Journal of
Data Acquisition and Processing
ISSN: 1004-9037
https://sjcjycl.cn/
DOI: 10.5281/zenodo.98549649

A SYSTEMATIC REVIEW ON MACHINE LEARNING MODELS FOR SHIP FUEL CONSUMPTION PREDICTION

Dhanshri Eknath Patil[1], Shailesh Kumar[2] , J.Somasekar[3]
[1] Ph.D. Scholar, Department of CSE, JJTU university.
[2] Department of CSE, Gopalan College of Engineering and Management, Bangalore.
[3]Department of CSE, Faculty of Engineering and Technology, Jain University, Global Campus, Bangalore.

Abstract: As fuel is one of the largest operating expenses, reducing the fuel consumption of vessels can increase efficiency and profitability in ship management. However, estimating the fuel consumption of a ship is a challenging task because the rate of fuel consumption of the vessel directly depends on several external factors, like the main engine, the weight of the containers, the ship's draught, the state of the sea, the weather, etc. The potential for saving fuel is feasible for both newly built ships as well as for ships already in service if greater energy efficiency measures are implemented. The parameters that can influence fuel reduction are ship speed, trim, weather conditions (wave and wind), mean draft, etc. Due to engines' increased power, vessels are the biggest consumers of gasoline. A ship's energy needs are mostly met by propulsion (82%), electric power generation (17%), and limited steam generation (1%). In this paper, various machine learning algorithms are reviewed to estimate the fuel consumption of ships. The findings presented in this paper can be used as a reference for creating a better ship energy efficiency management plan.

Keywords: vessel, energy efficiency, machine learning, predicting fuel consumption

I. Introduction

It has been noted during the past several years that there has been a need to increase the global fleet due to the high demand for shipping products by sea. This had the effect of rapidly increasing average fuel usage during the same period. Due to this reality, fuel prices have grown dramatically [1][2]. In 2014, the International Marine Organization (IMO) reported that the marine sector produced 2.5% of the world's greenhouse gas emissions [3]. The global organizations working to control greenhouse gas emissions have turned their attention to the environmental damage brought on by growing fossil fuel consumption. Every year, the number of emissions from maritime transportation rises because of the marine vessels' increased use of fossil fuels. Consequently, negative effects including acid rain, climate change, and global warming are seen. Because the amount of emissions gases released into the environment directly relates to the amount of fuel consumed, researchers have been investigating a number of different approaches and methods to deliver more efficient fuel usage on vessels. Some of these methods include hull cleaning [4], trim [5], wind energy [6], and solar energy [7].

The crew must have the right instruments for decision-making in order to understand the impacts of the waves, the breeze, steering position, velocity, and trimming in real time, therefore operational efficacy is an important consideration. Measurement of current energy use can be used to achieve this. An evaluation of the current fuel consumption is required in order to determine the ship's pace, trim, and bearing at their best potential settings. This functions as the basis for an optimization tool, as well as for the crew's manual decision-making and adjustments during operation [8].

The International Maritime Organization's members approved a first plan in 2018 to cut ship emissions to half what they were in 2008 by 2050. Ship Energy Efficiency Monitoring Plans, Energy Efficiency Design Indexes, and Fuel Efficiency Operation Indicators are just a few of the laws being implemented to cut down on ship emissions [9]. The cost of gasoline accounts for between 50 and 60 percent of a shipping company's operational expenses, so the industry is instituting procedures and management methods to reduce fuel use and save money [10].

The primary diesel engine's fuel oil consumption is currently a key factor in maintaining ship energy efficiency. When a specific ship voyage is being conducted, the amount of fuel oil consumption will be calculated quantitatively. On the other side, this fuel oil utilisation will show how effectively the ship is using its energy resources. The primary diesel engine on board really uses the most fuel oil when compared to the other engines. Statistics on fuel oil use have been gathered and contrasted with those from other businesses. The increased use of fuel oil in the transportation sector, notably the marine sector, is being addressed.

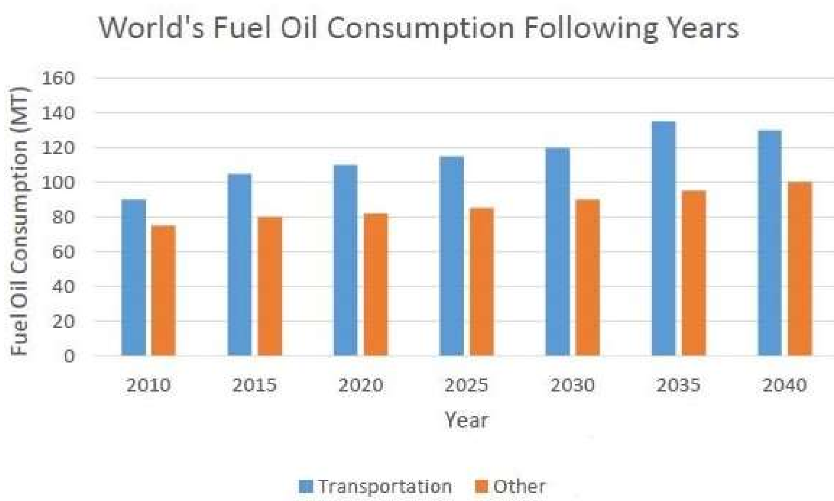

Figure 1: Fuel oil use worldwide from years 2010 to 2040 [22]

The maritime and transportation sectors rely heavily on fuel oil consumption forecasts. Machine learning (ML) is particularly the most promising tool for estimating and optimising fuel use using various techniques like supervised, unsupervised, etc [3]. A system can learn from actual measurement information based on previous data according to the scientific field of machine learning (ML). It is therefore a tool that assesses the system's condition, evaluates its performance in the past, and seeks to improve it. With some of the data, the algorithm is trained, and then it is tested with the remaining data. By managing the train-test procedure while applying statistical approaches, accurate estimating systems can be created using ML algorithms and methods from statistics. The company and scientists can gain knowledge about fuel consumption from a marine vessel's predicted fuel consumption with a low erroneous rate. The management of energy efficiency, therefore, places a high value on ML.

Based on different current models, vessel ship fuel consumption optimisation research was conducted in this paper. We have reviewed several machine learning algorithms which predict a reduction in fuel consumption.

II. Fuel Consumption Forecasting using Machine Learning

Fuel consumption is inversely proportional to vessel velocity and has a significant impact on both operational expenses and the growth in greenhouse gas (GHG) emissions. In addition, because of the fundamental principles underlying it, fuel consumption is a multifaceted construct that occasionally can produce debatable and ambiguous findings, making a broad explanation almost impossible [11]. It is important to remember that a ship's total fuel consumption can be determined by adding the gasoline used by the primary and auxiliary engines while the ship is docked and while it is at sea.

The purpose of this research was to develop a fuel consumption strategy to aid ship managers in making decisions, and therefore we recommend that the main dependent factor (1) be the quantity of gasoline used per unit of sail distance. This makes it easier to determine energy efficiency while considering environmental conditions.

$$Fuel\ efficiency\ [ton/nautical\ mile] = \frac{Fuel\ consumption\ per\ unit\ time\ [ton/hour]}{Sailing\ distance\ per\ unit\ time\ [nautical\ mile/hou\ \ ]} \quad (1)$$

With the help of machine learning, it is possible to analyse the functionality of current systems, ascertain their state, and then enhance their performance to produce more precise results. Using early learning procedures, it might reprogram computers when new information is presented. Machine learning has been used multiple times to grow the green shipping sector, particularly in figuring out the optimum ship fuel consumption for both fuel economy and environmental preservation. To this end, data were collected during testing and training on board to construct a forecasting model that could be compared to real data to determine the best possible fuel-efficient configuration for the ship [12].

In order to create accurate fuel consumption prediction models [1], this research makes use of data collected from a container ship in the 13,000 TEU class, as well as statistical and domain-specific methods for choosing model inputs. These techniques offer practical applicability while avoiding overfitting and multicollinearity. Both Artificial Neural Networks (ANNs) and Multiple Linear Regression (MLRs) were used as prediction models, with ANN-based models showing superior prediction accuracy across both approaches. Based on an analysis of the sensitivity of the draught under typical operating conditions, the ANN model achieves accuracy in the range of 0.9709 to 0.9936, and the design draught of the target ship was pretty near to the optimum draught, which delivers the best consumption of fuel efficiency. The linear regression model's prediction accuracy improved when curve fitting was used, while ANN models performed worse since the nonlinearity was mirrored through the hidden layer. The ANN model (rather than the regression model) with the LASSO regularisation provided the best overall prediction performance (instead of using the domain knowledge approach). Following the identification of parameters with domain understanding and LASSO regularization, it is recommended to use ANN to predict fuel consumption as it had the lowest error in forecasting when compared to real fuel utilization among the model situations utilized in the study.

Marine boat fuel consumption estimates are difficult to make since a variety of external factors, such as the functioning of the primary engine, the amount of weight of the freight, the ship's draft, the state of the sea, weather conditions, etc., directly affect fuel consumption price [3]. In this paper, various prediction model has been used for estimating fuel consumption in a container ship. A container ship has been the subject of several established prediction models, including Multiple Linear Regression, Ridge and LASSO Regression, Support Vector Regression, Tree-Based Algorithms, and Boosting Algorithms. The K-fold cross-validation establishes the models' correctness. Correlation analysis is used to analyze the connections between the variables, and error metrics such as the root mean squared error, mean absolute error, and degree of determination are employed to assess the accuracy of estimation models. The closest estimate of the actual fuel consumption data is produced using the methods of multiple linear regression and ridge regression, which have error values of 0.0001 root mean square, 0.002 mean absolute, and 99.9 coefficients of determination. There is a close relationship between fuel consumption and factors like primary engine speed, primary engine cylinder values, recirculation air, and shaft indicators. The optimum fuel oil consumption optimization method is made possible by estimating actual values using several models. The authors have proposed a study [3], it will be possible to monitor how the ship's main engine is operating based on how much fuel is being consumed, intervene early in abnormal situations, keep emission values under control, and plan for the fuel needs and associated costs to be used in accordance with the ship's route. The proposed methodology can also be used to optimise the ship's routes by using it on various routes.

In [8], we see an example of a machine learning algorithm that can automatically estimate ships' dynamic fuel usage given data for time periods ranging from 12 to 96 hours. Predicting the fluctuating fuel oil consumption is critical for providing real-time energy efficiency information to the operator and ship owner. Using the currently available data that was retrieved from a machinery logging system, the author developed an auto-machine learning optimization strategy [8]. Data for this study came from a cruise ship operating in the Baltic Sea between Stockholm and Mariehamn that was built in 2004. The idea behind auto machine learning (AutoML) is to automate the data scientist’s work by executing optimization procedures on selecting the optimum pre-processing of data, algorithm, and tweaking of hyper-parameters. The approach proposes that instant fuel use can be forecast without the extra expenditure of adding more sensors by fusing operation data that is already available on many ships with midday reports or occasional bunker intervals.

In order to help ship operators design operating procedures that take both financial and environmental considerations into account in order to maximize energy efficiency, the authors have created a decision support system based on Artificial Neural Networks (ANNs) [13]. The research provides two novelties: the first one involves forecasting ship fuel usage using an approximate method called ANN. The second is to provide a tool that will enable decision-making so that ship personnel can make the best choices in real time for energy-efficient ship operations. In this study, we use data from noon reports from ships to build an ANN model to forecast fuel use during ship operations. The gathered data shows that a neural network is able to learn very accurately how input factors and a ship's fuel consumption are correlated. Since there are a variety of uncontrollable factors in the marine environment that affect fuel consumption, the author suggests that future research look into the correlations between other input variables and fuel usage. It is recommended that the development of additional decision support systems is also possible for a larger number of vessels with a variety of features as well as different ship types like bulk carriers, containers, and so forth.

Tayfun Uyanik et. al., [14] proposed a multiple linear regression method (equation 2) for predicting fuel consumption in a commercial ship. The purpose of the authors' investigation was to ascertain how much fuel was utilised on the voyage. The internal and external factors that affect the ship's fuel usage were assessed after the actual voyage data collected from the ship was examined. The prediction result was successfully estimated for 12-day voyage portion data out of 23-day data considered. According to the author, increasing the number of voyage days will raise the success rate of the estimates. x is the dependent variable. y, an unrelated variable. For i = 0 to n, the coefficients are displayed as r_i.

$$x = r_0 + y_1 * r_1 + y_2 * r_2 + \ldots + y_n r_n \qquad (2)$$

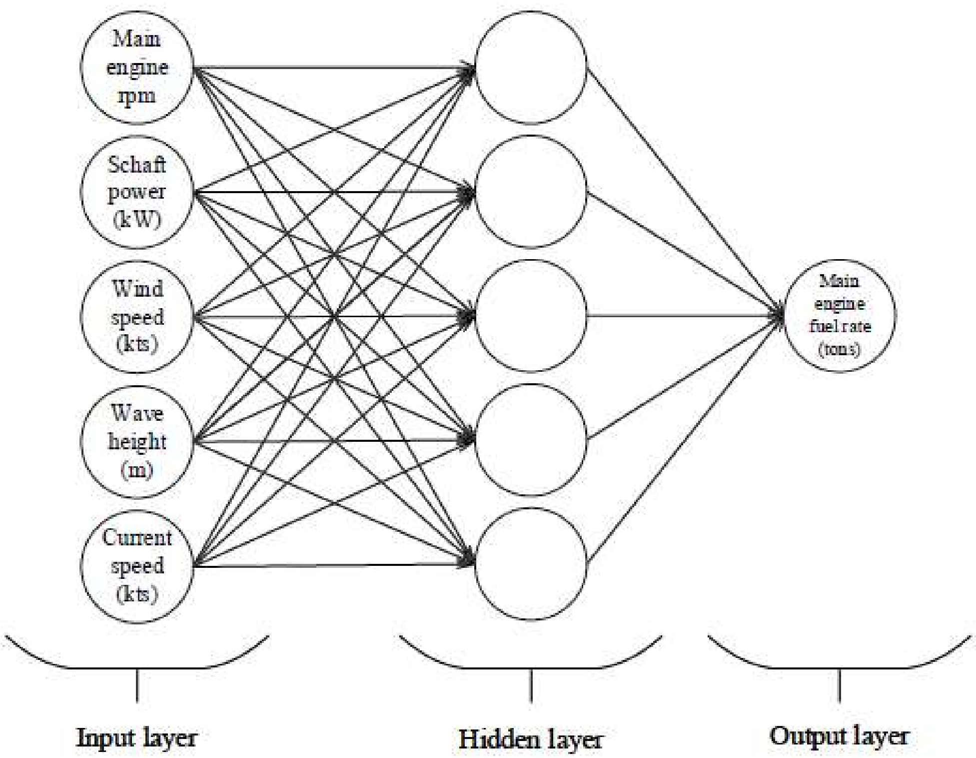

Figure 2: Machine learning approach for estimating fuel consumption [14].

Predicting how much fuel ships will need is a key step in the optimization process [15]. Two datasets were used to compare the fuel consumption of a cruise ship, one with the influence of maritime ambient variables and the other one without. Both the Back-Propagation Neural Network (BPNN) and the Gaussian Process Regression (GPR) have been proposed by the authors [16] to estimate the fuel consumption of container ships. These two approaches' prediction abilities were contrasted and analyzed. The results demonstrated that both approaches were capable of properly forecasting ship fuel consumption, particularly when applied to datasets including influences from maritime environmental conditions such as waves, wind, and currents. When comparing GPR and BPNN, the former has a slightly greater average accuracy for forecasting (mean R2 = 0.9817), while the latter takes significantly less time to run (mean T = 2236.4s vs. 14.7s). GPR's longer runtime makes it less appealing for online and in-the-moment estimates of ship fuel use. Under different marine environmental conditions, the ship's fuel consumption at different velocities and trims can be predicted remotely and in real-time. In order to achieve the aims of optimizing ship consumption of fuel, saving on operating expenses, and reducing global carbon emissions, this function allows the captain to select the optimal speed of the ship and shape (Specifically, the optimal ship's draught and speed difference).

Using mixes of shallow and deep learning, Ioannis Panapakidis et al. devised a way to forecast the fuel usage of a passenger ship [16]. The task is done on a Ro/Pax ship leaving from a Greek port. The route adopted in this work is Patras–Igoumenitsa–Bari itinerary. The Ro/Pax vessel is intricately designed because it provides passengers with lodging, dining, and entertainment in addition to transportation. Ro/Pax vessels are made to transport both people and vehicles (such as trucks and cars) [17]. The Long Short-Term Memory (LSTM) and Elman Neural Network (ENN) must operate in serial for the suggested model to function. An excellent forecast of the fuel requirement, based on precise models, can significantly enhance a vessel's operational performance.

The optimum shipping route can save costs, increase earnings, and boost shipping businesses' ability to compete. When selecting a liner shipping route, the cost of fuel—which accounts for the majority of a ship's running costs—is a key consideration. Using an Asymmetric Traveling Salesman Problem (ATSP) method, where the consumption of fuel model for the route is calculated via deep machine learning, the authors of this paper [18] discuss a solution that finds the optimum functioning path for container ships in order to save fuel costs. All five of these factors—average speed, sailing time, vessel capacity, the speed of the wind, and wind direction—are input into the model. In this research work, the authors have considered the optimal route Tanjung Pelepas → Shekou → Colombo → Nansha New Port → Qingdao → Vung Tau → Busan → Hong Kong → Salalah → Yantian → Singapore → Shanghai → Tanjung Pelepas, that corresponds to fuel cost estimated at 98,769.6 USD. Deep learning relies heavily on the quality of the learning dataset because it is a data-driven technique. This approach provides highly accurate predictions when the recorded dataset has a high degree of convergence. To boost the effectiveness of the model, however, when the data set is fragmented, other methods, such as theory-driven procedures, must be added.

Luan Thanh Le at. et, [19] present a multilayer perceptron artificial neural network (MLP ANN) as a machine-learning method that was designed to calculate ship fuel consumption. In this study, we analyze actual operational information from 100-143 container vessels to determine the fuel consumption of five distinct container boats based on size using four inputs (mean sailing speed, mean voyage duration, mean cargo weight and mean ship capacity). The best hyper-parameters were identified through iterative testing in order to balance the running duration and the convergence value. A comparison was carried out with the existing model to understand the accuracy achieved through the MLP ANN model with four inputs. In addition to demonstrating the critical role slow-steaming plays in decreasing fuel consumption and emissions, the optimized approach may offer shipping companies precisely the amount of slow-steaming required to achieve their energy efficiency targets [28].

The container port's ship-related CO_2 emissions should be estimated [20]. The Ship Energy Efficiency Management Plan (SEEMP) considers the important factor of CO_2 emissions. When a ship enters a port, its operations, such as maneuvering and berthing, are the first ones that are used to estimate its carbon dioxide emissions. In this research article [20], Random Forest Regression (RF) was used to examine the energy usage and CO_2 emissions of the ship at the default configuration, and k-folds cross-validation was used to confirm its efficiency. The model's accuracy was determined to be 98.85% through random forest model training and k-folds cross-validation. The analysis's findings indicated that there are five factors that can have an impact on how much CO_2 is emitted: main engine power; auxiliary engine power; port basin waiting time; maneuvering time; and berthing time. By implementing a number of journey optimizations, having a knowledgeable operator, and using cold ironing where possible, CO2 emissions can be cut by 20%, as discussed in the context of a fuel-efficient operation. The proposed method used in this article can be considered for container ports in poor nations like Indonesia where environmental health is not given top concern.

In [21], based on machine learning, a probability model for fuel oil consumption has been developed. In this study, the presented methodology is applied to the construction of a fuel oil consumption probability model. The fuel efficiency of maritime main diesel engines can be improved by using the Monte Carlo simulation method and Artificial Neural Networks (ANNs). The sample data was produced using the Monte Carlo simulation technique. Using an artificial neural network, a fuel oil consumption model is created. The proposed model for predicting future fuel oil consumption is based on a back-propagation training method of artificial neural networks. By examining information gathered from one bulk shipment run by the Vietnamese company VINIC Shipping, the suggested design has been put to the test in the real world [29].

Fuel efficiency is analyzed, and then several machine learning algorithms are compared in terms of their ability to predict fuel efficiency while taking into account a number of different factors.

Table 1: A overview of alternative machine learning algorithms for calculating ship energy use.

SL. No	References	Parameters	Algorithm/Methodology used	Performance
1	Kim et al. (2021)	Speed of the main engine, sailing speed, wind direction and speed, draft, etc.	Artificial Neural Network	The fit goodness is 0.9709–0.9936
2	Hu et al. (2019)	Information on draft, sail angle, wind speed and		The R2 is 0.9817

		direction, wave height, and wave direction	Back Propagation in Neural Networks (BPNN)	
3	Yuan et al. (2020a)	Static data, ship status information, and environmental data	Double-hidden-layer Back-Propagation Neural-Network (DBPNN).	The R2 is 0.9843
4	Moreira et al. (2021)	Wave angle, main engine speed, and effective wave height	Artificial Neural Network	-
5	Zhu et al. (2020)	Wind, water's surface speed, pitch, and trim	long short-term memory networks	The MSE can be improved by 11.8%.
6	Karagiannidis et al. (2019)	Factors such as current acceleration, draft, sailing direction, steering position, wave height, wind, etc.	Artificial Neural Network	The accuracy of the predicted fuel consumption is 98.7%.
7	Bui-Duy and Vu-Thi-Minh	Average wind speed and direction, sailing time, and speed of the sea	Deep- ANN	About 95% of predictions are accurate.

III. Conclusion

According to the thorough literature review conducted for this work, the majority of current research on ship fuel consumption models has been centered on machine learning-based prediction. Emission reduction and energy conservation are the main objectives of the project. Before a ship is even built, there is a significant gap in the available journey data, such as the normal fuel consumption for a given route. Research on ship resistance and the consideration of additional relevant parameters can raise the models' accuracy, but this comes at the expense of adding to the model's effort. The survey was carried out on various ships to understand the consumption of fuel based on multiple parameters, weather conditions, route of a ship, etc. The future model depends on energy efficiency optimisation techniques that should be utilised in conjunction with ship fuel consumption models. Ship energy efficiency optimization can be thought of as a two-pronged technique, with the supply side (on board the ship) corresponding to energy management and the demand side (onshore) to operation optimization. It must also aim to create a more comprehensive model that may be used to predict outcomes in a variety of circumstances with high accuracy. Some of the challenges and future work that need to be considered for improvement in ship fuel consumption:

i) Systematic approaches for tracking ship emissions and energy usage that can simultaneously manage a variety of data types and include modules for data preparation are still lacking. Deep mining of heterogeneous data from multiple sources has not been fully realised. The ability to dynamically analyze and predict emissions and energy consumption from ships using real-time data also needs further improvement. This means that we need to look into the multi-source heterogeneity big data characteristics in depth using multi-dimensional in-depth mining techniques. Models for estimating future energy use and emissions should ideally be developed using machine learning methods trained on large datasets to ensure maximum accuracy.

ii) Numerous time-varying elements (such as the breeze, wave, and trim) affect ship consumption of energy and pollutant gas emissions, necessitating more research on dynamic ship energy efficiency and emission analysis methodologies incorporating the combined impact of those components. More research is needed into the possibility of having the model's parameters train itself using AI so that it can better adapt to dynamic and ever-changing navigational environments. In order to accurately estimate a ship's energy use and emissions in real-time while also accounting for the effects of a wide variety of coupling factors, we need to develop more precise energy consumption models.

iii) More research into optimizing and controlling strategies for ship consumption of energy and pollutant emissions of gases is needed to meet the IMO-proposed reduction in emissions standards. Market mechanism-based measures, optimization of navigation, optimization control of power systems, etc., are all examples of what such methods could look like in order to help the marine industry grow sustainably.

iv) We should look at marine fuels more. Now that diesel engines are the most common choice for SFC vehicles, diesel fuel is used most commonly. The utilization of renewable energy vessels or hybrid ships, which run on fuels that are more efficient in terms of energy production, such as natural gas (LNG) fuel cell technology, methanol, and ammonia, can help to cut down on the amount of energy that is consumed by ships.

References

1. Ioannis Panapakidis, Vasiliki-Marianna Sourtzi, Athanasios Dagoumas, “Forecasting the Fuel Consumption of Passenger Ships with a Combination of Shallow and Deep Learning”, MDPI, Electronics Journal, 2020, vol. 9, pp. 1-25.
2. DNV-GL. Energy Transition Outlook 2017-Maritime Forecast to 2050; Det Norske Veritas—Germanischer Lloyd: Oslo, Norway, 2017.
3. Tayfun Uyanık, Caglar Karatug, Yasin Arslanoglu, “Machine learning approach to ship fuel consumption: A case of container vessel”, Transportation Research Part D, Elsevier, July 2020, vol. 84, 102389, pp. 1-14

4. Adland, Roar, Cariou, Pierre, Jia, Haiying, “The energy efficiency effects of periodic ship hull cleaning”, Journal of Cleaner Production, 2018, vol. 178, pp. 1–13.
5. Islam, Hafizul, Soares, Guedes, “Effect of trim on container ship resistance at different ship speeds and drafts”, Ocean Eng. 2019 vol. 183, pp.106–115.
6. Ionescu, Raluca Dora, Szava, Ioan, Vlase, Sorin, Ivanoiu, Mircea, Munteanu, Renata, “Innovative Solutions for Portable Wind Turbines, Used on Ships”, Procedia Technology, 2015, vol. 19, pp.722–729.
7. Wang, Haibin, Oguz, Elif, Jeong, Byongug, Zhou, Peilin, “Life cycle and economic assessment of a solar panel array applied to a short route ferry”, Journal of Cleaner Production, 2019, vol. 219, pp.471–484.
8. Ahlgren, F., Mondejar, M. E., & Thern, M., “Predicting dynamic fuel oil consumption on ships with automated machine learning”, Energy Procedia, 2019, vol. 158, pp.6126-6131.
9. Kim, Y.-R.; Jung, M.; Park, J.-B, “Development of a Fuel Consumption Prediction Model Based on Machine Learning Using Ship In-Service Data”, Journal of Marine Science and Engineering, 2021, vol .9, pp.137.
10. Gu, Y.; Wallace, S.W.; Wang, X, “Integrated maritime fuel management with stochastic fuel prices and new emission regulations”, Journal of the Operational Research Society, 2019, vol. 70, pp.707–725.
11. Meyer, J.; Stahlbock, R.; VoB, S, “Slow steaming in container shipping”, In Proceedings of the 45th Hawaii International Conference on System Sciences, Maui, HI, USA, 4–7 January 2012; pp. 1306–1314.
12. Singh, J., Dhiman, G., “A Survey on Machine-Learning Approaches: Theory and Their Concepts”, Materials Today: Proceedings, 2021, https://doi.org/10.1016/j.matpr.2021.05.335.
13. Bal Besikci E, et al., "An artificial neural network based decision support system for energy efficient ship operations", Computers and Operations Research (2015), http://dx.doi.org/10.1016/j.cor.2015.04.004i.
14. Tayfun Uyanik, Yasin Arslanoglu, Ozcan Kalenderli, “Ship Fuel Consumption Prediction with Machine Learning”, 4th International Mediterranean Science and Engineering Congress (IMSEC 2019), Pages: 757-759.
15. Z. Hu et al., “Prediction of Fuel Consumption for Enroute Ship Based on Machine Learning”, IEEE Access, 2019, Volume 7, pp. 119497-119505.
16. Ioannis Panapakidis, Vasiliki-Marianna Sourtzi and Athanasios Dagoumas, “Forecasting the Fuel Consumption of Passenger Ships with a Combination of Shallow and Deep Learning”, MDPI Electronics 2020, 9, 776, doi:10.3390/electronics9050776.
17. Marine Insight. What are Ro-Ro Ships? Available online: https://www.marineinsight.com/types-of-ships/ what-are-ro-ro-ships (accessed on 3 July 2019).
18. Linh Bui-Duy, Ngoc Vu-Thi-Minh, “Utilization of a deep learning-based fuel consumption model in choosing a liner shipping route for container ships in Asia”, The Asian Journal of Shipping and Logistics, vol. 37 2021 pp.1–11.

19. Luan Thanh Le, Gunwoo Lee, Keun-Sik Park & Hwayoung Kim (2020), “Neural network-based fuel consumption estimation for container ships in Korea”, Maritime Policy & Management, DOI: 10.1080/03088839.2020.1729437.
20. Ivan Dewanda Dawangi, Muhammad Arif Budiyanto, “Ship Energy Efficiency Management Plan Development using Machine Learning: Case Study of CO2 Emissions of Ship Activities at Container Port”, International Journal of Technology, 2021, doi: 10.14716/ijtech. v12i5.5183.
21. Tran Tien-Anh, “Comparative analysis on the fuel consumption prediction model for bulk carriers from ship launching to current states based on sea trial data and machine learning technique”, Journal of Ocean Engineering and Science (2021), doi: https://doi.org/10.1016/j.joes.2021.02.005
22. U.S. Energy Information Administration (EIA), International Energy Outlook 2013, DOE/EIA-0484, July 2013, Washington D.C: EIA.
23. Yuan, Z., Liu, J., Liu, Y., et al., “Fitting analysis of inland ship fuel consumption considering navigation status and environmental factors”, IEEE Access 8, pp. 187441–187454, 2020.
24. J. Somasekar, G. Ramesh, B. Eswara Reddy, Ching-Hao Lai et.al., A dataset for automatic contrast enhancement of microscopic malaria infected blood RGB images, Data in brief 27 (2019).
25. Moreira, L., Vettor, R., Guedes Soares, C., “Neural network approach for predicting ship speed and fuel consumption”, J. Mar. Sci. Eng. 9 (2), 119, 2021.
26. J. Somasekar and B. E. Reddy, "Contrast-enhanced microscopic imaging of Malaria parasites," 2014 IEEE International Conference on Computational Intelligence and Computing Research, Coimbatore, India, 2014, pp. 1-4, doi: 10.1109/ICCIC.2014.7238439.
27. J. Somasekar, B. Eswara Reddy, A Novel Two-Stage Thresholding Method for Segmentation of Malaria Parasites in Microscopic Blood Images. J. Biomed. Eng. Med. Imaging 2017, 4, 31–42.
28. Zhu, Y., Zuo, Y., Li, T., “Predicting Ship Fuel Consumption Based on LSTM Neural Network”, 7th International Conference on Information, Cybernetics, and Computational Social Systems (ICCSS). IEEE, pp. 310–313, 2020.
29. Karagiannidis, P, Themelis, N, Zaraphonitis, G, et al., “Ship fuel consumption prediction using artificial neural networks”, In: Proceedings of the Annual meeting of marine technology conference proceedings, Athens, Greece, 2019.