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Research Article

Predicting tanker main engine power using regression analysis and artificial neural networks

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ABSTRACT

The purpose-oriented design and planning of ships is maintained throughout production. Outer form of ship equipment starts with the steel construction process. The outer body production process moves ahead with painting, quality control tests, and bureaucratic procedures. In accordance with all these form and block operations, choosing a main engine suitable for all other technical parameters is vital, especially regarding ship speed and the amount of cargo it will carry. As a result, estimating main engine power is attempted with the help of artificial neural network (ANN) and regression analyses by considering a ship's technical parameters (e.g., draught, depth, deadweight tonnage [DWT], gross tonnage [GT], and engine power). This study conducts regression and ANN analyses over 836 tanker ships from the Marine Traffic database to predict main engine power using input parameters (deadweight (DWT), Length (L), Breadth (B), and gross ton (GT) values). The regression analyses show Model 7 to perform the best approximation with a determination value = 0.827 usable for estimating main engine power. After all the examinations, a very accomplished result of 0.98047 was additionally obtained from the ANN analysis. The study makes beneficial and innovative contributions to predicting tankers' required main engine power.

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INTRODUCTION

Ships are one of the least expensive logistics vehicles able to carry many different loads at once. Many technical parameters are taken into consideration when designing different types of ships. These parameters are vital to a ship's longevity and ability to safely navigate and must be determined very carefully and accurately. One of the most important of these parameters involves determining a ship's energy requirements and selecting the appropriate

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main engine and auxiliary machinery. The main engine market for ships reached nearly \$33 billion USD in 2020 and is forecasted to reach over \$40 billion USD by 2026, which shows an expected compound annual growth rate of 3.18% between 2021-2026 [1]. When considered multi-directionally in this context, choosing the main engine for a ship should involve noting energy efficiency, global economy, fuel, and the related regulations, emissions, ship speed, operational economy, propeller, waste heat recovery systems, and many other technical details. The literature has many computational and experimental studies that have been done on these issues. With recent developments in artificial intelligence, researchers have started to carry out studies apart from these that will make estimation about ships' various aspects using a multitude of methods. One of these is artificial neural networks (ANNs), which have been used successfully over a wide range of different areas beyond ships, such as in different branches of social and natural sciences and medical treatments Another additional important method involves the various linear and non-linear types of regression analyses. ANNs and regression analyses all provide specific valuable data to a forecast between the inputs and outputs.

Barua et al. [2] developed machine learning models that can be applied to various aspects of international freight management and made certain operational predictions. Bodunov et al. [3] demonstrated an approach using geospatial data for port destination classification and estimated time of arrival (ETA) determinations. Bui-Duy and Vu-Thi-Minh [4] used an algorithmic solution from an asymmetric traveling salesman problem (ATSP) in which the fuel consumption model for the route is estimated based on the deep machine learning method. In order to minimize fuel costs, they attempted to optimize route selection for container ships using five inputs: average speed, sailing time, ship capacity, wind speed, and wind direction.

Cepowski and Chorab [5] developed a study based on data beginning in 2015 to estimate the main engine power requirements and fuel consumption needs for commercial cargo ships (bulk carriers, tankers, and container ships). The study is based on simple mathematical structures that can be easily applied in the design stage as well as in ecological studies. Cui et al. [6] performed bulk carrier structural design optimization, which uses machine learning for optimization and improves the optimization's adaptability to the dynamic design environment. Jeong et al. [7] carried out a study with the help of the programs R and Python, estimating lead times for manufacturing, ship block assembly, reel fabrication, and dyeing using machine learning technology to propose a new management method for process lead time using a master data system for the time element in production data.

Cepowski [8] presented a forecasting tool to predict the main engine power for container ships built between 2005 and 2015 using basic design variables. Cepowski [9] also presented regression formulas for the preliminary design of tankers, bulk carriers, and container ships based on data from ships built between 2000-2018. The authors indicated the formulas to be able to be used for estimating total engine power using a ship's deadweight or Twenty-Foot-Equivalent Unit (TEU) capacity. Moreover, Cepowski and Chorab [10] developed preliminary design formulas for container ships using a database of container ships built between 2015-2020. Uyanık et al. [11] carried out various prediction models such as multiple linear regressions, Ridge and LASSO regression, support vector regression, tree-based algorithms, and elevation algorithms in order to determine the relationships among parameters for fuel consumption in a container ship such as main engine speed, main engine cylinder values, scavenge air, and shaft indicators. Gkerekos et al. [12] used algorithms such as support vector machines (SVMs), random forest regressors (RFRs), extra tree regressors (ETRs), ANNs, and community detection algorithms to estimate ships' main engine fuel consumption. [13] proposed an unconventional technique for estimating ship performance using noon reports as a decision support system (DSS) based on ANN multi-regression methods. Tarelko and Rudzki [14] applied ANN-based decision support systems that use certain operational data to predict ship speed, travel time, and fuel consumption for reaching a destination. Farag and Olcer [15] used a combination of ANN and multiple regression techniques to estimate ships' power and fuel consumption. The model they proposed was developed by processing dense datasets instead of ships' traditional noon reports. Peng et al. [16] discussed how to estimate ships' energy consumption in the port of Jingtang, China using five different machine learning regression models and strategies for reducing ships' energy consumption.

Yan et al. [17] created a ship energy efficiency optimization model that takes into account multiple environmental factors by analyzing the energy transfers among the hull, propeller, and main engine. The results show the proposed method to be able to effectively reduce ships' energy consumption and CO_2 emissions. Yan et al. [18] proposed a two-stage estimation and reduction model for dry cargo ship fuel consumption, validating a fuel consumption prediction model based on random forest regression. The forecast model takes into account vessel sailing speed, total cargo weight, and sea/weather conditions and then estimates the main engine's hourly fuel consumption. Yuan and Nian [19] also developed a Gaussian process meta model for predicting ships' fuel consumption under different scenarios. Their model takes into account not only the effects of operating conditions such as speed and trim, but also the effects of weather conditions such as wind and wave effects. Tran [20] used the ANN method to run estimations for a bulk carrier's main diesel engine belonging to a Vietnamese company and on low sulfur content fuel consumption in ECA zones as well as heavy fuel oil consumption on 2-year voyages [21].

Several researchers have also applied ANN-based regression analyses in a variety of fields for predicting physics-based shaft power for large merchant ships [22], predicting main engine failures [23], predicting main engine fuel consumption for more efficient ship operations [24], assigning a simple process for pre-processing the huge amount of data collected from automated data logging & monitoring (ADLM) systems [25], estimating motor yacht weight displacement based on design variables, predicting emission analyses (NO_X, SO_2, CO_2, VOC, PM, and CO) for Turkey's Izmir and Mersin ports [26], and proposing a dynamic calculation method of ship exhaust emissions based on real-time ship trajectory data [27].

This study attempts to determine the power of ship main engines using parameters such as draught, depth, deadweight tonnage (DWT), gross tonnage (GT), and engine power. The results from the approach using ANNs have good agreement with the literature. Another approach was additionally taken using various regression analyses, the results from which showed positive effects in estimating ship main engine power.

MATERIALS AND METHODS

Database

Marine Traffic is an open, community-based project that provides real-time information about ship locations using a database of vessel-identifying information including International Maritime Organization (IMO) number. This study uses the Marine Traffic database as a data source. The database contains more than 80 technical specifications (e.g., type, shipbuilder, year built, draught, depth, DWT, GT, engine power) of more than 900,000 ships and can be considered an up-to-date document on the world fleet.

Non-Linear Regression

Nonlinear regression analyzes data fit to a model expressed as a mathematical function. Simple linear regression relates two variables in a linear relationship, while nonlinear regression relates them nonlinearly (curved). The goal of the model is to minimize the sum of the squares, being a measure tracking the Y observations' variance from the nonlinear function used to predict Y. This is computed by first finding then squaring and adding the difference between the fitted nonlinear function and every Y datum in the set.

The general form of a non-linear regression equation is:

$$Y(x) = f\left(x_i, A_0 + A_1 + A_2 + \ldots, + A_n\right) \tag{1}$$

where Y is the estimate of the dependent variable (engine power). Equation 1 has the coefficients A_0, A_1, …, A_n as regression weight coefficients showing how the independent variables affect the dependent variable.

$$R_i = Y_i - f\left(x_i, A_0 + A_1 + A_2 + \ldots, + A_n\right) \tag{2}$$

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 in order to calculate the regression coefficients.

$$\underbrace{\begin{bmatrix} \frac{\partial_f}{\partial_{A_{i1}}} & \frac{\partial_f}{\partial_{A_{i2}}} & \cdots & \frac{\partial_f}{\partial_{A_{1m}}} \\ \frac{\partial_f}{\partial_{A_{21}}} & \vdots & \ddots & \frac{\partial_f}{\partial_{A_{2m}}} \\ \vdots & \vdots & \cdots & \\ \frac{\partial_f}{\partial_{A_{n1}}} & \frac{\partial_f}{\partial_{A_{n2}}} & \cdots & \frac{\partial_f}{\partial_{A_{nm}}} \end{bmatrix}}_{B} \cdot \underbrace{\begin{bmatrix} \Delta A_1 \\ \Delta A_2 \\ \vdots \\ \Delta A_m \end{bmatrix}}_{\Delta A} = \underbrace{\begin{bmatrix} R_1 \\ R_2 \\ \vdots \\ R_m \end{bmatrix}}_{R} \tag{3}$$

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

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

in which ΔA is the coefficient from the non-linear regression, calculated as:

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

Equation 4 allows the regression coefficients (A_0, A_1, A_2, … A_n) to be calculated with respect to minimum total sum of squares (RSS) and the high coefficient of determination (R^2).

Eight different non-linear models are shown in Table 1. The models used the variables of *DWT*, *L*, *B*, and *GT* to estimate best *Y* value (engine power).

Artificial Neural Network

ANNs are an information processing technology inspired by the working logic of the human brain. The algorithm of the simple biological nervous system is modeled using ANN. In other words, it is the digital representation of biological neuron cells and the synaptic connections these cells have with one another.

A layer perceptron is used in the ANN model structure [28]. The *F* function used for each output neuron in the perceptron layers can be defined as follows:

$$F(x) = \sum_{i=1}^{N} v_i \varphi\left(\omega_i^T x + b_i\right) \tag{6}$$

where $\varphi\left(\omega_i^T x + b_i\right)$ is an alternating continuous function, I_m is an m-dimensional unit hypercube of interval $[0, 1]^m$, C

Table 1. Non-linear regression models

Model Number	Used parameters
Model 1	$A_0 + A_1$
Model 2	$A_0 + A_1\ L/B + A_2\ L/DWT^{1/3}$
Model 3	$A_0 + A_1\ L/B + A_2\ L/DWT^{1/3} + A_3\ GT/DWT$
Model 4	$A_0 + A_1\ L/B + A_2\ L/DWT^{1/3} + A_3\ DWT^{1/3}$
Model 5	$A_0 + A_1\ L/B + A_2\ L/DWT^{1/3} + A_3\ GT/DWT + A_4\ DWT^{1/3}$
Model 6	$A_0 + A_1\ L/B + A_2\ L/DWT^{1/3} + A_3\ GT/DWT + A_4$
Model 7	$A_0 + A_1\ L/B + A_2\ L/DWT^{1/3} + A_3\ B/DWT^{1/3} + A_4\ GT/DWT + A_5$
Model 8	$A_1\ L/B + A_2\ L/DWT^{1/3} + A_3\ B/DWT^{1/3} + A_4\ GT/DWT + A_5$

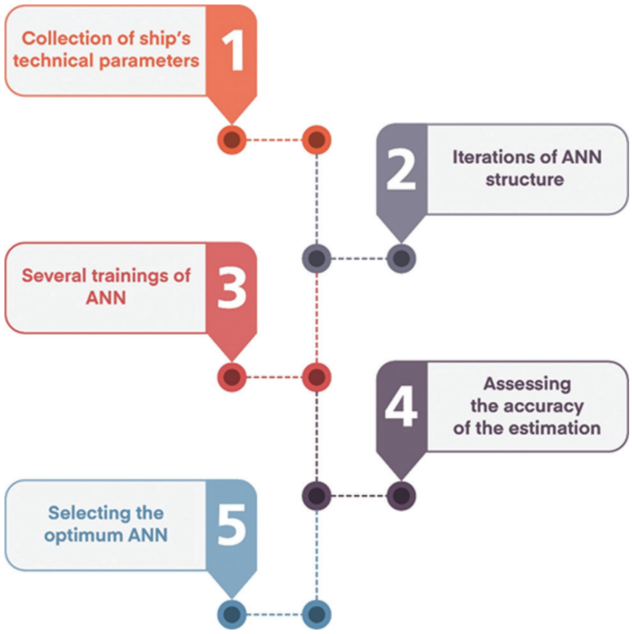


Figure 1. Flowchart of the ANN research framework.

(I_m) is the space of continuous functions in I_m, N is the limit, v_i and b_i are function coefficients and real vectors in R, and ω_i is the weighing factor (in R^m, $i = 1, \ldots, N$). The F function is independent from φ, and $x \in I_m$. Thus, for any e > 0, the following expression holds:

$$|F(x) - f(x)| < \varepsilon \tag{7}$$

The ANN dataset was calculated using ship data base by 14 inputs and 1 output data. For validation, the dataset is divided into 134 samples for validation and testing and 568 samples for training. Trial results have shown the Levenberg–Marquardt method to perform better compared to other algorithms [29–31]. Some parameters have been excluded the data set for simplification, with only 8 input parameters being used. As a result, the output calculation convergence is adequate. The training, validation, and testing of the 8-input ANN system is then performed in order. Figure 2 shows the perceptron model that was used.

The logsig activation function is employed in the hidden layer, and the purelin activation function is utilized in the output layer. General definitions are expressed in the following equations. The ANN's inside activity U_i can be expressed as:

$$Sigmoid: f(x) = \frac{1}{1+e^{-x}} \tag{8}$$

$$u_i = \sum_{J=1} w_{ij} x_j + b_i \tag{9}$$

$$y_i = \varphi(u_i) = \varphi \sum_{j=1} \left[w_{ij} x_j + b_i \right] \tag{10}$$

The mean square error (*MSE*) is determined as a network performance function. The statistical methods of mean absolute percentage error (*MAPE*) and coefficient of determination (R^2) are used for network comparisons. These are expressed as:

$$MSE = \frac{1}{n} \sum_{i=1}^{N} (t_i - o_i)^2 \tag{11}$$

$$MAPE = \frac{1}{n} \sum \left| \frac{t_i - o_i}{o_i} \right| \times 100 \tag{12}$$

$$R^2 = 1 - \frac{\sum (t_i - o_i)^2}{\sum (t_i - \bar{o})^2} \tag{13}$$

where t is the target value, o is the output, $\bar{o}$ is the mean of the output, and n is the number of samples.

RESULTS AND DISCUSSION

The results from the 8 non-linear regression models are shown in Figure 3. While most non-linear regression models have high correlations, Models 2 (Figure 2b) and 3 (Figure 2c) have low correlations. The correlation has a relationship with R^2. Regression coefficients and the R^2 values are show in Table 2.

In addition to the poor fitting distributions, Model 2 and Model 3 have the lowest R^2 values. As such, they don't provide good approximations. The R^2 from Models 1, 4, and 5 are around 0.80 and are also able to be applied to the estimations. Models 6 and 8 have much better R^2 results. The best estimation is in Model 7, with an R^2 = 0.827; thus, it is the most proper model for estimating engine power using vessels' actual DWT, L, B, and GT values.

Data are currently available for more than 10,000 ships. These data involve 33 different pieces of information: ship ID#, ship name, type, distance traveled, draft, recorded speed (max / average), speed / course, IMO, MMSI, call sign, flag, AIS vessel type, length overall, breadth extreme, year built, status (active / passive), owner, manager, shipbuilder,

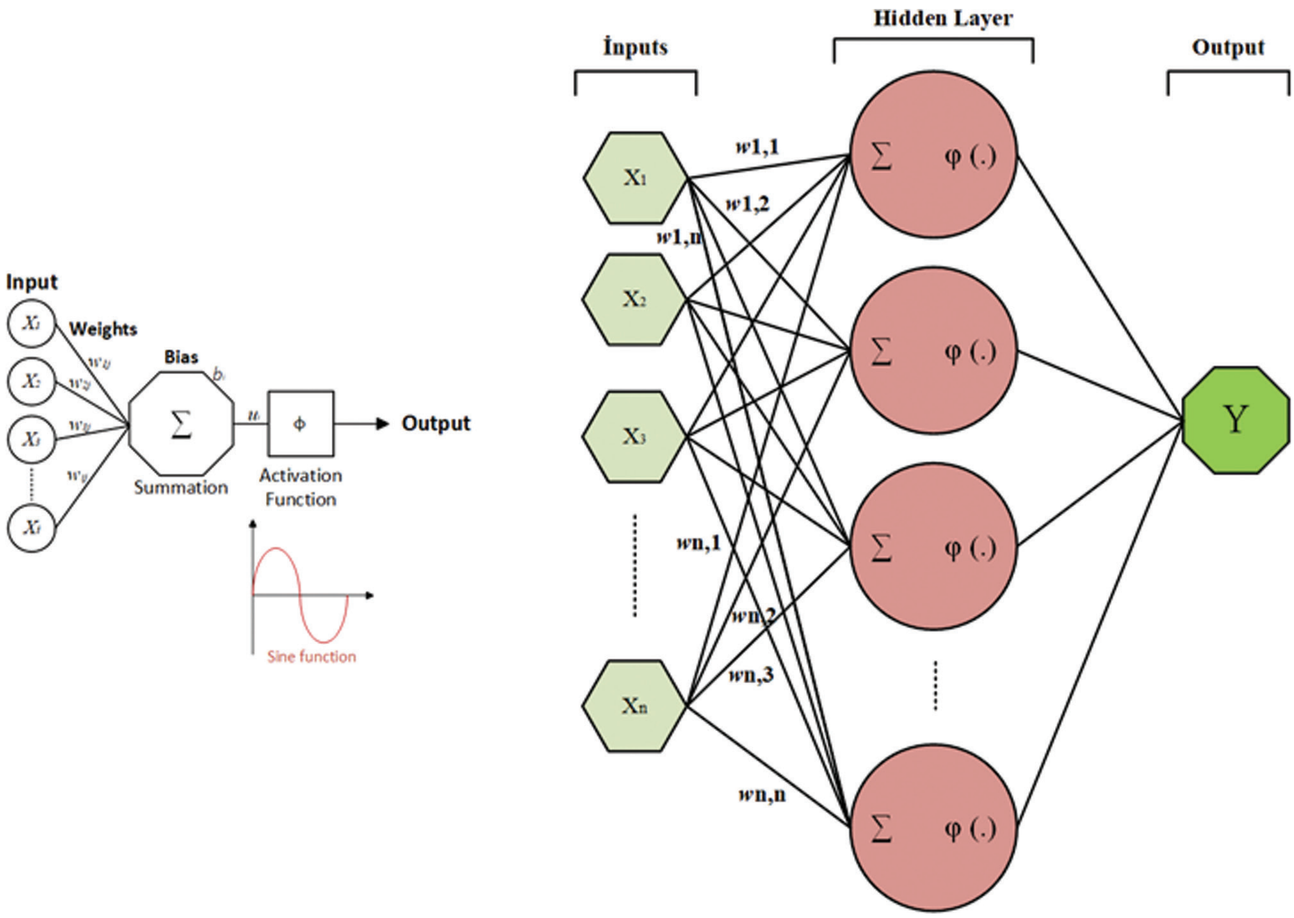
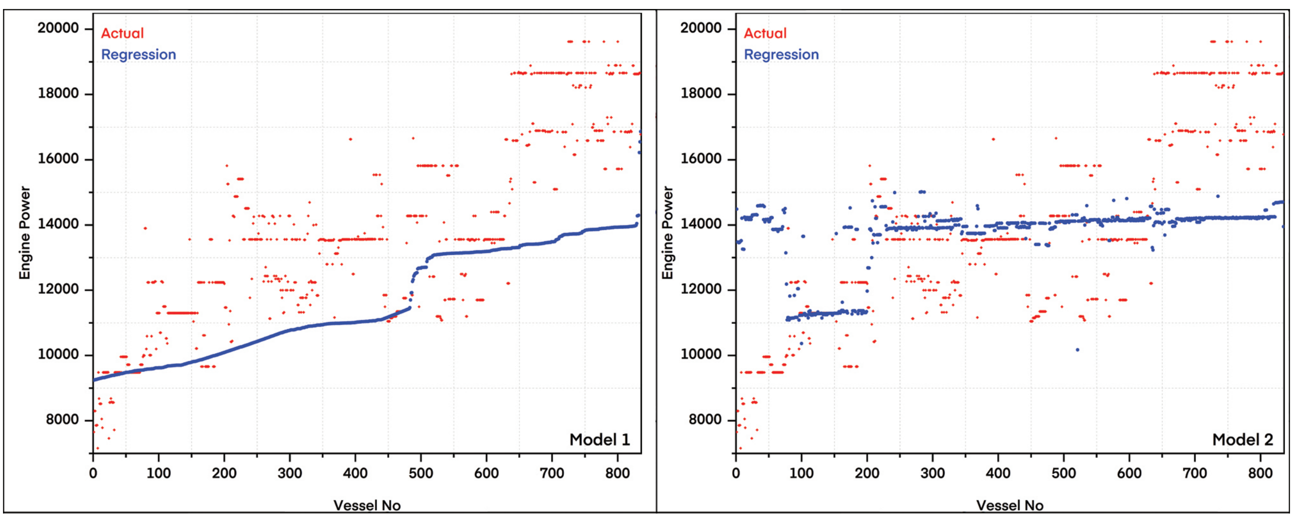


Figure 2. The basic working principles and architectural structure of ANN.



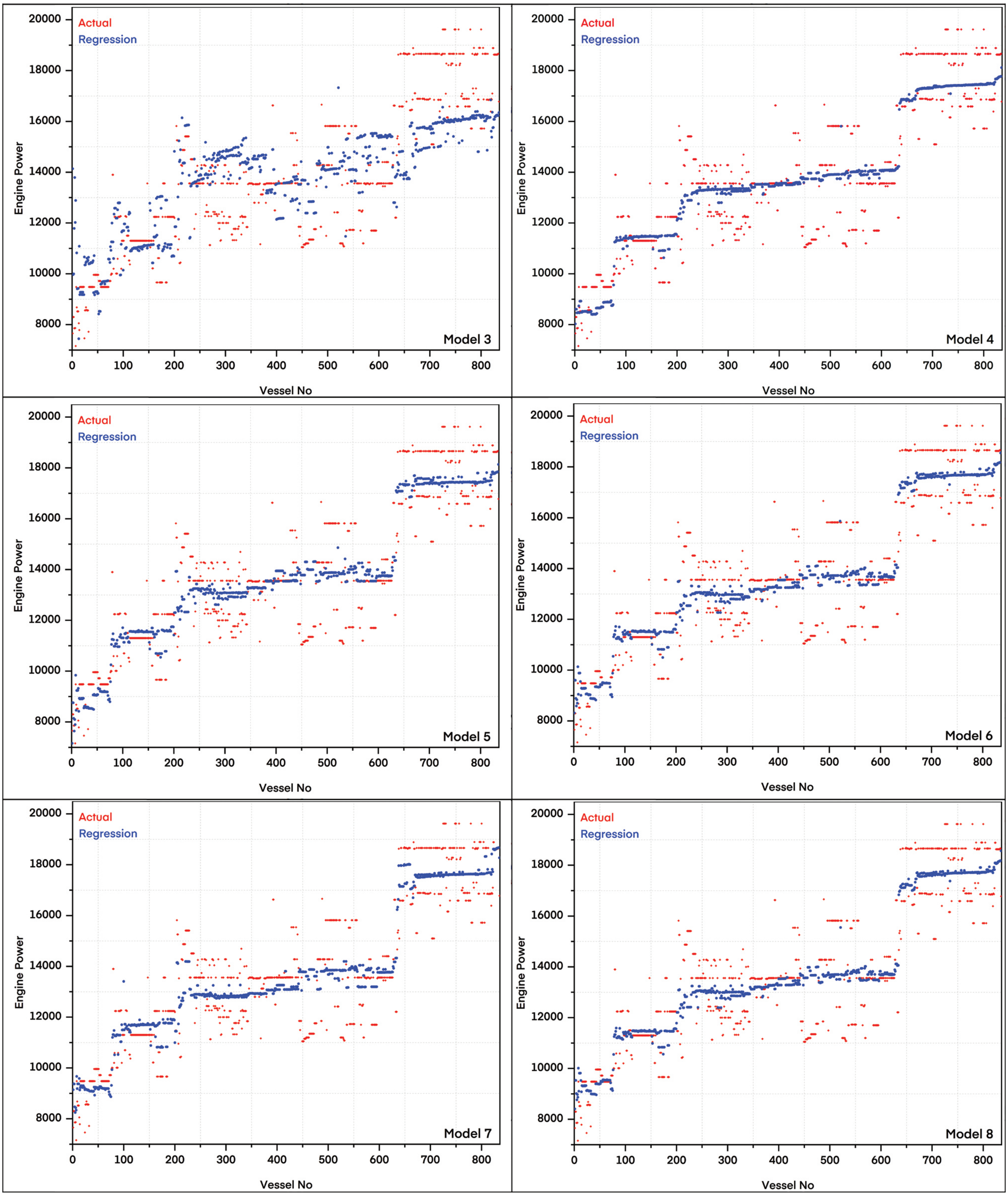


Figure 3. Non-linear regression models and the estimations from each model.

height, gross tonnage (GT), deadweight (DWT), displacement–lightship, displacement–summer, engine bore, engine builder, engine model, engine cylinders, engine RPM, engine stroke, propeller, and fuel type. First of all, the tanker-type ships were separated from the data; 836 tanker-type ships were analyzed by separating ships with

Table 2. Model coefficients and R^2 values

Model Number	A_0	A_1	A_2	A_3	A_4	A_5	A_6	R^2
Model 1	8,158	$5.24x10^{-5}$	1.588	-	-	-	-	0.801
Model 2	31,423	-1,729	-1446	-	-	-	-	0.121
Model 3	34,036	-2,725	5,697	-60,983	-	-	-	0.492
Model 4	-3,393	209.93	1,372	1,372	-	-	-	0.802
Model 5	-9,186	744.22	10.79	1,5181	0.091	-	-	0.801
Model 6	-7,455	322.93	1,458	9,025	$1.93\ x10^{-4}$	-	-	0.816
Model 7	-89,875	14,299	-16,061	104,620	6,786	$1.61x10^{-4}$	1.51	0.827
Model 8	-	-406.66	2,017.80	-5659	7,489	$1.44\ x10^{-4}$	1.52	0.815

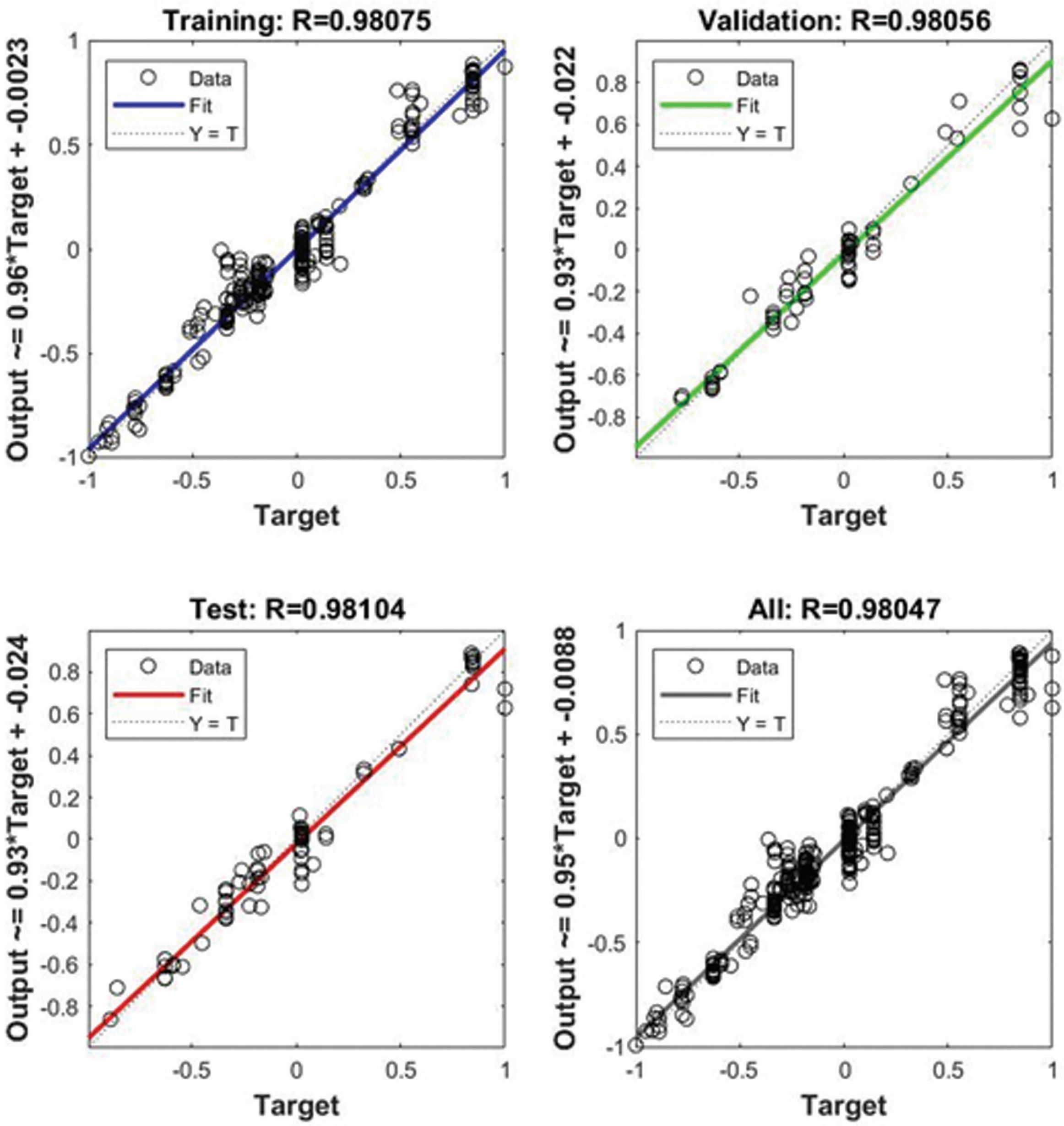


Figure 4. Regression graphs of the ANN results.

missing information from ships that had departed. Marine engineering experts examined the effects from 33 different pieces of information on 836 ship data regarding ship engine power. Thus, the 33 different variables were reduced to 14. The other 19 variables were determined to be ineffective on main engine power.

The ANN dataset of 836 samples was calculated using the ship database with 14 inputs (draught, recorded speed [Max / Average], overall length, breadth extreme, year built, height, gross tonnage [GT], deadweight [DWT], displacement–lightship, displacement–summer, engine bore, engine cylinders, engine RPM, engine stroke) and one output datum (engine power). For the validation, the dataset was separated into 134 samples for the validation and testing and 568 samples for the training. The analysis code and input parameters were revealed to be optimum at 8 variables due to overfitting with the 14-variable ANN analysis. For simplification, some parameters were excluded from the data set with only 8 input parameters (i.e., overall length, breadth extreme, year built, DWT, displacement–lightship, displacement–summer, engine stroke and engine cylinders) being used. As a result, the output calculation convergence was deemed to be adequate. The training, validation, and testing of the 8-input ANN system was then performed in that order. The perceptron consists of one hidden layer that was determined through trials with as few as 2 and up to as many as 50 layers.

The ANN analysis we made with 836 tanker ships saw the training rate to shift between 60%-80%, and the validation and testing rates to vary between 10%-20% in the numerical code. The best performance was obtained in Figure 4, with a training rate of 68%, a validation rate of 16%, and a test rate of 16%. The regression graph between the values obtained from the ANN analysis with actual ship engine power data is shown in Figure 3. When examining the studies in the literature, regression values greater than 0.96 show an ANN that is accurate. As a result of the ANN analysis, the correlation coefficients were found as 0.98075 for the training, 0.98056 for the validation, and 0.98104 for the testing. The results from all were examined, with a very successful result of 0.98047 being obtained.

Figure 5 as shown provides the actual main engine power data and the estimated main engine power values given from the ANN analysis. Figure 5 clearly shows how accurate the estimated results obtained with ANN are because of the proximity of the values. In addition, the actual data and artificial neural network estimates are seen to overlap at many points. These results are very satisfying for our study as well as for future studies.

As a result of being examined by experts, the ANN analysis with 14 input variables was reduced to 8 for the reasons mentioned in detail above. Figure 6 shows how these 8 input parameters directly related to the ship's main engine power yield results when made with 2, 3, 4, 5, 6, and 7 inputs. As seen in Figure 6, the *MSE* was found to be 6597.74 in the ANN analysis made with 2 inputs. Similarly, 3 inputs resulted in *MSE* = 1920.91, and *MSE* = 532.99 with 4 inputs. In the ANN analysis made with 5 inputs, *MSE* = 19.97. The results from the 5-input ANN analysis in the 8-input ANN analysis improved, albeit slightly. The best result for determining main engine power is revealed to be with 8 variables.

In some cases, the desired results in an ANN analysis cannot be obtained using overly complex neural network structures. In other words, a special neural network must be constructed for each problem. Due to reasons such as computation time, underfitting, overfitting and dropout,

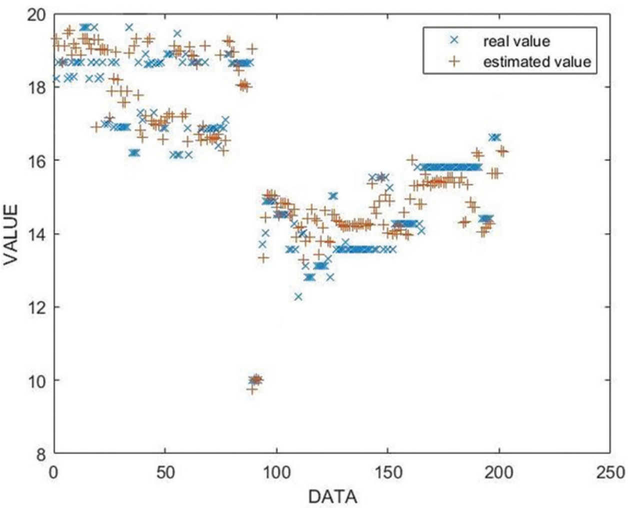


Figure 5. Presenting the ANN results alongside real marine engine power data.

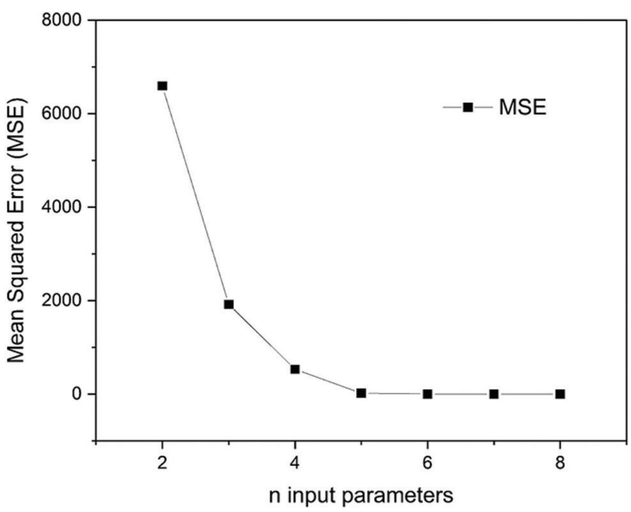


Figure 6. Mean Squared Error (MSE) of test results with the number of input parameters.

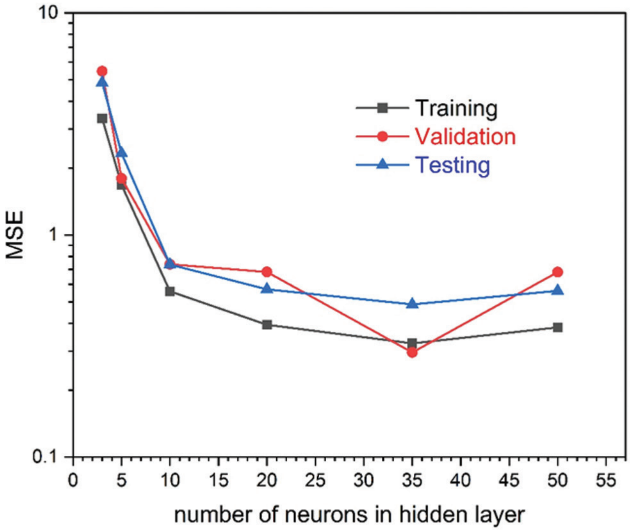


Figure 7. *MSE* for the training, validation, and testing results with the number of neurons in each hidden layer.

the number of middle layers and neurons in the ANNs vary. The results from the mean squared error value according to the number of neurons in the ANN analysis code are shown in Figure 7. When considering the training, validation, and testing values, the best result was concluded to have been obtained using 35 neurons. As the number of neurons increased to 50, the accuracy sensitivity was seen to decrease. When considering the ANN literature for this problem, the result can be obtained using a medium-simple neural network structure.

CONCLUSIONS

This study conducted regression and ANN analyses to predict the main engine power using various input parameters (i.e., DWT, L, B, and GT) using 836 tanker ships from the Marine Traffic database. The regression analyses show that, except for Models 2 and 3, the other models can be used for estimating, having $R^2 > 0.80$. However, Model 7 provides the best approximation ($R^2 = 0.827$) usable for estimating engine power. Moreover, the ANN analysis used 134 samples for the validation and testing and the rest of for training; the best performance was obtained with 68% for training, 16% for validation, and 16% for testing. As a result of the ANN analysis, the correlation coefficients for training, validation, and testing respectively are 0.98075, 0.98056, and 0.98104.

The results supplied using artificial neural networks and regressions show good relevance to tanker ship data and are characterized with a good level of prediction precision. The study is important in that it contributes innovative methods to developing highly accurate prediction models for tanker vessel main engine power.

AUTHORSHIP CONTRIBUTIONS

Authors equally contributed to this work.

DATA AVAILABILITY STATEMENT

The authors confirm that the data that supports the findings of this study are available within the article. Raw data that support the finding of this study are available from the corresponding author, upon reasonable request.

CONFLICT OF INTEREST

The author declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

ETHICS

There are no ethical issues with the publication of this manuscript.

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