational warnings. The International Hydrographic Organization (IHO) further contributes through the S-100 Universal Hydrographic Data Model, with relevant product specifications such as S-102 (bathymetric surface) and S-104 (water level information) being critical for accurate route optimization in constrained or shallow waters.

However, practical implementation remains uneven. Many optimization systems operate in silos and are not yet capable of ingesting standardized data streams [154] or aligning outputs with route exchange formats such as Route Exchange Format (RTZ). This limits the integration of predictive optimization tools into bridge systems, port platforms, and regional VTS. Moreover, backward compatibility with legacy onboard equipment and varying communication capabilities—especially for inland or small fleet operators—further complicates standard-compliant deployment [155].

Additionally, cybersecurity requirements, data ownership rights, and real-time data synchronization remain underdeveloped in many routing platforms. These factors hinder the seamless integration of AI-based or cloud-enabled decision support tools into regulated navigation environments.

To address these issues, future research should align algorithm development and system design with emerging standards like IALA S-421 (Route Information), S-124 (Navigational Warnings), and port community systems' APIs. Collaboration between technology providers, regulatory bodies, and ship operators is essential to ensure that trajectory optimization frameworks are not only performant but also interoperable, secure, and regulation-ready.

7. Conclusions

This review examined the state of the art in vessel trajectory optimization with a focus on supporting smart routing and sustainable shipping in both maritime and inland waterborne transport. By analyzing 93 scholarly sources, the study identifies six dominant thematic areas: (1) AI/ML-based ship trajectory prediction, (2) optimization and path planning algorithms, (3) data-driven methods using AIS and GIS, (4) weather routing and environmental models, (5) digital platforms and decision support systems, and (6) hybrid and rule-based systems for autonomous navigation.

The findings reveal a dynamic and multidisciplinary research landscape where artificial intelligence, operations research, and environmental modeling increasingly converge to enable intelligent routing strategies. While considerable progress has been made in

predictive accuracy, algorithm design, and simulation capabilities, several challenges remain. These include the lack of real-time adaptive systems, limited integration between forecasting and optimization components, insufficient attention to regulatory and environmental alignment, and the absence of explainable and trustworthy AI in safety-critical navigation contexts.

The supplemental analysis of concept clusters from Scopus further emphasizes the importance of connecting methods, technologies, and digital strategies into coherent, operationally viable solutions. Bridging these components is essential to achieving resilient, efficient, and regulation-compliant trajectory optimization systems.

To move the field forward, future research should focus on hybrid, interpretable, and policy-aware routing frameworks that are deployable in real-world operational environments. Emphasis should also be placed on inland and constrained waters, real-time data integration, and energy-centric optimization under uncertainty.

In conclusion, smart routing for sustainable shipping is not solely a computational challenge—it is an interdisciplinary endeavor that calls for innovation at the intersection of technology, regulation, and maritime operational practice. The insights provided in this review aim to guide further research and development toward greener, safer, and more intelligent waterborne transport systems.

In addition to the dominant focus on deep-sea navigation, it is important to highlight the significant potential for inland waterway research. Inland navigation presents unique challenges compared to ocean-going shipping, including restricted maneuvering space, shallow-water effects, higher traffic density, and stricter emission regulations in urban areas. At the same time, inland shipping offers substantial opportunities for reducing emissions, shifting modes, and decarbonizing supply chains, particularly in regional logistics networks. Therefore, reinforcing the role of inland navigation in trajectory optimization research is a critical step, as advances in this area can contribute directly to operational safety and sustainability goals. Addressing this gap is believed to constitute a significant opportunity for influential future research, aligning with the broader goals of green and intelligent transportation systems.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AIS	Automatic Identification System

AUV	Autonomous Underwater Vehicle
BiGRU	Bidirectional Gated Recurrent Unit
CFD	Computational Fluid Dynamics
COLREGs	International Regulations for Preventing Collisions at Sea
CNN	Convolutional Neural Network
ConvLSTM	Convolutional Long Short-Term Memory
DBSCAN	Density-Based Spatial Clustering of Applications with Noise
DL	Deep Learning
DNN	Deep Neural Network
DSS	Decision Support System
ENC	Electronic Navigational Chart
ETA	Estimated Time of Arrival
FIS	Fairway Information Services
GA	Genetic Algorithms
GIS	Geographic Information System
GRU	Gated Recurrent Unit
HPC	High Performance Computing
IALA	International Association of Marine Aids to Navigation and Lighthouse Authorities
IENC	Inland Electronic Navigational Chart
IHO	International Hydrographic Organization
IMO	International Maritime Organization
IoT	Internet of Things
LIME	Local Interpretable Model-Agnostic Explanations
LSTM	Long Short-Term Memory
MASS	Maritime Autonomous Surface Ship
MDPI	Multidisciplinary Digital Publishing Institute
MILP	Mixed-Integer Linear Programming
MHA	Multi-Head Attention Mechanism
ML	Machine Learning
MOPSO	Multi-Objective Particle Swarm Optimization
PSO	Particle Swarm Optimization
RIS	River Information Services
RMSE	Root Mean Square Error
RNN	Recurrent Neural Network
RTZ	Route Exchange Format
SHAP	SHapley Additive exPlanations
STMGCN	Spatio-Temporal Multigraph Convolutional Network
VAE	Variational Autoencoder
VHF	Very High Frequency (radio communication)
VTs	Vessel Traffic Services
XAI	Explainable Artificial Intelligence

Appendix A

Appendix A.1. CFD

Trajectory optimization is crucial for ensuring safe navigation and efficient transport of goods and passengers in both deep-sea vessels and inland water vessels [87]. The adoption of dynamics analysis theory and CFD approaches can achieve optimal design and energy efficiency improvement of ships, including hull optimization design and navigation state optimization [147]. CFD technology plays a significant role in ship hydrodynamic performance analysis, leading to the development of new ship forms and improved design [156].

CFD analysis helps reduce the cost of product development, understand flow physics, and improve design, such as in the development of improved propeller nozzle designs for offshore supply vessels [148]. CFD-based multi-objective optimization methods have

been developed for ship design, integrating CAD, CFD, and optimizer modules to achieve optimal propulsion and maneuverability performances [157].

Challenges and problems in the application of CFD-based energy-saving technology are discussed, highlighting the need for further research to achieve overall performance optimization of the integrated ship-engine-propeller-appendages system [147]. Research has been conducted to define and standardize operating modes for viscous simulations with a low number of cells, aiming to make them competitive in computational costs with panel methods, especially in the evaluation phase of different design alternatives [158].

Appendix A.2. High Performance Computing

Trajectory optimization is crucial for deep sea vessel navigation, inland water vessels, and MASS to ensure safety, efficiency, and reduced fuel consumption [48,87–89,93,95,122,159].

Advanced technologies such as PSO algorithms, genetic algorithms, and dynamic programming are used for trajectory optimization to reduce energy consumption, consider multiple objectives, and minimize fuel costs [48,88,89,93,95,159].

The optimization process involves considering factors such as ship technical characteristics, energy-saving technology options, weather conditions, and ship dynamics to generate optimal routes [48,88,93,122,159].

High-performance computing is utilized for trajectory optimization to handle the computational complexity of generating optimal routes, considering multiple objectives, and simulating ship dynamics [48,88,93].

References

1. Toskovic, A.; Petrovic, A.; Jovanovic, L.; Bacanin, N.; Zivkovic, M.; Dobrojevic, M. Marine Vessel Trajectory Forecasting Using Long Short-Term Memory Neural Networks Optimized via Modified Metaheuristic Algorithm. In *Trends in Sustainable Computing and Machine Intelligence*; Lanka, S., Sarasa-Cabezuelo, A., Tugui, A., Eds.; Springer Nature: Singapore, 2024; pp. 51–66, ISBN 978-981-99-9435-9.
2. Koumaniotis, E.K.; Kanellos, F.D. Optimal Routing and Sustainable Operation Scheduling of Large Ships with Integrated Full-Electric Propulsion. *Sustainability* **2024**, *16*, 10662. [\[CrossRef\]](#)
3. Kaklis, D.; Kontopoulos, I.; Varlamis, I.; Emiris, I.Z.; Varelas, T. Trajectory Mining and Routing: A Cross-Sectoral Approach. *J. Mar. Sci. Eng.* **2024**, *12*, 157. [\[CrossRef\]](#)
4. Mollaoglu, M.; Altay, B.C.; Balin, A. Bibliometric Review of Route Optimization in Maritime Transportation: Environmental Sustainability and Operational Efficiency. *Transp. Res. Rec. J. Transp. Res. Board* **2023**, *2677*, 879–890. [\[CrossRef\]](#)
5. Zygarlowska, E.; Dumard, C.; Rochut, B. Weather Routing Solutions towards Decarbonisation of Maritime Transport. In Proceedings of the EMS Annual Meeting 2024, Barcelona, Spain, 1–6 September 2024; EMS2024-1100. [\[CrossRef\]](#)
6. Moussa, A.A.; Ali, A.A.; Sayeh, M.E.E.; Shehata, A.S. A Novel Dynamic Route Optimization Method and Its Implementation Using Python to Optimize Ship Voyages Sailing Time Based on Weather Routing Techniques. *Preprint* **2024**. [\[CrossRef\]](#)
7. Zhang, X.; Fu, X.; Xiao, Z.; Xu, H.; Qin, Z. Vessel Trajectory Prediction in Maritime Transportation: Current Approaches and Beyond. *IEEE Trans. Intell. Transport. Syst.* **2022**, *23*, 19980–19998. [\[CrossRef\]](#)
8. Xiao, Y.; Li, X.; Yao, W.; Chen, J.; Hu, Y. Bidirectional Data-Driven Trajectory Prediction for Intelligent Maritime Traffic. *IEEE Trans. Intell. Transport. Syst.* **2022**, *24*, 1773–1785. [\[CrossRef\]](#)
9. Bi, J.; Cheng, H.; Zhang, W.; Bao, K.; Wang, P. Artificial Intelligence in Ship Trajectory Prediction. *J. Mar. Sci. Eng.* **2024**, *12*, 769. [\[CrossRef\]](#)
10. Takahashi, K.; Zama, K.; Hiroi, N.F. Ship Trajectory Prediction Using AIS Data with TransFormer-Based AI. In Proceedings of the 2024 IEEE Conference on Artificial Intelligence (CAI), Singapore, 25–27 June 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 1302–1305.
11. Huang, F.; Liu, Z.; Li, X.; Mou, F.; Li, P.; Fan, Z. Vessel Trajectory Prediction Based on AIS Data: Dual-Path Spatial–Temporal Attention Network with Multi-Attribute Information. *J. Mar. Sci. Eng.* **2024**, *12*, 2031. [\[CrossRef\]](#)
12. Li, H.; Jiao, H.; Yang, Z. AIS Data-Driven Ship Trajectory Prediction Modelling and Analysis Based on Machine Learning and Deep Learning Methods. *Transp. Res. Part E Logist. Transp. Rev.* **2023**, *175*, 103152. [\[CrossRef\]](#)
13. Li, H.; Jiao, H.; Yang, Z. Ship Trajectory Prediction Based on Machine Learning and Deep Learning: A Systematic Review and Methods Analysis. *Eng. Appl. Artif. Intell.* **2023**, *126*, 107062. [\[CrossRef\]](#)

14. Zou, S.; Liu, J.; Zhang, X.; Yu, Z.; Han, B.; Zhi, J. A Dynamic Spatio-Temporal Refinement Network for Multi-Vessel Trajectory Prediction. In Proceedings of the 2023 International Conference on Computer, Vision and Intelligent Technology, Chenzhou, China, 25–28 August 2023; ACM: New York, NY, USA, 2023; pp. 1–6.
15. Jia, H.; Yang, Y.; An, J.; Fu, R. A Ship Trajectory Prediction Model Based on Attention-BILSTM Optimized by the Whale Optimization Algorithm. *Appl. Sci.* **2023**, *13*, 4907. [\[CrossRef\]](#)
16. Wu, X.; Chen, J.; Xiong, C.; Liu, D.; Wan, X.; Chen, Z. Vessel Trajectory Prediction Method Based on the Time Series Data Fusion Model. *Promet-Traffic Transp.* **2024**, *36*, 1160–1175. [\[CrossRef\]](#)
17. Cen, J.; Li, J.; Liu, X.; Chen, J.; Li, H.; Huang, W.; Zeng, L.; Kang, J.; Ke, S. A Hybrid Prediction Model of Vessel Trajectory Based on Attention Mechanism and CNN-GRU. *Proc. Inst. Mech. Eng. Part M J. Eng. Marit. Environ.* **2024**, *238*, 809–823. [\[CrossRef\]](#)
18. Wang, W.; Xiong, W.; Ouyang, X.; Chen, L. TPTrans: Vessel Trajectory Prediction Model Based on Transformer Using AIS Data. *Int. J. Geo-Inf.* **2024**, *13*, 400. [\[CrossRef\]](#)
19. Liu, R.W.; Liang, M.; Nie, J.; Lim, W.Y.B.; Zhang, Y.; Guizani, M. Deep Learning-Powered Vessel Trajectory Prediction for Improving Smart Traffic Services in Maritime Internet of Things. *IEEE Trans. Netw. Sci. Eng.* **2022**, *9*, 3080–3094. [\[CrossRef\]](#)
20. Xiao, Y.; Hu, Y.; Liu, J.; Xiao, Y.; Liu, Q. An Adaptive Multimodal Data Vessel Trajectory Prediction Model Based on a Satellite Automatic Identification System and Environmental Data. *J. Mar. Sci. Eng.* **2024**, *12*, 513. [\[CrossRef\]](#)
21. Yang, F.; He, C.; Liu, Y.; Zeng, A.; Hu, L. Vessel Trajectory Prediction Based on Automatic Identification System Data: Multi-Gated Attention Encoder Decoder Network. *J. Mar. Sci. Eng.* **2024**, *12*, 1695. [\[CrossRef\]](#)
22. Yang, C.-H.; Lin, G.-C.; Wu, C.-H.; Liu, Y.-H.; Wang, Y.-C.; Chen, K.-C. Deep Learning for Vessel Trajectory Prediction Using Clustered AIS Data. *Mathematics* **2022**, *10*, 2936. [\[CrossRef\]](#)
23. Suo, Y.; Chen, W.; Claramunt, C.; Yang, S. A Ship Trajectory Prediction Framework Based on a Recurrent Neural Network. *Sensors* **2020**, *20*, 5133. [\[CrossRef\]](#)
24. Yang, C.-H.; Wu, C.-H.; Shao, J.-C.; Wang, Y.-C.; Hsieh, C.-M. AIS-Based Intelligent Vessel Trajectory Prediction Using Bi-LSTM. *IEEE Access* **2022**, *10*, 24302–24315. [\[CrossRef\]](#)
25. Liu, R.W.; Liang, M.; Nie, J.; Yuan, Y.; Xiong, Z.; Yu, H.; Guizani, N. STMGCN: Mobile Edge Computing-Empowered Vessel Trajectory Prediction Using Spatio-Temporal Multigraph Convolutional Network. *IEEE Trans. Ind. Inf.* **2022**, *18*, 7977–7987. [\[CrossRef\]](#)
26. Ma, K.; Han, Q.; Yao, J.; Zhang, Y. DM-BDD: Real-Time Vessel Trajectory Prediction Based on Diffusion Probability Model Balancing Diversity and Determinacy. In Proceedings of the 2024 International Joint Conference on Neural Networks (IJCNN), Yokohama, Japan, 30 June–5 July 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 1–8.
27. Wang, X.; Xiao, Y. A Deep Learning Model for Ship Trajectory Prediction Using Automatic Identification System (AIS) Data. *Information* **2023**, *14*, 212. [\[CrossRef\]](#)
28. Hao, S.; Liu, J.; Zhang, X.; Shi, Q.; Zhi, J.; Jiang, X. Multi-Ship Trajectory Prediction Framework for High-Density Maritime Traffic Areas Based on BI-GRU and GAT. In Proceedings of the 2023 11th International Conference on Information Systems and Computing Technology (ISCTech), Qingdao, China, 30 July–1 August 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 333–337.
29. Lu, X.; He, M.; Ma, J.; Wang, H.; Shao, Y. Vessel Trajectory Prediction with the Introduction of Channel Information. In Proceedings of the 2023 7th International Conference on Transportation Information and Safety (ICTIS), Xi'an, China, 4–6 August 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 2286–2293.
30. Drapier, N.; Chetouani, A.; Chateigner, A. Enhancing Maritime Trajectory Forecasting via H3 Index and Causal Language Modelling (CLM). *arXiv* **2024**, arXiv:2405.09596. [\[CrossRef\]](#)
31. Capobianco, S.; Millefiori, L.M.; Forti, N.; Braca, P.; Willett, P. Deep Learning Methods for Vessel Trajectory Prediction Based on Recurrent Neural Networks. *IEEE Trans. Aerosp. Electron. Syst.* **2021**, *57*, 4329–4346. [\[CrossRef\]](#)
32. Xiao, Z.; Fu, X.; Zhang, L.; Zhang, W.; Liu, R.W.; Liu, Z.; Goh, R.S.M. Big Data Driven Vessel Trajectory and Navigating State Prediction With Adaptive Learning, Motion Modeling and Particle Filtering Techniques. *IEEE Trans. Intell. Transport. Syst.* **2022**, *23*, 3696–3709. [\[CrossRef\]](#)
33. Zhuang, C.; Chen, C. Research on Autonomous Route Generation Method Based on AIS Ship Trajectory Big Data and Improved LSTM Algorithm. *Front. Neurobot.* **2022**, *16*, 1049343. [\[CrossRef\]](#)
34. Wu, W.; Chen, P.; Chen, L.; Mou, J. Ship Trajectory Prediction: An Integrated Approach Using ConvLSTM-Based Sequence-to-Sequence Model. *J. Mar. Sci. Eng.* **2023**, *11*, 1484. [\[CrossRef\]](#)
35. Liu, R.W.; Liang, M.; Nie, J.; Deng, X.; Xiong, Z.; Kang, J.; Yang, H.; Zhang, Y. Intelligent Data-Driven Vessel Trajectory Prediction in Marine Transportation Cyber-Physical System. In Proceedings of the 2021 IEEE International Conferences on Internet of Things (iThings) and IEEE Green Computing & Communications (GreenCom) and IEEE Cyber, Physical & Social Computing (CPSCom) and IEEE Smart Data (SmartData) and IEEE Congress on Cybermatics (Cybermatics), Melbourne, Australia, 6–8 December 2021; IEEE: Piscataway, NJ, USA, 2021; pp. 314–321.
36. Wang, P.; Pan, M.; Liu, Z.; Li, S.; Chen, Y.; Wei, Y. Ship Trajectory Prediction in Complex Waterways Based on Transformer and Social Variational Autoencoder (SocialVAE). *J. Mar. Sci. Eng.* **2024**, *12*, 2233. [\[CrossRef\]](#)

37. Xia, C.; Qu, D.; Zheng, Y. TATBformer: A Divide-and-Conquer Approach to Ship Trajectory Prediction Modeling. In Proceedings of the 2023 IEEE 11th Joint International Information Technology and Artificial Intelligence Conference (ITAIC), Chongqing, China, 8–10 December 2023; IEEE: Piscataway, NJ, USA, 2023.
38. Bao, K.; Bi, J.; Gao, M.; Sun, Y.; Zhang, X.; Zhang, W. An Improved Ship Trajectory Prediction Based on AIS Data Using MHA-BiGRU. *J. Mar. Sci. Eng.* **2022**, *10*, 804. [\[CrossRef\]](#)
39. Kim, J.S.; Park, H.J.; Shin, W.; Park, D.; Han, S.W. WAY: Estimation of Vessel Destination in Worldwide AIS Trajectory. *IEEE Trans. Aerosp. Electron. Syst.* **2023**, *59*, 5961–5977. [\[CrossRef\]](#)
40. Li, M.; Li, B.; Qi, Z.; Li, J.; Wu, J. Enhancing Maritime Navigational Safety: Ship Trajectory Prediction Using ACoAtt-LSTM and AIS Data. *Int. J. Geo-Inf.* **2024**, *13*, 85. [\[CrossRef\]](#)
41. Yang, J.; Liu, J.; Li, X.; Liu, J. A Novel Clustering Method for Ship Trajectory Prediction. In Proceedings of the 2024 2nd International Conference on Computer, Vision and Intelligent Technology (ICCVIT), Huaibei, China, 24–27 November 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 1–5.
42. Düz, B.; Van Iperen, E. Ship Trajectory Prediction Using Encoder–Decoder-Based Deep Learning Models. *J. Locat. Based Serv.* **2025**, *19*, 146–166. [\[CrossRef\]](#)
43. Liu, X.; He, W.; Xie, J.; Chu, X. Predicting the Trajectories of Vessels Using Machine Learning. In Proceedings of the 2020 5th International Conference on Control, Robotics and Cybernetics (CRC), Wuhan, China, 16–18 October 2020; IEEE: Piscataway, NJ, USA, 2020; pp. 66–70.
44. Guan, J.; Liu, J.; Mo, Q.; Yang, Q. Deep Learning Based Ship Trajectory Prediction with AIS. In *Proceedings of the International Conference on Computer Graphics, Artificial Intelligence, and Data Processing (ICCAID 2023)*, Qingdao, China, 1–3 December 2023; Wu, H., Li, H., Eds.; SPIE: Bellingham, WA, USA, 2024; p. 20.
45. Li, T.; Li, Y.B. Prediction of Ship Trajectory Based on Deep Learning. *J. Phys. Conf. Ser.* **2023**, *2613*, 012023. [\[CrossRef\]](#)
46. Jebbor, I.; Benmamoun, Z.; Hachimi, H. Forecasting Supply Chain Disruptions in the Textile Industry Using Machine Learning: A Case Study. *Ain Shams Eng. J.* **2024**, *15*, 103116. [\[CrossRef\]](#)
47. Jebbor, I.; Hachimi, H.; Benmamoun, Z. Artificial Intelligence in Predicting Automotive Supply Chain Disruptions: A Literature Review. In *Advances in Intelligent Systems and Digital Applications*; Gherabi, N., Kacprzyk, J., Arezki, S., Eds.; Lecture Notes in Networks and Systems; Springer Nature: Cham, Switzerland, 2025; Volume 1486, pp. 11–21, ISBN 978-3-031-95329-3.
48. Liu, Y.; Zhang, Y.; Ge, S.S.; Liang, X.; Yuan, M.; Ee How, B.V. Energy-Efficient Trajectory Optimization and Safe Adaptive Neural Network Control for Green Ship. In Proceedings of the 2024 24th International Conference on Control, Automation and Systems (ICCAS), Jeju, Republic of Korea, 29 October–1 November 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 904–909.
49. Song, Y.; Cao, X. Review of Intelligent Ship Path Planning Algorithms. *Front. Manag. Sci.* **2024**, *3*, 90–101. [\[CrossRef\]](#)
50. Hu, X.; Hu, K.; Tao, D.; Zhong, Y.; Han, Y. GIS-Data-Driven Efficient and Safe Path Planning for Autonomous Ships in Maritime Transportation. *Electronics* **2023**, *12*, 2206. [\[CrossRef\]](#)
51. Basrur, C.; Singh, A.J.; Sinha, A.; Kumar, A.; Kumar, T.K.S. Trajectory Optimization for Safe Navigation in Maritime Traffic Using Historical Data. *LIPICs* **2022**, *235*, 5:1–5:17. [\[CrossRef\]](#)
52. Aguiar, M.; Sousa, J.B.D.; Dias, J.M.; Silva, J.E.D.; Mendes, R.; Ribeiro, A.S. Trajectory Optimization for Underwater Vehicles in Time-Varying Ocean Flows. In Proceedings of the 2018 IEEE/OES Autonomous Underwater Vehicle Workshop (AUV), Porto, Portugal, 6–9 November 2018; IEEE: Piscataway, NJ, USA, 2018; pp. 1–6.
53. Nutalapati, M.K.; Joshi, S.; Rajawat, K. Online Utility-Optimal Trajectory Design for Time-Varying Ocean Environments. In Proceedings of the 2019 International Conference on Robotics and Automation (ICRA), Montreal, QC, Canada, 20–24 May 2019; IEEE: Piscataway, NJ, USA, 2019; pp. 6853–6859.
54. Ali, N.; Hussain, A.; Bokhari, S.W.A. Optimizing Maritime Routes: A Multi-Method Analysis from Shanghai to Vladivostok. *Croat. Oper. Res. Rev.* **2025**, *16*, 73–83. [\[CrossRef\]](#)
55. Wongmayura, M.; Wasusri, T. Vessel Route Optimization For Offshore Marine Transport. In Proceedings of the 33rd International ECMS Conference on Modelling and Simulation, ECMS 2019, Caserta, Italy, 11–14 June 2019.
56. Ghnatios, C.; Lorenzo, D.D.; Champaney, V.; Ammar, A.; Elias, C.; Chinesta, F. Optimal Trajectory Planning Combining model-Based and Data-Driven Hybrid Approaches. *Adv. Model. Simul. Eng. Sci.* **2023**, *11*, 10. [\[CrossRef\]](#)
57. Guo, D.; Yin, Y.; Xiao, F. Overview of intelligent ship route optimization methods. *Chin. J. Ship Res.* **2023**, *18*, 151–161. [\[CrossRef\]](#)
58. Troupiotis-Kapeliaris, A.; Kastrisios, C.; Zissis, D. Vessel Trajectory Data Mining: A Review. *IEEE Access* **2025**, *13*, 4827–4856. [\[CrossRef\]](#)
59. Rong, Y.; Zhuang, Z.; He, Z.; Wang, X. A Maritime Traffic Network Mining Method Based on Massive Trajectory Data. *Electronics* **2022**, *11*, 987. [\[CrossRef\]](#)
60. Sha, H.; Han, Z.; Zhu, L. The Whole Process Route Planning Algorithm Based on AIS Spatio-Temporal Big Data Analysis. *Ships Offshore Struct.* **2024**, *20*, 912–926. [\[CrossRef\]](#)
61. Zhang, Y.; Shi, G.; Li, S.; Zhang, S. Vessel Trajectory Online Multi-Dimensional Simplification Algorithm. *J. Navig.* **2020**, *73*, 342–363. [\[CrossRef\]](#)

62. Huang, L.; Wan, C.; Wen, Y.; Song, R.; Van Gelder, P. Generation and Application of Maritime Route Networks: Overview and Future Research Directions. *IEEE Trans. Intell. Transport. Syst.* **2025**, *26*, 620–637. [\[CrossRef\]](#)
63. Liu, L.; Zhang, M.; Liu, C.; Yan, R.; Lang, X.; Wang, H. Shipping Map: An Innovative Method in Grid Generation of Global Maritime Network for Automatic Vessel Route Planning Using AIS Data. *Transp. Res. Part C Emerg. Technol.* **2025**, *171*, 105015. [\[CrossRef\]](#)
64. Xiao, Z.; Ponnambalam, L.; Fu, X.; Zhang, W. Maritime Traffic Probabilistic Forecasting Based on Vessels' Waterway Patterns and Motion Behaviors. *IEEE Trans. Intell. Transport. Syst.* **2017**, *18*, 3122–3134. [\[CrossRef\]](#)
65. Yao, F. A Ship Trajectory Analysis and Prediction System. In Proceedings of the 2023 2nd International Conference on Artificial Intelligence and Computer Information Technology (AICIT), Yichang, China, 15–17 September 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1–4.
66. Hoffmann, V.; Webert, J.-H.; Murray, B.; Graf, R. Data-Driven Construction of Maritime Traffic Networks for AI-Based Route Prediction. *J. Phys. Conf. Ser.* **2024**, *2867*, 012048. [\[CrossRef\]](#)
67. Yuan, X.; Wang, J.; Zhao, G.; Wang, H. Comprehensive Study on Optimizing Inland Waterway Vessel Routes Using AIS Data. *J. Mar. Sci. Eng.* **2024**, *12*, 1775. [\[CrossRef\]](#)
68. He, Y.K.; Zhang, D.; Zhang, J.; Zhang, M.Y.; Li, T.W. Ship Route Planning Using Historical Trajectories Derived from AIS Data. *TransNav* **2019**, *13*, 69–76. [\[CrossRef\]](#)
69. Huang, J.; Zhao, Y.; Qiao, Y. Research on Ship Route and Speed Optimization Considering Rolling Meteorological Data: Intelligent Decision Design Based on Genetic Algorithm. In Proceedings of the Seventh International Conference on Traffic Engineering and Transportation System (ICTETS 2023), Dalian, China, 22–24 September 2023; Ghanizadeh, A.R., Jia, H., Eds.; SPIE: Bellingham, WA, USA, 2024; p. 9.
70. Hanssen, G.L.; James, R.W. Optimum Ship Routing. *J. Navig.* **1960**, *13*, 253–272. [\[CrossRef\]](#)
71. Balas, M.; Prpić-Oršić, J.; Valčić, M. Emerging Stochastic Methods for Weather-Aware Ship Routing. In *Progress in Marine Science and Technology*; IOS Press: Amsterdam, The Netherlands, 2024; ISBN 978-1-64368-557-1.
72. Kytariolou, A.; Themelis, N. Optimized Route Planning under the Effect of Hull and Propeller Fouling and Considering Ocean Currents. *J. Mar. Sci. Eng.* **2023**, *11*, 828. [\[CrossRef\]](#)
73. Kobayashi, E.; Yoneda, S.; Morita, A. Advanced Route Optimization in Ship Navigation. In Proceedings of the 4th International Conference on Simulation and Modeling Methodologies, Technologies and Applications, Vienna, Austria, 28–30 August 2014; SCITEPRESS-Science and Technology Publications: Vienna, Austria, 2014; pp. 572–577.
74. Uchoa Simões, R.; Martins Teixeira De Freitas, A.A.; Hood Marques, C.; Caprace, J.-D. A Vessel Weather Routing Scheduler. In Proceedings of the 27o Congresso Internacional de Transporte Aquaviário, Construção Naval e Offshore, Galoa, Rio de Janeiro, Brazil, 23–25 October 2018.
75. Walther, L.; Rizvanolli, A.; Wendebourg, M.; Jahn, C. Modeling and Optimization Algorithms in Ship Weather Routing. *Int. J. e-Navig. Marit. Econ.* **2016**, *4*, 31–45. [\[CrossRef\]](#)
76. Durlik, I.; Miller, T.; Kostecka, E.; Łobodzińska, A.; Kostecki, T. Harnessing AI for Sustainable Shipping and Green Ports: Challenges and Opportunities. *Appl. Sci.* **2024**, *14*, 5994. [\[CrossRef\]](#)
77. Xiao, G.; Wang, Y.; Wu, R.; Li, J.; Cai, Z. Sustainable Maritime Transport: A Review of Intelligent Shipping Technology and Green Port Construction Applications. *J. Mar. Sci. Eng.* **2024**, *12*, 1728. [\[CrossRef\]](#)
78. Paladin, Z.; Šorović, M.; Bauk, S.; Knoors, F.; Stephens, J.; Kapidani, N.; Lukšić, Ž.; Mujalović, R. Maritime Transport And Logistics Digital Solutions Optimization Using Advanced Data Sharing Platforms: ePIcenter Projects' Case. In *Proceedings of the Resilience Through Digital Innovation: Enabling the Twin Transition*; University of Maribor Press: Bled, Slovenia, 2024; pp. 403–420.
79. Du, Y.; Li, C.; Wang, T.; Xu, Y. Special Issue on "Smart Port and Shipping Operations". *Marit. Policy Manag.* **2023**, *50*, 413–414. [\[CrossRef\]](#)
80. Zhao, L.; Xu, M.; Liu, L.; Bai, Y.; Zhang, M.; Yan, R. Intelligent Shipping: Integrating Autonomous Maneuvering and Maritime Knowledge in the Singapore-Rotterdam Corridor. *Commun. Eng.* **2025**, *4*, 11. [\[CrossRef\]](#)
81. Hirata, E.; Watanabe, D.; Lambrou, M. Shipping Digitalization and Automation for the Smart Port. In *Supply Chain-Recent Advances and New Perspectives in the Industry 4.0 Era*; Bányai, T., Bányai, Á., Kaczmar, I., Eds.; IntechOpen: London, UK, 2022; ISBN 978-1-80355-372-6.
82. Guerrero-Molina, M.-I.; Vásquez-Suárez, Y.-A.; Valdés-Mosquera, D.-M. Smart, Green, and Sustainable: Unveiling Technological Trajectories in Maritime Port Operations. *IEEE Access* **2024**, *12*, 47713–47723. [\[CrossRef\]](#)
83. Butsanets, A.; Ol'Khovik, E.; Karetnikov, V.; Senchenko, V. Issues of Building an Intelligent Water Transport Management System. *E3S Web Conf.* **2021**, *326*, 00029. [\[CrossRef\]](#)
84. Alzate-Montoya, P.M.; Giraldo-Ospina, V.; Duque-Hurtado, P. Trends and Strategies in Sustainable Maritime Transport: Insights from Global Research. *Rev. Investig. Desarro. Innov.* **2024**, *14*, 43–62. [\[CrossRef\]](#)
85. Liu, Y. Efficiency and Sustainability in International Maritime Logistics: The Role of Artificial Intelligence. *SHS Web Conf.* **2024**, *207*, 03004. [\[CrossRef\]](#)

86. Ichimura, Y.; Dalaklis, D.; Kitada, M.; Christodoulou, A. Shipping in the Era of Digitalization: Mapping the Future Strategic Plans of Major Maritime Commercial Actors. *Digit. Bus.* **2022**, *2*, 100022. [\[CrossRef\]](#)
87. Vierhaus, I.; Born, A.; Engler, E. Trajectory Optimisation for Inland Water Vessels Based on a next Generation PNT-Unit. In Proceedings of the 2012 6th ESA Workshop on Satellite Navigation Technologies (Navitec 2012) & European Workshop on GNSS Signals and Signal Processing, Noordwijk, NL, USA, 5–7 December 2012.
88. Shu, Y.; Xiong, C.; Zhu, Y.; Liu, K.; Liu, R.W.; Xu, F.; Gan, L.; Zhang, L. Reference Path for Ships in Ports and Waterways Based on Optimal Control. *Ocean. Coast. Manag.* **2024**, *253*, 107168. [\[CrossRef\]](#)
89. Fu, X.; Qian, D. Research on Automatic Trajectory Planning Method of Unmanned Ships Based on Multi-Objective Optimization. *IEEE Access* **2023**, *11*, 129829–129839. [\[CrossRef\]](#)
90. Yan, X.-P.; Li, C.; Liu, J.-L.; You, X.; Wang, S.-W.; Ma, F. Architecture and Key Technologies for New Generation of Waterborne Transportation System. *Jiaotong Yunshu Xitong Gongcheng Yu Xinxi/J. Transp. Syst. Eng. Inf. Technol.* **2021**, *21*, 22–29, 76. [\[CrossRef\]](#)
91. Huang, L.; Chen, J.; Xu, L.; Li, H.; Hao, G.; He, Y. Research on Decision-Making Methods for Autonomous Navigation in Inland Tributary Waterways. *Appl. Sci.* **2025**, *15*, 3823. [\[CrossRef\]](#)
92. Jia, L.; Wang, J.; Guo, Y. Intelligent Planning of Ship Route in Complex Waters Based on Chaos Genetic Algorithm. *Internet Technol. Lett.* **2024**, *7*, e320. [\[CrossRef\]](#)
93. Jeong, S.; Kim, T.-W. Generating a Path-Search Graph Based on Ship-Trajectory Data: Route Search via Dynamic Programming for Autonomous Ships. *Ocean Eng.* **2023**, *283*, 114503. [\[CrossRef\]](#)
94. Pietrzykowski, Z.; Magaj, J.; Maka, M. Safe Ship Trajectory Determination in the ENC Environment. In *Telematics-Support for Transport*; Mikulski, J., Ed.; Springer: Berlin/Heidelberg, Germany, 2014; Volume 471, pp. 304–312, ISBN 978-3-662-45316-2.
95. Yang, H.; Huang, Y.; Wen, Y.; Chen, L.; Zhu, M. Unit-Based Trajectory Planning Methods for MASS in Inland Waters. In Proceedings of the 2023 IEEE 26th International Conference on Intelligent Transportation Systems (ITSC), Bilbao, Spain, 24–28 September 2023; IEEE: Piscataway, NJ, USA, 2023; pp. 1806–1811.
96. Sarabia, M.C.; Ríos, J.H.; Paternina-Arboleda, C.D. Simulation-Based Decision Support Models for River Cargo Transportation. In Proceedings of the 2006 IEEE Systems and Information Engineering Design Symposium, Charlottesville, VA, USA, 28 April 2006; pp. 142–145.
97. Fagerholt, K. A Computer-Based Decision Support System for Vessel Fleet Scheduling-Experience and Future Research. *Decis. Support Syst.* **2004**, *37*, 35–47. [\[CrossRef\]](#)
98. Tsolakis, A.; Benders, D.; De Groot, O.; Negenborn, R.R.; Reppa, V.; Ferranti, L. COLREGs-Aware Trajectory Optimization for Autonomous Surface Vessels. *IFAC-PapersOnLine* **2022**, *55*, 269–274. [\[CrossRef\]](#)
99. Tsolakis, A.; Negenborn, R.R.; Reppa, V.; Ferranti, L. Model Predictive Trajectory Optimization and Control for Autonomous Surface Vessels Considering Traffic Rules. *IEEE Trans. Intell. Transport. Syst.* **2024**, *25*, 9895–9908. [\[CrossRef\]](#)
100. Hu, L.; Naeem, W.; Rajabally, E.; Watson, G.; Mills, T.; Bhuiyan, Z.; Raeburn, C.; Salter, I.; Pekcan, C. A Multiobjective Optimization Approach for COLREGs-Compliant Path Planning of Autonomous Surface Vehicles Verified on Networked Bridge Simulators. *IEEE Trans. Intell. Transport. Syst.* **2020**, *21*, 1167–1179. [\[CrossRef\]](#)
101. Yu, H.; Murray, A.T.; Fang, Z.; Liu, J.; Peng, G.; Solgi, M.; Zhang, W. Ship Path Optimization That Accounts for Geographical Traffic Characteristics to Increase Maritime Port Safety. *IEEE Trans. Intell. Transport. Syst.* **2022**, *23*, 5765–5776. [\[CrossRef\]](#)
102. Zhou, C.; Xiang, J.; Huang, H.; Yan, Y.; Huang, L.; Wen, Y.; Xiao, C. TTMRN: A Topological-Geometric Two-Layer Maritime Route Network Modeling for Ship Intelligent Navigation. *Ocean. Eng.* **2023**, *287*, 115884. [\[CrossRef\]](#)
103. Akdağ, M.; Pedersen, T.A.; Fossen, T.I.; Johansen, T.A. A Decision Support System for Autonomous Ship Trajectory Planning. *Ocean. Eng.* **2024**, *292*, 116562. [\[CrossRef\]](#)
104. Liu, Y.; Wang, T.; Xu, H. PE-A* Algorithm for Ship Route Planning Based on Field Theory. *IEEE Access* **2022**, *10*, 36490–36504. [\[CrossRef\]](#)
105. Huang, Y.; Zhao, S.; Zhao, S. Ship Trajectory Planning and Optimization via Ensemble Hybrid A* and Multi-Target Point Artificial Potential Field Model. *J. Mar. Sci. Eng.* **2024**, *12*, 1372. [\[CrossRef\]](#)
106. Hao, Y.; Wang, Y.; Han, Z. Automatic Planning Method of Seawater Navigation Trajectory Based on AIS Big Data. *Desalination Water Treat.* **2022**, *269*, 221–227. [\[CrossRef\]](#)
107. Wang, Z.; Yang, P.; Gao, D.; Bao, C. Path-Planning Algorithm Based on Elastic Force Contractions for Autonomous Navigation of Unmanned Container Ships in Waterborne Transportation. *Ocean. Eng.* **2024**, *310*, 118646. [\[CrossRef\]](#)
108. Topaj, A.; Tarovik, O. Hybrid Cell-Wave Algorithm for Ship Routing in Ice under Spatiotemporal Constraints. *Ocean Eng.* **2025**, *326*, 120863. [\[CrossRef\]](#)
109. Ridwan, A. Container Ship Planning Optimization Using Intelligent Meta-Heuristic Algorithms. *Ind. Eng. Manag. Syst.* **2022**, *21*, 460–468. [\[CrossRef\]](#)
110. Li, Q.; Li, B.; Sun, G.; Cui, X.; Mao, X. Trajectory Planning and Automatic Obstacle Avoidance Algorithm for Unmanned Surface Vehicle Based on Exact Penalty Function. *Chin. J. Ship Res.* **2021**, *16*, 89–95. [\[CrossRef\]](#)

111. Gomez, S.; Ivorra, B.; Ramos, A.M. Optimization of a Pumping Ship Trajectory to Clean Oil Contamination in the Open Sea. *Math. Comput. Model.* **2011**, *54*, 477–489. [\[CrossRef\]](#)
112. Szłapczyński, R. Evolutionary Sets of Safe Ship Trajectories with Speed Reduction Manoeuvres within Traffic Separation Schemes. *Pol. Marit. Res.* **2013**, *21*, 20–27. [\[CrossRef\]](#)
113. Miao, H.; Yang, J. Network Optimization Model of Inland Bulk Transportation Routes Considering Low Carbon Cost. *Wuhan Ligong Daxue Xuebao (Jiaotong Kexue Yu Gongcheng Ban)/J. Wuhan Univ. Technol. (Transp. Sci. Eng.)* **2017**, *41*, 839–843. [\[CrossRef\]](#)
114. Zvyagina, T.; Zvyagin, P. A Model of Multi-Objective Route Optimization for a Vessel in Drifting Ice. *Reliab. Eng. Syst. Saf.* **2022**, *218*, 108147. [\[CrossRef\]](#)
115. Liu, X.; Cheng, L.; Zhang, Q.; Jiang, L. Entry Trajectory Optimization for Hypersonic Vehicle Based on Time-Scales Separation Guidance with Waterweeds Algorithm. In Proceedings of the 2016 IEEE Chinese Guidance, Navigation and Control Conference (CGNCC), Nanjing, China, 12–14 August 2016; pp. 209–215.
116. Celis, C.; Sethi, V.; Zammit-Mangion, D.; Singh, R.; Pilidis, P. Theoretical Optimal Trajectories for Reducing the Environmental Impact of Commercial Aircraft Operations. *J. Aerosp. Technol. Manag.* **2014**, *6*, 29–42. [\[CrossRef\]](#)
117. Rudzińska, S.M.; Kaup, M.; Kalbarczyk-Jedynak, A. The Possibilities of Applying Artificial Intelligence in Maritime Navigation. *Procedia Comput. Sci.* **2024**, *246*, 5516–5524. [\[CrossRef\]](#)
118. Alfari, O.; Singhal, R.; Rouis, L.; Blanco, A.; Fahmy, F.; Hayes, M.; Jafarov, R.; AlDahmani, A.; AlZarooni, M.; Dolle, N.; et al. Incepting Caspian AI-Driven Well Trajectory Design: Simultaneous Multi-Objective Optimization for Near Real-Time Well Path Construction. In Proceedings of the SPE Gas & Oil Technology Showcase and Conference, Dubai City, United Arab Emirates, 21–23 April 2025.
119. Joo, M.; Gong, H.; Ma, C.; Gao, W. Intelligent Techniques and Explainable Artificial Intelligence for Vessel Traffic Service: A Survey. In *Explainable Artificial Intelligence for Intelligent Transportation Systems*; Springer: Berlin/Heidelberg, Germany, 2023; pp. 153–170.
120. Duan, H.; Liu, S.; Wu, J. Novel Intelligent Water Drops Optimization Approach to Single UCAV Smooth Trajectory Planning. *Aerosp. Sci. Technol.* **2009**, *13*, 442–449. [\[CrossRef\]](#)
121. Scarlat, C.; Ioanid, A.; Andrei, N. Use of the geospatial technologies and its implications in the maritime transport and logistics. *Int. Marit. Transp. Logist. J.* **2023**, *12*, 19–30. [\[CrossRef\]](#)
122. Kisialiou, Y.; Rialland, A.; Gribkovskaia, V. Ship Model-Based Route Optimisation for Decision Support in Deep Sea Shipping. *J. Phys. Conf. Ser.* **2024**, *2867*, 012012. [\[CrossRef\]](#)
123. Čižiūnienė, K. Information Technology Used in the Water Transport Sector. In *International Series in Operations Research and Management Science*; Springer: Cham, Switzerland, 2022; Volume 330, pp. 329–345.
124. Grifoll, M.; Martorell, L.; Castells, M.; De Osés, F.X.M. Ship Weather Routing Using Pathfinding Algorithms: The Case of Barcelona-Palma de Mallorca. *Transp. Res. Procedia* **2018**, *33*, 299–306. [\[CrossRef\]](#)
125. Rosenow, J.; Lindner, M.; Scheiderer, J. Advanced Flight Planning and the Benefit of In-Flight Aircraft Trajectory Optimization. *Sustainability* **2021**, *13*, 1383. [\[CrossRef\]](#)
126. Jiménez de la Jara, J.; Precioso, D.; Bu, L.; Redondo-Neble, M.V.; Milson, R.; Ballester-Ripoll, R.; Gómez-Ullate, D. HADAD: Hexagonal A-Star with Differential Algorithm Designed for Weather Routing. *Ocean. Eng.* **2025**, *319*, 120050. [\[CrossRef\]](#)
127. Wang, H.; Mao, W.; Eriksson, L. Benchmark Study of Five Optimization Algorithms for Weather Routing. In Proceedings of the International Conference on Offshore Mechanics and Arctic Engineering. American Society of Mechanical Engineers, Trondheim, Norway, 25–30 June 2017; Volume 7B-2017.
128. Pennino, S.; Scamardella, A. Weather Routing Model for Ship Motions Reduction and Fuel Saving. In *Proceedings of the Progress in Marine Science and Technology*; Rizzuto, E., Ruggiero, V., Eds.; IOS Press BV: Amsterdam, The Netherlands, 2022; Volume 6, pp. 323–330.
129. Slagtera, I.S.; Panga, I.Y.; Negenborn, R.R. Energy-Efficient Speed Planning Considering Delay and Dynamic Waterway Conditions for Inland Vessels. In Proceedings of the International Ship Control Systems Symposium, Liverpool, UK, 5–7 November 2024; Institute of Marine Engineering Science & Technology: London, UK, 2024.
130. Ashwin, R.; Ilamparithi Yaazharasu, C.R.; Ramana, P.T.; Shilpa, P.; Jeyakumar, G. Optimal Ship Route Search Based on Multi-Objective Genetic Algorithm. In Proceedings of the International Conference on Computing Communication and Networking Technologies, ICCCNT, Delhi, India, 6–8 July 2023; Institute of Electrical and Electronics Engineers Inc.: Piscataway, NJ, USA, 2023.
131. Guo, Y.; Wang, Y.; Chen, Y.; Wu, L.; Mao, W. Learning-Based Pareto-Optimum Routing of Ships Incorporating Uncertain Meteorological and Oceanographic Forecasts. *Transp. Res. Part E Logist. Transp. Rev.* **2024**, *192*, 103786. [\[CrossRef\]](#)
132. Hinnenthal, J.; Clauss, G. Robust Pareto-Optimum Routing of Ships Utilising Deterministic and Ensemble Weather Forecasts. *Ships Offshore Struct.* **2010**, *5*, 105–114. [\[CrossRef\]](#)

133. Abdalsalam, M.; Szlapczyńska, J. Towards Improved Ship Weather Routing Through Multi-Objective Optimization with High Performance Computing Support. *TransNav* **2025**, *19*, 93–103. [\[CrossRef\]](#)
134. Rabbani, M.; Sadeghsa, S.; Vaez-Alaei, M.; Farrokhi-Asl, H. Robust and Sustainable Full-Shipload Routing and Scheduling Problem Considering Variable Speed: A Real Case Study. *Sci. Iran.* **2019**, *26*, 1881–1897. [\[CrossRef\]](#)
135. Mathematical Models for the Optimisation of Maritime Routes in Container Transportation. In *Lecture Notes on Data Engineering and Communications Technologies*; Springer Nature: Cham, Switzerland, 2025; pp. 646–651, ISBN 978-3-031-82333-6.
136. Cao, Z.; Zhu, Z.; Lu, W.; Zhang, S. Risk-Aware Vessel Scheduling and Routing Optimization with CVaR and LSTM-MSNet Prediction. *J. Mar. Sci. Eng.* **2025**, *13*, 207. [\[CrossRef\]](#)
137. Zhao, X.; Guo, Y.; Wang, Y. Green Maritime Navigation: A Multi-Objective Voyage Optimization Approach Based on Data-Driven Heuristics and Emission Awareness. *Ocean. Eng.* **2025**, *318*, 120138. [\[CrossRef\]](#)
138. Kot, R. Multimodal Global Trajectory Planner for Autonomous Underwater Vehicles. *Electronics* **2023**, *12*, 4602. [\[CrossRef\]](#)
139. Li, X.; Yu, S. Three-Dimensional Path Planning for AUVs in Ocean Currents Environment Based on an Improved Compression Factor Particle Swarm Optimization Algorithm. *Ocean. Eng.* **2023**, *280*, 114610. [\[CrossRef\]](#)
140. Siron Santhiya, V.N.; Simon, J. A Novel Optimal Path Planning Procedure for Autonomous Underwater Vehicles. In Proceedings of the 2024 Second International Conference on Advances in Information Technology (ICAIT), Chikkamagaluru, Karnataka, India, 24–27 July 2024; IEEE: Piscataway, NJ, USA, 2024; pp. 1–6.
141. Zhang, C.; Ma, Y.; Thies, F.; Ringsberg, J.W.; Xing, Y. Towards Autonomous Inland Shipping: A Manoeuvring Model in Confined Waterways. *Ships Offshore Struct.* **2025**, *20*, 767–779. [\[CrossRef\]](#)
142. Li, D. Performance Optimization of Intelligent Perception System in Maritime Traffic Sensing and Management. In Proceedings of the 2025 International Conference on Multi-Agent Systems for Collaborative Intelligence (ICMSCI), Erode, India, 20–22 January 2025; IEEE: Piscataway, NJ, USA, 2025; pp. 1285–1290.
143. Braik, M.; Al-Hiary, H. A Novel Meta-Heuristic Optimization Algorithm Inspired by Water Uptake and Transport in Plants. *Neural Comput. Applic.* **2025**, *37*, 13643–13724. [\[CrossRef\]](#)
144. Drezner, Z.; Miklas-Kalczyńska, M. Solving Non-Linear Optimization Problems by a Trajectory Approach. *IMA J. Manag. Math.* **2024**, *35*, 537–555. [\[CrossRef\]](#)
145. Ghnatios, C.; Di Lorenzo, D.; Champaney, V.; Cueto, E.; Chinesta, F. Optimal Velocity Planning Based on the Solution of the Euler-Lagrange Equations with a Neural Network Based Velocity Regression. *DCDS-S* **2024**, *17*, 2323–2333. [\[CrossRef\]](#)
146. Lei, Y.-Z.; Cheng, Y.; Yang, X.T. An Optimization-Free Approximation Framework for Connected and Automated Vehicles Eco-Trajectory Planning Under Limited Computing Capacity. *Transp. Res. Part C Emerg. Technol.* **2025**, *171*, 104949. [\[CrossRef\]](#)
147. Wang, K.; Li, Z.; Zhang, R.; Ma, R.; Huang, L.; Wang, Z.; Jiang, X. Computational Fluid Dynamics-Based Ship Energy-Saving Technologies: A Comprehensive Review. *Renew. Sustain. Energy Rev.* **2025**, *207*, 114896. [\[CrossRef\]](#)
148. Tinsley, D. Advances in Performance. *Shipp. World Shipbuild.* **2006**, *207*, 12–18.
149. Xiao, G.; Amamoo-Otoo, C.; Wang, T.; Li, Q.; Biancardo, S.A. Evaluating the Impact of ECA Policy on Sulfur Emissions from the Five Busiest Ports in America Based on Difference in Difference Model. *Front. Mar. Sci.* **2025**, *12*, 1609261. [\[CrossRef\]](#)
150. Chen, X.; Wu, S.; Shi, C.; Huang, Y.; Yang, Y.; Ke, R.; Zhao, J. Sensing Data Supported Traffic Flow Prediction via Denoising Schemes and ANN: A Comparison. *IEEE Sens. J.* **2020**, *20*, 14317–14328. [\[CrossRef\]](#)
151. Golovan, A.; Mateichyk, V.; Gritsuk, I.; Lavrov, A.; Smieszek, M.; Honcharuk, I.; Volska, O. Enhancing Information Exchange in Ship Maintenance through Digital Twins and IoT: A Comprehensive Framework. *Computers* **2024**, *13*, 261. [\[CrossRef\]](#)
152. Dudchenko, S.; Tymochko, O.; Makarchuk, D.; Golovan, A. Application of fuzzy cellular automata to optimize a vessel route considering the forecasted hydrometeorological conditions. *East. Eur. J. Enterp. Technol.* **2024**, *2*, 28–37. [\[CrossRef\]](#)
153. Holovan, A.; Gritsuk, I.; Verbovskiy, V.; Kalchenko, V.; Grytsuk, Y.; Verbovskiy, O.; Dotsenko, S.; Lysykh, A.; Symonenko, R.; Subochev, O. Algorithmic Support and Efficiency Analysis of Comprehensive Prescriptive Maintenance for Cargo Ships Using Predictive Monitoring. *East.-Eur. J. Enterp. Technol.* **2025**, *3*, 13–26. [\[CrossRef\]](#)
154. Golovan, A.; Gritsuk, I.; Honcharuk, I. Reliable Ship Emergency Power Source: A Monte Carlo Simulation Approach to Optimize Remaining Capacity Measurement Frequency for Lead-Acid Battery Maintenance. *SAE Int. J. Electrified Veh.* **2023**, *13*, 179–189. [\[CrossRef\]](#)
155. Gritsuk, I.; Golovan, A.; Honcharuk, I.; Mickiene, R. Navigating Toward a Greener Future: An Analysis of Emission Reduction in Shipping. In *Green Energy and Technology*; Springer Science and Business Media Deutschland GmbH: Berlin/Heidelberg, Germany, 2025; Volume Part F503, pp. 373–380, ISBN 18653529.
156. Qian, J.-K.; Mao, X.-F.; Wang, X.-Y.; Yun, Q.-Q. Ship Hull Automated Optimization of Minimum Resistance via CFD and RSM Technique. *Chuan Bo Li Xue/J. Ship Mech.* **2012**, *16*, 36–43.
157. Tahara, Y.; Tohyama, S.; Katsui, T. CFD-Based Multi-Objective Optimization Method for Ship Design. *Int. J. Numer. Methods Fluids* **2006**, *52*, 499–527. [\[CrossRef\]](#)

158. Agrusta, A.; Bruzzone, D.; Zotti, I. Multi-Objective Optimisation of a Semi-Planing Hull Using CFD RANSE Simulations with Low Number of Cells. In *Towards Green Marine Technology and Transport*; CRC Press: Boca Raton, FL, USA, 2015; pp. 83–90.
159. Ballou, P.; Chen, H.; Horner, J.D. Advanced Methods of Optimizing Ship Operations to Reduce Emissions Detrimental to Climate Change. In *Proceedings of the OCEANS 2008, Quebec City, QC, Canada, 15–18 September 2008*.

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