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Analysis and prediction of ship energy efficiency based on the MRV system

Abstract

To reduce CO_2 emissions from shipping activities to, from, and within the European Union (EU) area, a system of monitoring, reporting, and verification (MRV) of CO_2 emissions from ships are implemented in 2015 by the EU. Although the MRV records in 2018 and 2019 have been published, there are scarce studies on the MRV system. In the current related studies, the majority of them are in a qualitative manner, and thus restrain the usefulness of the MRV and hinder the managerial insights that can be generated. To bridge this gap, this paper first analyzes and compares the MRV records in 2018 and 2019, and then develops prediction models for the annual average fuel consumption for each ship type combining ship features from an external database. The performance of the prediction models is accurate, with the mean absolute percentage error (MAPE) on the test set no more than 12% and the average R-squared of all the models at 0.78. Based on the analysis and prediction results, model meanings, implications, and extensions are thoroughly discussed. This study is a pioneer to analyze the emission reports in the MRV system from a quantitative perspective. It also develops the first average fuel consumption prediction models from a macro perspective using the MRV data. It can contribute to MRV data analysis and system improvement as well as green shipping strategies promotion.

Keywords

monitoring, reporting, and verification (MRV) regulation, CO_2 emissions from shipping, vessel fuel consumption, ship energy efficiency, GBRT for vessel fuel consumption prediction

1. Introduction

Shipping is an essential link in the global supply chain. While shipping is comparatively less polluting than other transport modes, greenhouse gases (GHGs), such as carbon dioxide (CO_2), methane (CH_4), nitrous oxide (N_2O), and ozone (O_3), emitted from vessels are not negligible (Shi et al., 2018; Xing et al., 2018; Wang et al., 2019). At global level, emissions from the maritime transport sector were accounted for 2.76% in 2012 of the global total CO_2 emissions and the percentage further increased to 2.89% in 2018 as reported by the 4th International Maritime Organization (IMO) GHG Study (IMO, 2020). Due to the expected growth of world economy and the associated transport demand, the emission percentage is expected to reach 5% in 2050 (European Commission, 2013a). Given this condition, the IMO has implemented measures to reduce the GHG emissions and thus to slow down the pace of climate change. Main measures include the energy efficiency design index (EEDI) for newly built ships from 2013 onwards, and the ship energy efficiency management plan (SEEMP) for existing ships. In addition, the energy efficiency operational indicator (EEOI) is suggested as a tool for SEEMP implementation, but only on a voluntary basis (Lu et al., 2014; Sampson et al., 2016).

CO_2 emissions from maritime transport related to the voyages within EU as well as the incoming and outcoming voyages of EU increased by 48% between 1990 and 2008 (European Commission, 2013a). The EU has set the goal to achieve a reduction in CO_2 emissions from maritime transport by 40% (if feasible 50%) by 2050 compared to 2005 level (European Commission, 2013b). The slow pace of decision-making at IMO motivated the EU to adopt its own regimes to monitor and reduce the CO_2 emissions from vessels. A system for accurate MRV of fuel consumption, CO_2 emissions, and transport work (product of cargo onboard and distance sailed) of ships with a gross tonnage above 5,000 arriving at, within, or departing from ports under the jurisdiction of a Member State (MS) of EU was proposed in 2015 and implemented since 1 January 2018. The main objective of the MRV system is to collect and publish accurate information on large ships' energy efficiency using EU ports and incentivize energy efficiency improvement (EU, 2015).

According to Article 9 of EU Regulation 2015/757 (EU, 2015), ship companies are responsible for their vessels' compliance with the MRV system. They need to monitor several voyage and emission related parameters on a per-voyage basis as required and also to report the aggregated parameters on an annual basis. After collecting such data from a vessel, a shipping company should first submit an emission report (ER) to a verifier, which is a legal entity carrying out verification activities. The verifier will evaluate the data and docs provided by the shipping company to check whether there are non-conformities or misstatements identified. If not, a verification report will be issued to the shipping company. The verified annual vessel-specific ER which contains the basic information of the ship, company, and verifier as well as the monitoring methods and results, is finally submitted to the Commission and the flag state by the shipping company by 30 April each year. The Document of Compliance (DOC) will then be issued to the ships by 30 June of the same year (European Commission, 2020). By 1 July, the Commission will make publicly available the MRV data.

The MRV data for 2018 and 2019 reporting period has already been published and can be accessed from the European Maritime Safety Agency (EMSA) website (THETIS-MRV, 2020). It is noted that ship identity, i.e., IMO number and vessel name, is also provided. However, to the best of our knowledge, there is no literature aiming to analyze and compare the key fields reported in the MRV system so far. In addition, it is widely accepted that accurate estimation of ship fuel consumption is the foundation of reducing fuel costs, and it is important as "Encouraging further efficiency and sustainability in the shipping sector through reduced fuel cost and better serving customers' expectations will maintain its competitiveness" (EU, 2011). However, there is no existing literature that develops prediction models for the annual average fuel consumption per sailing distance and thus to explore the information behind the raw data. These limitations significantly obstruct the value and implication of the MRV system. To bridge this gap, this study first thoroughly analyzes ship reports in 2018 and 2019 from the MRV system, and then proposes highly accurate machine learning based models for annual average fuel consumption prediction for each ship type. Based on the results, model implications and extensions are then discussed. The innovations and contributions of this study are summarized as follows.

From the perspective of MRV data analysis, ship reports via the MRV system in 2018 and 2019 are first analyzed and compared. Specifically, we explore ship related factors, ship sailing behaviors, and ship energy efficiency indicators. We found that the distributions of ship related factors were relatively similar in 2018 and 2019. For ship sailing behavior, the average sailing speed showed a slight decrease in 2019. As for ship energy efficiency factors, the percentage of data that were not applicable (e.g., null value, "not applicable" value, and "not-a-number" value) in 2019 was much smaller than that in 2018, which indicates that the MRV data quality significantly improved from 2018 to 2019. In addition, the total and average fuel consumption/CO_2 emissions for all ships and in separate ship types as well as the technical efficiency indicators all showed that ship energy efficiency improved from 2018 to 2019.

Apart from analyzing the MRV data, highly accurate machine learning models to predict the average fuel consumption per sailing distance is then developed and validated by combining the MRV system with an external database. We develop one regression model for each ship type with more than 500 valid records. The results show that the MAPE in the test set is within 12% and the average R-squared is 0.78, which we believe are promising and applicable in practice.

From the perspective of model meanings and implications, we argue that the MRV system itself and the developed prediction models can be further utilized by both policy makers and ship owners/operators to generate vessel management insights, rationalize commercial and political decisions, attract more attention to improving ship energy efficiency, and promote green shipping practices. More specific application scenarios include but are not limited to scheduling of ships' maintenance and management work, rationalizing decisions on ship chartering and charter rates, second-hand ship pricing, addressing the market failure in time charter market, and assisting in evaluating the investment of technological practices in green shipping. In addition, it is also the first study that provides a viable way to predict vessel fuel consumption from a macro perspective by combining the MRV system with external data sources.

2. Literature review

The literature on MRV system is scarce, and most of the related literature is published in 2018 and beyond. The literature can be roughly divided into qualitative and quantitative categories. For qualitative literature, analysis of the MRV system itself and comparisons of the monitoring methods adopted in the MRV system are discussed. Zaman et al. (2017) analyzed the opportunities and challenges of applying big data technologies in the shipping industry including the MRV system, as it heavily relies on collecting and reporting of massive shipping data. The authors stated that the big data technologies would increase the capability of performance monitoring, remove human error, and increase interdependencies of components. Nelissen and Faber (2014) examined the new obligations and costs associated with the implementation of the MRV system to the ship owners and operators from an economy perspective. The potential environmental benefit in terms of CO_2 reductions was also discussed. Faber et al. (2013) introduced and compared four fuel consumption and CO_2 emission monitoring methods that could be used in the MRV system in detail, i.e., methods based on bunker delivery notes, tank monitoring, flow meters, and direct emission monitoring. Particularly, the need for equipment, the associated costs, the monitoring quality, and the resulted emission reduction incentives of each monitoring method were compared. Castells-

Sanabra et al. (2020) analyzed eleven existing methods to monitor ship emission inventories considering the key MRV elements: quality, uncertainty, and confidence. The authors concluded that ship-based methods (SBMs) were the most appropriate to comply with MRV regulation. Psaraftis and Woodall (2019) connected the market-based measures (MBMs) to reduce GHG emissions from shipping with the MRV system. A practical implementation of the MRV system in the Ro/Ro sector was introduced, and the challenges encountered in the process were presented.

Regarding quantitative literature, by conducting online survey among maritime professionals, the potential barriers and industry's standpoint with regard to the implementation of the MRV system were discussed by Rony et al. (2019). Panagakos et al. (2019) gave an early assessment of the MRV regulation by calculating the MRV energy efficiency indicators on a global basis using the operational data of 1,041 dry bulk carriers. The result showed that the geographic coverage restrictions of the MRV system resulted in significant bias, and thus prohibited it from contributing to better decision-making by the market actors. Mannarini et al. (2020) augmented the original MRV data in 2018 with another three datasets and associated a geographical location with each Ro-Pax vessel. Energy efficiency indicators were then calculated and compared in different vessel clusters.

The MRV system is analyzed and compared with the data collection system (DCS) implemented by the IMO is several studies in a qualitative manner. By providing a holistic analysis of the MRV system and DCS, Akoel and Miler (2019) presented their economical and operational implications on the maritime transport processes. Deane et al. (2019) analyzed the MRV system and the DCS against the standards of transparency and answerability in different steps of the monitoring process. Wang et al. (2020) commented that there were three potential benefits of the MRV system and the DCS apart from fuel consumption and CO_2 emissions monitoring: "efficient ships will carry cargos and inefficient ships will be idle"; "ship owners will maintain their ships in excellent fuel-efficiency conditions"; and "charters can operate ships more efficiently based on historical data".

It can be concluded from the above review that most of the studies on the EU MRV system alone or with the IMO DCS are from a qualitative perspective, where extensive introduction, analysis, and discussion of various aspects of the MRV system (and DCS) are presented. Although quantitative analysis is conducted in three pioneer studies, they mainly aim at conducting online survey or analyzing only one ship type (i.e., dry bulk carriers or ferries). In addition, although the data in 2019 has been published in June 2020, only the MRV data in 2018 is used in current literature. To the best of our knowledge, there are neither studies analyzing the whole picture of the reports in the MRV system regarding various compulsory data fields nor studies comparing the records in 2018 and 2019. In addition, there is no model developed for fuel consumption or CO_2 emission prediction based on the MRV data to make full use of the ERs. These limitations will undoubtedly restrain the usefulness of the MRV data and hinder the managerial insights that can be generated. To bridge this gap, the records of 2018 and 2019 in the MRV system are first analyzed and compared in this study. By combining with the World Register of Ships database, accurate annual average fuel consumption prediction models for each ship type are then developed and validated. Finally, model meanings, implications, and extensions are thoroughly discussed.

3. Analysis of MRV data

In this section, we first give an overview of ship ERs reported via the MRV system. Then, we analyze and compare the MRV data in 2018 and 2019. The original data is downloaded from the THETIS-MRV database provided by EMSA. There are totally 12,155 reports in 2018 and 12,134 reports in 2019. An overview of the MRV data is presented in Appendix A. We analyze the MRV data from the following three perspectives: ship basic information, ship report information, and ship energy efficiency information.

3.1 Analysis of ship basic information in the MRV system

Two factors of ship basic information are analyzed in this section: ship type and ship flag state. Ship type is presented in the MRV data, while ship flag state is searched from a database called World Register of Ships based on ship IMO number. Regarding the types of ships that used EU ports in 2018 and 2019, Figure 1(1) shows that a total of 15 types of ships reported their ERs, and the ranking of ship types regarding the number of reports was the same in both years. The top five ship types all had more than 1,000 reports each year, and they contributed to more than 80% of the total MRV reports. Especially, the number of reports sent by bulk carriers showed a significant decrease from 3,810 in 2018 to 3,597 in 2019, and the number of reports from oil tankers increased from 1,876 in 2018 to 1,985 in 2019.

The distributions of ship flag states in 2018 and 2019 are shown in Figure 1(2). The rank of the top eight flag states remained unchanged from 2018 to 2019, and the top five flag states were in charge of about half of the ships reporting to the MRV system.

<Insert Figure 1 here>

3.2 Analysis of ship report information in the MRV system

We then analyze the verifiers the ships chose to verify and report their ERs. The distributions of verifiers selected in 2018 and 2019 are shown in Figure 2. As indicated in Figure 2, more than 90% of the ships reported their ERs via the top 10 verifiers in 2018 and 2019. Among them, DNV GL was the most popular verifier in both 2018 and 2019, which was employed by more than 20% of the ships reported to the MRV system. ABS Hellenic S.M. Ltd. (American Bureau of Shipping Hellenic Single Member Limited Liability Company) was the second popular verifier in both years which was selected by about 17% of the ships. Lloyd's Register Quality Assurance Ltd. was the third popular verifier in 2018 which held the market share of nearly 12%. However, only about 8% of the ships chose it in 2019, and it ranked no. 5 in that year.

<Insert Figure 2 here>

As mentioned in Appendix A, there are four monitoring methods of fuel consumption/CO_2 emissions, i.e., method A: BDN and periodic stock takes of fuel tanks; methods B: bunker fuel tank monitoring on board; methods C: flow meters for applicable combustion processes, and method D: direct CO_2 emissions measurements. Note that more than one method to monitor the fuel consumption/CO_2 emissions can be selected by one ship. The numbers of ships choosing each method in 2018 and 2019 are illustrated in Figure 3(1). It can be seen that there was a growing number of ships using monitoring method A from 2018 to 2019 as it is the simplest method requiring the least investment costs. Meanwhile, there was no ship using method D in 2018, while there were two pioneer ships adopting this method in 2019. The number of ships using methods B and C were similar in these two years.

Among the 12,155 ships reporting their ERs to the MRV system in 2018, 638 of them had zero annual total fuel consumption, which are obviously outliers. In 2019, the number of ships reporting zero total fuel consumption significantly reduced to 338 among all the 12,134 reports. Regarding the reports with non-zero fuel consumption, the mean value decreased from 4009.93 in 2018 to 3938.98 in 2019. We further divide the fuel consumption values into several bins and compare the percentage of ships with positive fuel consumption in each bin as shown in Figure 3(2). It shows that nearly half of the ships reporting positive annual total fuel consumption to the MRV system consumed no more than 2,000 m tonnes (mt) of fuel each year in both 2018 and 2019. Meanwhile, more than 20% of the ships consumed more than 5,000 mt fuel in each year. Figure 3(2) also indicates that the distribution of ship annual total fuel consumption was similar in both years.

As for the annual total CO_2 emissions which is highly related to the total fuel consumption, the number of ships reporting zero CO_2 emissions were the same as the number of ships reporting zero fuel consumption in 2018 and 2019, respectively. The mean value of annual total CO_2 emissions was 12525.31 and 12295.69 in 2018 and 2019, respectively, which also showed a decreasing trend like that in the annual total fuel consumption. We divide the ships into several bins according to the total CO_2 emission values as presented in Figure 3(3). It shows that more than 60% of the ships with reports in the MRV system emitted no more than 10,000 mt CO_2 of each year in 2018 and 2019. Meanwhile, more than 10% ships generated more than 25,000 mt CO_2 each year. Like the annual total fuel consumption, the distributions of annual total CO_2 emissions were similar in 2018 and 2019.

Based on the annual total fuel consumption and CO_2 emissions, we further calculate the equivalent types of fuel consumed by the ships. We deem it to be "equivalent" because different types of fuel might be used in different shipping activities, but we only have one ratio between the CO_2 emitted and the fuel consumed for each ship on an annual basis. The calculation method of equivalent fuel oil type is presented in Table 1.

<Insert Table 1 here>

Similar to the total fuel consumption and CO_2 emissions, 638 and 338 records are not applicable to calculate the equivalent fuel type. The mean value of the calculated carbon ratio is 3.133 in 2018 and 3.137 in 2019. The distribution of the equivalent fuel oil type in 2018 and 2019 is presented in Figure 3(4). It illustrates that except for the HFO, which was used by 84.76% ships in 2018 and by 82.57% ships in 2019, showed a downward trend, all the other fuel oil types showed an upward trend. Moreover, there was an obvious increasing trend in the adoption of LFO and LNG. This phenomenon can be explained by the fact that more ships would switch to fuel types with less sulphur content to comply with the sulphur emission control area (SECA) regulations, and thus the market share of HFO with high sulfur content significantly decreased from 2018 to 2019. Meanwhile, as the LNG infrastructure was constantly upgrading on board and in ports, more ships chose LNG in 2019. Therefore, it can be concluded that although the calculated carbon ratio was slightly increased by 0.004 from 2018 to 2019, the overall sulphur content in the ship fuel oil reduced, which could lead to reduction of SO_2 emissions.

<Insert Figure 3 here>

3.3 Analysis of ship energy efficiency information in the MRV system

Before examining the annual average energy efficiency provided in the MRV system, we first explore the annual average sailing speed of the ships based on the MRV data. We calculate the total sailing distance considering the annual average fuel consumption per distance (kg/nm) and the total fuel consumption (mt). By combining annual total time spent at sea (hours), annual average sailing speed (knots) can be calculated. 643 and 339 reports were not applicable in 2018 and 2019, respectively. For the 11,512 and 11,795 valid reports in 2018 and 2019, the mean value of annual average sailing speed was 11.03 and 10.96, respectively. The distributions are presented in Figure 4(1). It can be seen that the annual average sailing speed of most ships was no more than 15 knots, while less than 1% of the ships sailed at an average speed of more than 20 knots.

We then move on to analyze the annual average fuel consumption and annual average CO_2 emissions per distance (kg/nm) provided in the MRV data. For both fields, 640 and 339 records were not applicable ("divided by zero" in the original MRV data) in 2018 and 2019, respectively. For the annual average fuel consumption, the mean value was 137.01 in 2018 and it decreased to 132.75 in 2019. For the annual CO_2 emissions, the mean value was 427.94 in 2018 and it decreased to 414.95 in 2019 in compliance with the pattern in the annual average fuel consumption. The distributions of the annual average fuel consumption and CO_2 emissions in 2018 and 2019 are shown in Figure 4(2). It implies that the number of ships with average fuel consumption/CO_2 emissions "Not applicable" significantly reduced by nearly half from 2018 to 2019. Meanwhile, with similar total number of reports in both years, most new valid reports in 2019 were with average fuel consumption less than 200 mt and CO_2 emissions less than 600 mt. Therefore, both of the annual average fuel consumption and CO_2 emissions reduced from 2018 to 2019, indicating that the shipping industry has been driving to an environmentally friendly direction to a certain extent.

Finally, we analyze the ship technical efficiency indicator reported in the MRV system in 2018 and 2019. Ships should generally report the attained EEDI in accordance with MARPOL Annex VI. For those ships not covered by the EEDI, estimated index value (EIV) should be reported by the certain types of ships. Otherwise, this field is "Not applicable" in the MRV system. Both EEDI and EIV express the CO_2 emissions in grams per ship's transport work (tonne-nautical mile), with smaller values indicating more energy efficient ships. The equation to calculate EEDI is complex, so we only give a general form to calculate EEDI in Eq. (1). Its complete form can be found in MEPC (2014).

$$EEDI = \frac{CO_2 \text{ emission}}{\text{Transport work}}. \tag{1}$$

The equation to calculate EIV of a ship (excluding containerships and ro-ro cargo ships) is given in Eq. (2).

$$EIV = \frac{190 \times \sum_{i=1}^{NME} P_{ME_i} + 215 \times P_{AE}}{\text{capacity} \times V_{ref}}, \tag{2}$$

where P_{ME} is 75% of the total installed power of one main engine, NME is the number of main engines, P_{AE} is the auxiliary power, and V_{ref} is a ship's service speed. For the equations to calculate other ship types not covered by Eq. (2), readers are referred to MEPC (2013).

Among all the 12,155 ships reporting to the MRV system in 2018, 3,373 (27.75%) ships had "Not applicable" technical efficiency indicator, and 2,157 (17.75%) and 6,625 (54.50%) ships reported the EEDI and EIV, respectively. In 2019, only 354 (2.92%) of the total 12,134 ships reported "Not applicable" in this field, and there were 2,839 (23.40%) and 8,941 (73.69%) of the ships reporting EEDI and EIV, respectively. The remarkable reduction of the number of records with technical efficiency indicator "Not applicable" indicates that the rules and management schemes of the MRV system are becoming more efficient, and the data quality is constantly improving.

The distributions of the values of EEDI and EIV in 2018 and 2019 regarding all types of ships are shown in Figure 4(3). It is shown that null values, including the reports with blank or zero values for an indicator, reduced about two thirds from 2018 to 2019, which further implicates that data quality of the MRV regime is improving. Furthermore, regarding the EEDI, the mean value of all the valid records was 14.0 in 2018 and it significantly reduced to 6.75 in 2019. For the EIV index, the mean value of all the valid reports was 15.54 in 2018 and it reduced to 12.99 in 2019. These results are remarkable: for one thing, it is evident that data quality of the MRV regime notably improved from 2018 to 2019; for another, the mean values and distributions of the technical efficiency indicators show that the shipping activities involving ports in EU are becoming more environmentally friendly. This is a result of the joint efforts of effective and efficient regulations and controls.

<Insert Figure 4 here>

To explore the changes in the annual average fuel consumption and CO_2 emissions per sailing distance as well as the EEDI and EIV indicators over all voyages from 2018 to 2019 more deeply, we further calculate the mean values of the related data fields regarding the top 5 ship types in 2018 and 2019 (which contributed to more than 80% of the MRV reports in both years), respectively. Furthermore, we present the annual average energy efficiency per transport work (mass) of each ship type reported in the MRV system. The results and analysis are presented in Appendix B.

Based on the above analysis and comparisons regarding all ships and the classified ships in major types, we can draw the following conclusions. First, the distributions of the ship basic information provided by or derived from the MRV system as well as the selected verifiers are relatively similar in 2018 and 2019. Second, the data quality of the MRV system has significantly improved from 2018 to 2019. This indicates that the MRV system is gradually improving and the data is becoming more reliable. Third, the energy efficiency of the ships involved in commercial activities in the EU territory is enhanced in all voyages and in loaded voyages, and the GHG emissions from shipping activities and the sulphur content of the vessel fuel oil are gradually reducing.

4. Development of fuel consumption prediction models

In this section, one prediction model for the annual average fuel consumption per sailing distance is developed for one ship type with more than 500 valid records in the MRV system in 2018 and 2019 after data preprocessing. Compared to the tailored models developed for a single ship on an hourly or daily basis, the prediction models developed in this section are from a macro perspective on a yearly basis.

4.1 Data preprocessing

The initial dataset downloaded from the THETIS database provided by EMSA contains 12,155 reports in 2018 and 12,134 reports in 2019 (totally 24,289 MRV records). To develop the average fuel consumption prediction models, we use the calculated annual average sailing speed from the MRV system as an input. Furthermore, based on ship IMO number provided in the MRV system, we further incorporate several ship features from the World Register of Ships (WRS) database (WRS, 2020). The description and preprocessing method of the prediction target, i.e., the annual average fuel consumption per distance (kg/nm) and the features considered in the regression models are presented in Table 2.

<Insert Table 2 here>

After deleting the records with missing values and anomalies, there are a total of 19,487 valid records in 2018 and 2019 in the whole dataset. We mainly focus on the eight ship types with more than 500 valid records in the dataset listed as follows.

Ship type	Bulk carrier	Chemical tanker	Container and container/ro-ro ship	Gas carrier	General cargo ship	Oil tanker	Ro-pax ship	Vehicle carrier
No. of records	5,927	2,272	3,057	513	1,870	3,046	597	799

4.2 Model development

A detailed introduction of the gradient boosting regression tree (GBRT) model and the model evaluation metrics are given in Appendix C. In this study, we develop one GBRT model per ship type considered. The GBRT models are developed by using

Python to call the scikit-learn (sklearn) library. In each GBRT model, we first randomly divide the whole dataset to training set (80% records) and test set (20% records). The GBRT model is constructed on the training set, and its performance is validated on the test set. Specifically, we use 5-fold cross validation combined with grid search method on the training set using MSE as the metric to find the optimal values of the main hyperparameters. The tuning process can be found in Appendix C.

After constructing the GBRT models using the whole training set with the optimal hyperparameter values, model performance on the hold-out test set is presented in Table 3.

<Insert Table 3 here>

Table 3 shows that all the eight fuel consumption prediction models achieve quite satisfactory prediction performance on the test set under the condition that only macro level data is used. More specifically, the highest MAE among the eight models is from Ro-pax ship at 16.60, while the MAE of most of the other models is less than 15. Meanwhile, the R-squired of all the models are more than 0.6 with the mean at 0.78, and half of them are over 0.8, which indicates an accurate model fitting and prediction performance. The most striking result to emerge from the table is that the MAPE of all the models is less than 12%, which means that on average, the predicted annual average fuel consumption is within 12% more or less than the real annual average fuel consumption. Overall, the performance of the prediction models developed is accurate and acceptable. The results can be further analyzed to generate strategic and managerial implications for policy makers and shipping practitioner.

Apart from evaluating model performance, we also figure out the ten most important features for average fuel consumption prediction. Feature importance presented here is the impurity-based feature importance which can be derived directly from a constructed GBRT. In sklearn library, it is the total decrease in node impurity when using a feature for splitting (which is approximated by the proportion of samples reaching that node) averaged over all trees of the ensemble. The result and analysis are given in Appendix D.

5. Meanings, implication, and extensions of the analysis of MRV data and the prediction models

The meanings, implications, and extensions of the analysis of the MRV data and the fuel consumption prediction models proposed in section 4 can be summarized in Table 4. Detailed descriptions are given in the following subsections.

<Insert Table 4 here>

5.1 Providing vessel management insights

The development and validation of the ship fuel consumption prediction models provide a viable and effective way to combine the MRV system with external data sources, e.g., the World Register of Ships database. The results suggest that among all the features considered in the average fuel consumption prediction models, ship age, ship flag performance, ship RO performance, and the annual average sailing speed might vary in different years for one ship. Ship operators and managers can thus estimate their ships' fuel consumption rates under different conditions when features change. The prediction results can also help them to schedule their ships' maintenance and management activities more efficiently. In addition, ship owners can also benefit from these prediction results when choosing which flag to fly and the RO. On top of that, shipping companies can also leverage the prediction models to decide their ships' annual average sailing speed from a strategic perspective which can contribute to deploying and scheduling the shipping network.

5.2 Rationalizing commercial decisions

Fuel costs constitute a large proportion of ship operational costs (Wang et al., 2020). In time charter market where ship charterers need to pay for the fuel costs instead of ship owners, charterers would prefer more energy efficient ships. By exploring the MRV system where ship identifies are transparent, ship energy efficiency can be figured out. However, the hiring period can last days, months, and even years, and the ship energy efficiency might change due to several factors that are hard to capture like the wear of power and propulsion system. Therefore, ship energy efficiency in the near or far future cannot be obtained directly from the MRV system. Under this condition, the developed prediction models which can predict ship energy efficiency as ship age grows and some other features change can be used to rationalize the charterers' chartering in/out decisions and the owners' decisions on their vessels' charter rates. It can also be expected that ships that are more energy efficient would become more popular and earn higher charter rates, while the wipeout risk of energy inefficient ships is largely increased. Similarly, the average fuel consumption prediction models can also be applied to second-hand ships' market for second-hand vessel pricing and sale/purchase decisions as bunker/fuel consumption costs should be considered as an explanatory variable for pricing modeling (Pruyn et al., 2011).

5.3 Rationalizing political decisions

The analysis of the MRV data in 2018 and 2019 and the average fuel consumption prediction models could help policy makers to evaluate and adjust the strategic plans for CO_2 emission reduction by shedding light on the energy efficiency of each individual ship in the coming years. Such strategic plans include but are not limited to the EU 2011 White Paper on Transport (EU, 2011) and the IMO's goal to reduce total annual GHG emissions from shipping (IMO, 2018). In addition, it is believed that the MRV system is a critical step for any MBMs to reduce GHG emissions from ships implemented in the future, such as the emissions trading system, levy on bunker fuels, and hybrid with EEDI as a benchmark (Lagouvardou et al., 2020). It is interesting to note that although the MRV system is designed to monitor CO_2 emissions, the sulphur content in fuel is also required to be "specified" if monitoring methods (a) and (b) are used, and "monitored" if method (c) is used. Such information might be useful to the enforce the global sulphur cap from 2020 onward (Psaraftis and Woodall, 2019). To maximize its utility, we also suggest the MRV system to publish the specific amount of fuel of each type consumed by the ships, and more information about the sailing routes which allows for combining with sea and weather data to achieve more accurate predictions.

5.4 Attracting more attention to improving ship energy efficiency

The analysis of the MRV system and the prediction models developed in this study can help to deal with a market failure in the current time charter market: more energy efficient ships do not earn enough time charter rates they deserve to cover the investment and management costs (Wang et al., 2020), which makes the owners reluctant to carry out such investments. The main reason is that although ship owners know the fuel efficiency of their ships, they cannot guarantee that to the charterers as it can be influenced by various conditions in a complex manner featured with uncertainties. Therefore, charters are only willing to accept charter rates considering verifiable conditions such as ship age and some other ship conditions (Wang et al., 2020). This situation can be improved by leveraging the prediction models, where the predicted annual average fuel consumption per sailing distance with MAPE within 12% can help access ship energy efficiency and thus motivate charterers to pay much higher rates for more energy efficient ships. This will in return motivate ship owners to pay more attention to improving ship energy efficiency and to maintaining their ships in excellent conditions. Additionally, the outliers presented in the published MRV data and the predicted fuel consumption value for individual ships can provide reference and guideline to ship selection and procedure optimization in vessel inspections, such as the flag state control, port state control, classification society inspection, and tanker vetting, and thus to motivate the ship owners and operators to improve their ships' energy efficiency.

5.5 Promoting green shipping practices

The analysis of the MRV system and the proposed annual average fuel consumption prediction models can also promote the application of both technological and operational green shipping practices, and thus to make shipping activities greener. One example is that the MRV data and the prediction models can assist in the investment of technological practices. If ship managers or operators plan to upgrade the ship power and propulsion system or invest in cleaner fuels or alternative energy sources, they can either search for example ships in the MRV database to exam their performance or use the proposed average fuel consumption prediction models to estimate the ship energy efficiency after such investment. Another example is that if ship operators or charterers plan to decide the average sailing speed of their ships for a period, e.g., for several months or a year to reduce the total fuel consumption and CO_2 emissions at a strategic level, they do not need to collect ship operational data from scratch. Instead, they can use the related data fields provided in the MRV system (Wang et al., 2020) and the prediction results generated by the average fuel consumption prediction models. Alternatively, if they would just like to explore how much fuel can be saved if operating the ship at a lower operational speed, they can first search for similar ships in the MRV system and then compare the energy efficiencies when operating under different average speeds. They can also use the developed prediction models directly to predict the annual average fuel consumption rates under different average sailing speeds.

6. Conclusion and future work

To reduce GHG emissions from the shipping industry, EU proposed and implemented the MRV regulation in 2015 to collect and publish the emission reports of ships over 5,000 tonnes using EU ports, and the records in 2018 and 2019 have been published. However, it is noted that the MRV data is far from fully utilized as most of the current literature on the MRV system is in a qualitative manner. Although there are a few studies developing quantitative models to analyze the MRV data, they only focus on one ship type. To bridge this gap, ship reports in the MRV system in 2018 and 2019 are first analyzed and compared in this study. We find that the MRV data quality has significantly improved from 2018 to 2019, as there are much less “not applicable” records in the system. Furthermore, several emission and technical indicators regarding all ships and ships in different types show that ship energy efficiency is enhanced. The GHG emissions from shipping activities and the sulphur content of the vessel fuel oil are also gradually reducing.

After data preprocessing, one GBRT model is developed for one ship type for predicting the annual average fuel consumption. Model performance on hold-out test sets shows that the MAPE of all the models is within 12% and the average R-squared is 0.78. In addition, feature importance is generated and analyzed based on the GBRT models. Based on data analysis and fuel consumption prediction models development, model meanings, implications, and extensions are thoroughly discussed. We argue that the analysis results and prediction models can contribute to commercial and political decision making and promote GHG reduction plans.

This paper makes the first attempt to analyze the emission reports in the MRV system from a quantitative perspective. It also develops the first annual average fuel consumption prediction models from a macro perspective using the MRV data. Besides, model implications and extensions are also discussed in this study. It is also noted that unlike the fuel consumption prediction models using noon reports and sensor data which are from a micro perspective and are able to consider the surrounding sea and weather conditions, it can be hard to directly combine such information in the prediction analysis based on the MRV data due to a lack of specific voyage information. Therefore, for future work, the MRV data can be further combined with the automatic identification system (AIS) to incorporate sailing route related features. Furthermore, sea and weather conditions and the emission regulations along the routes can also be taken into account to enhance the prediction accuracy and practicability. Besides, more comprehensive ship features, especially those related to ship structures and power systems, as well as ship maintenance data (e.g., dry docking and hull and propeller cleaning records) can be integrates into the fuel consumption prediction models.

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