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Full Length Article

Data fusion and machine learning for ship fuel efficiency modeling: Part I – Voyage report data and meteorological data

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ABSTRACT

The International Maritime Organization has been promoting energy-efficient operational measures to reduce ships' bunker fuel consumption and the accompanying emissions, including speed optimization, trim optimization, weather routing, and the virtual arrival policy. The theoretical foundation of these measures is a model that can accurately forecast a ship's bunker fuel consumption rate according to its sailing speed, displacement/draft, trim, weather conditions, and sea conditions. Voyage report is an important data source for ship fuel efficiency modeling but its information quality on weather and sea conditions is limited by a snapshotting practice with eye inspection. To overcome this issue, this study develops a solution to fuse voyage report data and publicly accessible meteorological data and constructs nine datasets based on this data fusion solution. Eleven widely-adopted machine learning models were tested over these datasets for eight 8100-TEU to 14,000-TEU containerships from a global shipping company. The best datasets found reveal the benefits of fusing voyage report data and meteorological data, as well as the practically acceptable quality of voyage report data. Extremely randomized trees (ET), AdaBoost (AB), Gradient Tree Boosting (GB) and XGBoost (XG) present the best fit and generalization performances. Their R^2 values over the best datasets are all above 0.96 and even reach 0.99 to 1.00 for the training set, and 0.74 to 0.90 for the test set. Their fit errors on daily bunker fuel consumption are usually between 0.5 and 4.0 ton/day. These models have good interpretability in explaining the relative importance of different determinants to a ship's fuel consumption rate.

1. Introduction

Reducing bunker fuel consumption of ships are paramount for the shipping industry with both commercial and environmental implications. Shipping companies have been always striving to reduce their bunker fuel costs of their fleets in marine operations because bunker fuel cost typically accounts for about 20%–61% of a ship's operating costs (Meng et al., 2017; Soner et al., 2018). Meanwhile, reduction in bunker fuel consumption lies in the core of progressively stricter regulations on ship emissions proposed by the International Maritime Organization (IMO, 2020) and other international or national organizations such as European Union (EU, 2021), because ship emissions, especially CO_2, NO_x and SO_x, are proportional to the bunker fuel consumption (Adland et al., 2019).

Shipping industry stakeholders, such as shipping companies, IMO, EU, and other governmental organizations, are making unprecedented efforts to reduce bunker fuel consumptions of ships and the accompanying emissions. Due to the expensiveness of technical solutions, shipping companies have been passionate in adopting various operational measures to reduce bunker fuel consumption, including weather/environmental routing, speed optimization, trim optimization, and virtual (just-in-time) arrival policy (IMO, 2012; Coraddu et al., 2017; Li et al., 2018; Wan et al., 2018; Merkel et al., 2022). IMO has been calling on the shipping industry to implement the Data Collection System (EEOI, AER, DIST, TIME), Energy Efficiency Design Index (EEDI), Ship Energy Efficiency Management Plan (SEEMP), and in-progress Energy Efficiency eXisting ship Index (EEXI) and Carbon Intensity Index (CII) (Wang et al.,

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2021; Yan et al., 2021). EU also rolled out its Monitoring, Reporting and Verification (MRV) system from 2018.

However, during this process, many frustrations are heard from the shipping industry. In sailing speed optimization, a ship's fuel efficiencies, usually measured as its *fuel consumption rate* in terms of metric ton (MT) per hour, or MT per day, in different weather and sea conditions are hard to be captured by deck officers. Therefore, a simple *sprint-and-loiter* practice is widely adopted (Johnson and Andersson, 2011; C-MAP, 2022). Regarding trim optimization, it is believed that trim optimization can save 4%–6% (even up to 15%) of bunker fuel, according to various reports issued by IMO and DNV. However, in our collaboration with some shipping companies, we heard many complaints about the current trim optimization practice. Captains at sea feel that trim charts/tables/matrices based on model ship tests or computational fluid dynamics (CFD) calculation are not convincing, because these trim charts/tables/matrices cannot reflect the influence of weather and sea conditions on trim optimization and the suggested optimal trim values sometimes even cannot guarantee the full submergence of the propellor in sea water. Third, our discussion with seafarers also saw their complaints about the weather routing services provided by Weather Information Service Providers (WISPs). The weather routing services of WISPs are expensive, and the data received by ships may be outdated or delayed. Therefore, many deck officers having been relying more and more on manual voyage/route planning with the assistance of real-time weather information websites, such as *Windy.com*. Fourth, when it turns to the virtual (just-in-time) arrival policy, Rehmatulla et al. (2017), Adland et al. (2020) and Merkel et al. (2022) report that a major barrier to this policy is incapability of quantitively assessing the bunker fuel consumption in different speed-weather scenarios and precisely calculating the cost savings of the policy for each voyage.

All these frustrations are boiled down, if not fully, to how we can quantify the synergetic impacts of many factors (speed, draft/displacement, trim, weather conditions, sea conditions) on a ship's bunker fuel consumption rate. A latest review paper, Yan et al. (2021), also points out that the basis of all operational measures for ship bunker fuel savings and emission mitigation is the quantitatively modeling the relationship between fuel consumption rate and its determinants, including sailing speed, draft/displacement, trim, weather conditions, and sea conditions, but it is not a trivial work.

As stated by Yan et al. (2021), there are two elementary factors that determine the accuracy of ship fuel efficiency modeling: choice of data, and choice of models. There are several data sources that can support ship fuel efficiency modeling of a shipping company: voyage report data, sensor data, automatic identification system (AIS) data, ship mechanical data, ship maintenance data, and meteorological data. Haranen et al. (2016) and Yan et al. (2021) categorize ship fuel efficiency models as three classes: white-box models (WBMs), black-box models (BBMs), and grey-box models (GBMs), and discuss the advantages and disadvantages of each model class and the importance of selecting specific models.

The systematic review of Yan et al. (2021) summarizes the existing research efforts of data collection and ship fuel efficiency analysis with varieties of models, especially machine learning (ML) models. However, few of them consider the complementary roles of different data sources. For instance, the quality of voyage report data about snapshotted weather and sea conditions is questionable, but this might be remedied by the publicly accessible meteorological data, such as the data of wind, waves, and sea water temperature from European Centre for Medium-range Weather Forecasts (ECMWF) (Hersbach et al., 2018), and the data of sea currents from Copernicus Marine Service (CMEMS) (Rio et al., 2014). Meanwhile, through AIS data, we can access the sailing trajectory of a ship over a day and the data about the positions of the ship might help us to find more accurate weather and sea condition data from meteorological data. As another example, sensor data provides high-quality information on a ship's sailing profile including wind conditions, but the information of waves, sea water temperature, and sea currents is often absent. This may be complemented by the detailed meteorological data that is publicly accessible.

Therefore, the following research questions (RQs) could be asked by both academics and industry professionals:

- **RQ1.** Is it possible to combine/fuse different but complementary data sources for the sake of modeling accuracy for ship fuel efficiency analysis? And how these data sources can be fused?
- **RQ2.** Compared to a single data source, what are the benefits of fusing different data sources in terms of modeling accuracy and generalization?
- **RQ3.** Selection of datasets and choice of models are two different decision dimensions but they rely on each other. When these two decisions are interwoven, how can we select the best datasets and best models?

The rest of the paper is organized as follows. Section 2 reviews the relevant literature and clarifies the research gaps. Section 3 outlines our research efforts, contributions, and boundary. Section 4 introduces the rationale and solution to fuse voyage report data and meteorological data, and the resultant datasets. Section 5 describes the technical details of eleven ML models for ship fuel efficiency modeling. Section 6 selects the best datasets and evaluates the fit and generalization performances of ML models through experiments with eight containerships. Finally, conclusions are drawn in Section 7.

2. Literature review and research gaps

2.1. Literature review

Our studies focus on accurately modeling the relationship between ship fuel consumption rate (MT/h or MT/day) and several determinants, including sailing speed, draft/displacement, trim, weather conditions, and sea conditions, by using machine learning models. In this regard, Yan et al. (2021) conduct a systematic literature review for academic papers and technical reports published from 2008 (one year before the implementation of IMO EEOI) to 2021. In this taxonomy, machine learning models represent one of the two types of BBMs, in parallel with statistical BBMs. To avoid duplicating the systematic review of Yan et al. (2021), we will only have a quick review about the BBM literature that involves two or more data sources, because our studies are addressing the research questions about the benefits of fusing several data sources and using machine learning models.

Bocchetti et al. (2015) collect the data of a cruise ship from voyage report (a.k.a. n*oon report*) and onboard sensors about ship maintenance and operations and sea and weather conditions, and develop a multiple linear regression (MLR) model. Their research purpose is to predict the fuel consumption of this cruise ship in a voyage, rather than that in a day or hour. Meanwhile, a systematic query is absent to how to select the best dataset by considering all the possible datasets that can be produced by voyage report and sensor data.

Adland et al. (2018) consider voyage report and hull maintenance data of a fleet of eight sister Aframax crude oil tankers, and perform a MLR analysis on fuel consumption rate. Their research purpose is to assess the impact of hull cleaning on ship fuel efficiency and thus they combine the voyage reports of eight ships together. This is different from our studies that aim to build ship-specific fuel efficiency models for the applications of daily marine operations at sea, relying on daily operational data sources including voyage reports, sensor data, AIS data, and meteorological data.

As far as we know, the study of Lee et al. (2018) is the first attempt to combine two daily operational data sources at sea for ship fuel consumption rate estimation. They fuse the data about voyages and meteorological data from CMEMS and develop a data mining algorithm that mines the impact of wind on ship fuel consumption rate. However, the adopted data about voyages is not voyage report data but "voyage abstract data" in which there is only one data entry for each voyage. This limitation on data availability makes the authors rely on a polynomial regression model of ship fuel efficiency proposed by Yao et al. (2012).

Gkerekos et al. (2019) utilize voyage report data and the data from an automated data logging & monitoring (ADLM) system. The data from the ADLM system is sensor based but its sampling frequency, hourly, is lower than traditional sensor data which generally has a data entry about every 10–15 min. Meanwhile, they regard voyage report and ADLM data as two independent data sources and their purpose is to compare the performance of machine learning models on these two different data sources. The possibility of fusing different data sources is not discussed.

Man et al. (2020) make pioneering efforts to fuse different data sources by considering five ferries and collecting their sensor data, AIS data, meteorological data, and the captains' log on the estimated time of arrival (ETA) and summarized fuel consumption in each journey. Though four data sources are mentioned, their study mainly combines sensor data and meteorological data. Their AIS data from a Swedish company is not reliable to track the ship probably because the voyages of ferries between Gothenburg and Kiel are rather short compared to commercial cargo ships at open sea. This paralyzes the main advantage of AIS data and makes them approach a linear interpolation method to calculate the sailing trajectories of these ferries. Six datasets are produced after data fusion and tested with a multi-layer perceptron model and a self-organizing map model. The prediction target of their machine learning models is ship fuel consumption in a journey, rather than fuel consumption rate, which is different from our studies and from most studies reviewed by Yan et al. (2021). Their data structure and the nature of short sea sailing of the five ferries under investigation could challenge the applicability of their data fusion plans and experimental findings to the shipping practice of cargo ships such as containerships and oil tankers.

Farag and Ölçer (2020) adopt an artificial neural network (ANN) model to estimate a tanker ship's brake power based on serval determinants such as sailing speed and weather and sea conditions. They utilize a dataset provided by NAPA Group that is extracted from the ship's automatic continuous monitoring system (ACMS), AIS data, and meteorological data, but NAPA hides the details on how these data sources are combined.

Uyanık et al. (2020) combine voyage report and sensor data and populate 75 variables/features into their machine learning models. This is appropriate because their research purpose is to monitor engine performance and their models will be used by engine rooms. This is significantly different from our studies that target ship fuel efficiency models to be used by deck officers and captains for their daily sailing planning.

2.2. Research gaps

Contrasting the research questions proposed in Section 1 with literature review conducted in Section 2.1, we can easily see the following research gaps posed by existing literature:

- Existing studies of ship fuel efficiency analyses that combine/fuse multiple data sources and explore their complementary roles are rare.
- Among these rare studies, only Lee et al. (2018), Man et al. (2020), and Uyanık et al. (2020) propose clear data fusion solutions and fuel efficiency models/algorithms from the perspective of a ship's daily sailing operation.
- To address the industry frustrations in speed optimization, trim optimization, water routing, and virtual arrival policy, a reliable model is needed to accurately estimate a ship's bunker fuel consumption rate (MT/day, MT/h) based on several determinants outside of a ship's engine (sailing speed, draft/displacement, trim, weather conditions, and sea conditions). None of Lee et al. (2018), Man et al. (2020), and Uyanık et al. (2020) achieve this, not to mention a systematic research effort to construct promising fused datasets from voyage report, AIS data, sensor data, and meteorological data and to select the best datasets according to the fit and generalization performances of multiple machine learning models.

3. Research efforts, contributions, and scope/boundary

To address the research questions and gaps identified and build reliable fuel consumption rate forecast models that can be used in energy-efficient operational measures (speed optimization, trim optimization, water routing, and virtual arrival policy), we approached different industry stakeholders and collected/purchased all the four most relevant data sources that a shipping company can access, for eight modern mega containerships in different sizes: voyage report data, sensor data, AIS data, and meteorological data.

Then we analyzed the data structure of these data sources and proposed the following three possible data fusion/combination solutions, by discussing with a global shipping company, envisaging the possible industry application scenarios, and considering the endogeneity issue pointed by Yan et al. (2021):

- Data fusion solution 1 (**DFS1**): voyage report data + meteorological data.
- Data fusion solution 2 (**DFS2**): voyage report data + meteorological data + AIS data.
- Data fusion solution 3 (**DFS3**): sensor data + meteorological data.

Readers might wonder whether it is possible to propose other data fusion solutions, such as the fusion of meteorological data and AIS data, or the fusion of sensor data, AIS data, and meteorological data. First, it is not sensible to only fuse meteorological data and AIS data because neither of these two data sources contains the information about the ship's bunker fuel consumption, actual drafts, and trim settings, which are essential for ship fuel efficiency analysis. Second, **DFS3** is proposed driven by the rationale that sensor data has incomplete information about weather and sea conditions. For instance, the sensor data we collected only contains the information about wind conditions, while the information about waves, sea currents, and sea water temperature is absent. However, it will bring no additional benefits if AIS data is further fused into **DFS3**, because sensor data already possesses the detailed information about the ship's geographical positions and AIS data does not provide any additional information to sensor data that is useful for ship fuel efficiency analysis.

For each data fusion solution, we constructed all the possible datasets by taking into account the industry applications and the impact of endogeneity on feature/variable selection. Then we tested the fit and generalization performances of machine learning models widely adopted in literature over these possible datasets. When the decisions of dataset selection and model choice are interwoven, we adopted a voting scheme to enable machine learning models to vote for best datasets.

Experiments with these industry data and machine learning models revealed many useful insights into the benefits of fusing these different data sources, selection of the best datasets, and choice of the best machine learning models. Using the same ships, it also allowed us to compare the benefits of different data sources and compare the benefits of different data fusion solutions.

We will report the research towards data fusion solution (DFS1) with voyage report data and metrological data in this paper, and research findings towards the other two data fusion solutions (DFS2, DFS3) in another two following papers. **For the first time, this series of three studies provide industry professionals with clear answers to RQ1 to RQ3 with extensive and intensive experimental evidence from different sizes of mega containerships. These studies lay a solid theoretical foundation to accurately quantify a ship's fuel consumption rate in the energy-efficient operational measures being promoted by IMO, including sailing speed optimization, trim optimization, route selection (weather routing), and the virtual arrival policy**.

To avoid possible confusions, we define our research scope/boundary as follows.

(a) We only consider the fuel consumption of the main engine (M/E) of a ship, but will not consider its auxiliary engines and boilers.
(b) For the purpose of applications of models to sailing speed optimization, trim optimization, route optimization, and the virtual arrival policy, our studies only adopt the features outside of a ship's mechanical system (engine and propulsion) as the input variables of a model, including sailing speed, draft/displacement, trim, and factors about weather and sea conditions. We will not consider the technical features regarding engine and propellor performance such as engine RPM, engine power, shaft power, and propellor pitch. See the discussion of Yan et al. (2021) on the endogeneity issue and application scenarios of different types of models.
(c) The output/dependent variable of our model, i.e., the prediction target, is the fuel consumption rate in terms of MT/day (or equivalently MT/h), rather than fuel consumption in a voyage or journey in term of MT or specific fuel oil consumption (SFOC) in terms of g/kWh.
(d) Accordingly, only data sources relevant to a ship's voyage management and sailing behaviours will be utilized, including voyage report data, sensor data, AIS data, and meteorological data. Other data sources discussed by Yan et al. (2021) and ship fuel efficiency models based on those sources are not relevant to energy-efficient operational measures for voyage management (speed optimization, trim optimization, route selection/weather routing, virtual arrival policy).
(e) We only test the machine learning models, especially those widely adopted in literature. We will not consider WBMs, statistical BBMs or GBMs that are discussed in Yan et al. (2021). See Yan et al. (2021) for a detailed discussion about the pros and cons of each type of models.

4. Fusion of voyage report data and meteorological data

4.1. Voyage report data, meteorological data, and rationale of data fusion

Voyage report of a ship is a summary of the daily sailing situation submitted by the captain to the onshore officers so that the onshore officers can understand the ship's real sailing conditions. Usually, the captain will report the data at noon every day, and thus voyage report data is also called *noon report data*. Ship voyage reports are usually filled out manually by the crew based on the readings of the instruments on board or eye inspection with personal experience. Voyage report data includes many sailing features of the ship, such as displacement, draft, trim, speed, true course, geographic location, Greenwich Mean Time, the fuel consumptions of the main engine, auxiliary engines, and boilers, weather conditions, and sea conditions.

Voyage report data of eight mega containerships is provided by a global container shipping company, and the particulars of these eight containerships can be seen in Table 1. The sailing period recorded by the data spans from February 2014 to March 2016. A data preprocessing procedure that removes invalid data entries was employed to ensure the quality of datasets. Particularly, the data entries with N/A values, speeds below 12 knots or above 30 knots, sailing time less than 10 h, or ship status being not "sailing at sea" were all deleted in data preprocessing. For the sailings of about two years, after preprocessing, ships S1 to S8 have 320, 296, 389, 380, 329, 402, 407 and 440 data entries, respectively, in their voyage reports.

Motivated by the study of Du et al. (2019), this study selects the fuel consumption rate of the main engine (ton/day) in the voyage report as the output variable (target) of the ship fuel efficiency model. The input/independent variables (features) of the model include displacement (MT) (equivalent to draft (m)), trim (m), sailing speed (knots), sea water temperature (°C), wind direction, wind force (Beaufort scale number), wave (swell) direction, wave (swell) height (m), sea current direction, and sea current speed (knots). The directions of wind, waves, and sea currents in the voyage report are recorded by the crew as fuzzy numbers denoting their approximate directions relative to the ship's heading, which are illustrated in Fig. 1. For readers who are interested in the distributions of our voyage report data entries over these important features, see Fig. 2 for ships S5 and S8 as examples.

Table 1
Particulars of eight ships used for experiments.

Ship	Year built	Capacity (TEU)	Size (length × beam)	Draft recorded: Avg/Max (m)	Speed recorded: Avg/Max (knots)
S1	2013	14,000	398 m × 51 m	13.5/25.1	13.9/23.3
S2	2013	14,000	398 m × 51 m	14.1/21.5	13.8/23.3
S3	2012	11,000	347 m × 45 m	13.7/23.8	12.7/23.6
S4	2012	11,000	347 m × 45 m	12.1/15.7	12.9/24.4
S5	2013	9,200	328 m × 45 m	11.7/19.3	12.4/24.0
S6	2014	9,200	328 m × 45 m	12.6/23.5	12.8/22.3
S7	2013	9,200	328 m × 45 m	12.4/17.4	12.3/23.1
S8	2013	8,100	320 m × 46 m	12.0/22.3	12.4/23.9

Source: FleetMon.com. Accessed on 8 February 2022.

Yan et al. (2021) point out that weather and sea conditions recorded by voyage report are snapshotted information by the deck officer. For instance, the wind speed/force and direction in a voyage report data entry are from the deck officer's one read of their anemometer, and the time of the deck officer's reading the anemometer can be random on the given day. Apart from the snapshotting method, our conversation with industry collaborators show that wave and sea current conditions recorded in voyage report depend highly on the deck officer's eye inspection and personal experience. These issues could all erode the data quality of voyage report on weather and sea conditions.

To remedy the data quality issue of voyage report on weather and sea conditions, our industry collaborators suggested us approaching some publicly accessible meteorological data sources to retrieve more reliable data of weather and sea conditions. Our research shows that ECMWF provides the finest data for wind, waves, and sea water temperature in the granularity of 0.25° (longitude) × 0.25° (latitude) × 1 h (time), while CMEMS (a.k.a. "Copernicus") provides the finest data for sea currents in the granularity of 0.25° (longitude) × 0.25° (latitude) × 3 h (time). These data sources are also adopted by *Windy.com* which is widely used by deck officers around the world for manual voyage planning.

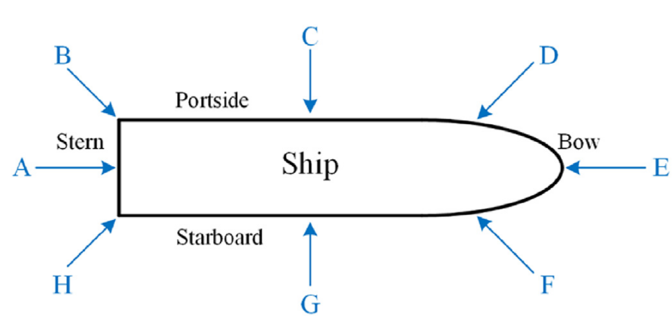
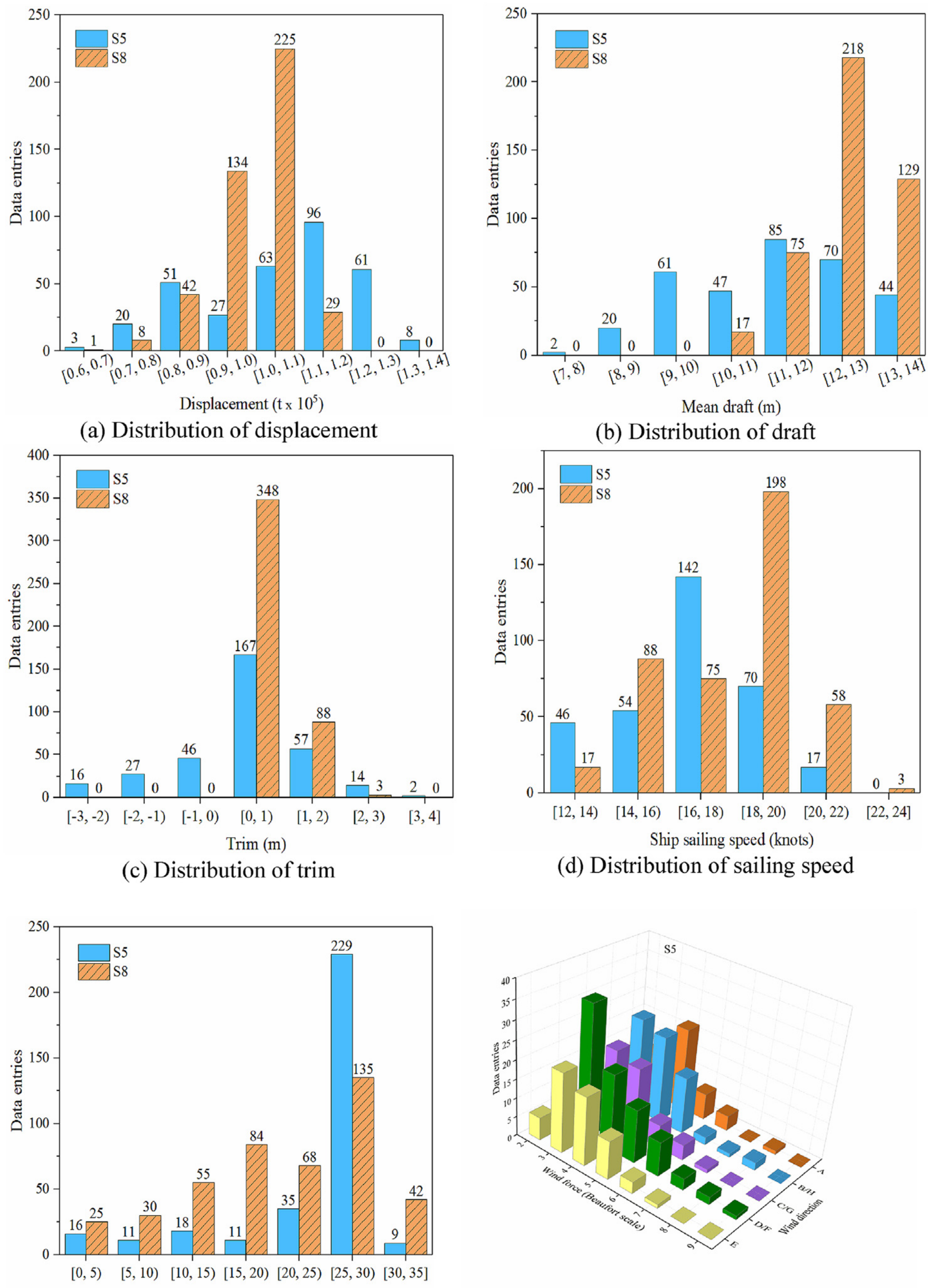


Fig. 1. Illustration of wind/wave/sea current directions. Source: Meng et al. (2017).



(a) Distribution of displacement

(b) Distribution of draft

(c) Distribution of trim

(d) Distribution of sailing speed

(e) Distribution of seawater temperature

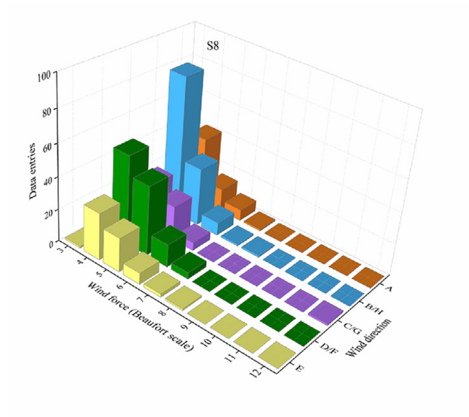
(f) Wind direction and wind force distribution of S5

Fig. 2. Distribution of the voyage report data entries of ships S5 and S8.

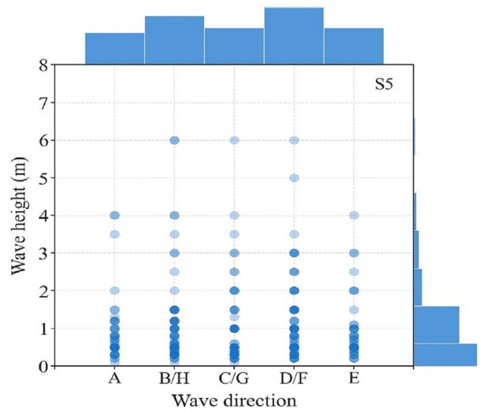
ECMWF data on 12 variables/parameters is retrieved, including "*Significant height of combined wind waves and swell*" (paramId: 140229), "*Mean wave direction*" (paramId: 140230), "*Mean wave period*" (paramId: 140232), "*Significant height of wind waves*" (paramId: 140234), "*Mean direction of wind waves*" (paramId: 140235), "*Mean period of wind waves*" (paramId: 140236), "*Significant height of total swell*" (paramId: 140237), "*Mean direction of total swell*" (paramId: 140238), "*Mean period of total swell*" (paramId: 140239), "*10 m U wind component*" (paramId: 165), "*10 m V wind component*" (paramId: 166), "*Sea surface temperature*" (paramId: 34). Note that waves consist of two components: swells and wind waves, and ECMWF provides the information about swells, wind waves, and the combined waves calculated from these two components. 3-hourly data on sea currents is retrieved from CMEMS (Copernicus), involving two variables: *eastward_sea_water_velocity* and *northward_sea_water_velocity*.

4.2. Approach of fusing voyage report data and meteorological data

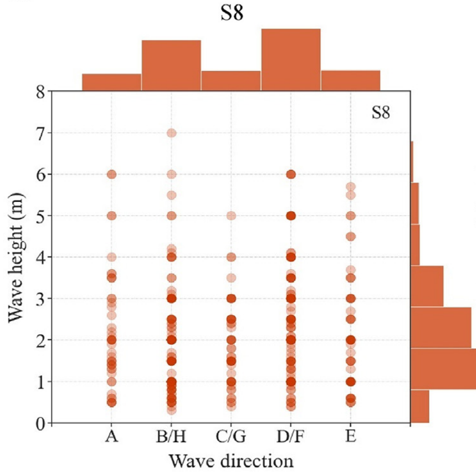
The first key step of fusing voyage report data and meteorological data is to estimate the sailing trajectory (hourly geographical positions) of the ship in a day. This estimation can be performed with the well-known great circle route. In the actual voyage of a ship, the great circle route is the shortest economic route in terms of distance. However, following the great circle route often requires the deck team to constantly change the course of the ship. Therefore, to facilitate navigation, the



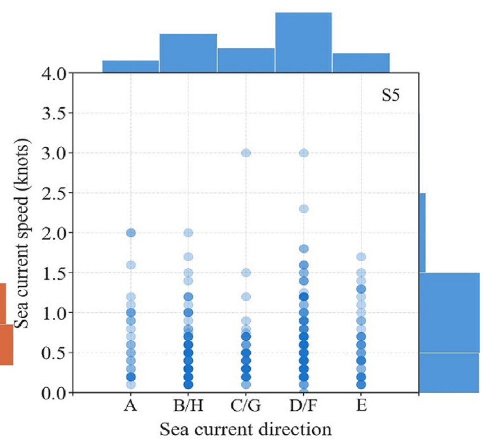
(g) Wind direction and wind force distribution of S8



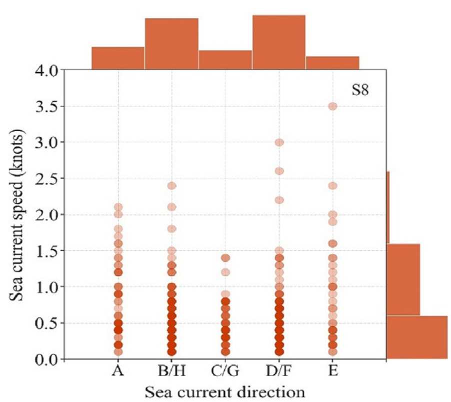
(h) Wave direction and wave height distribution of S5



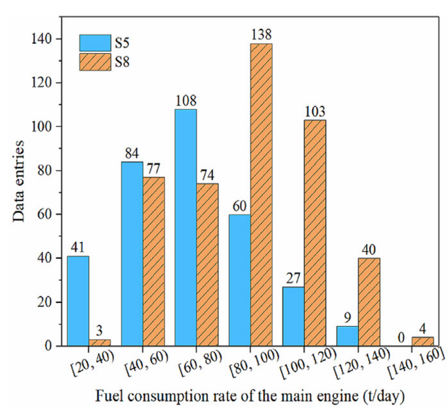
(i) Wave direction and wave height distribution of S8



(j) Sea current direction and sea current speed distribution of S5



(k) Sea current direction and sea current speed distribution of S8



(l) Distribution of fuel consumption rate of the main engine

Fig. 2. (*continued*).

great circle route is usually divided into several segments and then the ship sails along the rhumb line (or loxodrome) on each segment (Weintrit and Kopacz, 2011). Based on this, the latitude and longitude of each position the ship passes are calculated according to the rhumb line formulas (Bennett, 1996) shown below:

$$S = V \cdot h \tag{1}$$

$$\Delta\varphi = S \cdot \cos\overrightarrow{C} \tag{2}$$

$$\varphi_2 = \varphi_1 + \Delta\varphi \tag{3}$$

$$\varphi_m = \frac{\varphi_1 + \varphi_2}{2} \tag{4}$$

$$\Delta\lambda = S \cdot \sin\overrightarrow{C} \cdot \sec\varphi_m \tag{5}$$

$$\lambda_2 = \lambda_1 + \Delta\lambda \tag{6}$$

$$t_2 = t_1 + h \tag{7}$$

In these formulas, S is the sailing distance (n mile); V is the sailing speed (knots) reported by the voyage report; h is the sailing time (h); $\Delta\varphi$

is the latitude difference (°); $\overrightarrow{C}$ is the ship's course (°) reported by the voyage report since the rhumb line approach adopts a constant course for the ship, which should be converted to the range of 0°–90°, from north and south (e.g., courses 150° and 300° should be converted to 30° and 60° respectively.); φ_1 and φ_2 are the latitudes of the departure and arrival positions, respectively (°); φ_m is the average latitude between them (°); λ_1 and λ_2 are the longitudes of the departure and arrival positions, respectively (°); $\Delta\lambda$ is the longitude difference (°); t_1 and t_2 are the times of departure and arrival, respectively.

Second, the weather and sea conditions at each hourly position can be retrieved from ECMWF data on 12 variables and CMEMS (Copernicus) data on 2 variables. The wind/waves/sea currents direction obtained from meteorological data is the absolute direction. To obtain the directional information of wind/waves/sea currents relative to the bow of the ship, the "true course" information from the voyage report is used. Due to the symmetric structure of the ship, the relative wind/wave direction is between 0° and 180°. 0° represents the wind/waves/sea currents coming to the bow, and 180° represents the wind/waves/sea currents coming to the stern.

Due to the nature of voyage report data, it usually contains only one data entry per day. For a specific day (corresponding to a specific data entry of voyage report), meteorological data is used for the purpose of correcting the possibly inaccurate information of weather and sea conditions contained in this voyage report data entry. Therefore, it is necessary to average the weather/sea conditions along hourly geographical positions traveled through by the ship, and to use this daily average as the substitute for weather/sea condition information in this data entry corresponding to this specific day. The average method used is as follows:

$$\overline{W} = \frac{1}{M}\sum_{i=1}^{M} W_i \tag{8}$$

where $\overline{W}$ is the daily average weather/sea condition data; $M = 24$ is the number of hourly weather/sea condition data entries per day; W_i is the hourly weather/sea condition data. Note that the averaging method is widely adopted by meteorological services such as ECMWF to conduct data conversions between different granularities of longitude × latitude × time.

Table 2
Conversion of relative wind/wave/sea current direction data from precise values to fuzzy values.

Relative wind/wave direction angle (precise value)	Approximate wind/wave direction (fuzzy value)
0°–30°	E
30°–60°	D/F
60°–120°	C/G
120°–150°	B/H
150°–180°	A

The whole process of fusing voyage report data and meteorological data is illustrated in Fig. 3. Until now, all the information derived from meteorological data about weather and sea conditions is in the form the precise values. Specifically, the relative directions of wind/waves/sea currents are represented as the degrees relative to the ship's bow, and wind speed is in the unit of m/s. However, voyage reports use fuzzy values for these data. For the convenience of comparison experiments between precise values and fuzzy values, Tables 2 and 3 can convert precise values of weather and sea conditions to fuzzy values.

We generate nine possible datasets using voyage report data and meteorological data, by considering the target application scenarios in energy-efficient operational measures for voyage management, the endogeneity issue discussed by Yan et al. (2021), the fact that waves consist of swells and wind waves, and the experimental choice of using precise or fuzzy values for weather and sea conditions. See Table 4 for the details of these nine datasets.

5. Machine learning models

Not aiming to exhaust all the ML models, our studies cover a large range of widely adopted ML models , including decision tree-based models, ANN (Haykin, 2008), support vector machine (SVM) (Boser et al., 1992), ridge regression (Ridge) (Hoerl and Kennard, 1970), and LASSO (Tibshirani, 1996). Tree-based models include the basic decision tree (DT) model (Breiman et al., 1984) and models produced by two ensemble strategies. Extremely randomized trees (ET) (Geurts et al., 2006) and random forest (RF) (Breiman et al., 2001) are from the *bagging*

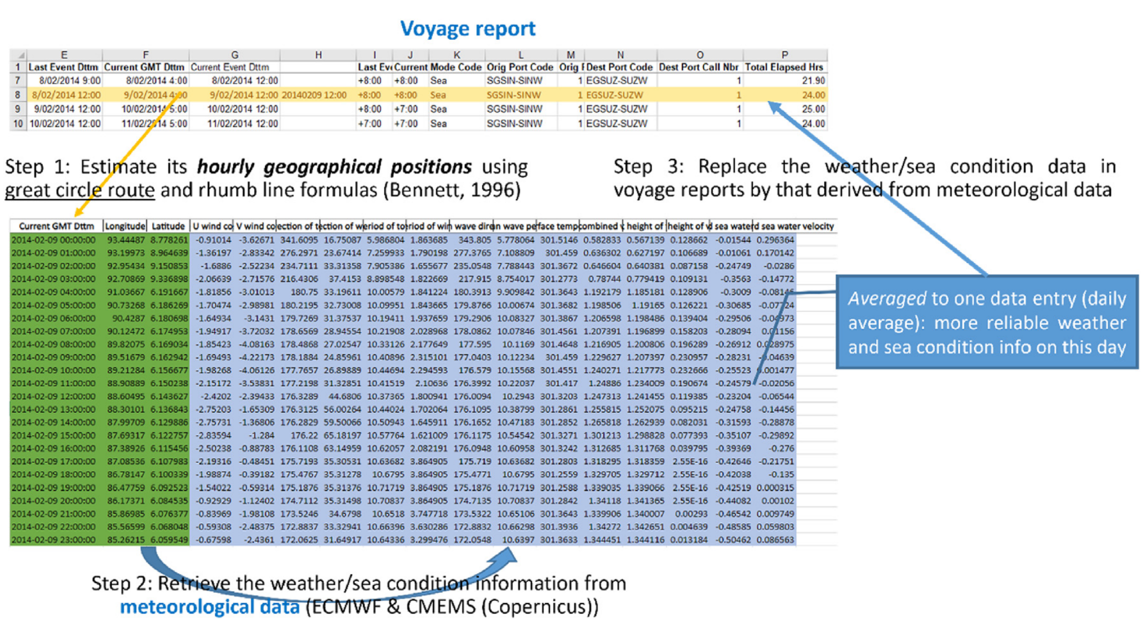


Fig. 3. Approach of fusing voyage report data and meteorological data.

Table 3
Wind force scale corresponding to different wind speeds (ISO 15016: 2015(E)).

Wind speed (m/s) - precise value	Wind force (Beaufort scale) - fuzzy value
0.0–0.2	0
0.3–1.5	1
1.6–3.3	2
3.4–5.4	3
5.5–7.9	4
8.0–10.7	5
10.8–13.8	6
13.9–17.1	7
17.2–20.7	8
20.8–24.4	9

ensemble strategy that trains multiple decision trees in parallel and uses the average of the outputs of multiple decision trees as the prediction. AdaBoost (AB) (Freund and Schapire, 1997; Drucker, 1997), gradient tree boosting (GB) (Friedman, 2001), XGBoost (XG) (Chen and Guestrin, 2016), and LightGBM (LB) (Ke et al., 2017) are from the *boosting ensemble strategy* that trains decision trees in sequence and improves the performance of trees step by step using the information of fitting errors and negative gradients.

Meanwhile, our studies do not aim to find dedicated variants for each type of ML models based on experiments and thus simply adopt the typical version of each of the eleven ML models. For instance, for ANN, we adopt a typical three-layer feedforward structure with the number of neurons in the hidden layer being the same as the input variables. Model training algorithms in our studies are implemented using Python 3.7.6. The XG model is developed using the XGBoost 1.2.0 library, the LB model is developed using the LightGBM 2.3.1 library, and the remaining models are developed using Scikit-learn 0.22.1.

Different ML methods have different requirements for data preprocessing. The main difference is whether to use data normalization. To clarify the impact of data normalization on the performances of ML models, the performances (R^2) of ML models before and after data normalization were compared in a preliminary study. This preliminary study reveals that the performances of SVM and ANN models after data normalization are significantly better than those before normalization, while other models do not see a significant difference. See Fig. A1 in Appendix. Therefore, our studies use data normalization for SVM and ANN but not for other models.

Table 4
Features contained in each dataset.

Original datasets	Data source	Features	Dataset								
			Set1	$Set2_{precise}$ [b]	$Set2_{fuzzy}$ [c]	$Set3_{precise}$ [b]	$Set3_{fuzzy}$ [c]	$Set4_{precise}$ [b]	$Set4_{fuzzy}$ [c]	$Set5_{precise}$ [b]	$Set5_{fuzzy}$ [c]
Voyage report data	Shipping company	Fuel consumption rate	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Sailing speed	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Displacement	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Trim	✓	✓	✓	✓	✓	✓	✓	✓	✓
		Wind speed	✓								
		Wind direction (Rel.)	✓								
		Swell height	✓								
		Swell direction (Rel.)	✓								
		Sea currents speed	✓								
		Sea currents direction (Rel.)	✓								
		Sea water temperature	✓								
Meteorological data	European Centre for Medium-range Weather Forecasts (ECMWF)	Wind speed		✓	✓	✓	✓	✓	✓	✓	✓
		Wind direction (Rel.)[a]		✓	✓	✓	✓	✓	✓	✓	✓
		Swell height		✓	✓	✓	✓	✓	✓		
		Swell direction (Rel.)[a]		✓	✓	✓	✓	✓	✓		
		Swell period									
		Wind wave height				✓	✓	✓	✓		
		Wind wave direction (Rel.)[a]				✓	✓	✓	✓		
		Wind wave period									
		Combined wave height				✓	✓			✓	✓
		Combined wave direction (Rel.)[a]				✓	✓			✓	✓
		Combined wave period									
		Sea water temperature		✓	✓	✓	✓	✓	✓	✓	✓
	Copernicus Marine Service	Sea current speed		✓	✓	✓	✓	✓	✓	✓	✓
		Sea current direction (Rel.)[a]		✓	✓	✓	✓	✓	✓	✓	✓

Notes.
[a] Relative directions of wind/waves/sea currents are calculated based on ship's "true course" information from voyage report data because "heading" information is absent from voyage report data.
[b] The subscript "precise" means the directions of wind/waves/sea currents are calculated as the angles relative to ship's heading measured by degrees.
[c] The subscript "fuzzy" means the precise information of directions of wind/waves/sea currents is converted to fuzzy data as per Table 2, and wind speed is represented by Beaufort scale numbers as per Table 3.

Table 5
The fit performance of eleven machine learning models for ship S1.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	*Set1*	**0.846**	**0.643**	81.022	8.934	6.851	7.995
	$Set2_{precise}$	0.828	0.640	82.878	9.051	6.940	8.279
	$Set2_{fuzzy}$	0.836	0.642	78.921	8.821	6.792	8.085
	$Set3_{precise}$	**0.847**	0.617	73.848	8.532	6.522	7.697
	$Set3_{fuzzy}$	**0.848**	0.627	73.402	8.479	6.495	7.662
	$Set4_{precise}$	**0.853**	0.613	71.091	8.348	6.369	7.558
	$Set4_{fuzzy}$	0.838	0.628	77.915	8.728	6.692	7.953
	$Set5_{precise}$	0.834	0.628	80.418	8.896	6.781	8.033
	$Set5_{fuzzy}$	0.828	0.640	82.894	9.035	6.922	8.213
ET	*Set1*	0.992	0.781	4.001	1.525	1.090	1.255
	$Set2_{precise}$	0.931	0.762	33.569	5.674	4.330	5.239
	$Set2_{fuzzy}$	0.934	0.757	32.173	5.444	4.137	4.981
	$Set3_{precise}$	0.965	0.762	17.043	3.524	2.699	3.245
	$Set3_{fuzzy}$	0.939	0.766	29.313	5.012	3.862	4.698
	$Set4_{precise}$	0.956	0.764	20.951	3.918	2.993	3.612
	$Set4_{fuzzy}$	0.950	0.759	24.199	4.495	3.471	4.198
	$Set5_{precise}$	0.947	0.769	25.433	4.623	3.520	4.237
	$Set5_{fuzzy}$	0.943	0.764	27.454	4.842	3.693	4.442
RF	*Set1*	0.964	0.761	18.837	4.321	3.194	3.721
	$Set2_{precise}$	0.940	0.754	28.914	5.304	3.978	4.747
	$Set2_{fuzzy}$	0.944	0.764	27.225	5.174	3.867	4.607
	$Set3_{precise}$	0.936	0.756	30.736	5.506	4.112	4.911
	$Set3_{fuzzy}$	0.941	0.765	28.610	5.310	3.965	4.721
	$Set4_{precise}$	0.942	0.758	27.841	5.210	3.875	4.612
	$Set4_{fuzzy}$	0.935	0.763	31.277	5.535	4.138	4.929
	$Set5_{precise}$	0.940	0.760	29.131	5.331	3.971	4.713
	$Set5_{fuzzy}$	0.938	0.765	30.079	5.418	4.035	4.804
AB	*Set1*	0.955	0.758	23.482	4.687	4.036	4.940
	$Set2_{precise}$	0.931	0.753	33.603	5.671	4.810	5.910
	$Set2_{fuzzy}$	0.942	0.756	28.226	5.008	4.124	5.025
	$Set3_{precise}$	0.938	0.752	29.988	5.180	4.370	5.371
	$Set3_{fuzzy}$	0.926	0.752	36.202	5.814	4.843	5.928
	$Set4_{precise}$	0.942	0.749	28.430	5.117	4.333	5.324
	$Set4_{fuzzy}$	0.940	0.753	29.483	5.111	4.246	5.189
	$Set5_{precise}$	0.953	0.759	22.810	4.475	3.728	4.565
	$Set5_{fuzzy}$	0.952	0.763	23.416	4.491	3.657	4.450
GB	*Set1*	0.987	0.764	6.570	2.238	1.633	1.893
	$Set2_{precise}$	0.942	0.725	27.933	4.962	3.778	4.485
	$Set2_{fuzzy}$	0.943	0.750	27.623	5.067	3.856	4.569
	$Set3_{precise}$	0.962	0.743	18.367	3.776	2.825	3.330
	$Set3_{fuzzy}$	0.963	0.753	18.109	3.775	2.839	3.361
	$Set4_{precise}$	0.951	0.730	23.216	4.268	3.205	3.816
	$Set4_{fuzzy}$	0.960	0.743	19.340	4.084	3.115	3.716
	$Set5_{precise}$	0.946	0.741	26.335	4.731	3.567	4.221
	$Set5_{fuzzy}$	0.953	0.761	22.634	4.487	3.474	4.054
XG	*Set1*	0.995	0.771	2.805	1.392	1.008	1.168
	$Set2_{precise}$	0.959	0.740	19.763	4.102	3.055	3.544
	$Set2_{fuzzy}$	0.958	0.742	20.247	3.983	3.016	3.505
	$Set3_{precise}$	0.953	0.734	22.403	4.236	3.177	3.695
	$Set3_{fuzzy}$	0.947	0.747	25.851	4.557	3.419	3.985
	$Set4_{precise}$	0.956	0.734	21.189	3.938	2.921	3.407
	$Set4_{fuzzy}$	0.947	0.742	25.472	4.665	3.576	4.195
	$Set5_{precise}$	0.950	0.743	24.275	4.412	3.404	3.978
	$Set5_{fuzzy}$	0.944	0.756	26.767	4.732	3.619	4.196
LB	*Set1*	0.989	0.755	5.857	2.183	1.652	1.924
	$Set2_{precise}$	0.942	0.722	28.076	4.938	3.764	4.463
	$Set2_{fuzzy}$	0.927	0.732	34.990	5.685	4.376	5.161
	$Set3_{precise}$	0.943	0.723	27.467	4.806	3.609	4.272
	$Set3_{fuzzy}$	0.945	0.728	26.553	4.756	3.628	4.271
	$Set4_{precise}$	0.937	0.723	30.701	5.313	4.035	4.803
	$Set4_{fuzzy}$	0.940	0.720	28.687	5.168	3.921	4.654
	$Set5_{precise}$	0.937	0.738	30.654	5.365	3.983	4.713
	$Set5_{fuzzy}$	0.931	0.741	33.492	5.687	4.279	5.080
SVM	*Set1*	0.861	0.784	73.082	8.540	6.365	7.156
	$Set2_{precise}$	0.861	0.792	66.834	8.149	6.039	6.934
	$Set2_{fuzzy}$	0.858	0.779	68.637	8.253	6.125	7.051
	$Set3_{precise}$	0.858	0.786	68.382	8.263	6.143	7.059
	$Set3_{fuzzy}$	0.854	0.782	70.155	8.367	6.227	7.172
	$Set4_{precise}$	0.859	0.789	68.027	8.237	6.119	7.043
	$Set4_{fuzzy}$	0.854	0.779	70.517	8.384	6.239	7.201
	$Set5_{precise}$	0.859	0.795	68.012	8.240	6.139	7.042
	$Set5_{fuzzy}$	0.857	0.791	68.653	8.279	6.145	7.050
ANN	*Set1*	0.869	0.781	68.911	8.290	6.391	7.296
	$Set2_{precise}$	0.829	0.744	83.006	8.767	6.810	8.060
	$Set2_{fuzzy}$	0.855	0.772	70.144	8.315	6.429	7.503
	$Set3_{precise}$	0.854	0.778	70.184	8.366	6.437	7.518
	$Set3_{fuzzy}$	0.846	0.780	73.937	8.593	6.608	7.710
	$Set4_{precise}$	0.832	0.751	80.837	8.611	6.638	7.968
	$Set4_{fuzzy}$	0.868	0.768	64.080	7.921	6.128	7.159
	$Set5_{precise}$	0.857	0.777	68.894	8.256	6.373	7.439
	$Set5_{fuzzy}$	0.826	0.755	83.604	8.970	6.959	8.300
Ridge	*Set1*	0.814	0.774	97.422	9.868	7.725	8.932
	$Set2_{precise}$	0.825	0.782	84.128	9.170	7.087	8.291
	$Set2_{fuzzy}$	0.824	0.778	84.830	9.208	7.104	8.321
	$Set3_{precise}$	0.830	0.784	81.939	9.050	6.993	8.192
	$Set3_{fuzzy}$	0.829	0.784	82.300	9.070	6.989	8.183
	$Set4_{precise}$	0.827	0.782	83.165	9.117	7.029	8.213
	$Set4_{fuzzy}$	0.826	0.779	83.945	9.160	7.068	8.272
	$Set5_{precise}$	0.827	0.785	83.282	9.124	7.022	8.215
	$Set5_{fuzzy}$	0.827	0.784	83.482	9.135	7.014	8.202
LASSO	*Set1*	0.814	0.773	97.552	9.875	7.711	8.917
	$Set2_{precise}$	0.825	0.781	84.185	9.173	7.100	8.309
	$Set2_{fuzzy}$	0.823	0.777	85.087	9.222	7.120	8.339
	$Set3_{precise}$	0.829	0.786	82.204	9.064	6.997	8.191
	$Set3_{fuzzy}$	0.828	0.785	82.832	9.099	7.002	8.184
	$Set4_{precise}$	0.827	0.785	83.345	9.127	7.044	8.235
	$Set4_{fuzzy}$	0.825	0.779	84.165	9.172	7.079	8.289
	$Set5_{precise}$	0.827	0.784	83.329	9.126	7.040	8.242
	$Set5_{fuzzy}$	0.826	0.783	83.567	9.139	7.031	8.226

In ML, some parameters' values need to be set prior to the learning process because they determine the structure of a ML model. These parameters are termed as *hyperparameters*. To maximize the performance of ML models, in the implementation of the above eleven ML models, it is necessary to adjust the corresponding hyperparameters according to the training dataset. Table A1 in Appendix lists the hyperparameters that need to be optimized for the eleven ML models. When experimenting with optimization approaches for hyperparameter optimization, the Bayesian Optimization (BO) method was identified as the best. In a preliminary study, we further experimented with the BO method based on tree-structured Parzen Estimators of hyperopt 0.2.2 library (*Hyperopt*) (Bergstra et al., 2013), the BO method based on extra trees regressor of scikit-optimize 0.7.4 library (*Skopt*), and the multi-step grid search method of scikit-learn 0.22.1 library (*Msgs*). Showing superior accuracy and least time consumption, Hyperopt was finally selected as the method of optimizing model hyperparameters. See Fig. 2A in Appendix.

Performance metrics that gauge the fit performances of ML models are defined in the following over the training set. The R^2 value over the test set, referred to as R^2 (test), is used to measure the generalization performance of a ML model.

$$R^2 = 1 - \frac{\sum_{t=1}^{k}\left(y_t - y_t\right)^2}{\sum_{t=1}^{k}\left(y_t - \overline{y}\right)^2} \tag{9}$$

$$MSE = \frac{1}{k}\sum_{t=1}^{k}\left(y_t - y_t\right)^2 \tag{10}$$

$$RMSE = \sqrt{\frac{1}{k}\sum_{t=1}^{k}\left(y_t - y_t\right)^2} \tag{11}$$

$$MAE = \frac{1}{k}\sum_{t=1}^{k}\left|y_t - y_t\right| \tag{12}$$

Table 6
Best performance of each machine learning model from nine datasets and the datasets that achieve the best performance. R^2 (with two decimal places) is considered as the first priority, and R^2 (test) (with two decimal places) is the secondary performance metric.

Ship	Model	Best R^2	Best R^2 (test)	Datasets
S1	DT	0.85	0.64	*Set1*
	ET	0.99	0.78	*Set1*
	RF	0.96	0.76	*Set1*
	AB	0.96	0.76	*Set1*
	GB	0.99	0.76	*Set1*
	XG	1.00	0.77	*Set1*
	LB	0.99	0.76	*Set1*
	SVM	0.86	0.80	$Set5_{precise}$
	ANN	0.87	0.78	*Set1*
	Ridge	0.83	0.79	$Set5_{precise}$
	LASSO	0.83	0.79	$Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$,
S2	DT	0.87	0.61	$Set2_{fuzzy}$
	ET	0.98	0.76	$Set4_{precise}$,
	RF	0.96	0.77	*Set1*
	AB	0.98	0.74	$Set4_{precise}$,
	GB	0.99	0.76	$Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$
	XG	0.99	0.77	$Set3_{precise}$
	LB	0.98	0.75	$Set3_{precise}$
	SVM	0.87	0.81	$Set2_{precise}$, $Set4_{precise}$, $Set4_{fuzzy}$
	ANN	0.91	0.80	$Set2_{precise}$, $Set4_{precise}$, $Set5_{precise}$
	Ridge	0.83	0.80	$Set3_{precise}$, $Set4_{precise}$
	LASSO	0.82	0.80	$Set2_{precise}$, $Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
S3	DT	0.87	0.7	$Set5_{precise}$
	ET	0.99	0.82	$Set3_{precise}$, $Set3_{fuzzy}$, $Set5_{fuzzy}$
	RF	0.96	0.81	$Set2_{precise}$, $Set5_{precise}$, $Set5_{fuzzy}$,
	AB	1.00	0.81	$Set4_{precise}$
	GB	0.98	0.82	$Set5_{precise}$
	XG	0.96	0.81	$Set3_{precise}$, $Set3_{fuzzy}$
	LB	0.96	0.81	$Set5_{precise}$
	SVM	0.85	0.82	$Set3_{fuzzy}$
	ANN	0.87	0.81	$Set2_{precise}$, $Set5_{precise}$
	Ridge	0.80	0.80	$Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$
	LASSO	0.80	0.80	$Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$
S4	DT	0.93	0.77	$Set4_{fuzzy}$
	ET	1.00	0.88	$Set5_{precise}$
	RF	0.98	0.86	$Set2_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
	AB	0.99	0.87	$Set3_{precise}$, $Set3_{fuzzy}$
	GB	0.99	0.87	$Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
	XG	1.00	0.87	$Set3_{precise}$
	LB	0.99	0.87	$Set5_{precise}$, $Set5_{fuzzy}$
	SVM	0.92	0.86	$Set3_{precise}$, $Set4_{precise}$, $Set5_{precise}$, $Set5_{fuzzy}$
	ANN	0.95	0.86	$Set3_{precise}$, $Set3_{fuzzy}$
	Ridge	0.83	0.82	*Set1*
	LASSO	0.83	0.81	$Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
S5	DT	0.95	0.8	$Set3_{fuzzy}$
	ET	1.00	0.90	*Set1*
	RF	0.98	0.88	*Set1*, $Set2_{fuzzy}$, $Set3_{fuzzy}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
	AB	1.00	0.89	$Set3_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
	GB	1.00	0.89	$Set2_{precise}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$
	XG	0.99	0.89	*Set1*, $Set3_{fuzzy}$, $Set5_{fuzzy}$
	LB	0.99	0.88	*Set1*, $Set3_{fuzzy}$, $Set5_{fuzzy}$
	SVM	0.93	0.88	*Set1*
	ANN	0.94	0.88	$Set2_{precise}$, $Set3_{precise}$, $Set4_{precise}$
	Ridge	0.89	0.88	$Set5_{fuzzy}$
	LASSO	0.89	0.87	$Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$
S6	DT	0.85	0.53	$Set4_{precise}$
	ET	0.99	0.77	*Set1*
	RF	0.96	0.77	*Set1*
	AB	0.98	0.76	$Set3_{precise}$
	GB	0.97	0.79	*Set1*
	XG	0.97	0.79	*Set1*
	LB	0.96	0.75	$Set3_{precise}$, $Set5_{precise}$, $Set5_{fuzzy}$
	SVM	0.85	0.77	$Set2_{precise}$
	ANN	0.88	0.76	$Set5_{precise}$,
	Ridge	0.78	0.75	$Set3_{precise}$
	LASSO	0.77	0.75	$Set3_{fuzzy}$
S7	DT	0.88	0.69	$Set5_{precise}$,
	ET	0.99	0.81	$Set3_{precise}$
	RF	0.97	0.80	$Set5_{precise}$, $Set5_{fuzzy}$
	AB	0.99	0.78	$Set4_{fuzzy}$, $Set5_{fuzzy}$
	GB	0.99	0.79	$Set3_{precise}$
	XG	0.99	0.78	$Set3_{precise}$
	LB	0.98	0.79	$Set3_{precise}$, $Set5_{fuzzy}$
	SVM	0.91	0.79	*Set1*
	ANN	0.90	0.77	$Set2_{precise}$, $Set4_{precise}$,
	Ridge	0.82	0.76	$Set2_{precise}$, $Set2_{fuzzy}$, $Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
	LASSO	0.82	0.76	$Set2_{precise}$, $Set2_{fuzzy}$, $Set3_{precise}$, $Set3_{fuzzy}$, $Set4_{precise}$, $Set4_{fuzzy}$, $Set5_{precise}$, $Set5_{fuzzy}$
S8	DT	0.92	0.77	*Set1*, $Set3_{precise}$
	ET	1.00	0.88	*Set1*, $Set3_{precise}$, $Set5_{precise}$, $Set5_{fuzzy}$
	RF	0.98	0.86	*Set1*, $Set3_{precise}$, $Set5_{precise}$, $Set5_{fuzzy}$
	AB	1.00	0.87	$Set5_{fuzzy}$
	GB	1.00	0.86	$Set3_{fuzzy}$
	XG	1.00	0.85	$Set3_{fuzzy}$
	LB	0.98	0.87	*Set1*
	SVM	0.91	0.87	$Set3_{precise}$, $Set4_{precise}$, $Set5_{precise}$
	ANN	0.92	0.86	$Set3_{precise}$, $Set4_{precise}$, $Set5_{precise}$
	Ridge	0.88	0.86	$Set5_{precise}$
	LASSO	0.88	0.85	$Set3_{precise}$, $Set4_{precise}$, $Set5_{precise}$

$$MAPE = \frac{100\%}{k} \sum_{t=1}^{k} \left| \frac{y_t - \hat{y}_t}{y_t} \right| \tag{13}$$

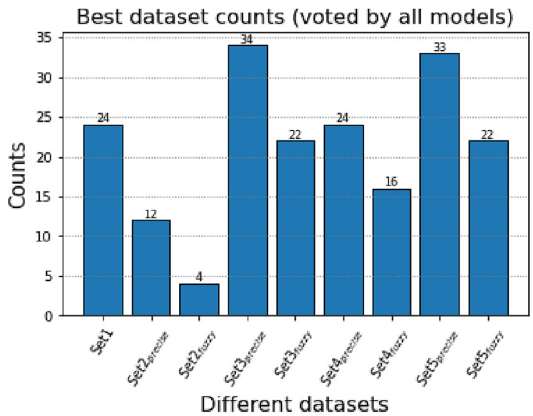
where y_t is the target value – actual ship fuel consumption rate (ton/day); $\hat{y}_t$ is the predicted output value - predicted ship fuel consumption (ton/day); $\overline{y}$ is the average of target values – average of actual ship fuel consumption rate (ton/day); k is the number of samples in the data set.

6. Experimental results and discussion

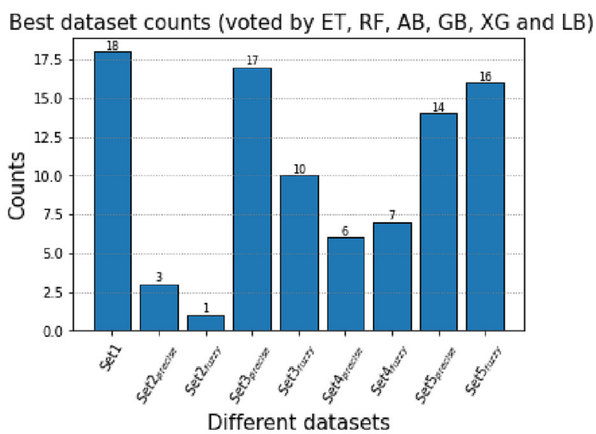
6.1. Performances of eleven ML models over nine datasets and selection of the best datasets

To evaluate the model performance as comprehensively as possible, each of nine datasets of each ship (for instance, *Set1* of ship S1) is randomly divided into two subsets, where the training set contains 80% of the data entries, and the test set contains 20% of the data entries. The training set is used for model hyperparameter optimization and model fitting, and the test set is used to assess the generalization performance of the model. On the training set, *Hyperopt*, a Bayesian optimization method, is used to optimize model hyperparameters, and the optimization objective is to maximize the R^2 value of *five-fold cross-validation*.

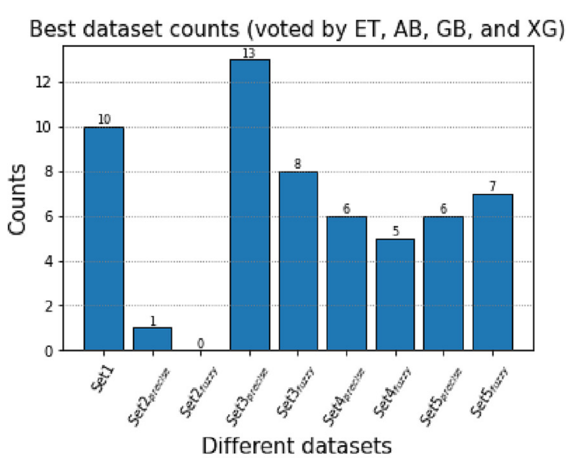
To obtain statistical comparison results and ensure the robustness of the comparison results, the random split of each dataset of each ship (for instance, *Set1* of ship S1) into a training set and a test set is conducted 20 times. For instance, *Set1* of ship S1 has 20 different splits of training set and test set. For each random split, the hyperparameters of the ML model under investigation are re-optimized and a model with the best hyperparameter values is trained. Therefore, 20 random splits of a dataset necessitate 20 runs of hyperparameter optimization and model training, resulting in 20 trained models (the same type of ML model with different hyperparameter values). The average performance of the 20 runs (trained models) is taken as the final result for model evaluation to eliminate the impact of disturbance caused by randomness in dataset division/split. The values of performance metrics of eleven ML models over nine datasets for ship S1 are tabulated in Table 5. As stated above, the figure in each cell of Table 5 is the average result of 20 runs corresponding to 20 random splits of the dataset. For instance, R^2 of the model DT over the dataset *Set1*, 0.846, is the average of 20 R^2 values



(a) Best dataset counts (voted by all models)



(b) Best dataset counts (voted by ET, RF, AB, GB, XG and LB)



(c) Best dataset counts (voted by ET, AB, GB, and XG)

Fig. 4. Best datasets voted by machine learning models.

Table 7
The performance of eleven machine learning models over dataset $Set3_{precise}$.

Ship	Model	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
S1	DT	0.847	0.617	73.848	8.532	6.522	7.697
	ET	0.965	0.762	17.043	3.524	2.699	3.245
	RF	0.936	0.756	30.736	5.506	4.112	4.911
	AB	0.938	0.752	29.988	5.180	4.370	5.371
	GB	0.962	0.743	18.367	3.776	2.825	3.330
	XG	0.953	0.734	22.403	4.236	3.177	3.695
	LB	0.943	0.723	27.467	4.806	3.609	4.272
	SVM	0.858	0.786	68.382	8.263	6.143	7.059
	ANN	0.854	0.778	70.184	8.366	6.437	7.518
	Ridge	0.830	0.784	81.939	9.050	6.993	8.192
	LASSO	0.829	0.786	82.204	9.064	6.997	8.191
S2	DT	0.820	0.589	112.089	10.461	7.916	9.230
	ET	0.974	0.765	15.842	3.377	2.445	2.780
	RF	0.950	0.740	31.494	5.541	4.007	4.662
	AB	0.961	0.743	24.755	4.778	4.073	4.729
	GB	0.992	0.760	5.008	1.817	1.234	1.378
	XG	0.991	0.765	5.421	1.949	1.186	1.277
	LB	0.980	0.748	12.589	3.053	2.179	2.442
	SVM	0.864	0.812	84.860	9.176	6.608	7.210
	ANN	0.908	0.791	56.693	7.365	5.581	6.171
	Ridge	0.826	0.802	108.847	10.429	8.011	9.055
	LASSO	0.824	0.796	110.162	10.492	8.034	9.042
S3	DT	0.865	0.684	98.572	9.705	7.042	8.343
	ET	0.985	0.821	10.758	2.846	1.716	2.181
	RF	0.956	0.802	31.781	5.576	3.587	4.463
	AB	0.991	0.812	6.328	2.183	1.712	1.998
	GB	0.964	0.819	26.559	4.694	2.836	3.642
	XG	0.961	0.810	28.714	5.030	3.052	3.828
	LB	0.947	0.804	38.795	5.845	3.853	4.853
	SVM	0.844	0.820	113.000	10.591	6.627	8.167
	ANN	0.874	0.798	91.583	9.475	6.480	7.992
	Ridge	0.801	0.796	144.061	11.987	8.329	10.615
	LASSO	0.799	0.796	145.425	12.043	8.323	10.619
S4	DT	0.916	0.746	68.063	8.094	6.036	6.523
	ET	0.998	0.872	1.434	0.901	0.627	0.687
	RF	0.975	0.853	20.349	4.497	3.331	3.618
	AB	0.986	0.865	11.021	3.144	2.591	2.905
	GB	0.989	0.866	8.845	2.500	1.838	1.957
	XG	0.995	0.869	3.758	1.585	1.140	1.201
	LB	0.987	0.855	10.943	2.871	2.200	2.340
	SVM	0.921	0.857	63.718	7.972	5.848	6.146
	ANN	0.947	0.856	42.555	6.513	5.034	5.502
	Ridge	0.833	0.811	135.334	11.629	9.033	9.406
	LASSO	0.832	0.809	135.961	11.656	9.053	9.417
S5	DT	0.947	0.785	29.488	5.182	3.764	5.625
	ET	0.997	0.892	1.413	0.854	0.619	0.935
	RF	0.981	0.874	10.498	3.225	2.390	3.663
	AB	0.995	0.886	2.543	1.525	1.209	2.217
	GB	0.993	0.887	3.519	1.359	1.021	1.610
	XG	0.993	0.878	3.601	1.605	1.133	1.749
	LB	0.987	0.873	7.382	2.350	1.758	2.725
	SVM	0.916	0.873	46.421	6.785	4.917	7.472
	ANN	0.935	0.879	36.157	5.956	4.544	7.075
	Ridge	0.889	0.868	61.610	7.846	5.934	9.109
	LASSO	0.888	0.868	61.988	7.870	5.953	9.129
S6	DT	0.832	0.576	69.684	8.275	6.119	8.113
	ET	0.979	0.752	8.706	2.743	2.010	2.678
	RF	0.953	0.740	19.498	4.382	3.173	4.211
	AB	0.980	0.755	8.175	2.647	2.186	3.210
	GB	0.971	0.770	11.917	3.111	2.384	3.226
	XG	0.959	0.771	17.299	3.835	2.890	3.902
	LB	0.963	0.754	15.520	3.514	2.682	3.646
	SVM	0.843	0.767	65.144	8.045	5.755	7.629
	ANN	0.859	0.772	58.184	7.599	5.750	7.603
	Ridge	0.775	0.745	93.218	9.652	7.454	9.977
	LASSO	0.774	0.744	93.502	9.667	7.443	9.960
S7	DT	0.880	0.683	48.319	6.903	5.173	6.749
	ET	0.987	0.805	5.176	1.848	1.259	1.639
	RF	0.961	0.794	15.501	3.920	2.867	3.740
	AB	0.982	0.777	7.272	2.415	1.888	2.558
	GB	0.986	0.785	5.466	2.156	1.442	1.880
	XG	0.986	0.784	5.731	2.093	1.424	1.808

(continued on next page)

Table 7 (*continued*)

Ship	Model	R^2	R^2 (test)	MSE	RMSE (ton/ day)	MAE (ton/ day)	MAPE (%)
	LB	0.982	0.785	7.152	2.366	1.742	2.283
	SVM	0.871	0.748	51.533	7.113	5.173	6.591
	ANN	0.892	0.771	43.321	6.515	5.071	6.587
	Ridge	0.820	0.758	72.381	8.498	6.520	8.315
	LASSO	0.819	0.758	72.827	8.524	6.550	8.374
S8	DT	0.916	0.769	50.649	6.985	4.922	5.949
	ET	0.995	0.876	2.783	1.404	0.907	1.120
	RF	0.976	0.855	14.566	3.798	2.624	3.187
	AB	0.991	0.863	5.365	2.114	1.693	2.148
	GB	0.985	0.860	9.102	2.427	1.670	2.075
	XG	0.979	0.856	12.821	2.974	2.114	2.589
	LB	0.976	0.852	14.749	3.261	2.338	2.882
	SVM	0.910	0.869	54.154	7.349	5.117	6.123
	ANN	0.924	0.862	46.222	6.733	4.964	5.959
	Ridge	0.879	0.853	72.818	8.529	6.512	7.959
	LASSO	0.878	0.852	73.581	8.573	6.525	7.966

corresponding to 20 runs of the DT model over *Set1*. The fourth column of Table 5 (labelled as "R^2 (test)") is the R^2 values on the test set. The results for ships S2 to S8 can be found in Tables A2 to A8 in Appendix.

One may have been aware that performance of ML models and quality of datasets are interwoven together and the job of selecting the best datasets from the results of eleven ML models, nine datasets, and eight ships (shown in Table 5 and Tables A2 to A8) is overwhelming, not to mention the possible contrasts of R^2 values over the training set versus the test set. To overcome this, we develop a *voting scheme* to select the best datasets. In this scheme, every ML model is a voter and votes for the best datasets, by considering R^2 (with two decimal places) as the first priority and R^2 (test) (with two decimal places) as the secondary performance metric. The R^2 metric, rather than other metrics such as RMSE and MAE, is used because the purpose of this voting scheme is to find the best dataset (combination of independent variables) and R^2 measuring how well the selected independent variables explain the variation in the dependent variable fits this voting purpose the best. For instance, in Table 5 for ship S1, the DT model finds the best R^2 value with two decimal places at 0.85 which is achieved over datasets *Set1*, $Set3_{precise}$, $Set3_{fuzzy}$, and $Set4_{precise}$. Over these four datasets, it finds the best R^2 (test) with two decimal places at 0.64 which is achieved over *Set1*. Therefore, the DT model of ship S1 votes for *Set1* as the best dataset. Similarly, we allow other ML models to vote for their best datasets and apply this voting scheme to all the eight ships. Voting results are shown in Table 6. The number of votes received by each of nine datasets under investigation is shown in Fig. 4.

Fig. 4 is the Tally sheet that counts the votes received by each dataset: Fig. 4(a) considers all models as voters; Fig. 4(b) does not consider DT, SVM, ANN, Ridge, and LASSO as voters because their fit performances are significantly worse than ET, RF, AB, GB, XG and LB and thus will not be preferred by industry applications; Fig. 4(c) further removes RF and LB from the voter list because they are "*dominated*" by ET, AB, GB, or XG against both R^2 and R^2 (test). For instance, in Table 6, LB is dominated by ET because neither of R^2 and R^2 (test) of the LB model is better than the ET model.

It can be seen from Fig. 4 that $Set3_{precise}$ and *Set1* receive the largest numbers of votes from best models. $Set3_{precise}$ receives 34 votes from all

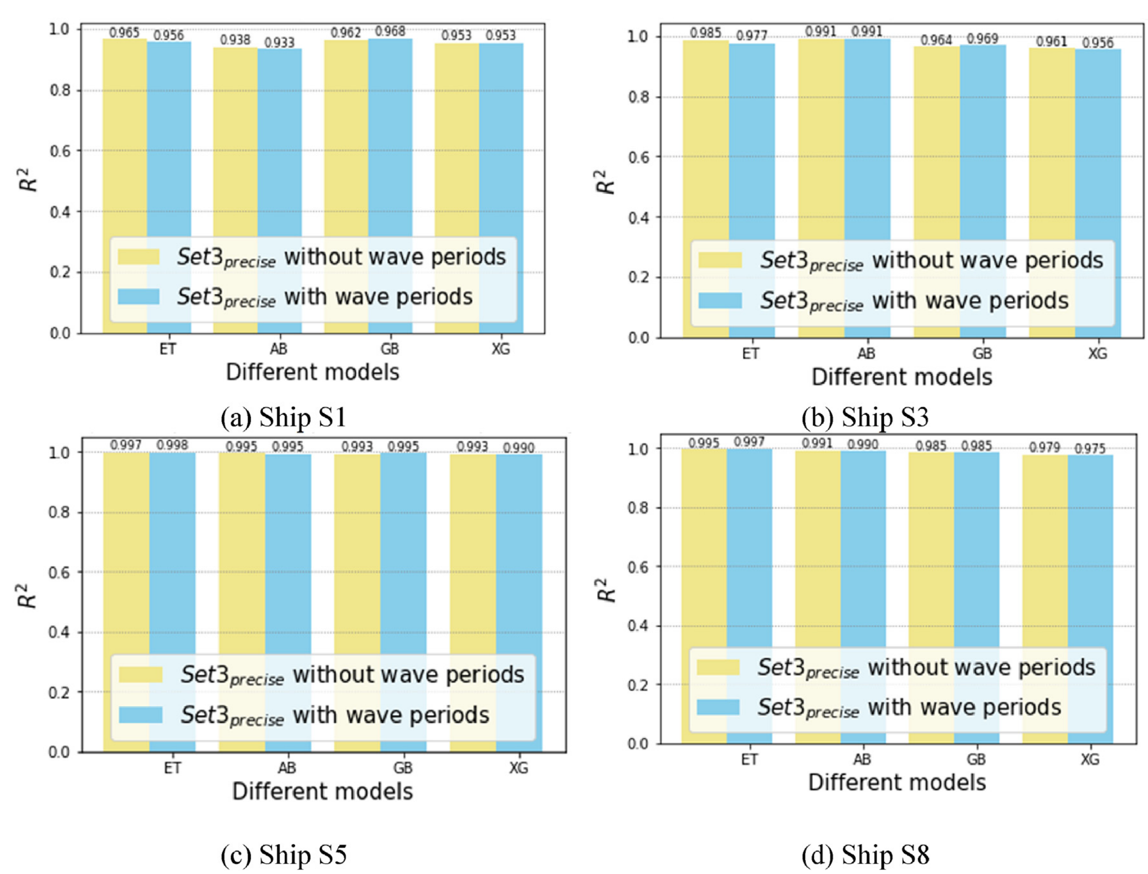


Fig. 5. Fit performance of four best models (ET, AB, GB, XG) over dataset $Set3_{precise}$ with and without wave period information.

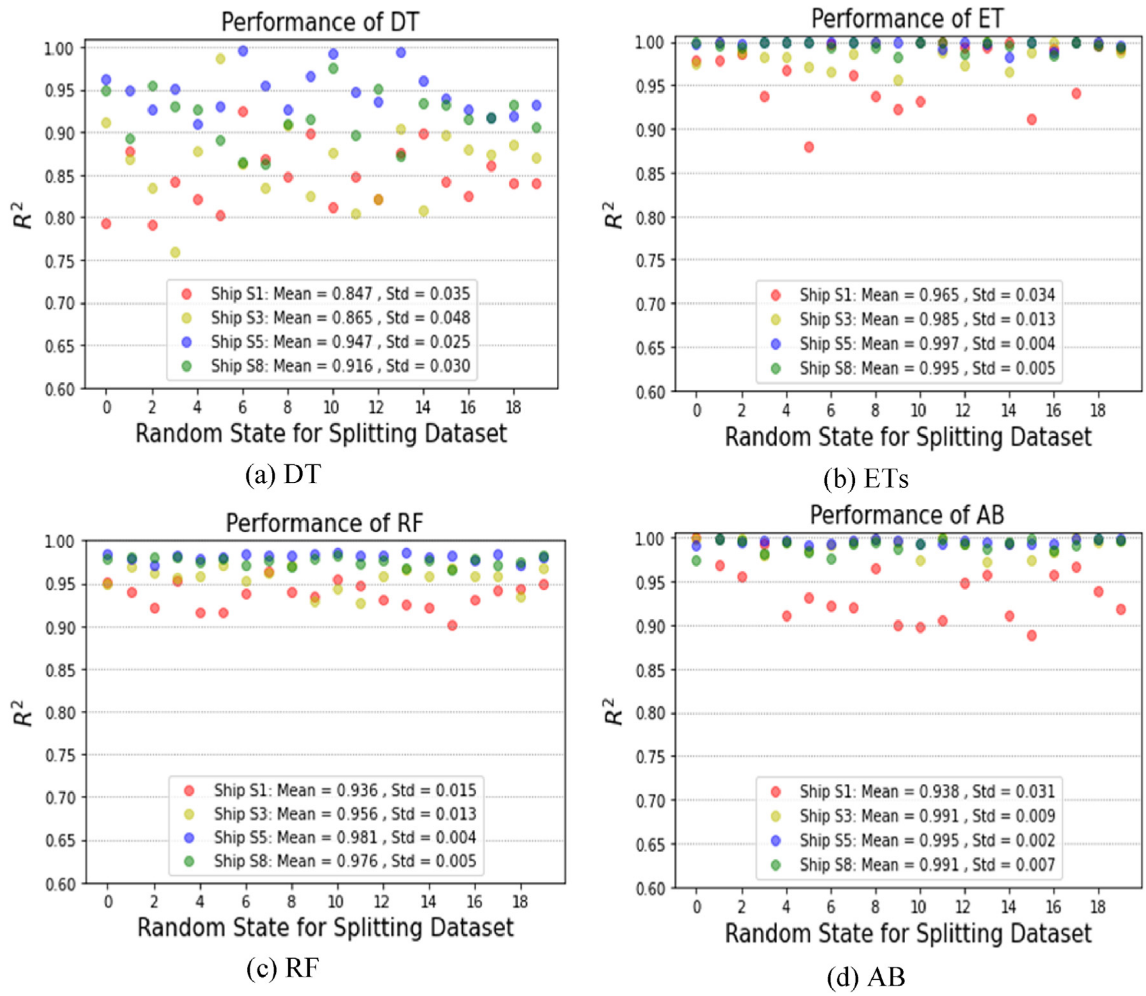


Fig. 6. R^2, mean and standard deviation of the models.

models, 17 votes from ET, RF, AB, GB, XG, and LB, and 13 votes from ET, AB, GB and XG. *Set1* receives 24 votes from all models, 18 votes from ET, RF, AB, GB, XG, and LB, and 10 votes from ET, AB, GB and XG. Therefore, it will be wise to choose $Set3_{precise}$ and *Set1* as the best datasets: $Set3_{precise}$ is the best; but the quality of the voyage report data *Set1* is also quite high. The advantage of $Set3_{precise}$ over *Set1* reveals the benefits of fusing/combining voyage report data and meteorological data.

6.2. Performance comparison of ML models

One may have found the performance differences of 11 ML models from Table 6. To further articulate the performances of these ML models over all the performance metrics, Table 7 is presented for the ML models over the best dataset $Set3_{precise}$.

Tables 6 and 7 both confirm that ET, RF, AB, GB, XG and LB are good candidate models that can be adopted by the shipping industry: their R^2 values over the best datasets are all above 0.96 and even reach the level of 0.99–1.00, while their R^2 performance over test data is in the range from 0.74 to 0.90. The remaining models, including DT, SVM, ANN, Ridge, and LASSO, are not recommended for industry applications because their R^2 values are usually below 0.90, while the values of performance metric R^2 over test data are not better or even worse than ET, RF, AB, GB, XG and LB.

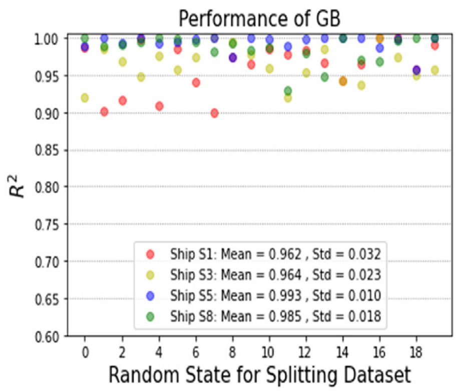
Further, the fit performances of RF and LB are usually slightly dominated by ET, AB, GB, and XG, against both R^2 and R^2 (test), which makes it safe for industry specialists to only install ET, AB, GB and XG into their machine learning model arsenal for ship energy efficiency modeling. Their fit errors on daily bunker fuel consumption, measured by RMSE and MAE, are usually between 0.5 and 4.0 ton/day, though fit errors might be over 4.0 ton/day occasionally if datasets are not carefully chosen.

The experimental results reported in Tables 6 and 7 also rank the performances of eleven machine learning models into four different tiers. The performances of the models in the same tier are quite close, while those of the models in different tiers are significantly different.

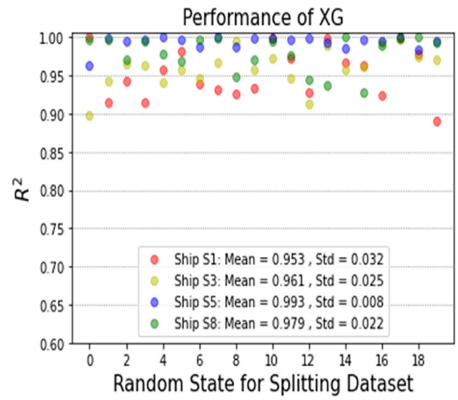
- Tier 1: ET, AB, GB, XG, and LB;
- Tier 2: RF;
- Tier 3: DT, SVM, ANN; and
- Tier 4: Ridge, LASSO.

6.3. Impact of wave periods

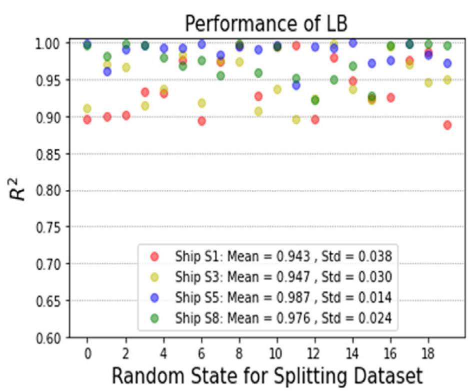
Wave period measures the time (in seconds) it takes for two



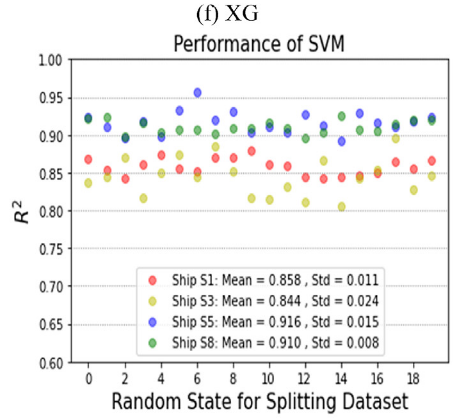
(e) GB



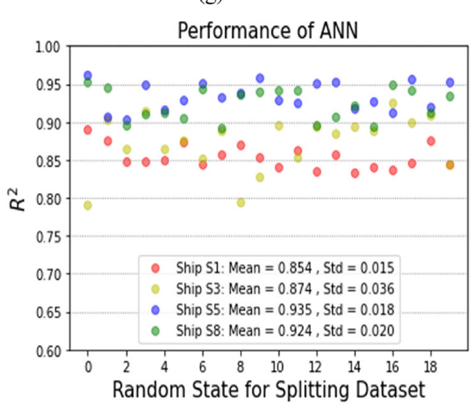
(f) XG



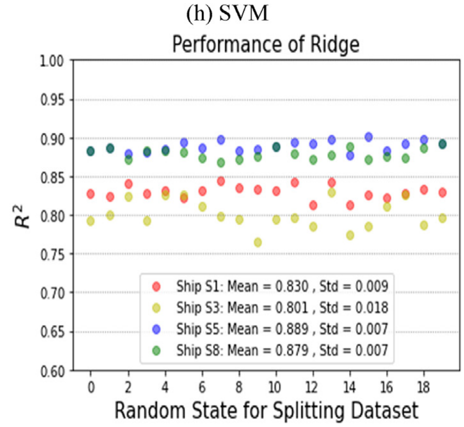
(g) LB



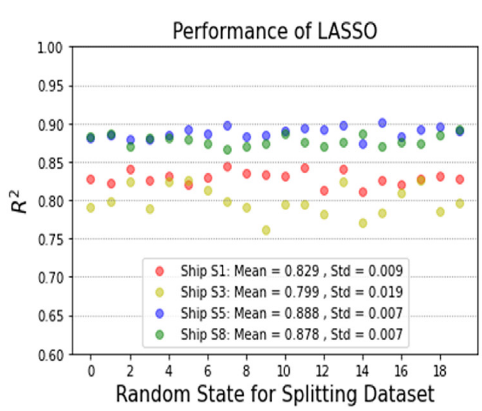
(h) SVM



(i) ANN



(j) Ridge



(k) LASSO

Fig. 6. (*continued*).

successive wave crests to pass a specific stationary point. A longer wave period means it takes more time for the next wave to come and indicates that stronger energy is contained in the waves traveling faster and deeper beneath the sea surface (Pecher and Kofoed, 2017). For instance, waves with a period of 16+ seconds are considered as powerful swells generated by distance storms. In principle, wave period has an impact on the resistance against a ship's movement at sea and thus on ship fuel consumption rate. However, none of the nine datasets under investigation so far considers the features about wave period. This is because our preliminary experiments found the triviality of wave period's impact on ship fuel consumption rate and excluding the features about wave period from consideration has enabled us to reduce the number of datasets experimented with to nine shown in Table 4.

To further assess whether the introduction of wave period information could improve the fit performance of ML models, we added the features about wave periods ("Swell period", "wind wave period", and "Combined wave period" in Table 4) into the best dataset $Set3_{precise}$, and re-experimented with four best models (ET, AB, GB, XG) for ships S1, S3, S5 and S8. Their fit performances over $Set3_{precise}$ with and without wave period information are shown in Fig. 5.

Fig. 5 indicates that including wave period information into models will not improve and even slightly reduce the fit performances of models. This might be explained by the fact that the impact of wave period on a mega containership's fuel efficiency at sea is negligible and adding it to models might introduce additional noises associated with its data. In another word, the impact of wave period on a big containership's fuel efficiency at sea could be covered by the random errors or noises of machine learning models, when voyage report data and meteorological data are used as the data sources.

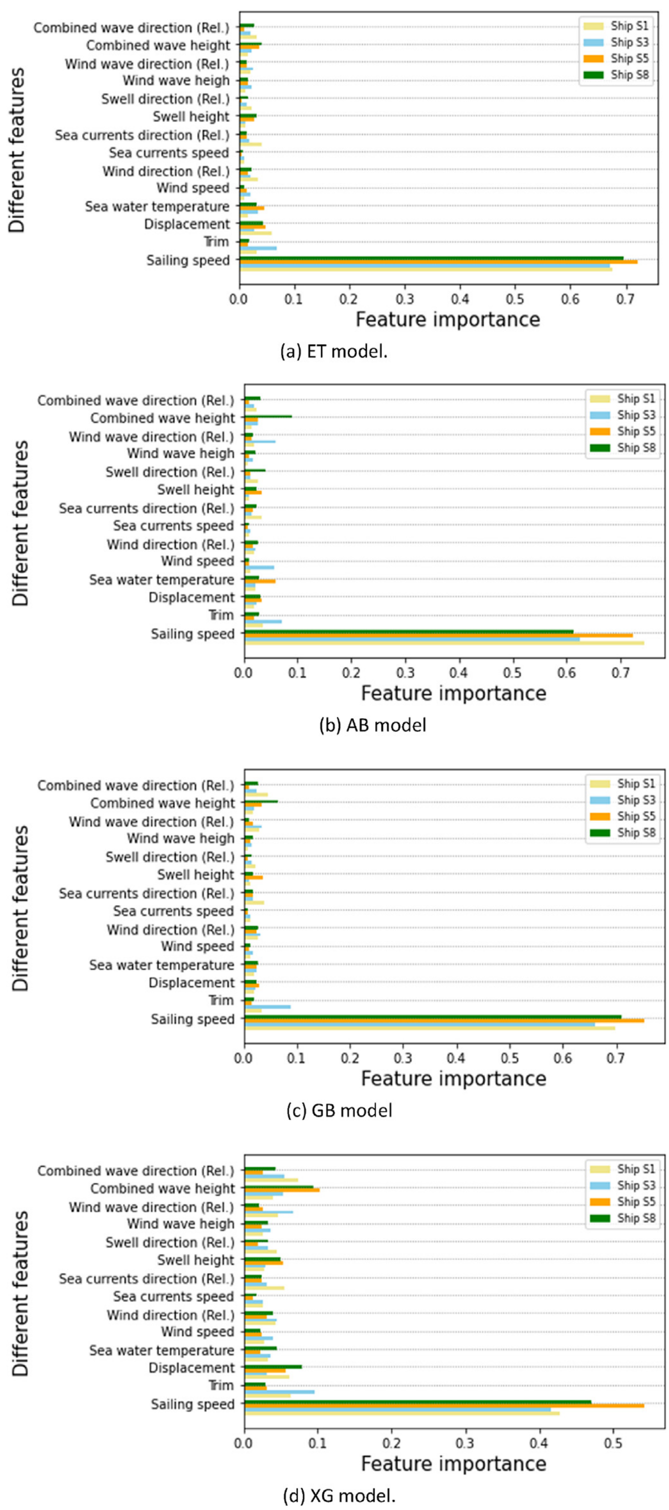


Fig. 7. The average relative importance of models input variables.

6.4. Robustness of ML models' performance

Sections 6.1 and 6.2 report the fit performance of eleven ML models, and the experiment result reported for each ML model over each dataset of each ship is based on the average of 20 runs corresponding to 20 random splits of the dataset into training set and test set. One may further ask a question 'do the fit performances of the models vary too much across the 20 runs?'. To answer this question about the robustness of ML models' performance against random splits of a dataset, we present the R^2 values of eleven ML models over the best dataset $Set3_{precise}$ for ships S1, S3, S5, and S8 in Fig. 6.

It can be seen from Fig. 6 that except DT, LB and ANN, the robustness of the remaining machine learning models is acceptable. RF possesses the highest robustness. The performances of the best models we recommended, including ET, AB, GB and XG, are robust enough for industry applications.

6.5. Relative importance of each determinant to ship fuel efficiency

Yan et al. (2021) point out that one of the major drawbacks of ML models is poor interpretability. However, one of the exceptions is that tree-based models possess the ability to quantitatively explain the relative importance of each input variable of the model to the dependant/output variable. The best ML models found by this study, including ET, AB, GB and XG, are all decision tree-based models. Therefore, we conducted the analyses of relative importance of each feature/determinant to ship fuel consumption rate, based on these four models over the best dataset $Set3_{precise}$ of ships S1, S3, S5 and S8, and collected the results in Fig. 7.

The Figs. 7(a)–7(c) reveal that sailing speed is the most important determinant of fuel consumption rate whose importance is between 0.6 and 0.8. This is consistent with the findings in ship propulsion theories.

Though displacement/draft is usually considered as the second important determinant in ship propulsion principles, such as the *Admiralty coefficient*, its impact on ship fuel efficiency at sea is basically lower than wave conditions if both swells and wind waves are considered. Apparently, the impact of displacement is significantly lower than the total impact of sea and weather conditions in shipping reality. This finding does not falsify the significant importance of displacement to ship fuel efficiency in calm waters, but ships eventually sail at sea with different weather and sea conditions rather than stay in calm waters.

When sea and weather conditions are considered, waves, consisting of swells and wind waves, play the most significant role. The impact of sea water temperature could be close to that of displacement/draft, which might be beyond the imagination of seafarers at sea. The impact of wind conditions (wind speed and direction) is close to that of sea water temperature and thus also close to the impact of displacement/draft. These results all confirm the importance of weather routing practice in saving bunker fuel and reducing ship emissions.

Seafarers at sea attach much importance to sea currents, but their impact on a ship's fuel efficiency in reality could be not comparable to other sea or weather conditions, such as waves, wind, or sea water temperature.

Trim's importance for ship fuel efficiency is usually less than 0.05 but sometimes can reach 0.1, which confirms the rationality of conducting trim optimization for ships. This result is consistent with that reported by the literature on trim optimization.

As shown in Fig. 7(d), compared to ET, AB, and GB, the XG model reduces the polarization of relative importance allocated to different variables. For instance, in XG's result, the importance of sailing speed decreases and that of weather and sea conditions increases. This could be related to the model structure of XG that introduces a regularization term to avoid overfitting and prevents one variable from attracting too much importance. This characteristic of XG model could have caused the inconsistence of its findings on relative importance of variables/features with other decision tree-based models such as ET, AB, and GB. Therefore, this study leans more on the consistent results of ET, AB and GB during the analysis towards feature importance.

7. Conclusions

Motivated by the data quality issue of voyage reports on weather and sea conditions caused by snapshotting and human eye inspection, this study fuses voyage report data and meteorological data, and constructs nine datasets from this data fusion solution. We experimented with these nine datasets and eleven widely-adopted ML models to quantify the relationship between a ship's bunker fuel consumption rate (MT/day, or MT/h) and its determinants, including sailing speed, displacement/draft, trim, wind, waves (swells and wind waves), sea currents, and sea water temperature, over eight 8,100-TEU to 14,000-TEU containerships from a global shipping company.

The best dataset we found, $Set3_{precise}$, reveals the benefits of fusing voyage report data and meteorological data and replacing the information of weather and sea conditions in voyage report by that from meteorological data. However, $Set3_{precise}$ is only sightly better than the original voyage report (*Set1*) which indicates that voyage report has rather acceptable (*hard-to-be-improved*) data quality for many application scenarios. This somewhat disapproves our industry collaborator's conjecture that retrieval of accurate information of weather and sea conditions from meteorological data sources would "*significantly*" improve the data quality for ship fuel efficiency analysis.

Among elven ML models, decision tree-based ensemble models, especially ET, AB, GB and XG, present the best fit and generalization performances. Their R^2 values over the best datasets are all above 0.96 and even reach the level of 0.99–1.00, while their R^2 performance over test data is in the range from 0.74 to 0.90. Their fit errors on daily bunker fuel consumption, measured by RMSE and MAE, are usually between 0.5 and 4.0 ton/day. Their performances against random divisions of the dataset into training and test sets are also quite robust. Therefore, it is safe for industry specialists to only install ET, AB, GB and XG into their machine learning model arsenal for ship energy efficiency analysis.

These four tree-based models are recommended also because of their ability to interpret the relative importance of different determinants/factors/features to a ship's fuel consumption rate. Our findings on the relative importance of sailing speed and trim are consistent with existing literature. However, all the tree-based models confirm that the impact of weather and sea conditions is significantly higher than that of the actual displacement/draft of a ship. This indicates the higher practical importance of weather routing studies compared to the studies that seek a sailing route of a ship to optimize its cargo load based on the Admiralty coefficient for the purpose of saving bunker fuel.

This is a pioneering study that combines several data sources to improve the accuracy of ship fuel consumption rate forecast targeting the industry applications in energy-efficient operational measures promoted by IMO, including speed optimization, trim optimization, weather routing, and the virtual arrival policy. The research scope/boundary discussed in Section 3 reflects our research limitations.

Replication and data sharing

Computer code in Python in this study is published in GitHub as a software infrastructure to reduce the exploration efforts of industry professionals. Best trained machine learning models are also published in GitHub, which enables maritime researchers to estimate the bunker fuel consumption rates of different sizes of mega containerships in different sailing speed, draft, trim and weather/sea conditions, though our raw data is confidential. The machine learning models published are completely black boxes, and one cannot conduct reverse engineering to access the original datasets. Readers can find the computer code and trained machine learning models in the URL: https://github.com/yuquandu/Data-driven-Ship-Fuel-Efficiency-Modeling.

Declaration of competing interest

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

Acknowledgements

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Appendix A

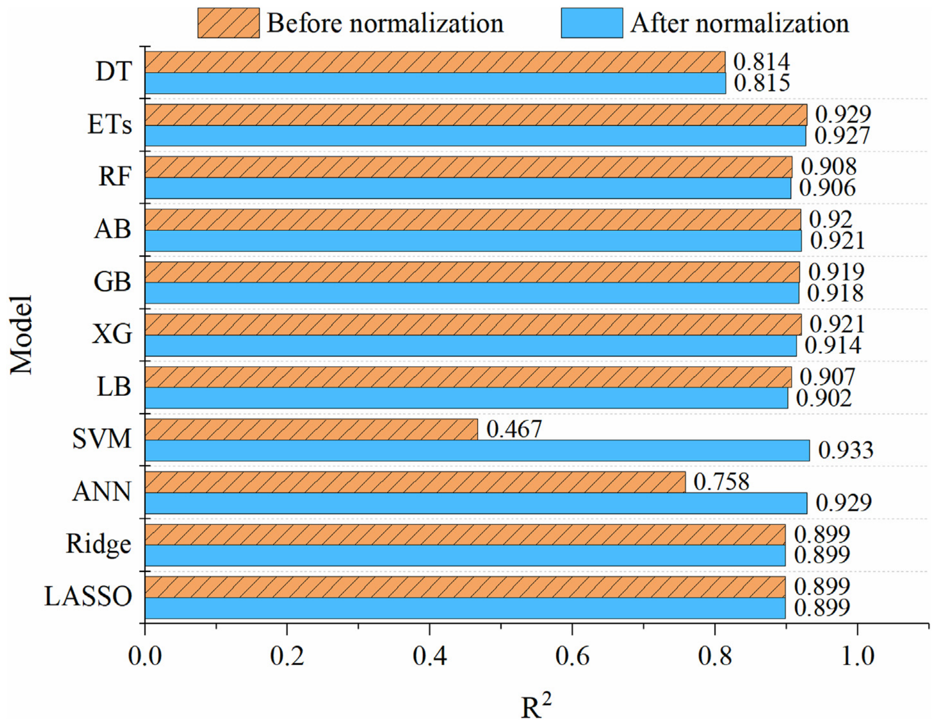
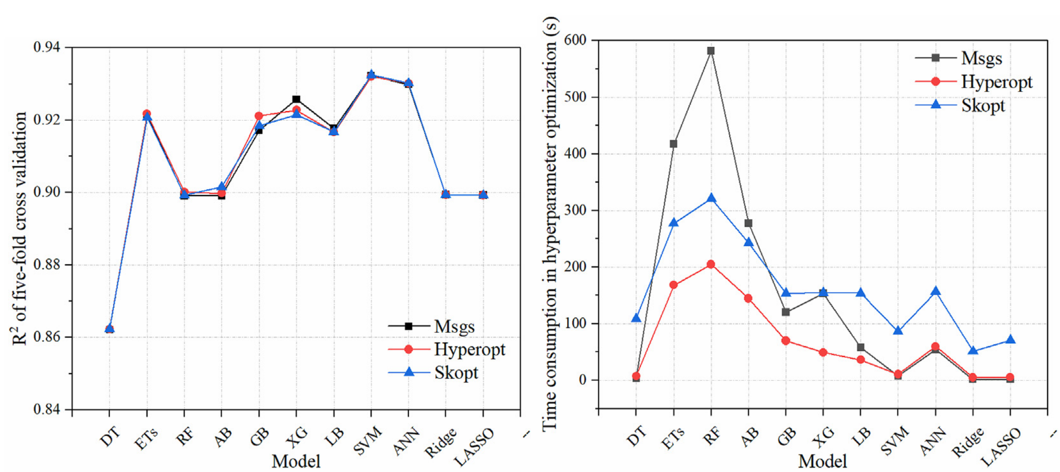


Fig. A1. The impact of data normalization on model performance of ship S5, over a dataset similar to $Set5_{precise}$ that was adopted in a preliminary study.



(a) R^2 (accuracy) comparison of hyperparameter optimization methods

(b) Time consumption comparison of hyperparameter optimization methods

Fig. A2. Comparison of three hyperparameter optimization methods for ship S8, over a dataset similar to $Set5_{precise}$ that was adopted in a preliminary study.

Table A1
Model hyperparameters to be optimized.

Model	Hyperparameters	Package/ Library	Package reference
DT	*max_depth* [2, 30], *min_samples_leaf* [1, 20], *min_samples_split* [2, 20], *max_features* [1, 15]	scikit-learn	scikit-learn, 2020
ETs	*max_depth* [2, 30], *min_samples_leaf* [1, 20], *min_samples_split* [2, 20], *max_features* [1, 15], *n_estimators* [10, 300]	scikit-learn	scikit-learn, 2020
RF	*max_depth* [2, 30], *min_samples_leaf* [1, 20], *min_samples_split* [2, 20], *max_features* [1, 15], *n_estimators* [10, 300]	scikit-learn	scikit-learn, 2020

(*continued on next column*)

Table A1 (*continued*)

Model	Hyperparameters	Package/ Library	Package reference
AB	*max_depth* [2, 10], *min_samples_leaf* [1, 20], *min_samples_split* [2, 20], *max_features* [1, 15], *n_estimators* [10, 300], *learning_rate* [0.00001, 1]	scikit-learn	scikit-learn, 2020
GB	*max_depth* [2, 10], *min_samples_leaf* [1, 20], *min_samples_split* [2, 20], *max_features* [1, 15], *n_estimators* [10, 300], *learning_rate* [0.00001, 1], *subsample* [0.4, 1]	scikit-learn	scikit-learn, 2020
XG	*max_depth* [2, 10], *n_estimators* [10, 300], *learning_rate* [0.00001, 1], *min_child_weight* [0, 10], *gamma* [0, 2], *colsample_bytree* [0.1, 1], *subsample* [0.4, 1], *reg_alpha* [0, 2], *reg_lambda* [0, 2]	XGBoost	XGBoost, 2020
LB	*max_depth* [2, 10], *n_estimators* [10, 300], *learning_rate* [0.00001, 1], *min_child_weight* [0, 10], *min_child_samples* [2, 100], *colsample_bytree* [0.1, 1], *subsample* [0.4, 1], *reg_alpha* [0, 2], *reg_lambda* [0, 2], *num_leaves* [5, 127], *min_split_gain* [0, 2]	LightGBM	LightGBM, 2020
SVM	*C* [0.00001, 100], *gamma* [0.00001, 1]	scikit-learn	scikit-learn, 2020
ANN	*Activation* [‘identity’, ‘tanh’, ‘logistic’, ‘relu’], *solver* [‘lbfgs’, ‘sgd’, ‘adam’], *alpha* [0.00001, 2], *learning_rate_init* [0.00001, 1], *beta_1* [0, 0.999], *beta_2* [0, 0.999]	scikit-learn	scikit-learn, 2020
Ridge	*alpha* [0, 10]	scikit-learn	scikit-learn, 2020
LASSO	*alpha* [0, 10]	scikit-learn	scikit-learn, 2020

Note: The brackets after the hyperparameter names list the value ranges of the hyperparameters.

Table A2
The fit performance of eleven machine learning models for ship S2.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	*Set1*	0.833	0.668	113.854	10.580	7.934	8.951
	$Set2_{precise}$	0.820	0.591	113.281	10.459	7.954	9.321
	$Set2_{fuzzy}$	0.871	0.612	80.754	8.724	6.480	7.612
	$Set3_{precise}$	0.820	0.589	112.089	10.461	7.916	9.230
	$Set3_{fuzzy}$	0.819	0.575	112.765	10.428	7.896	9.219
	$Set4_{precise}$	0.808	0.595	120.097	10.818	8.149	9.543
	$Set4_{fuzzy}$	0.814	0.591	116.912	10.691	8.068	9.324
	$Set5_{precise}$	0.823	0.615	110.287	10.266	7.739	9.008
	$Set5_{fuzzy}$	0.833	0.596	103.989	9.909	7.434	8.724
ET	*Set1*	0.971	0.786	19.857	4.055	2.986	3.306
	$Set2_{precise}$	0.960	0.755	24.360	4.399	3.253	3.686
	$Set2_{fuzzy}$	0.958	0.757	25.878	4.553	3.366	3.839
	$Set3_{precise}$	0.974	0.765	15.842	3.377	2.445	2.780
	$Set3_{fuzzy}$	0.970	0.763	18.735	3.789	2.711	3.086
	$Set4_{precise}$	0.977	0.764	14.537	3.128	2.237	2.530
	$Set4_{fuzzy}$	0.966	0.753	20.670	3.685	2.710	3.126
	$Set5_{precise}$	0.962	0.761	23.530	4.202	3.100	3.525
	$Set5_{fuzzy}$	0.973	0.759	16.740	3.553	2.608	2.959
RF	*Set1*	0.959	0.766	27.622	5.205	3.750	4.227
	$Set2_{precise}$	0.953	0.739	29.359	5.350	3.843	4.436
	$Set2_{fuzzy}$	0.957	0.744	26.791	5.118	3.763	4.381
	$Set3_{precise}$	0.950	0.740	31.494	5.541	4.007	4.662
	$Set3_{fuzzy}$	0.946	0.743	33.716	5.699	4.096	4.743
	$Set4_{precise}$	0.957	0.740	26.572	5.118	3.734	4.336
	$Set4_{fuzzy}$	0.947	0.743	33.116	5.695	4.054	4.702
	$Set5_{precise}$	0.953	0.739	29.568	5.382	3.900	4.537
	$Set5_{fuzzy}$	0.955	0.750	28.280	5.224	3.773	4.393
AB	*Set1*	0.968	0.762	21.779	4.305	3.609	4.143
	$Set2_{precise}$	0.964	0.732	22.762	4.602	3.941	4.548
	$Set2_{fuzzy}$	0.959	0.732	25.577	4.816	4.018	4.635
	$Set3_{precise}$	0.961	0.743	24.755	4.778	4.073	4.729
	$Set3_{fuzzy}$	0.962	0.739	23.645	4.672	3.976	4.617
	$Set4_{precise}$	0.978	0.739	13.828	3.528	2.989	3.464
	$Set4_{fuzzy}$	0.972	0.732	17.180	3.860	3.257	3.764
	$Set5_{precise}$	0.970	0.735	18.789	4.114	3.503	4.068
	$Set5_{fuzzy}$	0.972	0.737	17.302	3.979	3.369	3.948
GB	*Set1*	0.964	0.781	24.457	4.564	3.429	3.793
	$Set2_{precise}$	0.984	0.756	10.221	2.615	1.849	2.072
	$Set2_{fuzzy}$	0.987	0.750	8.325	2.190	1.584	1.767
	$Set3_{precise}$	0.992	0.760	5.008	1.817	1.234	1.378
	$Set3_{fuzzy}$	0.985	0.762	9.472	2.472	1.716	1.938
	$Set4_{precise}$	0.990	0.763	6.143	1.963	1.364	1.529
	$Set4_{fuzzy}$	0.990	0.755	6.254	1.885	1.401	1.570
	$Set5_{precise}$	0.975	0.747	15.364	3.270	2.336	2.634
	$Set5_{fuzzy}$	0.976	0.756	14.869	3.182	2.389	2.720
XG	*Set1*	0.975	0.781	16.733	3.503	2.631	2.868
	$Set2_{precise}$	0.985	0.759	9.566	2.542	1.691	1.837
	$Set2_{fuzzy}$	0.990	0.755	6.058	2.038	1.246	1.328
	$Set3_{precise}$	0.991	0.765	5.421	1.949	1.186	1.277
	$Set3_{fuzzy}$	0.982	0.759	11.047	3.003	1.792	1.921
	$Set4_{precise}$	0.984	0.770	10.314	2.587	1.638	1.760

(continued on next column)

Table A2 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set4_{fuzzy}$	0.988	0.761	7.480	2.197	1.362	1.457
	$Set5_{precise}$	0.967	0.754	21.190	4.015	2.689	2.956
	$Set5_{fuzzy}$	0.977	0.755	14.591	3.195	2.170	2.360
LB	$Set1$	0.946	0.761	36.850	5.784	4.429	4.834
	$Set2_{precise}$	0.981	0.736	11.640	2.940	2.158	2.384
	$Set2_{fuzzy}$	0.981	0.727	12.277	3.145	2.224	2.455
	$Set3_{precise}$	0.980	0.748	12.589	3.053	2.179	2.442
	$Set3_{fuzzy}$	0.982	0.741	11.425	3.003	2.145	2.400
	$Set4_{precise}$	0.975	0.753	15.660	3.469	2.582	2.863
	$Set4_{fuzzy}$	0.976	0.737	14.911	3.522	2.568	2.839
	$Set5_{precise}$	0.974	0.724	16.238	3.488	2.447	2.769
	$Set5_{fuzzy}$	0.971	0.731	18.560	3.787	2.594	2.943
SVM	$Set1$	0.848	0.797	103.306	10.147	7.260	7.779
	$Set2_{precise}$	0.868	0.812	82.693	9.063	6.443	7.021
	$Set2_{fuzzy}$	0.868	0.802	82.818	9.066	6.404	7.072
	$Set3_{precise}$	0.864	0.812	84.860	9.176	6.608	7.210
	$Set3_{fuzzy}$	0.871	0.799	81.178	8.918	6.364	7.014
	$Set4_{precise}$	0.870	0.814	81.122	8.974	6.442	7.034
	$Set4_{fuzzy}$	0.870	0.808	81.347	8.990	6.402	7.062
	$Set5_{precise}$	0.859	0.807	88.173	9.339	6.736	7.391
	$Set5_{fuzzy}$	0.867	0.795	83.747	9.040	6.466	7.202
ANN	$Set1$	0.876	0.787	84.367	9.093	6.935	7.682
	$Set2_{precise}$	0.907	0.800	57.855	7.489	5.695	6.295
	$Set2_{fuzzy}$	0.897	0.789	64.406	7.958	6.055	6.742
	$Set3_{precise}$	0.908	0.791	56.693	7.365	5.581	6.171
	$Set3_{fuzzy}$	0.893	0.803	67.203	8.110	6.127	6.837
	$Set4_{precise}$	0.908	0.803	56.949	7.439	5.643	6.227
	$Set4_{fuzzy}$	0.892	0.805	67.986	8.160	6.176	6.905
	$Set5_{precise}$	0.909	0.798	56.575	7.417	5.624	6.182
	$Set5_{fuzzy}$	0.893	0.787	66.436	8.051	6.101	6.783
Ridge	$Set1$	0.822	0.786	121.419	11.016	8.454	9.312
	$Set2_{precise}$	0.820	0.801	112.767	10.614	8.029	9.059
	$Set2_{fuzzy}$	0.813	0.791	116.890	10.806	8.083	9.148
	$Set3_{precise}$	0.826	0.802	108.847	10.429	8.011	9.055
	$Set3_{fuzzy}$	0.823	0.798	110.559	10.511	8.004	9.066
	$Set4_{precise}$	0.825	0.803	109.502	10.460	8.011	9.081
	$Set4_{fuzzy}$	0.821	0.798	112.098	10.584	8.023	9.111
	$Set5_{precise}$	0.821	0.804	112.183	10.587	8.050	9.089
	$Set5_{fuzzy}$	0.815	0.796	115.730	10.753	8.099	9.178
LASSO	$Set1$	0.822	0.785	121.508	11.020	8.471	9.331
	$Set2_{precise}$	0.819	0.798	113.218	10.635	8.023	9.028
	$Set2_{fuzzy}$	0.811	0.786	117.999	10.857	8.090	9.146
	$Set3_{precise}$	0.824	0.796	110.162	10.492	8.034	9.042
	$Set3_{fuzzy}$	0.821	0.797	112.336	10.595	8.043	9.099
	$Set4_{precise}$	0.824	0.800	110.115	10.490	8.007	9.039
	$Set4_{fuzzy}$	0.820	0.795	112.895	10.621	8.032	9.095
	$Set5_{precise}$	0.820	0.801	112.578	10.606	8.047	9.060
	$Set5_{fuzzy}$	0.815	0.796	115.774	10.755	8.086	9.150

Table A3
The fit performance of eleven machine learning models for ship S3.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	$Set1$	0.857	0.684	105.672	10.125	7.259	8.643
	$Set2_{precise}$	0.853	0.713	107.107	10.167	7.422	8.762
	$Set2_{fuzzy}$	0.845	0.700	112.697	10.432	7.586	9.080
	$Set3_{precise}$	0.865	0.684	98.572	9.705	7.042	8.343
	$Set3_{fuzzy}$	0.868	0.692	95.656	9.586	6.903	8.258
	$Set4_{precise}$	0.864	0.694	99.016	9.741	7.126	8.471
	$Set4_{fuzzy}$	0.874	0.678	90.962	9.304	6.662	7.963
	$Set5_{precise}$	0.870	0.701	94.794	9.586	6.956	8.295
	$Set5_{fuzzy}$	0.858	0.695	102.704	9.931	7.215	8.621
ET	$Set1$	0.977	0.800	17.021	3.911	2.462	2.964
	$Set2_{precise}$	0.973	0.821	19.352	3.820	2.270	2.890
	$Set2_{fuzzy}$	0.969	0.820	22.459	4.479	2.719	3.433
	$Set3_{precise}$	0.985	0.821	10.758	2.846	1.716	2.181
	$Set3_{fuzzy}$	0.986	0.818	10.342	2.391	1.438	1.823
	$Set4_{precise}$	0.975	0.821	18.085	3.943	2.304	2.928
	$Set4_{fuzzy}$	0.976	0.819	17.269	3.827	2.328	2.940
	$Set5_{precise}$	0.984	0.830	11.712	2.940	1.661	2.141
	$Set5_{fuzzy}$	0.985	0.824	11.150	2.920	1.767	2.250
RF	$Set1$	0.960	0.768	29.573	5.369	3.497	4.234
	$Set2_{precise}$	0.959	0.809	29.986	5.388	3.453	4.290
	$Set2_{fuzzy}$	0.963	0.801	27.032	5.170	3.369	4.169

(continued on next column)

Table A3 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set3_{precise}$	0.956	0.802	31.781	5.576	3.587	4.463
	$Set3_{fuzzy}$	0.952	0.805	34.613	5.786	3.654	4.563
	$Set4_{precise}$	0.959	0.804	29.892	5.406	3.491	4.325
	$Set4_{fuzzy}$	0.952	0.802	34.739	5.778	3.694	4.603
	$Set5_{precise}$	0.958	0.812	30.199	5.441	3.473	4.321
	$Set5_{fuzzy}$	0.959	0.806	29.588	5.388	3.409	4.241
AB	$Set1$	0.988	0.798	9.177	2.942	2.371	2.718
	$Set2_{precise}$	0.986	0.810	10.039	2.915	2.240	2.541
	$Set2_{fuzzy}$	0.984	0.805	11.278	3.202	2.508	2.796
	$Set3_{precise}$	0.991	0.812	6.328	2.183	1.712	1.998
	$Set3_{fuzzy}$	0.992	0.807	5.598	2.100	1.542	1.789
	$Set4_{precise}$	0.995	0.814	3.875	1.811	1.356	1.550
	$Set4_{fuzzy}$	0.992	0.801	5.657	2.166	1.647	1.869
	$Set5_{precise}$	0.994	0.813	4.175	1.738	1.313	1.514
	$Set5_{fuzzy}$	0.996	0.797	3.048	1.491	1.070	1.230
GB	$Set1$	0.962	0.776	28.220	4.726	3.221	3.841
	$Set2_{precise}$	0.968	0.814	23.569	4.167	2.747	3.412
	$Set2_{fuzzy}$	0.948	0.813	37.767	5.792	3.874	4.811
	$Set3_{precise}$	0.964	0.819	26.559	4.694	2.836	3.642
	$Set3_{fuzzy}$	0.968	0.812	23.652	4.569	2.741	3.501
	$Set4_{precise}$	0.956	0.818	32.004	5.489	3.562	4.440
	$Set4_{fuzzy}$	0.956	0.810	32.023	5.280	3.217	4.123
	$Set5_{precise}$	0.976	0.819	17.731	3.499	2.207	2.765
	$Set5_{fuzzy}$	0.969	0.816	22.829	4.478	3.030	3.732
XG	$Set1$	0.959	0.778	30.013	4.738	3.214	3.744
	$Set2_{precise}$	0.941	0.811	42.884	6.013	3.809	4.801
	$Set2_{fuzzy}$	0.950	0.799	36.417	5.386	3.565	4.427
	$Set3_{precise}$	0.961	0.810	28.714	5.030	3.052	3.828
	$Set3_{fuzzy}$	0.962	0.809	27.987	4.971	3.024	3.802
	$Set4_{precise}$	0.952	0.816	34.801	5.579	3.556	4.392
	$Set4_{fuzzy}$	0.949	0.807	37.325	5.970	3.839	4.756
	$Set5_{precise}$	0.951	0.816	35.428	5.466	3.558	4.432
	$Set5_{fuzzy}$	0.953	0.808	34.093	5.267	3.457	4.250
LB	$Set1$	0.935	0.766	48.608	6.560	4.506	5.448
	$Set2_{precise}$	0.946	0.809	39.482	5.955	3.895	4.905
	$Set2_{fuzzy}$	0.921	0.799	57.989	7.204	4.865	6.100
	$Set3_{precise}$	0.947	0.804	38.795	5.845	3.853	4.853
	$Set3_{fuzzy}$	0.952	0.801	35.030	5.577	3.723	4.654
	$Set4_{precise}$	0.951	0.805	35.768	5.641	3.702	4.652
	$Set4_{fuzzy}$	0.935	0.803	47.096	6.576	4.433	5.520
	$Set5_{precise}$	0.963	0.808	26.595	4.681	2.977	3.758
	$Set5_{fuzzy}$	0.939	0.798	43.912	6.098	4.029	5.143
SVM	$Set1$	0.812	0.791	138.669	11.753	7.557	8.957
	$Set2_{precise}$	0.837	0.823	117.826	10.819	6.698	8.237
	$Set2_{fuzzy}$	0.830	0.818	123.105	11.072	6.843	8.436
	$Set3_{precise}$	0.844	0.820	113.000	10.591	6.627	8.167
	$Set3_{fuzzy}$	0.847	0.817	111.184	10.490	6.551	8.120
	$Set4_{precise}$	0.844	0.822	113.090	10.598	6.624	8.169
	$Set4_{fuzzy}$	0.843	0.821	113.745	10.618	6.643	8.199
	$Set5_{precise}$	0.840	0.823	115.818	10.727	6.701	8.227
	$Set5_{fuzzy}$	0.833	0.821	121.038	10.973	6.888	8.472
ANN	$Set1$	0.829	0.780	126.769	11.217	7.780	9.353
	$Set2_{precise}$	0.865	0.809	98.002	9.850	6.647	8.181
	$Set2_{fuzzy}$	0.859	0.807	102.467	10.070	6.665	8.284
	$Set3_{precise}$	0.874	0.798	91.583	9.475	6.480	7.992
	$Set3_{fuzzy}$	0.859	0.796	101.857	10.026	6.907	8.541
	$Set4_{precise}$	0.861	0.800	100.566	9.972	6.828	8.394
	$Set4_{fuzzy}$	0.848	0.796	110.236	10.430	7.158	8.877
	$Set5_{precise}$	0.865	0.809	97.761	9.821	6.634	8.116
	$Set5_{fuzzy}$	0.853	0.801	106.070	10.237	6.811	8.423
Ridge	$Set1$	0.780	0.778	162.676	12.739	9.007	11.114
	$Set2_{precise}$	0.792	0.799	150.342	12.247	8.523	10.908
	$Set2_{fuzzy}$	0.790	0.798	151.889	12.310	8.513	10.899
	$Set3_{precise}$	0.801	0.796	144.061	11.987	8.329	10.615
	$Set3_{fuzzy}$	0.801	0.797	143.736	11.974	8.307	10.617
	$Set4_{precise}$	0.798	0.797	146.525	12.089	8.366	10.721
	$Set4_{fuzzy}$	0.798	0.798	145.947	12.066	8.335	10.674
	$Set5_{precise}$	0.795	0.803	148.003	12.151	8.436	10.765
	$Set5_{fuzzy}$	0.793	0.802	149.528	12.214	8.459	10.815
LASSO	$Set1$	0.779	0.778	163.445	12.769	9.011	11.128
	$Set2_{precise}$	0.792	0.798	150.396	12.249	8.514	10.895
	$Set2_{fuzzy}$	0.790	0.797	151.947	12.313	8.502	10.883
	$Set3_{precise}$	0.799	0.796	145.425	12.043	8.323	10.619
	$Set3_{fuzzy}$	0.799	0.798	145.550	12.049	8.307	10.630
	$Set4_{precise}$	0.797	0.796	147.092	12.112	8.361	10.718
	$Set4_{fuzzy}$	0.798	0.796	146.291	12.080	8.324	10.657

(*continued on next column*)

Table A3 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set5_{precise}$	0.795	0.803	148.077	12.154	8.433	10.758
	$Set5_{fuzzy}$	0.793	0.801	149.538	12.215	8.448	10.795

Table A4
The fit performance of eleven machine learning models for ship S4.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	$Set1$	0.906	0.758	81.312	8.851	6.363	6.681
	$Set2_{precise}$	0.926	0.750	59.829	7.503	5.663	6.124
	$Set2_{fuzzy}$	0.921	0.759	63.603	7.812	5.886	6.341
	$Set3_{precise}$	0.916	0.746	68.063	8.094	6.036	6.523
	$Set3_{fuzzy}$	0.921	0.755	63.698	7.776	5.796	6.220
	$Set4_{precise}$	0.917	0.758	67.295	7.920	5.904	6.372
	$Set4_{fuzzy}$	0.928	0.771	58.562	7.517	5.638	6.059
	$Set5_{precise}$	0.905	0.739	76.918	8.473	6.344	6.864
	$Set5_{fuzzy}$	0.918	0.764	66.324	7.897	5.900	6.326
ET	$Set1$	0.988	0.858	10.120	2.625	1.778	1.862
	$Set2_{precise}$	0.996	0.865	2.961	1.362	0.957	1.036
	$Set2_{fuzzy}$	0.998	0.862	1.882	1.077	0.738	0.796
	$Set3_{precise}$	0.998	0.872	1.434	0.901	0.627	0.687
	$Set3_{fuzzy}$	0.998	0.870	1.957	1.022	0.713	0.777
	$Set4_{precise}$	0.997	0.871	2.141	1.101	0.778	0.844
	$Set4_{fuzzy}$	0.997	0.867	2.092	0.994	0.710	0.779
	$Set5_{precise}$	0.999	0.875	1.183	0.904	0.623	0.675
	$Set5_{fuzzy}$	0.999	0.871	0.933	0.704	0.479	0.524
RF	$Set1$	0.974	0.848	22.794	4.752	3.335	3.501
	$Set2_{precise}$	0.977	0.855	18.989	4.350	3.226	3.528
	$Set2_{fuzzy}$	0.975	0.852	20.670	4.529	3.344	3.673
	$Set3_{precise}$	0.975	0.853	20.349	4.497	3.331	3.618
	$Set3_{fuzzy}$	0.974	0.856	20.789	4.535	3.341	3.631
	$Set4_{precise}$	0.974	0.855	21.029	4.568	3.359	3.660
	$Set4_{fuzzy}$	0.976	0.855	19.273	4.381	3.235	3.533
	$Set5_{precise}$	0.975	0.857	20.143	4.472	3.320	3.609
	$Set5_{fuzzy}$	0.975	0.859	20.015	4.457	3.275	3.570
AB	$Set1$	0.980	0.843	17.332	3.939	3.283	3.654
	$Set2_{precise}$	0.981	0.855	15.155	3.560	2.938	3.255
	$Set2_{fuzzy}$	0.980	0.856	16.402	3.758	3.082	3.408
	$Set3_{precise}$	0.986	0.865	11.021	3.144	2.591	2.905
	$Set3_{fuzzy}$	0.992	0.868	6.360	2.277	1.815	2.053
	$Set4_{precise}$	0.992	0.864	6.179	2.258	1.821	2.046
	$Set4_{fuzzy}$	0.992	0.864	6.345	2.272	1.806	2.021
	$Set5_{precise}$	0.991	0.864	7.066	2.371	1.903	2.139
	$Set5_{fuzzy}$	0.993	0.862	5.401	2.070	1.614	1.806
GB	$Set1$	0.977	0.851	19.591	4.196	3.176	3.352
	$Set2_{precise}$	0.986	0.863	11.541	2.974	2.340	2.505
	$Set2_{fuzzy}$	0.985	0.858	12.254	2.929	2.287	2.437
	$Set3_{precise}$	0.989	0.866	8.845	2.500	1.838	1.957
	$Set3_{fuzzy}$	0.986	0.869	11.433	2.985	2.229	2.395
	$Set4_{precise}$	0.991	0.870	7.282	2.380	1.819	1.934
	$Set4_{fuzzy}$	0.990	0.867	8.073	2.523	1.913	2.039
	$Set5_{precise}$	0.990	0.867	7.786	2.438	1.819	1.963
	$Set5_{fuzzy}$	0.986	0.868	11.156	2.861	2.190	2.362
XG	$Set1$	0.977	0.858	19.657	4.126	3.068	3.185
	$Set2_{precise}$	0.993	0.860	5.385	1.929	1.448	1.532
	$Set2_{fuzzy}$	0.993	0.864	5.871	2.111	1.576	1.681
	$Set3_{precise}$	0.995	0.869	3.758	1.585	1.140	1.201
	$Set3_{fuzzy}$	0.993	0.874	5.620	2.167	1.535	1.623
	$Set4_{precise}$	0.994	0.871	4.730	1.636	1.209	1.273
	$Set4_{fuzzy}$	0.990	0.868	7.942	2.402	1.785	1.886
	$Set5_{precise}$	0.993	0.869	5.929	1.909	1.441	1.535
	$Set5_{fuzzy}$	0.986	0.871	11.464	2.905	2.212	2.369
LB	$Set1$	0.968	0.844	28.153	5.010	3.861	4.044
	$Set2_{precise}$	0.980	0.850	15.758	3.612	2.794	2.972
	$Set2_{fuzzy}$	0.978	0.851	17.859	3.894	3.036	3.245
	$Set3_{precise}$	0.987	0.855	10.943	2.871	2.200	2.340
	$Set3_{fuzzy}$	0.987	0.861	10.620	2.951	2.264	2.432
	$Set4_{precise}$	0.986	0.857	11.242	2.921	2.241	2.385
	$Set4_{fuzzy}$	0.977	0.863	18.771	4.087	3.166	3.364
	$Set5_{precise}$	0.992	0.866	6.305	2.107	1.627	1.771
	$Set5_{fuzzy}$	0.987	0.868	10.615	2.972	2.300	2.509
SVM	$Set1$	0.906	0.842	81.874	9.015	6.318	6.374
	$Set2_{precise}$	0.920	0.852	64.910	8.026	5.944	6.337
	$Set2_{fuzzy}$	0.917	0.847	67.218	8.157	5.995	6.449
	$Set3_{precise}$	0.921	0.857	63.718	7.972	5.848	6.146

(*continued on next column*)

Table A4 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set3_{fuzzy}$	0.912	0.853	70.915	8.406	6.166	6.467
	$Set4_{precise}$	0.920	0.861	64.380	8.005	5.896	6.203
	$Set4_{fuzzy}$	0.913	0.855	70.163	8.353	6.150	6.479
	$Set5_{precise}$	0.921	0.863	64.323	8.003	5.923	6.291
	$Set5_{fuzzy}$	0.918	0.862	66.783	8.152	6.034	6.410
ANN	*Set1*	0.925	0.845	65.521	8.076	6.102	6.390
	$Set2_{precise}$	0.936	0.848	51.520	7.145	5.561	6.025
	$Set2_{fuzzy}$	0.939	0.851	49.215	6.999	5.433	5.884
	$Set3_{precise}$	0.947	0.856	42.555	6.513	5.034	5.502
	$Set3_{fuzzy}$	0.947	0.863	42.882	6.543	5.085	5.528
	$Set4_{precise}$	0.944	0.859	45.586	6.744	5.243	5.676
	$Set4_{fuzzy}$	0.942	0.855	47.334	6.865	5.320	5.759
	$Set5_{precise}$	0.939	0.866	49.545	7.025	5.477	5.914
	$Set5_{fuzzy}$	0.933	0.865	54.535	7.374	5.737	6.216
Ridge	*Set1*	0.825	0.821	152.631	12.351	9.343	9.548
	$Set2_{precise}$	0.824	0.805	142.173	11.919	9.220	9.569
	$Set2_{fuzzy}$	0.820	0.799	145.931	12.075	9.331	9.742
	$Set3_{precise}$	0.833	0.811	135.334	11.629	9.033	9.406
	$Set3_{fuzzy}$	0.828	0.806	138.677	11.771	9.128	9.537
	$Set4_{precise}$	0.833	0.812	135.132	11.620	9.021	9.387
	$Set4_{fuzzy}$	0.829	0.807	138.424	11.761	9.115	9.516
	$Set5_{precise}$	0.829	0.812	138.032	11.744	9.121	9.468
	$Set5_{fuzzy}$	0.826	0.808	140.883	11.865	9.207	9.606
LASSO	*Set1*	0.824	0.823	153.402	12.382	9.347	9.537
	$Set2_{precise}$	0.824	0.804	142.470	11.932	9.228	9.572
	$Set2_{fuzzy}$	0.819	0.799	146.410	12.095	9.344	9.750
	$Set3_{precise}$	0.832	0.809	135.961	11.656	9.053	9.417
	$Set3_{fuzzy}$	0.826	0.806	140.683	11.856	9.181	9.580
	$Set4_{precise}$	0.833	0.810	135.135	11.621	9.022	9.385
	$Set4_{fuzzy}$	0.828	0.806	139.214	11.793	9.132	9.526
	$Set5_{precise}$	0.829	0.811	138.350	11.758	9.127	9.471
	$Set5_{fuzzy}$	0.825	0.807	141.337	11.884	9.215	9.611

Table A5
The fit performance of eleven machine learning models for ship S5.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	*Set1*	0.939	0.821	33.699	5.588	4.144	6.259
	$Set2_{precise}$	0.938	0.795	34.454	5.745	4.239	6.417
	$Set2_{fuzzy}$	0.935	0.810	35.970	5.952	4.463	6.795
	$Set3_{precise}$	0.947	0.785	29.488	5.182	3.764	5.625
	$Set3_{fuzzy}$	0.948	0.798	28.634	5.139	3.789	5.696
	$Set4_{precise}$	0.938	0.786	34.047	5.667	4.152	6.186
	$Set4_{fuzzy}$	0.940	0.799	33.582	5.565	4.092	6.178
	$Set5_{precise}$	0.937	0.799	35.019	5.784	4.241	6.345
	$Set5_{fuzzy}$	0.941	0.811	32.605	5.613	4.060	6.073
ET	*Set1*	0.998	0.895	1.057	0.805	0.569	0.857
	$Set2_{precise}$	0.996	0.892	2.026	1.108	0.820	1.257
	$Set2_{fuzzy}$	0.994	0.889	3.403	1.580	1.182	1.787
	$Set3_{precise}$	0.997	0.892	1.413	0.854	0.619	0.935
	$Set3_{fuzzy}$	0.997	0.891	1.821	1.076	0.784	1.184
	$Set4_{precise}$	0.995	0.892	2.602	1.195	0.883	1.343
	$Set4_{fuzzy}$	0.997	0.888	1.705	0.950	0.681	1.028
	$Set5_{precise}$	0.998	0.890	0.845	0.785	0.560	0.856
	$Set5_{fuzzy}$	0.997	0.889	1.447	0.856	0.619	0.939
RF	*Set1*	0.982	0.884	9.951	3.140	2.354	3.594
	$Set2_{precise}$	0.981	0.874	10.785	3.268	2.396	3.663
	$Set2_{fuzzy}$	0.983	0.881	9.662	3.097	2.265	3.480
	$Set3_{precise}$	0.981	0.874	10.498	3.225	2.390	3.663
	$Set3_{fuzzy}$	0.981	0.882	10.352	3.195	2.354	3.614
	$Set4_{precise}$	0.982	0.873	9.889	3.137	2.295	3.509
	$Set4_{fuzzy}$	0.981	0.880	10.422	3.210	2.317	3.539
	$Set5_{precise}$	0.981	0.876	10.305	3.189	2.355	3.598
	$Set5_{fuzzy}$	0.982	0.881	10.256	3.184	2.356	3.630
AB	*Set1*	0.990	0.895	5.408	2.213	1.830	3.156
	$Set2_{precise}$	0.994	0.882	3.555	1.780	1.439	2.538
	$Set2_{fuzzy}$	0.992	0.890	4.604	1.967	1.620	2.822
	$Set3_{precise}$	0.995	0.886	2.543	1.525	1.209	2.217
	$Set3_{fuzzy}$	0.994	0.893	3.311	1.634	1.320	2.360
	$Set4_{precise}$	0.994	0.882	3.462	1.734	1.393	2.479
	$Set4_{fuzzy}$	0.995	0.890	2.588	1.508	1.191	2.135
	$Set5_{precise}$	0.995	0.886	2.965	1.629	1.315	2.379
	$Set5_{fuzzy}$	0.996	0.890	2.337	1.387	1.066	1.931
GB	*Set1*	0.993	0.895	3.885	1.743	1.360	2.158

(*continued on next column*)

Table A5 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set2_{precise}$	0.996	0.887	2.381	1.188	0.926	1.492
	$Set2_{fuzzy}$	0.990	0.888	5.618	1.854	1.419	2.233
	$Set3_{precise}$	0.993	0.887	3.519	1.359	1.021	1.610
	$Set3_{fuzzy}$	0.994	0.888	3.316	1.398	1.074	1.699
	$Set4_{precise}$	0.997	0.889	1.727	1.039	0.805	1.275
	$Set4_{fuzzy}$	0.995	0.891	2.928	1.162	0.867	1.355
	$Set5_{precise}$	0.996	0.884	2.061	1.052	0.818	1.293
	$Set5_{fuzzy}$	0.993	0.886	3.950	1.562	1.211	1.917
XG	$Set1$	0.990	0.892	5.361	1.995	1.520	2.370
	$Set2_{precise}$	0.993	0.873	3.883	1.589	1.173	1.842
	$Set2_{fuzzy}$	0.987	0.881	7.018	2.245	1.655	2.554
	$Set3_{precise}$	0.993	0.878	3.601	1.605	1.133	1.749
	$Set3_{fuzzy}$	0.989	0.888	5.924	2.046	1.490	2.314
	$Set4_{precise}$	0.994	0.878	3.149	1.496	1.041	1.616
	$Set4_{fuzzy}$	0.990	0.883	5.556	2.019	1.478	2.308
	$Set5_{precise}$	0.987	0.883	7.125	2.403	1.776	2.773
	$Set5_{fuzzy}$	0.993	0.886	3.759	1.666	1.228	1.927
LB	$Set1$	0.986	0.879	7.810	2.636	2.028	3.173
	$Set2_{precise}$	0.984	0.874	9.087	2.680	2.016	3.145
	$Set2_{fuzzy}$	0.984	0.882	9.066	2.728	2.073	3.215
	$Set3_{precise}$	0.987	0.873	7.382	2.350	1.758	2.725
	$Set3_{fuzzy}$	0.987	0.876	7.357	2.458	1.852	2.887
	$Set4_{precise}$	0.979	0.875	11.525	3.220	2.420	3.743
	$Set4_{fuzzy}$	0.980	0.877	11.114	3.131	2.393	3.696
	$Set5_{precise}$	0.984	0.871	8.646	2.662	1.998	3.104
	$Set5_{fuzzy}$	0.987	0.876	7.270	2.424	1.830	2.842
SVM	$Set1$	0.931	0.884	38.408	6.173	4.382	6.630
	$Set2_{precise}$	0.919	0.879	45.002	6.674	4.868	7.358
	$Set2_{fuzzy}$	0.919	0.883	44.677	6.633	4.835	7.319
	$Set3_{precise}$	0.916	0.873	46.421	6.785	4.917	7.472
	$Set3_{fuzzy}$	0.917	0.882	46.286	6.793	4.904	7.472
	$Set4_{precise}$	0.915	0.876	47.018	6.840	4.985	7.541
	$Set4_{fuzzy}$	0.917	0.879	45.834	6.758	4.928	7.496
	$Set5_{precise}$	0.924	0.878	41.942	6.444	4.689	7.114
	$Set5_{fuzzy}$	0.921	0.880	43.746	6.591	4.771	7.252
ANN	$Set1$	0.926	0.886	40.737	6.373	4.900	7.545
	$Set2_{precise}$	0.940	0.876	33.557	5.753	4.426	6.867
	$Set2_{fuzzy}$	0.930	0.876	38.794	6.188	4.724	7.295
	$Set3_{precise}$	0.935	0.879	36.157	5.956	4.544	7.075
	$Set3_{fuzzy}$	0.932	0.882	37.513	6.094	4.633	7.202
	$Set4_{precise}$	0.941	0.882	32.448	5.659	4.328	6.738
	$Set4_{fuzzy}$	0.929	0.878	39.150	6.229	4.760	7.381
	$Set5_{precise}$	0.928	0.876	39.757	6.269	4.802	7.409
	$Set5_{fuzzy}$	0.930	0.884	38.850	6.201	4.720	7.277
Ridge	$Set1$	0.875	0.868	69.368	8.325	6.341	9.937
	$Set2_{precise}$	0.883	0.873	65.112	8.066	6.112	9.419
	$Set2_{fuzzy}$	0.881	0.873	66.119	8.128	6.124	9.423
	$Set3_{precise}$	0.889	0.868	61.610	7.846	5.934	9.109
	$Set3_{fuzzy}$	0.888	0.870	62.092	7.876	5.983	9.191
	$Set4_{precise}$	0.887	0.871	62.716	7.916	6.011	9.210
	$Set4_{fuzzy}$	0.886	0.870	63.240	7.949	6.063	9.298
	$Set5_{precise}$	0.885	0.874	63.789	7.983	6.042	9.244
	$Set5_{fuzzy}$	0.885	0.875	63.975	7.995	6.045	9.248
LASSO	$Set1$	0.874	0.868	69.799	8.351	6.357	9.948
	$Set2_{precise}$	0.882	0.873	65.214	8.072	6.121	9.436
	$Set2_{fuzzy}$	0.881	0.873	66.225	8.135	6.131	9.439
	$Set3_{precise}$	0.888	0.868	61.988	7.870	5.953	9.129
	$Set3_{fuzzy}$	0.887	0.870	62.780	7.920	6.019	9.213
	$Set4_{precise}$	0.886	0.870	62.963	7.932	6.022	9.224
	$Set4_{fuzzy}$	0.886	0.871	63.365	7.957	6.070	9.298
	$Set5_{precise}$	0.885	0.874	63.959	7.994	6.054	9.256
	$Set5_{fuzzy}$	0.884	0.873	64.202	8.009	6.059	9.247

Table A6
The fit performance of eleven machine learning models for ship S6.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	$Set1$	0.837	0.636	67.292	8.143	5.917	7.777
	$Set2_{precise}$	0.812	0.542	77.709	8.758	6.526	8.686
	$Set2_{fuzzy}$	0.825	0.576	72.552	8.460	6.207	8.219
	$Set3_{precise}$	0.832	0.576	69.684	8.275	6.119	8.113
	$Set3_{fuzzy}$	0.813	0.579	77.414	8.738	6.468	8.593
	$Set4_{precise}$	0.852	0.530	60.986	7.701	5.653	7.536
	$Set4_{fuzzy}$	0.832	0.561	69.219	8.249	6.071	8.066

(continued on next column)

Table A6 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set5_{precise}$	0.832	0.578	69.447	8.227	6.047	8.027
	$Set5_{fuzzy}$	0.816	0.589	76.002	8.649	6.372	8.434
ET	$Set1$	0.985	0.765	6.050	1.928	1.359	1.796
	$Set2_{precise}$	0.982	0.755	7.287	2.366	1.743	2.313
	$Set2_{fuzzy}$	0.982	0.749	7.640	2.515	1.877	2.489
	$Set3_{precise}$	0.979	0.752	8.706	2.743	2.010	2.678
	$Set3_{fuzzy}$	0.976	0.744	9.938	2.705	1.995	2.654
	$Set4_{precise}$	0.986	0.747	5.823	2.122	1.533	2.036
	$Set4_{fuzzy}$	0.973	0.743	10.997	2.925	2.161	2.860
	$Set5_{precise}$	0.986	0.750	5.796	2.088	1.517	2.009
	$Set5_{fuzzy}$	0.971	0.735	12.056	3.189	2.388	3.162
RF	$Set1$	0.956	0.766	18.155	4.225	3.016	4.012
	$Set2_{precise}$	0.957	0.743	18.016	4.231	3.057	4.053
	$Set2_{fuzzy}$	0.956	0.747	18.125	4.227	3.108	4.136
	$Set3_{precise}$	0.953	0.740	19.498	4.382	3.173	4.211
	$Set3_{fuzzy}$	0.954	0.746	19.075	4.326	3.152	4.198
	$Set4_{precise}$	0.956	0.741	18.314	4.255	3.102	4.122
	$Set4_{fuzzy}$	0.952	0.747	19.918	4.437	3.247	4.325
	$Set5_{precise}$	0.956	0.741	18.403	4.261	3.092	4.101
	$Set5_{fuzzy}$	0.955	0.744	18.502	4.271	3.128	4.161
AB	$Set1$	0.969	0.770	12.857	3.481	2.871	4.105
	$Set2_{precise}$	0.973	0.752	10.958	3.199	2.673	3.873
	$Set2_{fuzzy}$	0.968	0.758	13.404	3.558	2.994	4.289
	$Set3_{precise}$	0.980	0.755	8.175	2.647	2.186	3.210
	$Set3_{fuzzy}$	0.974	0.760	10.820	3.157	2.664	3.851
	$Set4_{precise}$	0.977	0.747	9.492	2.996	2.541	3.702
	$Set4_{fuzzy}$	0.977	0.749	9.524	2.962	2.484	3.578
	$Set5_{precise}$	0.983	0.748	6.868	2.445	2.005	2.945
	$Set5_{fuzzy}$	0.971	0.752	12.050	3.405	2.911	4.181
GB	$Set1$	0.965	0.786	14.509	3.538	2.597	3.507
	$Set2_{precise}$	0.962	0.784	15.864	3.689	2.868	3.907
	$Set2_{fuzzy}$	0.963	0.780	15.468	3.513	2.763	3.749
	$Set3_{precise}$	0.971	0.770	11.917	3.111	2.384	3.226
	$Set3_{fuzzy}$	0.963	0.780	15.292	3.572	2.725	3.693
	$Set4_{precise}$	0.968	0.776	13.322	3.271	2.530	3.425
	$Set4_{fuzzy}$	0.968	0.778	13.396	3.319	2.549	3.451
	$Set5_{precise}$	0.962	0.771	16.035	3.730	2.902	3.958
	$Set5_{fuzzy}$	0.950	0.771	20.910	4.247	3.327	4.513
XG	$Set1$	0.966	0.786	14.223	3.620	2.692	3.641
	$Set2_{precise}$	0.957	0.785	17.661	3.806	2.941	4.004
	$Set2_{fuzzy}$	0.945	0.786	22.931	4.633	3.606	4.878
	$Set3_{precise}$	0.959	0.771	17.299	3.835	2.890	3.902
	$Set3_{fuzzy}$	0.966	0.776	13.923	3.361	2.538	3.412
	$Set4_{precise}$	0.958	0.770	17.405	3.889	2.959	3.993
	$Set4_{fuzzy}$	0.955	0.774	18.740	4.036	3.066	4.127
	$Set5_{precise}$	0.957	0.773	17.877	3.837	2.946	4.005
	$Set5_{fuzzy}$	0.940	0.777	24.886	4.800	3.711	5.024
LB	$Set1$	0.951	0.773	20.401	4.334	3.285	4.472
	$Set2_{precise}$	0.951	0.768	20.215	4.252	3.275	4.467
	$Set2_{fuzzy}$	0.936	0.772	26.454	4.902	3.810	5.175
	$Set3_{precise}$	0.963	0.754	15.520	3.514	2.682	3.646
	$Set3_{fuzzy}$	0.951	0.762	20.246	4.209	3.275	4.443
	$Set4_{precise}$	0.942	0.758	24.155	4.587	3.520	4.790
	$Set4_{fuzzy}$	0.936	0.768	26.469	4.900	3.800	5.151
	$Set5_{precise}$	0.962	0.752	15.655	3.592	2.706	3.679
	$Set5_{fuzzy}$	0.956	0.751	18.155	3.893	2.959	4.023
SVM	$Set1$	0.838	0.748	67.236	8.175	5.625	7.308
	$Set2_{precise}$	0.846	0.766	63.819	7.962	5.661	7.464
	$Set2_{fuzzy}$	0.832	0.754	69.485	8.311	5.956	7.829
	$Set3_{precise}$	0.843	0.767	65.144	8.045	5.755	7.629
	$Set3_{fuzzy}$	0.832	0.760	69.588	8.322	5.960	7.862
	$Set4_{precise}$	0.840	0.765	66.027	8.104	5.765	7.603
	$Set4_{fuzzy}$	0.828	0.762	71.019	8.420	5.973	7.859
	$Set5_{precise}$	0.844	0.767	64.564	8.020	5.739	7.570
	$Set5_{fuzzy}$	0.825	0.766	72.178	8.491	6.051	7.957
ANN	$Set1$	0.851	0.740	61.550	7.798	5.849	7.715
	$Set2_{precise}$	0.851	0.768	61.489	7.821	5.883	7.791
	$Set2_{fuzzy}$	0.847	0.759	63.370	7.935	6.000	7.927
	$Set3_{precise}$	0.859	0.772	58.184	7.599	5.750	7.603
	$Set3_{fuzzy}$	0.846	0.768	63.903	7.977	6.043	7.967
	$Set4_{precise}$	0.852	0.773	61.205	7.803	5.883	7.760
	$Set4_{fuzzy}$	0.849	0.760	62.489	7.871	5.952	7.852
	$Set5_{precise}$	0.875	0.759	51.893	7.155	5.453	7.254
	$Set5_{fuzzy}$	0.863	0.758	56.786	7.496	5.712	7.557
Ridge	$Set1$	0.758	0.729	100.434	10.018	7.588	10.192
	$Set2_{precise}$	0.762	0.736	98.605	9.927	7.566	10.137

(continued on next column)

Table A6 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set2_{fuzzy}$	0.758	0.734	99.954	9.994	7.577	10.120
	$Set3_{precise}$	0.775	0.745	93.218	9.652	7.454	9.977
	$Set3_{fuzzy}$	0.772	0.743	94.465	9.716	7.434	9.927
	$Set4_{precise}$	0.774	0.744	93.718	9.678	7.439	9.949
	$Set4_{fuzzy}$	0.770	0.743	95.067	9.747	7.424	9.909
	$Set5_{precise}$	0.768	0.742	95.854	9.788	7.559	10.138
	$Set5_{fuzzy}$	0.764	0.739	97.477	9.870	7.573	10.120
LASSO	$Set1$	0.753	0.724	102.272	10.109	7.629	10.199
	$Set2_{precise}$	0.762	0.736	98.666	9.930	7.562	10.136
	$Set2_{fuzzy}$	0.758	0.733	99.969	9.995	7.573	10.118
	$Set3_{precise}$	0.774	0.744	93.502	9.667	7.443	9.960
	$Set3_{fuzzy}$	0.771	0.745	94.691	9.728	7.429	9.920
	$Set4_{precise}$	0.774	0.743	93.686	9.676	7.435	9.942
	$Set4_{fuzzy}$	0.770	0.743	95.199	9.754	7.411	9.879
	$Set5_{precise}$	0.768	0.742	95.856	9.788	7.560	10.146
	$Set5_{fuzzy}$	0.764	0.739	97.494	9.871	7.573	10.120

Table A7
The fit performance of eleven machine learning models for ship S7.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	$Set1$	0.828	0.680	69.472	8.260	6.302	8.155
	$Set2_{precise}$	0.857	0.682	57.167	7.500	5.712	7.424
	$Set2_{fuzzy}$	0.849	0.660	60.603	7.737	5.932	7.752
	$Set3_{precise}$	0.880	0.683	48.319	6.903	5.173	6.749
	$Set3_{fuzzy}$	0.869	0.690	52.514	7.183	5.401	7.043
	$Set4_{precise}$	0.875	0.656	50.042	7.032	5.307	6.936
	$Set4_{fuzzy}$	0.861	0.667	55.626	7.387	5.599	7.303
	$Set5_{precise}$	0.881	0.694	47.827	6.863	5.127	6.665
	$Set5_{fuzzy}$	0.867	0.700	53.253	7.244	5.425	7.077
ET	$Set1$	0.956	0.806	17.780	3.880	2.884	3.713
	$Set2_{precise}$	0.972	0.801	11.382	3.040	2.178	2.834
	$Set2_{fuzzy}$	0.963	0.790	14.758	3.560	2.603	3.391
	$Set3_{precise}$	0.987	0.805	5.176	1.848	1.259	1.639
	$Set3_{fuzzy}$	0.978	0.798	8.693	2.379	1.664	2.155
	$Set4_{precise}$	0.985	0.801	6.087	2.040	1.419	1.851
	$Set4_{fuzzy}$	0.983	0.793	6.706	2.149	1.522	1.983
	$Set5_{precise}$	0.989	0.804	4.334	1.623	1.156	1.507
	$Set5_{fuzzy}$	0.979	0.799	8.329	2.549	1.855	2.405
RF	$Set1$	0.964	0.793	14.369	3.774	2.813	3.649
	$Set2_{precise}$	0.962	0.791	15.123	3.842	2.826	3.694
	$Set2_{fuzzy}$	0.962	0.788	15.442	3.899	2.887	3.800
	$Set3_{precise}$	0.961	0.794	15.501	3.920	2.867	3.740
	$Set3_{fuzzy}$	0.960	0.793	15.963	3.978	2.931	3.838
	$Set4_{precise}$	0.961	0.791	15.742	3.947	2.898	3.795
	$Set4_{fuzzy}$	0.963	0.789	14.852	3.828	2.850	3.746
	$Set5_{precise}$	0.966	0.796	13.853	3.691	2.705	3.528
	$Set5_{fuzzy}$	0.967	0.797	13.384	3.644	2.715	3.551
AB	$Set1$	0.964	0.790	14.672	3.464	2.781	3.712
	$Set2_{precise}$	0.975	0.770	10.014	2.848	2.207	2.964
	$Set2_{fuzzy}$	0.975	0.777	10.055	2.981	2.462	3.326
	$Set3_{precise}$	0.982	0.777	7.272	2.415	1.888	2.558
	$Set3_{fuzzy}$	0.980	0.782	7.977	2.604	2.149	2.934
	$Set4_{precise}$	0.982	0.776	7.209	2.516	2.080	2.838
	$Set4_{fuzzy}$	0.986	0.775	5.620	2.132	1.717	2.345
	$Set5_{precise}$	0.984	0.783	6.493	2.337	1.897	2.589
	$Set5_{fuzzy}$	0.987	0.783	5.343	2.100	1.752	2.417
GB	$Set1$	0.962	0.803	15.408	3.756	2.777	3.605
	$Set2_{precise}$	0.966	0.777	13.669	3.347	2.513	3.299
	$Set2_{fuzzy}$	0.967	0.782	13.148	3.471	2.602	3.411
	$Set3_{precise}$	0.986	0.785	5.466	2.156	1.442	1.880
	$Set3_{fuzzy}$	0.978	0.782	9.078	2.764	1.973	2.582
	$Set4_{precise}$	0.979	0.781	8.487	2.562	1.839	2.398
	$Set4_{fuzzy}$	0.977	0.780	9.243	2.751	2.065	2.709
	$Set5_{precise}$	0.974	0.786	10.452	2.955	2.139	2.784
	$Set5_{fuzzy}$	0.977	0.791	9.274	2.812	2.038	2.663
XG	$Set1$	0.972	0.813	11.021	3.022	2.222	2.865
	$Set2_{precise}$	0.972	0.777	11.392	3.120	2.269	2.926
	$Set2_{fuzzy}$	0.966	0.784	13.695	3.461	2.551	3.314
	$Set3_{precise}$	0.986	0.784	5.731	2.093	1.424	1.808
	$Set3_{fuzzy}$	0.980	0.791	8.192	2.475	1.677	2.138
	$Set4_{precise}$	0.979	0.784	8.576	2.711	1.867	2.394
	$Set4_{fuzzy}$	0.975	0.781	10.191	2.769	1.988	2.568
	$Set5_{precise}$	0.978	0.792	8.680	2.772	1.971	2.532

(*continued on next column*)

Table A7 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set5_{fuzzy}$	0.973	0.798	11.025	3.167	2.272	2.932
LB	$Set1$	0.957	0.789	17.547	4.044	3.053	3.968
	$Set2_{precise}$	0.978	0.766	8.892	2.744	2.051	2.693
	$Set2_{fuzzy}$	0.967	0.781	13.285	3.426	2.603	3.407
	$Set3_{precise}$	0.982	0.785	7.152	2.366	1.742	2.283
	$Set3_{fuzzy}$	0.975	0.779	10.039	2.861	2.175	2.840
	$Set4_{precise}$	0.981	0.775	7.814	2.542	1.865	2.427
	$Set4_{fuzzy}$	0.961	0.774	15.690	3.755	2.837	3.692
	$Set5_{precise}$	0.979	0.781	8.598	2.522	1.855	2.431
	$Set5_{fuzzy}$	0.979	0.787	8.541	2.673	1.945	2.545
SVM	$Set1$	0.906	0.786	38.185	6.078	4.323	5.574
	$Set2_{precise}$	0.870	0.744	52.317	7.160	5.243	6.699
	$Set2_{fuzzy}$	0.873	0.744	50.939	7.070	5.115	6.582
	$Set3_{precise}$	0.871	0.748	51.533	7.113	5.173	6.591
	$Set3_{fuzzy}$	0.866	0.746	53.727	7.249	5.261	6.730
	$Set4_{precise}$	0.873	0.745	50.841	7.045	5.125	6.552
	$Set4_{fuzzy}$	0.876	0.745	49.716	6.983	5.055	6.504
	$Set5_{precise}$	0.867	0.752	53.427	7.236	5.264	6.699
	$Set5_{fuzzy}$	0.863	0.750	54.999	7.343	5.366	6.862
ANN	$Set1$	0.863	0.786	55.639	7.392	5.651	7.274
	$Set2_{precise}$	0.902	0.770	39.097	6.203	4.856	6.310
	$Set2_{fuzzy}$	0.888	0.764	45.229	6.656	5.210	6.807
	$Set3_{precise}$	0.892	0.771	43.321	6.515	5.071	6.587
	$Set3_{fuzzy}$	0.896	0.760	41.782	6.386	4.981	6.481
	$Set4_{precise}$	0.897	0.767	41.488	6.373	4.959	6.441
	$Set4_{fuzzy}$	0.891	0.765	43.762	6.559	5.110	6.643
	$Set5_{precise}$	0.895	0.756	42.257	6.425	5.003	6.480
	$Set5_{fuzzy}$	0.884	0.755	46.486	6.748	5.244	6.798
Ridge	$Set1$	0.790	0.781	85.163	9.224	6.955	8.817
	$Set2_{precise}$	0.817	0.761	73.490	8.564	6.612	8.463
	$Set2_{fuzzy}$	0.816	0.761	74.035	8.596	6.669	8.578
	$Set3_{precise}$	0.820	0.758	72.381	8.498	6.520	8.315
	$Set3_{fuzzy}$	0.818	0.756	72.910	8.530	6.596	8.451
	$Set4_{precise}$	0.819	0.759	72.799	8.523	6.552	8.361
	$Set4_{fuzzy}$	0.818	0.758	73.098	8.541	6.609	8.473
	$Set5_{precise}$	0.818	0.761	73.217	8.547	6.587	8.422
	$Set5_{fuzzy}$	0.816	0.760	73.809	8.583	6.660	8.550
LASSO	$Set1$	0.789	0.781	85.405	9.238	6.961	8.819
	$Set2_{precise}$	0.816	0.760	73.729	8.577	6.627	8.498
	$Set2_{fuzzy}$	0.815	0.760	74.215	8.606	6.673	8.595
	$Set3_{precise}$	0.819	0.758	72.827	8.524	6.550	8.374
	$Set3_{fuzzy}$	0.816	0.759	73.644	8.573	6.627	8.498
	$Set4_{precise}$	0.817	0.758	73.386	8.557	6.591	8.435
	$Set4_{fuzzy}$	0.817	0.759	73.478	8.563	6.620	8.500
	$Set5_{precise}$	0.817	0.761	73.504	8.564	6.606	8.462
	$Set5_{fuzzy}$	0.815	0.761	74.089	8.599	6.666	8.564

Table A8
The fit performance of eleven machine learning models for ship S8.

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
DT	$Set1$	0.916	0.774	54.181	7.305	5.213	6.441
	$Set2_{precise}$	0.912	0.759	52.806	7.194	5.129	6.172
	$Set2_{fuzzy}$	0.905	0.766	57.141	7.487	5.353	6.419
	$Set3_{precise}$	0.916	0.769	50.649	6.985	4.922	5.949
	$Set3_{fuzzy}$	0.919	0.764	48.884	6.889	4.885	5.920
	$Set4_{precise}$	0.912	0.746	52.752	7.168	5.070	6.092
	$Set4_{fuzzy}$	0.904	0.759	57.557	7.549	5.362	6.450
	$Set5_{precise}$	0.914	0.759	51.752	7.105	5.020	6.054
	$Set5_{fuzzy}$	0.909	0.770	54.614	7.268	5.163	6.237
ET	$Set1$	0.998	0.882	1.556	0.811	0.551	0.679
	$Set2_{precise}$	0.997	0.872	1.552	0.879	0.565	0.694
	$Set2_{fuzzy}$	0.998	0.866	1.288	0.841	0.540	0.661
	$Set3_{precise}$	0.995	0.876	2.783	1.404	0.907	1.120
	$Set3_{fuzzy}$	0.997	0.872	1.940	1.024	0.652	0.801
	$Set4_{precise}$	0.996	0.871	2.382	1.227	0.799	0.993
	$Set4_{fuzzy}$	0.995	0.865	2.894	1.392	0.879	1.077
	$Set5_{precise}$	0.999	0.883	0.612	0.629	0.398	0.486
	$Set5_{fuzzy}$	0.996	0.877	2.216	1.169	0.771	0.947
RF	$Set1$	0.978	0.859	13.895	3.707	2.535	3.124
	$Set2_{precise}$	0.974	0.846	15.712	3.941	2.668	3.233
	$Set2_{fuzzy}$	0.977	0.846	14.095	3.740	2.546	3.081
	$Set3_{precise}$	0.976	0.855	14.566	3.798	2.624	3.187
	$Set3_{fuzzy}$	0.975	0.854	15.158	3.868	2.676	3.254

(*continued on next column*)

Table A8 (*continued*)

Model	Dataset	R^2	R^2 (test)	MSE	RMSE (ton/day)	MAE (ton/day)	MAPE (%)
	$Set4_{precise}$	0.976	0.847	14.789	3.811	2.615	3.173
	$Set4_{fuzzy}$	0.977	0.848	13.912	3.714	2.561	3.109
	$Set5_{precise}$	0.978	0.864	13.567	3.653	2.490	3.026
	$Set5_{fuzzy}$	0.976	0.861	14.658	3.788	2.569	3.128
AB	$Set1$	0.982	0.870	11.601	3.288	2.747	3.479
	$Set2_{precise}$	0.989	0.860	6.723	2.470	2.032	2.565
	$Set2_{fuzzy}$	0.990	0.863	5.990	2.329	1.896	2.390
	$Set3_{precise}$	0.991	0.863	5.365	2.114	1.693	2.148
	$Set3_{fuzzy}$	0.991	0.864	5.138	2.093	1.673	2.127
	$Set4_{precise}$	0.992	0.859	5.046	2.111	1.705	2.162
	$Set4_{fuzzy}$	0.992	0.861	4.835	2.069	1.654	2.102
	$Set5_{precise}$	0.993	0.870	4.374	1.789	1.402	1.780
	$Set5_{fuzzy}$	0.997	0.874	1.966	1.273	0.931	1.189
GB	$Set1$	0.983	0.875	10.771	3.062	2.188	2.750
	$Set2_{precise}$	0.978	0.855	13.587	3.035	2.111	2.607
	$Set2_{fuzzy}$	0.983	0.857	10.329	2.874	2.021	2.498
	$Set3_{precise}$	0.985	0.860	9.102	2.427	1.670	2.075
	$Set3_{fuzzy}$	0.995	0.857	3.004	1.287	0.842	1.048
	$Set4_{precise}$	0.988	0.852	7.318	2.176	1.474	1.838
	$Set4_{fuzzy}$	0.986	0.851	8.424	2.377	1.660	2.048
	$Set5_{precise}$	0.986	0.862	8.808	2.254	1.584	1.944
	$Set5_{fuzzy}$	0.988	0.866	7.600	2.117	1.463	1.809
XG	$Set1$	0.991	0.877	5.538	1.956	1.429	1.791
	$Set2_{precise}$	0.984	0.855	9.630	2.793	1.927	2.356
	$Set2_{fuzzy}$	0.986	0.856	8.638	2.520	1.735	2.124
	$Set3_{precise}$	0.979	0.856	12.821	2.974	2.114	2.589
	$Set3_{fuzzy}$	0.996	0.850	2.393	1.247	0.855	1.037
	$Set4_{precise}$	0.987	0.850	7.927	2.477	1.690	2.090
	$Set4_{fuzzy}$	0.989	0.844	6.722	2.123	1.467	1.806
	$Set5_{precise}$	0.975	0.862	15.510	3.650	2.627	3.198
	$Set5_{fuzzy}$	0.984	0.865	9.919	2.722	1.919	2.340
LB	$Set1$	0.979	0.871	13.718	3.540	2.601	3.309
	$Set2_{precise}$	0.976	0.841	14.612	3.308	2.379	2.931
	$Set2_{fuzzy}$	0.984	0.847	9.763	2.672	1.913	2.391
	$Set3_{precise}$	0.976	0.852	14.749	3.261	2.338	2.882
	$Set3_{fuzzy}$	0.982	0.853	10.653	2.726	1.918	2.392
	$Set4_{precise}$	0.972	0.846	16.669	3.865	2.817	3.487
	$Set4_{fuzzy}$	0.976	0.844	14.589	3.543	2.518	3.129
	$Set5_{precise}$	0.981	0.857	11.529	2.914	2.067	2.566
	$Set5_{fuzzy}$	0.968	0.855	19.211	3.849	2.753	3.397
SVM	$Set1$	0.900	0.862	64.371	8.014	5.742	6.905
	$Set2_{precise}$	0.903	0.862	58.473	7.635	5.275	6.257
	$Set2_{fuzzy}$	0.895	0.851	63.089	7.936	5.594	6.596
	$Set3_{precise}$	0.910	0.869	54.154	7.349	5.117	6.123
	$Set3_{fuzzy}$	0.901	0.858	59.486	7.706	5.436	6.468
	$Set4_{precise}$	0.910	0.870	54.276	7.358	5.123	6.137
	$Set4_{fuzzy}$	0.901	0.859	59.951	7.737	5.479	6.524
	$Set5_{precise}$	0.905	0.870	57.155	7.549	5.309	6.301
	$Set5_{fuzzy}$	0.898	0.860	61.411	7.828	5.547	6.547
ANN	$Set1$	0.914	0.857	55.217	7.398	5.605	6.809
	$Set2_{precise}$	0.916	0.849	50.726	7.075	5.203	6.214
	$Set2_{fuzzy}$	0.912	0.842	53.036	7.247	5.382	6.405
	$Set3_{precise}$	0.924	0.862	46.222	6.733	4.964	5.959
	$Set3_{fuzzy}$	0.910	0.858	54.260	7.342	5.454	6.491
	$Set4_{precise}$	0.920	0.862	48.397	6.914	5.080	6.086
	$Set4_{fuzzy}$	0.916	0.854	50.805	7.090	5.262	6.283
	$Set5_{precise}$	0.915	0.860	51.212	7.114	5.213	6.234
	$Set5_{fuzzy}$	0.910	0.856	54.312	7.342	5.411	6.426
Ridge	$Set1$	0.866	0.842	86.315	9.288	7.004	8.561
	$Set2_{precise}$	0.870	0.844	78.603	8.861	6.746	8.191
	$Set2_{fuzzy}$	0.865	0.839	81.580	9.027	6.944	8.384
	$Set3_{precise}$	0.879	0.853	72.818	8.529	6.512	7.959
	$Set3_{fuzzy}$	0.874	0.847	76.048	8.716	6.690	8.141
	$Set4_{precise}$	0.878	0.851	73.870	8.591	6.541	7.997
	$Set4_{fuzzy}$	0.872	0.846	76.952	8.768	6.731	8.177
	$Set5_{precise}$	0.879	0.855	73.221	8.552	6.522	7.973
	$Set5_{fuzzy}$	0.873	0.850	76.678	8.752	6.703	8.148
LASSO	$Set1$	0.865	0.842	87.140	9.332	7.023	8.576
	$Set2_{precise}$	0.869	0.843	78.883	8.876	6.752	8.189
	$Set2_{fuzzy}$	0.864	0.838	81.756	9.037	6.950	8.384
	$Set3_{precise}$	0.878	0.852	73.581	8.573	6.525	7.966
	$Set3_{fuzzy}$	0.872	0.848	77.013	8.771	6.702	8.135
	$Set4_{precise}$	0.877	0.850	74.067	8.602	6.544	7.999
	$Set4_{fuzzy}$	0.872	0.845	77.229	8.784	6.740	8.181
	$Set5_{precise}$	0.878	0.854	73.626	8.576	6.533	7.981
	$Set5_{fuzzy}$	0.872	0.849	77.215	8.782	6.711	8.148

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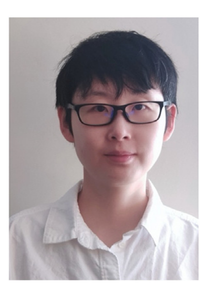

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