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Data analytics for fuel consumption management in maritime transportation: Status and perspectives

Abstract

The shipping industry is associated with approximately three quarters of all world trade. In recent years, the sustainability of shipping has become a public concern, and various emissions control regulations to reduce pollutants and greenhouse gas (GHG) emissions from ships have been proposed and implemented globally. These regulations aim to drive the shipping industry in a low-carbon and low-pollutant direction by motivating it to switch to more efficient fuel types and reduce energy consumption. At the same time, the cyclical downturn of the world economy and high bunker prices make it necessary and urgent for the shipping industry to operate in a more cost-effective way while still satisfying global trade demand. As bunker fuel consumption is the main source of emissions and bunker fuel costs account for a large proportion of operating costs, shipping companies are making unprecedented efforts to optimize ship energy efficiency. It is widely accepted that the key to improving the energy efficiency of ships is the development of accurate models to predict ship fuel consumption rates under different scenarios. In this study, the ship fuel consumption prediction models presented in the literature (including the academic literature and technical reports, which are a typical type of "grey literature") are reviewed and compared, and models that optimize ship operations based on fuel consumption prediction results are also presented and discussed. Current research challenges and promising research questions on ship performance monitoring and operational optimization are identified.

Key words

Maritime transportation, ship fuel consumption prediction, ship performance prediction, ship energy efficiency optimization, ship performance optimization

1. Introduction

1.1 Background

Seaborne transport is the most energy-efficient mode of transportation, and it forms the backbone of international trade and global supply chains (Christiansen et al., 2004; Kawasaki and Lau, 2020). According to the United Nations Conference on Trade and Development (UNCTAD), more than three fourths of merchandise traded globally by volume is carried by sea (UNCTAD, 2019). As the shipping industry is mainly powered by heavy fuel oil, it also creates a large environmental footprint due to its emissions of greenhouse gases (GHGs) and polluting substances (Cheaitou and Cariou, 2012; Adland et al., 2017; Cheaitou et al. 2020; Gu et al., 2020; Wang et al., 2021). As early as 1973, the International Maritime Organization (IMO) established the Marine Environment Protection Committee (MEPC) to address marine pollution and GHG emissions. In the years since, various global conventions and regulations have been proposed and implemented to reduce shipping emissions (Gholizadeh et al., 2020). The most important is the International Convention for the Prevention of Pollution from Ships (MARPOL) adopted by the IMO (MEPC), which addresses several marine pollution issues, such as oil spills, the transportation of noxious liquids and other harmful substances, sewage, garbage, and ship air pollution (IMO, 2011). In 1997, MARPOL Annex VI introduced regulations to prevent air pollution by limiting the emissions of sulfur oxides (SO_x), nitrous oxides (NO_x), and other ozone-depleting substances from ship exhausts (IMO, 1997). Regulations to reduce GHG emissions (e.g., carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and ozone (O_3)) from shipping activities were introduced in an amendment to MARPOL Annex VI in 2011 (MEPC, 2011). As a consequence of these regulations, sulphur emission control areas (SECAs) and nitrogen emission control areas (NECAs) have been established across the world, and various ship energy efficiency indicators and monitoring systems for reducing GHG emissions have been proposed (Tseng and Ng, 2020). The IMO has called on shipping companies to reduce their emissions to 50% of their 2008 levels by 2050. The major regulations on shipping emissions are summarized in Table 1.

Table 1. Regulations to reduce emissions from shipping

Regulation	Related documentation	Time of implementation	Organization	Object(s)	Area(s)	Main contents	Notes
SECAs	MARPOL Annex VI	1 Jan 2015	IMO (MEPC)	All ships sailing in SECAs	Four SECAs: the Baltic Sea, the North Sea, the North American Sea, and the United States Caribbean Sea	The maximum fuel sulphur content cannot exceed 0.1% m/m when sailing in SECAs	None
NECAs	MARPOL Annex VI	a) 1 Jan 2016, and b) 1 Jan 2021	IMO (MEPC)	New ships with marine diesel engines with output of 130 kW or higher and new engines installed in all ships on or after a) 1 Jan 2016, and b) 1 Jan 2021 sailing in NECAs	a) The North American area and the United States Caribbean Sea, and b) the North Sea and the Baltic Sea	NO_x regulations tier III is implemented in NECAs	NO_x regulations tier III requires that engines under 130, between 130 and 1199, and over 1200 propeller revolutions per minute (RPM) should have the total weighted cycle emission limit as 3.4, 2.4, and 2.0 (g/kWh) respectively
Global sulfur content limit in fuel	MARPOL Annex VI	1 Jan 2020	IMO (MEPC)	All existing ships	Areas outside SECAs	The maximum fuel sulphur content cannot exceed 0.5% m/m	None
European Union (EU) Monitoring Reporting and Verification (MRV)	EU regulation 2015/757	1 Jan 2018	EU	All ships with a gross tonnage above 5000 arriving at, within, or departing from ports under the jurisdiction of a Member State of EU	Global shipping lines with either origin or destination at the ports in the Member States of EU	Accurate monitoring, reporting, and verification of CO_2 emissions from related ships	The fuel consumption and CO_2 emission data per ship for 2018 and 2019 have already been published
IMO data collection system (DCS)	MARPOL Annex VI	1 Jan 2019	IMO (MEPC)	All ships with a gross tonnage of 5000 and above	Global	Reporting verified fuel consumption data via their flag states	Ships' names and IMO numbers will be anonymized when publishing
Energy efficiency operation index (EEOI)	MEPC.1 /Circ.684	July 2009	IMO (MEPC)	All existing ships	Global (voluntary)	Performance improvement by the efforts in operation	Average indicator of the ship/fleet operational efficiency of all types of fuels during a voyage (Operational CO_2 indicator)
Energy efficiency design index (EEDI)	Resolution MEPC.203(62)	Jan 2013	IMO (MEPC)	New and contracted ships on or after 1 Jan 2013 or delivered on or after 1 July 2015, and existing ships undergone major conversions	Global	Performance improvement of ship hardware	An index indicating the energy efficiency of a ship in terms of g CO_2/tonne/nautical mile for a specific ship operational condition (CO_2 design index)
Ship energy efficiency and management plan (SEEMP)	Resolution MEPC.203(62)	Jan 2013	IMO (MEPC)	All existing ships	Global	Several steps are required: planning, monitoring, self-evaluation, and improvements	Use EEOI as a benchmark
Combination measure of EEXI and CII	MEPC 75 virtual session	In progress	IMO (MEPC)	All existing ships	Global	Combination of technical and operational approaches to reduce ships' carbon intensity	EEXI is short for energy efficiency existing ship index, and it is based on EEDI. CII is short for carbon intensity indicator and should be recorded in ships' SEEMP

However, despite the growing number of strict environmental protection regulations implemented by the IMO and individual countries and regions, emissions from shipping continue to increase overall. The main fuel-based pollutants and GHG emissions in the international shipping industry between 2012 and 2017, according to estimates based on a top-down methodology in the fourth IMO GHG study (IMO, 2020), are summarized in Table 2. Although the total cargo loaded only slightly increased from 9,195 million tons in 2012 to 10,716 million tons in 2017 (UNCTAD, 2019), there was a significant increase in all types of emissions. The massive amounts of pollutants and GHGs emitted by the shipping industry are having an adverse impact on both human health and the global climate. As air emissions from vessels are proportional to the fuel consumption of the main and auxiliary engines (including boilers), especially in terms of the emissions of CO_2, NO_x, and SO_x (Kontovas, 2014; Adland et al., 2019; Peng et al., 2020; Wu and Wang, 2020), better management of fuel consumption during ship operation could improve the energy efficiency of ships and thus reduce their emissions (Perera and Mo, 2016).

Table 2. International shipping emissions from 2012 to 2017 (IMO, 2020)

Emission/Year	2012	2013	2014	2015	2016	2017
CO_2 (million tonnes)	614.1	612.3	634.2	657.9	675.3	693.4
CH_4 (tonnes)	10,156.8	10,120.6	10,414.9	11,205.9	11,745.4	12,397.5
N_2O (thousand tonnes)	34,296.5	34,270.0	35,568.4	36,942.3	37,957.5	39,059.2
SO_x (thousand tonnes)	8,260.2	7,888.9	7,825.3	8,116.6	8,943.3	9,252.3
NO_x (thousand tonnes)	14,927.4	14,606.2	14,683.6	15,357.1	15,780.8	16,201.9
NMVOC (thousand tonnes)	596.4	592.6	603.0	633.0	653.8	675.4
PM (thousand tonnes)	1,271.2	1,237.8	1,228.3	1,258.3	1,352.4	1,399.1
BC (thousand tonnes)	54.4	55.8	60.1	59.9	60.7	62.2

Note: NMVOC is the abbreviation for non-methane volatile organic compounds. PM is the abbreviation for particulate matters. BC is the abbreviation for black carbon.

1.2 Energy efficiency improvement and emission reduction strategies

In addition to stricter emissions regulations, high bunker prices that cyclically occur and downturns in the shipping market have also pushed the shipping industry to adopt measures to improve energy efficiency and thus to reduce emissions (Beşikçi et al., 2016). Currently, two main solutions are applied to improve ship energy efficiency: technical solutions and operational solutions (Leifsson et al., 2008; Wong et al., 2015; Coraddu et al., 2017; He et al., 2017; Theocharis et al., 2019). Technical solutions include upgrading propellers, optimizing vessel size, and designing the hull shape to reduce vessel resistance; using lightweight materials to reduce vessel weight; selecting efficient power systems and machinery; switching fuel type; using scrubbers; recovering waste heat; and using solar or wind power and shore power (Wan et al. 2018). There are three main categories of operational solutions according to the SEEMP, as listed in Table 3 (IMO, 2009; Ballou, 2013). Common operational measures adopted in the shipping industry include improving on-time arrival consistency using route optimization tools, reducing routing decision errors, reducing excessive vessel motions to minimize ship and cargo damage, increasing crew comfort, reducing the ship's structural maintenance, and routing optimization considering ECAs, as discussed by Ballou (2013). Given that the high volatility of the shipping market heavily affects shipping operators' revenues, slow steaming is commonly adopted, and the main effects of which are classified by Cariou et al. (2019) into three categories: economic implications, environmental implications, and service-related implications. Such analysis provides valuable insights of vessel management for both academic research and the shipping industry.

Table 3. Energy efficiency improving measures recommend by SEEMP

Category	Measures
Fuel efficiency operations	• Improving voyage planning by e.g., ship route optimization • Weather routing • Just-in-time arrival at ports • Speed optimization, including slow steaming, sailing at optimal speed, and gradual increase in speed when leaving port • Shaft power optimization, including running at constant RPM and usage of electronic engine management systems • Switching fuel type • …
Ship handling optimization	• Trim optimization • Ballast optimization • Propeller design and water inflow optimization • Optimized using of rudder and autopilot • Fleet management • Improving cargo handling • …
Maintenance	• Hull/propeller maintenance, including hull cleaning, repairing, and painting, and propeller cleaning and polishing • Marine engine maintenance • …

Nevertheless, it has been pointed out by Wan et al. (2018) that the technical measures currently available are struggling to steer the shipping industry in an energy-efficient and low-carbon direction because their application not only requires engineering innovation but also carries a hefty price tag: the average cost per ton of CO_2 reduction ranges from US$50 to $200, while the emissions trading price in the United States is US$5 to $15 per ton (Eide et al., 2011). In contrast, operational measures to improve energy efficiency carry much less cost and do not require an initial investment, and well-designed operational solutions can achieve promising energy savings (Wan et al., 2018). However, applying effective and efficient operational solutions is not a trivial task, as various factors can influence the actual fuel consumption of a ship in practice, which makes it difficult to capture the relationship between the influencing factors and the fuel consumption rate. As illustrated by Sourtzi (2019), ship design (e.g., main dimensions, propulsion system, propeller design, hull/steel structure and cargo arrangement), vessel operational performance (e.g., sailing speed, draft, trim, displacement, hull performance, and drydocking), and environmental conditions (e.g., wind, wave, and current conditions, water and air temperature, and water depth) all influence ship fuel consumption and therefore energy efficiency. Another barrier to implementing operational changes is that the shipping industry itself is reluctant to adopt energy efficiency measures. This is mainly due to a range of issues in the development and implementation of fuel consumption management strategies, namely split incentives in stakeholders, inadequate information and transparency about energy efficiency and incentive structures, information uncertainty, and decisions made for short-term gain (Poulsen, 2011; Mansouri et al., 2015). There is thus an urgent need to propose and promote more effective and applicable ship fuel management measures to reduce fuel consumption and improve energy efficiency. It is widely acknowledged that the basis of such measures is the accurate estimation of the relationship between a ship's fuel consumption and determinants such as mechanical factors, sailing behaviors, and environmental factors using appropriate prediction algorithms before (or during) a voyage (Pedersen and Larsen, 2009; Soner et al., 2018; Meng et al., 2016; Yang et al., 2019b; Farag and Ölçer, 2020). The focus of this review is therefore the literature on ship fuel consumption prediction models and fuel management models from the last 13 years (2008 to 2021). Literature from earlier periods is excluded because data-driven models for ship performance monitoring only started to appear in the last 13 years. The limited number of related papers and reports gives us an opportunity to summarize the details of the reviewed literature in lists and to make comprehensive comparisons of fuel consumption prediction models. Promising future research directions are outlined based on the findings of the review.

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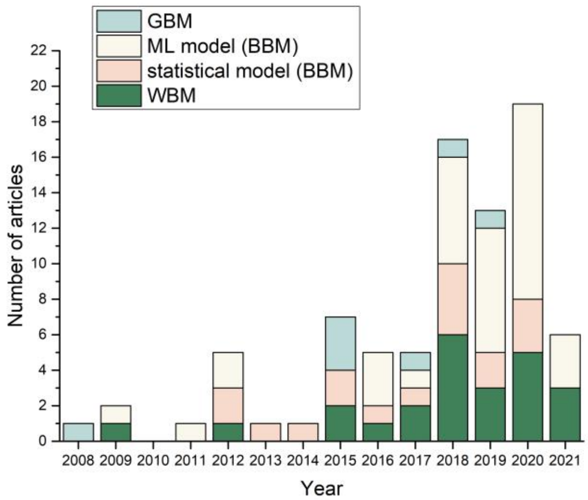
2. Literature review method and structure

Given the focus on fuel consumption prediction models and the fuel management models derived from them, we searched the Scopus, Google Scholar, and Science Citation Index databases using keywords related to fuel consumption prediction and management, such as “ship fuel consumption prediction,” “ship fuel consumption estimation,” “ship energy efficiency prediction,” “ship energy efficiency estimation,” “ship fuel efficiency,” “ship fuel management,” and “ship performance monitoring.” We identified relevant papers in the initial search and then checked the papers and reports cited by them and that cite them. Considering our main focus on fuel consumption prediction models, we excluded papers that only propose fuel management measures and assume that the relationship between fuel consumption and the various influencing factors (e.g., sailing speed) is deterministic. Finally, we identified 83 related papers, 53 of which propose fuel consumption prediction models for ship performance monitoring only (termed ship performance monitoring models) and 30 of which propose two-stage models for fuel consumption prediction and management to achieve ship operational optimization (termed ship operational optimization models). We classify these models into three categories, namely white-box models (WBMs), black-box models (BBMs), and grey-box models (GBMs) based on Haranen et al. (2016). Descriptions of the three categories and the number of related papers in each are presented in Table 4. We also analyzed the publishing years of the 83 papers according to the prediction models presented. The statistical models and machine learning (ML) models in BBMs were considered separately. The results are shown in Figure 1.

Table 4. Description and overview of the prediction models in this review

Type	Description (Haranen, 2016)	Examples (Yang et al., 2019)	Sub-types	No. of related papers
WBM	A WBM is based on a priori knowledge and physical principles of the vessel power system, and its structure and parameters are all known.	Holtrop-Mennen method (Holtrop, 1977, 1978, 1984; Holtrop and Mennen, 1978, 1982), Kristensen-Lützen method (Kristensen and Lützen, 2012).	None	24
BBM	A BBM is established using experimental or practical sailing data and is purely data driven. Therefore, no prior knowledge or physics insight is needed when training a BBM.	Statistical models (e.g., multiple linear regression), machine learning models (e.g., artificial neural networks, tree-based models, and support vector machines).	a) BBM based on statistical modeling: statistical models are used for fuel consumption prediction, which focuses on explaining the relationship between fuel consumption and various influencing factors. b) BBM based on ML: machine learning models are used for fuel consumption prediction, which focuses more on accurate prediction results and model generalizability.	a) 17 b) 35
GBM	GBMs are developed based on both the physical properties underlying WBMs and knowledge extracted from experimental or operational data in BBMs.	A WBM is first developed based on hydrodynamic knowledge, then a BBM is used to estimate or adjust some of the coefficients, as in Journée et al. (1987), Meng et al. (2016), and Yang et al. (2019).	None	7



Note: the number of papers in 2021 is not fully counted.

Figure 1. Summary of the reviewed papers by year

Figure 1 indicates that the number of papers on the predication of ship fuel consumption increased after 2014 and especially after 2018. Moreover, as shown in Table 4, about 63% of the papers develop BBMs for ship fuel consumption prediction, whereas more than 40% of the 83 papers use ML model based BBMs to predict fuel consumption. Figure 1 also shows that there has been an increasing trend of using BBMs based on ML for fuel consumption prediction. Between 2017 and 2020, the use of WBMs for fuel consumption prediction also showed an upward trend. In contrast, papers using GBMs for fuel consumption prediction are relatively evenly distributed over the 13-year review period.

3. Review of data and prediction models in current literature

3.1 Input data overview

Given the complexity of vessel engine power systems and sea and weather conditions, numerous ship-related internal factors and external environmental factors affect the fuel consumption rate and thus energy efficiency (Adland et al., 2021). We divided the data that serve as the inputs to the fuel consumption prediction models into four categories according to the data source: ship mechanical data, ship operational data, ship maintenance data, and sea and weather conditions. Ship mechanical data include parameters related to static ship dimensions and information about the power system. Ship operational data mainly comprise information on ship voyage and sailing behavior and ship mechanical conditions in operation, such as power system performance, displacement, and hull conditions. Ship maintenance data are mainly related to information on ship dry docking. Sea condition data cover sea water temperature, waves, swells, and currents, and weather condition data mainly cover wind and air pressure.

A major data source is the daily noon report prepared by the ship's chief engineer and sent by the ship's master to the shipping company and shore management (Pedersen and Larsen, 2009; Pedersen et al., 2015; Lu et al., 2015; Beşikçi et al., 2016; Meng et al., 2016; Yuan and Nian, 2018; Uyanık et al., 2019; Du et al., 2019; Adland et al., 2020; Işıklı et al., 2020). Although noon reports may differ, the main content is consistent: types of daily fuel consumption, basic voyage information (e.g., voyage number, date and time of report, load condition, and ship position), sailing behavior information (e.g., average sailing speed and sailing distance since last report, propeller slip, and average engine revolutions per minute), and sea and weather conditions (e.g., wind, current, wave, and swell conditions). However, as noon reports are completed manually, their accuracy cannot be guaranteed. Furthermore, only one record is made per day, which reduces the data quality and quantity (Bocchetti et al., 2013, 2015; Erto et al., 2015; Chaal, 2018; Farag and Ölçer, 2020).

For modern ships equipped with onboard sensors, sensor data serve as another important data source (Petursson, 2009; Petersen et al., 2012a, 2012b; Bocchetti et al., 2015; Jeon et al., 2018; Soner et al., 2018; Lepore et al., 2019; Capezza et al., 2019; Man et al., 2020; Farag and Ölçer, 2020; Wang et al., 2016, 2020). To obtain various types of data, different types of sensors should be installed onboard. For example, fuel consumption sensors, global positioning system (GPS) receivers, shaft power testers, wind speed sensors, and water depth sonars are installed on cruise ships to obtain instantaneous data on fuel consumption, ship navigation speed, speed and torque shaft, wind speed, and water depth (Wang et al., 2016). Fuel consumption sensors, GPS receiving devices, and shaft power meters are used in tankers to acquire real-time data on fuel consumption, ship navigation speed, longitude and latitude, and shaft speed and power (Wang et al., 2020).

Another widely adopted onboard system is the automatic identification system (AIS), which enables ships to broadcast and receive messages to and from other ships or coastal authorities that are also equipped with the AIS. The AIS provides static information (e.g., ship identity, size, and type), dynamic information (e.g., ship position, sailing speed, heading degree, rate of turn, navigation status, and reporting time stamp), and voyage-related information (e.g., destination, estimated time of arrival, and draught) (Yang et al., 2019a). Onboard sensors and the AIS provide consecutive data streams at a much higher frequency (e.g., every few seconds or minutes) and quality than noon reports. However, the data acquisition costs are much higher.

The engine room logbook, which tracks of all a ship's machinery parameters, performance, maintenance, and malfunctions, can provide both static and dynamic mechanical data during ship operation (Uyanık et al., 2020). Ship information is also provided by online resources (Huang et al., 2018; Man et al., 2020; Linh and Ngoc, 2020; Yan et al., 2020; Li et al., 2018, 2020). For example, static mechanical data and maintenance records can be found in Lloyd's Register and the World Shipping Register. The surrounding sea and weather data can be found on sea and weather forecast websites, such as National Marine Environmental Forecasting Center (NMEFC), National Oceanic and Atmospheric Administration (NOAA), Weathernews Inc. (WNI), Copernicus Marine Environment Monitoring Service (CMEMS), the European Centre for Medium-Range Weather Forecasts (ECMWF), etc. Detailed features of the four data categories used in current literature and their sources are shown in Table 5.

Table 5. Features and sources of common data categories

Data	Features	Sources
Ship mechanical data	Ship dimension: length, beam, gross tonnage, deadweight, berth number on cruise ships, etc. Power system: engine parameters, design speed, RPM at design speed, etc.	Onboard sensors, noon report, engine room logbook, AIS, etc.
Ship operational data	Ship voyage and sailing behavior: speed over ground (SOG), speed through water (STW), sailing time since last dry docking, sailing distance since last record, ship course, type of fuel used, fuel density and temperature, etc. Ship mechanical condition while operating: propeller pitch, rudder angle, main engine load and working hours, engine RPM, stabilizer fin operation time, turbo exhaust temperature, trim angle, draft, displacement, shaft generator, hull and propeller fouling condition, wetted surface area, etc.	Noon report, AIS, engine room logbook, Lloyd's Register, World Shipping Register, etc.
Ship maintenance data	Dry docking data, etc.	Records from shipping company, Lloyd's Register, World Shipping Register, etc.
Sea and weather condition data	Sea conditions: sea depth, sea water temperature and density, direction and value of wave, swell, and current, etc. Weather conditions: direction and value of wind, air density and temperature, etc.	Noon report, onboard sensors, online sea and weather forecast websites, etc.

3.2 General fuel consumption prediction procedure

To obtain accurate vessel fuel consumption prediction results, several key issues need to be considered (Zheng, 2021). First, the objectives, resources, and requirements of the ship energy efficiency management project must be clarified. The objectives may include the prediction target (e.g., ship fuel consumption rate, ship emission status, or ship energy efficiency indicator) and the prediction accuracy expected. Resources refer to the available data sources and computational power, if big data are being used. Requirements are related to the specific application context: who would the users of the ship fuel consumption prediction model be and what kind of presentation format would they expect? For example, academic researchers and technicians would expect more details of the fundamental theory and detailed implementation procedure of a prediction model, whereas the onboard crew would be more interested in the ease of use of the graphical user interface of the model and would pay less attention to the theories behind it. Another aspect of model requirements is the model transparency or explainability, that is, whether the underlying and working processes of the prediction model need to be completely or partially explainable or whether only high prediction accuracy is the goal.

Second, the datasets needed to fulfill the objectives identified in the first step should be selected, with consideration of the availability of data sources and shipping domain knowledge. The appropriate data (or features) should then be collected and combined from various datasets and sources. Data quality and quantity should be checked after data collection. Data pre-processing is then conducted, which includes, but is not limited to, data cleaning, feature dimension reduction, data transformation, and dataset splitting for prediction model training, validation, and testing.

Third, appropriate prediction models that fulfill the objectives and requirements identified in the first step must be selected, with consideration of the advantages and disadvantages of the different approaches presented in the literature and reports or adopted by the relevant authorities. The different types of vessel fuel consumption prediction models are classified and analyzed in the following sections. Alternatively, novel prediction models can be developed to achieve particular requirements or to improve prediction accuracy, with specific model parameters and hyperparameters determined as necessary. Finally, model performance must be validated, including in practical scenarios.

3.3 Review of white-box models (WBMs)

In WBMs, the basic model construction procedure is to calculate the resistances encountered by a ship from different sources based on physics principles and hydrodynamics laws. The total resistance consists of calm water resistance and the additional resistance presented by wind, waves, shallow water, and other external factors. Once the overall resistance condition is modeled, the engine power required to drive the ship at a certain speed and the corresponding fuel consumption rate can be calculated (Haranen et al., 2016). Emissions from ships, including those of various pollutants and GHGs, can then be calculated based on the engine power and fuel consumption results from the WBM. A total of 24 papers on WBMs were reviewed, of which 16 are on ship performance monitoring (listed in Table 6) and 8 are on ship operational optimization (listed in Table 7).

Table 6. Ship performance monitoring via WBMs (16 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Fuel consumption prediction model performance	Journal
Jalkanen et al. (2012)	A RoPax ship	Ship operational data from AIS; ship mechanical data from IHS Fairplay	Fuel consumption and ship emissions of pollutants and GHG in the Baltic Sea surrounding the Danish Straits	STEAM2	The performance is slightly better than STEAM	Atmospheric Chemistry and Physics
Goldsworthy and Goldsworthy (2015)	7125 vessels operating in the whole Australian region	Ship operational data from AIS in the whole Australian region; ship mechanical data from Lloyd's database	Fuel consumption and emissions of pollutants and GHG	A generic model based on ship activities	R^2 is 0.9787 for fuel consumption prediction for a bulk carrier for testing	Environmental Modelling & Software
Moreno-Gutiérrez et al. (2015)	Ships that passed through the Strait of Gibraltar during 2007	Ship operational data from dynamic AIS data; ship mechanical data from Lloyd's Register and IHS Fairplay	Fuel consumption, delivered power and the emissions of pollutants and GHG in 2007	9 generic inventory methods from papers and reports published in EU and USA	STEAM (Jalkanen et al., 2009) is the most realistic approach to calculate the energy consumption, while Goldsworthy (Goldsworthy and Renilson, 2013) is the most complete method which applies emission factors for total emission calculation	Energy
Rakke (2016)	A ship fleet consisting of about 16,000 ships	Ship operational and mechanical data from AIS and a public database	Ship fuel consumption and emissions of pollutants and GHG	Holtrop-Mennen model	The error rate is about 5% for a small number of ships for model testing	Master thesis at Norwegian University of Science and Technology (NTNU)
Tillig et al. (2017)	A tanker ship	Ship mechanical and operational data; sea and weather conditions based on simulation	Ship fuel consumption per route	A generic model with resistance prediction using Technical University of Denmark (DTU) method, Holtrop-Mennen method and computational fluid dynamics (CFD); power and RPM prediction using Holtrop-Mennen method	Not applicable	Proceedings of the Institution of Mechanical Engineers, Part M
Johansson et al. (2017)	Global ships in 2015	Ship operational data from AIS; ship mechanical data from IHS Fairplay and classification societies	Global ship fuel consumption and emissions of pollutants and GHG	STEAM3	The predicted global ship fuel consumption is qualitatively in agreement with those in the third GHG study of IMO and that reported by the International Energy Agency	Atmospheric Environment
Orihara and Tsujimoto (2018)	A tanker and a bulk carrier	Ship mechanical and operational data from ship logbook; sea and weather conditions from ship logbook	Ship speed, engine power, and fuel consumption	A physical simulation model	Not applicable	Journal of Marine Science and Technology
Tillig et al. (2018)	A RoRo ship and a tanker ship	Ship mechanical and operational data, and sea and weather conditions based on simulation	Ship fuel consumption prediction during design process	Monte Carlo simulation	The error rate is about 12% in very early design phase and less than 4% in very late design phase	Ships and Offshore Structures
Simonsen et al. (2018)	Three cruise ships	Ship mechanical and operational data from AIS;	Fuel consumption at sea and in port, respectively	Model proposed in IMO's third GHG emission study	R^2 between 0.3 and 0.4 in the test set	Energies

		port survey reports/real world data from *MS Finnmarke*n				
Huang et al. (2018)	Ships in Ningbo-Zhoushan port	Ship operational and mechanical data from AIS; sea and weather data from online resources	Fuel consumption and emissions of pollutants and GHG	A generic model based on ship activities considering the influences of ocean environment	The relative error rate is within 10%	Transportation Research Part D
Merien-Paul et al. (2018)	A bulk carrier	Ship operational data in different sailing statuses and the geo-spatial data	Fuel consumption	A generic model based on bottom-up fuel consumption prediction approach	Not applicable	Transportation Research Part D
Goldsworthy and Goldsworthy (2019)	Ships berthing at four ports in Australia in 2016	Ship operational data from AIS; ship mechanical data from IHS Markit Maritime & Trade	Fuel consumption and emissions of pollutants and GHG from auxiliary engines and boilers	A generic model based on Goldsworthy and Goldsworthy (2015) and Goldsworthy (2017)	Not applicable	Science of the Total Environment
Moreno-Gutiérrez et al. (2019)	A Ro-Pax ferry	Ship operational data from noon report; ship mechanical data from IHS	Ship fuel consumption and emissions of pollutants and GHG	4 existing general methods proposed in papers or by organizations and a newly proposed model combining the 4 existing models	The newly proposed model combines the advantages of the 4 methods and can be applied to different fleets	Science of the Total Environment
Tillig and Ringsberg (2019)	A tanker ship	Ship mechanical and operational data	Fuel consumption	A four degree-of-freedom simulation model	Not applicable	Ships and Offshore Structures
Medina et al. (2020)	A container ship	Ship operational data; wind data from ERA-5 database	Fuel consumption	A simple analytical model and a semi-empirical formula considering wind conditions	Not applicable	Transportation Research Part D

Table 7. Ship operational optimization via WBMs (8 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Fuel consumption prediction model performance	Optimization objective(s)	Decision variable(s)	Solution approach(es)	Journal
Li et al. (2018)	An oil tanker	Ship operational and mechanical data from experiment; sea and weather data from online resources	Fuel consumption per hour	A white-box simulation model based on Kwon's model	Not applicable	To minimize fuel consumption and maximize route cost reduction over a given route	Sailing speed	The internal penalty function	Ocean Engineering
Tillig et al. (2020)	A container ship and a tanker	Ship mechanical data and weather statistics from Monte Carlo simulation	Fuel consumption per hour	A pure white-box model based on Tillig et al. (2017, 2018), Tillig and Ringsberg (2019)	Not applicable	To minimize fuel consumption over a voyage	Sailing speed	Development of a simulation model called ShipCLEAN in Matlab	Transportation Research Part D
Wang et al. (2020)	A tanker ship	Ship operational data from onboard sensors; sea and weather data from ECMWF	Fuel consumption per nautical mile	A generic model considering multiple environmental factors	Not applicable	To minimize fuel consumption	Sailing route and sailing speed	Particle swarm optimization (PSO) algorithm	Ocean Engineering
Yang et al. (2020)	A tanker ship	Ship operational and mechanical data; sea and weather data from noon report	Fuel consumption per hour	The DTU-SDU (University of Southern Denmark) model	The overall average relative error of all segments on a route is 1.36%	To minimize fuel consumption over a given route	Sailing speed through water	Generic algorithm	Sustainability
Li et al. (2020)	A container ship	Ship operational and mechanical data from experiment; sea and weather data from online sources	Fuel consumption per hour	A white-box model based on Kwon's model and the International Towing Tank Conference (ITTC)	Not applicable	To minimize fuel consumption and the ship operating costs over a given route	Sailing speed	Linear approximation (COBYLA) in SciPy	Applied Ocean Research
Wang et al. (2021)	A tanker ship	Ship operational data and mechanical data from towing tank tests; sea and weather data from online resources	Fuel consumption per hour	A while-box model based on towing tank tests, ISO reports, and JONSWAP spectrum	Not applicable	To minimize fuel consumption and increase arrival punctuality over a voyage	Ship engine power	A combination of dynamic programming and generic algorithm	Transportation Research Part D
Fan et al. (2021)	A cruise ship	Ship operational data, mechanical data, sea and weather conditions from an onboard energy efficiency monitoring system	Fuel consumption per voyage	A generic model considering water velocity based on regression analysis	Not applicable	To minimize total fuel consumption over a voyage	Main engine speed	Dynamic programming algorithm	Proceedings of the Institution of Mechanical Engineers, Part M
Tzortzis and Sakalis (2021)	A container ship	Ship operational data, mechanical data, sea and weather conditions from onboard sensors	Fuel consumption	A white-box model based on several current models such as Holtrop (1984), Holtrop and Mennen (1982), ITTC (2021), and MAN (2018), etc.	Not applicable	To minimize total fuel consumption over a voyage	Sailing speed	Dynamic programming algorithm applied on a specific route after segmentation	Ocean Engineering

Most of the WBMs in the 24 papers listed in Tables 6 and 7 are based on ship operational data (23 papers) and mechanical data (21 papers), with half also relying on sea and weather data. None consider ship maintenance data (14 papers, especially those in recent years). In addition to fuel consumption prediction, nearly half of the models also predict ship emissions, including pollutants such as SO_2, NO_x, carbon monoxide (CO), PM and GHGs, such as CO_2 (9 papers). Most of the WBMs are developed by the authors themselves, although some papers adopt WBMs proposed by other organizations, such as the IMO, ITTC, and DTU-SDU, or by other authors. Two studies by Moreno-Gutiérrez et al. (2015 and 2019) compare the advantages and disadvantages of different types of WBMs and develop an improved WBM. Twelve of the 24 papers do not discuss the performance of fuel consumption prediction models, whereas in the papers in which model performance is presented, different test scenarios and metrics are used, making direct performance comparisons difficult. Of the 8 papers dealing with ship operational optimization models listed in Table 7, 5 discuss single-objective optimization models that aim to minimize fuel consumption, and the other 3 consider dual-objective optimization models that simultaneously minimize fuel consumption and maximize route cost reduction, minimize ship operational costs, or increase arrival punctuality. Six of the optimization models choose ship sailing speed as the decision variable, and 2 consider ship engine power and main engine speed. A detailed description of the approaches adopted in WBMs for ship fuel consumption prediction is given in Appendix B.1.

The main advantage of WBMs is that they can be applied at the initial stage of ship design and during sea trials, as the model structure and parameters are fully known from a priori knowledge and theoretical insights based on physical and hydrodynamics laws, naval architecture principles, computational fluid dynamics methods, and ship model tests. Furthermore, as WBMs are developed based on physics principles, they are transparent and explainable and are thus widely used in the shipping industry. Despite these advantages, there are some clear disadvantages of WBMs. First, WBMs use various assumptions from model structure to parameter estimation, and their performance is strongly influenced by these assumptions. The ship resistance components are treated separately and their interactions are ignored, which may result in inconsistencies in the WBMs developed (Haranen, 2016). As a result, the suitability and generalizability of WBMs can be poor (Haranen, 2016; Yang et al., 2019b). Second, as much a priori knowledge about the whole vessel system is needed to calibrate WBMs, their development and application may be restricted, because such knowledge may be difficult to comprehend for a non-expert. Third, as WBMs are deterministic models, which means that their structure and parameters are given and fixed and thus no randomness can be included to allow data uncertainty to be modeled, the models cannot learn from the data. Consequently, it is difficult to improve their performance given that data accumulate during ship operation. In addition, the deterministic property also makes WBMs vulnerable to noisy data, which are common in practice.

3.4 Review of black-box models (BBMs)

3.4.1 Review of BBMs based on statistical modelling

BBMs based on regression models are a type of classical model widely used in studies on ship fuel consumption prediction. The main procedure begins with feature/data acquisition and pre-processing. Then, reasonable assumptions are made, and suitable regression models are chosen. Next, the model parameters are estimated using real or simulated ship operational data, and finally, the model's fit and generalization abilities are validated. One stream of BBMs is based on statistical modeling for fuel consumption prediction, which mainly aims to identify the relationship between fuel consumption and sailing speed, as it is widely believed by researchers and practitioners that ship sailing speed is the most significant determinant of ship fuel consumption. A ship's fuel consumption rate at sea is usually treated as proportional to its sailing speed to a power of α. The cubic law, which adopts $\alpha = 3$, is particularly well known (Ryder and Chappell, 1980; Ronen, 1982, 2011; Wang and Meng, 2012; Du et al., 2019; Ronen et al., 2020); in practice, however, α can be smaller or larger than 3 depending on many factors, such as ship type, real sailing speed, and the surrounding sea and weather conditions (Wang and Meng, 2012).

Table 8. Power of speed-fuel consumption in current literature (6 papers/reports)

Literature	Shipping sector and fleet size	Range of power	Data resources
Notteboom and Cariou (2009)	Container ships	3.3	Ship operational and mechanical data from Lloyd's Fairplay Database
Wang and Meng (2012)	Container ships in a liner shipping network	2.7 to 3.3	Ship operational data provided by a global liner shipping company
MAN Diesel and Turbo (2018)	Tanker Bulk carrier Container ship Ro-pax	3.2 to 3.8 3.0 to 3.6 3.1 to 3.4 3.4 to 4.8	Not applicable
Adland et al. (2018)	8 crude Oil tankers	1.452 (laden) to 2.144 (ballast)	Ship operational data and sea and weather data from noon report; ship maintenance records
Kristensen (2019)	Oil tanker Bulk carrier Container ship	1.6 to 4.8 1.6 to 4.3 1.8 to 4.4	Ship mechanical data from Clarkson
Adland et al. (2020)	16 crude oil tankers	For Aframax tankers, the elasticity ranges from 0.114 to 3.783; for Suezmax tankers, the elasticity ranges from 0.760 to 3.667 in different speed intervals	Ship operational data and sea and weather data from noon report

Although the cubic law relation between a ship's sailing speed and the fuel consumption rate is widely adopted, Notteboom and Cariou (2009) conduct a pioneering study using regression analysis on ships' operational and mechanical data extracted from Lloyd's Fairplay Database and estimate an empirical relationship between sailing speed and installed power for container ships. Since then, numerous studies estimate the relationship between ship sailing speed and the corresponding fuel consumption rates for different ship classes under various conditions.

Many of the studies listed in Table 8 use ship operational data and mechanical data to calibrate the speed–fuel consumption curves, but most do not explicitly consider the influence of the surrounding sea and weather conditions. Adland et al. (2018, 2020) incorporate various such conditions, such as wind, swell, current, and waves, into their statistical fuel consumption prediction models. Adland et al. (2018) also focus on the impact of periodic hull cleaning and dry docking operations on vessels' energy efficiency and Adland et al. (2020) deeply explore fuel consumption–speed curves, both of which are important but challenging issues in vessel fuel consumption prediction and optimization. More sophisticated models that consider factors in addition to operational and mechanical factors, such as sea and weather conditions and ship maintenance data, are summarized in Table 9. Studies of ship operation optimization based on statistical models are presented in Table 10.

Table 9. Ship performance monitoring via BBMs based on statistical modelling (13 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Fuel consumption prediction model performance	Journal
Bocchetti et al. (2013)	Twin cruise ships	Ship operational data and sea and weather conditions from onboard data acquisition device	Fuel consumption per voyage	Multiple linear regression (MLR) analysis	Average R^2 is 0.9875 in the training set	Conference proceedings
Coraddu et al. (2014)	A RoPax vessel	Ship mechanical and operational data from ship monthly report	Fuel consumption per nautical mile and EEOI	Monte Carlo based simulation	Not applicable	Proceedings of the Institution of Mechanical Engineers, Part M
Bochetti et al. (2015)	A cruise ship	Ship maintenance and operational data, and sea and weather conditions from noon report and onboard sensors	Fuel consumption per voyage	MLR analysis	R^2 is at least 0.93 in the training set	Journal of Ship Research
Erto et al. (2015)	A cruise ship	Ship maintenance data and operational data, and sea and weather conditions from onboard sensors	Fuel consumption per mile	MLR analysis	R^2 is 0.94 in the training set	Quality and Reliability Engineering International
Bialystocki and Konovessis (2016)	A pure car and truck carrier	Ship operational data and sea and weather conditions from noon report	Fuel consumption per day	Polynomial regression	R^2 is 0.7557 in the training set	Journal of Ocean Engineering and Science
Jia et al. (2017)	483 VLCCs	Ship operational data from AIS; mechanical data from Clarksons World Fleet Register	Fuel consumption per voyage, GHG and pollutant emissions per voyage	Bottom-up vessel fuel consumption calculation	Not applicable	Transportation Research Part D
Lepore et al. (2018)	A Ro-Pax cruise ship	Ship operational data and sea and weather conditions from onboard multisensory system	Fuel consumption per hour	Multiway partial least-squares (PLS) regression	R^2 is 0.82 in cross validation	Quality and Reliability Engineering International
Adland et al. (2018)	8 crude Oil tankers	Ship operational data and sea and weather conditions from noon report; ship maintenance data provided by a shipping company	Fuel consumption per day	MLR analysis	R^2 ranges from 0.685 to 0.834 in the training set	Journal of Cleaner Production
Lepore et al. (2019)	A Ro-Pax cruise ship	Ship operational data and sea and weather data from onboard sensors	Fuel consumption per hour, energy efficiency initiative (EEI), and GHG emissions	Orthogonal least squares-partial least squares method	Not applicable	Quality Engineering
Capezza et al. (2019)	Two Ro-Ro Pax ships	Ship operational data and sea and weather conditions from onboard sensors	Fuel consumption per hour	PLS regression	Not applicable	Transportation Research Part D
Adland et al. (2020)	16 oil tankers	Ship operational data and sea and weather conditions from noon report	Fuel consumption per day	Piecewise linear regression	R^2 ranges from 0.739 to 0.885 when dividing the speed values into three endogenous thresholds	Transportation Research Part E
Işıklı et al. (2020)	A bulk carrier	Ship operational data and sea and weather conditions from noon report	Fuel consumption per day	Response Surface Methodology	R^2 is 0.8037 in test set	Journal of Cleaner Production
Le et al. (2020a)	Five classes of container ships grouped by size	Ship operational data per voyage and mechanical data provided by a Korean shipping company	Fuel consumption rate (ton/TEU/knot)	MLR analysis	MAPE ranges from 11.62% to 20.71% in cross validation	Maritime Policy & Management

Table 10. Ship operational optimization via BBMs based on statistical modelling (4 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Fuel consumption prediction model performance	Optimization objective(s)	Decision variable(s)	Solution approach(es)	Journal
Wang and Meng (2012)	Container ships in a liner shipping network	Ship operational data from a liner shipping company	Fuel consumption per day	Linear regression (LR)	R^2 is at least 0.96 in training set	To minimize fuel consumption in the liner shipping network	Sailing speed and the number of ships deployed on each route of a liner shipping network	A novel outer-approximation algorithm	Transportation Research Part E
Yao et al. (2012)	Container ships for a single shipping liner service	Ship operational data from a shipping company	Fuel consumption per day	LR	Not applicable	To minimize total bunker fuel related cost for a shipping liner service	Bunkering ports and amounts, and sailing speed	CPLEX	Computers & Operations Research
Lee et al. (2018a)*	A container ship	Ship operational data from a liner shipping company and sea and weather data from CMEMS	Fuel consumption per day	An LR model extended from Yao et al. (2012)	Error rate is 7.5% in the test set	To minimize fuel consumption and maximize service level agreement via a decision support system	Sailing speed	PSO algorithm	Computers & Operations Research
Lee et al. (2018b)	A container ship	Ship operational data and sea and weather conditions	Fuel consumption per unit time	Polynomial regression	The error is within 0.5% compared with the actual data	To minimize fuel consumption over a voyage	Heading angle and engine RPM	Non-dominated Sorting Genetic Algorithm (NSGA)-II	Ocean Engineering

Note *: DSS is implemented in the paper

All 17 of the papers listed in Tables 9 and 10 use ship operational data at sea, and 12 also consider the surrounding sea and weather conditions. Unlike studies on WBMs, most of which consider ship mechanical data, only 3 of these 17 papers use ship mechanical data. In addition, 3 papers consider ship maintenance data regarding dry docking, 2 papers predict ship energy efficiency indicators such as EEOI and EEI, and 2 papers predict GHG and pollutant emissions. The consideration of the above-listed factors is thus far rarer in BBM research than in studies on WBMs. Among the statistical models adopted for fuel consumption prediction, linear regression models, including simple linear regression and multiple linear regression, are the most popular, being used in 3 and 6 papers, respectively. Polynomial regression models are used in 2 papers. Piecewise linear regression is also used to allow multiple linear models to be fitted to the data in different ranges of X. In addition, 3 papers use PLS regression. As shown in the tables, most of the papers present model performance metrics (e.g., R^2, MSE, MAE, and MAPE) for either or both a training set and a test set, which differs from studies of WBMs. A detailed illustration of BBMs based on statistical modeling is given in Appendix B.2. In addition, although most of the papers only consider one specific vessel in developing tailored models for ship fuel consumption prediction, some of the studies consider a fleet containing several (sister) vessels, yielding prediction models that are more sophisticated and practical. For example, Adland et al. (2018) use noon reports of a fleet of 8 identical Aframax-size crude oil tankers, and those of a fleet of 10 Aframax product tankers and 6 Suezmax vessels (Adland et al., 2020) to identify the relationships between various influencing factors and vessel fuel consumption conditions. Le et al. (2020a) use the voyage records of more than 100 container ships to estimate fuel consumption.

Three of the 4 papers developing ship operational optimization models aim to minimize fuel consumption/costs; the fourth constructs a bi-objective function that minimizes fuel consumption and maximizes the service level agreement via a decision support system (DSS), aiming to support decision makers who are not experts in prediction and mathematical modeling and analysis (Lee et al., 2018). However, the decision variables of these 4 papers vary. One paper only considers sailing speed, while two papers consider sailing speed and the ship deployment/bunkering port and amount simultaneously. One paper also considers the heading degree and engine RPM when sailing.

3.4.2 Review of BBMs based on machine learning (ML)

Recent years have witnessed a boom in studies that develop BBMs based on ML for fuel performance monitoring, driven by the accessibility of massive amounts of data on ship energy efficiency, especially from onboard sensors, and increases in computational power. Similar to the procedure for developing BBMs based on statistical modeling, practical ship operational data should be collected and pre-processed, as data quality and quantity play major roles in all types of ML models. Suitable ML models are then chosen and developed based on the requirements, and the input data are then further pre-processed if necessary. Hyperparameters should be tuned based on the training and validation sets to improve the model's generalization ability. Finally, model performance is validated using the test set. Compared with statistical models, ML models are more suitable for dealing with high-dimensional data, and thus can incorporate a wider range of input features. However, their black-box nature decreases their interpretability compared with statistical modeling approaches. We summarize ship performance monitoring models and ship operational optimization models adopting BBMs based on ML in Tables 11 and 12.

Table 11. Ship performance monitoring via BBMs based on ML (20 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Fuel consumption prediction model performance	Journal
Pedersen and Larsen (2009)	A tanker ship	Ship operational data and sea and weather conditions from noon report	Fuel consumption per hour	ANNs	The error rate is about 7% in test set	Conference proceedings
Petersen et al. (2012a)	A ferry ship	Ship operational data and sea and weather conditions from onboard sensors	Fuel consumption per hour	ANNs	The root mean square error (RMSE) is 47.2 in the test set	Ship Technology Research
Petersen et al. (2012b)	A ferry ship	Ship operational data and sea and weather conditions from onboard sensors	Fuel consumption per hour	ANNs and Gaussian processes (GPs)	The RMSE for ANNs and GPs is 47.2 and 51.4, respectively in the test set	Journal of Marine Science and Technology
Wang et al. (2018)	A ship fleet of COSCO	Ship mechanical and operational data, and sea and weather conditions derived from the software of a shipping company	Fuel consumption per hour	LASSO regression	The mean absolute error (MAE) is 4.9 in test set	Transportation Research Part D
Soner et al. (2018)	A ferry ship	Ship operational data and sea and weather conditions from onboard sensors	Fuel consumption per hour	Tree-based models including bagging, random forest (RF), and bootstrap	The RMSE for bagging, random forest, and bootstrap is 45.2, 43.5, and 41.3, respectively in test set	Ocean Engineering
Jeon et al. (2018)	A bulk carrier	Ship operational data and sea and weather conditions from onboard sensors	Main engine fuel consumption per day	ANNs	Median R^2 is 0.9383 of tangent Sigmoid ANNs in test set	Journal of Mechanical Science and Technology
Yuan and Nian (2018)	An oil tanker	Ship operational data and sea and weather conditions from noon report	Fuel consumption per hour	GPs	The RMSE is 0.4418 in validation set	Conference paper
Gkerekos et al. (2018)	A reefer vessel	Ship operational data and sea and weather data from noon report	Fuel consumption per sailing distance	5 machine learning models: decision tree (DT), RF, support vector regressor (SVR), shallow and deep neural networks	R^2 ranges from 0.7 to 0.9 in k-folding	Conference proceedings
Gkerekos et al. (2019)	A bulk carrier	Ship operational data and sea and weather data from noon reports; automated data logging & monitoring (ADLM) systems	Fuel consumption per day	12 machine learning models: linear regression, LASSO, Ridge, elastic net, DT, RF, k-nearest neighbors (KNN), support vector machine (SVM), extra tree model, boosting model, bagging model, ANNs	When data from noon report is used, R^2 of the models ranges from 0.7011 to 0.9146 in test set; when data from ASLM systems are used, R^2 ranges from 0.7269 to 0.9729 in test set	Ocean Engineering
Soner et al. (2019)	A ferry ship	Ship operational data and sea and weather conditions from onboard sensors	Sailing speed through water and fuel consumption per hour	Ridge regression and LASSO regression	The RMSE in ridge and LASSO regression models is 48.7 L/h and 44.6 L/h, respectively, in the test set	Journal of Marine Science and Technology
Sourtzi (2019)	A passenger ship	Ship operational data and sea and weather data from electronic voyage reports extracted from the MRV software	Fuel consumption per hour	A multi-layer feed-forward neural network model	The mean absolute percentage error (MAPE) is 2.16% in the test set	Master thesis at the University of Piraeus
Panapakidis	A passenger	Ship operational data and sea and weather	Ship fuel	Long short-term memory	The MAPE of three case studies ranges from 2.177	Electronics

et al. (2020)	ship	conditions from voyage report	consumption per hour	(LSTM) and Elman neural network (ENN)	to 2.506	
Peng et al. (2020)	8019 ship records at the Jingtang Port	Ship arrival time, handling volume and goods, berth, type of trade et al. at Jingtang Port	Ship fuel consumption at port	5 machine learning models: gradient boosting regression (GBR), RF, BP neural network, liner regression and KNN	R^2 of the 5 models ranges from 0.46 to 0.91 in test set	Journal of Cleaner Production
Man et al. (2020)	Five ferries	Ship operational data from onboard sensors, ship log and AIS; sea and weather data from online sources and government department	Fuel consumption per journey	Multi-layer perceptron (MLP) and self-organizing map (SOM)	Average relative error is 140% in MLP and 110% in SOM in the test set	Applied Sciences
Farag and Olcer (2020)	A tanker ship	Ship operational data and sea and weather data from onboard sensors and weather hindcast information	Total energy consumed, total voyage fuel consumption, total CO_2 emissions, and average propulsion power	A combined ANN and MLR	The error rate is 0.43% in test set	Ocean Engineering
Uyanık et al. (2020)	A container ship	Ship operational data and sea and weather data from noon reports, engine logbook, and sensors	Fuel consumption per day	14 machine learning models: Ada boost, Bayesian ridge, DT, elastic net, GBR, hist gradient boosting, kernel ridge, KNN, LASSO regression, MLR, MLP, RF, ridge regression, SVM	R^2 ranges from 0.96502 to 0.99999 in validation set	Transportation Research Part D
Le et al. (2020b)	Five classes of container ships grouped by size	Ship operational data per voyage and mechanical data provided by a Korean shipping company	Fuel consumption per sailing distance	ANNs	MAPE ranges from 7.4 to 16.8	Maritime Policy & Management
Karagiannidis and Themelis (2021)	A container ship	Ship operational data and sea and weather conditions from onboard measuring device	Fuel consumption per day	ANNs with feature engineering	RMSE ranges from 0.64 to 3.42 in test set	Ocean Engineering
Kim et al. (2021)	A container ship	Ship operational data and sea and weather data from an onboard alarm monitoring and control system	Fuel consumption per sailing distance	ANNs and MLR	R^2 ranges from 0.8 to 0.9936 in test set	Journal of Marine Science and Engineering
Zhu et al. (2021)	A passenger ship	Ship operational data and sea and weather data from onboard sensors	Fuel consumption per sailing time	MLR, SVR, ANNs	ANN has the best performance, followed by LR and SVR	Journal of Marine Science and Engineering

Table 12. Ship operational optimization via BBMs based on ML (15 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Fuel consumption prediction model performance	Optimization objective(s)	Decision variable(s)	Solution approach(es)	Journal
Petersen (2011)	A domestic ferry	Ship operational data and sea and weather data from onboard sensors	Fuel consumption per hour	4 machine learning models: ANNs, GPs, Gaussian mixture model (GMM), time-delay networks	The RMSE of the models is about 50 L/h in test set	To minimize fuel consumption	Trim	Enumeration	Master thesis in DTU
Beşikçi et al. (2016)*	An oil tanker	Ship operational data and sea and weather data from noon report	Fuel consumption per hour	ANNs	R^2 is 0.759 in test set	To minimize fuel consumption	Sailing speed, RPM, trim, wind and sea effects	Developing a decision support system	Computers & Operations Research
Rudzki and Tarelko (2016)*	A tall ship	Ship operational, mechanical, and maintenance data, and sea and weather data from sea trials	Sailing speed and fuel consumption per hour	ANNs	The mean squared error (MSE) is 0.0813 in training set	To propose a two-objective optimization problem regarding fuel consumption and speed	Propeller pitch and engine rotation speed	Weighted-sum method considering two objectives	Ocean Engineering
Wang et al. (2016)	A cruise ship	Ship operational data and sea and weather data from onboard sensors	Wind speed, water depth, and fuel consumption per meter	Wavelet neural network	Not applicable	To minimize fuel consumption	Main engine speed	A dynamic optimization method proposed by the authors	Transportation Research Part D
Farag (2017)*	An oil tanker	Ship operational data and sea and weather data from the ship's automatic monitoring system, AIS, and weather hindcast information	Fuel consumption	ANNs and MLR analysis	Model accuracy is 97.45% in test set	To maximize ship energy efficiency	Sailing speed and heading angle	Development of a DSS by Excel and Matlab	Mater thesis at World Maritime University
Chaal (2018)*	A tanker ship	Ship operational data and sea and weather data from onboard sensors and software	Fuel consumption per hour	DT, AdaBoost DT, KNN and ANNs	R^2 ranges from 0.74 to 0.96 in test set	To minimize fuel consumption	Trim, trim and route	Generic algorithm	Master thesis at World Maritime University
Du et al. (2019)	Two container ships	Ship operational data and sea and weather data from noon report	Fuel consumption per day	ANNs	The RMSE ranges from 8.23 to 10.25 in test set	To minimize fuel consumption	Sailing speed, trim, speed and trim	Enumeration and dynamic programming	Transportation Research Part B
Zheng et al. (2019)	A cruise ship	Ship operational data from AIS	Fuel consumption per hour	ANNs	Model accuracy is more than 0.9 in test set	To minimize fuel consumption over a voyage	Sailing speed	Four improved PSO algorithms	Journal of Cleaner Production
Sun et al. (2019)	A bulk carrier	Ship operational data and sea and weather data from onboard sensors	Sailing speed and fuel consumption	ANNs	The MSE is 0.911×10^{-7} in the training set	To minimize EEOI	Engine revolution	Genetic algorithm	Journal of Marine Science and Engineering
Zhang et al. (2019)	A general cargo ship	Ship operational data from AIS and sea and weather	EEOI	ANNs	R^2 is about 0.96 in validation set	To optimize ship energy efficiency	Route	Ant colony algorithm	Ocean Engineering

		data from NMEFC							
Tarelko and Rudzki (2020)*	A tall ship	Ship operational data and sea and weather data from noon report	Fuel consumption per hour and sailing speed	ANNs	The error rate between 0.8% and 2.8% in test set	To minimize fuel consumption and maximize sailing speed	Sailing speed	MATLAB optimization toolbox	Neural Computing and Applications
Gkerekos and Lazakis (2020)	A crude oil tanker	Ship operational data from noon report, sea and weather data from CMEMS	Fuel consumption per hour	ANNs	R^2 is 0.894 in the test set	To minimize fuel consumption	Sailing route	Modified Dijkstra's algorithm	Ocean Engineering
Linh and Ngoc (2020)	A liner ship	Ship operational data from a shipping company; sea and weather data from online resources	Fuel consumption of a route	Deep ANNs with 10 hidden layers	The MAPE is 5.89% in test set	To minimize fuel cost	Route	Asymmetric traveling salesman problem algorithm	The Asian Journal of Shipping and Logistics
Yan et al. (2020)	A dry bulk ship	Ship operational data and sea and weather data from noon report and EMCWF	Fuel consumption per hour	RF	The MAPE is 7.91% in test set	To minimize fuel consumption over a voyage	Sailing speed	CPLEX	Transportation Research Part E
Tran (2020)	A bulk ship	Ship operational data and sea and weather data from noon report	Fuel consumption per voyage	A fuzzy c-means clustering method (unsupervised)	Not applicable	To optimize ship energy efficiency	Loading of ship	A fuzzy analytical hierarchy process (AHP) method	Ocean Engineering

Note *: DSS is implemented in the paper

Tables 11 and 12 show that 34 of the 35 papers leverage ship operational data to predict ship fuel consumption during sailing, and the other uses ships' trading and berthing information at port to predict in-port fuel consumption. Most of the papers consider sea and weather conditions in ship performance monitoring (31 papers). However, only 2 papers utilize ship mechanical data for fuel consumption prediction and only 1 uses maintenance data. Unlike WBMs, which are widely used to predict ship emissions as well as fuel consumption, ML models are seldom used to predict emissions (only 1 paper does so). Artificial neural networks (ANNs), including back propagation neural networks, multi-layer perceptron (MLP), and wavelet neural networks, are the most popular ML models, being used in 29 of the 35 studies. Linear regression models, including ordinary least squares (OLS), as well as regularized linear regression models, such as least absolute shrinkage and selection operator (LASSO) regression, ridge regression, and elastic net regression, are the next most popular, followed by tree-based models such as the decision tree (DT), random forest (RF), Adaboost DT, and gradient boosting DT models. Support vector machine (SVM) and k-nearest neighbor (KNN) ML models are also popular. All these models are supervised ML models, where the data label, i.e., the fuel consumption rate, is used in model training. Some unsupervised ML models are also used, such as self-organizing maps (SOM) (Man et al., 2020), the Gaussian mixture model (GMM) (Petersen, 2011), and fuzzy c-means clustering (Tran, 2020) models. In addition, although onboard sensors are widely used to collect nearly real-time ship sea trial data, no more than 10% of the 35 papers use deep learning models to achieve more accurately predict fuel consumption (3 papers).

Most of the papers developing BBMs for ship fuel consumption listed in Tables 11 and 12 present model performances for unseen data (e.g., on test and validation sets or in k-fold cross validation). This differs from WBMs, where one third of the papers do not give metrics for model performance in training, validation, or test sets, and also differs slightly from BBMs based on statistical modeling, where many papers only present model fitting performances for the training set. This is because WBMs are based on a priori knowledge and physical insights into a system with known structure and parameters to disclose the theoretical basis underlying various influencing factors and the prediction target. In contrast, BBMs based on ML more strongly emphasize the bias–variance tradeoff to achieve better model generalization ability. The mean squared error of a prediction model can be decomposed into two components: a bias component and a variance component. When model complexity increases, the variance tends to increase, and the squared bias tends to decrease. However, if the model is too complex, it will adapt too much to the training data and will not generalize well to unseen data (i.e., it will have large test errors). In contrast, if the model is not complex enough, it will underfit the training data and have large bias, again leading to poor generalization ability. Therefore, one of the goals of BBMs based on ML is accurate prediction of new and unseen data based on statistical patterns in a training set.

To explore the underlying of the models for ship fuel consumption prediction using ML-based BBMs, we briefly present the basic ideas underlying them and their pros and cons in Appendix B.3. For more comprehensive discussion and analysis of these models, readers are referred to Hastie et al. (2014) and Friedman et al. (2001).

Some papers compare the performance of different ML models using the same data set. For example, Petersen et al. (2012a, 2012b) and Soner et al. (2018, 2019) use ship operational data and the surrounding sea and weather data from the onboard sensors of a domestic ferry. Based on model validation results, it is concluded that bootstrap tree-based model is the most suitable model for fuel consumption prediction using this dataset (Soner et al., 2018), followed by RF and LASSO regression (Soner et al., 2018, 2019). GPs have the worst performance on the test set among all the ML models, possibly because they eschew the Gaussian assumption. In addition, Gkerekos et al. compares 5 ML models (2018) and, in another study, 12 ML models (2019), and Uyanık et al. (2020) compares 14 ML models for fuel consumption prediction. Gkerekos et al. (2018) shows that RF and SVR perform better than DT and ANNs with different structures, including deep neural networks. Uyanık et al. (2020) concludes that linear regression-based models, including Bayesian ridge, kernel ridge, multiple linear, and ridge models, perform better than all the ML models, including other types of linear regression models, tree-based models, KNN, and ANNs. Gkerekos et al. (2019) also compares the model performance using datasets from manually filled noon reports and onboard automated data logging & monitoring (ADLM) systems. The results show that model performance evaluated using the coefficient of determination (R^2) can be significantly improved if sensor data are used. In addition, SVM with a radial basis function (RBF) as the kernel has the best performance when using training data constructed from noon reports, and the extra trees model performs best when using training data constructed from ADLM systems.

Of the 15 papers developing two-stage models for ship operational optimization, 9 papers aim to minimize fuel consumption or fuel costs and 4 aim to optimize ship energy efficiency. Two papers aim to minimize fuel consumption while maximizing sailing speed. These 15 papers also consider other decision variables than sailing speed, such as trim settings, sailing route, loading of ships, and engine performance indicators. Five papers implement DSSs to better assist the decision makers.

Compared with WBMs, BBMs, whether based on statistical modeling or ML, have better fitting ability for training data and the highest prediction accuracy for unseen data. BBMs based on ML usually have better generalization ability than BBMs based on statistical modeling (Petersen et al., 2012b). Another advantage of BBMs over WBMs is that no a priori knowledge regarding the vessel physics is required, as BBMs are purely data-driven. In addition, because the model is calibrated and the parameters are estimated using experimental or operational data, BBMs can learn from real situations better as data accumulate, and in theory, their generalization performance and ability to handle noisy data should improve. According to the Vapnik–Chevronenkis (VC) dimension, a larger training dataset size should improve machine learning model performance by reducing overfitting (Juda and Le, 2019). However, noise and errors in the data from ships' noon reports and onboard sensors are likely to limit the improvement of model performance as data accumulate.

However, BBMs also have several disadvantages. As BBMs are purely data-driven, a large quantity of high-quality data is needed for model construction, and thus the data quantity and quality have substantial effects on model performance. Therefore, BBMs cannot to be used in the vessel design and initial sea trial stages, where data availability is limited. It should be noted from Tables 9 through 12 that the sample size of ship data used to construct BBMs based on statistical modeling and ML in the literature is usually small, as most studies consider only one or two vessels of the same type. The available data tend to be especially limited for models using noon reports.

Another main drawback of BBMs is their poor interpretability: the models are usually complex and difficult to intuitively explain. As they are trained in a purely data-driven way, they are not informed by basic vessel physical knowledge, and thus experts in the shipping industry have difficulty accepting them. The complex structure of ML models, combined with the large number of estimation parameters, endows them with a strong ability to learn the training data, including specific details and noise. However, this can weaken their generalization ability. For example, Friedman et al. (2001) states that ANNs, which learn a large number of weights, tend to overfit the data at the global minimum. Therefore, to improve model performance, regularization techniques should be adopted, such as the early stopping rule, validation sets, and weight decay. However, it is not trivial to find a balance between overfitting and model complexity, especially when the data contain noise, which will generate counterintuitive prediction results in the ML models. For example, if we increase the input sailing speed while keeping all other input variables fixed, we expect the predicted fuel consumption to increase; however, ML models may predict the opposite. Shipping experts may be highly resistant to ship fuel consumption prediction models that violate the concepts of domain knowledge and data science in such a serious way.

One last point concerns how the BBMs developed for ship fuel consumption prediction in the reviewed literature solve the common challenges in regression analysis, especially endogeneity and correlations. As both ship sailing speed and engine power (and thus fuel consumption) are set based on the surrounding sea and weather conditions together with other external factors, the problem of endogeneity in these studies is inevitable. Similarly, sailing speed and the surrounding sea and weather conditions are correlated: for example, the captain must slow down in bad weather for safety reasons. Both problems are seldom addressed by the BBMs based on statistical modeling in the reviewed literature. The only study that addresses the endogeneity problem is that by Adland et al. (2020), who proposes a novel framework to estimate the elasticity (including speed intervals) of the speed–consumption relationship to partially address the problem of endogeneity, which enables better exploitation of the explanatory variables and better explanation of the speed–consumption relationship. This initial but meaningful step toward solving more advanced challenges in vessel energy management and green shipping has significance for follow-up research. Regarding multicollinearity between features, it is reported in Le et al. (2020b) that a pairwise correlation between two independent variables indicates a potential multicollinearity problem, whereas further examination of tolerance and the variance inflation factor (VIF) does not yield any multicollinearity concerns. In addition, the authors claim that as their research focuses on fuel consumption prediction rather than identification of the factors affecting fuel consumption and their detailed effects, the problem of multicollinearity can be safely ignored. In addition, Lepore et al. (2019) and Capezza et al. (2019) develop PLS models to reduce multicollinearity by reducing the predictors to a smaller set of uncorrelated components and performing least squares regression on these components.

Endogeneity is seldom considered in the studies proposing BBMs based on ML, except for Du et al. (2019), in which the endogeneity of engine RPM, which depends on variables outside the engine, such as sailing speed, draft, trim, and sea and weather conditions, is considered in variable selection. In BBMs based on ML, correlations between features can be reduced by pre-processing data and adopting suitable ML models for fuel consumption prediction. The use of correlation analysis to identify and delete features that are highly correlated with each other, known as feature selection, is common before developing ML models: it can be found in Lee et al. (2018), Farag and Ölçer (2020), Karagiannidis and Themelis (2021), and Kim et al. (2021), where domain knowledge is used for feature selection; in Wijaya et al. (2020), where principal component analysis (PCA) is used; and in Kim et al. (2021), where LASSO is used. Moreover, some ML models can inherently overcome the problem of correlations between features. A typical example is ensemble tree-based models (e.g., random forest and gradient boosting decision tree), which are used in Soner et al. (2018), Chaal (2018), Gkerekos et al. (2019), Uyanık et al. (2020), Yan et al. (2020), Peng et al. (2020), and are resistant to collinearity for two reasons. First, only a random subset of features is used to construct each tree, and thus, it is likely that only one of a group of correlated features will be selected per tree. Second, if two or more highly correlated features are selected to construct the same tree, no explicit preference for one over the other(s) will be imposed when selecting the next leaf-splitting step, as the features can be regarded as interchangeable with respect to leaf impurity reduction. Another typical example is regularized linear regression models such as ridge regression and LASSO regression, where some features are retained while others are discarded by setting their coefficients to zero. Specifically, size constraints are imposed on the coefficients in ridge regression using L2 regularization (Gkerekos et al., 2019, Soner et al., 2019, Uyanık et al., 2020) and in LASSO using L1 regularization (Petersen et al., 2012, Gkerekos et al., 2019, Soner et al., 2019, Uyanık et al., 2020).

3.5 Review of grey-box models (GBMs)

There are two types of GBMs in the literature. In the first type, namely sequential GBMs, two or more models are developed in a series, including at least one WBM and one BBM, and then the WBM(s) and BBM(s) are combined to form a single GBM. For example, a BBM can be developed to process the raw data and the initial prediction results are then fed into a WBM, or vice versa (Leifesson et al., 2008, Coraddu et al., 2017). The other type is parallel GBMs. In one such case, a WBM is first established based on theoretical principles and vessel physical laws, and then the unknown parameters are estimated by BBMs from experimental data (Meng et al., 2016; Yang et al., 2019b). In another case, a priori knowledge (used in WBMs) is integrated into a BBM by introducing model regularization (Caraddu et al., 2017 and 2018). Currently, there are few GBMs for ship fuel consumption prediction. The existing ship performance monitoring models and operational optimization models based on GBMs are summarized in Tables 13 and 14, respectively.

Table 13. Ship performance monitoring via GBMs (4 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Prediction model performance	Journal
Leifsson et al. (2008)	A container ship	Ship operational and mechanical data; sea and weather data	Fuel consumption per hour	A WBM, a BBM, a sequential GBM, and a parallel GBM	GBMs can slightly improve the performance of WBM; the prediction accuracy of GBM and BBM is similar	Simulation Modelling Practice and Theory
Caroddu et al. (2015)	A Panamax chemical/product tanker	Ship operational and mechanical data, and sea and weather data from onboard sensors	Fuel consumption and shaft power	A WBM, a BBM, and a parallel GBM	The WBM performs worse; the GBM can achieve the same performance as the BBM using less historical data	Conference proceedings
Meng et al. (2016)	A container ship	Ship operational data and sea and weather data from noon report	Fuel consumption per day	GBMs with parameters estimated by sequential estimation procedure	R^2 of the first model is at least 0.928, root mean squared residuals of the second model is no more than 10 in training set	Transportation Research Part B
Yang et al. (2019b)	A crude oil tanker	Ship operational and mechanical data, and sea and weather data from noon report	Fuel consumption per day	A generic algorithm-based GBM	R^2 is 0.9003 in the training set	Annals of Operations Research

Table 14. Ship operational optimization via GBMs (3 papers)

Literature	Shipping sector and fleet size	Data type and resources	Prediction target(s)	Fuel consumption prediction model	Fuel consumption prediction model performance	Optimization objective(s)	Decision variable(s)	Solution approach(es)	Journal
Caraddu et al. (2017)	A tanker ship	Ship operational data and sea and weather data from onboard sensors	Shaft power, shaft torque, and fuel consumption	A WBM, a BBM, a naive GBM and advanced GBM (denoted by N-GBM and A-GBM)	Best MAPE of N-GBM and A-GBM is 0.79 and 0.92, respectively	To minimize fuel consumption	Trim	Enumeration	Ocean Engineering
Lu et al. (2015)*	Two tanker ships	Ship mechanical and operational data, and sea and weather conditions from noon report and NOAA	Ship fuel consumption per tonne of cargo and per nautical mile	A GBM based on modified Kwon's methods	The error rate is 5.12% for one tanker ship and 7.15% for the other tanker ship in test set	To minimize fuel consumption	Route	Setting up grid system on world map and selecting the optimal route manually	Ocean Engineering
Coraddu et al. (2018)	A tanker ship	Ship operational data and sea and weather data from onboard sensors	Shaft power, shaft torque, fuel consumption	A WBM, a BBM, a N-GBM, and a A-GBM	The MAPE is within 2% in the test set	To minimize fuel consumption	Trim	Enumeration	Soft Computing for Sustainability Science

Note *: DSS is implemented in the paper

Tables 13 and 14 show that all of the papers developing GBMs for fuel consumption prediction use ship operational data and sea and weather data, and most also use ship mechanical data (4 papers). However, ship maintenance data are not used in these models. Regarding the structure of the developed GBMs, 3 papers develop both sequential and parallel GBMs, and most of the others develop parallel GBMs. A more detailed illustration of the GBMs, especially what WBMs and BBMs they contain and how they are combined with each other, is given in Appendix 3.4.

An advantage of GBMs is that they can combine WBMs, which are explainable and based on solid physical insights, with BBMs, which have high accuracy. Theoretically, therefore, their performance should be better than that of BBMs and also partially explainable even with fewer historical training data (Yang et al., 2019b). This should largely prevent unreasonable prediction results that contradict domain knowledge, and guarantee prediction accuracy. Unfortunately, these trends are not obvious in current research results in the literature listed in Tables 13 and 14.

3.6 Review of technical reports

Technical reports published by the government, academic institutions, and companies on ship fuel consumption make up a body of "grey literature" that provide considerable insights into this area. The GHG studies published by the IMO, including the First, Second, Third, and Fourth IMO GHG Studies published in 2000, 2009, 2014, and 2020, respectively, are the most authoritative technical reports regarding ship fuel consumption and emission analysis. The 4th IMO GHG Study, which is the latest in this series, estimates the consumptions of different types of fuels and the emissions in international voyages from a more macro-scale perspective than most of the academic studies reviewed in this study (IMO, 2020). It adopts both a top-down approach (by leveraging World Energy Statistics, including fuel sales data and emission factors to estimate the total mass of fuel consumption and the corresponding emissions) and a bottom-up approach (by leveraging AIS-transmitted data to describe individual vessels' operational activity). Detailed instructions and formulas to estimate the specific fuel oil consumption and various types of emissions are given in the report. It also makes comparisons between the top-down and bottom-up estimation approaches for ship fuel consumption and emissions, and the bottom-up method is found to estimate absolute values that are consistently higher than those of the top-down method.

Apart from the IMO, research institutions and companies around the world also publish technical reports on ship fuel consumption prediction and analysis. For example, researchers from the Technical University of Denmark and University of Southern

Denmark propose and analyze methods to predict ship resistance and the corresponding propulsion power (Kristensen and Lützen, 2012). Various types of resistance, such as frictional resistance, incremental resistance, air resistance, steering resistance, and residual resistance, are considered to calculate a ship's total resistance, and the required effective power is then derived. Researchers from Chalmers University of Technology summarize models and methods for ship energy efficiency management (Tillig et al., 2015). Their report includes the components of a vessel as a whole system, models, and tools to monitor ship energy efficiency (classified into holistic models, subsystem models, and commercial tools and software), and energy-saving measures. The Arctic Climate Change, Economy and Society (ACCESS) adopts a semi empirical–analytical approach to calculate the fuel consumptions of bulk carriers, oil tankers, and LNG carriers under different ice conditions for the past (1960 to 2020) and present (1960 to 2020) and predicts them for the future using software called ICEROUTE (ACCESS, 2014). MAN Energy Solutions, a leading engine production company, published a report titled "Basic principles of ship propulsion" that clarifies elements of a ship's structure and propulsion system. The report presents the relationships between ship propulsion power and the influencing factors, such as the speed, environmental regulations, hull, and propeller, for different types of ships (MAN, 2018).

4. Future research questions

The development of data-driven ship performance monitoring models and operational optimization models in academic research is relatively new. We hope that we have provided glimpses of its potential to reduce the emissions of pollutants and GHG from international shipping activities and to decrease vessel operating costs for shipping companies.

It should be noted that in practice, given the fact that several factors are determined, including but not limited to the cargo intake, the surrounding sea and weather conditions, and the range of speed values given by commercial contracts, ship operators can only have limited degrees of freedom to control their vessels so as to reduce fuel consumption and emissions. The main objective of existing ship fuel consumption prediction models is to provide more accurate estimations of fuel consumption rates under various conditions, such as sailing at various speeds and trim settings under different sea and weather conditions and hull/propeller fouling conditions. Considering the actual performances achieved thus far, we propose four scenarios in which ship operators can consider using fuel consumption prediction models and voyage optimization models.

1) If ship maintenance records (e.g., drydocking, hull and proper cleaning) can be taken into account in the fuel consumption prediction model, fuel consumption rates under different fouling and degradation conditions can be estimated, which can give insight into vessel maintenance for ship operators.

2) When accurate weather forecasts within a short period can be obtained, dynamic and stochastic fuel consumption prediction and, subsequently, voyage optimization (e.g., speed and trim optimization) can be achieved by only considering the sub-voyage of two to three days ahead while taking into account the preset allowable arrival time to the end of each sub-voyage. If the sea and weather conditions change or the sub-voyage is completed, new dynamic and stochastic voyage planning should be made.

3) When accurate weather forecasts for a longer period than that needed to complete the voyage between a certain origin–destination pair can be obtained, given the earliest and latest allowable arrival times to the destination, speed and/or trim optimization can be conducted for the whole voyage.

4) The ship fuel consumption prediction models developed under different sea and weather conditions can also shed light on weather routing to enhance maritime safety while reducing fuel consumption and emissions, as they can predict fuel consumption rates under various sea and weather conditions in different geographical locations.

Based on the above summary and comparison of the three types of models for ship fuel consumption prediction, namely WBMs, BBMs based on statistical modeling/ML, and GBMs, together with the ship operational optimization models based on the fuel consumption prediction results, we outline some promising future research questions from three perspectives: data, prediction models, and management strategies, as listed in Table 15.

Table 15. Outline of future research questions

Category	Questions
Data	a. How to consider more valid features, e.g., hull and propeller roughness, ship damage, and engine performance degradation in fuel consumption prediction models?
Prediction models	a. How to construct GBMs by combining WBMs and BBMs more effectively?
	b. How about applying deep learning models for fuel consumption prediction?
	c. How to incorporate domain knowledge into BBMs?
	d. How to develop a comprehensive fuel consumption prediction model for different types of ships?
	e. How about comparing the newly proposed ship performance monitoring tools in the papers with the existing tools proposed by organizations (e.g., IMO, ITTC) and analyzing their pros and cons?
	f. What are the advantages and disadvantages of various machine learning models for fuel consumption prediction?
Management strategies	a. How to measure and reduce the inaccuracy of the fuel consumption prediction model in the first stage brought to the operational optimization model in the second stage?
	b. How to combine the ever-changing sea and weather conditions with ship operational optimization models, especially in a real-time manner?
	c. How to consider the fluctuations of fuel prices and freight rates in operational optimization?
	d. How about combining the ship performance monitoring models with liner shipping network design, such as fleet deployment, and cargo routing?
	e. How to conduct sensitivity analysis based on the prediction results to generate managerial insights?

4.1 Data

Research questions regarding the data used in fuel consumption prediction models aim to take a wider range of relevant features into account to achieve more accurate prediction results. For example, Adland et al. (2018)'s study of the effects of hull damage, hull and propeller fouling, and engine degradation on fuel consumption relies on both before–after and difference-in-difference estimators. These findings are instructive to ship operators and can serve as key building blocks for the optimization of vessel maintenance intervals. Meanwhile, such conditions can be difficult to observe and evaluate in practice, and thus no studies directly take their impact into consideration. In addition, ship maintenance records, which can be used to improve the overall ship safety level and energy efficiency, are accessible from shipping companies and vessel databases. Therefore, we expect that taking ship maintenance data into account in ship performance monitoring can make fuel consumption prediction more accurate and efficient. Nevertheless, as shown in Section 3, few ship fuel consumption prediction models take the time since last dry docking into consideration (Bocchetti et al., 2015; Erto et al., 2015; Rudzki and Tarelko, 2016; Adland et al., 2018, 2020), and other ship maintenance information, such as hull and propeller cleaning, main engine maintenance, and major overhaul information, is seldom considered.

4.2 Prediction models

Research into fuel consumption prediction models aims to improve their performance from three perspectives: improvement of prediction accuracy, development of unified models, and comparison of different models. In addition to incorporating more valid features to improve model accuracy, other strategies, such as developing GBMs that combine WBMs and BBMs more effectively and developing deep learning-based prediction models if data quantity allows, are also promising alternatives. In addition, if domain knowledge can be contained in BBMs, such as the monotonicity and convexity of speed-to-fuel consumption prediction, it can not only improve prediction performance but also significantly improve the interpretability and credibility of BBMs.

Current BBMs developed for fuel consumption are usually tailored, which means that they are trained using the sailing data of a single ship, and thus their accuracy can only be guaranteed if applied to monitor the performance of that ship. As calibrating fuel consumption prediction models can be a complex and time-consuming process, this tailored property has restricted the generalization of BBMs. This situation could be improved if unified BBMs that can be universally applied were developed.

Some ship fuel consumption and emission prediction models are proposed and implemented in practice by organizations, companies, and research institutes, such as those summarized in Section 3.5. In addition, various ship performance monitoring models are developed and validated in academic papers, but few are compared with existing models using uniform datasets and evaluation metrics. Therefore, the pros and cons and the suitable application scenarios of the newly proposed models are not clear, which may inhibit their potential to reduce ship emissions. Another issue is the lack of comparison and systematic analysis of the various ML models used for fuel consumption prediction using different datasets. Tables 11 and 12 show that tree-based models such as RF have superior performance compared with other popular ML models (Gkerekos et al., 2018, 2019). However, in our experience, the tree-based models may not be suitable for direct application to fuel consumption prediction without modification. The main reason is that the output of tree-based models is not continuous when all other features are fixed while the values of one feature, such as sailing speed, change from small to large (Yan et al. 2020). This discontinuous output is totally contradictory to domain knowledge in the shipping industry and is inappropriate as an input into the subsequent operational optimization models.

4.3 Management strategies

The first research question associated with ship fuel consumption management strategies is how to reduce the influence of the inaccuracy of fuel consumption prediction models on the subsequent ship operational optimization model. One viable way is to reduce the inaccuracy of the fuel consumption prediction model in the first stage. However, it can be difficult to further improve the prediction accuracy given limited data quality and quantity, and the generalization error cannot be fully eliminated. Therefore, other ways to reduce such adverse influences, especially considering the relationship between the fuel consumption prediction and management models, are worthy of investigation. Another question is how to consider the fluctuation of the factors with uncertainty in the ship operational optimization model, such as the ever-changing sea and weather conditions, fuel prices, and freight rates. In addition, as few studies (one exception being Wang and Meng [2012]) combine data-driven ship fuel consumption prediction models with liner shipping network design, such research questions remain to be investigated. In addition, managerial insights generated from sensitivity analysis based on fuel consumption prediction models developed from experimental or operational data are also worthy of investigation, as they can be a guideline for daily vessel operations.

4.4 Some other common challenges in regression models

Finally, other common challenges in regression models, such as endogeneity and collinearity, are not adequately considered and addressed in the literature on ship fuel consumption prediction. Vessel propulsion systems are quite complex: various internal and external factors interact and can influence actual fuel consumption, but such factors cannot be fully captured and considered in a single model. In addition, in actual voyages, ship sailing speed and engine power are simultaneously set based on various external factors, such as the sea and weather conditions. Consequently, the problem of endogeneity is inevitable in ship fuel consumption prediction models. Sailing speed, which is regarded as the most important determinant of fuel consumption rates, is influenced by various surrounding factors, especially the sea and weather conditions, and the features considered in fuel consumption prediction models might be highly correlated.

Vessel fuel consumption prediction models based on ML rely heavily on feature engineering, which includes valid feature selection, new feature construction, feature washing and encoding, and feature importance identification, and they therefore can be viewed as a pure black box in the prediction step: all related features after processing are input into a certain ML model or an ensemble of homogeneous or heterogeneous ML models, and the result is generated as the output of the prediction model (Friedman et al., 2001). Therefore, the problem of endogeneity is rarely discussed in the context of ML-based prediction models. The problem of feature correlation can also be addressed in the process of feature engineering, especially by feature selection through filter-based (by considering the relevance of each feature and the prediction target), wrapper-based (by considering the influence of each feature on the prediction performance), and embedded methods (conducted by a specific prediction model) (Harrington, 2012).

Endogeneity and feature correlation problems can heavily degrade the applicability and performance of BBMs based on statistical modeling. For example, severe multicollinearity increases the variance of the coefficient estimates by making them very sensitive to minor changes in the model. Consequently, the coefficient estimates are unstable and difficult to interpret, and the statistical power of the prediction model is weakened. In addition, one of the most important OLS assumptions is that the errors are uncorrelated with the dependent variables. If this assumption is violated, an OLS model can produce biased and inconsistent parameter estimates, and the hypothesis tests will produce misleading results. How to overcome the problems of multicollinearity and endogeneity in BBMs based on statistical modeling is therefore worthy of further investigation.

5. Conclusion

This paper reviews the literature on ship fuel consumption prediction and the ship energy efficiency management and optimization models developed over the past 13 years. Major recent emission control regulations and ship energy efficiency indicators are first reviewed. Next, strategies to improve ship energy efficiency recommended by SEEMP and adopted by the shipping industry in practice are discussed. The features and sources of the main datasets, namely ship operational data, mechanical data, maintenance data, and sea and weather data used for ship fuel consumption prediction models, are presented, and the prediction model construction procedure and the related literature published in the past 13 years are reviewed. We divide fuel consumption prediction models in the academic literature into three main categories: white-box models (WBMs), black-box models (BBMs), and grey-box models (GBMs) that combine WBMs and BBMs. As there are only 84 related papers and reports, we list their details and make a comprehensive comparison of ship performance monitoring models, such as the data required for model calibration, their pros and cons, and their applicable scenarios. We provide a detailed illustration of the approaches developed for the three types of models from various perspectives. Technical reports, a typical type of grey literature published by the government, academic institutions, and companies, are also covered in this review to give a more comprehensive picture of the literature on ship energy consumption management. Finally, current research challenges and promising research questions are outlined.

This paper is the first comprehensive review of the literature on ship fuel consumption prediction and management. Accurate fuel consumption prediction is the foundation of improving vessel energy efficiency and thus reducing pollutant and GHG emissions from the shipping industry. It is also a fundamental step toward zero-emission shipping. The content of this review will be of interest to academic scholars, shipping industry practitioners, and maritime policy makers. It can thus help to address one of the most important and urgent contemporary issues faced by the IMO and the whole maritime industry: achieving environmental sustainability in shipping.

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Appendix A. List of acronyms used in the review

Abbreviation	Explanation	Abbreviation	Explanation
ACCESS	Arctic Climate Change, Economy and Society	LSTM	long short-term memory
AHP	analytical hierarchy process	MAE	mean absolute error
AIS	automatic identification system	MAPE	mean absolute percentage error
ANNs	artificial neural networks	MARPOL	The International Convention for the Prevention of Pollution from ship
ASLM	automated data logging & monitoring	MEPC	Marine Environment Protection Committee
BBM	black-box model	ML	machine learning
BC	black carbon	MLP	multi-layer perceptron
CFD	computational fluid dynamics	MLR	multiple linear regression
CII	carbon intensity indicator	MRV	Monitoring Reporting and Verification
CMEMS	Copernicus Marine Environment Monitoring Service	MSE	mean squared error
CO	carbon monoxide	NECAs	nitrogen emission control areas
DCS	data collection system	NMEFC	National Marine Environmental Forecasting Center
DSS	decision support system	NOAA	National Oceanic and Atmospheric Administration
DT	decision tree	NSGA	non-dominated sorting genetic algorithm
		OLS	ordinary least squares
ECMWF	The European Centre for Medium-Range Weather Forecasts	PCA	principal component analysis
EEDI	energy efficiency design index	PLS	partial least-squares
EEI	energy efficiency initiative	PM	particulate matters
EEOI	energy efficiency operation index	PSO	Particle swarm optimization
EEXI	energy efficiency existing ship index	R^2	coefficient of determination
ENN	Elman neural network	RBF	radial basis function
EU	European Union	RF	random forest
GBM	grey-box model	RMSE	root mean square error
GBR	gradient boosting regression	RPM	revolutions per minute
GHG	greenhouse gas	SECAs	sulphur emission control areas
GMM	Gaussian mixture model	SEEMP	ship energy efficiency and management plan
GPS	global positioning system	SOM	self-organizing map
GPs	Gaussian processes	STEAM	ship traffic emission assessment model
IMO	International Maritime Organization	SVM	support vector machine
ITTC	International Towing Tank Conference	SVR	support vector regressor
KNN	k-nearest neighbors	UNCTAD	United Nations Conference on Trade and Development
LASSO	absolute shrinkage and selection operator	WBM	white-box model
LR	linear regression	WNI	Weathernews Inc.

Appendix B. A more detailed illustration of the prediction approaches

B.1 WBMs

WBMs based on solid physical insights are the most classical and well-studied stream of methods for ship fuel consumption prediction, as their structure is completely known and the parameters are estimated through theoretical methods and towing tank tests. As vessel fuel consumption estimation approaches based on WBMs are complex and are largely based on physical theories, especially in the calculation of resistances from multiple sources, their detailed presentation is outside the scope of this study. Readers are referred to Schneekluth and Bertram (1998) and to Newman (2018) for more information on calm-water resistance estimation, and to Salvesen (1978), Kwon (2008), Panigrahi et al. (2012), and Cai et al. (2014) for a more detailed introduction to added resistance calculation. In this review, we mainly discuss the different types of resistance encountered by a ship when sailing, as shown in Table B.1.

Table B.1. Summary of common resistances encountered by a ship in sailing

Source of resistance	Description	Influencing factors	Related literature/estimation methods
Total hull resistance	A ship experiences a force acting opposite to its direction of motion as it moves through calm water.	Sailing speed, hull form (draft, beam, length, wetted surface area), and water temperature	The procedures proposed by Holtrop and Mennen (1982), by Kristensen and Lutzen (2012), and by ITTC (2008); The resistance curve from CFD computations, and the results of towing tank tests
Wave making resistance	As a ship moves through water, many wave systems are created and interact by adding or reducing each other's effects.	Ship hull shape, seakeeping characteristics of the ship, and sea spectrum	The procedures proposed by Salvesen (1978), by Kwon (2008), by Panigrahi et al. (2012), by ITTC (2014), and by Liu and Papanikolaou (2016)
Ocean currents	Ocean currents can be categorized into global and tidal current, and they can either accelerate or retard a ship depending on its direction. It is also the main cause of the difference between speed through water and speed over ground of a sailing ship.	Ship' heading and sailing speed over ground, current velocity and direction	The procedure proposed by Windeck (2013) and Cai et al. (2014)
Winds	Winds contribute to the creation of waves and act as a force on the vessel as wind resistance.	Ship's heading and sailing speed over ground, the cross-sectional area of a ship above the waterline, wind velocity and direction	The procedures proposed by Kristensen and Lutzen (2012), Windeck (2013), ITTC (2014); Wind tunnel test and the CFD simulation
Ocean waves	Ocean waves are caused by external factors such as wind and storm, which are different from the wave making resistance. They expend a ship's energy by increasing the wetted surface area of the hull, rolling, pitching, and heaving.	Ship' heading and sailing speed over ground, wave velocity and direction	The procedure proposed by ITTC (2014); Seakeeping experiments and simulations, slender-body theory, 3D panel methods, and the CFD simulation
Shallow waters	The resistance faced by a ship increases when sailing in shallow water, which is defined by the absolute water depth and the ship's draught, due to several factors: 1) shallow water increases the water flowing speed under the hull and thus increases the viscous resistance on the hull; 2) the faster moving water decreases the pressure under the hull and thus increase the wetted surface area; 3) wave making resistances increases in shallow water.	Water depth, ship hull conditions, and sailing speed	The procedure proposed by Schlichting (1934, 1979); The CFD simulation
Hull fouling	Hull fouling of a ship increases surface roughness and thus increases the viscous and friction resistances	Ship hull form and scale, and the hull fouling conditions	The procedure proposed by Foteinos et al. (2017), Oliveira et al. (2018), Song et al. (2020); The CFD simulation and towing tests

After the total resistance faced by a ship is estimated, it is possible to calculate the towing power to move the ship through water given a required sailing speed. The towing power can be calculated as the product of the total resistance and the required speed over water. The required nominal power of the propulsion engine can be determined, and the fuel consumption of the ship can be estimated based on the power requirement in different sailing activity phases (Zis et al., 2020).

B.2 BBMs based on statistical modelling

Given n ship operational records, the set of k influencing factors (called predictor variables) is denoted by X, with one influencing factor denoted by x_i, and the observed fuel consumption rate (called the response variable) is denoted by y. The details of BBMs based on statistical modeling are summarized in Table B.2.

Table B.2. Summary of popular BBMs based on statistical modelling in ship fuel consumption monitoring

Model	Basic ideas	Assumption	General format	Common parameter estimation approach
Simple linear regression	Study the relationship between the $k=1$ predictor variable denoted by x and the response variable y in a linear form.	• The relationship between X and y is linear and additive. • The errors are independent, normally distributed with mean zero and a constant variance.	$y=\beta_0+\beta_1 x+\varepsilon$	Least squares
Multiple linear regression	Study the relationship between the $k, k \geq 2$ predictor variables in set X and the response variable y in a linear form.	• In multiple linear regression, the predictor variables are independent of each other.	$y=\beta_0+\beta_1 x_1+\beta_2 x_2+ \ldots+\beta_k x_k+\varepsilon$	
Polynomial regression	The nonlinear relationship between X and y is modelled as an nth degree polynomial in X.	• The relationship between X and y is linear or curvilinear. • The errors are independent, normally distributed with mean zero and a constant variance. • The predictor variables are independent of each other.	$y=\beta_0+\beta_1 X+\beta_2 X^2+\beta_3 X^3+ \ldots+\beta_h X^h+\varepsilon$	Least squares
Piecewise linear regression	X is partitioned into intervals with a separate line segment fitted to each interval.	The assumptions of simple linear regression	Suppose there are two breakpoints: x' and x''. Then $y=\begin{cases}\beta_0^{'}+\beta_1^{'}x, \ for\ x \leq x',\\ \beta_0^{''}+\beta_1^{''}x, \ for\ x'<x \leq x'',\\ \beta_0^{'''}+\beta_1^{'''}x, \ for\ x>x''.\end{cases}$	LOESS (locally estimated scatterplot smoothing) estimation for breakpoints, and least squares for parameter estimation in the simple linear regression in each interval
Partial least squares regression	A linear regression model based on principal components regression to deal with the situation where the number of predictor variables is larger than the observations, or when there is multicollinearity among X.	\	Please refer to 'Algorithm 3.3 *Partial Least Squares*' in Section 3.5 of Hastie et al. (2017).	Please refer to Haenlein and Kaplan (2004).

B.3 BBMs based on ML

Details of the BBMs based on ML techniques are summarized in Table B.3.

Table B.3. Summary of popular BBMs based on ML in ship fuel consumption monitoring

Model	Basic idea	Sub classes used in the related literature	Pros	Cons
ANN	A supervised model aims to extract linear combinations of the inputs as derived features, and then model the target as a nonlinear function of these features.	Back propagation neural networks, MLP, wavelet neural networks, deep learning models	• Good at modeling nonlinear data with a large number of inputs • A flexible model where several layers of neurons can be contained	• A pure black-box model lacking interpretability • Computationally expensive if many layers of neurons are contained • Easy to overfit the data, especially in case of limited data
LR	A supervised model assumes that the regression function is linear in the inputs. The inputs multiplied by some constants are added up to get the output.	OLS	• Easy to understand and implement • Computationally inexpensive • Able to provide an adequate and interpretable description of how the inputs affect the output • Able to outperform fancier nonlinear models especially with small numbers of training cases	• Too strong assumption regarding the linear relationship between the inputs and the output • Easy to be influenced by outliers and noises in data • The prediction ability on unseen data may not be satisfactory
Regularized LR	A type of restricted LR model based on shrinkage methods applied to the regression coefficients to reduce variance.	LASSO, ridge regression, elastic net regression	• Address the problem of multicollinearity in data when LR is applied • Reduce the problem of overfitting • Relative interpretability can be retained	• Weaken the interpretability of an LR model due to feature selection • Complicate the LR model by introducing more hyperparameters
Tree-based models	A supervised model successively splits the data into smaller segments until all the target variables are the same or until the dataset can no longer be split.	DT, RF, Adaboost DT, gradient boosting DT	• A single tree is easy to understand and interpret, which also allows for visual representation • Little data preprocessing is needed, and can even deal features with missing values • Feature selection happens automatically when a tree grows • Single DTs are easy to be ensembled • Different types of pruning methods can be applied to improve model generalization ability	• A single DT with high variance is highly like to overfit the data • Lack smoothness in the prediction surface in regression setting
SVM/SVR	A supervised model aims to split the data using a decision boundary (hyperplane). The prediction results are regarded to be more		• Kernels can be used to effectively deal with high-dimensional data • Work very well when there is clear margin of	• Easy to be influenced by noises in data, especially those causing overlapping • Not suitable for large datasets

	reliable if the data points are farther from the decision boundary.	separation between classes • As only a subset of training points (i.e., support vectors) is used in the decision function, it is memory efficient	
KNN	A supervised model aims to find the K most similar (closet) training samples of a certain test sample where the closeness is evaluated by distance (e.g., Euclidean distance, Cosine distance, and Manhattan distance)	• Very intuitive and easy to implement, as there is no 'training' step to build the model like the other ML models • It can immediately adapt when new training data are collected	• The speed of algorithm declines very fast as the number of samples/features grows • Very sensitive to outliers • A priori specification of the value of 'K' is needed
SOM	An unsupervised model which can be viewed as a constrained version of K-means clustering, in which the prototypes are encouraged to lie in a one- or two-dimensional manifold in the feature space	• The data can be interpreted and understood to some extend • Able to deal with large and complex datasets with a short amount of time	• Large amount of data is needed to develop meaningful clusters • Hard to deal with categorical data
GMM	An unsupervised and probabilistic model that assumes all the data points are generated from a mixture of a finite number of Gaussian distributions with unknown parameters. A GMM model is implemented by expectation-maximization (EM) algorithm	• It is one of the fastest algorithms for learning mixed models • It is more flexible in terms of cluster covariance allowing for soft classification	• Might take a long time to run than other similar models such as K-means • Based on the assumption of Gaussian distribution of the data points
Fuzzy c-means clustering	An unsupervised and soft clustering method where each data point can belong to more than one cluster with the basic idea similar to K-means	• Allow for soft classification as the data points can belong to more than one cluster with a likelihood • To deal with datasets with overlaps better	• A priori specification of the value of 'c' is needed • Sensitive to noises in data • Euclidean distance measures can unequally weight underlying factors

B.4 GBMs

Details of the GBMs developed in current literature are summarized in Table B.4.

Table B.4. A more detailed description of the GBMs proposed in current literature

Literature	WBM used	BBM used	How to combine the WBM and BBM	Findings
Leifsson et al. (2008)	A generic model based on physical principle	A feed forward ANN model	• A serial GBM: a set of input features is first fed into the WBM, and the estimated fuel flow rates and the vessel's speed through water are fed to the BBM to predict the real fuel flow rate and the vessel's speed through water • A parallel GBM: the set of input features to both the WBM and BBM is the same, with the WBM predicting the fuel flow rate and the vessel's speed through water and the BBM modeling the residual of the predicted and actual fuel flow rate and vessel speed	• The performance of the serial and parallel GBM is similar • There is a slight improvement of the GBMs developed over the WBM • The performance of the developed GBMs is similar to that of the BBM • The extrapolation ability and the ability to incorporate physical phenomena in model development are illustrated by model simulations
Coraddu et al. (2015)	A generic model based on the knowledge of physical processes	Regularized least squares	The a priori knowledge considered in the BWM is included in the BBM using Gaussian kernel in the regularization process	• GBM can incorporate the a priori knowledge of a WBM into a BBM while slightly improving the prediction accuracy of the BBM • Less data (about only half) is needed to construct a GBM compared to the BBM with the same performance
Lu et al. (2015)	A generic model with still water resistance modelled by Holtrop and Mennen's method and added resistance modelled by a modified Kwon's method	Speed-power curve estimated from ship operational records	The total power transmission efficiency from brake power of the main engine to the final effective power in the WBM is estimated from the speed-power curve calibrated from ship sea trial documents	Apart from the ability to predict ship fuel consumption under various conditions, the proposed GBM can also be used to examine the fouling effects of hull and propeller, and the engine degradation trends
Meng et al. (2016)	Two generic models considering various fuel consumption influencing factors such as sailing speed, displacement, wind, and wave	A least squares method and a sequential parameter estimation procedure for parameter estimation of the WBMs	• Parameters of the first nonlinear regression model considering speed and displacement are estimated by a linear least-square method • Parameters of the second nonlinear regression model are estimated by a sequential calibration procedure with the trust region algorithm	Besides data quality, the form of the regression model developed for fuel consumption prediction and the optimization algorithm used for coefficient calibration together govern the fitting performance

		developed		
Coraddu et al. (2017)	A WBM based on the knowledge of physical underling processes	Regularized least squares, LASSO regression, and RF	• A Naive approach (N-GBM): the output of the WBM is used as a new feature of the BBM • An advanced approach (A-GBM): the regularization process in the BBM is changed to include some a priori information	• Both the N-GBM and A-GBM improve the BBM just by few percentages regarding model accuracy • WBM can help GBM to obtain higher accuracy with respect to BBM by using much less data • An onboard trim optimization method is proposed based on the fuel consumption prediction results of the GBMs
Coraddu et al. (2018)	A WBM based on the knowledge of physical processes	Regularized least squares, LASSO regression, and RF	• An N-GBM: the output of the WBM is used as a new feature of the BBM • An A-GBM: the regularization process in the BBM is changed to include some a priori information	• GBM can combine the high prediction accuracy of BBM while reducing the amount of data required and the total computation time for training the model by adding WBM components
Yang et al. (2019)	A procedure based on basic principles of ship propulsion	A generic model to estimate the unknown parameters of the WBM	Fuel consumption is first modelled considering wind and waves factors in a WBM. The problem of parameter estimation of the developed WBM is formulated as a least squares minimization model and solved by a generic algorithm based on real operational data. The developed model is called GA-based GBM	• The developed GA-based GBM can make full use of the collected data and estimate all parameters together in one-time run • The developed GA-based GBM can provide accurate fuel consumption estimation for all weather directions • The output of WBM is always among the seven most important features for the GBMs

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