Brodogradnja/Shipbuilding/Open access Volume 74 Number 1, 2023

Umit Gunes

http://dx.doi.org/10.21278/brod74105 ISSN 0007-215X
eISSN 1845-5859

Estimating bulk carriers' main engine power and emissions

UDC 629.546.2:621.43.018.7:316.4.063.5
Original scientific paper

Summary

Great importance is had in understanding the current situation of maritime transport and making predictions about its future. Maritime transport is an essential part of transportation, and correctly predicting installed main engine power has great significance in maritime transport with regard to fuel consumption and the generation of emissions. Nonlinear regression is a method with great potential in making predictions, as it allows for more realistic models to be developed using multiple variables. Vessels' dimensions of carrying capacity, gross tonnage, length, and breadth significantly impact the required main engine power. This article will calculate and estimate the installed main engine power for bulk carriers through nonlinear regression using data for the as yet highest number of bulk carriers (n = 9,174 ships) and compare the results with the studies in the literature. The developed model has an accuracy of 93.2% for six different bulk carrier types (Small, Handysize, Handymax, Panamax, Capesize, and Large Capesize). In addition, the study calculates the emissions these ships produce (NOx, SO_2, CO_2, HC, PM), estimating and demonstrating a nonlinear linear regression model for these ships' emission amounts. The performed analyses have found the main engine power required per unit of load to decrease as ship size increases. However, these analyses also show the emissions generated per unit of load to decrease as size increases, with Large Capesize vessels being found to have the lowest fuel consumption and emission generation per unit of load.

Keywords: bulk carrier; engine power; nonlinear regression; maritime transport; emission

1. Introduction

Calculating and estimating a ship's main engine power is essential in terms of economics, as well as for comprehensively calculating emissions and their various sub-components. The use of data in the literature for improving ship emission calculations significantly developed with Eyring et al.'s two-part study [1, 2] that used 1950-2000 data to make short-term (until 2020) and long-term (until 2050) predictions. They estimated carbon emissions based on a technology-driven model and a business-as-usual model for an all-diesel fleet. In addition, Kalajdzic [3] investigated bulk carriers' power reduction concerns in light of the new energy efficiency rules.

Heating, ventilation, and air conditioning systems are significant power consumers on ships that run at a constant load, and using a variable speed compressor in its place has significantly reduced emissions [4]. Başhan et al. [5] compared emissions versus fuel types for diesel generators used in crane operations and found them to have roughly 40% lower costs compared to Marine Gas Oil by calculating NO_x, SO_2, CO_2, PM, and HC emissions. Engine power probabilities are used to calculate NO_x emissions for bulk carriers, and the certified values are shown to require refinement by using weighted factors; doing this revealed 7% lower emissions at sea and 32% lower at port [6]. The methods have also been shown to overestimate SO_2 emissions. The recommendation is that onboard controls are more effective at reducing SO_2 emissions due to the variable sulphur content found in marine fuels [7]. Another issue regarding emission reduction is having ship designs satisfy current energy efficiency requirements [8].

Tasdemir et al. [9] used artificial neural networks (ANN) and a fuzzy expert system to predict performance and emissions for a gasoline engine. Their results showed ANN and fuzzy expert systems to be reliable for practical designs and experimental work in the automotive and engineering fields. Özener et al. [10] investigated the ANN approach for estimating engine emissions and performance of a turbocharged engine, showing both ANN to be effective and neural network performance to be increasable with the use of additional relevant input data.

Abramowski [11] used neural networks to apply a seven-variable solution vector for optimizing cargo ship design parameters. This parametric model is particularly suitable for determining effective ship power due to the model's simplicity. Gurgen et al. [12] used ANNs to estimate chemical tanker characteristics in the preliminary ship design stage, revealing ANNs to have prediction levels that significantly match the sample data for chemical tankers. Meanwhile, Jeon et al. [13] used ANN to predict ship fuel consumption using the vast volume of data collected from smart ships to streamline a model for predicting fuel consumption; this proved to be more accurate than the polynomial regressions, thus supporting vector machines. De Winter et al. [14] showed random forest regressors to provide better estimations than the empirical design equations, therefore demonstrating a practical application for naval architects. Okumuş et al. [15] studied main and auxiliary ship engine power using regression-based machine learning algorithms to increase the accuracy of ship engine power estimation and allow for the construction of more environmentally friendly ships. Due to their importance in providing data for fuel consumption and exhaust emissions, the Gaussian mixture model and deep neural network have also been studied over large vessels to predict main engine power [16].

Sahin et al. [17] set out to develop an ANN approach to forecast the Baltic Dry Index, a shipping sector indicator of global economic activity. Using Baltic Dry Index data from 2010-2016, they developed three ANN models: one involving weekly data from the Baltic Dry Index, one on weekly data regarding crude oil prices, and a combination of the two. Next, Cong et al. [18] looked at multivariate nonlinear regression to optimize emissions for a dual-fuel marine engine and showed this method to be applicable for optimizing engine parameters regarding various variables. Yang et al. [19] also used an ANN model to predict efficiency and emissions in a gasoline engine. Their results emphasized how one ANN model can take the place of several other traditional design testing methods to predict emissions and efficiency more accurately and cost-effectively.

Adamowski et al. [20] compared multiple linear and nonlinear regression with ANN, wavelet ANN, and autoregressive integrated moving average methods to predict water demands in Montreal. They found the wavelet ANN to have the best accuracy at predicting water demands based on daily data from 2001-2009 involving precipitation, temperature, and water demand. Adamowski et al. concluded this model to be particularly effective for estimates, which leads one to wonder about its effectiveness in other areas and fields. Gunes et al.'s [21] study also aimed to conduct nonlinear regression and ANN analyses to run estimates of tanker main engine power. Their regression analyses revealed one model to provide the best estimation for this, with the ANN analysis further improving its estimation strength.

One prolific set of studies in the literature involves Yildiz [22] developing a new model to predict the residual resistance of a trimaran vessel using an ANN and Cepowski's [23] development of a transfer function for bulk carriers to forecast added wave resistance from irregular head waves using an ANN with several inputs. Cepowski [24] then went on to use simple linear regression and multivariate linear regression analyses to approximate the preliminary parametric design of new container ships and the required main engine power based on data regarding the length between perpendiculars and the total number of containers to be carried for ships constructed between 2005-2015. Cepowski [25] used more comprehensive data for ships built between 2000-2018. He again used regression analyses to estimate total engine power, now using ship deadweight and TEU together with ship velocity for greater accuracy. Previous regressions [26] were found to be only accurate for medium-size ships or average speeds in the case of MAN Diesel's nominal engine power diagrams. The new estimator was accurate for contemporary ships, applicable to preliminary ship design, and able to help develop ship design theory. Cepowski [27] also used an ANN possessing a 6-neuron input (each with hidden layers) and a single-neuron output to again forecast ship added-resistance in normal head waves, this time involving the design elements of ship length, breadth, draught, and Froude number. Cepowski and Chorab [28] further studied ANNs for estimating engine power and fuel consumption of bulk carrier, tanker, and container ships' engines to update propulsion system design equations, with the inputs for the ANN being deadweight, TEU capacity, and ship speed. Meanwhile, Xhaferaj [29] compared the accuracy of a computer algorithm built to forecast ship resistance and power regarding standard hulls.

The present study looks at the most comprehensive analyses regarding calculations and estimations of ships' installed main engine power and performed nonlinear regressions to cover all ship types and sizes instead of just certain ones. Bejan et al.'s [30] study had previously presented the relationship between size (Dead Weight Ton, *DWT*) and main engine power by using a power law regression model for all ship types and sizes. This current study estimates main engine power and emission amount by considering not only *DWT*, but also many other main factors, including *GT, L, B, T,* an also computes emission amounts.

2. Materials and Methods

2.1 Database

This study uses the Marine Traffic Database [31], as it offers the most comprehensive data on ships, which is needed for conducting the analyses. The database contains over 80 technical specifications (e.g., type, shipbuilder, year built, draught, depth, *DWT*, Gross Tonnage [GT], engine power) of around 1 million ships and thus can be considered an up-to-date document regarding the world fleet. The database also has 75 subcategories for ships, with the Marine Traffic webpage showing 11,351 active bulk carriers, of which this paper uses 9,174 (80%) in the analysis, with bulk carriers categorized under six groups (i.e., Small, Handysize, Handymax, Panamax, Capesize, and Large Capesize) for making detailed analyses. The analyses only consider the ships with active statuses, ignoring those with under construction, cancelled order, decommissioned, lost, laid up, or under repair statuses. In addition, Very Large Bulk Carriers (VLBCs), these have been excluded from the analyses due to their small number. Table 1 provides scantling information regarding the bulk carrier types.

Table 1 Bulk carrier types [32,33]

Bulk carrier types	Dimensions	Ship size (scantling)
Small Overall ship length up to	approx. 115 m	Up to 10,000 DWT
Handysize Scantling draught up to	approx. 10 m	10,000-35,000 DWT
Handymax Overall ship length (re: port facilities in Japan)	max. 190 m	35,000-55,000 DWT
Panamax Ship breadth equal to Overall ship length up to (re: port facilities) Overall ship length up to (re: canal lock chamber) Passing ship draught up to	max.: 32.2 / 32.3 m 225 m 294.13 m 12.04 m	55,000-80,000 DWT
Capesize Breadth	approx. 43-45 m for 90,000-180,000 DWT	80,000-200,000 DWT
Large Capesize Breadth	above 50 m	200,000-300,000 DWT
VLBC (Very Large Bulk Carrier) Overall ship length	above 330 m	More than 300,000 DWT

Figure 1 shows the number of bulk carriers used in this analysis based on type. While Panamax is the most common type with 3,035 ships, the second most common is Capesize with 2,393. Handymax and Handysize types respectively number 1,651 and 1,647, while Large Capesize and Small ships have the lowest numbers with 246 and 158, respectively.

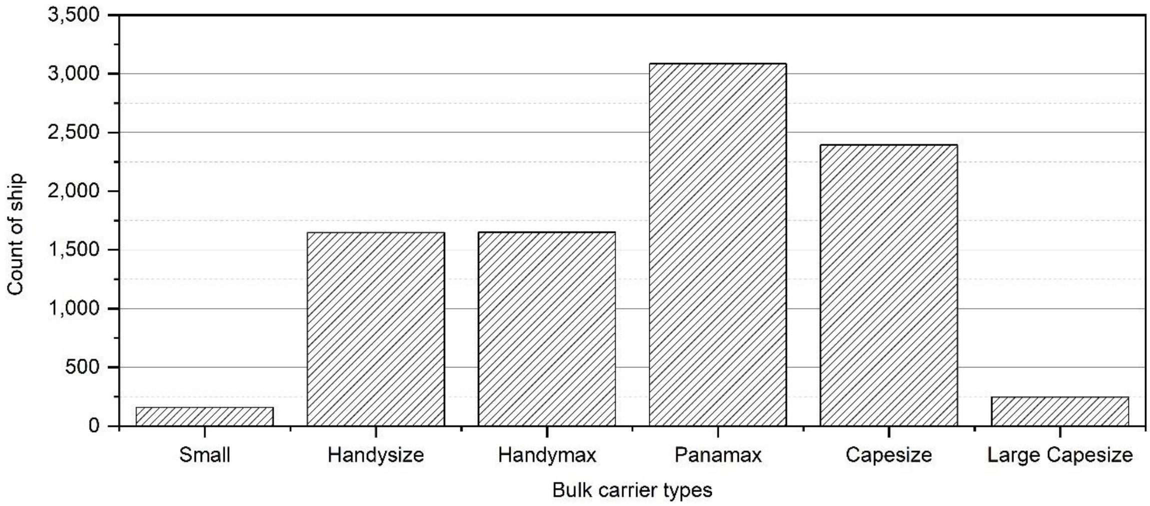

Fig. 1 Number of bulk carriers

Figure 2 lists the number of bulk carriers by ship's flag. Panama ranks first with 2,206 ships. The reason is the taxation advantage presented by ships bearing the Panama flag. The Marshall Islands rank second with 1,321 ships, and Liberia is third with 1,004.

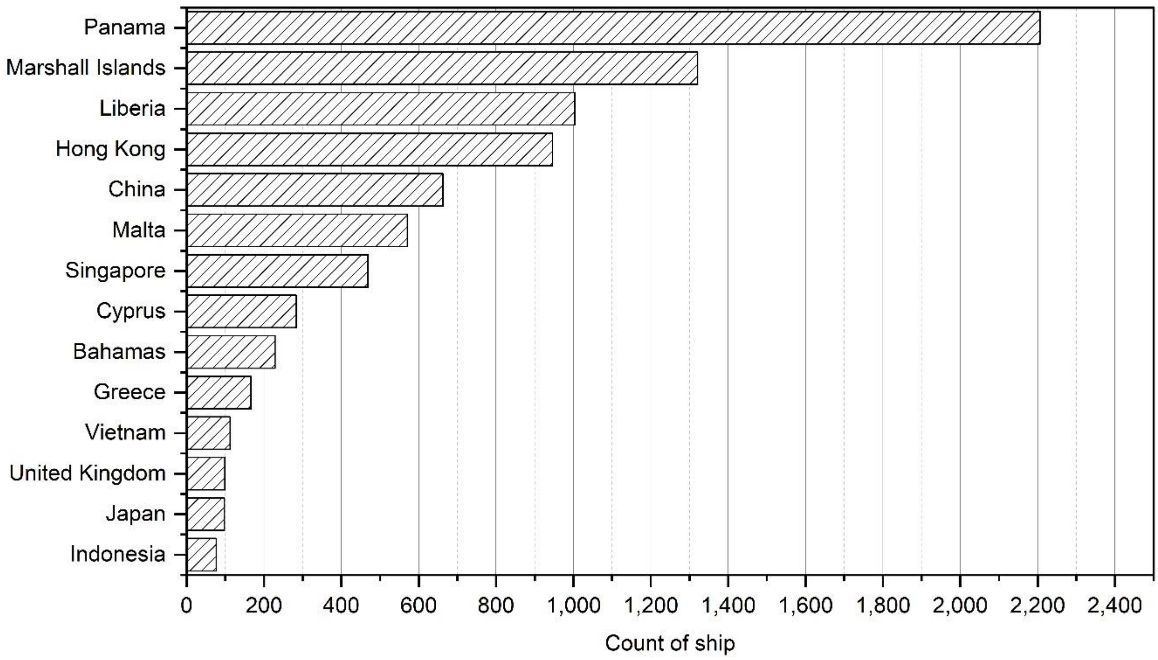

Fig. 2 Flags of the bulk carriers

Figure 3 shows the bulk carriers' main engine RPM values. While ships operating in the 90-99 RPM range rank first with 1,703 ships, ships in the 120-129 RPM range rank second with 1,620. Third place sees 1,145 ships operating in the 100-109 RPM range, and fourth has 1,003 ships operating in the 110-119 RPM range. Fifth place has 835 ships operating in the 80-89 RPM range, and sixth place has 440 ships operating in the 130-139 RPM range. Ships operating in other RPM ranges correspond to 9.4% of all ships and have RPM values of less than 80 or greater than 140. RPM data directly affects a ship's economic navigation, slow steaming status, and produced power and therefore the amount of fuel it consumes.

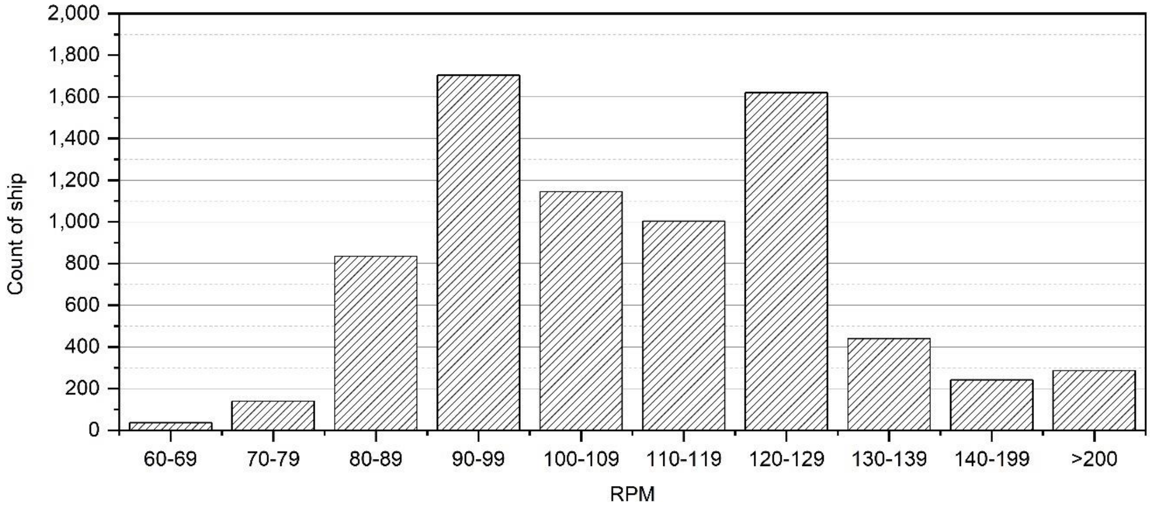

Fig. 3 RPM of the bulk carriers' main engine

Figure 4 shows the average speed of bulk carriers while underway. The ships can be seen to mainly operate between 7-13 knots, with most ships operating at a speed of 11 knots, followed by 12 and then 10 knots. The percentage of bulk carriers operating at speeds under 7 knots or over 13 knots is 11%.

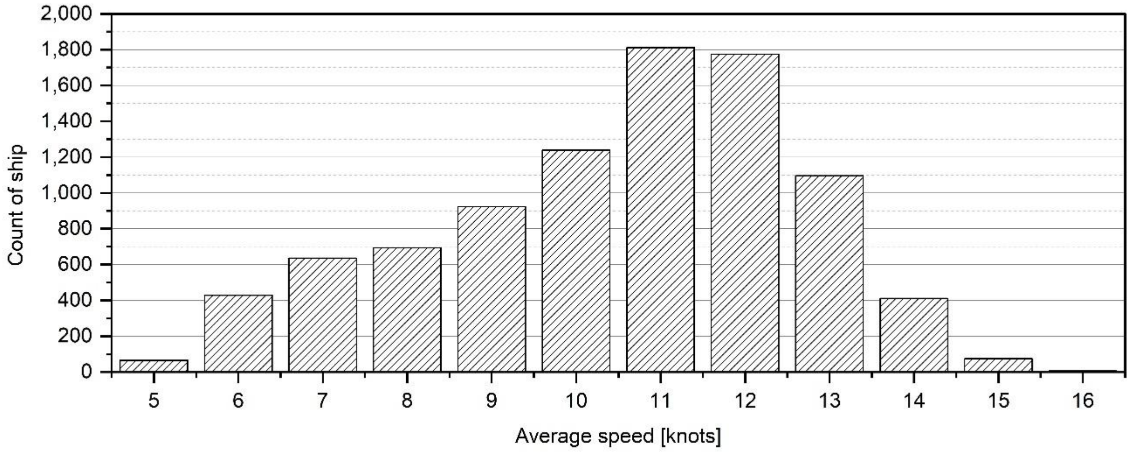

Fig. 4 Average speed of the bulk carriers

Table 2 contains the technical characteristics of the 9,174 bulk carriers used in this study. These characteristics include average *GT*, *DWT*, year of construction, breadth, installed engine power, and draught for each type of ship. This situation reveals the current state of the bulk carrier market and draws a projection of fleets' need to renovate their ships and what size to build new ships.

Table 2 Summary of bulk carriers' average technical information

	Small	**Handysize**	**Handymax**	**Panamax**	**Capesize**	**Large Capesize**
Ave. GT	3,458.83	17,885.19	26,476.98	35,809.98	66,205.76	106,364.03
Ave. DWT	5,379.71	28,345.62	44,178.94	64,521.15	125,809.97	206,992.89
Ave. Year Built	2006	2006	2007	2010	2011	2012
Ave. Breadth	15.28	26.77	30.63	32.30	39.41	49.96
Ave. Engine Power	1,780.29	6,084.15	7,699.34	9,114.20	13,684.95	17,193.03
Ave. Draught	5.14	7.87	8.89	10.02	12.27	13.63

2.2 Nonlinear Regression

Nonlinear regression examines data fitted to a mathematical model given as a function. Simple linear regression establishes a linear relationship between two variables, whereas nonlinear regression establishes nonlinear correlations [34]. Cakici and Aydin used a nonlinear regression method for ship design and prediction [35]. The model's objective is to minimize the residual sum of squares (RSS), a measure of the variance between the observations of Y and the nonlinear function used to forecast Y. A nonlinear regression equation has the following general form:

$$Y(x) = f\,(x_i, (c_1 + c_2 + \ldots, + c_n) + (a_1 + a_2 + \ldots, + a_n)) \qquad (1)$$

where Y is the estimate of the dependent variable (engine power), and Equation (1) has the coefficients c_0, c_1, …, c_n as regression weight coefficients showing how the independent variables affect the dependent variable.

$$R_i = Y_i - f(x_i, (c_1 + c_2 + \ldots, + c_n) + (a_1 + a_2 + \ldots, + a_n)) \qquad (2)$$

Equation (2) shows R as the residual value, which is the difference between the actual value and the mean value that the model predicts for that actual value.

In Equation (2), all variables should be written as a matrix to calculate the regression coefficients.

$$\underbrace{\begin{bmatrix} \frac{\partial f}{\partial c_{11}} & \frac{\partial f}{\partial c_{12}} & \cdots & \frac{\partial f}{\partial c_{1m}} \\ \frac{\partial f}{\partial c_{21}} & \vdots & \ddots & \frac{\partial f}{\partial c_{2m}} \\ \vdots & \vdots & \cdots & \\ \frac{\partial f}{\partial c_{n1}} & \frac{\partial f}{\partial c_{n2}} & \cdots & \frac{\partial f}{\partial c_{nm}} \end{bmatrix}}_{D} \cdot \underbrace{\begin{bmatrix} \Delta A_1 \\ \Delta A_2 \\ \vdots \\ \Delta A_m \end{bmatrix}}_{\Delta A} = \underbrace{\begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_m \end{bmatrix}}_{R} \tag{3}$$

Equation (3) shows the D matrix cannot be inverted because it is not square. To invert it, it is turned into a square matrix by adding the transpose of the D matrix (D^T) to both sides as:

$$D^T \Delta A = D^T R \tag{4}$$

where ΔA is the coefficient from the nonlinear regression, which is calculated as:

$$\Delta A = (D^T \Delta D)^{-1} D^T R \tag{5}$$

Equation (4) allows the regression coefficients ($c_1 + c_2 + \ldots, + c_n$) and power coefficients ($a_1 + a_2 + \ldots, + a_n$) to be calculated for the minimum RSS and high coefficient of determination (R^2). The least-squares method (LSM) is used to calculate the best algorithm of the RSS for the nonlinear regression. When finding the minimum RSS using LSM, all coefficients are calculated for this result. LSM asserts the curve that best fits a given set of observations to have the minimum RSS from the provided data points as shown in Equation (6).

$$RSS = \sum_{i=1}^{n} \underbrace{\left[y_i - f_{x_i} \right]}_{R}^{2} \tag{6}$$

To find the best model, the study analyses the parameters in combination with DWT, Length, Draught, Breadth, and Gross Tonnage to find the best estimate of ship power. Table 3 shows the Pearson correlation for the ship particulars, with draught having the smallest correlation compared to all other parameters and as such has been removed from the models.

Table 3 Pearson correlation for the ship's particular

Parameter	**Engine Power**	**DWT**	**Length**	**Draught**	**Breadth**	**Gross Tonnage**
Engine Power	1	0.95	0.941	0.554	0.93	0.954
DWT	0.95	1	0.958	0.559	0.943	0.998
Length	0.941	0.958	1	0.568	0.934	0.96
Draught	0.554	0.559	0.568	1	0.546	0.561
Breadth	0.93	0.943	0.934	0.546	1	0.953
Gross Tonnage	0.954	0.998	0.96	0.561	0.953	1

To calculate the nonlinear problem, the study uses the Levenberg-Marquardt (L-M) algorithm [36], which combines the Gauss-Newton and steepest descent methods. The technique is effective in most situations and has become the standard for nonlinear least square routines.

2.3 Initial Values and Normalization

Choosing meaningful initial values (c_1 or a_1) is the essential part of the L-M algorithm, as the results are affected by the initial selected values. For this reason, a new algorithm was developed for identifying significant initial values. First, a power law fitting of the y-value was performed against each x-variable, using this on the fitted slope to provide the initial coefficient estimate for each x-variable. This method of defining the initial coefficient gives reasonable values for calculating all parameters in the nonlinear regression.

Several methods exist for normalizing data. In our analysis, all values are divided by their maximum value, thus converting the value from 0 to 1 in order to find a reasonable result from the analysis. Table 4 shows the normalization of the parameters and the derivative parameters. For weighting, the variance ~ yfit method is used due to the accuracy of current data trends.

Table 4 Normalization of the parameters

New parameter	Calculation	Maximum values
DWT^*	DWT / DWT_{max}	211182
GT^*	GT / GT_{max}	109716
L^*	L / L_{max}	312
B^*	B / B_{max}	50.5

2.4 Emissions

Emission factors are required to calculate emissions. Table 5 shows the types of emissions generated in bulk carriers based on energy consumed (kWh). ENTEC [37] calculated the values in the table for 31,000 ships worldwide.

Table 5 Emission factors for "at sea" operations [g/kWh] regarding bulk carriers in 2020 [37]

NO_X	SO_2	CO_2	HC	PM
15.3	10.6	627	0.59	1.61

Equation (7) shows the calculation of annual emissions as follows:

$$E = P \times EPP \times YWH \times 10^{-6} \tag{7}$$

where E is emissions (tons), P is installed engine power (kW), EPP is emissions per unit of engine power (g/kWh), and YWH is yearly working hours (h).

3. Results and Discussion

Equation (8) defines the nonlinear model for estimating engine power and emissions for all sizes of bulk carrier types.

$$\beta = c_1 DWT^{*a_1} + c_2 GT^{*a_2} + c_3 L^{*a_3} + c_4 B^{*a_4} \tag{8}$$

where β correlation function, c_i, and a_i are the respective regression and power coefficients. The individual correlation for engine power was analyzed with a single correlation. Engine power's relation with DWT / DWT_{max} is shown in Figure 5a, with GT / GT_{max} in Figure 5b, with L / L_{max} in Figure 5c, and with B / B_{max} in Figure 5d.

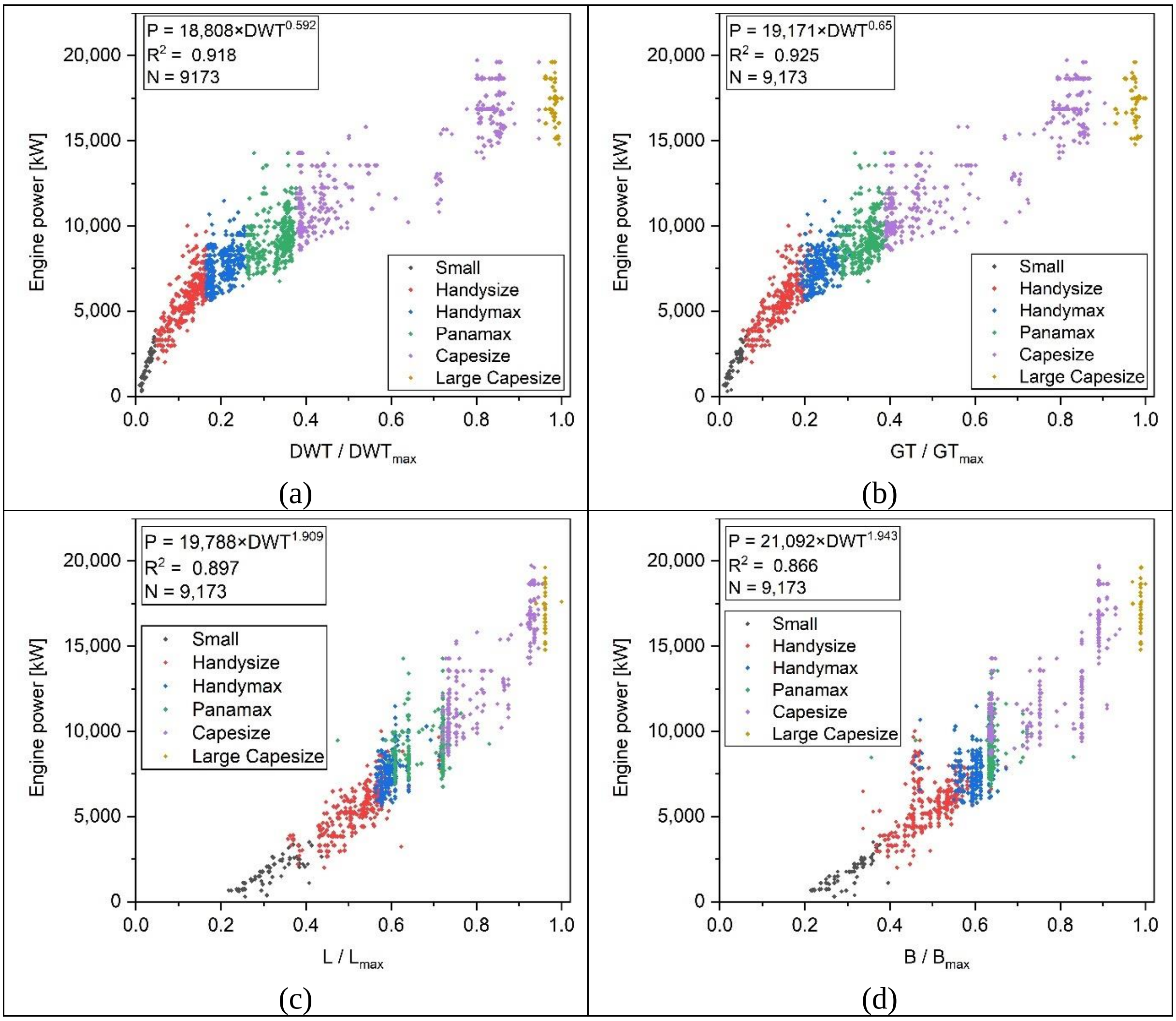

Fig. 5 Correlation between engine power and DWT / DWT_{max} (a), GT / GT_{max} (b), L / L_{max} (c), and B / B_{max} (d).

The initial coefficient of the parameters shown in Figures 5a, 5b, 5c, and 5d are listed in Table 6. These initial values provided high correlation results in the nonlinear regression, with better nonlinear regression results depending on reasonable initial values.

Table 6 Initial coefficients of the parameter

Parameter	**c_i**	**a_i**	**R^2**
DWT	18,808	0.592	0.918
GT	19,171	0.65	0.925
L	19,788	1.909	0.897
B	21,092	1.943	0.866

Tables 7 and 8 show the results of performing the nonlinear regression analysis over the model created according to Equation (8) covering all bulk carrier types (R^2 = 0.932).

Table 7 Power coefficients of engine power emission factors based on Equation (8).

a_1	**a_2**	**a_3**	**a_4**
0.445	0.635	2.018	1.880

After finding power coefficients for the installed main engine power and emissions (Table 7) using Equation (8), regression coefficients for engine power were also found using nonlinear regression. Table 8 additionally shows the regression coefficients for the emission factors. All the coefficient in Table 7 and Table 8 can be used in Equation (8) to estimate main engine power and the amount of the emissions (NO_x, SO_2, CO_2, HC and PM).

Table 8 Regression coefficients for engine power and emission factor based on Equation 8.

Correlation functions (β)	c_1	c_2	c_3	c_4
Engine power	0.445	0.635	2.018	1.880
NO_X	1.08×10^4	2.45×10^5	1.5×10^4	1.94×10^4
SO_2	7.45×10^3	1.70×10^5	1.07×10^4	1.35×10^4
CO_2	4.41×10^5	1.00×10^7	6.34×10^5	7.97×10^5
HC	4.15×10^2	9.44×10^3	5.96×10^2	7.50×10^2
PM	1.13×10^3	2.58×10^4	1.63×10^3	2.05×10^3

The difference between the actual and estimated values shows the success of the nonlinear model. The present model also has very high prediction. As seen in Figure 6, the difference between the actual and estimated values is quite low. Error rates for 6,519 ships (71% of all ships) are less than 10% and between 10%-20% for 2,021 ships (22% of all ships). This model's estimations successfully estimate engine power using the ship parameters *DWT*, *GT*, *L*, and *B*.

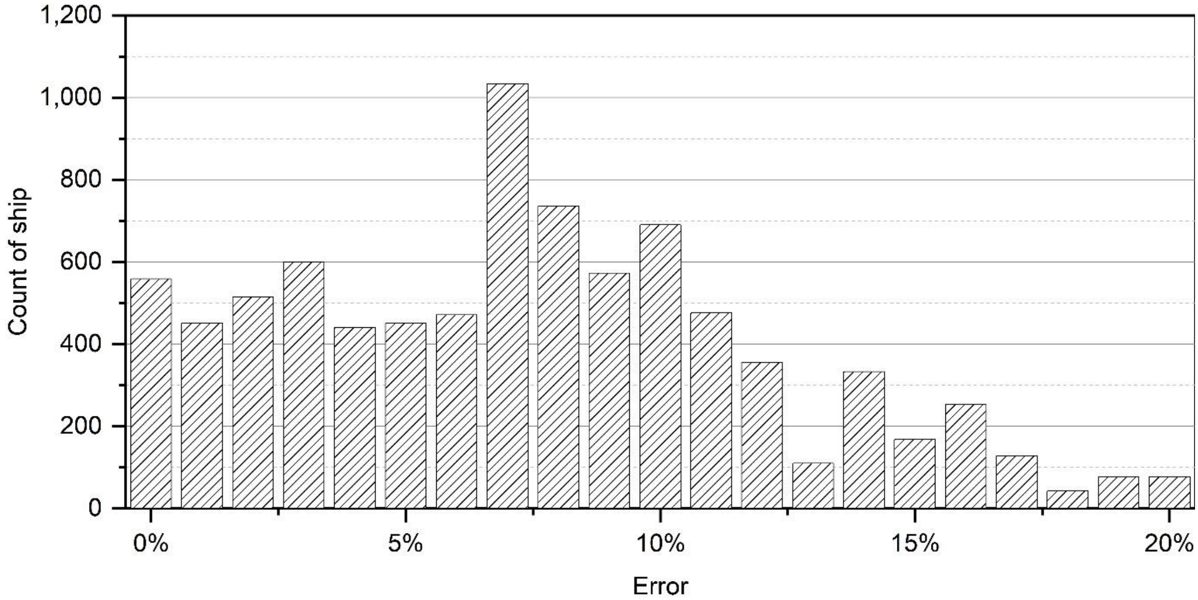

Fig. 6 The difference between the real engine power and the estimated values.

Table 9 shows the total emission amounts in bulk carriers as calculated using Tables 7 and 8. When examining the total emission amounts, the ships that cause the most emissions are seen to be Capesize-type ships, producing 37% of the total emissions from bulk carriers. After Capesize ships, Panamax ships cause the second highest total emissions at 32%, with Handymax-type ships in third at 14%, Handysize ships in fourth at 11%, and Large Capesize ships in fifth at 5%. The ship type that causes the least emissions overall is the small ship type at 0.1%.

Table 9 Total amount of annual emissions [tons] for the bulk carrier types

Bulk Carrier Type	Total NO_X	Total SO_2	Total CO_2	Total HC	Total PM
Small	0.025×10^6	0.017×10^6	1.05×10^6	0.989×10^3	2×10^3
Handysize	0.92×10^6	0.636×10^6	37×10^6	0.035×10^6	96×10^3
Handymax	1.16×10^6	0.807×10^6	47×10^6	0.044×10^6	122×10^3
Panamax	2.5×10^6	1.7×10^6	105×10^6	0.099×10^6	271×10^3
Capesize	3.0×10^6	2.08×10^6	123×10^6	0.115×10^6	316×10^3
Large Capesize	0.388×10^6	268×10^3	15×10^6	0.014×10^6	40×10^3

Table 10 shows bulk carriers' ratio of total emissions to load carried. While the ships with the lowest emissions per unit of load (*DWT*) are Small, the ships with the most emissions per unit load are the Large Capesize ships. Ship size increases are closely related to the energy demand per load unit, as studies have shown increased vehicle or animal size to decrease the energy demand per unit of load carried [27], [36]. Therefore, as the power consumed per unit of load decreases, the amount of emissions generated per unit of engine power also decreases.

Table 10 Emissions per load (*DWT*) for the bulk carrier type

Bulk Carrier Type	$\sum NO_X/\sum DWT$	$\sum SO_2/\sum DWT$	$\sum CO_2/\sum DWT$	$\sum HC/\sum DWT$	$\sum PM/\sum DWT$
Small	3.04×10^{-2}	2.10×10^{-2}	1.24×10^{0}	1.17×10^{-3}	3.20×10^{-3}
Handysize	1.97×10^{-2}	1.37×10^{-2}	8.07×10^{-1}	7.60×10^{-4}	2.07×10^{-3}
Handymax	1.60×10^{-2}	1.11×10^{-2}	6.56×10^{-1}	6.17×10^{-4}	1.68×10^{-3}
Panamax	1.30×10^{-2}	8.98×10^{-3}	5.31×10^{-1}	5.00×10^{-4}	1.36×10^{-3}
Capesize	9.99×10^{-3}	6.92×10^{-3}	4.09×10^{-1}	3.85×10^{-4}	1.05×10^{-3}
Large Capesize	7.62×10^{-3}	5.28×10^{-3}	3.12×10^{-1}	2.94×10^{-4}	8.02×10^{-4}

Table 11 shows the average emissions bulk carriers generate. The table calculates the total emissions for each ship type by dividing by the total number of that ship. While small ships produce the fewest emissions on average, Large Capesize ships produce the most. As a result, average emissions increase in proportion with ship size, while the emissions produced per unit of load decrease.

Table 11 Average amount of annual emissions (tons) by bulk carrier ship type

Bulk Carrier Type	Ave. of NO_X	Ave. of SO_2	Ave. of CO_2	Ave. of HC	Ave. of PM
Small	163.4	113.2	6,697.4	6.3	17.2
Handysize	558.5	387.0	22,888.6	21.5	58.8
Handymax	706.8	489.7	28,964.9	27.3	74.4
Panamax	836.7	579.7	34,287.6	32.3	88.0
Capesize	1,256.3	870.4	51,482.8	48.4	132.2
Large Capesize	1,578.3	1,093.5	64,680.2	60.9	166.1

4. Conclusions

Emissions have been a significant threat to the environment since the Industrial Revolution, and the most critical factor behind emissions is undoubtedly transportation. Maritime transport makes up a considerable part of all transportation activities, and the most crucial element in calculating marine emissions is the proper calculation of main engine power.

The main engine power of bulk carriers of known length, breadth, *DWT*, and *GT* can be calculated with a low error rate using nonlinear regression analysis by developing the calculations with data from the most extensive number of ships in the literature (N = 9,174).

This study has conducted a holistic assessment of bulk carrier emissions by calculating generated emissions in addition to bulk carriers' main engine power and uses the analyses performed herein to provide method of calculating the emissions of bulk carriers based on installed engine power. In addition, the effects of emissions have been calculated not only for general bulk carriers but also for six main groups based on ship size.

Power demand per unit of load is lower for larger ships than for smaller ships. Thus, smaller ships are used for domestic transportation, while bigger ships are used for international transport. Because bigger ships are more efficient than smaller ships, their travel range is greater than for small ships. This is also valid for emissions per unit of load. Therefore, bigger ships produce fewer emissions per unit of load compared to smaller ships.

Regarding average generated emissions, the biggest ships have the highest emissions, while the smallest ships have the lowest emissions. Capesize and very Large Capesize ships do not have suitable ports worldwide. Because a limited number of countries such as China, Singapore, the United States, and Italy have such ports, these countries and the cities and inland waters where these ports are located are exposed to more intense emissions.

Ships take up the largest share of transportation, and their volume of emissions is relatively high. Due to the carbon tax, ships now need to seek alternative fuels or improve their current emissions. In addition, they must reduce their emissions indirectly by slowing down due to engine power and shaft power limitations based on IMO’s mandatory ruling for existing ships. Therefore, logistic time will take longer because of ships’ decreased speeds. This article reveals the advantages and disadvantages of the various carrier ship types, and this information will be beneficial for those ordering ships to be newly built with regard to what would be the most advantageous.

5. Abbreviation List

ANN	Artificial Neural Network
Ave.	Average
B	Breadth
DWT	Deadweight Tonnage
E	Emissions
EPP	Emissions per unit of power
GT	Gross Tonnage
HC	Hydrocarbons
L	Overall Length
L-M	Levenberg-Marquardt
LSM	Least-Squares Method
MGO	Marine Gas Oil
P	Engine Power
PM	Particulate Matter
RSS	Residual Sum of Squares
T	Draft
TEU	Twenty-Foot Equivalent Unit

VLSFO	Very Low Sulphur Fuel Oil
YWH	yearly working hours
β	Correlation functions

REFERENCES

[1] Eyring, V., 2005. Emissions from International Shipping: 1. The Last 50 Years, *Journal of Geophysical Research*, 110(D17), D17305. https://doi.org/10.1029/2004JD005619

[2] Eyring, V., 2005. Emissions from International Shipping: 2. Impact of Future Technologies on Scenarios until 2050, *Journal of Geophysical Research*, 110(D17), D17306. https://doi.org/10.1029/2004JD005620

[3] Kalajdzic, M., Vasilev, M., Momčilović, N., 2022. Power Reduction Considerations for Bulk Carriers with Respect to Novel Energy Efficiency Regulations, *Brodogradnja*, 73, 61–74. https://doi.org/10.21278/brod73205

[4] Başhan, V., Parlak, A., 2015. Effects of Using Variable Speed Compressors in Hvac Systems on Emissions from Marine Auxiliary Diesel Engines, *International Conference on Energy Systems 2015*, Istanbul, Turkey.

[5] Başhan, V., Çakır, M., Sönmez, H. İ., 2018. Cost efficiency and emission analysis of a bulk carrier cranes operation, *Journal of ETA Maritime Science*, 6(1), 27–36. https://doi.org/10.5505/jems.2018.73645

[6] Cheng, C.-W., Hua, J., Hwang, D.-S., 2017. NOx Emission Calculations for Bulk Carriers by Using Engine Power Probabilities as Weighting Factors, *Journal of the Air & Waste Management Association*, 67(10), 1146–1157. https://doi.org/10.1080/10962247.2017.1356763

[7] Ekmekçioğlu, A., Kuzu, S. L., Ünlügençoğlu, K., Çelebi, U. B., 2020. Assessment of Shipping Emission Factors through Monitoring and Modelling Studies, *Science of The Total Environment*, 743, 140742. https://doi.org/10.1016/j.scitotenv.2020.140742

[8] Kalajdžić, M., Vasilev, M., Momčilović, N., 2022. Power Reduction Considerations for Bulk Carriers with Respect to Novel Energy Efficiency Regulations, *Brodogradnja*, 73(2), 79–92. https://doi.org/10.21278/brod73205

[9] Tasdemir, S., Saritas, I., Ciniviz, M., Allahverdi, N., 2011. Artificial Neural Network and Fuzzy Expert System Comparison for Prediction of Performance and Emission Parameters on a Gasoline Engine, *Expert Systems with Applications*, S0957417411007251. https://doi.org/10.1016/j.eswa.2011.04.198

[10] Özener, O., Yüksek, L., Özkan, M., 2013. Artificial Neural Network Approach to Predicting Engine-out Emissions and Performance Parameters of a Turbo Charged Diesel Engine, *Thermal Science*, 17(1), 153–166. https://doi.org/10.2298/TSCI120321220O

[11] Abramowski, T., 2013. Application of Artificial Intelligence Methods to Preliminary Design of Ships and Ship Performance Optimization, *Naval Engineers Journal*, 125(3), 87-98.

[12] Gurgen, S., Altin, I., Ozkok, M., 2018. Prediction of Main Particulars of a Chemical Tanker at Preliminary Ship Design Using Artificial Neural Network, *Ships and Offshore Structures*, 13(5), 459–465. https://doi.org/10.1080/17445302.2018.1425337

[13] Jeon, M., Noh, Y., Shin, Y., Lim, O.-K., Lee, I., Cho, D., 2018. Prediction of Ship Fuel Consumption by Using an Artificial Neural Network, *Journal of Mechanical Science and Technology*, 32(12), 5785–5796. https://doi.org/10.1007/s12206-018-1126-4

[14] de Winter, R., van Stein, B., Bäck, T., Muller, T., 2021. Ship Design Performance and Cost Optimization with Machine Learning, *20th conference on Computer and IT Applications in the Maritime Industries*, Mülheim, Germany.

[15] Okumuş, F., Ekmekçioğlu, A., Kara, S. S., 2021. Modelling Ships Main and Auxiliary Engine Powers with Regression-Based Machine Learning Algorithms, *Polish Maritime Research*, 28, 83-96. https://doi.org/10.2478/pomr-2021-0008

[16] Zhang, J.-Q., Su, W., Zhang, J.-W., Wu, J.-Z., Cai, C., Guo, Y.-P., Lei, H., 2021. Main Engine Power Prediction for Large Vessels Based on Gaussian Mixture Model and Deep Neural Network, *Journal of Ship Mechanics*, 25(12), 1623–1634.

[17] Sahin, B., Gürgen, S., Ünver, B., Altın, İ., 2018. Forecasting the Baltic Dry Index by Using an Artificial Neural Network Approach, *Turkish Journal of Electrical Engineering & Computer Sciences*., (26), 1673–1684. https://doi.org/10.3906/elk-1706-155

[18] Cong, Y., Gan, H., Wang, H., Hu, G., Liu, Y., 2021. Multiobjective Optimization of the Performance and Emissions of a Large Low-Speed Dual-Fuel Marine Engine Based on MNLR-MOPSO, *Journal of Marine Science and Engineering*, 9(11), 1170. https://doi.org/10.3390/jmse9111170

[19] Yang, R., Yan, Y., Sun, X., Wang, Q., Zhang, Y., Fu, J., Liu, Z., 2022. An Artificial Neural Network Model to Predict Efficiency and Emissions of a Gasoline Engine, *Processes*, 10(2), 204. https://doi.org/10.3390/pr10020204

[20] Adamowski, J., Fung Chan, H., Prasher, S. O., Ozga-Zielinski, B., Sliusarieva, A., 2012. Comparison of Multiple Linear and Nonlinear Regression, Autoregressive Integrated Moving Average, Artificial Neural Network, and Wavelet Artificial Neural Network Methods for Urban Water Demand Forecasting in Montreal, Canada, *Water Resources Research*, 48(1). https://doi.org/10.1029/2010WR009945

[21] Gunes, U., Bashan, V., Ozsari, I., Asım Sinan Karakurt, 2023. Predicting Tanker Main Engine Power Using Regression Analysis and Artificial Neural Networks, *Sigma Journal of Engineering and Natural Sciences*.

[22] Yildiz, B., 2022. Prediction of Residual Resistance of a Trimaran Vessel by Using an Artificial Neural Network, *Brodogradnja*, 73(1), 127–140. https://doi.org/10.21278/brod73107

[23] Cepowski, T., 2016. Approximating the Added Resistance Coefficient for a Bulk Carrier Sailing in Head Sea Conditions Based on Its Geometrical Parameters and Speed, *Polish Maritime Research*, 23(4), 8–15. https://doi.org/10.1515/pomr-2016-0066

[24] Cepowski, T., 2017. Prediction of the Main Engine Power of a New Container Ship at the Preliminary Design Stage, *Management Systems in Production Engineering*, 25(2), 97–99. https://doi.org/10.1515/mspe-2017-0014

[25] Cepowski, T., 2019. Regression Formulas for the Estimation of Engine Total Power for Tankers, Container Ships and Bulk Carriers on the Basis of Cargo Capacity and Design Speed, *Polish Maritime Research*, 26(1), 82–94. https://doi.org/10.2478/pomr-2019-0010

[26] Piko, G. P., 1980. Regression Analysis of Ship Characteristics, Australian Government Pub. Service, Canberra.

[27] Cepowski, T., 2020. The Prediction of Ship Added Resistance at the Preliminary Design Stage by the Use of an Artificial Neural Network, *Ocean Engineering*, 195, 106657. https://doi.org/10.1016/j.oceaneng.2019.106657

[28] Cepowski, T., Chorab, P., 2021. The Use of Artificial Neural Networks to Determine the Engine Power and Fuel Consumption of Modern Bulk Carriers, Tankers and Container Ships, *Energies*, 14(16), 4827. https://doi.org/10.3390/en14164827

[29] Xhaferaj, B., 2022. Investigation on Some Conventional Hulls Forms of the Predictive Accuracy of a Parametric Software for Preliminary Predictions of Resistance and Power, *Brodogradnja*, 73(1), 1–22. https://doi.org/10.21278/brod73101

[30] Bejan, A., Gunes, U., Sahin, B., 2019. The Evolution of Air and Maritime Transport, *Applied Physics Reviews*, 6(2), 021319. https://doi.org/10.1063/1.5099626

[31] Marine Traffic, 2019. Marine Traffic: Global Ship Tracking Intelligence [Online]. Available: https://www.marinetraffic.com/en/data/?asset_type=vessels. accessed 22nd October 2019.

[32] Man Disel & Turbo, *Propulsion Trends in Bulk-Carriers*, Man Disel & Turbo.

[33] Man Disel & Turbo, 2014. Propulsion of 200,000-210,000 Dwt Large Capesize Bulk Carrier, Copenhagen.

[34] Seber, G. A. F., Wild, C. J., 2003. Nonlinear Regression, *Wiley-Interscience*, Hoboken, N.J.

[35] Cakici, F., Aydin, M., 2014. Effects of Hull Form Parameters on Seakeeping for YTU Gulet Series with Cruiser Stern, *International Journal of Naval Architecture and Ocean Engineering*, 6(3), 700–714. https://doi.org/10.2478/IJNAOE-2013-0206

[36] Press, W. H., Teukolsky, S. A., Vetterling, W. T., Flannery, B. P., 2007. 15.5 Nonlinear Models, Numerical Recipes 3rd Edition: The Art of Scientific Computing, *Cambridge University Press*.

[37] ENTEC, 2005. European Commission Directorate General Environment Service Contract on Ship Emissions: Assignment, Abatement and Market-Based Instruments.

[38] Bejan, A., 2012. Why the Bigger Live Longer and Travel Farther: Animals, Vehicles, Rivers and the Winds, *Scientific Reports*, 2, 594. https://doi.org/10.1038/srep00594

Submitted 25.11.2022

Accepted 05.01.2023.

Umit Gunes

Yildiz Technical University, Department of Naval Architecture and Marine Engineering, Besiktas, Istanbul, Turkey

Correspondence: ugunes@yildiz.edu.tr