State-of-the-art machine learning applications for ship performance modeling: a comprehensive review from design and operation to

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State-of-the-art machine learning applications for ship performance modeling: a comprehensive review from design and operation to maintenance and retrofit

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HIGHLIGHTS

- A comprehensive review of machine learning methods for ship performance modeling.
- Lifecycle-based organization covering design, operation, maintenance and retrofit.
- Clarification of model categories and common terminologies.
- Discussion of research gaps and future directions for ship performance modeling.

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Design
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Maintenance
Retrofit

ABSTRACT

Accurate ship performance modeling, which characterizes the relationships among ship speed, engine power, fuel consumption, and emissions, under varying operational and environmental conditions. It is essential for analyzing and optimizing ship energy efficiency, and it plays a crucial role in supporting shipping decarbonization targets and ensuring compliance with International Maritime Organization (IMO) regulations. Most existing reviews focus mainly on the operational stage, while no comprehensive study has yet covered the entire ship lifecycle. However, data availability, modeling objectives, and method selection vary significantly across different stages, including design, operation, maintenance, and retrofit. This paper provides an overview of recent studies to summarize the current status, development trends, and progress of machine learning applications in ship performance modeling across various stages of the ship lifecycle. A structured review framework is proposed, categorizing the literature according to different lifecycle stages, design, operation, maintenance, and retrofit, and highlighting representative studies and methods. The review also clarifies commonly used terminologies and model classifications, and compares their principles, data requirements, and applicability. Finally, recent advances in machine learning techniques are discussed in relation to their applications and challenges at each stage, followed by insights and recommendations for future research and development.

1. Introduction

1.1. Background

Maritime shipping provides cost-efficient transportation services [151] and accounts for more than 80% of global trade volume [166]. At the same time, it represents the largest energy-consuming mode within the transportation sector [293]. The resulting maritime fuel consumption inevitably leads to substantial greenhouse gas (GHG) emissions, accounting for approximately 2.89% of global anthropogenic emissions [82]. Shipping related GHG emissions, particularly CO_2 and NO_x, contribute substantially to global warming and its associated environmental impacts, including glacier retreat, sea level rise,

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ocean acidification, and disruptions to both marine and terrestrial ecosystems. In addition, sulfur oxide (SO_x) emissions, especially SO_2 from ship exhaust, can react with atmospheric moisture to form acid rain, degrading soil and water quality, and posing serious respiratory and cardiovascular health problems, particularly for populations in coastal regions [182]. A joint report by the Global Maritime Forum, Boston Consulting Group, and the World Economic Forum estimates that shipping emissions generate annual external costs of USD 250–300 billion, covering health, environmental, and climate impacts that are largely borne by society rather than internalized by the industry. In response, the International Maritime Organization (IMO) has progressively introduced mandatory energy-efficiency measures, including the Energy Efficiency Design Index (EEDI), the Energy Efficiency Existing Ship Index (EEXI), and the Carbon Intensity Indicator (CII) [163,257,297].

A single ocean-going ship may consume several thousand tons of fuel during a voyage, with fuel costs often exceeding 60% of total operational costs [259]. Even a modest 1% improvement in energy efficiency can generate substantial economic benefits, allowing shipping companies operating multiple ships to achieve considerable annual savings [86]. Consequently, the advancement of energy-efficiency optimization technologies is not only critical for complying with increasingly strict emission regulations but also essential for enhancing the profitability and competitiveness of the shipping industry [181].

The ship's propulsion system encompasses the entire process of energy generation, transmission, conversion, and consumption, involving the coordination of multiple onboard components and their interaction with the surrounding navigation environment [80]. In particular, the main engine generates power by burning fuel, which is then transmitted through the shaft and converted by the propeller to overcome external resistance, thereby driving the ship forward [186]. Ship energy consumption varies under different influences, primarily operational conditions and met-ocean factors, both of which directly affect the efficiency of the propulsion system [218]. Accordingly, reliable ship performance modeling, which captures the relationships among ship speed, required engine power or energy consumption, and emissions across varying operational profiles and met-ocean conditions, is fundamental to energy efficiency optimization and a wide range of downstream applications [23].

1.2. Motivation and outline

According to established methodologies and principles, the relevant ship performance models can be broadly classified into white-box models (WBMs) [67], black-box models (BBMs) [329], and gray-box models (GBMs) [225]. In a conventional regression framework, the available dataset $\mathcal{D}_n := \{(\boldsymbol{x}_i, y_i)\}_{i=1}^n$ comprises multiple sample tuples $(\boldsymbol{x}_i, y_i)$, where each element of the vector $\boldsymbol{x}$ is referred to as an input feature for estimating the energy consumption output y [235]. When inferring a digital model from the real-world system, the primary effort involves providing an approximation $\mathfrak{M}$: $\boldsymbol{x} \to y$ of the unknown true energy consumption model $\mathfrak{S}$: $\boldsymbol{x} \to y$. The model $\mathfrak{S}$ can be viewed, from a probabilistic perspective, as a conditional probability $\mathbb{P}(y|\boldsymbol{x})$, which represents the probability of the output y given that $\boldsymbol{x}$ is observed as an input [46]. In this case, the model $\mathfrak{M}_{\mathrm{WBM}}$ is constructed based on deterministic physical mechanisms or engineering laws from $\mathfrak{S}$, such as the engine power curves, propeller characteristics, energy transfer coefficients, and hydrodynamic effects of irregular wind and waves, among others. On the other hand, $\mathfrak{M}_{\mathrm{BBM}}$ is trained on a series of historical observations from $\mathfrak{S}$, i.e., $\mathcal{D}_n$, which are typically extracted and fused from automatic identification system (AIS) or other sensor records, noon reports, full-scale sailing measurements, and met-ocean data. To leverage their complementary advantages, the WBM and BBM are combined to build a $\mathfrak{M}_{\mathrm{GBM}}$, which incorporates both prior information and statistical inference.

As a prominent topic in maritime research with significant practical implications and aligned with downstream needs, numerous innovations [329] and reviews [68] on ship performance modeling have emerged in recent years. The recent emergence and advancement of machine learning (ML) methods have revolutionized traditional modeling paradigms that rely heavily on physical laws and engineering principles, offering a new data-driven perspective. However, the systematic analysis primarily focuses on modeling principles and relevant parameters, while overlooking the differences between various application scenarios. To bridge the research gap, this work provides a comprehensive review of the current progress in ML-based ship performance models, offering the guidance on selecting appropriate methods for practical applications. More specifically, in addition to models for daily operations discussed in existing review papers, efforts are made to generalize and summarize performance models for the initial design and subsequent retrofit phases. In these application scenarios, access to historical records from actual voyages may be limited if the ship is not in service, and additional consideration should be given to the characteristics of other energy-efficient equipment, such as the driving force of wings in wing-diesel engine-powered hybrid ships [225]. Although existing research includes relevant attributes of the target ship type in model surveys, it does not analyze the underlying principles that explain the differences [288].

The remainder of this paper is organized as follows. Section 2 introduces the systematic literature review, including the scope, search strategy, publication trends, and terminology. Section 3 presents the ML application in ship design, introducing hull parameterization, dimensionality reduction, supervised ML, and reinforcement learning. Section 4 addresses ship operation, including feature engineering, BBMs and GBMs for operation. Section 5 presents ship maintenance and retrofit, with dedicated subsections on anti-biofouling performance models and retrofit modeling. Section 6 provides a discussion of current challenges and outlines future research trends. Finally, Section 7 concludes the paper.

2. Systematic literature review

2.1. Scope and literature scan approach of this review

To support the intelligent and sustainable development of the shipping industry, this paper reviews the applications of ML-based performance models within this field. The research scope focuses on four key aspects that are particularly relevant throughout the entire lifecycle of a ship: design, operation, maintenance, and retrofit. This review aims to demonstrate how ML techniques can be integrated as evaluators or predictors of ship-specific performance across various stages, to meet essential navigational requirements or achieve desired levels of profitability and sustainability, thereby offering valuable references for both academia and industry.

The literature scan for this study was conducted based on the Web of Science Core Collection database, where the search conditions were defined by topic terms including "ship", "ship", "performance model", "design", "operation", "maintenance", and "retrofit", with logical operators such as "AND", "OR", and "NOT" applied to refine the search parameters. Furthermore, to highlight the transition in ship performance modeling, from principle-driven physical models to data-driven ML algorithms, the publication period was set from 2010 to 2025, despite the relatively limited number of early studies on ML and AI. More specifically, Table 1 provides a brief summary of the search conditions and corresponding results. Evidently, as the longest stage in a ship's lifecycle, operation has garnered the most extensive research attention in the field

Table 1
Literature search conditions and results: (1) ship design; (2) ship operation; (3) ship maintenance and retrofit.

Conditions	Results
Database	Web of Science Core Collection
Language	English
Paper type	Article; Proceeding paper; Review article; Early access
Time range	January 2010–Jun 2025
Query	• (1): TS = (ship OR ship) AND TS = (design) AND TS = (performance model) NOT TS = (operation) NOT TS = (maintenance) NOT TS = (retrofit) AND PY = (2010–2025) • (2): TS = (ship OR ship) AND TS = (operation) AND TS = (performance model) NOT TS = (design) NOT TS = (maintenance) NOT TS = (retrofit) AND PY = (2010–2025) • (3): TS = (ship OR ship) AND TS = (maintenance OR retrofit) AND TS = (performance model) NOT TS = (design) NOT TS = (operation) AND PY = (2010–2025)
Number of papers	• (1): Total: 474 Last 5 years: 208 • (2): Total: 1351 Last 5 years: 696 • (3): Total: 164 Last 5 years: 90

of performance modeling. In contrast, ship retrofit, particularly aimed at energy conservation and emission reduction, has only recently begun to receive increasing attention as part of efforts to achieve sustainable development in the shipping industry.

2.2. Publication trends from 2010 to 2025

Based on the relevant papers collected in Section 2.1, representative terms were extracted using CiteSpace (v.6.3.R1, 64-bit), which applies natural language processing techniques to analyze paper titles, abstracts, and keywords. Three keyword co-occurrence maps are presented in Fig. 1, with high-frequency keywords related to applications and technologies respectively shown on the left and right sides of each subgraph. All figures presented in this study are processed or integrated using Microsoft Visio 2019 Professional for visualization purposes only, aiming to improve clarity and readability, without altering any underlying results. Certain subgraphs are obtained from publicly available online sources, with attribution explicitly provided via footnotes, while those inspired by specific studies have been properly cited to ensure academic transparency. Among them, “prediction” and “validation” represent the direct functions of ship performance models, whereas “optimization” and “management” are considered downstream tasks aimed at effectively translating advanced technologies into practical benefits. Meanwhile, distinct application stages exhibit identifiable differences in the focus and priorities of ship performance modeling. For example, in the initial design stage, the core task typically involves designing and optimizing the “hull” and “propeller” to achieve optimal “hydrodynamic performance”. In contrast, for a ship in service, performance models are primarily used to predict “fuel consumption”, “energy efficiency”, or “emissions” during operation, aiding in the assessment of profitability or sustainability and informing subsequent maintenance or retrofit plans. Furthermore, Fig. 1(c) illustrates, to a certain extent, the strategies and directions that have attracted extensive attention during the ship maintenance and retrofit, such as “condition based maintenance”, “alternative fuel”, and “wind-assisted ship propulsion”.

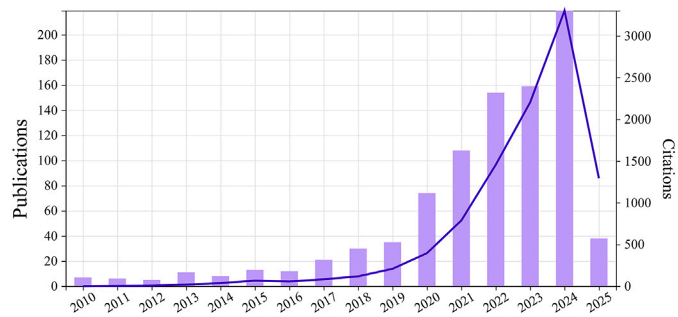


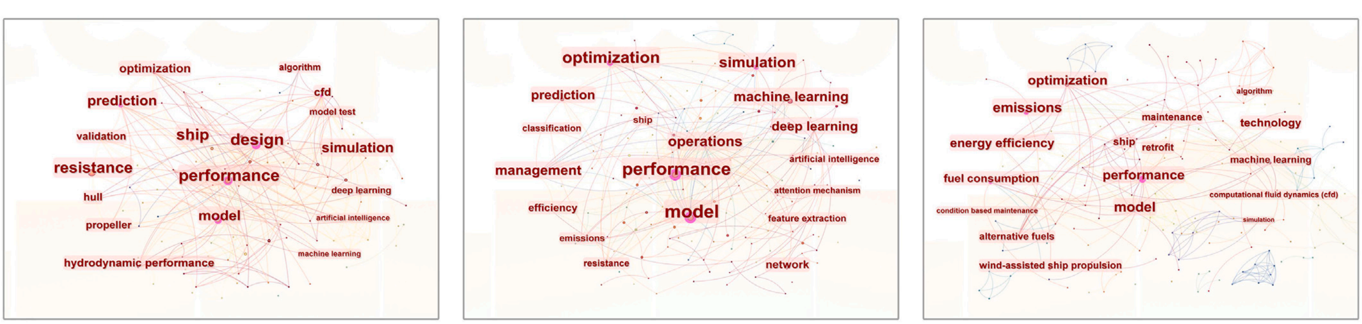
Fig. 2. Number of published papers and citations related to ML-based ship performance models from January 2010 to June 2025.

In early research on ship performance modeling, physical methods, such as empirical formulas, model tests, and numerical simulations, were primarily employed. In recent years, the advancement of high-performance computing and the maturation of AI technologies have accelerated the digitalization of the shipping industry. Furthermore, driven by the advocacy of the IMO and national agencies for enhanced ship navigation data recording, a large volume of shipborne sensor data has been transmitted and collected. As a result, an acceptable alternative has emerged in which actual data is utilized to predict relevant ship performance metrics, reducing the reliance on complex physical theories or engineering laws inherent in principle-driven models. By identifying terms such as “machine learning”, “data-driven” and “artificial intelligence” from the collected papers, Fig. 2 illustrates the annual trend of ML-based performance models in the shipping industry.

Since 2020, a notable surge has occurred in both the number of publications and their citations, underscoring the accelerated development of this field, accompanied by markedly heightened interest and engagement from both researchers and practitioners.

2.3. Terminologies

Before delving into ship performance modeling at each stage, this section first provides brief definitions of terminologies, to clarify the



(a) Ship design (b) Ship operation (c) Ship maintenance and retrofit

Fig. 1. Keyword co-occurrence maps of ship performance model applications across the entire lifecycle.

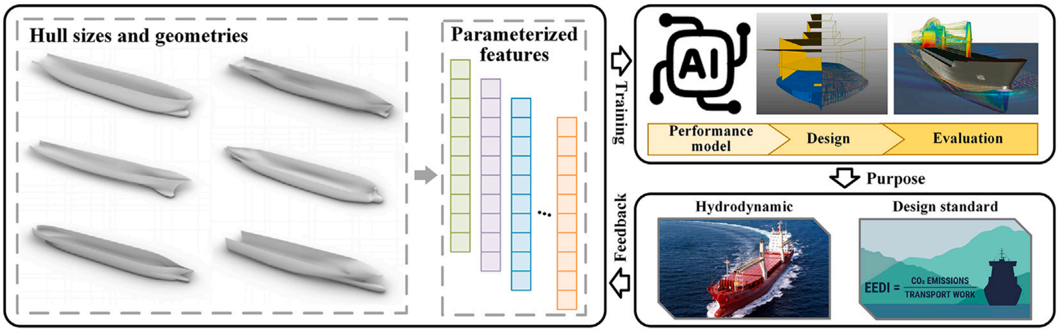


Fig. 3. Overview of ship performance modeling in the design stage. Note: Some illustrative subgraphs are sourced from the Internet and do not convey any analytical results.

core scientific issues that this review focuses on. The performance of a ship during real ocean sailing is influenced by multiple factors, primarily including the ship's design parameters, loading conditions, propulsion system's working status, and external met-ocean disturbances. To accurately assess and predict ship-specific navigation performance, the industry typically relies on advanced numerical models, commonly referred to as ship performance models.

For traditional physics-based methods, ship performance modeling typically follows a multi-stage, continuous computational process structured as: "hydrodynamic performance (resistance) – speed (or speed loss) – energy consumption – emissions". Owing to their greater flexibility, the data-driven approaches can directly model specific performance indicators by utilizing relevant input variables, thereby eliminating the need for complex sequential calculations.

Taken together, the four specific aspects mentioned above delineate the principal research problems addressed in this review of ML-based ship performance modeling, explicitly excluding model-free unsupervised techniques, such as anomaly detection.

3. Ship design

3.1. Basic description

As the initial stage of their lifecycle, the design of ships has long been a primary focus in the shipping industry. Historically, ship design and construction were largely empirical processes, with naval architects relying on accumulated knowledge and employing scaled models or simplified physical experiments to optimize hull forms. Although early approaches were labor-intensive and primitive, they laid the foundation for modern naval architecture and contributed to the centuries-long prosperity of maritime transport [27]. The rise of computational fluid dynamics (CFD) in the late 20th century marked a significant advancement, enabling the simulation of hydrodynamic performance and offering detailed insights into fluid-structure interactions that had previously been beyond reach [116].

However, traditional ship design, characterized by reliance on high-fidelity CFD techniques requiring extensive computational resources, is increasingly regarded as insufficient to meet the rising demands for efficiency, sustainability, and cost-effectiveness in the modern shipping industry [264]. Recent advancements in ML for engineering design have demonstrated the ability to generate novel and reliable designs, as well as high-performing system-level solutions, with significantly reduced design cycles [36,189]. Hence, ship design can substantially benefit from these advancements.

In naval architecture, ML-based hull form design constitutes a fundamental task to minimize resistance or energy consumption, leveraging advanced data-driven techniques to evaluate and optimize the hydrodynamic performance across diverse hull sizes and geometries [109], as shown in Fig. 3. Within this context, both supervised learning and reinforcement learning (RL) have found extensive applications.

3.2. Data preparation

3.2.1. Acquisition

Compared with other lifecycle stages, ML-based ship design is often more strongly constrained by limited and insufficiently representative data, as actual sailing measurements are unavailable prior to the ship's in-service period. Regression-based approaches for estimating the hydrodynamic characteristics of new ships (e.g., calm-water resistance) therefore typically rely on datasets derived from existing hull forms. For example, Winter and Stein [304] developed an ML model trained on 1219 container ships using principal design variables such as length between perpendiculars, overall breadth, and block coefficient, whereas Yu and Wang [321] employed a substantially larger dataset comprising over 20,000 samples.

Public datasets widely used in engineering design, such as ShapeNet[1] and the UIUC airfoil coordinates database[2], offer thousands of diverse cases. By contrast, comparably comprehensive and publicly accessible datasets for ship hull design remain limited. For example, Bagazinski and Ahmed [15] introduced SHIP-D[3], a large-scale dataset comprising 30,000 ship hulls, including parameterized geometries, meshes, point clouds, image representations, and 32 hydrodynamic coefficients across varying operating conditions. Wider availability of high-quality hull-form datasets within the research community would substantially accelerate the advancement of data-driven ship design.

3.2.2. Preprocessing

(1) Hull parameterization

Hull parameterization is a fundamental step in ship hull design, playing a key role in optimizing and refining ship hydrodynamic performance. The core concept involves representing hull geometry through a set of design variables, allowing systematic exploration and efficient adjustment of diverse design configurations to meet various operational requirements. Moreover, accurate hull parameterization facilitates the integration of ML algorithms that depend on precise and well-defined input features.

Among various representations for complex designs, such as graphs [99], images [152], vectors [71], and free form deformation techniques [50], vectored parameterization stands out as the most common method. It offers sufficient flexibility to capture. Analyses by Khan et al. [125] and Wang et al. [300] showed that 26 and 32 parameters, respectively,

1 https://shapenet.org
2 https://m-selig.ae.illinois.edu/ads/coorddatabase.html
3 https://github.com/noahbagz

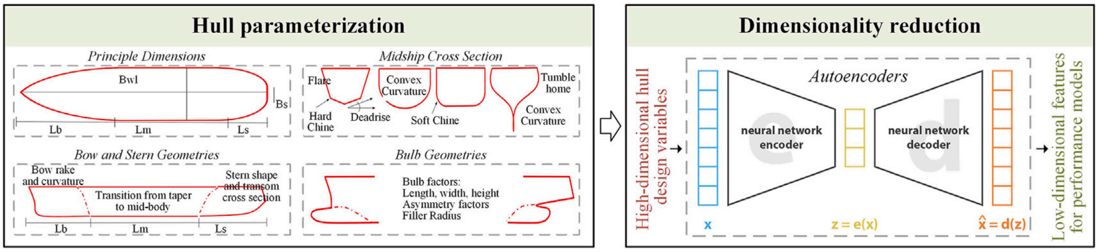


Fig. 4. Hull parameterization [15] and dimensionality reduction for performance modeling in ship design.

Table 2
Frequently-used dimensionality reduction techniques for performance modeling in ship design.

Category	Method/reference	Advantages	Disadvantages
Linearity	PCA Zhang et al. [334]	Maximal variance retention; Orthogonal component transformation; Computational efficiency	Linear assumption limitation; Sensitivity to feature scaling; Interpretability loss
	KLE D'Agostino et al. [57]	Optimal MSE representation; Uncorrelated component decomposition; Continuous/discrete process applicability	Covariance matrix dependence; High computational complexity; Gaussian process limitation
Nonlinearity	t-SNE Thakur et al. [260]	Preserves local structure; Effective for visualization; Handles non-linearities	Computationally expensive; Non-convex optimization; No out-of-sample extension
	AE Seo et al. [233]	Flexible architecture; Unsupervised feature learning; Scalable to high-dimensional data	Risk of trivial identity mapping; No inherent probabilistic framework; Latent space lacks interpretability
	VAE Wang et al. [300]	Probabilistic latent space; Generative capability; Regularized latent structure	Approximate posterior; Blurry reconstructions; Training instability

are sufficient to reconstruct complex hull surface features with reasonable accuracy. Moreover, the SHIP-D dataset, which consists of 30,000 ship hulls for design optimization, employs a 45-dimensional parameterization to represent a diverse range of hull forms, as shown in Fig. 4. Among them, seven terms describe the main principal dimensions, four terms define the midship cross section, twenty terms characterize the geometry of the bow and stern, and fourteen terms represent the bulb geometries, with a more detailed introduction available in the study by Bagazinski and Ahmed [15].

(2) Dimensionality reduction

The learning process of ML-based models can be hindered by high-dimensional design spaces derived from the baseline/parent hull parameterization, often resulting in the well-known curse of dimensionality [37]. A common solution is dimensionality reduction via feature extraction [1], as illustrated in Table 2. It extracts latent features from the design space to form a new set of parameters for hull shape modification, enabling faster convergence in optimization with fewer computationally intensive evaluations [126]. Specifically, principal component analysis (PCA) is a classical method that reduces dimensionality by identifying feature correlations and projecting the data onto a lower-dimensional space [335]. As a variant of PCA for continuous stochastic processes, the Karhunen-Loève Expansion (KLE) enables low-dimensional representations of high-dimensional random fields while minimizing information loss [172]. To address non-linearities in the design space, t-distributed stochastic neighbor embedding (t-SNE), and the non-linear extensions of PCA (such as kernel PCA and local PCA) have been introduced into ship design applications [56]. In addition, widely used deep learning solutions include autoencoder (AE) [233], featuring an encoder network with progressively decreasing layer sizes to extract essential features (as illustrated in Fig. 4), and variational autoencoder (VAE), which incorporates a probabilistic latent space for more expressive representations [300]. Table 2 presents the detailed comparison of the frequently-used dimensionality reduction methods in the ship design stage.

Furthermore, several advanced feature extraction techniques, although widely successful in other fields, remain largely unexplored in the ship design stage. For example, singular value decomposition (SVD), nonnegative matrix factorization (NMF), linear discriminant analysis (LDA), and local Fisher discriminant analysis (LFDA) are classified as linear methods, with the first two sharing matrix factorization principles similar to PCA. In contrast, manifold-based nonlinear techniques, including isometric feature mapping (Isomap), locally linear embedding (LLE), and uniform manifold approximation and projection (UMAP), preserve the underlying geometry of the data and the relationships among samples, enabling compact representations in lower-dimensional spaces. For more in-depth exploration, the following representative review studies provide a more comprehensive overview: Ayesha et al. [14], Anowar et al. [10], Fathi Hafshejani and Moaberfard [70], and Saberi-Movahed et al. [226].

3.3. *Supervised ML in ship design*

Generally, naval architects can perform regression analyses to predict the hydrodynamic performance of new ship designs based on existing hull forms, by utilizing supervised ML to approximate the mapping between sampled input-output pairs [145]. One of the earliest applications in this context can be traced to the empirical algorithms developed by Holtrop and Mennen [102], which utilize statistical methods to approximate ship calm water resistance based on data collected from extensive towing tank model tests. The rapid advancement of artificial intelligence (AI), coupled with the availability of high-performance computing, has significantly simplified the traditionally time-consuming ship design process, extending the applicability of regression models beyond the initial design stage [107]. In recent studies on ML applications in ship design, neural networks have emerged as the dominant framework, followed by other intelligent algorithms, as illustrated in Fig. 5, with detailed descriptions provided in Sections 3.3.1 and 3.3.2.

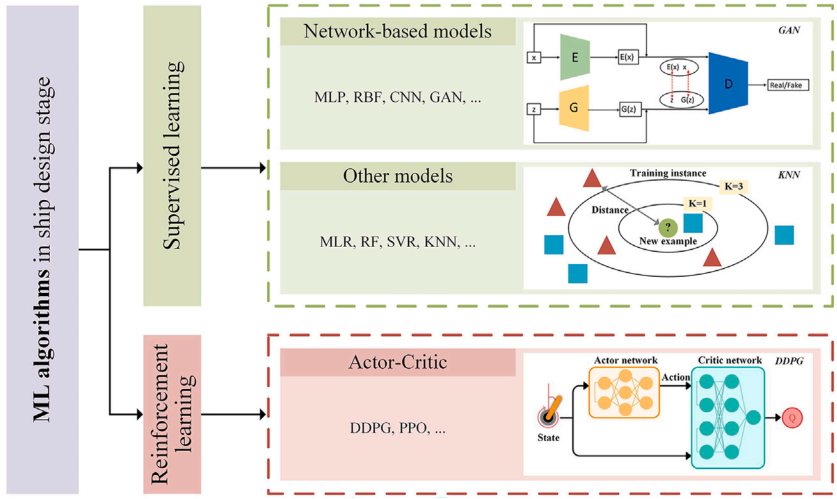


Fig. 5. General classification of ML-based methods for ship performance modeling in hull design.

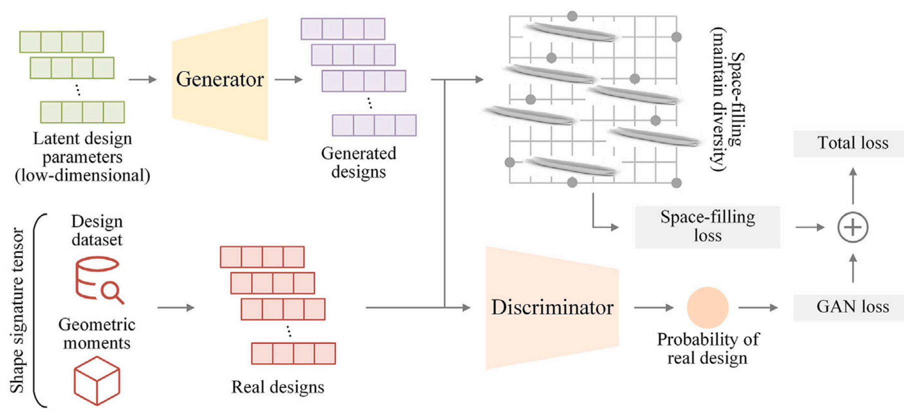


Fig. 6. An example of a ship hull design based on GAN [124].

3.3.1. *Network-based models*

With their powerful nonlinear fitting capabilities, ANNs have revolutionized the ship design process and emerged as the most widely adopted method [6,12]. Trained on hydrodynamic evaluations of a wide range of hull forms, deep neural networks (DNNs) can effectively capture the relationship between hull geometries and their corresponding performance characteristics [11,35,217]. Building on this foundation, a novel ML application in ship design and optimization is realized through the development of an extensive hull form database [15], enabling rapid retrieval via efficient search mechanisms. Furthermore, ANNs can effectively model nonlinear hydrodynamic phenomena in propeller design [253,308], a highly sophisticated task that involves evaluating numerous design variants. Employing a radial basis function (RBF) as activation functions, RBF networks [234,331] typically achieve faster training speeds than traditional multi-layer perceptrons (MLPs) [131,333]. For the complex hull form data, the CNN is capable of extracting features out of data that are structured in space, enhancing training accuracy. For complex hull form data, convolutional neural networks (CNNs) are capable of extracting spatially structured features through convolution calculations, thereby enhancing training accuracy [2,129,237]. In the study by Khan et al. [124], ShipHullGAN, a generic parametric modeler built using deep convolutional generative adversarial networks (GANs), is introduced for the versatile representation and generation of ship hulls, with a rough illustration shown in Fig. 6. Similarly, the validity of other generative networks, such as the diffusion probabilistic model (DPM) [16] and VAEs [100], has also been demonstrated in the ship design stage, gradually supplanting traditional methods like the Gaussian mixture model (GMM) [52]. Table 3 summarizes the widely-used network-based methods in ship design.

3.3.2. *Other models*

In addition to neural networks, other ML algorithms have also found broad application in the ship design stage. First, classical statistical regression methods with lightweight structures, such as multiple linear regression (MLR) [316] and Gaussian process regression (GPR) [108], can serve as efficient surrogates for computationally expensive high-fidelity CFD simulations in hull form design. In the study by Walker et al. [281], ensemble learning methods, such as random forest (RF) and extreme gradient boosting (XGBoost), are shown to be effectively trained on experimental hydrodynamic datasets, enabling accurate prediction and optimization of hull geometries with enhanced adaptability. Furthermore, support vector regression (SVR) has also been widely utilized in the evaluation of resistance during the ship design phase [62,196,202].

3.3.3. *Summary*

As a primary branch of ML, supervised learning has been extensively applied in the ship design stage, giving rise to numerous high-quality methods. Compared to high-fidelity CFD, supervised ML algorithms offer significantly higher computational efficiency, although network-based models may still involve relatively long training times and complex parameter tuning processes. However, the high dimensionality of hull

Table 3
Frequently-used network-based models for ship performance modeling in hull design, with case-specific accuracy evaluated by R^2 ("N/A": not reported).

Model	Details	Reference	Case ship	Target performance	R^2
MLP	• $Z_l = W_l A_{l-1} + b_l,\ \ A_l = \sigma(Z_l)$, • $\delta_l = (W_{l+1}^T \delta_{l+1}) \odot \sigma'(Z_l)$, where A: forward signal; δ: backward gradient; σ: activation function; W: weight matrix; b: bias vector.	Wei et al. [303]	Destroyer	Resistance	0.88
		Kim et al. [130]	Small ship	Resistance	0.76
		Ao et al. [13]	Container ship	Resistance	N/A
CNN	• $O(i,j) = \sum_m \sum_n I(i+m, j+n) \cdot K(m,n) + b$, where O: output features after convolution; I: input features; K: convolution kernel; b: bias vector. m, n: Scale of convolution kernel.	Yu et al. [322]	Aframax tanker	Resistance	N/A
		Shen et al. [236]	Destroyer	Resistance	N/A
		Seo et al. [233]	LNG carrier	Stress distribution	0.99
GAN	• $\min_G \max_D V(D,G) = \mathbb{E}_{x\sim p_t(x)}[\log D(x)] + \mathbb{E}_{z\sim p_z(z)}[\log(1 - D(G(z)))]$, where $p_t(x)$: true data distribution; $p_z(z)$: noise distribution, e.g., $z \sim \mathcal{N}(0,1)$; G: generator; D: discriminator.	Trinh et al. [268]	Crude oil carrier	Form factor	N/A
		Sun et al. [247]	Crude oil carrier	Stress distribution	0.99
		Sun and Chen [246]	Bulk carrier	Stress distribution	0.99

design variables may hinder effective pattern learning and increase the risk of overfitting. Compared with other stages, the use of ML in ship design is still at an early phase, and many advanced models have yet to be validated in practical applications. Although newly generated hull designs may demonstrate strong theoretical advantages, such as improved hydrodynamic performance, they still require comprehensive numerical analysis or model testing to confirm practical feasibility. Furthermore, due to the inherent limitations in the interpretability of ML models, stakeholders still have not fully embraced their use in handling the primary decision-making processes in shipbuilding tasks, which are time consuming and cost intensive.

3.4. RL in ship design

The design optimization of ship hull forms based on ML technologies and hydrodynamic theory typically focuses on reducing resistance and enhancing energy efficiency, serving as a critical component in the intelligent design and manufacturing of green ships [343]. Generally, the design schemes produced by the models discussed in Section 3.3 still require further processing through traditional optimization algorithms, such as genetic algorithm (GA) [241] and particle swarm optimization (PSO) [314], to identify the optimal design that satisfies predefined objectives and constraints. As a distinctive application of DNNs, deep reinforcement learning (DRL) features inherent decision-making capabilities and has emerged as an optimization agent integrated into the fields of ship control [51]. DRL has been recognized as a promising solution for problems involving high-dimensional variables or strong nonlinearity, where traditional algorithms often struggle to find global optima [78], making it a promising approach for application in ship design.

3.4.1. Actor-critic models

Ship hull design and optimization involve numerous continuous design variables, whereas value-based DRL methods, such as deep Q-network (DQN) [153], require a discretized action space, leading to a combinatorial explosion. Besides, in high-dimensional spaces, DQN must maintain huge Q-tables or networks, resulting in low exploration efficiency and a tendency to fall into local optima.

As a strategy capable of achieving long-term optimization in ship design, such as multi-step hull form adjustments, the Actor-critic framework effectively mitigates the overestimation bias inherent in value-based methods. In the study by Oh et al. [205], two DRL algorithms, proximal policy optimization (PPO) and deep deterministic policy gradient (DDPG), which are improved versions of the Actor-critic architecture, are creatively applied to ship hull design, as shown in Fig. 7. The results, compared with GA and PSO, show that the optimal hull resistance values are similar, but the DRL model required five times less time. Similarly, the effectiveness of DDPG is verified in the design of submarine hull forms, with the objective of maximizing stealth performance [318]. The optimization process incorporates functional constraints for the examined hull forms, including geometric constraints related to the hull form and dynamic stability constraints concerning hydrodynamic maneuvering characteristics.

3.4.2. Summary

DRL offers a novel, high-performance paradigm for automated ship design, a task that was traditionally accomplished by integrating supervised ML models and multi-objective optimization algorithms. However, practical implementation challenges persist. To be specific, DRL necessitates a considerable amount of interactive data, which poses difficulties for its direct application in industrial design. Additionally, the trained DRL strategy may only be applicable to specific ship types or working conditions, necessitating retraining when the ship type changes. In terms of potential enhancement strategies, transfer learning can accelerate the learning process, by equipping DRL agents with parameters derived from neural networks pre-trained on ideal hull forms. With the development of efficient DRL algorithms through physics-informed hybrid modeling, the issue of generating hull shapes that violate physical principles and rely on post-processing corrections will be alleviated to some extent, making the transition from laboratory-based research to industrial applications more feasible.

3.5. Digital technology in ship manufacture

As a continuation of ship design, this section provides a brief overview of ship manufacturing, highlighting the application of AI-enabled technologies, though it falls outside the main scope of performance modeling.

With the ongoing digitalization and intelligent transformation of shipbuilding, traditional labor-intensive manufacturing practices have undergone substantial change [159]. Ship construction comprises multiple steps, each requiring specialized processing techniques for steel plates and involving diverse materials, components, tools, and equipment. By integrating big data, the Internet of Things, cloud computing, artificial intelligence, and cyber-physical systems, digital workshops enable efficient data exchange across facilities, ensuring timely resource allocation and reducing the risk of production delays [332]. Meanwhile, given the large scale and operational complexity of shipbuilding, safety risks remain an important concern. Intelligent positioning systems support rapid incident reporting, precise location tracking, and efficient personnel evacuation [294].

Furthermore, intelligent ship manufacturing increasingly employs enabling technologies, such as digital twins and augmented reality (AR), to support production activities within the Industry 4.0 framework [42].

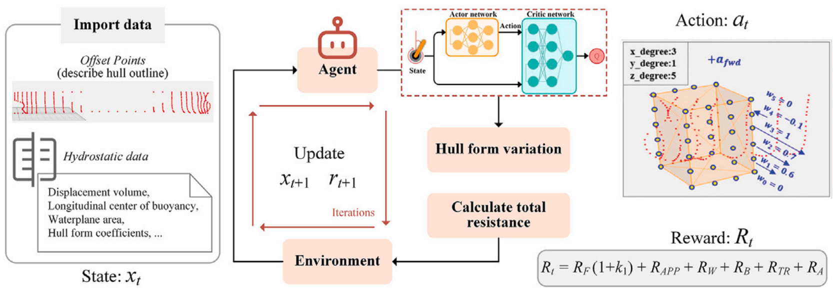


Fig. 7. An example of ship hull design based on DDPG [205].

Digital twins facilitate real-time monitoring and virtual testing, enabling the identification of potential issues prior to production, thereby reducing errors and improving operational efficiency [138]. By overlaying digital information onto physical environments, AR tools enable workers to interact with 3D models, receive immediate feedback, and access detailed instructions within their field of view, supporting the execution and coordination of complex shipbuilding tasks [230,344]. The integration of AR into training programs, often hands-on and requiring familiarity with complex structures, can shorten learning curves, lower training costs, and enhance workplace safety [251,278]. A review of the literature indicates that handheld tablets are the most commonly used AR devices, followed by head-mounted displays [252]. An interactive AR application, ShipAR[4], developed using Unity alongside the XR Interaction Toolkit, AR Foundation, and ARCore, is publicly available as a teaching platform. It features seven representative 3D ship models, Cruise, Rescue, Ro-Ro, Passenger Catamaran, Offshore, Tanker, and Naval ships, each accompanied by concise annotations and corresponding 2D sectional drawings.

3.6. Methodological applicability across design tasks

Sections 3.3 and 3.4 summarize existing ML-based performance models used in data-driven ship design and examine their methodological characteristics. Building on this foundation, this section synthesizes the applicability of major method categories to representative design tasks, providing practical guidance for model selection. The following discussion is grounded in empirical evidence reported in the literature. Given the case sensitivity of data-driven models, preliminary experimentation remains essential for identifying the most suitable approach.

Within the ship design stage, generative models such as GANs constitute one of the most prominent learning frameworks, due to their ability to learn underlying data distributions and generate synthetic samples without explicit labeling. This capability enables moving beyond the inherent conservatism of traditional parametric design approaches, which are often constrained to predefined ship types and design spaces. Accordingly, GAN models are particularly suitable for exploratory design tasks requiring substantial innovation beyond existing ship types. These demands are increasingly driven by regulatory shifts (e.g., IMO emission-reduction targets) and emerging Industry 4.0 technologies, including alternative fuels and autonomous ships [120].

For more conventional design tasks, such as predicting hydrodynamic characteristics from existing hull forms, relatively simple architectures (e.g., MLPs) often provide sufficient predictive capability without requiring excessively large datasets. At this stage, design and optimization are closely integrated. When ML-based performance models are coupled with heuristic optimization algorithms, ensemble approaches such as bagging-based RF can offer a practical balance between computational efficiency and predictive robustness.

[4] https://shorturl.at/KfQnv

Despite recent progress in data-driven ship design, the field has not yet matured to a stage where fully standalone practical deployment is feasible. Experience-based judgment or physics-based simulation therefore remains essential for validation, particularly for GAN-based BBMs that may generate hull forms deviating substantially from established ship types.

4. Ship operation

4.1. Basic description

In maritime operations, ship performance modeling plays a critical role in assessing voyage costs and associated emissions. A key challenge at this lifecycle stage is the accurate estimation of ship-specific operational performance, particularly energy consumption. These estimates support optimization strategies for sailing plans and fleet management, thereby enhancing operational efficiency and facilitating emission reduction [86]. Modeling becomes more challenging under the real-world ocean environments, and the complex operating conditions of onboard propulsion systems, as illustrated in Fig. 8.

Unlike physics-based methods [140], data-driven models during ship operations do not adhere to a fixed configuration of influencing factors within a predefined sequential calculation process. Nevertheless, given the available dataset, a well-considered arrangement of input features is essential for achieving an optimal balance between the accuracy and applicability of the model. For instance, real-time monitoring data of the main engine undoubtedly enhances the estimation accuracy, but it also imposes higher demands on the data acquisition and transmission capabilities of the sensors in practical applications [338].

As the most prevalent application, ML-based ship performance modeling in operations leverages abundant prior knowledge and historical data to support flexible implementation via purely data-driven BBMs and physics-informed hybrid GBMs. During this application phase, users can make relatively independent decisions by relying on the information at hand, such as detailed parameters of actual ship systems or extensive datasets encompassing diverse operational and hydro-meteorological conditions. Furthermore, the integration of various external factors, such as policies, fuel prices, and shipping schedules, enhances the realism of the model, enabling it to better capture the complexities of real-world maritime operations and improve its applicability to practical decision-making [147,161,339].

4.2. Data preparation

4.2.1. Acquisition

For ship performance modeling during the operational stage, input features are typically categorized into two groups: ship operational variables and external environmental variables [291,309]. More specifically, commonly used input features, illustrated here through energy consumption modeling, are summarized in Table 4, with their selection determined by data availability and model requirements.

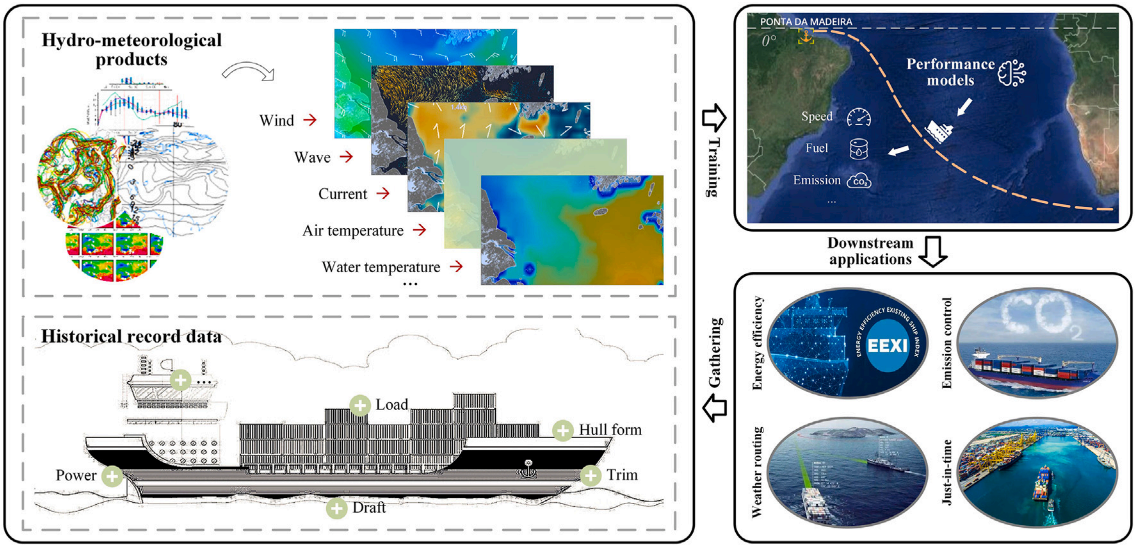


Fig. 8. Overview of ship performance modeling in the operational stage. Note: Some illustrative subgraphs are sourced from the Internet and do not convey any analytical results.

Table 4
Mainstream input features for ship energy consumption modeling in daily operation, with the ratio derived from 80 relevant studies [5,40,93,165,198,307,311].

Category	Feature	Ratio	Zhang et al. 2024b	Ruan et al. 2024	Fan et al. 2024a	Cai et al. 2024	Han et al. 2024a	Kim and Roh 2024	Shu et al. 2024	Yan et al. 2024	Wang et al. 2023a	Agand et al. 2023	Chen et al. 2023	Xie et al. 2023	Nguyen et al. 2023	Ma et al. 2023	Wang et al. 2023b	Li and Li 2023
Operation	Sailing speed	83%	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■	■
	Draft	40%	■	■		■		■	■	■				■				
	Engine power	33%		■	■		■						■				■	
	Trim	28%	■				■	■						■	■		■	
	Engine RPM	25%			■			■				■						
	Displacement	24%	■	■			■								■			
	Heading	21%	■			■						■				■	■	■
	Rudder angle	9%						■								■		■
Met-ocean	Wind	75%	■	■	■	■	■	■		■	■	■	■	■	■	■	■	■
	Wave	46%	■			■	■	■		■			■	■	■		■	
	Current	36%	■	■		■		■	■			■			■			■
	Swell	10%					■	■										
	Water temperature	10%					■	■					■		■			
	Depth	9%			■										■			
	Air temperature	5%	■					■										
	Air pressure	3%						■										

For ML applications targeting in-service ships, model training can utilize operational data extracted from noon reports [209], sailing logs [187], and onboard sensor records [17], often complemented by hydro-meteorological observations [288], forecasts [178], and reanalysis datasets [146] provided by meteorological agencies. For newly commissioned ships, limited historical data may hinder reliable model training, making data from sister ships a practical alternative [88]. However, large-scale ship navigation datasets remain largely inaccessible to the public due to their commercial sensitivity (owned by shipping companies). Consequently, smaller well-structured datasets released by research institutions [213] serve as valuable resources for methodological validation and exploratory research. Regarding met-ocean conditions, data products are typically obtained from meteorological agencies or commercial providers, with ERA5[5] from the European Centre for Medium-Range Weather Forecasts (ECMWF) representing one of the most widely used reanalysis datasets. When onboard sensors are available, met-ocean observations encountered during voyages can also be integrated into performance models, supporting more accurate training and predictions.

[5] https://www.ecmwf.int/en/forecasts/dataset/ecmwf-reanalysis-v5

Table 5
Frequently-used feature selection methods for performance modeling in ship operation.

Principle	Method/Reference	Advantages	Disadvantages
Filter	Pearson coefficient Fan et al. [63]	Simple and fast computation; Easy to interpret results	Only detects linear relationships; Ignores feature interactions
	Maximum information Ruan et al. [225]	Captures linear/non-linear relationships; Robust to noise	Computationally intensive; May overfit with small samples
Wrapper	Exhaustive search Coraddu et al. [46]	Guaranteed optimal subset; Comprehensive evaluation	Computationally prohibitive; Impractical for high dimensions
	Greedy search Coraddu et al. [46]	Computationally efficient; Scalable to high dimensions	Suboptimal solutions; Sensitive to initial conditions
Embedded	Regularization Ma et al. [183]	Embedded feature selection; Handles multicollinearity	Requires hyperparameter tuning; May shrink important features
	Tree-based method Wang et al. [284]	Handles non-linear relationships; Robust to outliers	Feature importance may be biased; May overfit without pruning

4.2.2. Preprocessing

(1) Multimodal heterogeneous data fusion

Modern ships are increasingly equipped with sensing systems such as visible-light and infrared cameras, navigation radars, and AIS, each offering complementary capabilities under different lighting and weather conditions, sensing ranges, update frequencies, and detection resolutions [262]. The multimodal and heterogeneous nature of these data streams makes manual integration impractical at scale. AI-enabled data fusion therefore represents an important way of enhancing situational awareness and supporting reliable maritime analytics.

(2) Data cleaning

Raw operational datasets typically comprise multiple voyages of a case ship, including both docking and sailing periods, with the latter being the primary focus for performance modeling. Beyond excluding in-port data, rigorous cleaning is essential to mitigate anomalies and outliers that might otherwise reduce model reliability.

Abnormal values, such as missing data or measurements inconsistent with physical principles, often arise from random or systematic errors during data acquisition, transmission, or storage. Reported studies commonly identify such records through case-specific thresholds. Regarding met-ocean data, Wang et al. [301] note that observations indicating wind speeds exceeding 0.2m/s alongside zero wave heights, or zero current speeds, should be treated as abnormal because they contradict marine meteorology. By applying the spatio-temporal coherence of met-ocean fields, these anomalies can be corrected by referencing validated measurements from neighboring locations.

Ship motions, including pitch, roll, and heave, can change sensor-to-flow angles during navigation, thereby reducing the beam-pointing accuracy of Doppler logs used for speed through water measurements. As a result, these measurements often carry substantial uncertainty, making filtering or interpolation necessary to ensure data reliability.

Outliers, defined as observations that deviate markedly from the central distribution. Since most ML models learn underlying data structures, moderate outlier removal can improve predictive stability, whereas excessive filtering risks distorting the true distribution. The complementary error function [285] offers a validated detection approach by mapping standardized deviations to probabilities and identifying rare events.

Data cleaning is inherently case dependent, and even established techniques require preliminary experimentation to calibrate parameters for specific datasets. When executed carefully, cleaning procedures correct sensor-induced anomalies and filter distribution-disruptive extremes, thereby establishing a reliable foundation for ML-based ship performance modeling.

(3) Feature engineering

The relationships between ship performance and its potential influencing factors are highly complex and nonlinear, involving couplings and interactions among the features [66]. Freed from the constraints of deterministic physical mechanisms, ML-based models allow for the use of a broader range of potential input features in performance estimation, enhancing flexibility in modeling. However, autocorrelation or noise in redundant input variables can lead to multicollinearity [238] or overfitting [320], compromising the model accuracy and increasing its computational cost. Hence, feature engineering is crucial, as shown in Table 5 and Fig. 9, which can evaluate the statistical robustness of the constructed model and assess whether it appropriately describes the importance of known features from a theoretical perspective.

Pearson product-moment correlation coefficient analysis is a common method for assessing data correlation by measuring the linear relationship between two variables. As a simplified strategy without pre-modeling, the Pearson coefficient heat map of the integrated dataset can provide rough prior knowledge for feature selection [142]. To handle more complex nonlinear relationships, the maximum information coefficient is employed in relevant studies [225]. In the study of Coraddu et al. [46], an exhaustive search with brute force, though the most accurate but also the most computationally expensive, is designed, in which multiple incomplete models with every possible feature configuration are compared with the full version. To maintain lower computational demand, a time-efficient greedy procedure can be adopted, at the expense of not guaranteeing the full correctness of the results [81]. Additionally, the regularization method based on the least absolute shrinkage and selection operator (LASSO) can drive certain parameters to zero using an ℓ_1 penalty, thereby achieving feature importance ranking [183]. Inspired by the permutation test [83], the importance score obtained from the out-of-bag error in RF performs a stable feature selection procedure in related studies [284].

Regarding the influencing factors, the majority of studies, whether based on statistical regression or deep learning, indicate that ship sailing speed and brake power are the primary input variables in estimating fuel consumption [121,258,306]. Indeed, as widely accepted traditional concepts in the shipping industry and maritime research suggest, the approximate changes in fuel consumption are generally described using a cubic representation of sailing speed [4]. Apart from sailing speed, ship draft [97], displacement [214] and trim [292], determined by gross tonnage, cargo conditions, ballast water, etc., are proven to be influential to energy consumption based on ship kinetics [219]. Moreover, both ship sailing speed and fuel consumption are regarded as relevant to external met-ocean environments, e.g., wind and wave, which can primarily be attributed to the additional resistance they introduce [65,290]. In particular, for certain specialized ships, such as polar ships [170,175], inland ships [75,324], etc., additional consideration should be given to the corresponding features as input variables.

However, concrete studies have been reported, presenting controversial views that stem from regression analyses based on historical data. For instance, the cubic law between propulsion power and ship speed is replaced by a linear relationship in the study by Kowalak [136],

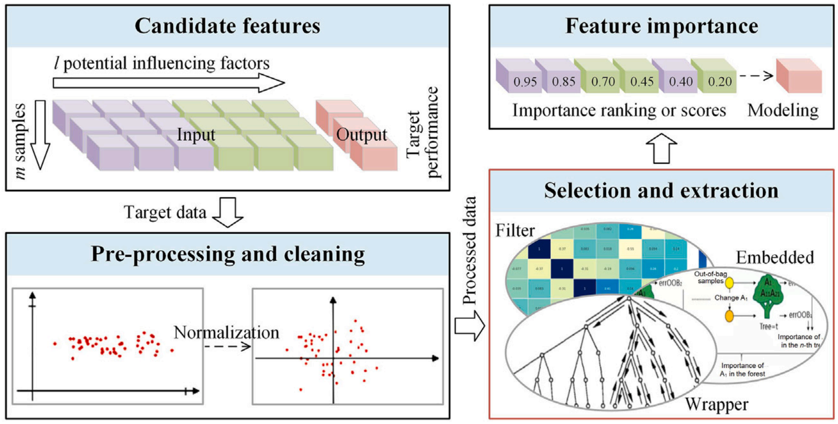


Fig. 9. Feature engineering for performance modeling in ship operations.

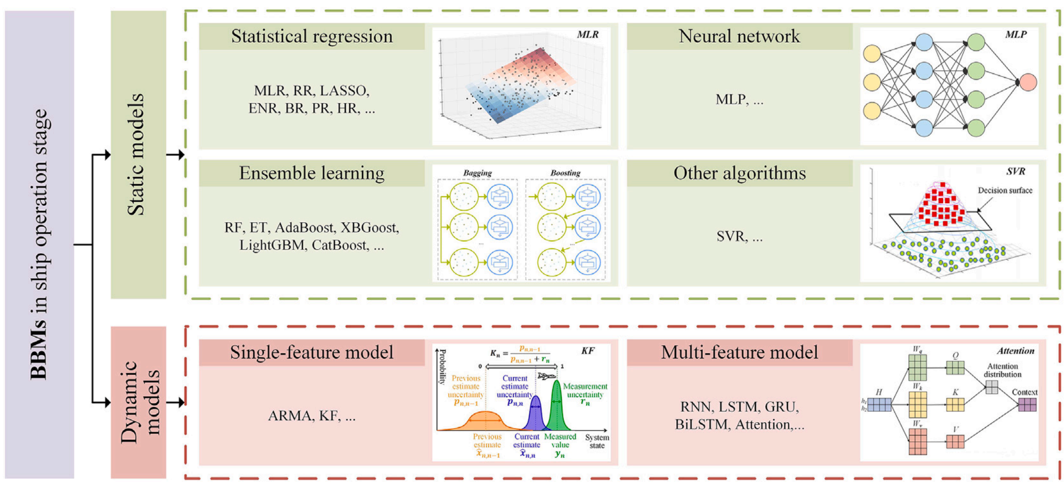


Fig. 10. General classification of ML-based BBMs for ship performance modeling in operation.

while Kristensen [137] asserts that the coefficient varies depending on ship types, oscillating between approximately 1.5 and 4.8. These differing conclusions may be linked to the datasets selected for investigation, which cannot guarantee the generalizability and interpretability. In addition, variations in loading conditions, scheduled routes, voyage seasons, etc., may also contribute to different statistical relationships between features.

4.3. BBMs in ship operation

BBMs can capture nonlinear relationships among relevant variables from multidimensional observational data, providing substantial flexibility for ship performance modeling. For operational ships, regardless of type (e.g., bulk carriers or container ships), the fundamental principles of performance modeling remain largely consistent. Compared with original design or retrofitting tasks, which typically lack full-scale data reflecting actual operating conditions in advance, BBMs are more widely applied at the ship operation stage of the lifecycle.

In general, existing methods can be categorized into two types: static models and dynamic models, with the latter accounting for temporal dependencies, as shown in Fig. 10. The individual contributions in each category are presented in Sections 4.3.1 and 4.3.2, respectively.

4.3.1. Static models

Static BBMs typically focus on establishing relationships among relevant variables using available measurements, without accounting for potential time-dependent characteristics during ship operation. Specifically, static models for ship performance can be broadly classified into statistical regression, ensemble learning, neural networks, and other intelligent algorithms, as shown in Table 6.

(1) Statistical regression

As one of the most classical methods in regression analysis, MLR captures ship navigation characteristics by incorporating a wide range of influencing factors [133]. By minimizing the squared variance between the ground truth and estimated results, the optimal regression coefficients of MLR are obtained by the least squares method (LS) [30]. Considering the challenges of multicollinearity for the standard LS, ridge regression (RR) incorporates an ℓ_2 penalty to reduce model complexity and prevent overfitting [223]. While LASSO employs an ℓ_1 penalty, which not only reduces complexity but also drives certain parameters to zero, thereby facilitating feature selection [296]. Additionally, the effectiveness of several relatively less common methods, such as elastic net regression (ENR) [162], Bayesian regression (BR) [208], polynomial regression (PR) [273], and Huber regression (HR) [150], has been empirically validated in related studies using real-world cases.

(2) Ensemble learning

To improve the accuracy and robustness of performance estimation, ensemble learning, which combines several weak learners into a more comprehensive model, has been widely adopted in maritime research. Based on the dependency among individual learners, mainstream ensemble learning methods can be categorized into Bagging and Boosting, with the former focusing on reducing variance and the latter aiming to control deviation, from the perspective of error decomposition [53]. The Bagging-based RF model, which aggregates outputs from

Table 6
Frequently-used static models for ship performance modeling in daily operation: (1) statistical regression; (2) ensemble learning; (3) neural network; (4) other intelligent algorithms, with case-specific accuracy evaluated by R^2 ("N/A": not reported).

	Model	Details	Reference	Case ship	Target performance	R^2
(1)	MLR	• $y = \beta_0 + \beta_1 x_1 + \cdots + \beta_n x_n + \epsilon$, where β_0: intercept; ϵ: error; $\{\beta_i\}_{i=1}^n$: regression coefficients.	Gao et al. [76]	LPG carrier	Fuel consumption	0.97
			Nguyen et al. [199]	Bulk carrier	Fuel consumption rate	0.77
			Uyanık et al. [273]	Container ship	Engine power	0.99
	LASSO	• $\hat{\beta} = \mathrm{argmin}(\|y - X\beta\|_2^2 + \lambda\|\beta\|_1)$. where $\|\cdot\|_1$: ℓ_1.	Piao et al. [216]	Training ship	Fuel consumption	0.88
			Zhou et al. [341]	Tuna seiner	Speed through water	N/A
(2)	RF	• $H(x) = \frac{1}{T}\sum_i^T h_i(x)$, where T: amount of trees in forest; $h_i(x)$: output of i-th decision tree.	Fan et al. [64]	LPG carrier	Fuel consumption	0.95
			Kim and Roh [128]	LNG carrier	Speed over ground	0.73
			Lee et al. [154]	Smart ship	Carbon emission	0.90
	XGBoost	• $F(x) = \sum_i f_i(x)$. where $f_i(x)$: output of i-th regressor.	Handayani et al. [96]	Container ship	Fuel consumption	0.99
			Lang et al. [144]	Chemical tanker	Engine power	0.99
(3)	MLP	• $Z_l = W_l A_{l-1} + b_l,\ \ A_l = \sigma(Z_l)$, • $\delta_l = (W_{l+1}^T \delta_{l+1}) \odot \sigma'(Z_l)$, where A: forward signal; W: weight matrix; b: bias vector; δ: backward gradient; σ: activation function.	Luo et al. [180]	Container ship	Fuel consumption	0.98
			Nguyen et al. [197]	Bulk carrier	Fuel consumption rate	0.98
			Bassam et al. [22]	Car ferry	Speed (unspecified)	0.95
			Šilas et al. [349]	Container ship	PM concentration	0.90
			Moreira et al. [193]	Container ship	Speed (unspecified)	0.88
(4)	SVR	• $f(x) = \sum_i(\alpha_i - \beta_i)K(x_i, x) + b$, where $K(x_i, x)$: kernel function.	Ruan et al. [224]	VLCC	Fuel consumption	N/A
			Cammin et al. [29]	Container ship	Air emission inventory	0.78
	KNN	• $F(x) = \frac{1}{K}\sum_i^K f_i(x)$, where K: amount of neighbors.	Lan et al. [143]	VLOC	Fuel consumption	0.73
			Wang et al. [284]	Bulk carrier	Speed through water	0.89

multiple uncorrelated decision trees (DTs) [310] by averaging or weighted averaging, exhibits strong performance in estimating ship speed and energy consumption [85,263]. Without the need to compute optimal split points, extra trees (ET) [142] generally achieve higher computational efficiency than RF. As for Boosting-related algorithms, XGBoost [245] minimizes the loss function using gradients and Hessian matrices, while adaptive boosting (AdaBoost) adjusts weights to emphasize hard-to-learn samples [272]. Alongside XGBoost, the light gradient boosting machine (LightGBM) [312] and categorical boosting (CatBoost) [244] are recognized as the three mainstream enhancements of gradient boosting regression tree (GBRT) [63], with their performance validated in energy consumption estimation studies.

(3) Neural network

ANNs, represented by MLP, which have emerged as the most prevalent BBMs for a variety of practical engineering challenges in recent years, demonstrate adaptive learning mechanisms, robust nonlinear mapping capabilities, and efficient parallel information processing abilities [179,266]. Through the interconnections and activation functions among neurons, ANNs can effectively capture the intricate relationships between ship performance and its influencing factors [54]. With the increasing availability of data and the continuous enhancement of computing power, deep learning networks are widely used in estimating ship speed, consumption, emissions, and other navigation-related indicators. Additionally, ANN-related methods, such as the Levenberg-Marquardt-ANN [239], ANN-driven SVR [84], and ANN-based transfer learning [180], demonstrate superior performance in batch tests by optimizing internal parameters.

(4) Other intelligent algorithms

In addition to the aforementioned BBMs, various other intelligent algorithms are also employed in tasks related to ship performance estimation. As one of the most popular ML algorithms, SVR can perform linear or nonlinear classification, regression, and even outlier detection tasks. By selecting an appropriate kernel function, SVR effectively captures the nonlinear relationships and complex patterns in the ship performance modeling problem [287,325]. Furthermore, the unsupervised k-nearest neighbor algorithm (KNN), relatively infrequently applied in maritime studies, does not adhere to a traditional learning process; rather, it partitions the feature space based on distance metrics to execute classification or regression tasks [336].

4.3.2. Dynamic models

In contrast to static models grounded in cross-sectional (static) data, dynamic models learn from variable temporal sequences. Throughout a voyage, the continuous operation of the propulsion system naturally generates time-series data, such as engine power, heading, and speed, that constitute chronologically ordered observations [338]. Met-ocean conditions similarly exhibit spatio-temporal dynamics. By capturing both explicit and latent temporal structures, dynamic models offer a more realistic representation of ship performance, enabling improved characterization of temporal dependencies and changing operating conditions. When critical inputs are unavailable, these models can infer system behavior from short-term historical observations, thereby preserving practical applicability [88]. Therefore, multiple dynamic models have been established to serve as standards for performance comparison and foundations for subsequent innovation, with some typical baselines illustrated in Table 7.

(1) Single-feature models

The single-feature models often utilize state equations to derive the navigation characteristics of ships, providing benefits such as simplified calculations and reduced data requirements. For instance, an earlier study assessed short-term ship motion models based on the autoregressive moving average (ARMA) and Kalman filter (KF), which have a general application in the prediction of time series [106]. Building upon these basic models, more effective variant models, e.g., autoregressive integrated moving average (ARIMA) and extended Kalman filter (EKF), have been developed and validated within related maritime research [338]. Furthermore, an enhanced version of ARIMA that incorporates additional input variables, referred to as ARIMAX, can address the fuel consumption prediction problem involving multiple features, distinguishing it from the standard model [164].

(2) Multi-feature models

Considering that single-feature methods are limited in effectively integrating the influence of hydro-meteorological conditions, there has been a growing interest in prediction models that utilize multiple input features [38]. While traditional dynamic methods, such as ARIMA, perform well under linear relationships, recurrent neural networks (RNNs) offer an advantage by not being constrained by these fixed assumptions, allowing them to accommodate complex nonlinear relationships [164]. Specifically, the output from the hidden layer at a given time step is

Table 7
Frequently-used dynamic models for ship performance modeling in daily operation: (1) single-feature model; (2) multi-feature model, with case-specific accuracy evaluated by R^2 ("N/A": not reported).

	Model	Details	Reference	Case ship	Target performance	R^2
(1)	ARMA	• $\hat{x}_t = \phi_1 x_{t-1} + \dots \phi_p x_{t-p} + \dots \theta_q \epsilon_{t-q} + \epsilon_t$, where ϕ: autoregressive coefficient; θ: moving average coefficient; ϵ_t: noise.	Yang et al. [315] Wang et al. [284]	Bulk carrier Bulk carrier	Fuel consumption Speed through water	N/A 0.83
	KF	• $\hat{x}_t = \hat{x}_t^- + K_t(z_t - H\hat{x}_t^-)$, where $\hat{x}^-$: prior state; K: Kalman gain; H: measurement matrix; z: observation.	Bi et al. [24] Guo et al. [88]	Training ship Bulk carrier	Trajectory Speed through water	N/A 0.84
(2)	RNN	• $h_t = \tanh(W_i x_t + W_h h_{t-1} + b_h)$, • $y_t = W_o h_t + b_o$, where h: hidden state; W: weight matrix; b: bias vector.	Li et al. [160] Yuan et al. [323]	Smart ship Inland ship	Trajectory Fuel consumption	N/A 0.85
	LSTM	• $\xi_t = \sigma(W_\xi x_t + W_\xi h_{t-1} + b_\xi)$, $\xi = i, f, o$, • $\tilde{c}_t = \tanh(W_c x_t + W_c h_{t-1} + b_c)$, • $c_t = f_t \odot c_{t-1} + i_t \odot \tilde{c}_t$, • $h_t = o_t \odot \tanh(c_t)$, where i, f, o: input, forget and output gate; h, c: hidden and cell state.	Wang et al. [299] Han et al. [94] Cai et al. [28] Feng et al. [72]	Tug Bulk carrier Ro-Ro ship Bulk carrier	Trajectory Fuel consumption Fuel consumption Carbon emission	N/A 0.90 0.96 0.54
	BiLSTM	• $\overrightarrow{h}_t = \mathrm{LSTM}(x_t, \overrightarrow{h}_{t-1})$, $\overleftarrow{h}_t = \mathrm{LSTM}(x_t, \overleftarrow{h}_{t-1})$ • $h_t = [\overrightarrow{h}_t; \overleftarrow{h}_t]$, where $\overrightarrow{h}_t$, $\overleftarrow{h}_t$: forward and backward signals.	Guo et al. [87] Liu and Chen [173]	Container ship Cargo ship	Fuel consumption Fuel consumption	0.91 0.93
	Attention	• $\mathrm{Attention}(Q, K, V) = \mathrm{softmax}(\frac{QK^T}{\sqrt{d_k}})V$, where Q: query; K: key; V: value; d_k: dimension of K.	Zhao et al. [337] Zhang et al. [329]	Bulk carrier Bulk carrier	Carbon emission Fuel consumption	0.97 N/A

fed back as input into the hidden layer during the next time step, in contrast to traditional ANNs, where each node connects only to the next layer [73]. To effectively capture long-term dependencies in sequence data, long short-term memory networks (LSTM), an improved version of RNN, employ a unique gating mechanism that allows for the selective retention and abandonment of information, while alleviating the issues of gradient explosion and vanishing [28]. Compared to LSTM, the gated recurrent unit (GRU), with only two gating mechanisms in its simplified architecture, achieves faster model training and parameter tuning, effectively reducing computing resource usage while maintaining performance [174]. Moreover, to comprehensively capture the ship navigation characteristics under complex met-ocean and operational conditions, the bidirectional layer is employed in standard LSTM, known as BiLSTM, which learns from both forward and backward information within the input data stream [329]. Recently, the introduction of attention mechanisms has broken through the traditional RNN framework, achieving more efficient parallel computing. With attention mechanisms, the Transformer allows for dynamic focus on various segments of the input data stream, thereby emphasizing local critical information relevant to energy consumption [279]. In time series analysis, integrating the attention mechanism into LSTM (as shown in Fig. 11) has become a mainstream approach for achieving more accurate and robust estimates of ship energy consumption, driving the emergence of many effective modeling strategies [110,329].

4.3.3. Summary

Theoretically, data-driven techniques can capture complex relationships among relevant features by extracting hidden information from multi-dimensional data, even implicitly incorporating previously unmodeled physical phenomena. However, the inclusion of specific details or noise in extensive input features can lead to overfitting in model training.

In practical applications, constructing network-based models typically requires the accumulation of extensive operational data from the case ship, which places strict demands on the acquisition frequency and quality of data from monitoring systems. For newly built ships, domain adaptation and feature transfer based on their sister ships may be essential to ensure the validity of the performance model in the operational context, due to the lack of sufficient records. Moreover, during practical navigation, the time-variant nature of the data may not satisfy the assumption of independent and identically distributed (IID) samples, leading to certain deviations between theoretical results and practical information. Despite the development of various advanced methods, no single approach has been identified that is applicable across all scenarios, and the theoretical foundations required for the interpretability of BBMs remain limited.

4.4. GBMs in ship operation

WBMs are based on prior knowledge and physical principles, with their accuracy largely determined by the assumptions and uncertainties embedded in the model. By contrast, BBMs do not require prior knowledge and are often more accurate than WBMs. However, they typically demand large amounts of full-scale measurement data, suffer from poor interpretability and limited extrapolation ability, and may yield unreasonable predictions when applied to unseen data. To leverage their complementary advantages, WBMs and BBMs are combined to form GBMs, which integrate both the physical properties underlying WBMs and the knowledge from operational data in BBMs. Given their superior interpretability and extrapolation capabilities, the advancement of GBMs presents considerable potential for reliable ship performance modeling. Depending on how physics and data are integrated, GBMs can generally be categorized into connected and embedded modeling, as shown in Fig. 12. Beyond the connected-form GBMs in Section 4.4.1, Section 4.4.2 highlights an advanced physics-informed neural network (PINN) that embeds the partial differential equations (PDEs) into its loss function to incorporate domain knowledge into the learning process.

4.4.1. Connected GBMs

In the study by Journee [119], a prediction method was proposed to describe the relationship between ship fuel consumption and its determinants (e.g., trim, heading, speed), which adjusts the parameters of the principle-driven WBM based on hydrodynamic principles using actual monitored data. The proposed semi-mechanical and semi-statistical model can be regarded as an earlier pioneering work in gray-box modeling of ship performance estimation. This serial modeling method introduces BBMs to WBMs, focusing on the identification or optimization of unknown or variable parameters in theoretical models through

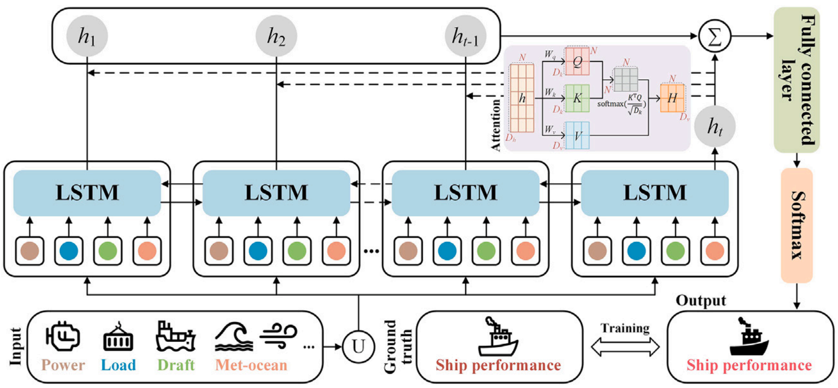


Fig. 11. An example of ship performance modeling in daily operations based on BiLSTM and attention mechanisms [337].

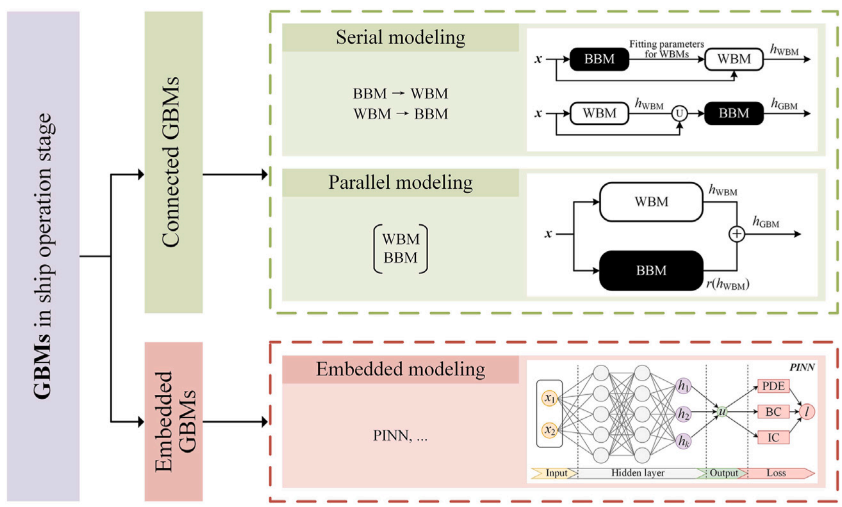


Fig. 12. General classification of ML-based GBMs for ship performance modeling in daily operation.

Table 8
A brief outline of the BBM-based connection-modeled GBMs in ship operation.

Connection	Details	Instruction	Reference
Serial modeling	$\mathcal{D}'_n := \{([\boldsymbol{x}_i; h_{\mathrm{WBM}}(\boldsymbol{x}_i)], y_i)\}_{i=1}^{n}$, $h_{\mathrm{GBM}} = h_{\mathrm{BBM}}([\boldsymbol{x}; h_{\mathrm{WBM}}(\boldsymbol{x})])$.	The WBM feeds a preliminary result to the BBM, which provides the final estimation of performance as the output of GBM.	Liang et al. [167] Zhao et al. [337] Fan et al. [64]
Parallel modeling	$\mathcal{D}'_n := \{(\boldsymbol{x}_i, y_i - h_{\mathrm{WBM}}(\boldsymbol{x}_i))\}_{i=1}^{n}$, $h_{\mathrm{GBM}} = h_{\mathrm{BBM}}(\boldsymbol{x}) + h_{\mathrm{WBM}}(\boldsymbol{x})$.	The BBM fits the residual between the WBM output and the desired ship performance, and is then combined with the WBM output.	Ruan et al. [224] Han et al. [95] Park et al. [212]

data-driven methods, commonly referred to as parameter identification GBM or physics-guided parameterization [177,187]. For example, building upon the WBM, which is grounded in prior knowledge of the propulsion system, Yang et al. [313] designed unknown parameters using the LS and GA, specifically the relationship between fuel consumption and its determinants. The GA-based GBM for fuel consumption estimation demonstrated superior fitting performance, particularly under oblique weather conditions, when validated against real operational data collected from a crude oil tanker over a 7-year sailing period.

Following the IMO's advocacy for recording ship navigation data, a substantial volume of shipping data has been collected and stored. To better leverage the data-fitting capabilities of BBMs, BBM-based connection-modeled GBMs have garnered increasing attention among maritime researchers, in contrast to parameter identification GBMs, which typically use the WBM as the core component. Specifically, the modeling methods for hybrid GBMs are based on BBMs learned from historical observations, with mechanistic WBMs integrated in either a serial or parallel configuration [288]. In Table 8, we detail two connection modeling approaches, where $\mathcal{D}_n := \{(\boldsymbol{x}_i, y_i)\}_{i=1}^{n}$ represents the measurement dataset, and $\mathcal{D}'_n$ denotes the generated dataset in GBM from which the BBM learns. In addition, the vector $\boldsymbol{x}$ represents the factors influencing the ship performance output y, while h is the output function, with subscripts corresponding to various models. The parallel modeling is theoretically justified within the regularization context, while the serial modeling is more intuitive as it provides all available knowledge for the BBM learning process. Preliminary results by Leifsson et al. [158] suggest that the difference between the two approaches is relatively marginal. A subsequent attempt by Coraddu et al. [45] modified the training process to incorporate prior information into the ship performance estimation model. Experimental results based on real-world

Table 9
Mainstream ML-based models in connected GBMs for ship performance modeling in daily operation [204,317,342,348].

		Ruan et al. 2025	Zhou et al. 2025	Fan et al. 2025	Liang et al. 2025	Zhao et al. 2025a	Ruan et al. 2024	Yang et al. 2024c	Park et al. 2024	Cai et al. 2024	Zwart et al. 2023	Odendaal et al. 2023	Ma et al. 2023	Guo et al. 2022	Coraddu et al. 2017
Model	LASSO						■						■		■
	ENR	■					■								
	RF	■		■			■	■						■	■
	XGBoost	■											■		
	ANN (MLP)			■	■						■	■			
	SVR	■					■								
	LSTM / BiLSTM		■			■				■					
Connection	Serial	■	■	■	■	■	■	■		■	■	■	■	■	■
	Parallel	■					■		■						■

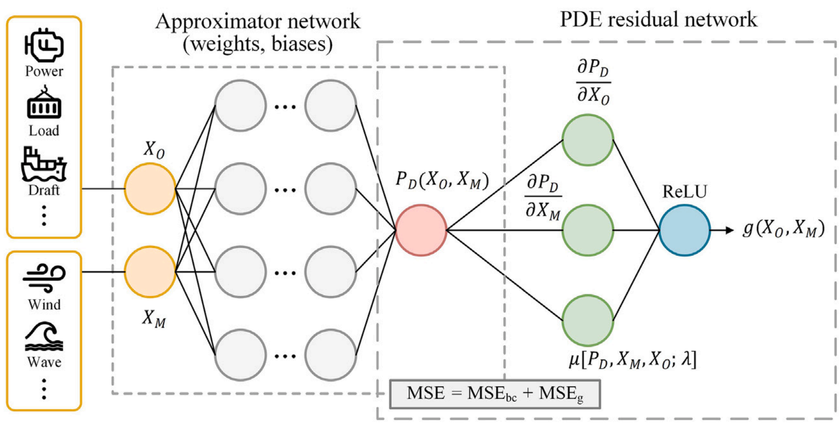


Fig. 13. An example of ship performance modeling in daily operation based on PINN [146].

operational data show that the constructed GBM achieves the same or even superior performance compared to state-of-the-art BBMs, while requiring fewer historical records. From a probabilistic perspective, the performance model can be abstracted as a conditional probability $\mathbb{P}(y|\boldsymbol{x})$, which represents the probability of the output y given that $\boldsymbol{x}$ has been observed as an input. The parallel-connected GBM alters the conditional probability $\mathbb{P}(y|\boldsymbol{x})$, while the serial-connected one modifies the whole joint probability $\mathbb{P}(y, \boldsymbol{x})$, thereby deeply influencing the nature of the problem [46]. As a novel approach to modeling ship performance, research on GBMs remains in its infancy. In addition to the representative models presented in Table 9, the effectiveness of various ML-based BBMs, such as MLR, RR, DT, ET, AdaBoost, LightGBM, CatBoost, and GBRT, has also been validated in serial or parallel GBM frameworks in related studies.

4.4.2. Embedded GBMs

In recent works, ANNs generally serve as the base model in GBMs, trained on data extracted and merged from ship AIS and hydrometeorological forecasts, yielding accurate performance estimations [203]. Raissi et al. [220] developed a PINN that incorporates the Navier-Stokes equations, where the inclusion of physics-based constraints reduces model flexibility but introduces physics-informed regularization compared to traditional deep learning approaches. When applied to ship speed and energy consumption estimation, the PINN maintains high accuracy while offering improved interpretability [283].

More specifically, the PINN is capable of solving supervised learning problems while simultaneously adhering to physical laws expressed by general non-linear PDEs. In ship performance modeling, the PDE to describe the relationships between ship operational conditions X_O, met-ocean data X_M, and target performance P_D can be defined as a generalized form:

$$a_1 \frac{\partial P_D}{\partial X_M} + a_2 \frac{\partial P_D}{\partial X_O} + \mu[P_D, X_M, X_O, \lambda] = 0, \tag{1}$$

where $\mu[P_D, X_M, X_O, \lambda]$ is the non-linear function. As illustrated in Fig. 13, the described PINN consists of two interconnected networks: the approximator, a fully-connected feed-forward neural network with trainable weights and biases, and the residual network, which computes the residual term g via automatic differentiation to incorporate physical constraints. The residual network computes the mean squared error MSE_g based on the governing physical constraints, while the left segment evaluates the discrepancy arising from the boundary conditions MSE_{bc}, introduced by the learning network. These two ation represents the longest phase of its lifecyc collaboratively function to minimize the aggregate residuals, termed as MSE. Following this paradigm, a recent study constructs a PINN with simplified PDEs linking propulsion power, draft, and calm water speed, augmented by XGBoost-based speed loss estimation, to predict the actual speed of ocean-crossing ships [146].

Beneficial due to the high flexibility and the expressive ability in function approximation, PINNs in other research fields have been extended to solve various classes of PDEs [326], leading to the development of variants such as hp-VPINN [127], CPINN [115], and XPINN [114], among others. However, given the complexity of formulating PDEs suitable for describing ship performance under actual sailing environments, the effective application of PINNs in ship operations still requires further theoretical investigation and practical exploration.

4.4.3. Summary

Through various modeling methods, GBMs can embed the prior knowledge of WBMs into BBMs, achieving comparable performance with the latter while requiring less historical data. Meanwhile, the enhancement in interpretability provides a significant advantage in extrapolation and generalization, freeing the model from the necessary assumption of IID to a certain degree. Compared to state-of-the-art WBMs, GBMs exhibit higher accuracy by incorporating influencing factors or parameters beyond the established physics or engineering laws. However, different construction methods lead to varying preferences in GBMs for detailed initial information regarding the physical characteristics of the true systems or a broader dataset that encompasses a wide range of operating conditions.

When GBMs are applied to actual voyages, the long training time associated with their complex structures may hinder timely model updates based on newly acquired data streams. The GBMs facilitate the application of data-driven techniques in maritime practice, as they are developed based on domain knowledge, making them more acceptable to skeptical practitioners. However, discussions regarding the application of GBMs for energy-efficient shipping operations remain in the preliminary stage, marked by insufficient in-depth research and limited practical attempts.

4.5. Methodological applicability across operational tasks

Ship operation represents the longest phase of its lifecycle and has consequently attracted substantial research attention in performance modeling. However, the selection of input features and ML methods remains highly task dependent. Accordingly, this section synthesizes the methodological applicability across representative operational tasks to support informed model selection. The following discussion is grounded in empirical evidence and should not be interpreted as universally applicable, given the case sensitivity of data-driven models.

In feature engineering, including real-time navigation variables (e.g., engine power and RPM) can improve estimation accuracy. However, reliance on real-time inputs increases demands on sensor data transmission and may introduce reliability risks. For example, in high-traffic waterways such as the Suez Canal, communication congestion can disrupt signal transmission between shipborne systems and shore stations, occasionally resulting in contact losses lasting several hours [101]. As an alternative, dynamic models such as LSTM and BiLSTM infer navigation patterns from short-term historical data and have been shown to mitigate prediction challenges arising from missing information. Although single-feature models (e.g., ARIMA) are generally outperformed by multi-feature approaches, their low computational cost makes them suitable for short-term tracking tasks. Within decomposition–prediction–summation frameworks, these lightweight models can effectively capture stable trend components, as demonstrated in sailing time prediction [301]. Overall, dynamic models are often better suited to tasks involving trajectory and motion dynamics, where temporal dependencies play a critical role.

Met-ocean forecast products inherently contain uncertainties despite continuous improvements in forecasting accuracy. Training with observational data enables a more faithful reconstruction of historical conditions and supports robust model calibration. However, discrepancies between forecasted and actual conditions are unavoidable in forward-looking evaluations, introducing input deviations that may propagate into prediction errors. Correcting forecast biases is therefore essential for reliable deployment. Emerging studies have begun integrating meteorological uncertainty directly into ML models, representing a promising but still developing research direction [87,178,280]. For example, uncertainty can be internalized during training by combining ensemble-derived means or probability distributions.

Selecting between BBMs and GBMs remains a persistent challenge in ML-based ship performance modeling. Benchmark studies consistently indicate that ensemble approaches such as RF achieve strong computational efficiency and predictive capability, supporting their widespread use in tasks related to speed, energy consumption, and emissions. However, BBMs are inherently sensitive to distribution shifts. For example, validation experiments involving test ships operating beyond the training speed range have reported that RF performed poorly [88]. This limitation reduces their suitability in scenarios characterized by evolving operational profiles, such as container ships with frequent speed variations, and newly commissioned ships lacking historical records. By contrast, when operational conditions remain relatively stable, such as ships operating under discretized constant-speed strategies or near-coast ships exposed to mild met-ocean variability, BBMs often provide a practical balance between predictive accuracy and computational cost. Given their case sensitivity, preliminary experimentation is advisable to assess the methodological suitability of a given dataset.

Establishing GBMs in maritime applications remains challenging due to the complexity of ship–environment interactions. Despite the success of PINNs in other engineering domains, the governing PDEs describing ship performance are difficult to formulate with sufficient accuracy in real wave conditions, constraining their practical applicability. Connected GBMs that incorporate empirical white-box modules offer a more practical alternative. However, scenario-sensitive parameters must be carefully calibrated for specific ships and operating regions to prevent unreliable predictions. In practical deployments, priority should be given to translating theoretical capability into operational value rather than adopting sophisticated frameworks that are either poorly adaptable or impose excessive computational demands. Among connection strategies, parallel configurations, where a physical module generates a coarse estimate that is subsequently refined by a data-driven component, can enhance model trustworthiness by reducing reliance on unexplainable factors. This structure is particularly advantageous for short voyage performance evaluation (e.g., sailing time and energy use), where it helps prevent physically unreasonable outputs such as negative values or exceeding engine limitations [337]. Serial embedding does not consistently provide this benefit.

5. Ship maintenance and retrofit

Beyond its application in the daily operation of in-service ships, ML-based performance models also play a crucial role in the maintenance and retrofit stages, which are systematically reviewed in Sections 5.1 and 5.2, respectively.

5.1. Ship maintenance

5.1.1. Basic description

For ocean-going ships that have been in service for an extended period, microorganisms, algae, and larger marine sessile organisms may attach to their structures below the waterline (primarily hulls and propellers), particularly in waters with favorable temperature and salinity conditions or in eutrophic environments such as ports [267,305]. According to research statistics, for a 100,000 DWT tanker, biofilm or hard fouling can increase resistance by up to 30%, resulting in an additional fuel consumption of approximately 12 tons per day, or a cumulative 10% increase over ten years of operation [254,255].

Furthermore, onboard equipment, especially critical rotating machinery such as engines [295], bearings [340], and thrusters [92], may deteriorate or sustain damage from continuous operation, leading to reduced output power and potential threats to navigational safety. Health monitoring and early fault detection are crucial for improving the reliability and availability of maritime equipment.

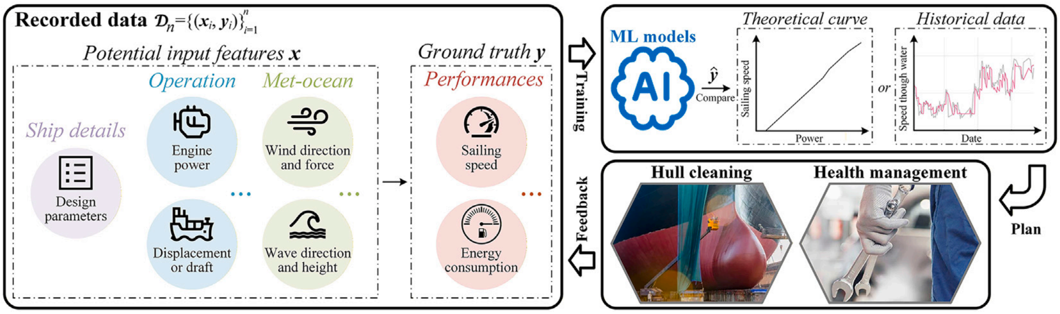


Fig. 14. Overview of ship performance modeling in the maintenance stage. Note: Some illustrative subgraphs are sourced from the Internet and do not convey any analytical results.

With the advancement of sensor-based data acquisition and transmission, along with the continuous development of AI, digital ship maintenance through ML techniques has become increasingly feasible. Hence, a systematic review of various ML-based ship performance models employed to facilitate ship maintenance is conducted to provide references for relevant researchers and maritime practitioners. Specifically, studies applying ML-based performance models to hull cleaning are highlighted in Section 5.1.3. While Section 5.1.4 provides a concise introduction to shipboard equipment health management strategies, such as anomaly detection. Although this topic lies outside the scope of ship performance modeling in this study, several representative review papers are included to guide readers seeking further information.

5.1.2. Data preparation

During ship maintenance, data acquisition and preprocessing are largely similar to the practices adopted in the operational stage. The key distinction is the need for additional reference data to determine whether the ship operates within acceptable performance conditions. For example, in biofouling assessment aimed at informing cleaning decisions, ML-based performance models estimate speed loss under specific operational and environmental conditions, and benchmark these estimates against the ship's performance in a fully (or nearly fully) clean state. Similarly, deviations between actual fuel consumption and theoretical values derived from manufacturer-provided power curves can signal abnormal engine behavior or potential damage.

5.1.3. Performance models in anti-biofouling

For a 176-meter-long tanker, biofouling is estimated to increase frictional resistance by 32% after one year of operation [274]. More seriously, Schultz [232] reported that heavy calcareous fouling can lead to powering penalties of up to 86% at the cruising speed of a mid-sized naval surface combatant. Hull cleaning [49] is an essential and routine condition-based maintenance process intended to reduce hydrodynamic resistance, mitigate speed loss, and minimize fuel consumption, as illustrated in Fig. 14. Various ship hull cleaning techniques, such as manual cleaning, powered rotary brush systems, and non-contact technologies, are employed to remove marine biofouling from ship structures below the waterline [249]. In the study by Swain et al. [249], both the cost-effectiveness and robustness of using unmanned underwater vehicles for cleaning tasks were demonstrated, supporting the development and application of AI-based cleaning technologies. Relevant studies indicate that cleaning the hull in dry-dock is more effective than underwater cleaning, reducing fuel consumption by approximately 17% and 9%, respectively, based on their numerical results [3].

The ISO 19,030 standard [112] outlines methodologies for quantifying the impact of biofouling on hull and propeller performance and defines a suite of maintenance-related indicators. Specifically, it recommends comparing measured or estimated performance data against an ideal speed-power reference curve and continuously monitoring this relationship to reliably evaluate performance changes. Towing tests with flat plates covered with artificial barnacles can examine how varying coverage percentages affect ship resistance and effective power, over a range of Reynolds numbers [271]. For traditional numerical computation methods, studies that employ fitted empirical formulas to quantify the influence of environmental factors on ship performance and by extension, assess biofouling impact can be found in Carchen et al. [32] and Valchev et al. [276]. In addition, integrating CFD with specific roughness functions allows for the estimation of fouling impact on ship resistance and propulsion performance [69,242].

In contrast to principle-driven approaches that require detailed prior knowledge of underlying physical or engineering laws, data-driven ML techniques primarily rely on data analytics to capture relevant performance characteristics, offering greater flexibility and practicality in frequent proactive maintenance. The effect of fouling can be assessed by predicting changes in ship performance parameters, commonly referred to as key performance indicators (KPIs), such as power increase and speed loss [31,206]. In the field of biofouling, the commonly used ML-based models largely overlap with those applied in ship operations, as both aim to evaluate navigational performance, though the former places greater emphasis on performance degradation relative to theoretical conditions [20]. For example, Laurie et al. [148] evaluated five different ML regression models, including MLR, RF, AdaBoost, ANN, and KNN, to predict ship shaft power, and used the resulting predictions to generate simulated power-speed curves for assessing performance deterioration caused by biofouling. In the study by Duan et al. [55], performance models evaluating the impact of hull roughness on main engine load indicate that RF outperforms MLP, as well as statistical regression methods such as LASSO, RR, and PR. Coraddu et al. [47] proposed an extreme learning machine (ELM) method to estimate speed loss caused by marine fouling, demonstrating that their approach provides more accurate and consistent predictions than the ISO 19,030 standard. Compared with other methods, ANNs [210,243] are more widely applied in this field, which can monitor ship performance using in-service data and predict fouling-caused performance deterioration, as shown in Table 10. Furthermore, by integrating image processing techniques with AI, biofouling detection can be reliably performed using CNNs [185,248]. The effectiveness of ML-based models in monitoring biofouling has also been demonstrated on specialized ships, such as a multi-purpose research ship [44] and a battery-powered hybrid electric ship [61].

In recent years, the application of ML-based models to biofouling assessment has transformed traditional hull cleaning practices, which were previously based on scheduled or reactive procedures with excessive downtime, into a predictive and proactive practice. Compared with physical methods, AI technologies are better suited to handling the continuously accumulated data generated during ship navigation, enabling the ongoing optimization of performance models [77]. Moreover,

Table 10
Mainstream ML-based models for monitoring biofouling on ship hulls and propellers [58,60,89,105,188,190,191,261,270].

		Coraddu et al. 2019a	Coraddu et al. 2019b	Erol et al. 2020	Laurie et al. 2021	Mannix et al. 2021	Sundar et al. 2021	Gupta et al. 2022	Tsompopoulou et al. 2022	Milovanovic 2023	Mittendorf et al. 2023	Erdal and Johansson 2024	Themelis et al. 2024	Huang et al. 2024	Kim and Roh 2024	Eftekhar et al. 2025	Mittendorf et al. 2025
Model	MLR			■	■						■						
	RF				■							■	■		■		
	AdaBoost				■												
	ANN (MLP)				■			■	■	■	■				■	■	■
	ELM		■														
	SVR	■															
	KNN	■			■												
	LSTM													■			
	CNN					■	■										
KPI	Shaft power				■			■	■		■		■		■		■
	Resistance															■	
	Speed / Speed loss		■	■				■		■		■		■			
	Fouling condition	■				■	■										

studies have demonstrated that RL can determine the optimal path for autonomous cleaning robots, reducing water consumption by approximately 10% while maintaining ship maintenance standards and preventing hull deformation [149]. Similarly, Wei et al. [302] established a multi-state biofouling growth model based on a Markov chain and derived the optimal cleaning strategy using RL.

5.1.4. Overview of shipboard maintenance strategies

Modern marine systems and equipment (MSAE) comprise complex mechanical, electrical, and hydraulic subsystems, consisting of interrelated components. A failure in any component may lead to changes in the overall health condition of the system. Corrective maintenance (CM), also known as reactive or run-to-failure maintenance, is a passive strategy in which maintenance actions are initiated only after equipment failure occurs [118]. However, this traditional approach has increasingly revealed limitations, including missed repair opportunities and increased operational costs. With advances in digital technologies and data analytics, increasing automation has accelerated the transition toward preventive maintenance (PM) as a key approach in modern shipboard maintenance.

Preventive maintenance can be broadly categorized into four types: predetermined maintenance (PrM), proactive maintenance (PaM), predictive maintenance (PdM), and prescriptive maintenance (RxM) [211]. PrM, based on predefined schedules, remains the dominant strategy on many ships, including inspection- and time-based maintenance practices. PaM focuses on addressing the root causes of failures through approaches such as risk-based maintenance (RBM) and reliability-centered maintenance (RCM), with the goals of reducing repair costs, improving system reliability, and extending equipment lifespan. For marine diesel engines, RCM is commonly implemented through performance degradation modeling supported by condition monitoring or Markov-based methods [269].

Predictive maintenance (PdM) relies on data-driven techniques to analyze sensor data and identify emerging failure patterns [195,231,347]. As a subset of PdM, condition-based maintenance (CBM) has seen growing adoption of ML methods, including SVM, RF, and ANN, for equipment such as gas turbines, oil purifiers, and lubrication systems [156,184,207]. More recently, prognostics and health management (PHM) has emerged as a computational alternative to traditional CBM, encompassing health monitoring, fault diagnosis, health prognosis, and maintenance decision-making. For example, LSTM-based models have been applied to fault prognostics in marine diesel engines, enabling accurate RUL predictions across multiple fault types [91]. Similar approaches have been used to evaluate RUL in marine selective catalytic reduction systems using architectures such as MLP, LSTM, and GRU [155]. Despite their reliance on ML techniques, these studies primarily focus on equipment health assessment rather than ship performance prediction. As such, this research stream falls outside the central scope of this review, which emphasizes models for predicting resistance, speed, fuel consumption, and emissions, and should be regarded as a distinct research domain. To guide interested readers, several comprehensive review articles on maritime PHM are summarized here: Ellefsen et al. [59], Zhang et al. [330], Hu et al. [104], Zio [346], and Liang et al. [168]. Within PHM frameworks, digital twins are increasingly used to simulate complex system dynamics through continuous data exchange between physical assets and their virtual models [277]. Real-time sensor data enable virtual models to support condition monitoring and informed maintenance decisions [192].

Unlike PdM, which focuses on forecasting failure timing, prescriptive maintenance (RxM) extends this capability by identifying root causes, recommending mitigation strategies, and evaluating their potential operational impact [18]. For instance, a GAN-based maintenance framework integrated with failure mode and effects analysis (FMEA) has been proposed to address multiple diesel generator failure modes, including turbocharger wear and fuel injection malfunctions [319].

5.1.5. Summary

Compared to CFD-based simulation methods, ML applications in the ship maintenance stage require neither complex prior knowledge nor time-intensive experimental procedures. Specifically, within the incremental learning framework, the established performance models can be adaptively refined using newly acquired ship data, eliminating the necessity for complete model retraining. This enables the ML-based models to provide continuous and precise assessment of navigation performance deterioration attributable to biofouling accumulation. The ML-based models demonstrate sufficient sensitivity to detect incipient performance degradation patterns, facilitating early warnings prior to the

Table 11
Mainstream alternative energy source strategies for retrofitting ships: A compendium of practical measures rather than ML-based models.

Energy	GHG control (%)	Cost (%)	Primary ship types	Perception	Reference
LNG	25–30	11–70	LNG carrier	Diverse	Liu et al. [171]
Methanol	0–95	12–16	Container ship, tanker, tug	Positive	Ammar [8]
Hydrogen	0–100	100–160	Ferry, cruise ship, tug	Diverse	Gay et al. [79]
Ammonia	0–100	15–50	Tanker, bulker, bunkering ship	Positive	Kim et al. [132]
Batteries	0–100	35–180	Ferry, container ship, Ro-Ro	Positive	Kersey et al. [122]
Biofuels	17–59	13–20	Container ship, Ro-Ro	Diverse	Sagin et al. [227]
Nuclear	100	400–500	Icebreaker	Negative	Lin et al. [169]

escalation of cumulative fouling effects, which prevents both exorbitant maintenance expenditures and significant energy efficiency losses.

However, substantial variations in ship design and operational profiles pose urgent-to-solve challenges to model generalizability. A single performance model often fails to accommodate these heterogeneities, necessitating ship-specific or fleet-specific customized training protocols. Furthermore, performance degradation can stem from diverse sources beyond biofouling, such as adverse weather conditions. The model must therefore be capable of distinguishing between gradual biofouling accumulation and transient interference factors; failure to do so may result in false diagnostics that lead to inappropriate maintenance decisions. Physics-informed GBMs may help alleviate this challenge to some extent, although they have not so far seen widespread application in the field of ship maintenance.

5.2. Ship retrofit

5.2.1. Basic description

As the dominant energy consumer and emissions contributor within the transportation sector, the maritime industry is under mounting pressure to reduce its carbon footprint [298]. To support the IMO's decarbonization agenda [111], in addition to operation-based solutions such as optimizing sailing plans for ocean-going ships [39], modular retrofitting of existing ships has also emerged as a promising direction to reduce navigational resistance and improve energy efficiency, drawing increasing attention in recent years [134]. Retrofitting ships with alternative green energy sources represents the most straightforward pathway to decarbonizing shipping activities [141]. A rough summary of alternative energy sources in the maritime field is presented in Table 11, with relevant data primarily drawn from the comprehensive studies by Balcombe et al. [21], Zincir and Arslanoglu [345], and Kondratenko et al. [135]. Note that the retrofitting cost is expressed as a proportion of the market value of a non-retrofitted ship, while the perception reflected may not represent that of the general public.

Green energy retrofitting essentially entails a full-system upgrade of the ship, covering both the engine and auxiliary equipment. In this context, the corresponding performance modeling can directly adopt ML-based models used in the design and operation stages, treating the retrofitted ship as a new entity independent of its original configuration [117]. In contrast, our paper focuses more on the performance modeling of ships with localized retrofitting on the hull and propeller, as these design-based modifications can alter the ship hydrodynamic and propulsion performance, rather than just the power source. As shown in Table 12, retrofitting based on ship design improvements yields a limited but reliable effect, achieved by enhancing the energy efficiency of ships.

5.2.2. Data preparation

Retrofitting represents a unique stage in a ship's lifecycle, where the goals of performance modeling and the corresponding data needs differ from those before and after the retrofit. During the pre-retrofit feasibility stage, the lack of actual navigation records typically requires the use of data from existing ships for ML model development, similar to the data-driven approach adopted in ship design. At this stage, hydrodynamic characteristics are commonly analyzed to estimate potential performance gains. A retrofit decision is then made by considering factors such as retrofit costs, service life, and expected operational benefits. Once the retrofit is completed, its real gains can be assessed using ML models trained on the ship's own navigation data. Performance evaluation and operation optimization largely align with practices in the operational stage, including similar data preparation procedures. Notably, retrofits involving additional onboard systems require integrating additional features. For example, when modeling wind-assisted propulsion ships, variables describing sail operation should be measured and considered.

5.2.3. Performance models in ship retrofit

Energy-efficient equipment can be retrofitted to ships already in service to meet profitability or sustainability requirements set by owners or authorities [98,157]. Hence, to mitigate the risks associated with investing in new technologies and to effectively monitor retrofitted ships, performance models that assess the sophisticated impact of retrofitting measures are essential, as shown in Fig. 15.

Common hull retrofitting options generally include innovative bulbous bow features [215] and small appendages such as gate rudder systems [228] and hydrofoils (a general term for underwater foils, whether installed at the bow or stern) [200]. For the propulsion system, Bakica et al. [19] installed a new four-bladed propeller with modern geometry on the Croatian fishing fleet, while Bonthu et al. [26] retrofitted an old whale-watching boat with a larger propeller and a new reduction gear. Based on data collected from automated logging and meteorological service providers, received before and after the ship retrofit, Nikolaidis and Themelis [201] quantified the effect of the new propeller on energy efficiency utilizing ANNs. However, the lack of sufficient training data has made CFD simulations the primary, and in many cases the only, tool for both the initial exploration and validation of the aforementioned retrofitting and related practices [33,194,256].

Wind-assisted ship propulsion (WASP) [43] is considered a promising energy-saving retrofitting measure, primarily including Flettner rotors, wing sails, and towing kites [123]. Among these, Flettner rotors [265] offer the most significant potential for decarbonization. For the performance study of WASP, Lu and Ringsberg [176] developed a four-degrees-of-freedom model, while empirical formulas, such as the Holtrop-Mennen [102], Kwon [139], and ITTC [113], are also commonly used [286,289]. To investigate an autonomous navigation and control strategy, Zhang et al. [327] examined two types of wind-assisted ships, rotor-assisted and wing-assisted, and discussed three key aspects: operational principles, installation methods, and performance modeling. Additionally, once retrofitting measures are implemented on the ships, their performance in real operations can be evaluated using ML-based methods, trained on actual sailing records [9]. For example, Çelik et al. [34] predicted the retrofitted total hull resistance using a well-trained MLP, whereas Guzelbulut et al. [90] developed the MLP-based performance model to evaluate the energy consumption of a wind-assisted ship. As the most commonly used type of performance model, additional ANN-based BBMs for WASP are presented in the studies by Zhang et al. [328], Reche-Vilanova et al. [222], Reche-Vilanova et al. [221], and

Table 12
Mainstream design improvement strategies for retrofitting ships: A compendium of practical measures rather than ML-based models.

Category	Retrofitting option	GHG control (%)	Primary ship types	Reference
Hull	Gate rudder system	5–14	Container ship	Sasaki et al. [229]
	Hydrofoils	0–10	Patrol ship, motor yacht	Hou et al. [103]
	Bulbous bow	0–16	Amphibious ships, fishing ship	Szelangiewicz et al. [250]
Propeller	Dimensions or geometries	0–15	Support ship, fishing ship	Bakica et al. [19]
	Gearbox	0–30	Whale-watching boat	Bonthu et al. [26]
WASP	Flettner rotors	10–20	Chemical tanker, Oil carrier	Vahs [275]
	Towing kite	1–12	Bulker	Delft et al. [48]
	Wing sails	0–8	Bulker, LPG carrier	Shukla and Ghosh [240]

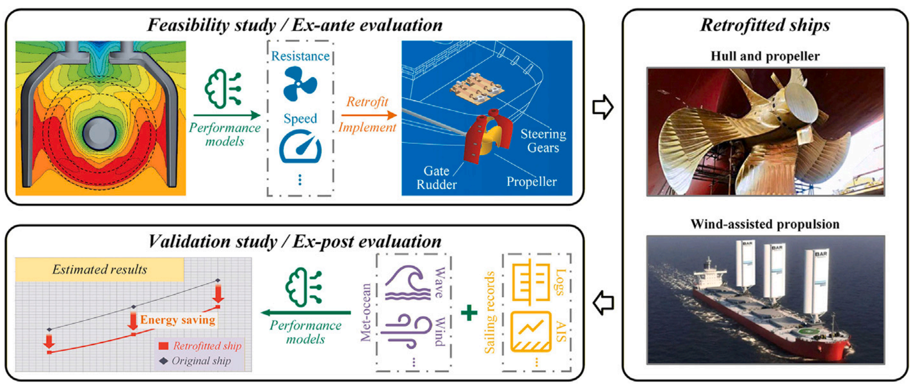


Fig. 15. Overview of ship performance modeling in the retrofit stage. Note: Some illustrative subgraphs are sourced from the Internet and do not convey any analytical results.

Chien et al. [41]. Trained on data collected from various sensors installed on the wing-diesel hybrid ship, several representative ML algorithms, including statistical regression (MLR and RR), ensemble learning (RF, ET, XGBoost, AdaBoost, and LightGBM), and SVM, are evaluated for predicting main engine fuel consumption [142]. Furthermore, the design implications and emissions reduction potential of implementing WASP can be verified using ANN-based GBMs [98]. In the study by Wang et al. [282], a parallel GBMs based on RF was adopted to predict the fuel consumption of a wing-diesel hybrid ship. Based on noon report data from the case ship, both parallel and serial GBMs are employed, along with six ML algorithms, including RR, LASSO, ENR, DT, RF, and SVR, to construct twelve combinations of performance models [225]. On the other hand, the potential of smart control systems using RL for the autonomous sailing of wing-diesel hybrid ships is explored by Bink [25].

5.2.4. Summary

Ship retrofitting represents a distinct stage in the ship's lifecycle, with its performance modeling integrating characteristics from both the design and operation. As a relatively novel and highly heterogeneous area of research, ship retrofitting has so far failed to accumulate a substantial number of benchmark cases to support the large-scale training of ML-based performance models. Hence, prior to the actual implementation of retrofitting measures, i.e., during the early design stage, physical models represented by CFD serve as the primary methods of performance modeling.

Once retrofitting measures are implemented on ships, dedicated ML-based performance models can be developed. Theoretically, existing ML-based models used in ship daily operations hold the potential to be adapted as performance models for retrofitted ships, provided that additional input features reflecting the retrofitting measures are integrated. For example, in the study by Ruan et al. [225], new features characterizing wing thrust and wing thrust power were incorporated into the performance modeling of a wing-diesel hybrid ship, based on fundamental ML algorithms. The application of ML in the ship retrofitting is a significant emerging trend, and although still in its early stages, more research will probably focus on BBMs and GBMs as retrofitting years increase and data gradually accumulates.

5.3. Methodological applicability across maintenance and retrofit tasks

Methodological applicability considerations for performance modeling in maintenance and post-retrofit stages align with those discussed for ship operation (Section 4.5), as these tasks share similar data characteristics and operational constraints. For pre-retrofit feasibility assessments, methodological selection may instead follow principles comparable to those outlined for ML-based ship design (Section 3.6), where scenario exploration and evaluation play a more prominent role.

6. Discussion and future research trends

After a detailed review of the specific applications of ML-based performance models across the entire lifecycle of ships, this section concludes by summarizing the current state of development and highlighting several promising future research directions, offering insights to relevant researchers and practitioners.

6.1. Discussion of ML-based models in different stages

The recent progress in AI has accelerated ML-based ship performance modeling, largely driven by shipborne sensor data collected under IMO and national authorities, which reduces dependence on the complex physical and engineering principles underlying traditional models. Across the ship lifecycle, including design, operation, maintenance, and retrofit, stage-specific characteristics (as listed in Table 13) shape the distinct developmental paths of ML-based performance models.

Currently, the application of ML-based models in the ship design stage remains in its early stages, with experience- and simulation-based

Table 13
Summary of ship performance modeling across the entire lifecycle.

Lifecycle	Modeling purpose	Data source	Prevalent model	Target output	Downstream task
Design	Evaluation of given hull form; Innovative design generation	Hull forms from existing ships	MLP; CNN; GAN	Resistance; Stress distribution	Hull optimization for improved hydrodynamic characteristics
Operation	Navigation tracking; Cost accounting; Emission estimation	Sailing records from shipboard instrumentation; Weather forecasts or observations	MLP; RF; BiLSTM	Speed/Speed loss; Fuel consumption;Emission	Navigation optimization for cost savings and/or energy efficiency and/or emission control
Maintenance	Condition monitoring; Plan for cleaning and repairing	Ship sailing and weather data; Reference values under theoretical condition	MLP; RF; MLR	Shaft power; Resistance; Speed/Speed loss	Maintenance schedule optimization for assured safety and/or lucrativity
Retrofit	Pre: Feasibility study. Post: Effect validation; Operation evaluation of retrofitted ships	Pre: Data from other ships. Post: Own data	MLP; BiLSTM; Attention	Resistance; Fuel consumption	Pre: Retrofitting strategy adjustment. Post: Retrofitted ship navigation optimization

approaches continuing to be the dominant methodologies. Most data-driven models reported in the literature rely either on information from sister ships or, more broadly, on extensive publicly available datasets that include thousands of hulls, highlighting the inherent data constraints. Furthermore, the mathematical representation of hull geometry remains primarily empirical and poses significant challenges. Even when the parameter space is extended to dozens of dimensions, achieving a systematic reconstruction of a ship hull is still not competitive in comparison with simulation methods or model tests. More importantly, although newly generated hull designs may demonstrate strong theoretical advantages, such as improved hydrodynamic performance, they still require comprehensive numerical analysis or model testing to confirm practical feasibility. At the current stage, ML techniques in ship design remain insufficiently mature for standalone deployment and are therefore better positioned as supplementary decision-support tools.

In contrast, during operation and maintenance, performance modeling is particularly compatible with ML techniques, with its basis in empirical formulas from decades past, whose coefficients were derived from real-world sailing data. At these phases, various ML models, including black-box and gray-box approaches, have witnessed extensive theoretical advancements and practical implementations. A notable example is the GAN, originally employed during the design stage, where the adversarial loss between generated and real hulls is straightforward, but its application has still not been widely extended to subsequent lifecycle stages.

Similar to models from the design or operation stages, ship retrofit performance modeling focuses on the particular goals and requirements of the tasks it addresses. Specifically, in evaluating the feasibility of unimplemented retrofitting, performance models primarily target a new ship design, with particular attention given to modified or newly added components. Once the retrofit device is installed, its effectiveness can be evaluated using extensive ML-based models, trained on historical sailing data, to verify whether the modifications meet the expected performance criteria.

6.2. Concerns and priorities of performance modeling in different stages

Because modeling objectives vary across lifecycle stages (see Table 13), the criteria defining a high-quality performance model likewise differ. This section synthesizes the key evaluation elements and criteria that should guide model development at each stage, highlighting stage-specific priorities and methodological implications.

From a practical standpoint, generalization is typically a primary priority in ship design. High-dimensional parameterizations of hull size and geometry can hinder effective pattern extraction in ML models, thereby increasing the risk of overfitting even when datasets originate from a single ship type. Consequently, models may exhibit substantial deviations when applied to new ships. Approaches that constrain model complexity (e.g., regularization) or embed domain knowledge (e.g., causal learning) can enhance generalization robustness. For generative models such as GANs, alignment with established maritime practices and regulatory constraints is equally critical, as designs that fail to meet established structural requirements are unlikely to be adopted, regardless of their theoretical performance advantages. Design choices are also shaped by intended service routes. For example, the Malacca Strait's draft limitation of 21 meters has led 300,000 DWT ships to favor increased breadth and length to maximize cargo capacity [74]. Accordingly, when formulating adversarial objectives in GAN-based frameworks, including constraint-aware penalties or rewards can guide generated hull forms toward feasible and operationally compliant designs.

In the operational stage, predictive accuracy is typically a primary priority, as even moderate errors in fuel consumption estimates can significantly influence voyage-level profitability. Regulatory developments, such as the forthcoming IMO carbon pricing rules, further heighten the need for reliable emissions estimation to avoid financial risks associated with non-compliance. Computational efficiency represents another critical consideration, given that performance models are often deployed while ships are navigating. Beyond hardware acceleration strategies such as parallel computing, incremental learning frameworks that consider newly acquired data without full model retraining offer a practical way for real-time or fast adjustment. Generalization requirements also vary with environmental changes. Ships operating on ocean-cross routes or in regions such as the Cape of Good Hope typically demand greater robustness than those serving near-coast routes characterized by milder and more stable met-ocean conditions. Dynamic models capable of capturing spatio-temporal dependencies, as well as domain adaptation techniques for effective feature transfer, can help mitigate inaccuracies associated with distribution drift.

In the maintenance stage, performance modeling places particular emphasis on predictive accuracy, as prediction errors often carry asymmetric operational consequences. For example, while identical error magnitudes may be assigned to RUL predictions of 5 and 7 months during model training, their practical implications differ substantially: the former may trigger earlier maintenance and associated costs, whereas the latter could increase the risk of in-service failure and compromise safety. Although similar considerations arise in operational applications, their significance is greater in safety-critical maintenance tasks and is therefore highlighted at this lifecycle stage.

Accordingly, loss functions that include directional penalties are preferable to standard mean-squared-error formulations, enabling controlled bias toward safety-aware predictions while remaining close to the ground truth.

Ship retrofitting represents a distinct lifecycle stage. When evaluating unimplemented retrofit plans for technical feasibility or economic viability, the guiding principles of performance modeling largely align with those applied during ship design. In particular, retrofits involving modifications to the ship's superstructure, such as the installation of wind-assisted propulsion systems, require route-specific regulatory constraints to be explicitly incorporated into the modeling framework. For example, the Suez Canal enforces a maximum height of 68 meters due to the vertical clearance of the El-Ferdan Railway Bridge [7], making height restrictions a critical design constraint. Following implementation, performance evaluation naturally transitions toward operational assessment and maintenance planning, consistent with the lifecycle considerations outlined earlier.

6.3. Outlook of future research

6.3.1. Explainable performance model

Despite satisfactory estimation results achieved by ML-based ship performance models using advanced enhancement strategies, these models are fundamentally constrained by limited interpretability, with outputs that heavily depend on data volume and quality, limiting their transferability to new scenarios. In this regard, the GBM method remains implicit, primarily based on data-driven BBMs. From a theoretical perspective, PINNs provide a promising avenue, but the practical challenge of formulating PDEs that accurately capture ship performance under actual sailing conditions still prevents their broader adoption. With its long-standing operational history, the shipping industry has accumulated a considerable body of experiential knowledge. The urgent task is to systematically integrate this expertise into advanced AI-driven models, thereby enabling solutions that are both practically implementable and broadly accepted within the industry.

6.3.2. Automatic algorithm design

In our study, the comprehensive review of ML applications throughout the ship lifecycle highlights the introduction and training of numerous data-driven models. Researchers have extensively compared the results of different ML-based models across various datasets, but a universally superior method has still not been identified. Meanwhile, for identical performance indicators, such as fuel consumption during ship operation, various studies have adopted differing sets of input features, reflecting the diversity in modeling strategies and potentially affecting comparative outcomes. This reflects a common understanding in ML: no single algorithm consistently dominates across all applications. Within the shipping industry, multiple factors, such as the ship type, sailing area, weather conditions, and operational profiles, differ across voyages, creating a wide variety of complex real-world cases. It is apparent that determining the most suitable ML-based performance model for a given application is both time-consuming and complex, often requiring an extensive and systematic evaluation of existing methods. Recent breakthroughs have propelled the development of automated ML, whose primary objective is to automate key aspects of the modeling process, including hyperparameter optimization, algorithm selection, and workflow composition. With the rapid advancement of large language models (LLMs), their rich domain knowledge and ability to transfer across applications without retraining have attracted increasing attention for LLM-based automated algorithm design techniques.

6.3.3. End-to-end learning

From a general perspective, ship performance modeling is framed as a regression problem, where the core objective is to ensure that outputs approximate the ground truth as closely as possible. These results are subsequently integrated into optimization tasks to support decision-making, such as identifying optimal hull configurations, sailing routes, or retrofit measures. As an illustrative example, fuel consumption estimation during the ship operation relies on training the model with historical met-ocean data and sailing measurements, enabling the most precise representation of the ship's navigational characteristics. Nevertheless, in actual practice, the cumulative measurements from ship operations and encountered met-ocean environments are limited and cannot represent all possible scenarios, which inevitably contain deviations and uncertainties for future sailing predictions. These prediction errors cannot be corrected solely through improvements to the ML-based model, and they can propagate through subsequent optimization processes, ultimately yielding plans and results that are unreliable. Hence, the development of end-to-end frameworks is essential, in which performance models are designed not to achieve maximum predictive accuracy, but to generate plans that deliver the most effective outcomes in practical settings, whether implemented under RL or "predict-then-optimize" frameworks.

7. Conclusion

Serving as the cost evaluation criterion, the ship performance modeling represents the core component and essential prerequisite for ship efficiency optimization and related applications, with its accuracy directly determining the reliability of downstream tasks. The recent emergence and advancement of ML methods have revolutionized traditional modeling paradigms that rely on physical laws and engineering principles, offering a new data-driven perspective. Over the entire ship lifecycle, covering design, operation, maintenance, and retrofit, stage-specific characteristics contribute to the distinct developmental paths of ML-based performance models. Accordingly, this study presents a comprehensive review, emphasizing the critical but commonly overlooked variation among application stages, with the goal of offering systematic guidance for selecting and implementing appropriate modeling methods.

Specifically, our study begins by presenting an overview of research trends in ship performance models from 2010 to 2025, where the notable surge in both the number of publications and their citations since 2020 underscores the accelerated development of ML-based applications. Meanwhile, keyword co-occurrence mapping demonstrates discernible variations in both the focus and research priorities of performance modeling across the various application stages. Thereafter, the paper delineates the objectives and methodologies specific to each stage within the ship lifecycle, based on a systematic summary and discussion of existing ML-based performance models as detailed in each corresponding section. Compared with other stages, the relative lack of recorded sailing data has resulted in a delayed adoption of ML techniques in ship design, leaving experience- and simulation-based approaches as the prevailing methods. Despite the widespread adoption of ML and AI in shipping-related studies, further progress in model interpretability, algorithm adaptability, and end-to-end frameworks is critical for promoting the translation of theoretical capabilities into practical benefits.

CRediT authorship contribution statement

Yuhan Guo: Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Conceptualization. **Xiao Lang:** Writing – review & editing, Writing – original draft, Visualization, Supervision, Methodology, Investigation, Formal analysis, Conceptualization. **Yiyang Wang:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Formal analysis, Conceptualization. **Xiaonan Zhang:** Writing – original draft, Methodology, Investigation, Formal analysis, Conceptualization. **Xu Zhao:** Writing – original draft, Software, Investigation, Formal analysis, Conceptualization. **Shanshan Fu:** Writing – review & editing, Validation, Investigation, Formal analysis, Conceptualization. **Wengang Mao:** Writing – review & editing, Supervision, Investigation, Funding acquisition, Formal analysis, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

Data will be made available on request.

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