Global Journal of Engineering and Technology Advances

eISSN: 2582-5003

Cross Ref DOI: 10.30574/gjeta

Journal homepage: https://gjeta.com/

Global Journal of Engineering and Technology Advances

Global Scholar Press, INDIA

(RESEARCH ARTICLE)

Check for updates

A generic model towards maximizing the performance of ship propulsion system using artificial neural network

Odokwo V. E [1,*], Nkoi, B [2], Orji C. U [3] and Tamunodukopipi D. T [3]

[1] *Center of Excellence in Offshore and Marine Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Rivers State, Nigeria*

[2] *Department of Mechanical Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Rivers State, Nigeria.*

[3] *Department of Marine Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Rivers State, Nigeria.*

Global Journal of Engineering and Technology Advances, 2022, 12(03), 042–051

Publication history: Received on 02 August 2022; revised on 17 September 2022; accepted on 19 September 2022

Article DOI: https://doi.org/10.30574/gjeta.2022.12.3.0154

Abstract

In this study, optimization based on artificial neural network (ANN) was established to predict the optimal performance parameters of the system, leading to an optimized propulsion system. Optimization related works on propulsion system investigated by researchers are based on specific fuel consumption, emission characteristics, trim and draft optimization using conventional methods amongst others. This creates a gap for a research window in this direction which this work tries to fill by optimizing overall ship propulsion system efficiency using ANN. The models computational development for this research were actualized using ANN tool box in MATLAB. Attention was given to performance parameter that influences the overall performance of the propulsion system. Hence, the overall ship efficiency, η_{sp} and energy efficiency design index (EEDI) constitute the parameters of interest to be optimized. A comprehensive ANN program code was developed and implemented to create, configure, train and optimize these parameters of interest. Various ANN-based models of a two layered multilayer perceptron (MLP) structure with different configurations were trained and investigated. Results analysis from MATLAB simulation yields η_{sp} *of* 0.507398386 and EEDI of 3.490301699 g of CO_2/tm. Results show that the MLP configuration of 14-20-7 gives an optimal model for the ANN. The resulting model could predict the optimized performance output of the system with high degree of accuracy with a minimum mean square error (MSE) at 206 epochs. This point gives the lowest MSE performances value of 3.2923e-10 and regression plot between 0.99999 and 1. The percentage parametric optimization of the propulsion system parameters in ANN gives a 2.4% improvement of η_{sp} and 3.5% improvement of EEDI. These indicate that the use of ANN for parametric optimization of propulsion system is satisfactory

Keywords: Optimization; Generic Models; Propulsion; Artificial Neural Network; Ship Efficiency

1. Introduction

Propulsion system are essential component of a ship required for navigation and maneuverability of vessels. Stringent requirements are placed on the design of propulsion system so as to meet certain standards: load on the engine, specific fuel consumption (sfc) minimization, CO_2 emission abatement and energy efficient design index (EEDI) regulations which is an indication of ship's energy efficiency [1]. The International Maritime Organization (IMO) came up with MARPOL Annex VI to mitigate emissions and prohibit deliberate emission of ozone-depleting substances from vessels [2]. To adopt these standards and abet emissions, vessels have to adopt the use of lighter fuels or the installation of

* Corresponding author: Odokwo, V. E
Center of Excellence in Offshore and Marine Engineering, Rivers State University, Nkpolu-Oroworukwo, Port Harcourt, Rivers State, Nigeria.

scrubbers yet zero emissions have not been achieved. A particular source holds that internal combustion engines are inefficient because they waste more energy produced in the form of heat and emissions than they utilize the energy. Some of the energy is lost to obey the thermodynamic laws, while some are lost to mechanical components that help produce the useful energy [3].

Notably, engine emissions are directly related to engine power employed for achieving the desired speed of a ship. To reduce emission, IMO formulated EEDI as a means to estimate CO_2 emission performance applied to ships of 400 gross tonnages and above. Although EEDI is primarily developed as one of the greenhouse emissions reduction measures, it is also considered as an indicator of energy efficiency of a ship and ship propulsion system [4]. Present day economy requires minimum time and money spent in developing and preparing for experimentation and analysis [5]. The development and implementation of digital technology can significantly increase the effectiveness of research, development and parametric analysis of engineering systems by maximizing the replacement of costly and time-consuming analysis with virtual ones without sacrificing quality and accuracy [6].

The use of mathematical model allows a systematic and analytical assessment of propulsion configuration and reduces the use of experimental or hardware model tests. A computer-based analysis is extremely useful because rudimentary physical processes occurring in design and off-design operation provides the basis of design evaluation and review [1]. With rapid development of computer capacity, machine learning and intelligent algorithms application in engineering, some new methodologies and optimizations techniques have emanated in order to make system performance optimization swift and more accurate [7]. It therefore makes engineering sense to take advantage of the very desirable characteristics and the versatility of software to create models, simulate and optimize engineering systems with high degree of predictability, precision and accuracy [8].

Artificial neural network (ANN) has shown over time to be a strong and reliable alternative to conventional modeling and optimization methodologies due to their independence and adaptability to new conditions [9]. Engineering application has harnessed ANN model capability to handle multiple input variables to predict multiple output variables and its ability to learn about the system to be modeled without prior knowledge of the process relationships. One fundamental aspect to be explored is the capability of ANN to accommodate a real time simulation which would demonstrate the actual operational conditions [10]. In this work, ANN based on Multilayer perceptron (MLP) with several layers feed-forward neural network and back propagation training algorithm based on Levenberg-Marquardt optimization is established to analyze, predict and optimization of Moving Tanker (MT) Diamond propulsion system to achieve the best performance scenario and its robustness on EEDI.

2. Material and methods

Energy balance principles and thermodynamics relationships will be adopted in modeling the marine diesel engine. The propulsor and transmission system will be modeled using the dimensionless coefficients based on Wageningen B series polynomial equations while the optimization of the propulsion system will be brought to fruition with artificial neural network (ANN).

2.1. Analytical model of the propulsion plant

The modeling will capture only important performance variables of the propulsion system paramount to this work. This approach and methods adopted for this research are favoured because of its ability to capture and represent the engine characteristic with sufficient accuracy. According to Aleksandr *et al.* [11] the overall turbocharger efficiency, η_{TC} of a marine diesel engine is estimated from the expression of equation (1):

$$\eta_{TC} = \left(\frac{\dot{m}_a}{\dot{m}_g}\right)\left(\frac{C_{p_a}}{C_{p_g}}\right)\left(\frac{T_{c_1}}{T_{t_3}}\right)\left[\frac{\left(\frac{P_{c_2}}{P_{c_1}}\right)^{\left(\frac{\gamma_c-1}{\gamma_c}\right)}-1}{1-\left(\frac{P_{t_4}}{P_{t_3}}\right)^{\left(\frac{\gamma_g-1}{\gamma_g}\right)}}\right] \text{……………. (1)}$$

Similarly, Guan *et al.* [12] provides the relationship for obtaining the engine brake specific fuel consumption which is a measure of the fuel efficiency and the brake thermal efficiency which is also a measure of the overall efficiency of the diesel engine as given by equations (2) and (3):

$$bsfc = \frac{\dot{m}_f}{B_P} = \frac{3.6\times10^6}{\eta_b\times Q_L} \text{…………………………..(2)}$$

$$\eta_b = \frac{3600 \times Brake\ Power}{Feul\ Energy} = \frac{3600 B_P}{\dot{m}_f Q_L} \text{ .... (3)}$$

2.1.1. Propulsion system hydrodynamic modelling

From the perspective of two stroke marine diesel engine, the brake power, B_P is transmitted to the delivered powered and is given by the expression of equation (4):

$$P_D = 2\pi n_P Q_P \eta_R = B_P \eta_S \text{ .... (4)}$$

The propeller quasi propulsive coefficient that gives a description of the vessels propulsion system efficiency is obtained from the expression:

$$\eta_D = \frac{P_E}{P_D} = \frac{R_T V_S}{\omega M_D} = \frac{R_T V_S}{2\pi n M_D} = \frac{R_T V_S}{T_P V_A} \times \frac{T_P V_A}{\omega Q_P} \times \frac{Q_P}{M_D} \text{ .... (5)}$$

After proper substitution and evaluation of equation (5) and taking into account the mechanical efficiency of the shaft line, the propulsive coefficient is obtained from the relationship given in equation (6):

$$\eta_P = \frac{P_E}{P_D} = \eta_H \times \eta_o \times \eta_R \times \eta_s \text{ .... (6)}$$

The quotient, ship effective power divided by the engine fuel power given by equation (7), is use to estimate the total ship propulsion system efficiency.

$$\eta_{sp} = \frac{P_E}{Q_f} = \eta_b \eta_P = \eta_b \times \eta_H \times \eta_o \times \eta_R \times \eta_s \text{ .... (7)}$$

Where: $Q_f = Fuel\ power\ or\ energy$ and $\eta_P = propulsive\ efficiency$

2.1.2. Modelling EEDI and overall ship efficiency

For a 2-stroke marine diesel engine propulsion system having direct drive and considering only the propulsion power, the EEDI can be obtained from the expression in equation (8):

$$EEDI = \frac{\left(f_j \times P_{ME} \times SFC_{ME} \times C_{f_{ME}}\right) + \left(P_{AE} \times SFC_{AE} \times C_{f_{AE}}\right)}{f_i \times f_c \times f_w \times Capacity \times V_s} \text{ .... (8)}$$

The auxiliary engine power, P_{AE} required to supply the necessary power for propulsion machinery and accommodation, can be defined according to Equation (9):

$$P_{AE} = \begin{cases} 0.025 \times MCR_{ME} + 250 & MCR_{ME} \geq 10{,}000 kW \\ 0.05 \times MCR_{ME} & MCR_{ME} < 10{,}000 kW \end{cases} \text{ ... ...(9)}$$

The overall efficiency of a vessel is the ratio of the work output to the work input or energy input express mathematically by equation (10):

$$\eta_{ship} = \frac{work\ output}{work\ input} = \frac{Ship\ effective\ power}{Energy\ supplied} = \frac{P_E}{\dot{m}_f \times LCV} = \frac{P_E}{Q_f} \text{ .... (10)}$$

Substituting appropriately and according to Gerasimos & Vasileios [13] and Feiyang *et al*. [14], the overall efficiency of a vessel is given by the relationship of equation (11):

$$\eta_{ship} = \frac{P_E}{Q_f} = \eta_b \times \eta_p = \eta_b \times \eta_H \times \eta_R \times \eta_O \times \eta_s \text{ .... (11)}$$

But we know that the power of the main engine is expressed as shown in equations (12):

$$P_{ME} = \frac{P_E}{\eta_s \times \eta_H \times \eta_R \times \eta_O} = \frac{\eta_b \times P_E}{\eta_{ship}} \text{ .... (12)}$$

The expression for EEDI and the overall ship efficiency after appropriate evaluation and substitution becomes:

$$EEDI = \frac{f_j \times \eta_b \times P_E \times SFC_{ME} \times C_{f_{ME}}}{f_i \times f_c \times f_w \times \eta_{ship} \times V_s \times Capacity} + \frac{P_{AE} \times SFC_{AE} \times C_{f_{AE}}}{f_i \times f_c \times f_w \times V_s \times Capacity} \ldots\ldots\ldots(13)$$

Keeping other parameters and terms constant and simplifying equation (13) appropriately yields the expression relating EEDI and overall ship efficiency as given by equation (14):

$$EEDI = \frac{K_{10} \times P_E}{\eta_{ship}} + K_{11} \ldots\ldots\ldots\ldots\ldots (14)$$

Where:

$$K_{10} = \frac{f_j \times \eta_b \times SFC_{ME} \times C_{f_{ME}}}{f_i \times f_c \times f_w \times V_s \times Capacity} \text{ and } K_{11} = \frac{P_{AE} \times SFC_{AE} \times C_{f_{AE}}}{f_i \times f_c \times f_w \times V_s \times Capacity}$$

2.1.3. Programming the NN model

MATLAB version R2019a was used to write script files for developing MLP-ANN models and performance functions for calculating the model performance error statistic using MSE. Brake specific fuel consumption (bsfc), brake thermal efficiency,η_b, propulsive efficiency, η_P, overall ship efficiency, η_{sp} and energy efficiency design index (EEDI) constitutes the parameters of interest to be optimized and also serve as the output parameters of the ANN. To obtain a maximally trained and optimized ANN structure for better generalization characteristic of the propulsion system model, a comprehensive computer code was generated and run in MATLAB for neurons ranging from 5 to 40. A flow chart to demonstrate the ANN optimization process of the vessel propulsion system is shown in Fig. 1. After inputting and normalizing the data sets, they are randomly partitioned by default in MATLAB into training-90%, validation-5% and testing-5%. This is followed by specifying the structure of the NN-MLP and configuration of the network by assigning the number of neurons, training function and transfer functions for the hidden and output layers. At this point the network is ready for the training process to commence and this is repeated several times for the same adjusted factors, so that the best performance among the trials is identified, chosen and recorded.

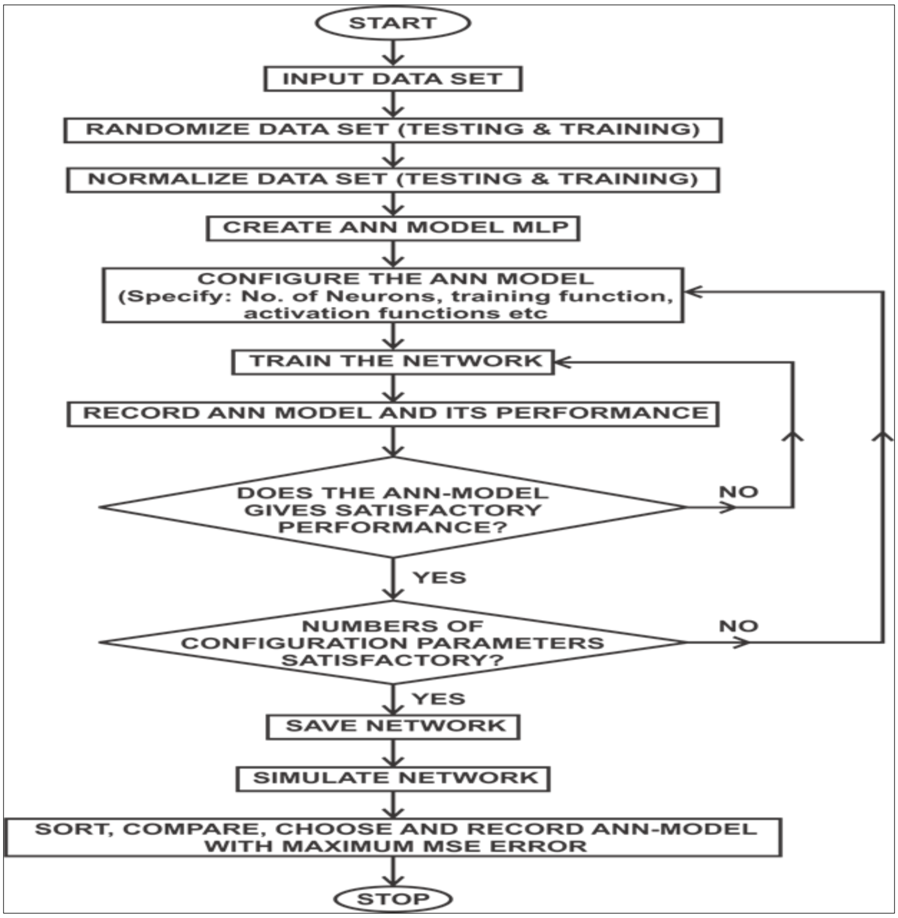

Figure 1 Flow Chart of ANN Computer Code for MLP of Propulsion System

The process is repeated in two main loops of the code for different numbers of neurons (5 to 40), various back-propagation training functions, and a combination of different transfer functions for the hidden and output layers. propagation training functions, and a combination of different transfer functions for the hidden and output layers. The results of all the performances of the network is recorded and sorted on the basis of their performance measure-MSE. In this study, two thousand epochs will be considered for the entire training process. This is to ensure that the training would not be stopped before reaching a dominating local minimum, from which the optimal ANN model was identified from the sorted results.

3. Results and discussion

A thorough investigation of the robustness of an optimized parametric series of MT Diamond propulsion system using ANN was evaluated and analyzed. To keep the scope of this research within reasonable limits, focus was accorded to performance parameters that is expected to produce significant impact on the overall performance of the propulsion system.

To obtain an optimized structure and to ensure a good optimization of the propulsion system model, a comprehensive training of a two-layered MLP architecture in MATLAB environment was carried out. Fig. 2 shows a computational framework for the propulsion system analysis, simulation and optimization. This provided the platform for computation, data generation and assessing the characteristics the propulsion system performance parameters with EEDI.

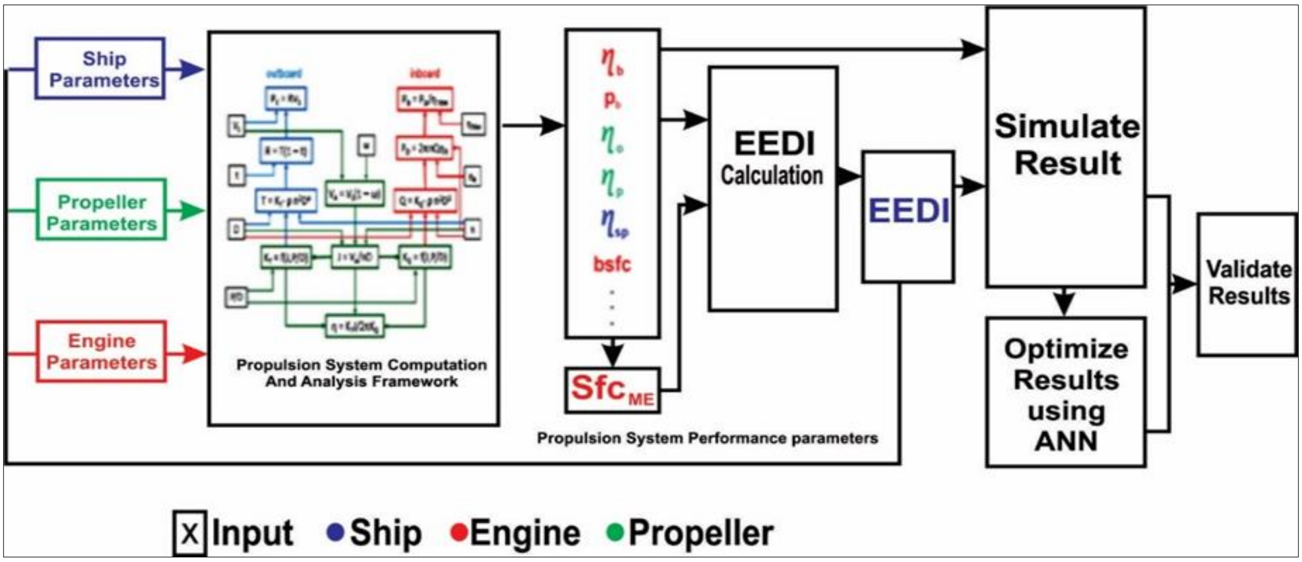

Figure 2 Framework for Propulsion System Analysis and Optimization

Different ANN structures were trained using partitioned data sets for training, validation and testing purposes. Fig. 3 shows a schematic MLP model of the ANN architecture for the propulsion system optimization with two layers. As shown, the inputs and desired outputs correspond to fourteen and seven parameters respectively. The ANN can be named 14-H-7 according to its structure with one hidden layer. After series of optimum validation check, the data sets were pegged and partitioned into 90%-training, 5%-testing and 5%-validation owing to the small nature of the data sets. These produces series of uniform target output over several training processes. An optimal ANN architecture having minimum MSE was selected and tested again to ensure good generalization characteristics of the optimized propulsion system model.

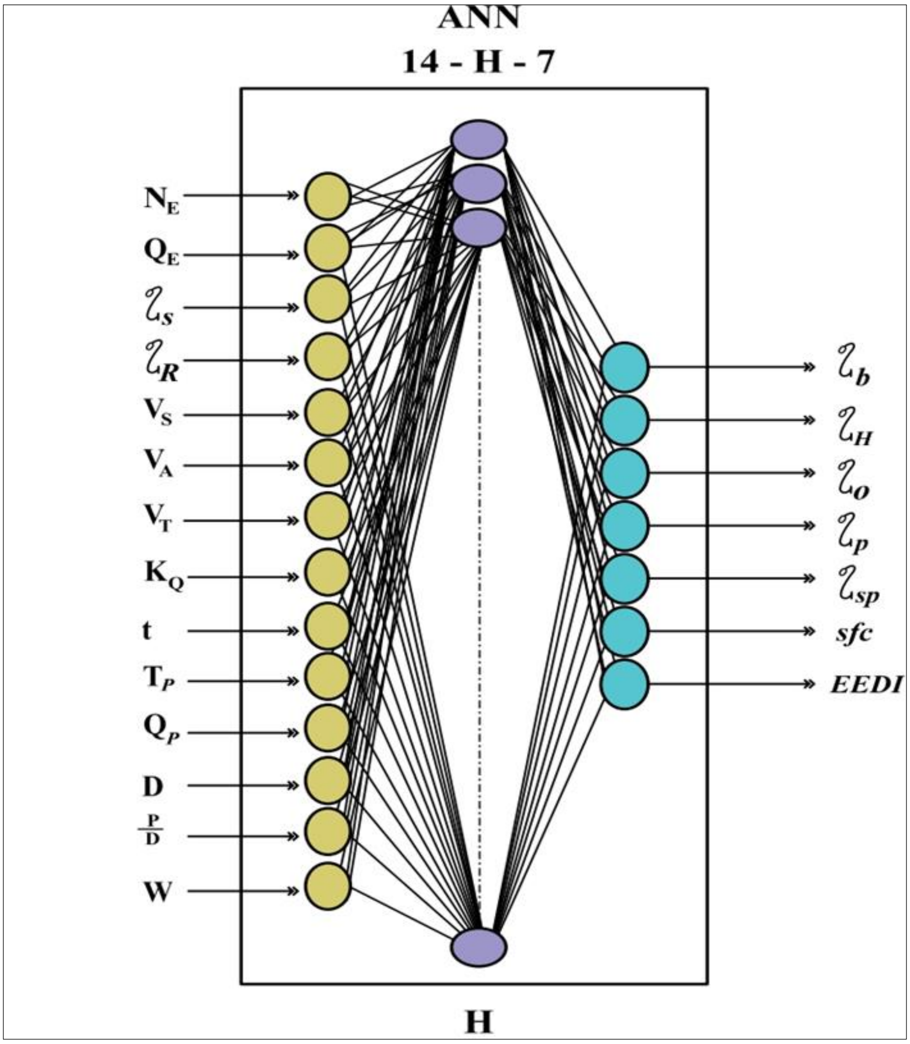

Figure 3 Schematic of the ANN Structure for the Propulsion System Optimization

The results from the models of different configuration of the ANN architecture were compared and presented in Table 1, this gives the best performance considering different MLP structures and training functions.

Table 1 Best Performance for Different ANN Configurations

Training Function	MLP Structure	Hidden layer transfer function	Output layer transfer function	Best validation performance epoch	Best validation performance (MSE)
Trainlm	14-5-7	Tansig	Logsig	37	6.2387e-06
Trainlm	14-5-7	Tansig	Tansig	51	4.3310e-10
Traingdm	14-5-7	Tansig	Tansig	13	2.8329 e-11
Trainlm	14-20-7	Tansig	Purlin	206	3.2923e-10
Trainbr	14-15-7	Tansig	Logsig	12	1.7729 e-10
Trainlm	14-20-7	Logsig	Tansig	26	3.2923 e-9
Traingd	14-25-7	Logsig	Tansig	270	2.2941 e-10
Trainlm	14-30-7	Tansig	Purlin	Nil	Nil

The optimal ANN architecture with the best configuration and performance (the least MSE) has 20 neurons as shown in Fig. 4, a graph of ANN training against number of neurons. Before this point, the performance of the network configuration was relatively constant between 0 and 4 neurons during training of the ANN model, but rose rapidly from 5 neurons and climaxed at 20 neurons. After 20 neurons, the performance starts to depreciate indicating a drop in performance of the model as the number of neurons increases beyond 20 neurons. This informed the decision of selecting the ANN model with 20 neurons as the best architecture for the propulsion system optimization.

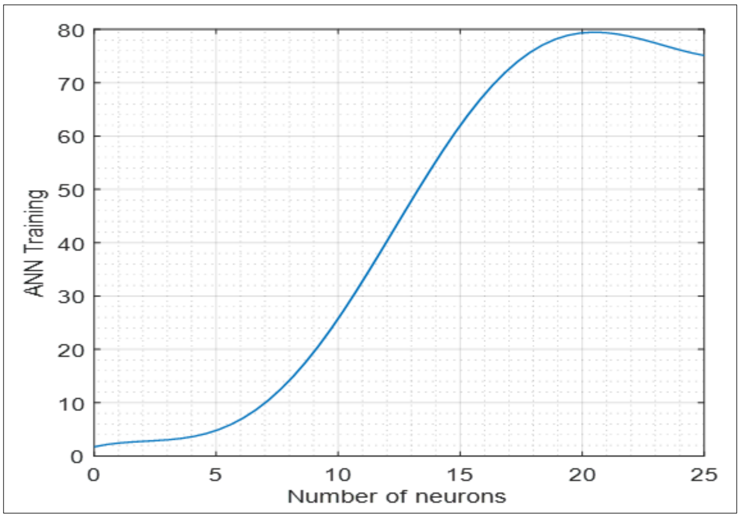

Figure 4 Graph of ANN Training against Number of Neurons

Based on the data, ANN training state was deployed to learn the dataset for the prediction and optimization of the propulsion system. Fig. 5 shows a graph of the propulsion system efficiencies on EEDI obtained after training the data sets. This graph was generated to identify what can be called recessive and dominant parameters by plotting all the propulsive efficiencies against the number of data points. Careful scrutiny of the diagrams indicates that the overall ship efficiency, η_{sp} have a dominant positive representation of the performance parameters of the propulsion system with a root square value of 0.9535 when the decay constant of the EEDI is 0.049s^{-1}. This shows that continuous improvement and optimization of overall ship efficiency help to impact positively and give a better performance and also buttresses the validity of the model developed in this work.

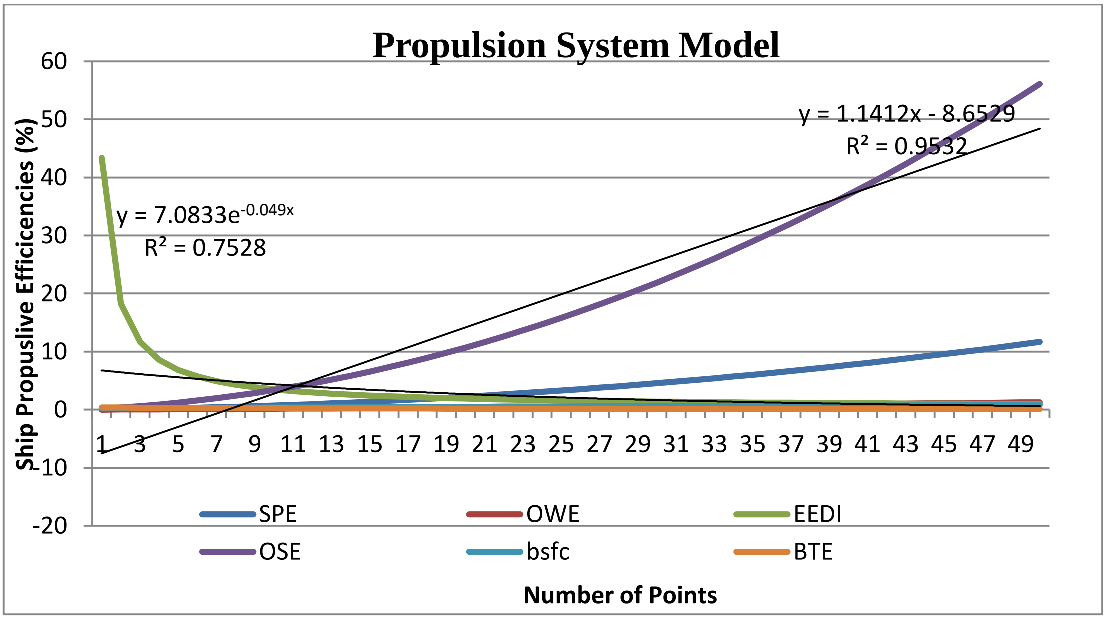

Figure 5 Influence of Propulsion System Efficiencies on EEDI

Where: BTE = Brake Thermal Efficiency, bsfc = Brake Specific Fuel Consumption, SPE = Ship Propulsive Efficiency, OSE = Overall Ship Efficiency, OWE = Open Water Efficiency and EEDI = Energy Efficiency Design Index.

The MLP network architecture for the propulsion system optimization with 7 neurons in the output layer representing the output performance parameters of interest is as shown in Fig. 7. One hidden layer was used, with the activation function as Tan sigmoid (Tansig) and linear purline in the output layer.

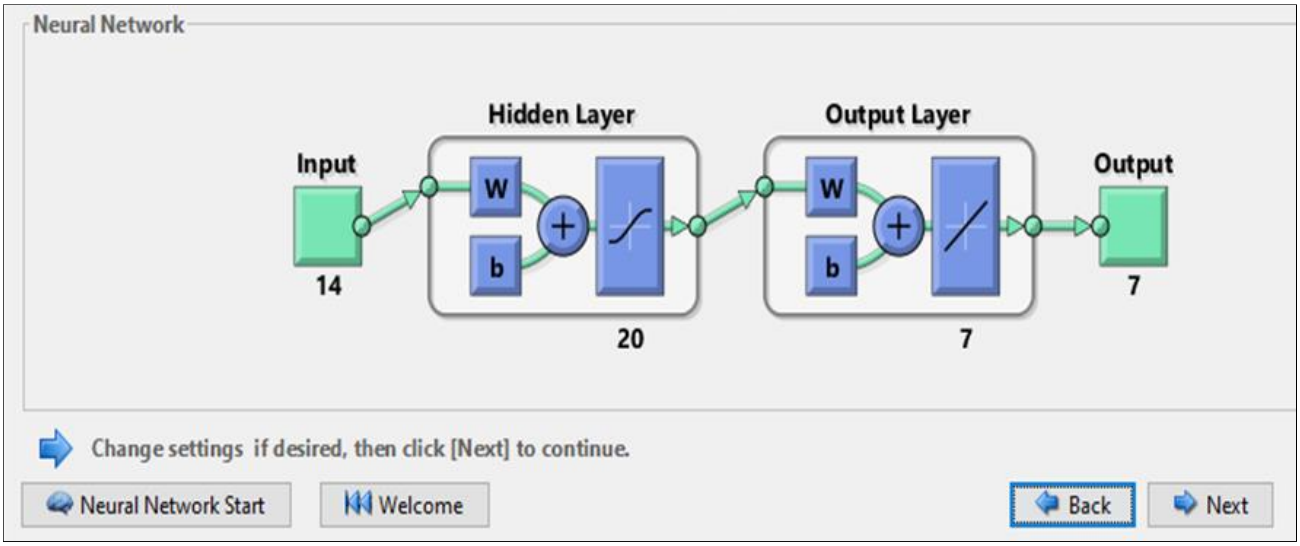

Figure 6 MLP Network Architecture for The Propulsion System Optimization

Fig. 8 shows details of the best trained network based on the average performance of all the trained structures. The graph also indicates the performance of the ANN for training, validation & test and it can be seen that the iteration in which the validation performance error reached the minimum is 206. MSE of the performance at this point is obviously very low. The training continued for 44 more iterations before the training stopped. This point gives the lowest MSE performances value of 3.2923e-10.

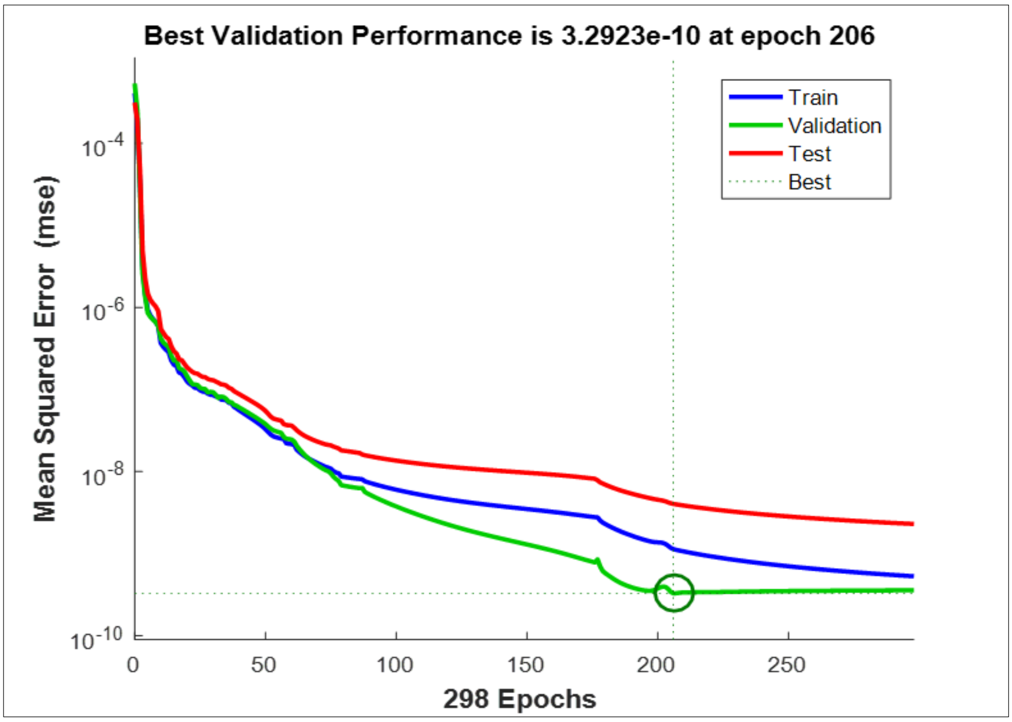

Figure 7 Performance of the Optimal MLP Network

The coefficient of correlation (R) or the regression plot between MATLAB results and the predicted values is another indicator to check the validity of the ANN model. The nearer the value of R to 1, the closer the relationship between the target value and predicted values by ANN. From Fig. 9, it can be observed that the correlation coefficients concerning regression analysis between corresponding targets and network responses are 1 during the training, 0.99999 during the testing and validation. Better correlation was accomplished in the training data set, because the data set were more evenly distributed along the fitness line. Also, the overall regression coefficient was 1 which is a strong positive linear relation [15, 16]. The overall performance of the propulsion system model in terms of training is 1. This shows a good prediction to increase the performance of Propulsion performance parameters.

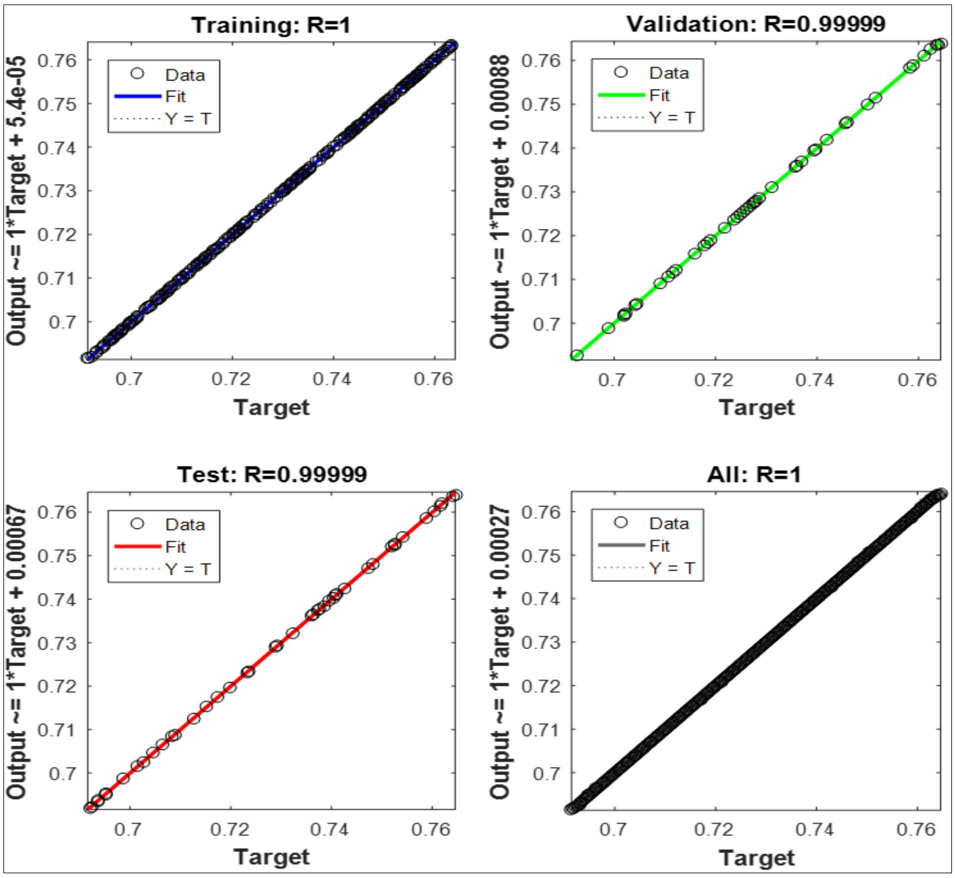

Figure 8 Regression Plot of the Optimal MLP Network Architecture

4. Conclusion

In this research, an ANN-based methodology was employed for the propulsion system optimization. ANN code generation on the basis of combinations of various training functions, number of neurons and transfer functions was developed. The ANN methodology provided a comprehensive view of the performance of over 250 ANN models for the propulsion system optimization. A method which involves data validation has evolved in this work based on extensive data validation check carried out on several configurations of over 250 ANN architectures which help to partition small data sets and pegged it at 90% for training, 5% for testing and 5% for validation.

Results show that the MLP configuration of 14-10-7 gives an optimal model for the ANN. The resulting model could predict the optimized performance output of the system with a minimum MSE at 206 epochs. This point gives the lowest MSE performances value of 3.2923e-10 and regression plot between 0.99999 and 1. Also, this gives a 2.4% improvement of η_{sp} and 3.5% improvement of EEDI. These results indicate that the use of ANN for parametric optimization of propulsion system is satisfactory. The mathematical models and the simulation proved satisfactory, authenticating the validity of the model. The results presented are evident to conclude that the aim of optimizing the propulsion system of a vessel using ANN was achieved.

Compliance with ethical standards

Acknowledgments

The authors would like to thank Shell Petroleum Development Company (SPDC) for providing the facilities at the Centre of Excellence in Offshore and Marine Engineering at Rivers State University, where this research was carried out. Also, let me specially thank Prof. Engr. Cdr. E. A. Ogbonnaya for his unflinching support during the period of this research.

Disclosure of conflict of interest

There are no conflicts of interest in this manuscript.

References

[1] Odokwo, V. E., Ogbonnaya, E. A. & Barinyima, N. Modeling and Simulation of Ship Propulsive Efficiencies Related Characteristics with Energy Efficiency Design Index in Focus. American Journal of Science, Engineering and Technology. 2022, 7(2), 50-56. doi: 10.11648/j.ajset.20220702.14

[2] Anon. Emission Standards. [Online] 2022. [Accessed 8 August 2022]. Available at: https://dieselnet.com/standards/inter/imo.php,

[3] Anon. Rentar Fuel Catalyst. [Online 2018. [Accessed 8 August 2022]. Available at: https://rentar.com/efficient-engines-thermodynamics-combustion-efficiency/

[4] Golam-Zakaria, N.M. & Sohanur, R. Energy Efficiency Design Index for Inland Vessels in Bangladesh. Procedia Engineering: 10th International Conference on Marine Technology, MARTEC. 2017, 194 (2017) 362 – 369.

[5] Jun-Rui J. Research on Ship Power Plant Simulation System Based on LabVIEW and MATLAB Mixed Programming. 2nd International Conference on Automation, Mechanical Control and Computational Engineering (AMCCE 2017). Advances in Engineering Research, 2017, 118 (2), 89-95.

[6] Vladimir B., Sergei A., Andrey M. & Arkaprava D. Mathematical Model of Thermodynamic Processes in the Intake Manifold of a Diesel Engine with Fuel and Water Injection. Energies. 2020, 4315(1), 1-18.

[7] Huilin R., Yu D., & Congbiao S. Influence of EEDI (Energy Effciency Design Index) on Ship–Engine–Propeller Matching. Marine Science and Engineering. 2019, 1 (1), 1-22.

[8] Odokwo, V. E. & Ogbonnaya, E. A. Performance optimization of combined gas and steam power plant using artificial neural network. Indian Journal of Engineering, 2019, 16 (1), 35-45.

[9] Asgari, H., Venturini, M., Chen, X.Q. & Sainudiin, R. Modelling and Simulation of the Transient Behaviour of an Industrial Power Plant Gas Turbine. ASME Journal of Engineering for Gas Turbines and Power. 2016, 136(6), 61-69.

[10] Eddy S. K., Eko B. D., Adi S. & Mohammad I. I. Neural Network-Based Engine Propeller Matching (Nnepm) For Trimaran Patrol Ship. Applied Mechanics and Materials. 2019, 493 (2), 388-394.

[11] Aleksandr G. K., Sergey V. K. & Dmitriy S. V. A mathematical model of a diesel engine for simulation modelling of the control system. Global Journal of Pure and Applied Mathematics. 2016, 12 (1), 213-228.

[12] Guan, C. Theotokatos, G., Zhou, P. & Chen, H. Analysis of Two Stroke Marine Diesel Engine Operation Including Turbocharger Cut-Out by Using a Zero-Dimensional Model. Energies, 2015, 8 (3), 5738-5764.

[13] Gerasimos, T. & Vasileios T. A Computational study on the performance and emissions parameters mapping of a ship propulsion system. Journal of Marine Engineering and Technology. 2016, 16 (1), 1-39.

[14] Feiyang Z., Wenming Y., Woei W. T., Siaw K. C. & Wenbin Y. An Overall Ship Propulsion Model for Fuel Efficiency Study. The 7th International Conference on Applied Energy – ICAE2015. Energy Procedia. 2015, 75 (1), 813 – 818.

[15] Asgari, H. *Modelling, Simulation and Control of Gas Turbines Using Artificial Neural Networks.* [Ph. D Thesis]. New Zealand; University of Canterbury Christchurch, 2014.

[16] Ogbonnaya, E. A, Adigio, E. A, Ugwu, H. U & Anumiri, M. C. Advance Gas Turbine Rotor Shaft Fault Diagnosis Using Artificial Neural Network. International Journal of Engineering and Technology Innovation, 2013, 3 (1), 58-69.