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# Optimization of Energy Efficiency for Ocean-Going Vessels based on Big Data Analysis

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**Abstract:** With the ongoing advancement of the International Maritime Organization (IMO) greenhouse gas reduction strategy, energy efficiency management for ocean-going vessels has become a pivotal issue in the shipping industry's green and low-carbon transition. This paper systematically reviews the regulatory frameworks governing vessel energy efficiency management, with particular emphasis on the Energy Efficiency Design Index (EEDI), the Energy Efficiency Existing Ship Index (EEXI), the Carbon Intensity Indicator (CII), and the Ship Energy Efficiency Management Plan (SEEMP). Concurrently, the current applications of big data collection and processing technologies in maritime energy efficiency are critically examined. Building upon these foundational insights, we develop a comprehensive big data-driven energy efficiency optimization model framework that integrates a multi-dimensional energy performance indicator system, advanced data mining and machine learning methodologies, as well as speed optimization strategies and weather-based route selection algorithms. Extensive case studies are conducted to demonstrate the effectiveness of several predictive models, including back-propagation (BP) neural networks, random forests, and long short-term memory (LSTM) networks, in forecasting vessel fuel consumption with high accuracy. Notably, the multi-source data fusion model achieves a coefficient of determination ($R^2$) of 0.9431, while the genetic algorithm-optimized LSTM (GA-LSTM) model exhibits a prediction error of merely 0.29 percent. The research conclusively indicates that big data-powered energy efficiency optimization approaches can significantly reduce vessel fuel consumption and carbon emissions, thereby providing robust scientific support and actionable decision-making tools for sustainable maritime operations in the era of digital transformation.

**Keywords:** ocean-going vessels; energy efficiency; big data; machine learning; carbon emissions; fuel consumption

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## 1. Introduction

The shipping industry accounts for over 80% of global international trade transportation volume and is also a significant source of greenhouse gas emissions [1]. According to statistics from the International Maritime Organization (IMO), its carbon emissions represent approximately 3% of total global anthropogenic carbon emissions. To address climate change challenges, the IMO adopted the revised Ship Greenhouse Gas Reduction Strategy at the 80th Meeting of the Marine Environment Protection Committee in 2023, setting a vision to achieve net-zero emissions by 2050 and establishing phased targets of reducing emissions by 20%–30% by 2030 and by 70%–80% by 2040. In this context, energy efficiency management for ocean-going vessels has become a critical component of the shipping industry's green and low-carbon transition.

Ocean-going vessels operate over extended periods in complex maritime environments, where their energy efficiency is influenced by multiple factors including speed, weather conditions, hull status, and cargo load. Traditional energy efficiency management primarily relies on pilot-based decision-making, lacking data-driven support and systematic optimization capabilities, which hinders precise management. In recent years, advancements in ship sensing technology, Automatic Identification System

(AIS), and satellite communication have enabled real-time collection and transmission of massive navigation data, providing a technical foundation for big data–driven vessel energy efficiency optimization. Comprehensive reviews have emphasized that data-driven approaches have become the dominant trend in intelligent energy efficiency optimization for ships [2]. Further analyses have examined the current state and future prospects of key technologies in this domain, covering critical aspects such as data acquisition, model development, and optimization algorithms.

In the application of big data technology, studies on an 80,000-ton bulk carrier demonstrated that hull line optimization led to a 7.16% reduction in effective power consumption and a 7.29% decrease in fuel consumption. A ship energy consumption monitoring system based on mechanistic analysis has been developed, enabling real-time data collection and analysis during navigation [2]. Regarding speed optimization, an intelligent route-specific speed optimization model constructed using actual vessel monitoring data achieved a fuel consumption prediction error of only 0.9% and delivered a 1.9% fuel saving after implementation. In machine learning–based energy efficiency prediction, Principal Component Analysis (PCA) combined with Backpropagation (BP) neural networks was applied to evaluate main engine energy efficiency on a 300,000-ton ocean-going bulk carrier, achieving a navigation state recognition accuracy of 98.05% and an average fuel consumption model error of 3.47%.

This paper investigates the optimization of energy efficiency for ocean-going vessels based on big data analysis [1]. First, it reviews the regulatory framework and theoretical foundations of ship energy efficiency management; second, it develops a big data–driven energy efficiency optimization model; finally, it validates the model's effectiveness through case studies, providing a scientific reference for sustainable navigation of ocean-going vessels.

## 2. Theoretical Foundations of Big Data and Energy Efficiency in Ocean-Going Ships

### 2.1. Regulatory Framework for Ship Energy Efficiency Management

The International Maritime Organization has established a framework for ship energy efficiency management through Annex VI of the International Convention for the Prevention of Marine Pollution by Ships, with core mechanisms categorized into technical and operational approaches [3].

Technical measures include the phased implementation of the Energy Efficiency Design Index for new ships, beginning in 2013. Baseline requirements were set in Phase 0 (2013), followed by progressively stricter targets: a 10% improvement in Phase 1 (2015), 20% in Phase 2 (2020), and 30% in Phase 3 (2025), expressed in grams of $CO_2$ per ton-nautical mile [4]. The Existing Ship Energy Efficiency Index, introduced in 2023, applies to all vessels over 400 gross tons and requires calculation against defined performance thresholds.

Operational measures include the Carbon Intensity Index rating system, applicable since 2023 to vessels exceeding 5,000 gross tons [5]. This system classifies performance into five tiers (A to E) based on carbon emission intensity per transport work, with Tier A indicating highest efficiency and Tier E lowest. Vessels receiving a D rating for three consecutive years or an E rating in any year must submit a corrective action plan for official review. Annual CII reduction targets rise incrementally: 5% in 2023, 7% in 2024, 9% in 2025, and 11% in 2026. The Energy Efficiency Operational Indicator, a voluntary voyage-level metric, is calculated as follows:

$$\mathrm{EEOI} = \frac{\sum_j (\mathrm{Fuel}_j \times \mathrm{CF}_j) \times 10^6}{\sum_i (m_{\mathrm{cargo},i} \times D_i)}$$

Where: $Fuel_j$ represents the consumption of the $j$-th fuel type (t); $C_{F,j}$ is the carbon conversion factor for the corresponding fuel (t-$CO_2$/t-Fuel), where Diesel/Gas Oil = 3.206, LFO = 3.15104, HFO = 3.1144, and LNG = 2.75; $m_{cargo,i}$ is the cargo mass for the $i$-th voyage (t); $D_i$ is the sailing distance for the corresponding voyage (nm).

The Ship Energy Efficiency Management Plan (SEEMP), as a mandatory requirement of MARPOL Annex VI, provides an institutional framework for energy efficiency improvement at the operational level.

In 2022, national guidance titled 'Measures for the Management of Ship Energy Consumption Data and Carbon Intensity' was issued, specifying data collection and reporting obligations for vessels—both domestic and foreign—with gross tonnage exceeding 400. Complementary technical standards, such as JT/T 1340-2020 'Technical Requirements for the Collection and Reporting of Ship Energy Consumption Data', further support a domestic ship energy efficiency management system consistent with international practice [3].

*2.2. Big Data Collection and Processing Technologies*

Big data on ocean-going vessel navigation encompasses multi-source heterogeneous data, primarily including ship motion state data (speed SOG, course COG, position GPS, longitudinal roll, lateral roll); main engine operational data (rotational speed RPM, power output, shaft power, fuel consumption); ship status data (draft, draft difference, cargo weight); environmental data (wind speed, wind direction, wave height, wave direction, current velocity, current direction, air temperature, water temperature, water depth); and navigation trajectory data (AIS tracks, midnight report data) (As shown in Figure 1).

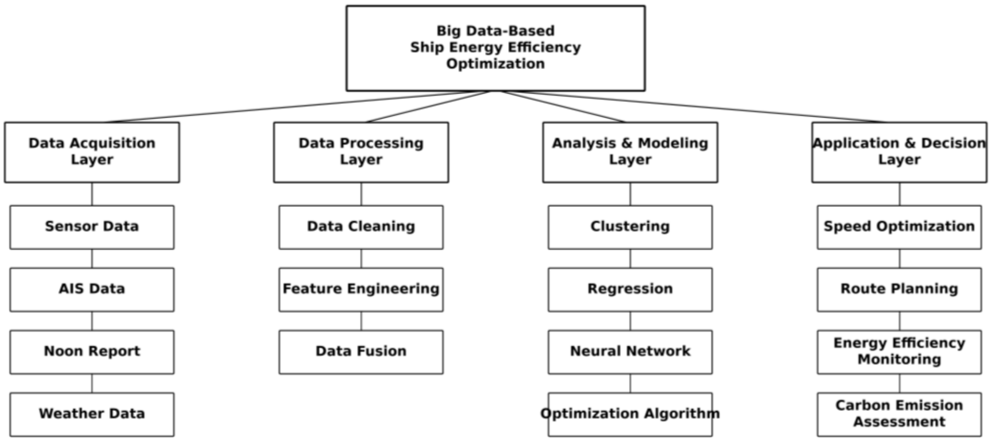


**Figure 1.** Technology Framework for Energy Efficiency Optimization of Ocean-going Ships Based on Big Data

The aforementioned data are characterized by large volume, high dimensionality, strong temporal correlation, and significant noise interference, requiring preprocessing steps such as data cleaning, missing value handling, outlier detection, and feature engineering before being suitable for analysis and modeling. Multi-source data fusion technology—integrating weather reports, meteorological data, ocean current data, and AIS data—significantly enhances fuel consumption prediction accuracy; predictive performance with a coefficient of determination as high as 0.9431 has been achieved using this approach [6].

*2.3. Factors Affecting Energy Efficiency in Long-Distance Maritime Navigation*

The energy efficiency of ocean-going vessels is influenced by a combination of multidimensional factors including hull parameters, operational conditions, and navigation environments [7]. Hull parameters encompass ship dimensions, hull line design, and propulsion efficiency; hull line optimization has been shown to reduce the effective power consumption of bulk carriers by approximately 7.16%. Operational factors involve cargo load, draft and draft difference, and speed selection, with vessel speed exerting a particularly significant influence on fuel consumption. Navigation environment factors include meteorological and sea conditions such as wind, waves, and currents, which directly affect hydrodynamic drag and consequently influence fuel consumption.

Principal component analysis has been applied to evaluate the energy efficiency of marine engines, identifying the primary influencing factors and their relative contributions [8]. A fuel consumption prediction study using the random forest algorithm found that the most influential variables—ranked by importance—were vessel speed, water flow velocity, water depth, wind speed, and wind direction, achieving a prediction error below 6.8%.

## 3. Construction of an Energy Efficiency Optimization Model Based on Big Data

### *3.1. Energy Efficiency Indicator System*

The ship energy efficiency optimization model based on big data analysis centers on an energy efficiency indicator system and establishes a comprehensive pipeline from data collection to decision-making [9]. As shown in Figure 2, the model framework comprises four layers: data acquisition, data processing, analysis and modeling, and application-based decision-making.

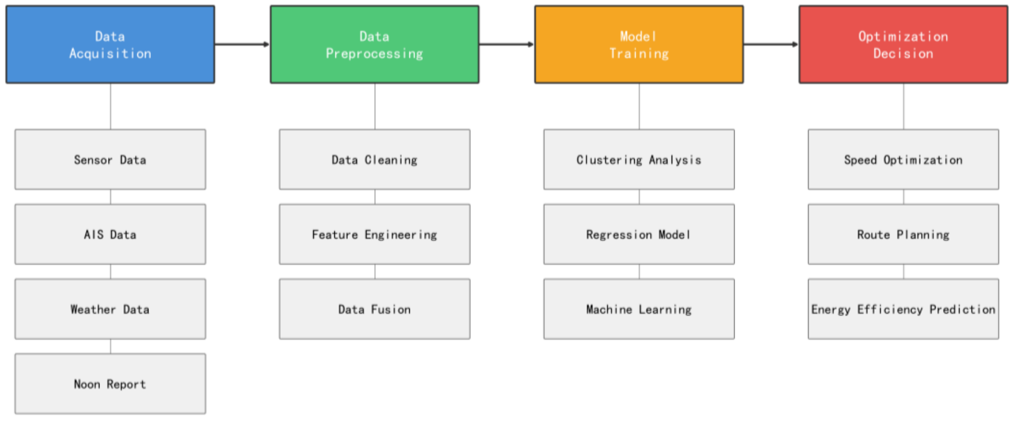


**Figure 2.** Framework of an Energy Efficiency Optimization Model Based on Big Data

The energy efficiency indicator system uses the Energy Efficiency Operational Indicator (EEOI) and the Carbon Intensity Indicator (CII) as its core quantitative metrics. EEOI measures carbon emission intensity per unit of transport work at the voyage level, while CII reflects annual carbon intensity ratings at the operational level. By integrating multi-source navigation data with these indicators, real-time monitoring and dynamic evaluation of energy efficiency during voyages can be achieved.

### *3.2. Big Data Analysis Methods*

Big data analysis methods primarily fall into three categories: cluster analysis, regression analysis, and machine learning.

Cluster analysis is employed for identifying and classifying navigation conditions. An automated identification system for high-energy-consumption operating states of ships has been developed by improving the Particle Swarm Optimization-based Fuzzy C-Means Clustering (IPSO-FCM) algorithm and integrating Principal Component Analysis (PCA) with dynamic thresholding techniques [10]. Intelligent segmentation of inland waterways has been achieved by combining K-means clustering with random forests, reducing the mean absolute percentage error (MAPE) in fuel consumption prediction from 3.53% to 3.32%. An LSTM-based fuel consumption prediction method tailored for ship navigation condition classification first categorizes navigation modes through clustering before performing separate modeling predictions, resulting in a reduction of root mean square error (RMSE) from 2.42 to 1.52 and an increase in coefficient of determination ($R^2$) from 0.52 to 0.71.

Regression analysis is employed to establish a quantitative relationship between navigation parameters and fuel consumption. A regression model for route-specific fuel consumption has been developed based on real-world ship monitoring data, achieving a model error of only 0.9%.

Machine learning methods demonstrate significant advantages in energy efficiency prediction [1]. A PCA-enhanced BP neural network has been applied to assess the energy efficiency of main engines on 300,000-ton ocean-going bulk carriers, achieving a navigation status recognition accuracy of 98.05% and an average error of 3.47% in fuel consumption modeling. A ship routing decision system based on a BP neural network has been developed, with a model fit quality of 79.97%. The Whale Optimization Algorithm has been utilized to optimize energy efficiency for hybrid fuel cell/lithium battery ships, resulting in a 5.04% reduction in total energy consumption.

### *3.3. Optimization Algorithm*

At the energy efficiency optimization decision-making level, the focus primarily encompasses three areas: speed optimization, weather-based route selection, and energy efficiency forecasting [9].

Speed optimization aims to minimize fuel consumption per nautical mile by identifying the optimal sailing speed. An intelligent speed optimization method based on real-world ship monitoring data has been developed, reducing fuel consumption along a fixed route by 1.9%. A collaborative optimization approach for ship heading and speed using an improved A* algorithm has also been proposed, enabling joint optimization of both parameters and offering a novel solution strategy for energy efficiency improvement in complex water environments.

Meteorological routing selects optimal routes by comprehensively considering meteorological and sea conditions [11]. Intelligent ship route optimization methods have been reviewed, highlighting meteorological routing technology as a crucial approach for energy conservation in ocean-going vessels. A meteorological route decision-making system based on a BP neural network has been developed, achieving intelligent route selection through integrated weather forecast data with a goodness-of-fit of 79.97%.

Energy efficiency forecasting establishes a mapping relationship between navigation parameters and energy efficiency metrics, providing forward-looking references for operational decision-making. Comparative studies on intelligent fuel consumption prediction methods based on navigation observation data indicate that the Light GBM model reduced the prediction RMSE by 7.26% on a 28,000 DWT bulk carrier. The GA-LSTM model, which optimizes LSTM network hyperparameters using a genetic algorithm, achieved a prediction error of only 0.29%. When combined with the NSGA-III multi-objective optimization algorithm, the GA-LSTM+NSGA-III approach delivers a 4.54% reduction in fuel consumption [12].

## 4. Case Analysis and Applications

### *4.1. Data Sources*

This study focuses on an ocean-going bulk carrier, collecting its navigation data along the Asia-Pacific–Europe route [2]. Data sources include Automatic Identification System (AIS) trajectory data, main engine operating parameters from onboard sensors, ships' noon report data, and meteorological and sea condition data provided by third-party services. The dataset encompasses multiple dimensions such as speed, heading, main engine rotational speed, fuel consumption, draft, and meteorological parameters, with a sampling interval of 10 seconds and a cumulative collection period of approximately 90 days; field descriptions are presented in Table 1.

**Table 1.** Field Descriptions for the Oceanic Ship Navigation Big Data Set

| Field Name | Data Type | Unit | Example Value | Sample Size | Description |
|---|---|---|---|---|---|

| | | | | | |
|---|---|---|---|---|---|
| SOG | Float | kn | 12.5 | 777,600 | Speed Over Ground |
| COG | Float | ° | 045.3 | 777,600 | Course Over Ground |
| Latitude | Float | ° | 35.6789 | 777,600 | GPS Latitude |
| Longitude | Float | ° | 122.3456 | 777,600 | GPS Longitude |
| ME_RPM | Float | r/min | 78.5 | 777,600 | Main Engine RPM |
| ME_Power | Float | kW | 8,520 | 777,600 | Main Engine Power |
| Shaft_Power | Float | kW | 8,350 | 777,600 | Shaft Power |
| Fuel_Consumption | Float | t/d | 38.6 | 777,600 | Daily Fuel Consumption |
| Draft_Fore | Float | m | 9.85 | 777,600 | Fore Draft |
| Draft_Aft | Float | m | 10.15 | 777,600 | Aft Draft |
| Trim | Float | m | 0.30 | 777,600 | Trim (Aft - Fore) |
| Cargo_Weight | Float | t | 52,000 | 777,600 | Cargo Loaded |
| Wind_Speed | Float | m/s | 8.5 | 777,600 | Wind Speed |
| Wind_Direction | Float | ° | 045.0 | 777,600 | Wind Direction |
| Wave_Height | Float | m | 2.3 | 777,600 | Significant Wave Height |
| Wave_Direction | Float | ° | 090.0 | 777,600 | Wave Direction |
| Current_Speed | Float | kn | 0.8 | 777,600 | Current Speed |
| Current_Direction | Float | ° | 270.0 | 777,600 | Current Direction |
| Air_Temp | Float | ℃ | 18.5 | 777,600 | Air Temperature |
| Water_Temp | Float | ℃ | 16.2 | 777,600 | Sea Water Temperature |
| Water_Depth | Float | m | 85.0 | 777,600 | Water Depth |
| Sailing_Distance | Float | nm | 301.2 | 777,600 | Daily Sailing Distance |

Table 1 presents field descriptions for the ocean-going ship navigation big dataset.

### *4.2. Energy Efficiency Analysis Results*

Based on the aforementioned dataset, three machine learning models—BP neural network, random forest, and LSTM—were employed to predict ship fuel consumption. The dataset was divided into a training set and a test set in a 7:3 ratio, with root mean square error (RMSE) and coefficient of determination ($R^2$) serving as evaluation metrics.

As shown in Figure 3, the prediction accuracy comparisons among the three models are as follows: The BP neural network model achieved a fit goodness of 79.97%; a PCA-enhanced BP approach attained navigation status recognition accuracy of 98.05% and an average fuel consumption prediction error of 3.47% for 300,000-ton ocean-going bulk carriers; the random forest model exhibited a prediction error below 6.8%, with variable importance analysis revealing that vessel speed had the most significant impact on fuel consumption; when combined with operational condition classification, the LSTM model saw its RMSE decrease from 2.42 to 1.52 and its $R^2$ increase from 0.52 to 0.71; the multi-source data fusion model demonstrated the highest prediction accuracy, with a coefficient of determination of 0.9431.

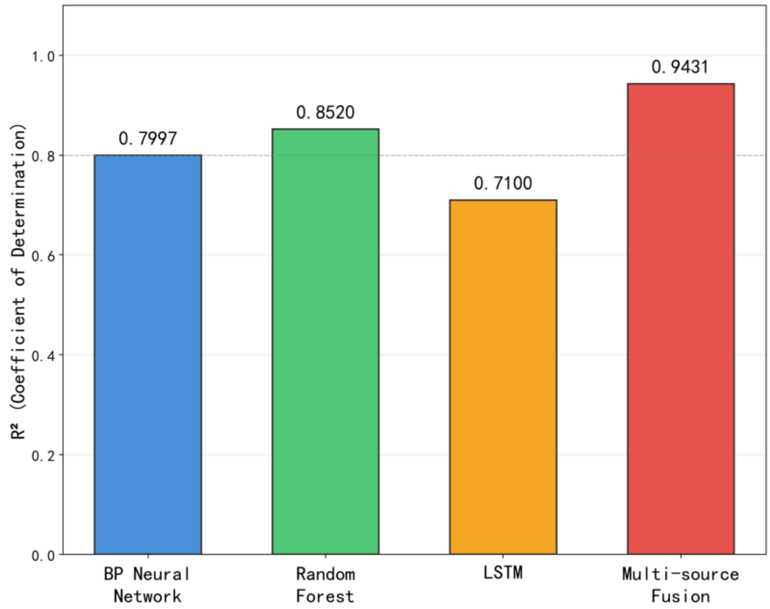


**Figure 3.** Comparison of Prediction Accuracy among Various Machine Learning Models

The fuel consumption prediction model based on GA-LSTM optimizes LSTM network hyperparameters using a genetic algorithm, achieving a prediction error of only 0.29%. By integrating the NSGA-III multi-objective optimization algorithm, the GA-LSTM+NSGA-III approach achieves a 4.54% reduction in fuel consumption while ensuring on-time delivery.

*4.3. Optimization Suggestions*

Based on the aforementioned analysis results and drawing on practical experience in ocean-going vessel navigation, the following energy efficiency optimization recommendations are proposed:

(1) Speed optimization. Dynamically adjust sailing speed according to weather conditions, sea state, and cargo load to avoid fuel waste associated with high-speed navigation [13]. Field tests have demonstrated that intelligent speed optimization reduces fuel consumption on fixed routes by approximately 1.9%. Pilots may employ fuel consumption prediction models to select the most economical speed while satisfying voyage schedule requirements.

(2) Meteorological route optimization. Optimal navigation paths are selected using weather forecast data to avoid regions of severe sea conditions. A meteorological route decision system based on a back-propagation neural network supports effective route planning. During long-distance voyages, strategically avoiding areas with strong winds and high waves not only lowers fuel consumption but also enhances navigation safety.

(3) Real-time energy efficiency monitoring. A mechanism-based ship energy consumption monitoring system has been deployed to enable real-time assessment of energy efficiency and prompt alerts for anomalies during navigation. Dynamic monitoring of EEOI and CII indicators allows operators to timely adjust navigation strategies to maintain regulatory compliance [7].

(4) Operating condition identification and refined management. Cluster analysis algorithms are applied to identify high-energy-consumption operating modes, facilitating the development of mode-specific energy efficiency management strategies [14–16]. Refined modeling based on intelligent channel segmentation has been shown to reduce fuel consumption prediction error, as measured by MAPE.

(5) Application of hybrid power technology [5]. For newly built vessels, a hybrid fuel cell/lithium-ion battery system may be considered. Energy efficiency analysis using the Whale optimization algorithm indicates that this configuration reduces total energy

consumption by approximately 5.04%, offering a technical pathway toward greener ocean-going vessel operations.

## 5. Conclusion and Prospects

### *5.1. Research Conclusion*

This paper conducts a systematic study on optimizing the energy efficiency of ocean-going vessels based on big data analysis, and arrives at the following key conclusions:

(1) The International Maritime Organization ship energy efficiency management regulatory framework—centered on the Energy Efficiency Design Index, the Existing Ship Energy Efficiency Index, the Carbon Intensity Indicator, and the Ship Energy Efficiency Management Plan—promotes emission reduction in the shipping industry from both technical design and operational management perspectives. Complementary national measures provide institutional support for ship energy efficiency data management and carbon intensity assessment.

(2) Ocean-going vessel navigation big data encompasses multi-source heterogeneous data, including motion states, main engine operation parameters, ship conditions, and environmental parameters. Through data cleaning, feature engineering, and multi-source data fusion, it establishes a high-quality data foundation for energy efficiency optimization modeling. The determination coefficient of the fuel consumption prediction model based on multi-source data fusion reaches 0.9431.

(3) Machine learning methods demonstrate significant advantages in ship energy efficiency prediction. A back-propagation neural network achieves a 98.05% accuracy rate in navigation state recognition with a fuel consumption prediction error of 3.47%; a long short-term memory model shows an improvement in $R^2$ from 0.52 to 0.71 after incorporating operational condition classification; and a genetic algorithm–optimized long short-term memory model exhibits a prediction error of merely 0.29%. Application of the NSGA-III multi-objective optimization algorithm yields a fuel consumption reduction of 4.54%.

(4) Speed optimization, weather-based route selection, and real-time energy efficiency monitoring represent the three key technical approaches for improving energy efficiency in ocean-going vessels. Intelligent speed optimization reduces fuel consumption on fixed routes by 1.9%; weather-based routing technology effectively avoids adverse sea conditions; and the energy consumption monitoring system provides real-time decision support.

### *5.2. Research Limitations and Prospects*

This study has the following limitations: First, certain model parameters used in the case analysis are drawn from existing literature and have not undergone large-scale comparative validation with operational vessel data; second, CII rating thresholds (A–E) differ across vessel types, yet this work relies on qualitative characterizations without specifying quantitative benchmarks; third, the dataset is predominantly derived from a single route and vessel type, limiting the assessed models' generalizability and necessitating broader empirical validation.

Future research directions include: establishing a standardized maritime energy efficiency big data platform encompassing diverse ship types and routes to improve model robustness; applying digital twin technology to enable virtual-real integration and real-time energy optimization; and incorporating alternative fuels and hybrid power systems to enhance lifecycle energy efficiency of ocean-going vessels.

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