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A comprehensive review on the prediction of ship energy consumption and pollution gas emissions

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ABSTRACT

Ship energy consumption and emission prediction are critical for ship energy efficiency management and pollution gas emission control, both of which are major concerns for the shipping industry and hence continue to attract global attention and research interest. This article examined the energy efficiency data sources, big data analysis for energy efficiency, and analyzed the ship energy consumption and emission prediction models. The ship energy consumption and pollution gas emission prediction models are comprehensively summarized based on the modeling method and principles. The theoretical analysis and artificial intelligence-based ship energy consumption model, as well as the top-down and bottom-up ship emission prediction models, are thoroughly examined in terms of influencing factors, model accuracy, data sources, and practical applications. On this basis, the challenges of ship energy consumption and emission prediction are discussed, and future research suggestions are proposed, providing a foundation for the development of ship energy consumption and emission prediction technologies. The analysis results show that the principles, parameters of concern, and data quality all have a significant impact on the performance of the prediction models. Consequently, the prediction model's accuracy can be improved by combining intelligent algorithms and machine learning. In the future, high precision, self-adapting, ship fuel consumption and emission prediction models based on artificial intelligence technology should be further studied, in order to improve their prediction performance, and thus providing solid foundations for the optimization management and control of the ship energy consumption and emissions.

1. Introduction

Maritime transport plays an essential role in international trade and economic development (UNCTAD/RMT/2020, 2020). However, with the increase in global shipping trade volume, emissions from the shipping industry have also become a global concern (Wan et al., 2016). According to the International Maritime Organization (IMO), ships account for approximately 2.89% of global CO_2 emissions. If the status quo remains, CO_2 emissions will continue to rise by 50–250% by 2050 (IMO, 2014). To reduce carbon emissions in the shipping industry, IMO proposed the initial strategy for reducing GHG emissions from ships and committed to reducing total annual GHG emissions by 50% by 2050 compared to 2008 (IMO, 2018). Meanwhile, IMO also put forward the SEEMP (Ship Energy Efficiency Management Plan), EEDI (Energy Efficiency Design Index), EEXI (Energy Efficiency Existing Ship Index), CII (Carbon Intensity Indicator), and other energy-saving and emission-reduction measures (IMO, 2012, 2020).

Furthermore, fuel consumption costs account for 60% or more of the ship voyage costs (Faber et al., 2012), and thus have a considerable impact on shipping companies' economies. Therefore, the development and application of energy efficiency optimization technologies for ships will not only meet the increasingly stringent energy efficiency and emission regulations, but also the urgent needs of shipping companies to improve the economic efficiency and competitiveness of their fleets (Szlapczynska and Szlapczynski, 2019; Wen et al., 2017), which is

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Abbreviations

AIS	Automatic Identification System
STEEM	Ship Traffic, Energy and Environment Model
STEAM	Ship Traffic Emission Assessment Model
WRF-Chem	Weather Research and Forecasting with chemistry
SENEM	Ship's ENergy Efficiency Model
LASSO	Least Absolute Shrinkage and Selection Operator
UAV	Unmanned Aerial Vehicles
DWT	Deadweight Tonnage
IMO	International Maritime Organization
SEEMP	Ship Energy Efficiency Management Plan
EEDI	Energy Efficiency Design Index
EEXI	Energy Efficiency Existing Ship Index
CII	Carbon Intensity Indicator
DBPNN	Back Propagation Neural Network with double hidden layers
ITTC	International Towing Tank Conference
JONSWAP	Joint North Sea Wave Atmosphere Program
ISO	International Organization for Standardization
CFD	Computational Fluid Dynamics
DTU	Technical University of Denmark
ANN	Artificial Neural Network
ECA	Emission Control Area
MLR	Multiple Linear Regression
MR	Multivariable Regression
BPNN	Back Propagation Neural Network
LM	Levenberg-Marquardt
DBN	Deep Belief Networks
RBM	Restricted Boltzmann Machines
DNN	Deep Neural Network
FOC	Fuel Oil Consumption
FCR	Fuel Consumption Rate
CNN	Convolutional Neural Network
RMSE	Root Mean Square Error
MAE	Mean Absolute Error
SVR	Support Vector Regression
SVMs	Support Vector Machines
ETRs	Extra Trees Regressors
ET	Extra Trees
RF	Random Forest
CCS	China Classification Society
RNN	Recurrent Neural Network
LSTM	Long Short-term Memory
MLPN	Multilayer Perceptron Network
GP	Gaussian Process
GPR	Gaussian Process Regression
DT	Decision Tree
GA	Genetic Algorithm
RPM	Revolutions Per Minute
GHG	Green House Gas
ADLM	Automated Data Logging & Monitoring system
SDU	University of Southern Denmark
AMS	Alarm Monitoring System
CMS	Continuous Monitoring System
EEOI	Energy Efficiency Operational Indicator
KNN	K-Nearest Neighbor
MC	Metocean Condition
AML	Auto Machine Learning
MSE	Mean Squared Error
RR	Ridge Regression
XGB	XGBoost
ML	Machine Learning
R^2	Coefficient of Determination
A-GBM	Advanced approach GBM
N-GBM	Naive approach GBM

critical to the development of low-carbon shipping (Le et al., 2020a).

The ship energy system involves the whole process of energy generation, conversion, transmission and consumption. The main engine generates power by burning fuel, which is transmitted and converted by the shaft and propeller to overcome the navigation resistance of the ship. The operation status and efficiency of the ship's energy system will change due to the influence of various factors, such as the ship's navigation environment and operating conditions, which will further affect the ship's energy consumption and thus the pollution gas emissions. To enhance energy efficiency and manage emissions (Bialystocki and

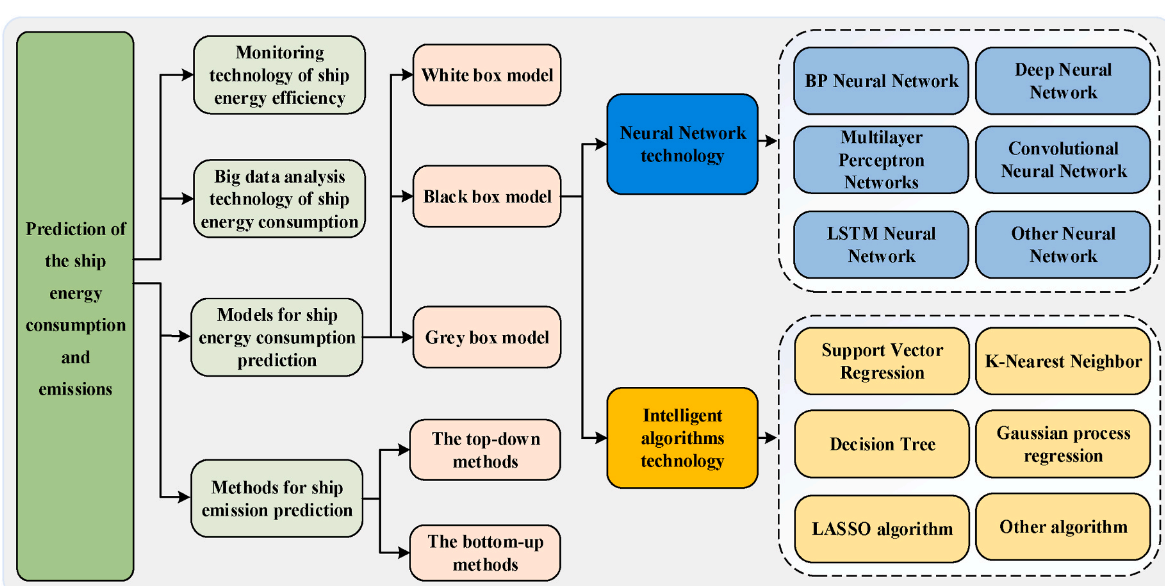

Fig. 1. Topology of the ship energy consumption and emission prediction technology.

Konovessis, 2016; Simonsen et al., 2018; Tillig and Ringsberg, 2019), effective ship energy consumption and emissions prediction are essential. Either, ship fuel consumption and emission prediction technology provide foundations for energy efficiency optimization and emission control (Krata and Szlapczynska, 2018; Moreno-Gutiérrez et al., 2019). However, to the best of our knowledge, there is a lack of systematic analysis of prediction methods, principles, parameters of concern, data sources, model accuracy, and application performance in the existing research, making it difficult to provide support for selecting suitable prediction methods for various application scenarios.

To close the gap, the current progress made on ship energy consumption and emissions prediction is reviewed comprehensively in this paper. In addition, the characteristics and application of prediction models based on different methods (as shown in Fig. 1), have been discussed in terms of construction principle, model structure, parameters of concern, and prediction performance, in order to provide a guidance for the study and application of the prediction and management of ship energy consumption and emissions. The main objectives of this work are concluded as follows:

1) To analyze the characteristics and performance of different prediction models in terms of theoretical principle, model structure, parameters of concern, model accuracy and adaptability, and also the limitations of different types of models, which are the keys to achieve the ship energy efficiency optimization.
2) To illustrate the challenges and prospects on the ship energy consumption and pollution gas emissions in terms of big data analysis, model accuracy, model adaptability, and optimization control measures.
3) To provide an essential guidance for future research on optimization methods and decision-making system development for ship energy consumption and emissions, thereby promoting the green development of the shipping industry.

The remainder of this paper is organized as follows: **Section 2** introduces the data acquisition of ship energy efficiency. **Section 3** discusses the big data analysis technology for ship energy efficiency. **Section 4** presents the progress on models for ship energy consumption prediction, including the white box model, black box model, and grey box model. Afterwards, **Section 5** summarizes the progress on methods for ship emission prediction. Finally, the challenges and prospects for the predictions of ship energy consumption and emissions are outlined in **Section 6**.

2. Data acquisition of ship energy efficiency

The energy efficiency optimization technology of ships can provide effective strategy for ship's energy-efficient operation (Fan et al., 2016), and bring economic benefits for shipping companies (Wang et al., 2015a; Du et al., 2019). Big data source and analysis are the essential foundations for the effective prediction of the ship energy consumption and emissions. Some energy efficiency monitoring and management systems have been developed, as shown in Table 1. These systems can obtain related data and achieve the optimization of ship energy efficiency.

The ship energy efficiency management system can realize continuous monitoring and prediction of ship performance (Trivyza et al., 2022), and the evaluation and optimization management of the ship fleet performance (Wang et al., 2018a), which can support fuel management, energy efficiency evaluation, and navigation optimization under different working conditions (Zhang et al., 2019). In addition, based on the acquisition and analysis of big data, the optimal decisions on navigation can be realized (Lee et al., 2018a), by adopting advanced

Table 1
The ship energy efficiency monitoring and management systems.

System	Functions	Type of ships	Reference
Ship Energy efficiency Monitoring System of Marorka	Power optimization, speed optimization, loading optimization, route optimization, fleet optimization	Bulk carriers, container ships, oil tankers	(https://www.marorka.com/products/#marorka-onboard)
Ship Performance Monitoring System of Kyma	Power optimization, loading optimization, fleet optimization	Bulk carriers, container ships	(https://kyma.no/ship-performance/)
Ship Energy efficiency Monitoring System of SeaTechnik	Real-time monitoring and optimization of ship performance	Bulk carriers, container ships	(https://www.trelleborg.com/en/marine-and-infrastructure/products-solutions-and-services/marine/ship-performance-technology)
NAPA Energy Efficiency Management Module	Speed optimization, loading optimization, route optimization, fleet optimization	Bulk carriers, ore carriers	(https://www.napa.fi/software-and-services/ship-operations/napa-fleet-intelligence/)
ECO-Assistant Software System	Loading optimization	Bulk carriers, container ships	(https://www.dnv.com/cn/services/page-1422)
Rolls-Royce Energy Management System	Power monitoring and optimization	Bulk carriers, container ships	(https://www.rolls-royce.com/media/press-releases/2017/31-05-2017-rr-launches-next-generation-energy-management-system.aspx)
Integrated Monitoring System of Ship Energy Efficiency of ABB	Speed optimization	Container ships, Ro-Ro ships	(https://new.abb.com/marine/systems-and-solutions/digital/control-and-monitoring)
Ship Navigation Optimization System of Jeppesen Marine	Power optimization, speed optimization, route optimization	Container ships	(https://ww2.jeppesen.com/marine)
Ship energy efficiency System of CCS	speed optimization, loading optimization, fleet optimization	Bulk carriers, container ships	He et al. (2021)
SHIPMANAGER-88	Loading optimization	Container ships	(http://www.techmarine.net/main.htm)

optimization algorithms (Lazarowska, 2014) and decision-making systems (Vettor and Soares, 2016). However, the degree of network connection, and integration of on-board equipment, shore-based equipment, and ship-to-shore communication equipment needs to be improved (Wang et al., 2015b). The synchronous sharing of ship-shore data information of energy efficiency will be the key to the optimization control and improvement of ship energy efficiency.

3. Big data analysis for ship energy efficiency

Ship energy consumption and emission are not only related to the ship parameters, but also related to navigational environment (Fan et al., 2021), sailing state (Lu et al., 2015), ship loading (Tran, 2020), hull fouling (Adland et al., 2018), applied antifouling coating (Farkas et al., 2021; Seok and Park, 2020), etc. Therefore, the related data are diverse and huge (Lensu and Goerlandt, 2019; Wang et al., 2016a), and the data types are complex and diverse (Zhu et al., 2021). With the development of big data analysis technology (Kambatla et al., 2014), the ship's energy consumption characteristics can be explored (Munim et al., 2020; Yan et al., 2021), and the influencing factors of ship's energy efficiency and their coupling relationship can be investigated (Chen et al., 2010). On these bases, the ship's energy efficiency level can be analyzed and evaluated (Gonzalez et al., 2018), thus providing foundations for the model establishment of ship energy efficiency (Lepore et al., 2019; Man et al., 2020).

(1) Analysis of ship energy efficiency characteristics based on big data

The related data on ship energy consumption can be obtained by the real-time monitoring tool of energy efficiency (Chi et al., 2018; Tsujimoto and Orihara, 2019) and fuel consumption monitoring system (Capezza et al., 2019). On this basis, the big data analysis technology can be adopted to evaluate the energy efficiency level of the energy-consumed equipment and to reveal the causes of low energy efficiency, thus realizing the intelligent analysis and optimization decisions which are difficult to achieve only depending on the operators' experience (Jeon et al., 2021; Lee et al., 2018b). Therefore, a big data collection and processing scheme is vital for ship energy consumption analysis (Perera and Mo, 2016). The data mining and analysis of ship sailing speed, fuel consumption, and navigational environment can be carried out based on the big data analysis platform. Furthermore, the related intelligent optimization decisions of ship energy efficiency can be achieved by adopting the big data technology (Wang, 2018). It can provide an effective method for the optimization management of ship energy efficiency.

(2) Influencing factors analysis of ship energy efficiency based on big data

Ship energy consumption is influenced comprehensively by multiple parameters, including the sailing state, navigational conditions, etc. Among others, the navigational environmental factors (wind, wave, and current) directly influence the navigation resistance and thus affect the ship's fuel consumption (Anan et al., 2017). Therefore, the analysis of the navigational environment characteristics is of great significance to the ship energy consumption prediction. Based on the big data analysis of navigational environment, the temporal and spatial distribution characteristics for different sailing time and routes can be excavated, contributing to the relationship analysis between ship energy consumption and navigational environment (Yan et al., 2018). The intelligent analysis and prediction of navigational environment based on big data can be realized by adopting the machine learning algorithms, such as *k*-means and neural networks (Wang et al., 2017). In addition, the correlation among the influencing factors of ship energy consumption can be achieved by adopting the association analysis method (Gao, 2019). The influence law of those parameters on ship's energy consumption can be obtained, which is a solid foundation for establishing the ship energy consumption model that considers multiple influencing factors.

(3) Evaluation benchmark of ship energy efficiency based on big data

During the ship navigation, there exist obvious differences in the navigational status and energy efficiency level under different navigational conditions (Themelis et al., 2018). In order to evaluate a ship's energy efficiency, it is necessary to carry out an identification of ship navigational status. On this basis, the ship energy efficiency can be evaluated according to different navigational states. Thus, the evaluation benchmark of ship energy efficiency under different navigation conditions can be established, making it convenient for the comparative analysis of ship energy efficiency. The Neural Network-based method can be used to evaluate the ship energy efficiency level under the current navigational condition, and finally realize the comparative analysis of different ship energy efficiency levels (Liu et al., 2018a). On this basis, the decision-making of ship energy consumption under different navigational environments can be realized, to improve the ship's energy efficiency effectively (Tsitsilonis and Theotokatos, 2018).

4. Models for ship energy consumption prediction

According to the established ways and principles, the ship energy consumption models mainly include the white box model (WBM), black box model (BBM), and grey box model (GBM). The three kinds of models have different characteristics in the interpretability, prediction accuracy, demand for historical data, and extrapolation ability, as shown in Table 2.

4.1. White box model of ship energy consumption prediction

The WBM of fuel consumption prediction is based on the known physical laws and relations, including the ship resistance obtained by regression method (Adland et al., 2020), ship model towing test or Computational Fluid Dynamics (CFD) analysis (Islam and Soares, 2019), the energy transferring relationship (Nakamura and Naito, 1977), and the engine fuel consumption characteristics, etc. However, at present, there is still a lack of accurate formulas to dynamically describe the relationship between energy consumption and the complex influencing factors. The relevant studies, which take the total voyage cost as optimization criteria, establish the fuel consumption prediction model based on the constant relationship between fuel consumption and sailing speed (Qi and Song, 2012; Sheng et al., 2019). However, the relationship between fuel consumption and sailing speed are different due to the influence of environmental factors and loading conditions (Berthelsen and Nielsen, 2021). Therefore, the dynamical relationship between fuel consumption and sailing speed can improve the accuracy and performance of the prediction models for varying operational conditions.

Environmental factors have a huge influence on the navigational resistance of ships (Chen et al., 2013), thus affecting the ship's energy consumption (Sun et al., 2013; Tillig et al., 2017). The navigation resistance analysis is the key to establish the energy consumption model,

Table 2
Comparative analysis of ship energy consumption prediction models.

Category	Interpretability	Prediction accuracy	Demand for historical data	Extrapolation ability
WBM	Good	Average	No need	Good
BBM	Poor	Good	Need much historical data	Poor
GBM	Good	Good	Need a bit historical data	Good

which mainly includes calm water resistance and additional resistance (Fan et al., 2018). The studies of calm water resistance mainly consist of the methods based on the theoretical formula and the CFD analysis (Holtrop and Menmen, 1982). In addition, wind, waves, and currents would also result in additional resistance (Li et al., 2018; Medina et al., 2020). There are two main methods to quantify the influence of wind, waves, and currents on ship's navigation resistance. One approach estimates the speed loss under the given engine power (Li et al., 2020; Karagiannidis and Themelis, 2021). For example, Yang et al. (2020) established a fuel consumption prediction model by considering the influence of currents on the ship speed loss. In addition, Jasna and Faltinsen (2012) estimated the ship speed loss and associated CO_2 emissions in a seaway. The other method calculates the added resistance at a specific speed (Wang et al., 2020a, 2021a). The influence of wind added resistance and wave added resistance are considered for the fuel consumption prediction model (Wang et al., 2021b). On this basis, the energy consumption under different sailing conditions can be predicted based on the energy transfer relationship between the ship hull, propeller, and main engine.

The different navigational environments will also influence the navigational states of the ship and the operational states of the power system (Tillig et al., 2018, 2020), thus affecting the propulsion characteristics of the propeller and the dynamic fuel consumption characteristics of the main engine (Wang et al., 2015c). Therefore, when establishing the energy consumption model according to the ship-engine-propeller coupling relationship, the influence of navigational environment factors on the ship navigation resistance and the characteristics of the ship propulsion system should be comprehensively considered (Trodden et al., 2015; Wang et al., 2016b). The analysis of ship energy consumption based on the energy transferring relationship is shown in Fig. 2 (Pedersen and Larsen, 2009). It is vital to improve the accuracy of the ship energy consumption model by obtaining the dynamic relationship between the navigational environment and the ship-engine-propeller operating state (Wang et al., 2018b), and thus effectively describing the dynamic characteristics of the ship propulsion system under different conditions (Tzortzis and Sakalis, 2021; Wang et al., 2020b).

Table 3 analyzes the characteristics of various WBMs for predicting ship energy consumption. From the table, we can know that WBMs can be used to forecast fuel consumption for most types of ships. However, the required model parameters should be obtained from the operational information, although some information is difficult to obtain. This may cause some discrepancies between the predicted and actual fuel consumption under different navigational environments. Moreover, the WBMs only consider a part of the influencing factors, ignoring the possibility of mutual influence among various factors, making the WBMs vulnerable in practical application, weakening the performance of ship energy consumption prediction and optimization.

4.2. Black box model of ship energy consumption prediction

The BBM can process multi-dimensional data and extract hidden information from complex data sets, thus providing a reliable basis for the study on the optimization model of ship's fuel consumption (Tarelko and Rudzki, 2020; Sun et al., 2019). In recent years, the development of big data technology and machine learning algorithm has made the establishment of the BBM for the energy consumption prediction more accurate and effective (Schoen et al., 2019; Planakis et al., 2022). The main methods for predicting ship energy consumption are the Neural Network-based methods (Le et al., 2020b; Tran, 2021), and the intelligent algorithms (Peng et al., 2020a), as shown in Fig. 3.

4.2.1. Prediction of ship energy consumption based on neural network

Neural Network has good nonlinear mapping ability, adaptive learning ability, and parallel information processing ability (Illahi et al., 2019; Tran, 2019), and thus it has been widely used in prediction (Wysocki et al., 2019; Yuan et al., 2019). Neural Network is the most typical BBM which has good performance in ship energy consumption prediction (Kim et al., 2021; Zheng et al., 2019; Gkerekos and Lazakis, 2020), and it mainly includes BPNN, MLPN, LSTM, DNN, and CNN.

1) BPNN

BPNN is one of the most widely used neural network models for prediction. It is a network model trained by error backpropagation (Chen et al., 2018). The BPNN-based modeling method for the energy efficiency analysis and prediction showed higher prediction accuracy, compared with the traditional prediction method using the empirical formula (Yan et al., 2015). Hu et al. (2019) established a prediction model of ship fuel consumption considering the influence of environmental factors by adopting BPNN and GPR methods, which can predict real-time fuel consumption under different speeds, trim and environmental conditions. In addition, Yuan et al. (2020a) proposed a prediction model of ship fuel consumption considering the multi-source information of ship navigational status and environmental factors based on DBPNN, which has better performance than SVR, LSTM in predicting fuel consumption of inland ships. Moreover, Moreira et al. (2021) achieved the prediction of the ship speed and fuel consumption by establishing a neural network system. The established model can determine the relationship between the sailing speed and the respective propulsion configuration for certain sea conditions.

2) MLPN

MLPN consists of three or more layers and has a similar structure to a single-phase perceptron. Still, there is at least one intermediate layer between the input layer and output layer, called the hidden layer, to learn nonlinear data information. The MLPN method can also be used for

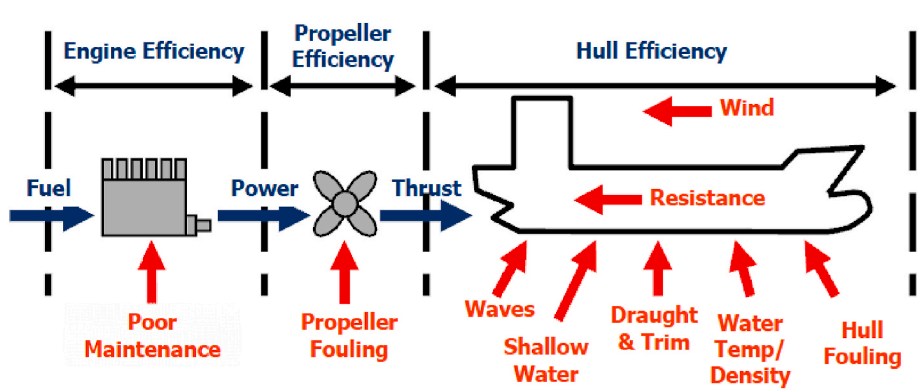

Fig. 2. Analysis of ship energy consumption based on energy transferring relationship (Pedersen and Larsen, 2009).

Table 3
Analysis of different WBMs for ship energy consumption prediction.

Target Ship	Methods	Parameters of concern	Prediction/Energy saving effect	Data sources	Applications	Reference
Oil tanker	Townsin and Kwon	Wind, wave, engine speed, etc.	The power calculation error is 3%–4%	Log data	Speed optimization	Li et al. (2018)
Bulk cargo ship	Holtrop and Mennen	Sailing speed, engine speed, power, wind and wave, current speed, water depth	Not mentioned	Data acquisition system	Energy efficiency analysis	Fan et al. (2018)
Container ship	Kwon, Aertssen and ITTC	Sailing speed, direction and grade of wind and waves	The maximum error is less than 4%	Not mentioned	Speed optimization	Li et al. (2020)
Inland river cruise ship	Regression analysis method	Engine power and speed, sailing speed, wind speed, water depth, etc.	The R^2 is 0.9793	Ship energy efficiency monitoring system	Speed optimization	Fan et al. (2021)
Tanker	DTU and SDU	Sailing speed, wind and wave direction, wind and wave grade, current speed, etc.	The overall average relative error is 1.36%	Logbook	Speed optimization	Yang et al. (2020)
Tanker	Semi-empirical method	Water speed, wind and wave direction, wind and wave grade	The average relative error of operational energy efficiency is about 5.12%	National Oceanic and Atmospheric Administration (NOAA)	Route optimization	Lu et al. (2015)
Inland river fleet	Holtrop and Mennen, Kwon, Townsin, Hu	Wind speed and direction, water depth, current speed, wave height, sailing speed, etc.	Reduce fleet energy consumption by 6.8%	Energy efficiency data acquisition system	Fleet optimization	Wang et al. (2020a)
Chemical tanker	ISO, semi-empirical model	Sailing speed, wave, wind, current, water depth, etc.	Reduce fuel consumption by about 5.6%	The onboard voyage planning system	Voyage optimization	Wang et al. (2021a)
Super-large ore carrier	Holtrop-Mennnen and Kwon	Sailing speed, engine speed, shaft power, wind speed and direction, wave height	Reduce fuel consumption by about 6.8%	Energy efficiency system, European Medium-Term Weather Center	Speed and route optimization	Wang et al. (2021b)
Container and oil tanker	4 DOF model and Monte Carlo simulations	Sailing speed, wind speed and direction, wave height, draft and trim, power	The power prediction error is within 4%	Random weather statistics	Speed optimization	Tillig et al. (2020)
Cruise ship	Holtrop and Mennen, Kwon, Townsin, Hu	Sailing speed, shaft speed, FCR, wind speed, water depth, etc.	Reduce the fuel consumption by 19.04% with speed reduction	On-board sensors	Main engine speed optimization	Wang et al. (2016b)
Cruise ship	Holtrop and Mennen, Kwon, Townsin; Hu	Wind speed and direction, water depth and speed, sailing speed, engine speed and torque	Improve fuel consumption by about 2%	On-board sensors	Speed optimization	Wang et al. (2018b)
Container ship	Holtrop, Mennen, ITTC	Draft, trim, power, sailing speed, sailing route, wind speed and direction	Reduce fuel consumption by about 2%	On-board sensors	Speed optimization	Tzortzis and Sakalis (2021)
Super-large ore carrier	Holtrop-Mennnen, improved Kwon	Shaft power, sailing speed, wind speed and direction, wave height and direction	Reduce fuel consumption by about 4%	Energy efficiency system, European Medium-Term Weather Center	Speed and route optimization	Wang et al. (2020b)

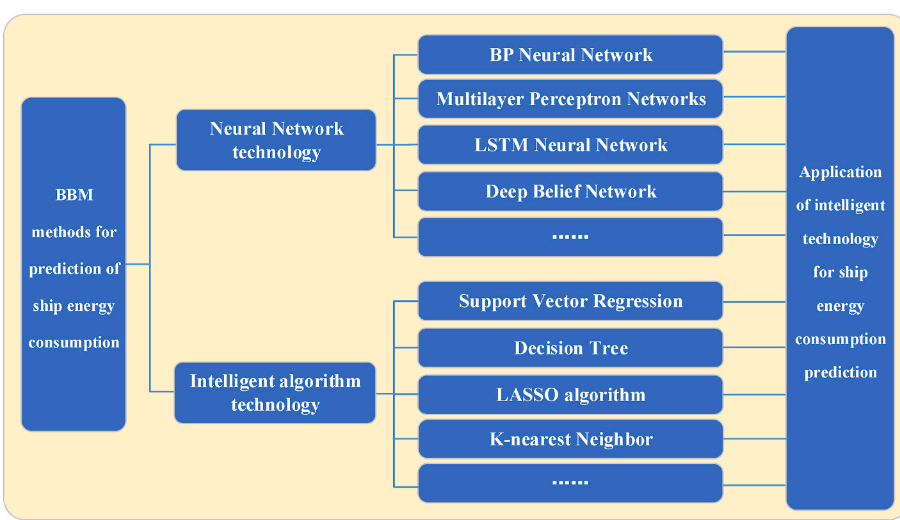

Fig. 3. The BBMs for ship energy consumption prediction.

establishing the fuel consumption prediction model, and has better prediction accuracy for the ship fuel consumption, compared with the prediction results of Multiple Regression Analysis (Beşikçi et al., 2016). Ye and Xu (2016) established a BBM for fuel consumption prediction of the passenger roller ships based on single-hidden-layer MLPN methods, and then compared the prediction accuracy for five different input features. In addition, Jeon et al. (2018) proposed a prediction model of the main engine fuel consumption based on MLPN through big data analysis, including data acquisition clustering compression and expansion. In order to improve the accuracy of the prediction model, different numbers of hidden layers and neurons, and different types of activation functions were tested, and their effects on the accuracy and efficiency of the prediction model were studied. The results showed that the MLPN model could predict the fuel consumption of the ship's main engine more accurately and effectively, compared with the polynomial regression and SVM.

3) LSTM

LSTM is a temporal recursive neural network (Li and Cao, 2018; Yuan et al., 2018). Compared with other neural networks, LSTM can solve complex multi-input variable problems more effectively (Zhang et al., 2018). Wang and Chen (2020) constructed a real-time prediction model of main engine fuel consumption by adopting an RNN-LSTM algorithm based on the actual operation data of the main engine and ship navigation status. The model can predict the real-time fuel consumption of main engine under normal sailing conditions. Zhu et al. (2020) established a prediction model of fuel consumption by using LSTM, which not only utilizes the existing characteristic variables (wind, speed, drat, trim, etc.), but also uses the previous fuel consumption state and FCR data to predict the current fuel consumption. Experimental analysis showed that the prediction accuracy can be improved by 11.8%, compared with the traditional artificial neural network. In addition, Yuan et al. (2020b) established a model for the real-time prediction of the FCR based on the LSTM, which took into account the real-time navigational status and environmental factors. Experiments showed that the performance of this model is better than that of the regression model and traditional RNN.

4) DBN

DBN is a typical deep learning method, which is superimposed by RBM units. Generally, the approach of layer by layer training is adopted to obtain the excellent model initialization parameters (Karagiannidis et al., 2019; Wang et al., 2020c). By using the DBN method, the random influencing factors of ship fuel consumption, such as meteorological sea state, can be analyzed, and the correlation between the meteorological state and the ship fuel consumption can be studied, which is very important for the prediction of ship's fuel consumption under different sea conditions. For example, Shen et al. (2017) established a prediction model of ship fuel consumption considering different marine weather conditions based on the DBN algorithm to dynamically predict ship fuel consumption under various marine meteorological conditions. Compared with BPNN and SVR, the prediction model based on the DBN algorithm is more reliable and effective in terms of accuracy and efficiency.

5) CNN

CNN is a kind of deep-feedforward Neural Network. It has strong

Table 4
Analysis of different Neural Network-based models for ship's energy consumption prediction.

Target ship	Method	Parameters of concern	Prediction accuracy	Data sources	Model outputs	Reference
Bulk carrier	ANN	Main engine load, operating parameters, weather conditions (wind, wave), etc.	The determination coefficient is 0.9055 for 100% MCR	Noon report data	Fuel consumption	Tran (2021)
Bulk carrier	ANN	Wind speed and direction, wave height, current speed, engine speed	Not mentioned	Voyage data	EEOI, FCR, etc.	Sun et al. (2019)
Container ship	ANN	Main engine speed, sailing speed, wind speed and direction, draft, course, etc.	The fit goodness is 0.9709–0.9936	AMS	Fuel consumption per unit distance	Kim et al. (2021)
Container ship	BPNN	Draft, trim, sailing speed, wind speed and direction, wave height and direction	The R^2 is 0.9817	Noon report data	Fuel consumption per 100 nautical miles	Hu et al. (2019)
Cargo ship	DBPNN	Ship static information, ship status data, and environment data	The R^2 is 0.9843	Ship monitoring system	Fuel consumption	Yuan et al. (2020a)
Container ship	ANN	Effective wave height, main engine speed, relative wave angle	–	Route planning software	Sailing speed, fuel consumption	Moreira et al. (2021)
Tanker	MLPN	Sailing speed, engine speed, draft, trim, wind and sea state	The R^2 is 0.834	Noon Report data	Ship fuel consumption per hour	Beşikçi et al. (2016)
Ro-Ro ship	MLPN	Draft, trim, wave, wind, rudder angle	The relative error is 2%	Acquisition data from sensors	Average FCR	Ye and Xu (2016)
Sea-River-through ships	LSTM	Sailing speed, draft, main engine speed, shaft power	The RMSE is 2.714.5.	Acquisition data from sensors	Fuel consumption of the main engine	Wang and Chen (2020)
Ro-Ro passenger ship	LSTM	Wind, sailing speed over the water, pitch, and trim	The MSE can be improved by 11.8%.	Technical University of Denmark	Fuel consumption	Zhu et al. (2020)
Inland waterway cargo ship	LSTM	Latitude and longitude, engine speed, water depth and speed, wind speed and direction, etc.	Fuel consumption can be reduced by 33.54%	Acquisition data from multi-source sensors	Fuel consumption	Yuan et al. (2020b)
Container ship	ANN	Current speed, draft, sailing direction, rudder angle, wave height, wind, etc.	Fuel consumption prediction accuracy is 98.7%	LAROS Remote Monitoring System	Fuel consumption of the main engine	Karagiannidis et al. (2019)
Tanker	DNN	Draft, engine speed and power, sailing speed, wave height and direction, etc.	The R^2 of the fuel consumption prediction is 89.4%	ADLM system, weather provider CMEMS	Fuel consumption on the route	Gkerekos and Lazakis (2020)
Multiple ships	DBN	Draft, wind direction, course, load, wave height, etc.	The MRE of the model is 0.3539	Ship navigation monitoring system	Fuel consumption	Shen et al. (2017)
VLCC	ANN	Sailing speed, power, wind speed and direction, wave height and direction, etc.	Fuel consumption prediction accuracy is 99.6%	Automatic continuous monitoring system (ACMS), AIS, and weather forecast	Ship braking power, brake specific fuel consumption value (B.S.F.C)	Farag and Ölçer (2020)
Container ship	Deep-ANN	Average sailing speed, sailing time, wind speed and direction	The prediction accuracy is about 95%	A worldwide leading shipping company, CMEMS	Fuel consumption	Bui-Duy and Vu-Thi-Minh (2021)

feature extraction ability and is specially used for processing network structure data (Le et al., 2019). It constructs several filters which can extract the features of the input data and uses these filters to extract the representative features hidden in the input data layer by layer. At the same time, sparse connection and parameter weight sharing mechanism are combined to reduce the dimension of data sampling in time and space, and thus reducing the number of training parameters, and can effectively avoid overfitting (Kim and Cho, 2019). In order to make the fuel consumption model based on data learning more accurate, Zhao (2021) adopted the CNN to analyze the data of a large shipping database on the ship performance and navigation information, to make up for the deficiency of initial data analysis, and improve the integrity and quality of the database.

6) Summary

The comparative analysis of energy consumption prediction models based on Neural Networks is shown in Table 4. It can be noted that:

(a) The research on neural network-based fuel consumption prediction models covers a wide range of ship types, with different application performances for different types of ships.
(b) The prediction performance of different Neural Network structures varies, with BP performing well in multidimensional data fitting and processing. The time series characteristics of the fuel consumption data can be well captured by the LSTM-based prediction model, which improves dynamic prediction performance. As a result, it is critical to select a model that is appropriate for case-specific application.
(c) The quantity and quality of data sources have a direct effect on the prediction models' performance. The low acquisition frequency and accuracy of log data could not meet the Neural Network-based prediction model's requirements.
(d) Combining the Neural Network model with advanced algorithms (e.g., GA and LM) can further improve the prediction performance (Bui-Duy and Vu-Thi-Minh, 2021; Alonso et al., 2007). Therefore, enhancing the Neural Network structure and exploring suitable combination algorithms is one of the important developing research directions for the Neural Network-based fuel consumption prediction models.

4.2.2. *Ship energy consumption prediction based on intelligent algorithms*

The application of an intelligent algorithm is also an effective method to predict the ship energy consumption. It mainly includes SVR, DT, RF, LASSO, KNN, and GP algorithms.

1) SVR algorithm

SVR is a regression algorithm derived from SVM (Zhu et al., 2019), suitable for smaller training sets (Liu et al., 2016). It has solid theoretical basis and appropriate generalization, and accuracy in dealing with nonlinear problems (Alsarraf et al., 2019). In addition, the kernel function in SVR is used to calculate the inner product, to avoid the complexity caused by multiple design variables when introducing dimensions (Feng et al., 2018). Kim et al. (2020) adopted SVR to predict the propulsion power. The results showed that the SVR-based method was reliable for predicting ship propulsion power. Ghanbari et al. (2015) adopted the SVR to study the engine performance and emission parameters. They proposed that the parameters, such as kernel function parameters and penalty factor settings, have a specific impact on the prediction performance of the SVM. In addition, Pagoropoulos et al. (2017) proposed to use the SVM to evaluate ship energy efficiency, and verified the effectiveness of the SVM-based method.

2) DT algorithm

DT is a tree-structured machine learning algorithm, which is simple, efficient, and explanatory solid (Shaikhina et al., 2019; Daga et al., 2017). It doesn't need to impose complex parameter structures when dealing with large and complex datasets, and better prediction results can be quickly obtained (Song and Ying, 2015; Ahmad et al., 2017). The prediction of ship energy consumption based on DT selects the best features and eigenvalues through the principle of least square error. By inputting the eigenvalues of the test sample, the prediction results can be obtained through the DT-based fuel consumption model. Soner et al. (2018) analyzed the ship performance under operating conditions by developing a DT-based model. The results showed that the model has better predictive performance in ship performance monitoring, and has a higher accuracy rate than the ANN.

3) RF algorithm

RF is an integrated algorithm based on DT, which combines multiple decision trees and can effectively avoid the overfitting problem of DT (Massoud et al., 2019). The study on the RF algorithm-based fuel consumption prediction showed that the RF-based model performed better than other machine learning algorithms for a specific case study (Gkerekos et al., 2019). Mou et al. (2017) established a fuel consumption prediction model by adopting the RF algorithm based on the operation data for a cruise ship along the Yangtze River. The prediction error of the model was within 6.8%, and the modeling process was more straightforward than that of the BPNN and SVR models. In addition, Yan et al. (2020) developed a fuel consumption prediction model based on RF by using the noon report data of a dry bulk carrier. They realized the fuel consumption prediction under different speeds, cargo loading, and navigational environment conditions. The results showed that the prediction performance of the model is better than that of ANN, SVR, and LASSO-based models.

4) LASSO algorithm

LASSO is a biased estimation method for processing data with complex collinearity, which can reduce the regression coefficients of independent variables, and is less dependent on the size of the regression coefficients of the dependent variables due to the allocation of an adjustment parameter (Tran et al., 2012). The LASSO regression model is usually used to generate a solution and improve the interpretability of the solution. Zhou et al. (2021) established a LASSO regression model to realize the prediction of ship fuel consumption which considers wind, wave, current, and other meteorological data. The proposed multi-objective optimization method based on the LASSO model can achieve the optimization decision of ship navigation path. In addition, Wang et al. (2018c) established a LASSO-based fuel consumption prediction model considering sea and weather conditions using the actual ship operation data and weather data. The comparison analysis results showed that the LASSO-based method is superior to traditional methods, and has better interpretability, generalization ability, and numerical stability.

5) KNN algorithm

KNN is a supervised learning algorithm. It aims to label or predict the class of unlabeled data points or samples automatically. KNN has being easy to understand, easy to implement, and no need to estimate parameters. It is commonly used to deal with classification problems and to solve regression problems (Duca et al., 2017; Rezaei et al., 2020). Chaal (2018) established a KNN-based BBM of ship energy consumption based on the operation data of a VLCC ship. The results showed that the prediction accuracy of the KNN-based model could reach more than 80%. In addition, Gkerekos et al. (2019) adopted the KNN-based method to predict ship fuel consumption. The prediction accuracy of the KNN-based model can reach about 95% by using the data collected from the automatic data collection system.

6) GP algorithm

GP has a strong learning ability and strong generalization ability in dealing with complex regression problems. It is widely used in the research of ship energy systems and the evaluation of ship energy performance. The analysis results on the prediction performance of ship fuel consumption under different working conditions showed that the GP-based model has good prediction performance with an RMSE of 0.4218 (Yuan and Wei, 2018). In addition, Yuan and Nian (2018) established a GP metamodel to predict the fuel consumption of ships in different scenarios by comprehensively considering navigation status and weather conditions. The influence of various factors on ship fuel consumption is analyzed using the GP model. The results showed that the input factors of the model have a significant effect on the ship fuel consumption, and the GP metamodel has good accuracy and effectiveness for fuel consumption prediction. This method can be further used to evaluate the impact of different factors on ship's energy consumption.

7) Other algorithms

In addition to the above-mentioned intelligent algorithms, some other intelligent algorithms, including the Ridge regression (Melkumova and Shatskikh, 2017; Moreno-Salinas et al., 2019), boosting algorithm (Jin et al., 2019), Response Surface Methodology (RSM) (Işıklı et al., 2020), the sparse regression method (SRM) (Wang et al., 2021c), and AML (Ahlgren and Thern, 2018), etc., also can be used to achieve the prediction of ship fuel consumption. Uyank et al. (2020) adopted multiple machine learning algorithms for the prediction of fuel consumption, and achieved a better energy consumption optimization result. In addition, Nwaoha et al. (2017) proposed a structured framework to solve the uncertainty problem of ship FCR by combining the fuzzy rule base and utility theory methods. The results showed that the combined algorithm could effectively predict the FCR of ships. In addition, Ahlgren et al. (2019) developed a machine learning model to predict the fuel consumption of the main engine, by combing the genetic algorithm to select and optimize the super parameters of the model. This model can achieve better prediction performance. Moreover, Hu et al. (2021) integrated ET, RF, XGB, and MLR methods to establish a mixed fuel consumption prediction model. The advantages of each algorithm can be fully reflected by combining multiple algorithms. Thus, the robustness of the model can be improved, and the generalization ability of the model can be enhanced.

8) Summary

Different intelligent optimization algorithms have different adaptability and performance when used with various data sources and characteristics. The analysis of intelligent algorithm-based ship fuel consumption prediction models is shown in Table 5. It can be noted that:

(a) Model parameters. The model's prediction performance can be improved by considering the influence of multiple factors.
(b) Prediction accuracy. The prediction model's performance differs depending on the algorithms and data sets used. More extensive input characteristics can thus improve the model's prediction accuracy.
(c) Data sources. A large amount of high-quality data and adequate data preprocessing are required to improve the performance of

Table 5
Analysis of different intelligent algorithm-based models for ship energy consumption prediction.

Target ship	Methods	Parameters of concern	Prediction accuracy	Data sources	Model applications	Reference
Bulk cargo ship	SVR	Sailing speed, draft, engine speed, wave height, wind vector, etc.	The R^2 of the model is 89.78%	Shipboard measurements and NOAA database	Prediction of ship propulsion power	Kim et al. (2020)
Ferry steamer	Bagging, RF, and bootstrap	Rudder angle, trim, sailing speed, course, wind speed and direction, etc.	The RMSE is 45.2, 43.5, and 41.3, respectively	Automatic data acquisition system	Fuel consumption prediction	Soner et al. (2018)
Reefer vessel, Bulk carrier	DT, RF, KNN, SVM, ANN, etc.	Sailing speed, engine speed, current speed, wind speed and direction, sea condition, draft, etc.	The R^2 range from 0.7269 to 0.9729	ADLM system	Prediction of fuel consumption	Gkerekos et al. (2019)
Cruise Ship	RF	Water depth and speed, engine speed, sailing speed, etc.	The relative error is 0.05%–6.86%	Information acquisition system	Prediction of ship fuel consumption	Mou et al. (2017)
Dry bulk carrier	RF Regression	Sailing speed, wave height and direction, wind direction, etc.	The MAPE of the model is 7.91%	Noon Report	Ship speed optimization	Yan et al. (2020)
Container ship	LASSO	Sailing speed, draft, course, current speed, wind, wave, etc.	The MAPE is 9.2482%, and RMSE is 1.6458	AIS, CMEMS	Ship route optimization	Zhou et al. (2021)
Container ship	LASSO	Sailing speed, course, wave height, wind scale, etc.	The MAE is 4.9	Fleet management system	Prediction of ship fuel consumption	Wang et al. (2018c)
VLCC	KNN, DT, AdaBoost	Sailing speed, course, engine speed, loading, weather, etc.	The R^2 range from 0.74 to 0.96	Data acquisition sensors	Trim and route optimization	Chaal (2018)
Chemical ship	GP	Sailing speed, course, wind speed and direction, wave height and direction	The RMSE of the model is 0.3963	AIS system, Noon Report, weather report	Speed optimization, trim optimization, route optimization	Yuan and Wei (2018)
Tanker	GP	Sailing speed, draft, trim, wind speed and direction, wave height and direction	The RMSE of the model is 0.4418	AIS data, shipboard measurements, Noon Report	Speed optimization, trim optimization	Yuan and Nian (2018)
Container ship	LASSO, SVR, KNN, DT, RF, etc.	The external environment, engine parameters, etc.	The R^2 range from 0.965 to 0.999	Noon Report, engine room logbook, and sensors	Prediction of fuel consumption	Uyank et al. (2020)
Cruise Ship	AML	Exhaust gas temperature, engine speed, supercharger speed, etc.	The standard deviation is about 0.0056	Valmarine logging servers, logbook	Prediction of fuel consumption	Ahlgren and Thern (2018)
Cruise Ship	AML	Engine speed, turbine speed, exhaust gas temperature, etc.	The R^2 is 0.9936	Ship recording system	Prediction of fuel consumption	Ahlgren et al. (2019)
Bulk cargo ship	RSM	Weather conditions, engine speed, sailing speed, load, etc.	The R^2 is 89.28%	Noon Report	Prediction of fuel consumption	Işıklı et al. (2020)
Container ship	ET, RF, XGB, and MLR	Fuel consumption, speed, trim, draft, course, wind, wave	The R^2 is 0.9938	Fuel consumption data logging	Ship speed optimization	Hu et al. (2021)

the energy consumption prediction model. Evidently, more and more researchers are using multi-source data to improve data acquisition accuracy and prediction performance.

(d) Model applications. Since different intelligent algorithms are adapted to specific data sources and data characteristics, no single algorithm can be applied to all data sets. It is therefore paramount to select a suitable intelligent algorithm for given data characteristics and application cases. Consequently, the combination of machine learning with multi-algorithm integrated models will emerge as the leading research content in the future, since it can synthesize the advantages of each algorithm thus further improving the performance of energy consumption prediction models (Öztürk and Başar, 2021), as well as facilitating the achievement of dynamic prediction based on real-time influencing factors (Zaccone et al., 2018).

4.3. Grey box model of ship energy consumption prediction

There are two main ways to establish the GBMs for energy consumption prediction. One method is to identify the unknown parameters in the theoretical model through statistical regression, called parameter identification GBM in this paper. The other way is to combine the WBM and the BBM in series or parallel, called the combined GBM (Ljung, 2001; Coraddu et al., 2017).

For the parameter identification GBM, Meng et al. (2016) adopted the regression analysis method to establish a GBM of ship FCR, which considered the influencing factors of sailing speeds, sea conditions, and weather conditions. In addition, Yang et al. (2019) established a ship fuel consumption model considering sailing speed, displacement, and marine environment, and estimated the unknowns in the model by the Least Square method and GA. The established model has high effectiveness for the prediction of fuel consumption. Moreover, Lu et al. (2013) proposed a prediction method of ship fuel consumption based on Kwon's additional resistance analysis. They established a ship operating performance model which considered ship loading, sailing speed, waves, etc. On this basis, the noon report data is used to improve the model's accuracy. The improved ship performance prediction model is more accurate and can be used to analyze ship fuel consumption under different sea conditions.

For the combined GBM, Leifsson et al. (2008) put forward two different combination methods through a serial and parallel connection between the WBM based on mechanism analysis and the BBM based on a feed-forward Neural Network. The fuel consumption through the GBM can be reduced by about 65% compared with the WBM. Yuan et al. (2020c) established a fuel consumption optimization model by combining the WBM with the BP model in series and parallel respectively based on the data of ship sailing speed and fuel consumption. In addition, Coraddu et al. (2015) proposed two different forms of GBM for the fuel consumption of a chemical tanker by combining WBM and BBM. The proposed GBM-based trim optimization method can reduce ship fuel consumption effectively. Zwart (2020) established a GBM for dynamic fuel consumption prediction by combing the regression model with ANN based on the noon report data. Moreover, Odendaal (2021) proposed a serial configuration ANN-GBM. On this basis, the designed energy consumption of a new yacht can be predicted accurately by using the actual voyage data.

The analysis of GBMs for ship energy consumption prediction is shown in Table 6. It can be noted that:

(a) The performance of GBM depends on the quality of the underlying data. To cover a broader range of associated features and obtain more accurate prediction results, a wider variety of high-quality data should be obtained from onboard sensors and meteorological centers.

(b) The main research targets for the existing models are oil tankers and container ships. The GBM can be extended to other types of ships by considering the characteristics of specific ships. The GBM can thus be used as the foundation for ship energy efficiency management plan, and applied to online real-time operation optimizations, such as sailing speed and route optimization, and trim optimization.

4.4. Analysis of different types of models for ship energy consumption prediction

The different types of models for ship energy consumption prediction have different characteristics. An analysis on the advantages and main limitations of each model types are important and beneficial for the practical applications.

4.4.1. The white box model

The WBM of fuel consumption prediction is based on the known physical laws and relations, and has good interpretability. However, the construction of the model needs a series of parameters and knowledge, including ship basic parameters, resistance characteristics, main engine operation characteristics curve, propeller operation characteristics curve and so on. However, these parameters are not constant and change with the navigation environment and operational conditions (e.g. ship fouling, weather conditions). The superposition of these parameters would increase the prediction error and thus the performance is strongly affected by these parameters and assumptions, which limits the application of the model.

Table 6
Analysis of GBMs for ship energy consumption prediction.

Target ship	Modeling method	Parameters of concern	Prediction/Energy saving effect	Data sources	Model Applications	Reference
Oil tanker	Serial combination	Main engine speed, sailing speed to the ground, draft	The MAPE is 0.8%–10%	Data logging system	Shaft Power and fuel consumption prediction, trim optimization	Coraddu et al. (2017)
Container ship	Parameter identification	Sailing speed, displacement, sea conditions, and weather conditions	The RMSE is about 6%	Shipping log data	Fleet deployment planning management	Meng et al. (2016)
Oil tanker	Parameter identification	Sailing speed, displacement, weather conditions	The accuracy is 92.5%	Noon Report	Fuel consumption optimization and greenhouse gas emissions	Yang et al. (2019)
Oil tanker	Parameter identification	Sailing speed and direction, draft, FCR	The prediction error is 5–7%	NOAA and noon report	Ship performance prediction and route optimization	Lu et al. (2013)
Container ship	Serial-parallel combination	Engine speed, draft, wind speed and direction	The RMSE can be reduced by 65%	Ship energy management system	Speed and fuel consumption optimization	Leifsson et al. (2008)
Cargo ship	Serial combination	Sailing speed, draft, engine power and speed	The R^2 is 0.945	Fuel consumption report	Speed and fuel consumption optimization	Yuan et al. (2020c)
Oil tanker	Serial combination	Engine speed, sailing speed, draft	The MAPE is 1.5%–8.5%	Data logging system	Shaft Power and fuel consumption prediction	Coraddu et al. (2015)
Chemical tanker	Serial combination	Sailing speed to the water, draft, trim, wind, and waves	The accuracy is 6.58%	Voyage report data	Trim optimization	Zwart (2020)

In addition, the structure and parameters are given and fixed for the WBMs. Therefore, it is difficult to improve performance by updating the model structure and the built-in parameters based on the real-time dynamic information and thus it is weak to adapt to the dynamic operational conditions. Moreover, it is hard to consider all the influencing factors effectively, such as the environmental or operational factors that affect propulsion power or fuel consumption. Therefore, the accuracy and prediction performance in practical application would be influenced.

4.4.2. The black box model

The model's prediction performance can be improved by considering the influence of multiple factors. However, the endogenous problem of multiple parameters is rarely considered for the intelligent algorithm-based prediction model. In addition, the prediction model's performance depends on the algorithms and data sets used. More extensive input characteristics can thus improve the model's prediction accuracy. However, the model structure would be relatively complex, and the specific details and noise in a large amount of data would limit the model's generalizability.

The Neural Network-based prediction model has good prediction accuracy, however, it is usually complex and difficult to explain. An improper hidden layer and neuron number would result in a longer training time and poor performance. In addition, the acquisition frequency and low accuracy of log data could not meet the Neural Network-based prediction model's requirements. The construction of the model requires the accumulation of a large number of high-quality operation data for a long time. With the increase of specific details and noise, the generalization ability will be weakened and the problem of over-fitting will occur.

Most Neural Network-based models are static prediction models based on the known historical data. However, the data is time-variant during practical navigation, resulting in some deviations between theoretical results and practical information. Therefore, future research on the Neural Network-based fuel consumption prediction models should shift from static to real-time dynamic prediction (Farag and Ölçer, 2020).

4.4.3. The grey box model

The commonly used GBM modeling method combines BBM and WBM in series or parallel connection. Compared to the WBM, the GBM has higher prediction accuracy. Similarly, the GBM has a significant advantage of extrapolation compared to BBM, which eliminates the problem of inaccurate prediction without considering influencing factors or parameters beyond the model's range. However, when the GBM mainly relies on physical laws, detailed initial information about the physical characteristics of the ship's operation is required. When the GBM mainly relies on historical data, a broader set of data is required to describe as many operating conditions as possible. Therefore, the performance of the model not only depends on the quantity and quality of data, but also influenced by the model structure, assumptions and the physical laws.

All in all, different types of models have different adaptability and performance. Therefore, it is critical to select a model that is appropriate for case-specific application. The analysis of the adaptability of different types of models to achieve effective prediction of ship fuel consumption across different ship types is a critical content worth further investigation in the future.

5. Methods for ship pollution gas emission prediction

Under the background of low-carbon shipping, it is essential to control the emissions to achieve the green development of the shipping industry (Lan et al., 2020). Ship emission prediction is a necessary basis for realizing effective emissions control (Shen et al., 2020). However, the generation mechanism of ship exhaust gas is complicated, and the influencing factors are various (Seithe et al., 2020). The fuel type, navigation state, and marine environment would influence the pollution gas emissions (Planakis et al., 2021; Zhen et al., 2020). The ship pollution gas emission predictions are of great significance to realizing the pollutant gas emission control in the shipping industry (Ma et al., 2020). There are mainly two kinds of methods, namely the top-down and the bottom-up methods, to achieve the pollution gas emission prediction from ships (Gu and Xu, 2013; Tan et al., 2014; Wang et al., 2008).

5.1. Ship pollution gas emission prediction based on the top-down methods

The top-down method is based on the fuel consumption of the main engine, generator, boiler, and other equipment to calculate the pollution gas emissions. Specifically, the fuel consumption can be obtained through statistics of the information from the engine log and oil record books. Then the pollution gas emissions can be obtained based on the fuel consumption multiplied by the corresponding emission factors (Liu et al., 2018b). This method doesn't need specific parameters of ships and meteorological environment data. If the total fuel consumption of all kinds of ships is obtained, then the total emissions in a specific area can be calculated. In addition, the accuracy of the estimated results can be verified by comparing with the amount of fuel consumption (Zhou et al., 2012). Endresen et al. (2007) analyzed the fuel consumption of international ships based on the data of the global statistical report on marine fuel consumption. They selected emission factors according to the fuel type and engine type, and calculated the pollution gas emissions of ocean-going ships over 100 gross tons worldwide by adopting the top-down method. Hulskotte and Denier van der Gon (2010) analyzed the pollution gas emissions of the berthed ships by using the information on the fuel consumption and emission factors. In addition, Corbett et al. (1999) estimated the global emissions of NO_x and SO_2 from ships by using the top-down method. Moreover, Wang and Corbett (2007) studied the benefits of the policy of reducing pollution from offshore ships on the west coast of the United States with the top-down method. The research showed that if the sulfur content of fuel oil is less than 1.5%, the SO_x emissions of all ships in California will be reduced by about 21,000 tons.

5.2. Ship pollution gas emission prediction based on the bottom-up methods

The bottom-up method is the emission calculation method based on the ship activity level. The fuel consumption of the ship is usually calculated based on the installed power, sailing time, FCR, and emission factors (Merien-Paul et al., 2018). Based on the data of sailing speed, route, and sailing time, the corresponding emission factors can be obtained according to the installed power. Then the total amount of pollution gas emissions from the ship can be calculated. Juan et al. (2018) proposed a bottom-up method for calculating greenhouse gas emissions based on the ship operational data, by adopting four existing methods for energy consumption and emissions calculation. It can eliminate the uncertainty of average fuel consumption and improve the reliability and accuracy of calculation results. Chang et al. (2014) analyzed the emissions of sulfur dioxide, nitrogen oxides, and particulate matter from ships in Incheon Port during berthing, loading, unloading, and departure. The results showed that Incheon Port emits 990 tons of sulfur dioxide, 1551 tons of nitrogen oxides, and 142 tons of PM every year, and most of the pollution gas emissions occur during the cruise navigation. In addition, Song (2014) adopted the bottom-up method to analyze the emissions of ship exhaust pollutants in Shanghai Yangshan Port. Chang et al. (2013) made a comparative analysis of the bottom-up and top-down methods for the greenhouse gas emissions prediction, and found that there were some differences between these two ways. Xing et al. (2016) analyzed the emissions of pollution gases from ships by top-down method and bottom-up method, respectively, by considering different loads of ships. The results showed that the top-down emission measurement method is simple and easy to achieve, while the bottom-up emission measurement result is relatively more accurate. Moreover, Huang et al. (2017) proposed a bottom-up method considering the marine environment, which combined the data set of AIS with the marine environment information, analyzed the influence of wind, waves, and currents on the ship sailing speed, and calculated the greenhouse gas emissions from ships in Ningbo-Zhoushan Port. Peng et al. (2020b) adopted a stratified random sampling method to take sample ships to reduce the uncertainty caused by missing static data, and analyzed the total emissions of 34,788 vessels sailing on the Yangtze River. The proposed method could reduce the uncertainty in calculating regional emissions by about 30%. When the sampling ratio was greater than 10%, the relative error was less than 3.5%, improving the accuracy of ship emissions calculation.

In addition, Wang et al. (2007) analyzed the ship emissions between North American ports based on the ship traffic, energy and environment model (STEEM), as shown in Fig. 4. The established model took into account the information of the sailing route, draft, and historical operation data of ships, and showed good accuracy in calculating regional emissions. Jalkanen et al. (2009) put forward the Ship Traffic Emission Assessment Model (STEAM), which used the information provided by the AIS to improve the spatial resolution of the model, and considered the influence of waves on ship emissions. The prediction error of fuel consumption in the model is less than 6%, which can realize the analysis of the total emissions of nitrogen oxides, carbon dioxide, and sulfur dioxide from Baltic ships. Based on the STEAM, Zhang et al. (2017) analyzed the exhaust emissions of Nanjing Longtan Container Terminal by combining AIS data with the ship profile database. Johansson et al. (2013) adopted the STEAM to evaluate the impact of Nordic emission control areas on ship emissions. In addition, Sofiev et al. (2018) estimated the ship pollutant emissions using the STEAM model, and studied the influence of low-sulfur fuel on human health and climate. Weng et al. (2019) calculated the exhaust emissions from ships in the Yangtze River Estuary by using the STEAM model. They analyzed the influence of ship types, and operating conditions on the ship emissions. The results showed that most of the ship emissions occurred under the conditions of slow driving and normal cruise, mainly distributed in the port area, the intersection area, and the north channel of the Yangtze River Estuary.

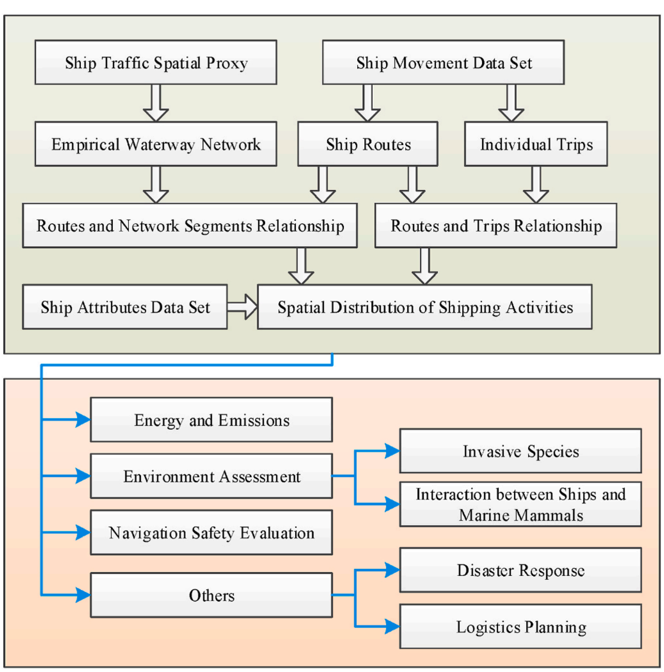

Fig. 4. The process of the STEEM (Wang et al., 2007).

Based on the STEAM, Jalkanen et al. (2011) proposed a STEAM2 model that considered the influence of sailing route, speed, engine load, fuel sulfur content, and environmental conditions. They added the particulate matter and carbon monoxide emission calculation, which can further improve the model performance. Then, Marelle et al. (2016) adopted WRF-Chem combined with the STEAM2 model to analyze the pollution emissions of ships in northern Norway. The results showed the STEAM2 model has good accuracy in fleet emission calculation. It can effectively reduce the analysis error for individual ship's emission by combining WRF-Chem with the STEAM2 model. In addition, Moreno-Gutiérrez and Durán-Grados (2020) put forward the SENEM, which considered and quantified variables such as marine meteorological conditions, hull and propeller status, and the effectiveness of the method has been verified with four Ro-Ro ships.

5.3. Analysis of different prediction methods for ship pollution gas emission

Table 7 summarizes and analyzes the ship pollution gas emission prediction methods from the aspect of the target area, methods, influencing parameters, and data sources. It can be noted that:

(a) The bottom-up method outperforms the top-down method in terms of prediction accuracy because it employs more precise parameters, such as fuel emission factors under various operating conditions. As a result, the bottom-up method has more applications for ship emission prediction than the top-down method, which explains why it was preferentially adopted for regional ship emission prediction in the past (Xing, 2017).

(b) The top-down method ignores the emission difference under practical operating conditions of ship equipment, resulting in prediction deviations. The bottom-up method, on the other hand, considers the influence of the marine environment, hull and propeller state, and propulsion system performance, which improves prediction accuracy. Besides, the emission factor, which is related to the main engine's fuel consumption under different operating conditions, is a variable parameter. However, this parameter is treated as a fixed value in most of the existing studies, which affects the model's prediction performance. Therefore, the study of prediction models considering the varying sailing conditions is of great significance, towards the improvement of ship emission prediction performance (Moreno-Gutiérrez et al., 2015).

(c) The top-down method relies on fuel sales data, fuel consumption statistics, the noon report, or customized data collection systems to forecast regional or global ship emissions. The bottom-up method, on the other hand, is mainly based on automatic data collection system. The use marine engine logs and ship questionnaires for data collection has also been reported in some studies. Nonetheless, the low quality of the collected data still affects the model's prediction accuracy. The application of state-of-the-art data acquisition systems is therefore critical for improving prediction performance.

(d) Currently, there is no systematic theory or method for calculating and analyzing ship emissions. The monitoring of energy consumption and pollution gas emissions still remains the basis for ship pollution gas emission control. Therefore, the development of systematic monitoring and intelligent analysis systems for pollution gas emissions is a necessary future trajectory for ship emission control (Antonio et al., 2017).

6. Conclusions and discussions

Effective prediction of ship energy consumption and emissions is essential to realize the optimal management and control of ship energy consumption and emissions, in order to achieve energy saving and

Table 7
Comparison analysis of different prediction methods for ship pollution gas emission.

Target area/ship	Methods	Parameters of concern	Data source	Reference
Global ships	Top-down, bottom-up	Ship installed power, ship position, etc.	International Comprehensive Ocean-Atmosphere Data Set. Automated Mutual-Assistance Vessel Rescue System	Wang et al. (2008)
Ships of 100 gross tons and above	Top-down	Fuel type, fuel consumption, and fuel sulfur content, etc.	Coal and oil statistics of the United Nations and oil statistics of the International Energy Agency, etc.	Endresen et al. (2007)
89 ships in Rotterdam Port	Top-down	Ship type, fuel consumption, fuel type, and engine type	Questionnaire survey on 89 ships	Hulskotte and Denier van der Gon (2010)
Global ships	Top-down	Ship parameters, fuel consumption, and fuel sulfur content, etc.	Marine exhaust emission test data. International navigational fuel usage information	Corbett et al. (1999)
Ships in West Coast waters of the United States	Top-down	Fuel consumption, ship traffic intensity	International fuel sales data, the fuel consumption of world freight fleet	Wang and Corbett (2007)
A Ro-Ro ship with 4030 DWT	Bottom-up	Speed, marine environment, hull and propeller fouling, trim, etc.	Ship noon report	Juan et al. (2018)
Inchon Port	Bottom-up	Ship parameters, fuel type and consumption, sailing speed, etc.	Incheon Port Authority, European Environment Agency	Chang et al. (2014)
Shanghai Yangshan Port	Bottom-up	Ship parameters, sailing speed, ship voyage, etc.	AIS	Song (2014)
Inchon Port	Top-down, bottom-up	Navigation state, fuel consumption, voyage, etc.	Incheon Port Authority Database	Chang et al. (2013)
"Yu Kun" ship	Top-down, bottom-up	Fuel consumption, fuel type, ship parameters, sailing state, etc.	Logbook, oil record book	Xing et al. (2016)
Ningbo-Zhoushan Port	Bottom-up	Ship type, meteorological environment, and navigation state	AIS	Huang et al. (2017)
The Yangtze River	Bottom-up	Ship type, the density of ships, power of the main engine	AIS	Peng et al. (2020b)
North America	Bottom-up	Ship type, Ship parameters, sailing route, draft, etc.	International comprehensive marine and atmospheric data set, etc.	Wang et al. (2007)
The Baltic	Bottom-up	Ship parameters, actual sailing speed, etc.	AIS	Jalkanen et al. (2009)
Nanjing Longtan Container Terminal	Bottom-up	Ship type, ship parameters, sailing speed, route, etc.	AIS, ship profile database, and field survey data.	Zhang et al. (2017)
Nordic emission control area	Bottom-up	Ship type, ship parameters, sailing speed, route, etc.	AIS, IHS Fairplay	Johansson et al. (2013)
Global ships	Bottom-up	Ship equipment parameters, sailing speed, route, etc.	AIS	Sofiev et al. (2018)
Yangtze River Estuary	Bottom-up	Ship parameters, navigation state, voyage time and position, etc.	AIS, CCS Database, Lloyd's Classification Society Database	Weng et al. (2019)
Sea around Danish Strait	Bottom-up	Ship parameters, navigation state, engine load, fuel sulfur content, etc.	AIS, IHS Fairplay, internal ship database	Jalkanen et al. (2011)
Northern Norway	Bottom-up	Ship parameters, navigation state, engine load, fuel sulfur content, etc.	Arctic climate change, AIS, etc.	Marelle et al. (2016)
Ro-Ro ships	Bottom-up	Ship parameters, meteorological conditions, water displacement, main engine power, fuel consumption, etc.	On-board sensor collection	Moreno-Gutiérrez and Durán-Grados (2020)

emission reduction in the shipping industry. Although some researches on the prediction of ship energy consumption and pollution gas emissions have been conducted, some challenges remain.

1) There is still lack of systematic ship energy consumption and emissions monitoring methods that can simultaneously handle varying data types, with modules for data preprocessing and analysis method, etc. Either, the deep mining of multi-source heterogeneous data has not been fully realized. Dynamic analysis and prediction of ship energy consumption and emissions using real-time data also needs further improvement. Consequently, a thorough investigation of the multi-dimensional in-depth mining method of multi-source heterogeneous big data characteristics is required. To establish high-precision energy consumption and emission prediction models, big data-based machine learning algorithms should be used, which will continuously improve prediction accuracy and practical application performance.
2) Ship fuel consumption and emission prediction models are the basis for optimal ship energy consumption and emissions management strategies. However, the applicability and performance analysis of those models for various ships and conditions remains inadequate. Selecting a suitable modeling method is the key to achieving an accurate prediction for various ship characteristics and operation modes. To promote the development of ship energy consumption management and emission control, it is necessary to develop high precision and applicable prediction models for different types of ships and working conditions. Furthermore, ship-shore integrated intelligent ship energy consumption and emission monitoring systems should be developed to improve the application performance of the prediction methods.
3) Since ship energy consumption and pollution gas emissions are influenced by multiple time-varying factors (e.g., wind, wave, and trim), further research on dynamic ship energy consumption and emission analysis methods considering the coupling effects of those factors is required. In addition, research on the self-learning of model parameters based on artificial intelligence should be strengthened, to improve the model's adaptability to complex and time-varying navigational conditions. Similarly, high-precision energy consumption models based on self-learning parameters should be developed using advanced artificial intelligence to achieve effective dynamic prediction of ship energy consumption and emissions under the coupling effect of multiple influencing factors.
4) Further research should be done on the optimization and control strategies of ship energy consumption and pollution gas emissions to meet the emissions reduction requirements proposed by IMO. Such strategies should also consider market mechanism-based measures, navigation optimization, power system optimization control, etc., to promote sustainable development of the shipping industry.

For all that, the studies on the energy efficiency optimization and emission control measures illustrated that the goal of the carbon neutral transportation and fulfillment of the IMO's GHG emissions reduction requirements may not be realized in the long term (The goal is to reduce carbon intensity by at least 40% by 2030, compared with 2008 levels, and aim for a 70% reduction by 2050), without low-carbon energy transition in the shipping industry. At the present stage, about 95% of ships use diesel as the main power energy. To achieve the carbon neutral transportation and fulfil the IMO's GHG emissions reduction requirements, it is necessary to get rid of the dependence on diesel power in the future. The application technology of low-carbon and zero-carbon energy sources, such as LNG, batteries, hydrogen fuel cells, methanol, ammonia and shore power, should be investigated. In addition, the green and intelligent technologies, such as intelligent power optimization, energy efficiency management, carbon capture and storage, should be studied, and meanwhile, the management mechanisms such as carbon tax and carbon trading should be developed in the future work.

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.

Data availability

No data was used for the research described in the article.

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