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Calculating the main engine power of fishing vessels with artificial neural networks analysis

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Abstract – Fishing vessels carry out the majority of the world's fishing. All other vessel types will be inspired by advancements in fishing vessels. Determining the ship's main engine power is crucial for both energy efficiency and environmental considerations because of this. The fishing and shipping industries are just now starting to realize how important artificial intelligence technology is. In this investigation, a model of an artificial neural network (ANN) was used to forecast the power of the main engine and the emissions of pollutants from fishing vessels. The model takes into account 12 characteristics, including the maximum speed, width, year of construction, kind of ship, overall length, displacement-light ship, DWT, gross tonnage, engine cylinder, and engine stroke. The ANN analysis has been trained to produce reliable results using the data of 800 fishing vessels, which is quite a lot in comparison to the research in the literature. In order to produce the fewest errors and most accurate results, numerous artificial neural network models have been designed. When the findings of the artificial neural network study were compared to actual values, it became clear that the MSE and regression results had produced very accurate results. Various hidden neuron numbers have been tried, along with performance outcomes, in order to make accurate predictions with the greatest degree of precision in ANN analysis. The created model can be applied to research on fishing vessel energy utilization and fuel consumption.

Keywords – Fishing vessels, engine power; artificial neural network; maritime transport; emission air pollution.

I. Introduction

With the development of technology in the modern world, artificial intelligence (AI) has become increasingly well-known. In many professions, AI is currently regarded as the most efficient and important tool for finding solutions. The shipping and maritime transport industry has just recently begun to recognize the significance of artificial intelligence. The International Marine Organization (IMO) implements the appropriate controls and penalties to lessen the pollution that ships and marine transportation emit. The actions to be performed in maritime transport also set an example for terrestrial installations and automobiles because the pollutant emissions from ship transportation account for a sizeable share of the total emissions. Through regression calculations using data from 9,174 modern bulk carriers divided into six different bulk carrier sizes, Gunes [1] computed main engine power and emissions. His regression model accurately predicted the outcomes with a 93.2% rate. The fuel type and main engine power are the key factors of ship emissions. The more dangerous fuel ingredients are minimized by the restrictions the IMO has enacted. But in addition to many other things, the main engine's power is important for energy efficiency. The optimal method for determining a ship's main engine power has thus been the subject of numerous studies in the literature. In order to precisely estimate the precise fuel consumption of a ship's main engine, Jeon et al. [2] presented regression analysis employing data gathering, clustering, and big data analysis methods in an artificial neural network (ANN) and tried several variants. The Baltic Dry Load Index (BDI) was explored using ANNs by Sahin et al. [3], who also provided a comparison of the outcomes and performances of three distinct ANN models. Preliminary design and engine power statistics for tanker, bulk, and container ships were reported by Cepowski et al. [4] after performing a regression analysis on data pertaining to ships constructed between 2000 and 2018. Code was written by Xhaferaj [5] to parametrically estimate ship resistance and main engine power, and the findings were validated using data and conventional boats. Another work by Theodoropoulos et al. [6] used the Gaussian mixture model (GMM) and ANN approaches to predict ship main engine power, fuel consumption, and emissions estimations. Cepowski et al.'s [7] estimation of the ideal container ship length combined multiple nonlinear regression (MNLR) and artificial neural network (ANN) techniques, and they compared their findings. Four different[8] approaches were suggested by Barua et al. [8] after examining features of international freight forwarding management (IFTM) that could be enhanced with machine learning. In order to estimate ship main engine fuel consumption, Gkerekos et al. [9] conducted a comparative examination of several regression techniques while taking into account the data gathering methods used by two different ships. An optimization research on the impacts of course, speed, and mechanical, environmental, and other parameters on a ship's main engine power was published by Yan et al. [10]. In order to lower power consumption and boost energy efficiency, Kalajdzic et al. [11] conducted research on the IMO's highly valued Energy Efficiency Design Index (EEDI) and Energy Efficiency Existing Ship Index (EEXI). They presented numerical comparative results for 153 bulk carriers constructed between 2000 and 2020. In order to estimate engine power and the fluctuating fuel consumption for tanker, bulk, and container ships, Cepowski et al. [12] established equations. They then compared the performance of the equations they created using numerous modifications for ANNs. In order to determine the necessary power and precise fuel consumption of ships when at sea, Farag et al. [13] looked into ANN and multiple regression models. They also demonstrated how the proposed models were consistent with earlier studies.

In contrast to research in the literature, this study conducts a thorough data analysis to present an ANN study with 12 input parameters for 800 fishing vessels. By utilizing various ANN models and sequences, it is possible to identify the models that produce the best accurate results. The study also discusses the model performances and the outcomes, demonstrating that ANNs may be used in fishing vessels to swiftly and precisely provide the required outcomes.

II. Materials and Method

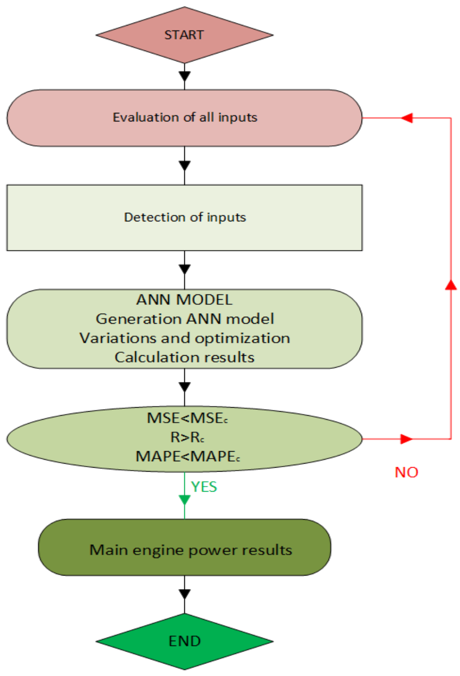

Fig. 1 Analysis process for main engine power

ANNs are a type of information processing technology that models its operations after the way the human brain works. ANN is specifically a digital representation of real neuron cells and the synapses that connect them, and it is used to replicate the algorithmic process of the basic biological nervous system. The initial values of the weights are chosen at random. The output value is then calculated using the subsequent equations:

$$net_j = w_{0j} + \sum_{i=1} x_i w_{ij} \tag{1}$$

$$output_j = f(net_j) \tag{2}$$

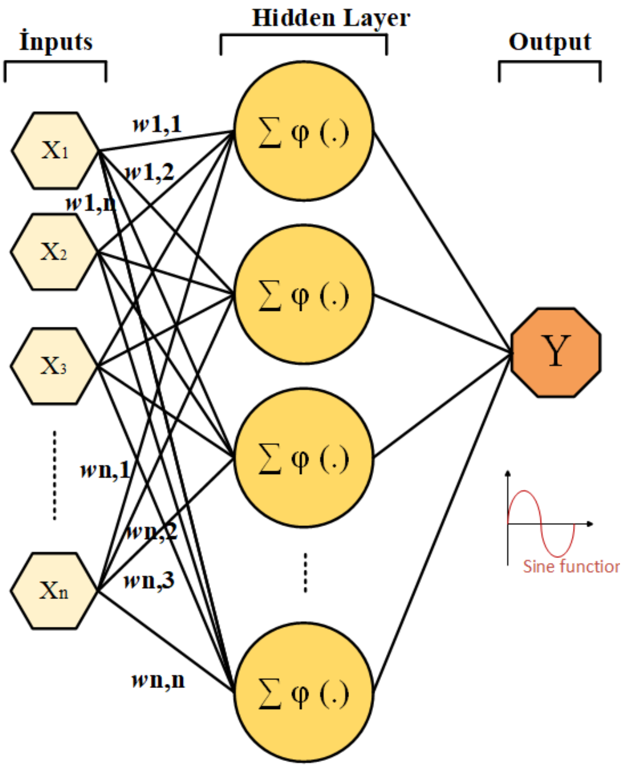

Fig. 2 Architectural structure of artificial neural network.

To get the node's output, an activation function called f transfers the final total. The log-sigmoid (logsig) function and the purelin function, whose general definitions are given in the following equations, are used, respectively, in this work as the hidden-layer and output-layer activation functions:

$$Sigmoid: f(x) = \frac{1}{1+e^{-x}} \quad (3)$$

$$u_i = \sum_{J=1} w_{ij} x_j + b_i \quad (4)$$

$$y_i = \varphi(u_i) = \varphi \sum_{j=1} [w_{ij} x_j + b_i] \quad (5)$$

Where x is the value of the input, n is the number of inputs per neuron, output j is the value of the output for the hidden nodes, m is the number of neurons in the hidden layer, output k is the value of the output for output nodes, and p is the number of neurons in the output layer. Also, w_{ij} is the weight between the input neurons and the hidden neurons.

It has been determined that the mean square error (MSE) is a good indicator of network performance. Coefficients of determination (R^2) are also used for network comparisons. The following is a list of these:

$$MSE = \frac{1}{n} \sum_{i=1}^{N} (t_i - o_i)^2 \quad (6)$$

$$R^2 = 1 - \frac{\sum (t_i - o_i)^2}{\sum (o_i - \bar{o})^2} \quad (7)$$

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.

Using 12 input and 1 output data, the ANN dataset was generated from the ship database. The dataset for the analysis of fishing vessels was split into 560 samples for training and 120 samples for validation and testing. The 12 parameters of maximum speed, breadth, year of construction, ship type, LOA, light displacement, summer displacement, fuel type, DWT, gross tonnage, engine cylinder size, and engine stroke length were used in the ANN analysis performed in the MATLAB program to calculate the boundary conditions. Trial results show that the Levenberg-Marquardt technique performs better than other algorithms [14], [15], and the model only requires 12 input parameters because more specific parameters were omitted from the dataset for the sake of simplification. The output calculation convergence is therefore sufficient. After that, the 12-input ANN system was trained, verified, and put to the test. Figure 2 shows the perceptron model that was used.

Table 1. Values for the training parameters used in the artificial neural network models

Training Parameters	**Values**
Maximum number of epochs to train	1,000
Maximum validation failures	100
Performance goal	0
Minimum performance gradient	1.00E-05
Initial μ	0.01
Decrease factor for μ	0.01
Increase factor for μ	1
Maximum value for μ	1.00E+8
Epochs between displays	10

III. Results and Discussion

Figures 3–7 show the results for main engine power values for fishing vessels using ANN. According to the ANN model's function, the quantity of hidden neurons, and changes in parameter values, the results are computed and shown.

The code flow chart is detailed in Figure 1. The MATLAB software was used to test transfer functions in this code research. The tansig-purelin transfer function and the trainlm function, which produce quick and precise calculations in terms of MSE, produced the best results. Fishing vessel findings from the ANN analysis are displayed in the study.

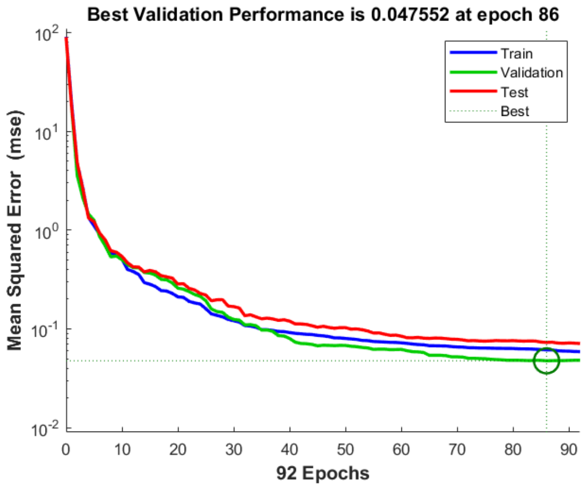

Fig. 3 An analysis of the most accurate neural network model for fishing vessel data.

Figure 3 shows the performance graph for the ANN model built over the fishing vessels data. The developed artificial neural network (ANN) model made a total of 92 iterations, with the best validation performance being obtained on the 86nd iteration.

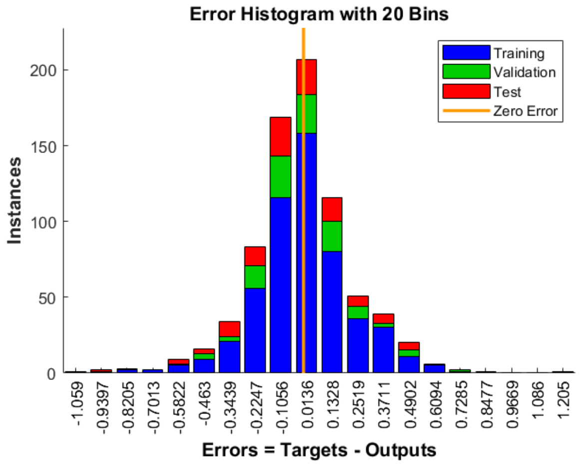

Fig. 4 Errors in the distribution of residuals as well as discrepancies between the target values and the results of the ANN for fishing vessels.

It's crucial to recognize how the ANN model and the actual values differ. The majority of the results from the ANN study, which was carried out with 800 fishing vessels, are displayed in Figure 4. Results that were accurately calculated are represented by the orange line. When examining the vast range of outcomes, it is evident that the distribution falls between -0.5 and +0.5. As a result, it is demonstrated that an accurate ANN model may be used to estimate the main engine powers of actual ships.

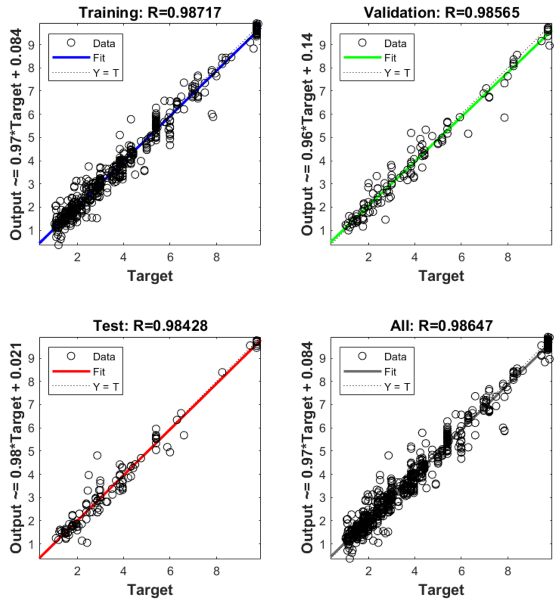

Fig. 5 Regression graphs for fishing vessel models using the most precise neural network models.

Figure 5 exhibits the study findings utilizing data from 800 fishing vessels and displays the regression graph between the values predicted by the ANN model and the actual main engine power levels. The correlation coefficients for training, validation, testing, and overall are 0.98647, 0.98565, 0.98428, and 0.98428, respectively. It is abundantly evident that the ANN model's findings are consistent because the R values are so near to 1.

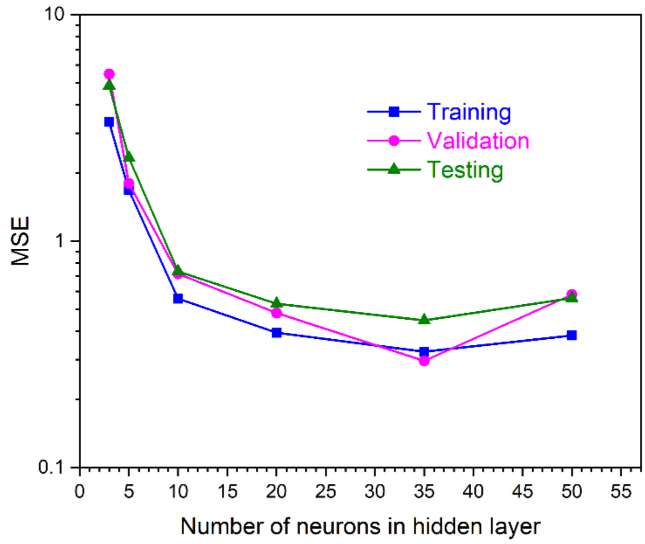

Fig. 6 Using the amount of neurons in each hidden layer, the MSE for the training, validation, and testing results.

In some circumstances, extremely complicated neural network topologies are unable to produce the necessary results in an ANN study. In other words, each task requires the development of a unique neural network. The number of middle layers and neurons in the ANNs varies according to factors including computation time, underfitting, overfitting, and dropout. Figure 6 displays the findings from the mean squared error value according to the quantity of neurons in the ANN analysis code. The best result was determined to have been attained utilizing 35 neurons when the training, validation, and testing values were taken into account. The accuracy sensitivity was shown to decline as the number of neurons reached 50. According to the ANN literature for this issue, the solution can be reached by employing a medium-simple neural network architecture.

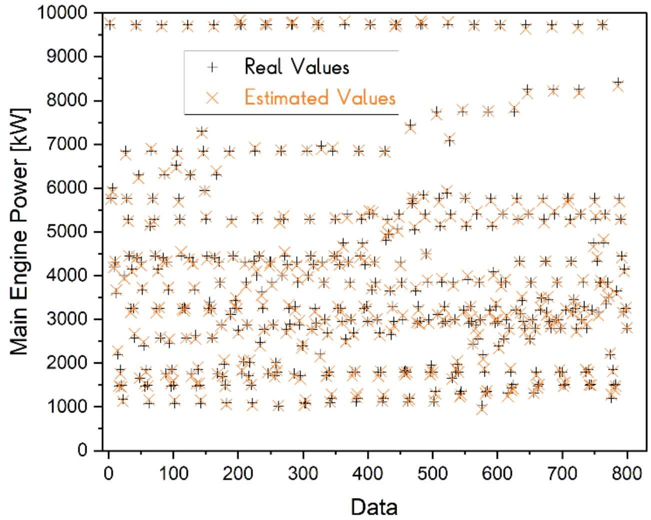

Fig. 7 Results from ANNs are shown alongside actual data on marine engine power for fishing vessels.

Actual ship main engine power data and predicted ship main engine power values derived from the ANN analysis are shown in Figure 7. Most of the values in the analysis done for fishing vessels are shown to overlap in Figure 7. The figures demonstrate that extremely precise and sensitive results were obtained. The MSE values from the outcomes of the ANN study are detailed in Figure 6. However, there were inconsistencies found in some ship statistics. Large datasets should yield better results, although ANNs have been shown to occasionally make mistakes. More accurate outcomes can be attained by removing these ship data points. However, as doing differently would not be a good behavior for scientific development, the ANN analysis was carried out over all the data. Overall, the consistency of the findings has been completely acceptable for both this study and subsequent ones.

IV. CONCLUSION

Using indices like the EEDI, EEOI, and EEXI, the IMO aims to meet the highest efficiency and lowest emissions standards with relation to energy aboard ships. Therefore, it is necessary to determine the main engine power needed for ships. AI should be employed for these things because it's one of the key technological instruments available today. It is quicker and simpler to use an ANN than conventional techniques to calculate ship main engine power during the design phase. Among the research in the literature, this study offers the most thorough ANN analysis of ship data. With information on a total of 800 fishing vessels, a thorough analysis study was conducted. The ship's maximum speed, breadth, year of construction, kind of ship, length overall, light displacement, summer displacement, fuel type, DWT, gross tonnage, engine cylinder size, and engine stroke length were the 12 inputs used in this precise study to determine the outputs relating the main engine power. The paper outlines the stages of the intricate ANN analyses, the performance metrics, and the prediction accuracy, and it comes to the conclusion that the regression graphs of the ANN analysis for fishing vessels are 0.98647. In order to compare outcomes, the study also provides actual data on fishing vessels as well as predicted results. Calculating MSE values has demonstrated the correctness of the results. The ANN analysis with 35 neurons was found to have produced the best results as the number of hidden neurons was examined under various ANN structure configurations. The study has the ability to direct subsequent research. Additionally, it can contribute significantly to the advancement of AI research for many uses in marine transport and for other types of ships.

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