Yayın Geliş Tarihi: 03.09.2024
Yayına Kabul Tarihi: 06.11.2024

Online Yayın Tarihi:30/12/2024

DOI: 10.54410/denlojad.1542984
Araştırma Makalesi (Research Article)

Mersin Üniversitesi
Denizcilik ve Lojistik
Araştırmaları Dergisi
Cilt:6 Sayı:2 Yıl:2024
Sayfa:113-129

E-ISSN: 2687-6604

Artificial Neural Network Approach for Main Engine Power Prediction of General Cargo Vessels

Emrullah ÇİRÇİR[1]
Samet GÜRGEN[2]

ABSTRACT

Before starting the physical construction of ships, it is critical to determine some important parameters in the pre-design stage. The traditional method for determining the main engine power and main ship parameters is hydrodynamic model tests. However, this process is quite time-consuming and costly. In this study, main engine power prediction for general cargo ships was performed by artificial neural network (ANN) method instead of traditional method. The model input parameters included ship length overall, breadth, gross tonnage, DWT and ship service speed. In the study conducted using a large data set, 70% of the data was separated for training, 15% for validation and the remaining 15% for testing. In each experimental run, different numbers of hidden neurons were randomly assigned and a total of 1000 models were created. The R values for the best model obtained were 0.992, 0.988 and 0.986 for the training, validation and test datasets, respectively. Mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) values remained consistently low across all normalized datasets, ranging from 0.0128 to 0.0148 for MAE and 0.0178 to 0.0238 for RMSE. The results showed that the ANN model had high predictive ability.

[1]Yüksek Lisans Öğrencisi, İskenderun Teknik Üniversitesi, Barbaros Hayrettin Gemi İnşaatı Ve Denizcilik Fakültesi, Gemi İnşaatı ve Gemi Makineleri Mühendisliği Bölümü, İskenderun, Türkiye https://orcid.org/0009-0000-4450-3054, emrcircir@gmail.com

[2]Dr. Öğr. Üyesi, İskenderun Teknik Üniversitesi, Barbaros Hayrettin Gemi İnşaatı ve Denizcilik Fakültesi, Gemi İnşaatı ve Gemi Makineleri Mühendisliği Bölümü, İskenderun,Türkiye,https://orcid.org/0000-0001-7036-8829, sametgurgen66@gmail.com

Keywords: *General cargo vessel, Main engine power, Prediction model, Artificial neural network*

Genel Kargo Gemilerinin Ana Makine Gücü Tahmini İçin Yapay Sinir Ağı Yaklaşımı

ÖZET

Gemilerin fiziksel inşasına başlamadan önce, ön tasarım aşamasında bazı önemli parametrelerin belirlenmesi kritik öneme sahiptir. Ana motor gücü ve ana gemi parametrelerinin belirlenmesi için kullanılan geleneksel yöntem hidrodinamik model testleridir. Ancak bu süreç oldukça zaman alıcı ve maliyetlidir. Bu çalışmada, genel kargo gemileri için ana motor gücü tahmini, geleneksel yöntem yerine yapay sinir ağı (YSA) yöntemi ile gerçekleştirilmiştir. Model giriş parametreleri gemi toplam uzunluğu, genişliği, gros tonajı, DWT ve gemi servis hızıdır. Büyük bir veri seti kullanılarak yürütülen çalışmada, verilerin %70'i eğitim, %15'i doğrulama ve kalan %15'i test için ayrılmıştır. Her deneysel çalışmada, farklı sayıda gizli nöron rastgele atanarak toplam 1000 model oluşturulmuştur. Elde edilen en iyi model için R değerleri eğitim, doğrulama ve test veri setleri için sırasıyla 0,992, 0,988 ve 0,986 olmuştur. Ortalama Mutlak Hata (MAE) ve Kök Ortalama Karesel Hata (RMSE) değerleri, tüm normalleştirilmiş veri kümelerinde tutarlı bir şekilde düşük kalmış ve MAE için 0.0128 ile 0.0148 ve RMSE için 0.0178 ile 0.0238 arasında değişmiştir. Sonuçlar YSA modelinin tahmin kabiliyetinin yüksek olduğunu göstermiştir.

Anahtar Kelimeler: *Genel kargo gemisi, Ana makine gücü, Tahmin modeli, Yapay sinir ağı*

1. INTRODUCTION

The process of designing a ship is complicated and iterative procedure. Determining the main characteristics of a commercial ship is the first step in the design process. The ship's dimensions are usually established in the pre-design stage according to main design characteristics that match the needs of the owner. Four fundamental parameters are typically included in these design specifications: class society, maximum speed, range, and cargo capacity. Furthermore, limitations imposed by ports and canals may result in early restrictions on a ship's main dimensions. Concept design, preliminary design, contract design, and detailed design are the four main phases of the ship design process. Evans (1959) introduced this concept, which is traditionally defined as an iterative process (Gürgen et al., 2018; Majnarić et al., 2022).

One of the important parameters to be determined in the ship pre-design stage is the ship main engine power. The traditional method for its calculation is based on hydrodynamic model tests. However, this approach quite time-consuming and costly. Developing prediction models by using the limited information in the pre-design stage with machine learning methods is one of the most practical solutions (Ekinci et al.,2011). Historically, statistical regression methods were used to calculate engine power for standard merchant ships (Cepowski and Chorab, 2021). Piko (1980) created nonlinear regression models to estimate ship length, breadth, draft, power, and speed. Zelazny (2015) focused on presenting regression equations for forecasting propulsion power in container ships, tankers, and bulk carriers. The limited size of the dataset and the lack of consideration for capacity characteristics restricted his investigation. Regression models were used by Cepowski (2019) to predict ship main engine power. The study included deadweight or TEU capacity and ship speed into account as independent variables. Models for tankers, bulk carriers, container ships, and their numerous subtypes were provided in the study. Main engine power prediction methods for general cargo ships were introduced by Okumuş and Ekmekçioğlu (2021). Their approach combined regression-based machine learning algorithms such as KNearest Neighbors, polynomial regression, and Gradient Boosting Machine regression. In a more recent development, Okumuş et al. (2021) used regression-based algorithms to create prediction models for the main engine and auxiliary engine powers of seven different types of ships. Eighty percent of the dataset was used for training, while the remaining twenty percent was set aside for the model's performance analysis. The outcomes demonstrated the higher predictive accuracy of gradient boosting machine regression techniques over alternative algorithms. Güneş (2023) used a large dataset of bulk cargo ships to create a nonlinear regression prediction model for main engine power. This study encompassed a wide range of significant factors, including gross tonnage (GT), length (L), breadth (B), and draft (T), in addition to the analysis of deadweight tonnage (DWT). As a result, a model was created that demonstrated an impressive accuracy rate of 93.2% for six different kinds of bulk cargo ships.

In addition to the studies using the regression model mentioned above, there are also studies using artificial neural networks (ANNs) for estimating the main engine power. The creation of prediction models for chemical tanker engine power was undertaken by Ekinci et al. (2011). In their investigation, an extensive assessment of the model's performance was conducted using eighteen different approaches, from conventional regression techniques to ANN. Cepowski and Chorab (2021) carried out important work that aimed to provide models for calculating the main engine power and fuel consumption in bulk carriers, container ships, and tankers. The authors compared multilayer models with a linear model that included two neurons in each of the input and output layers and no hidden layer. Their results demonstrated that, in terms of predicting accuracy, the more straightforward ANN model without hidden layers performed better than the complex multilayer ANN model. Özsarı (2023) used ANN to estimate the main engine power for cargo, tanker, and container ships. The models acquired throughout the study were also used for emission analysis. For estimating main engine power, 14 input parameters were employed. Güneş et al. (2023) used 836 tanker ships from the Marine Traffic database to perform regression and ANN analysis in order to predict the main engine power. The study's input parameters included deadweight, length, breadth, and gross ton values. The results of the ANN and regression analysis show that the data pertaining to tanker ships may be significantly applied. Gürgen (2023) predicted the main engine power in reefer ships using an ANN based method. Ship service speed and deadweight tonnage were included in the study as the ANN model's input variables. The Levenberg-Marquardt optimization technique was used to train the model, experimenting with various numbers of hidden neurons to find the optimal network configuration. The results showed that the suggested model could accurately predict the reefer ship main engine power.

In this study, ANN was used to conduct an exhaustive investigation in order to predict the main engine power for general cargo ships. Regression-based studies are available in the literature to estimate general cargo ships' main engine power. To the best of our knowledge, there has not been a main engine prediction research using the ANN approach for general cargo ships. Predicting the main engine's power accurately at the pre-design stage produces more accurate results in subsequent design stages, allowing for cost and weight analysis in addition to information on fuel consumption and exhaust gas emissions. The findings can be used to improve energy efficiency and optimize ship design.

2. MATERIALS AND METHODS

The data used in the study was obtained from IHS Markit Sea-web ship (2021), one of the world's most comprehensive maritime databases. Initially, 3092 ships built between 2000 and 2021 were collected using this database. The data was carefully examined before proceeding to the modeling phase. The elimination of sister ships and the removal of noisy or missing data were part of this process. After the data pre-analysis, a revised collection of 1310 ships was identified for the modeling procedure. Basic statistical information on the characteristics of these ships is shown in Table 1.

Table 1: The statistical values of the data set

	Min	Max	Mean

Length [m]	26.71	199.99	105.808
Breadth [m]	6.8	32.26	16.331
Deadweight [ton]	161	62000	7616.895
Service Speed [kn]	6	20.8	12.20
Draught [m]	1.85	13.5	6.302
GT [ton]	110	40300	5376.596
Main Engine Power [kW]	187	16520	2847.567

Figure 1 shows the number of ships by year of construction after the data set selected for the prediction model is assessed. 2008 is the most significant year in terms of shipbuilding with 109 ships. A decrease was noted in the next years as a result of the worldwide economic crisis of 2008.

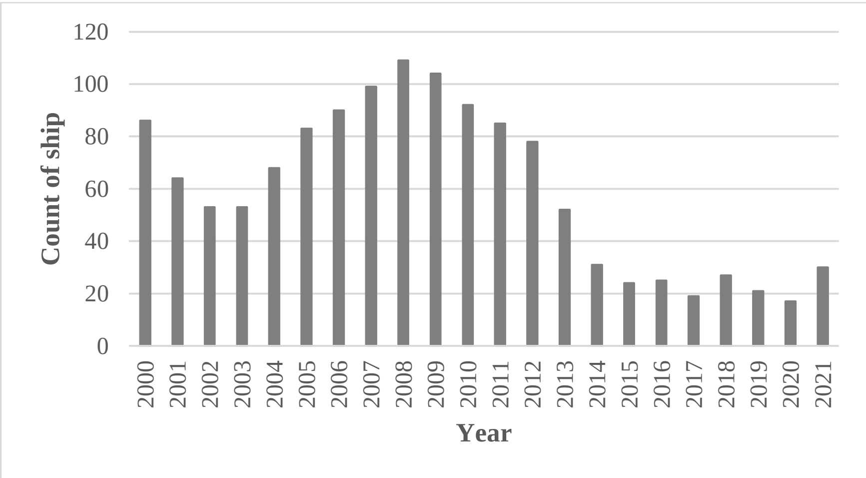

Figure 1: The built year of general cargo vessels in the dataset

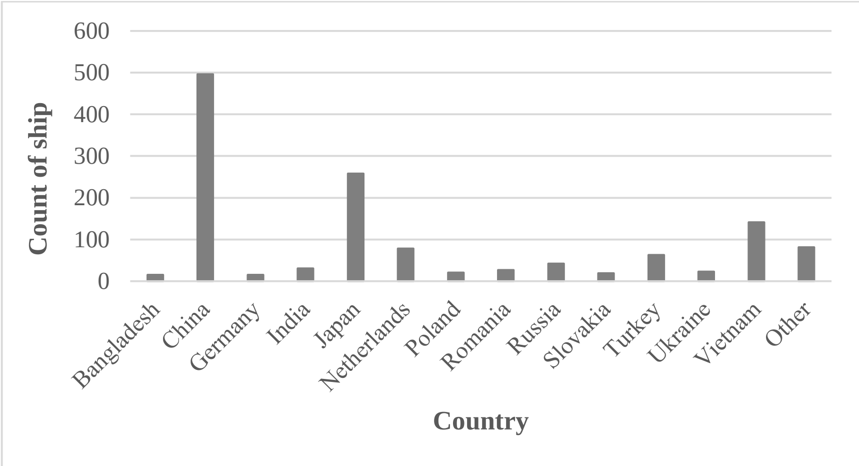

Figure 2: Country of build of general cargo vessels in the dataset

Figure 2 displays the quantity of ships based on the nations in which they were constructed. This graph depicts the nations that constructed more than 15 ships within the specified years. With 496 ships, China was the country that produced the greatest number of ships, according to this statistic. Vietnam had 141 ships and Japan had 258 ships following this.

In this study, the ANN method was used to estimate the main engine power of general cargo ships. The human cortex exhibits extraordinary intricacy, with around 10 billion neurons and around 60 trillion synapses interconnecting these neurons. The brain contains an enormous amount of nerve cells that create a complex network, which is known as the nervous system. The communication of information between neurons is influenced by a complicated mechanism that takes place between dendrites and axons. Dendrites collect sophisticated data from synapse-generated impulses and convey it to the nucleus to commence processing. Axons facilitate communication by transmitting processed output information to neighboring neurons. ANNs mimic the neural interaction in the human cortex, inspired by this natural mechanism, enabling them to perform complex information processing tasks (Beale et al., 1996; Haykin, 1994).

ANNs can be characterized in terms of five fundamental elements: input, weights, summation function, activation function, and output. Inputs involve data acquired from diverse sources, such as its environment or other cells. Weights are essential indicators that demonstrate the impact of information on the cell. The summing function computes the aggregate of all inputs to get the total input to a cell. The activation function governs the response of the cell by processing the net input derived by the summation function. At this stage, different activation functions, including as linear, sigmoid, and hyperbolic tangent, can be utilized. The final output of the ANN is the value produced by the activation function. This value can be either conveyed to the outside world or used as input for another cell (Bayindir et al., 2012; Gürgen, 2022).

Multi-layer ANNs are composed of three essential layers: input, hidden, and output. However, there are basic ANN models that are capable of solving just linear problems. These models are often restricted to the input and output layers. However, basic ANN models are frequently inadequate for addressing the complicated engineering challenges that are prevalent in today's world. Thus, complex ANN models with one or many hidden layers are frequently employed (Beale et al., 1996). Figure 3 depicts the standard structure of a multi-input neuron, which is a part of a multi-layer ANN model.

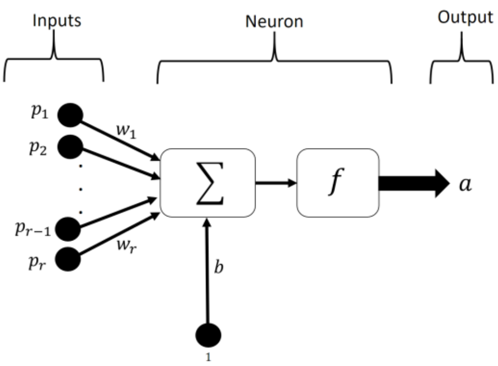

Figure 3: Multi-input neuron structure (Beale et al., 1996)

In Figure 3, inputs are represented by the symbol *p*. The inputs and bias (*b*) values are sent to the summation function by being multiplied by their respective weight values (*w*). Subsequently, this information undergoes an activation function to obtain the neuron output (*a*). This process can be mathematically expressed as follows:

$$a = f\left(b + \sum_{i=1}^{r} p_i \cdot w_i\right) \tag{1}$$

ANNs employ a basic backpropagation algorithm to facilitate their learning process. This approach operates by iteratively modifying the weights of matrices in the direction opposite to the gradient of the mean squared error function. Although the backpropagation algorithm is successful, it is widely recognized that it often converges slowly in practical applications, requiring significant computer resources. In order to deal with this difficulty, a variety of optimization approaches have been integrated into the backpropagation process. The Levenberg-Marquardt algorithm, as proposed by Hagan and Menhaj (1994), stands out as a prominent optimization method. The Levenberg-Marquardt algorithm is a second-order gradient approach used for nonlinear models, based on the least squares method. The backpropagation algorithm can be easily included with the aim of enhancing the effectiveness of the training process (Da Silva et al., 2017).

3. IMPLEMENTATION

Accurately defining the input and output variables is crucial in the creation of a prediction model. The dataset's characteristics, the nature of the problem, and the objectives help determine which input parameters are significant for the model. Increasing the number of input parameters may improve the model's performance, enabling it to acquire more complicated relationships and operate with additional features. Nevertheless, it may increase the possibility of overfitting, particularly when dealing with a limited dataset. Hence, it is crucial to employ a well-rounded strategy when choosing input parameters. The goal is to guarantee that the model focuses exclusively on vital properties by excluding extraneous or low-information-carrying elements.

When conducting scholarly research on predicting the power of a ship's main engine, the often used input variables are cargo capacity (DWT or TEU) and ship speed. In addition, some studies additionally integrated the parameters such as length, breadth and gross tonnage. However, Özsarı's study (2023) took into account an excessive number of input factors for the main engine prediction model. The engine stroke length and cylinder size were two of the fourteen input factors in the research. The study claimed that employing a wide range of input factors serves the objective of decreasing the error to an acceptable degree. However, this strategy resulted in a higher level of complexity in the model and needed the inclusion of an excessive amount of hidden neurons. Furthermore, in both regression and ANN modeling studies, the main objective is to create a model that can be used in real-life situations. Ship main engine power prediction models are valuable tools for naval architects during the pre-design stage. In the early stages of the design process, details like the engine cylinder size and engine stroke length are still unknown. These specific variables are determined at a later stage, once the main engine power has been determined. In this study, in order to effectively use the model during the early ship design stage, input variables were determined as ship length overall, breadth, gross tonnage, DWT and ship service speed. Figure 4 displays the structure of the ANN model that estimates the main engine power of general cargo ships.

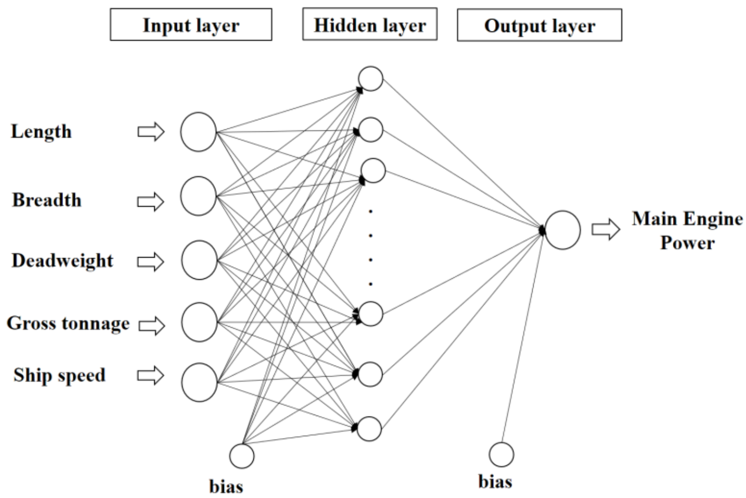

Figure 4: The main engine power prediction model

When creating prediction model with ANN, the dataset is divided into three distinct parts: the training set, the validation set, and the test set. The network is trained using the training dataset. The validation dataset plays a vital role in monitoring the training process, ensuring that the model does not just memorize the data. The test dataset is employed to assess the performance of the trained network. This study utilizes 70% of the data for training purposes, while 15% is allocated for validation and a final 15% is used for testing. The partitioning is performed randomly for each iteration in the training stage of the ANN. Before proceeding to the training phase, it is crucial to normalize the data. The sigmoid transfer function, as depicted in Equation 2, is frequently employed in the hidden layers in multi-layered networks. The sigmoid function's inherent characteristics cause input values to reach a saturation point after a specific threshold. This highlights the need for normalization to guarantee an effective beginning to the training process. All data set were normalized between 0 and 1. Prior to training the network, it is necessary to establish its architecture. A common neural network architecture used for curve fitting problems is the multi-layer perceptron. This architecture consists of hidden layers with sigmoid activation functions and an output layer with a linear activation function. Therefore, in this study, the network structure was chosen as multi-layer perceptron.

$$y(x) = \frac{1}{1+e^{-x}} \tag{2}$$

The feed-forward backpropagation network type was selected and the Levenberg-Marquardt algorithm was used to adjust the weights of the network during the training stage. The mean squared error (MSE), a commonly used performance metric, was chosen as the indicator of performance. In order to avoid the process of memorizing during training, a method of early stopping was implemented. This technique involves monitoring the error of the validation dataset for a given number of epochs. If a consistent increase in error is seen, the training process is stopped. The validation check number in this study was configured to be 40. During network training, it is possible for the performance surface to become trapped in a local minimum, resulting in poor performance. Therefore, a single training study may not produce the best potential performance. Therefore, in order to get a global minimum, it is necessary to retrain networks with varying numbers of neurons multiple times in order to acquire the most optimal network. This study involved a total of 1000 training sessions, where the number of hidden neurons was assigned at random between 1 and 30 for each session. After completing the training, an evaluation of the network's performance was carried out utilizing metrics that included mean absolute error (MAE), root mean squared error (RMSE), and regression analysis. MAE and RMSE are expressed as:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(t-p)^2} \tag{3}$$

$$\text{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|t-p\right| \tag{4}$$

where *t* ise the target value, *p* is the prediction value and *n* is the number of ship.

4. RESULTS AND DISCUSSIONS

Model training was provided with the code written in Matlab environment. Training was repeated 1000 times in total, with a different number of random hidden neurons each time. As a result of the experimental study, the structure with 22 hidden neurons was determined as the most suitable model. The performance graph of this model is shown in Figure 5. After the 75th epoch, the error increased continuously for 40 epochs (validation check number) for the validation data set. Therefore, the training process was stopped at the end of the 75th epoch and this point is known as the memorization point. The generalization ability of the models trained after this point decreases.

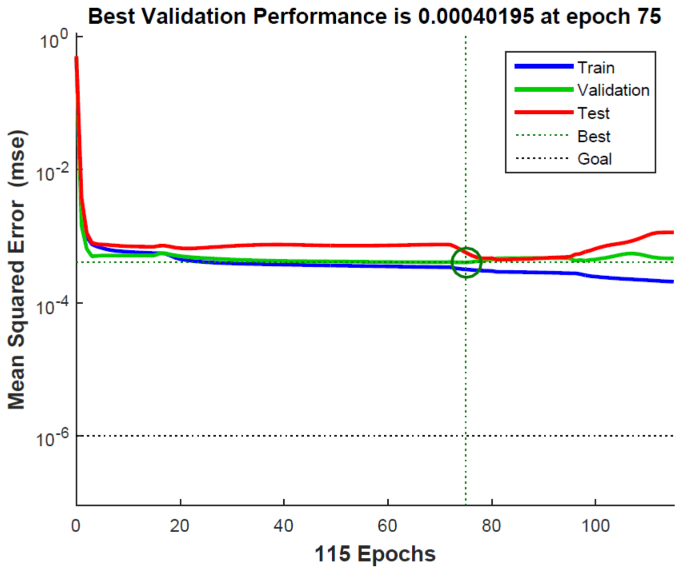

Figure 5: The performance of the main engine power prediction model at the training stage

For performance evaluation, regression analysis was first performed. Figure 6 shows the R values for the training, validation, test and all data sets of the model that estimates the main engine power of general cargo ships. When viewed from the perspective of the training data set, the value of 0.992 indicates that the training process was successful. The R values for the validation and test data sets, which were data that the model did not see during the training phase, were obtained as 0.988 and 0.986. This result indicated that the generalization ability of the model was high. When all data were considered together, the R value was calculated as 0.99 and it was clear that the general performance of the model was high. The coefficient of determination (R^2), which shows the extent to which a model explains the change in the dependent variable, was another important indicator. R^2 values were calculated as 0.983, 0.977 and 0.971 for training, validation and test data, respectively.

Other important indicators used in the performance analysis of modeling studies were MAE and RMSE values. Table 2 shows the MAE and RMSE values of normalized data sets. The MAE value for the training data set was calculated as 0.0128 and the RMSE value as 0.0178. These results showed that the model presented in terms of the training data set was compatible with the real data. The MAE value for the validation data set was obtained as 0.0137 and the RMSE value as 0.0200. These results showed that the model did not face the overfitting problem. The MAE value for the test data set was calculated as 0.0148 and the RMSE value as 0.0238, and it was understood that the model's prediction success on real-world data was high. When the entire data set was considered together and the calculation was made to determine the overall performance of the model, the MAE value was obtained as 0.0132 and the RMSE value as 0.0192. When all the results were evaluated together, the calculated low MAE and RMSE values showed that the model effectively predicted the main engine power of general cargo ships.

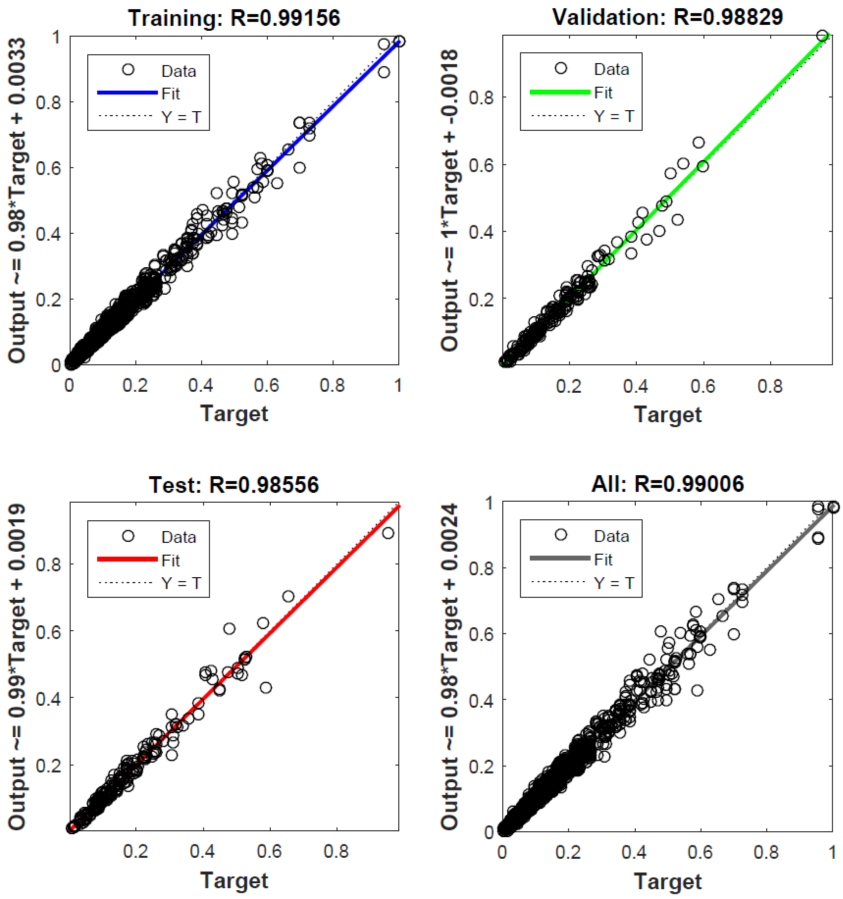

Figure 6: Regression graphics of the main engine power prediction model

Table 2: Performance results of the main engine power prediction model

	Training	**Validation**	**Test**	**All**
RMSE	0.0178	0.0200	0.0238	0.0192
MAE	0.0128	0.0137	0.0148	0.0132

The error histogram showing the model's prediction errors is given in Figure 7. When the error distribution was examined, it was seen that a significant amount of data was located around the zero error line. The errors, which were distributed approximately between -800 and +800 kW, had a pattern that follows a normal distribution. These results showed that the error values produced by the model were acceptable and the prediction ability was satisfactory.

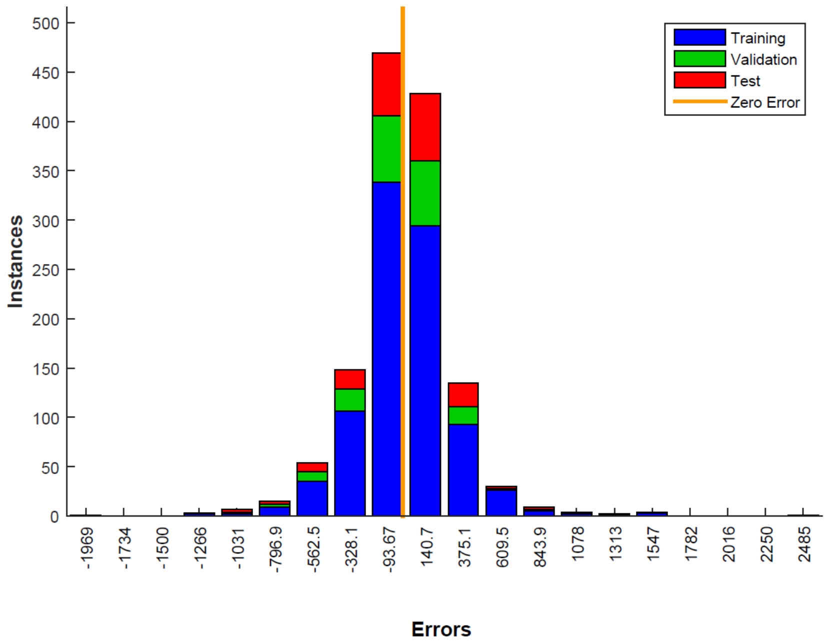

Figure 7: Error histogram of the main engine power prediction model

5. CONCLUSIONS

Determining the main engine power in the early stages of ship design is an important step. The correct estimation to be performed at this stage will be valuable for the later stages of the ship design. Systematic analyses can be carried out for various calculations such as cost and weight depending on the main engine. In this study, a model was developed using ANN to estimate the main engine power of general cargo ships.

A total of 1310 ships were identified for the process of modeling in the study. The prediction model utilized ship length overall, breadth, gross tonnage, DWT and ship service speed as input factors, with the main engine power in kW as the output. The training period employed the Levenberg-Marquardt optimization algorithm. The dataset was partitioned, assigned 70% for training, 15% for validation, and another 15% for testing.

During the examination, 1000 runs were conducted, with the number of hidden neurons being assigned randomly between 1 and 30 for each run. After the training periods, the model that exhibited the highest performance was chosen. This model was composed of 22 hidden neurons.

Regression analysis was first performed for the performance analysis of the created model to estimate the main engine power for general cargo ships. The R values, which indicate the model's fit, were quite acceptable. The R value was 0.992 for the training data, 0.988 for the validation dataset, and 0.986 for the test dataset. The model's total performance, assessed for all datasets, resulted in a R value of 0.990, suggesting highly satisfactory results. The MAE and RMSE were utilized to further assess the model's performance. The MAE and RMSE values observed in the training, validation, and test datasets, as well as for the overall dataset, indicate a robust fit and accurate prediction of the main engine power. The error rates were notably low, with MAE values ranging from 0.0128 to 0.0148 and RMSE values ranging from 0.0178 to 0.0238. In addition, an error histogram was used to display the distribution of prediction errors. The errors were found to be concentrated around the zero line, with a range of around -800 to +800 kW. The constructed model demonstrated robust prediction skills, as evidenced by its adherence to a normal distribution pattern and the tolerable size of errors. Overall, the study concluded that the prediction model obtained by using ANN approach successfully and accurately estimates the main engine power of general cargo ships.

Declaration of generative AI in scientific writing

During the preparation of this work the authors used ChatGPT in order to improve readability and language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article. The AI tool was not involved in any part of the research process, analysis, or generation of insights, nor was it used in conceptualizing or developing the scientific content of the paper.

Data availability

Ship data was taken from IHS Markit Sea-web™, a paid database offering over 600 data fields on over 220,000 ships of 100 GT and above. Access was provided by Iskenderun Technical University at 2021. Data will be made available on request

REFERENCES

Bayindir, R., Colak, I., Sagiroglu, S. Kahraman, H.T. (2012). Application of adaptive artificial neural network method to model the excitation currents of synchronous motors, 11th International Conference on Machine Learning and Applications, 12-15 December 2012, pp. 498-502, Boca Raton, FL, USA

Beale, H.D., Demuth, H.B., Hagan, M. (1996). Neural Network Design, Boston, USA.

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 (101), 82-94.

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.

Da Silva, I.N., Spatti, D.H., Flauzino, R.A., Liboni, L. H.B., dos Reis Alves, S.F. (2017). Artificial Neural Networks, Springer International Publishing.

Ekinci, S., Çelebi, U.B., Bal, M., Amasyali, M.F., Boyaci, U.K. (2011). Predictions of oil/chemical tanker main design parameters using computational intelligence techniques. Applied Soft Computing, 11(2), 2356-2366.

Evans, J. (1959). Basic design concepts. Journal of the American Society for Naval Engineers, 71(4), 671-678.

Güneş, U. (2023). Estimating bulk carriers' main engine power and emissions. Brodogradnja, 74(1), 85-98.

Güneş, U., Bashan, V., Ozsarı, İ., Karakurt, A.S. (2023). Predicting tanker main engine power using regression analysis and artificial neural networks. Sigma J Eng Nat Sci, 41(2): 216-225.

Gürgen, A. (2022). Güve-Alev Optimizasyon Algoritması Kullanarak Pleurotus cornucopiae var. citrinopileatus Mantarı Ekstraksiyon Koşullarının Optimizasyonu. Düzce Üniversitesi Bilim ve Teknoloji Dergisi 10(3): 1508-1523.

Gürgen, 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.

Gürgen, S. (2023). Artificial Neural Network-Based Approach to Predict Main Engine Power in Reefer Ships, 3. International Mediterranean Congress, 17-18 April 2023, pp. 718-725, Mersin, Türkiye.

Hagan, M. T., Menhaj, M.B. (1994). Training feedforward networks with the Marquardt algorithm. IEEE transactions on Neural Networks 5(6): 989-993.

Haykin, S. (1994). Neural Networks: A Comprehensive Foundation, Prentice Hall PTR.

Majnarić, D., Šegota, S. B., Lorencin, I., and Car, Z. (2022). Prediction of main particulars of container ships using artificial intelligence algorithms. Ocean Engineering, 265, 112571.

Okumuş, F., Ekmekçioğlu, A. (2021). Modeling of General Cargo Ship's Main Engine Powers With Regression Based Machıne Learning Algorithms. Mersin University Journal of Maritime Faculty, 3(1), 1-8.

Okumuş, F., Ekmekçioğlu, A., Kara, S.S. (2021). Modelling ships main and auxiliary engine powers with regression-based machine learning algorithms. Polish Maritime Research (1): 83-96.

Ozsari, I. (2023). Predicting main engine power and emissions for container, cargo, and tanker ships with artificial neural network analysis. Brodogradnja 74(2): 77-94.

Piko, G. (1980). Regression analysis of ship characteristics: Australian Government Publishing Service.

Sea-Web Ships. 2021. Data base: https://maritime.ihs.com (accessed at 2021)

Żelazny, K. (2015). A method for determination of service speed useful in the preliminary design of cargo vessels under statistical weather conditions occurring on shipping route. Szczecin: Publishing House of West Pomeranian University of Technology in Szczecin.