Artificial neural network based prediction of ship speed under operating conditions for operational optimization

Ameen M. Bassam[a,*], Alexander B. Phillips[c], Stephen R. Turnock[b], Philip A. Wilson[b]

[a]*Naval Architecture and Marine Engineering Department, Faculty of Engineering, Port Said University, Port Fouad, Egypt*
[b]*Fluid Structure Interactions Group, University of Southampton, Boldrewood Innovation Campus, SO16 7QF, UK*
[c]*National Oceanography Centre, Southampton, SO14 3ZH, UK*

Abstract

Ship speed is one of the most fundamental parameters which influences ship design, the energy efficiency of its operation, and safety. Therefore, ship speed selection and prediction under various environmental and operational conditions are of great concern recently for optimizing ship design and operational performance. Among the different approaches that address the ship speed topic, data-driven methodologies and Artificial Neural Network (ANN) techniques are attracting widespread interest due to its efficiency, accuracy, robustness, flexibility, and fault tolerance. Consequently, this study investigates multiple ANN model sizes and architectures to determine the suitable network parameters for ship speed prediction. Thus, we have a good balance between the model's prediction accuracy and computational complexity. For this study, a publicly-available high-quality operational dataset suitable for benchmarking the results is utilized. This analysis also includes the effect of the data quantity and sampling duration on the data correlation and the ANN performance. The results indicate that the proposed ANN model can accurately predict ship speed under real operational conditions with an error of less than 1 knot. Furthermore, it has been shown that the proposed model can help with the decision-making and optimization processes of voyages planning and execution.

Keywords: Ship speed prediction, Data-driven model, Machine learning, Artificial neural network, MATLAB

1. Introduction

Improving the operational efficiency of seaborne transportation and reducing its environmental impact have received much attention by ship owners, maritime regulators, and decision makers in recent years. This is due to the fact that the total shipping greenhouse gas (GHG) emissions and its share in the global anthropogenic emissions have increased by 9.6% and 4.7% respectively between 2012 and 2018 according to the most recent GHG study by the International

*Corresponding author
Email address: ab2e12@alumni.soton.ac.uk, ameen@eng.psu.edu.eg (Ameen M. Bassam)

Maritime Organization (IMO) despite implementing more rigorous regulations (Faber et al., 2020). Moreover, with the projected growth in seaborne trade and the continued increase of ships number and size, ship emissions are expected to increase by 90% to 130% of 2008 emissions by 2050 (Faber et al., 2020). Therefore, greater efforts are necessary for further GHG emissions reduction (Gössling et al., 2021).

Current mandatory technical and operational measures adopted by the IMO to reduce shipping emissions include the Energy Efficiency Design Index (EEDI) for new ships built from 2013 onwards, and the Ship Energy Efficiency Management Plan (SEEMP) for all ships (Rehmatulla et al., 2017; Bazari and Longva, 2011). Moreover, the Marine Environment Protection Committee (MEPC) of the IMO has adopted new mandatory measures which are the Energy Efficiency Existing Ship Index (EEXI) and the Carbon Intensity Indicator (CII) for all ships to further reduce ships fuel consumption and GHG emissions to meet the IMO target of 50% emission reduction in 2050 compared to 2008 (De Oliveira et al., 2022).

Among the different types of energy efficiency measures available, measures mainly based on speed (i.e. slow steaming) and measures that have a speed element (i.e. voyage execution and weather routing) are considered the most effective for ship operational efficiency (Poulsen et al., 2022; Rehmatulla and Smith, 2015). This can be explained as a cubic relationship can be assumed between ship speed and ship required power which can be used to give an indication of the consumed energy during a ship voyage (Dalheim and Steen, 2021; Molland et al., 2017). Also, ship speed has a non-linear relationship with fuel consumption, fuel cost and emissions (Psaraftis and Kontovas, 2013). Therefore, a small variation in ship speed can have a significant impact on the ship power and consequently its fuel consumption, energy efficiency and emissions (Dalheim and Steen, 2021). Also, speed related measures do not require major installation and application costs or physical modifications to the ship before its application and can be implemented quickly without affecting the ship operation (Poulsen et al., 2022; De Oliveira et al., 2022). However, speed selection and adjusting during the design stage and operation of a ship depend on the shipping sector and its trading pattern, ship payload and fuel consumption, fuel price, freight rate, etc. which will influence ship's profitability and energy efficiency (Poulsen et al., 2022; Rehmatulla and Smith, 2015). Therefore, accurate prediction of ship speed in real operational conditions as well as in design stage is extremely valuable prior to implementing any EEDI or SEEMP measures for better ship operation monitoring and performance evaluation.

The economically and environmentally efficient operation of vessels depend considerably on ship speed selection and prediction in different operational conditions. In this respect, ship speed is required to assess the ship's EEDI alongside its capacity and CO_2 emissions. Moreover, accurate ship speed estimation is a necessary prerequisite for an accurate prediction and optimization of ship fuel consumption (Zhou et al., 2021; Bialystocki and Konovessis, 2016). In addition, ship speed is a key input variable in estimating ship emissions and a key driver of the rate of emissions growth (Faber et al., 2020). Furthermore, an accurate ship speed prediction is required for efficient voyage planning and execution which includes ship weather routing and trajectory prediction to satisfy both the commercial and environmental constraints (Poulsen et al., 2022; Zis et al., 2020). Likewise, inaccurate ship speed prediction impacts the ship's estimated time of arrival (ETA) which will affect the operational efficiency of ports and its call optimization framework (Park et al., 2021). It is also essential to forecast ship speed accurately for developing navigational assistance systems, maneuvering optimization, traffic control and collision prevention techniques for safe ship operation (Wang et al., 2022b; Huang et al., 2020; Du et al., 2019; Gan et al., 2016). The accurate forecast and monitoring of ship speed can also help with identifying the impact of biofouling on the ship performance and speed loss during service which significantly impacts the ship operational performance and profitability (Tarełko, 2014; Farkas et al., 2020).

Traditional techniques of speed prediction include regressing the data obtained during ship speed trails on full-scale and model-scale experimental work to obtain the relation between ship speed, power and propeller speed (ITTC, 2017b,a). Ship speed performance can be also approached computationally by analyzing the flow around the ship using different numerical methods of computational fluid dynamics (CFD) (Molland et al., 2017) or by using the mathematical modeling and numerical simulation method (Nielsen et al., 2019). Physics-based models also include using in-service propeller measurements of torque and rotational speed to model the ship speed as suggested in (Dalheim and Steen, 2021). However, physics-based methods are usually limited to a specific ship characteristics beside the cost, time, and effort spent on ship trails and experimental work (Wang et al., 2022b). Moreover, CFD models are computationally expensive, complex and time-consuming (Petersen et al., 2012). Aside from traditional models, ship operational data and environmental measurements can be utilized to drive the ship speed based on data-driven different techniques such as Machine Learning (ML) which doesn't need much physical knowledge about the ship with more robust prediction and ease of implementation than theoretical models (Bassam et al., 2022; Soner et al., 2019). Furthermore, a hybrid approach that incorporates physics-based model and data-driven model, normally referred to as grey model, has been proposed for ship speed prediction but it still has the physics-based model limitation (Wang et al., 2022b; Liu et al., 2020).

Along with the growing interest in ship performance monitoring and optimization for more efficient operation, ML models have gained increasing attention owing to its capability of dealing with high-dimensional data with a nonlinear structure such as ship operational data and extracting valuable information from this raw data (Dalheim and Steen, 2020; Soner et al., 2019). This attention is also being driven by the increasing number of ships equipped with sensors and the increasing rate of data generation due to the rapid development of sensor technology and data acquisition systems (Dalheim and Steen, 2020; Shenoi et al., 2015). Therefore, more advanced, proper, and robust techniques are required to process this big data which is difficult to process using traditional data processing techniques (Soner et al., 2019; Shenoi et al., 2015).

2. Related work

Various data-driven ML methodologies have been investigated for ship speed prediction in the literature for ship performance monitoring and optimization. Due to its simplicity and ease of implementation and interpretation, Linear Regression (LR) has been proposed for ship speed prediction and used as a baseline for comparison with other models. LR was used in (Berthelsen and Nielsen, 2021) to predict the speed-power relationship utilizing noon reports of 88 tankers. In (Mao et al., 2016), LR was compared with the autoregressive and the mixed effects models to predict ship speed as a function of the main engine speed and weather conditions for a containership collected over 28 voyages in the North Atlantic. Also, LR was compared with the generalized additive models and projection pursuit regression models in (Brandsæter and Vanem, 2018) for the prediction of ship speed in terms of shaft thrust, ship motion, trim, and draft, and the wind conditions available from full scale sensor measurements. For a bulk carrier, LR was also considered in a quantitative and qualitative comparison with several widely-used data-driven methods for ship speed prediction where random forest (RF) outperformed other models considering the ship dynamic information and metocean forecasts (Wang et al., 2022b). A new method based on RF was also proposed for the same bulk carrier by introducing the historical speed sequential data to the RF model to improve its accuracy for short-term speed prediction (Wang et al., 2022a). Moreover, the ability of the RF and two gradient boosting methods to predict the ship speed in ice condition was demonstrated in (Rao et al., 2021) with an average mean absolute error of 3.5 knots in a ship operational speed range of 0 to 20 knots.

Due to its power and efficiency in describing nonlinear systems, Gaussian Process (GP) model has been also employed to predict the speed and engine power of a containership in (Yoo and Kim, 2019) using the real ship operational data and weather data. Likewise, GP model yielded the best results in predicting ship speed when compared to linear regression, Support Vector Machine (SVM), regression trees, and ensembles of trees models for a case study utilizing a high-quality operational dataset of a ferry (Bassam et al., 2022). Using the same dataset, a GP model was also compared to a shallow Artificial Neural Network (ANN) model to predict the ship fuel consumption and speed where the ANN model provided better performance with a root mean square error (RMSE) of 0.32 knots compared to a RMSE of 0.63 knots for the GP model (Petersen et al., 2012). For the same ferry, tree-based regression methods adopting bagging, random forest, and bootstrap techniques have been compared to the GP and ANN models and the ANN model as well performed marginally better than the tree-based and GP models (Soner et al., 2018). Moreover, shrinkage regression models such as the Ridge and the Least Absolute Shrinkage and Selection Operator (LASSO) models have been investigated in (Soner et al., 2019) utilizing the same ferry operational dataset, and both methods provided better speed prediction than the GP model in (Petersen et al., 2012) with a RMSE of 0.52 knots and 0.45 knots for the Ridge and LASSO models respectively, but the ANN model still provided a better speed prediction accuracy.

For operational optimization, a shallow ANN model with 1 hidden layer, as a black box model, was combined with a physically-based model to predict the ship speed and fuel flow rate of an ocean vessel which improved significantly the prediction accuracy of the physically-based model (Leifsson et al., 2008). Likewise, a shallow ANN model yielded the best performance in predicting the ship power and speed compared to nonlinear versions of the principal component and partial least squares regression models for ship hydrodynamic performance monitoring (Gupta et al., 2022). Furthermore, because of its generalization and extrapolation capabilities, a deep ANN model with 2 hidden layers was also used as a black box model for a decision-making support system in which the outputs were the ship speed and hourly fuel consumption (Rudzki and Tarelko, 2016). The ANN approach was also shown to be more accurate and efficient that SVM and polynomial regression for the prediction ship speed and fuel consumption utilizing a simulated data from a weather routing code in (Moreira et al., 2021). Moreover, for ship maneuvering simulation, shallow and deep neural network models with different architectures were used to predict ship speed in different directions of surge, sway and yaw based on data obtained from model-scale or full-scale maneuvering trails or from a maneuvering mathematical model (Moreira and Soares, 2003; Hao et al., 2022). The integration of an optimization technique such as particle swarm optimization (PSO), orthogonal least square or fuzzy logic approach with ANN models were also proposed for more accurate ship speed prediction (Valčić et al., 2011; Gan et al., 2016).

From the above, it can be seen that modeling and predicting ship speed is an active research area utilizing different machine learning techniques for different purposes. Among these techniques available, artificial neural network based models have been found more accurate in prediction due to their high inference accuracy, flexibility, robustness, fault tolerance, adaptability, scalability, generalization and extrapolation capabilities in many successful applications. This includes ship speed prediction as shown in the literature, prediction of ship resistance and added resistance, fuel and energy consumption, emissions, power, ship trajectory, etc. (Simsir et al., 2014; Parkes et al.; Peng et al., 2020; Cepowski, 2020; Karagiannidis and Themelis, 2021; Sun et al., 2022). However, previous studies proposed different artificial neural network (ANN) architectures and parameters which are inconclusive as to which architecture is more suitable for accurate ship speed prediction. Therefore, this study investigates the performance of shallow and deep ANN models with different architectures and sizes for better ship speed prediction accuracy. The investigation includes the influence of the number of hidden layers and neurons as well as the influence of the utilized dataset size on the performance of the ANN models and their computational complexity. The effect of the utilized dataset size on the interrelation between different ship operational parameters is also examined through a correlation analysis. Moreover, a sensitivity analysis is performed to study the effect of varying the number of ANN training cycles on the model prediction accuracy. Furthermore, computational experiments are conducted to investigate the generalization capability and functionality of the developed ANN model.

The rest of the paper is organized as follows; Section 3 provides a short description of ANN systems and the working principle. Section 4 gives a brief description of the utilized ship and the operational dataset preprocessing. Meanwhile, Section 5 elaborates on the used methodology and simulation parameters. In Section 6, the simulation results are presented and analyzed. Finally, Section 8 presents the overall conclusions and recommendations.

3. Artificial neural networks

Inspired by the human brain biological nervous system, a mathematical model is developed which consists of neurons grouped into layers. These layers are mainly the input, output, and one or more hidden layers (Hagan et al., 1997). The number of hidden layers defines the network depth, where a network with more than 1 hidden layer is a deep neural network. The layers and neurons are connected to process the data where the strength of each connection is indicated by a unique weighting. These weights are adjusted during the network training according to a specific learning rule using the available dataset. In view of our problem of predicting the ship speed as a function of other ship operational variables, it is a regression supervised machine learning problem.

The main basic steps for applying an artificial neural network to map the nonlinear inputs and output include preprocessing the data, selecting the network architecture, training the network, validating the network, testing and evaluating the network. As shown in Figure 1, in this study the provided data from the vessel database is preprocessed and divided into three branches for training, validating, and testing data. This data is then used with different ANN model sizes and architectures to determine the suitable network parameters for ship speed prediction in terms of prediction accuracy and computational complexity. These steps are described briefly in the following sections.

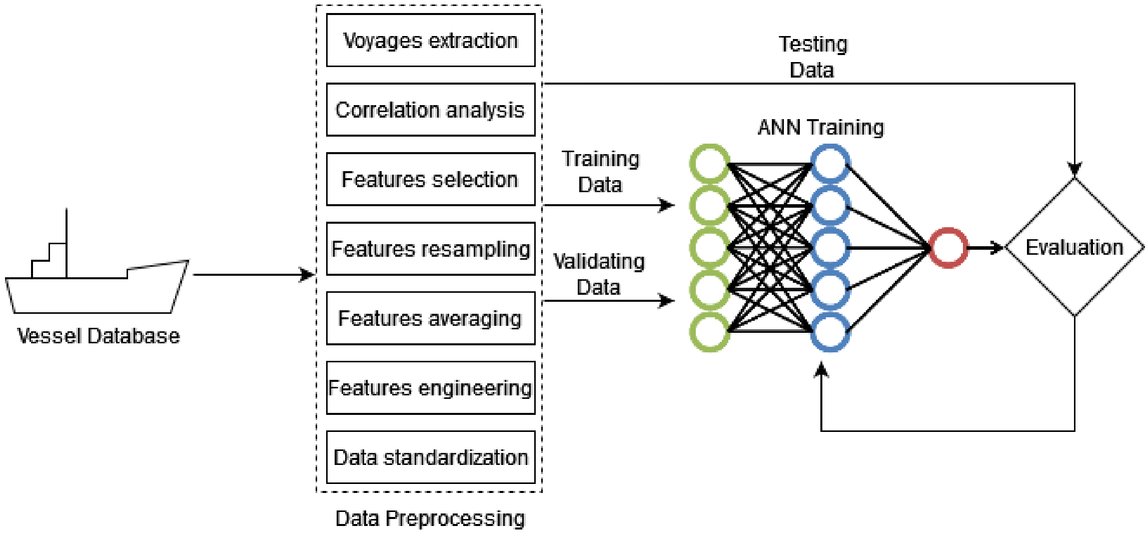


Figure 1: Flow diagram of the proposed methodology

4. Data description & preprocessing

A high-frequency real ship operational dataset suitable for benchmarking the results is used to train the ANN in this study. This dataset is obtained from the passenger and car ferry *'MS Smyril'* which operates around the Faroe Islands sailing two or three voyages daily between the capital Tórshavn to the southernmost island Suduroy and its main specifications are shown in Table 1.

Table 1: Specifications of the *'MS Smyril'* ferry

Parameter	Value
Length	123 *m*
Breadth	22.7 *m*
Draft	5.6 *m*
Passenger capacity	975
Car capacity	970 *m* / 200 cars
Service speed	21 *kn*
Main engines	4 * MAN B&W 7L32/40

The data was recorded using an automated data acquisition system installed onboard the ship over a duration of two months and more than 250 trips (Petersen et al., 2012). The data collection system consisted of a computer placed on the ship to collect the data from the measuring devices and store it for further analysis. The measuring devices included a Doppler speed log and GPS for ship speed measurements, an inclinometer for the trim angle measurements, and two radars for water level measurements placed on both sides of the ship. Measurements also included the port and starboard rudder angle, port and starboard propeller pitch, and the wind angle and direction. A full description of the data acquisition system components and its measurement frequency can be found in (Soner et al., 2019; Bassam et al., 2022; Propulsion modelling).

The selected measurements used to train the ANN models for ship speed prediction in this study are presented in Table 2. These measurements are chosen for their significant influence on the ship speed and performance (Soner et al., 2018; Yoo and Kim, 2019). It should also be mentioned that ship speed over ground is used in this analysis due the higher reliability and accuracy of the GPS besides the difficulty and uncertainty of speed through water measurements (Dalheim and Steen, 2021; Gupta et al., 2022). Moreover, ship speed over ground is influenced by the sea currents and takes it into consideration.

Table 2: Selected parameters and measurement frequency (Propulsion modelling)

Feature	Measurement unit	Measurement frequency (Hz)
Ship speed	Kn	1
Trim angle	degree	3
Port water level measurement	m	3
Starboard water level measurement	m	3
Port propeller pitch	$Volt$	1
Starboard propeller pitch	$Volt$	1
Port rudder angle	$Volt$	1
Starboard rudder angle	$Volt$	1
Wind angle	degree	0.5
Wind speed	m/s	0.5

Due to the varying sampling rate of the installed ship monitoring devices, different measurements were first resampled on MATLAB at an average frequency of 1 Hz utilizing the linear interpolation method as suggested in (Gupta et al., 2022). Then, to further decrease the measurements noise, signal averaging is performed over a suitable window size or sampling period. It should be noted that different window sizes have been proposed in the literature which includes 15 minutes (Gupta et al., 2022), 10 minutes (Leifsson et al., 2008), or 5 minutes (Brandsæter and Vanem, 2018). Therefore, a sensitivity analysis of different sampling periods is made in this study. However, this step should made for the most relevant variables which can be selected through feature selection.

In order to improve the ANN model prediction accuracy, reduce its computational cost and the overfitting risk, feature selection is firstly performed to ensure that the features which are highly correlated to the ship speed are selected and used for the model training. Due to the nonlinear nature of the ship operational data, distance correlation (Székely et al., 2007) is used in this study to evaluate the interrelation between the ship speed and other measured operational parameters. Unlike linear correlation usually used in the literature (Brandsæter and Vanem, 2018; Gkerekos et al.; Moreira et al., 2021), distance correlation can capture the nonlinear association between variables with more reliability and robustness.

Moreover, to further improve the data representation and the ANN model performance, feature engineering is also performed by generating new variables from the raw data to better describe the underlying problem. In this respect, the measured water level at both the port and starboard ship sides were transformed into the draft amidships. Also, in order to overcome the wind direction discontinuity between 0° and 360°, the measured apparent wind speed and angle were transformed into two new variables which are called crosswind and headwind. Moreover, the trim angle measurements were also corrected to calculate the real ship trim angle via the inclinometer calibration constant.

As shown in Figure 2, the distribution of the processed ship operational dataset is illustrated where most of the ship speed is in the 15 to 25 knots range with the propellers' pitch between 70% and 90%. Also, the trim angle represents a ship trim range of -1.5 to 1.25 m with a ship draft between 5 and 6 m related to the ship loading and refuelling. Moreover, the relative headwind and crosswind varies between 0 to 35 Kn. It can be seen that different variables retain their distribution shape for different sampling periods but with different data frequency. This is because, reducing the data window size will increase the available number of samples. The resulted sample size is 5425, 2653, and 1732 observations using a 5, 10, and 15 minutes window size respectively.

In the meantime, sample size also affects the correlation estimation. A small sample size often results in an inaccurate and unstable correlation estimation (Schönbrodt and Perugini, 2013). This is due to the fact that a small sample size may not reflect the data population accurately which can result in a spurious correlation coefficient. However, the required sample size for a stable estimates of the correlations depends on the data homogeneity, the effect size measure for correlation, the corridor of stability around the true correlation, the requested confidence, and the nature of the study itself. Therefore, in order to investigate the effect of sample size on correlation estimates, the correlation analysis in this study is made with different sample sizes according to the utilized sampling period of the recorded data as discussed earlier.

As indicated in Table 3, by increasing the sample size, the correlation estimation uncertainty is reduced and its stability is improved. Distance correlation ranges between 0 and 1 where 0 indicates no correlation and 1 is total correlation. Since the propeller pitch and rudder angle have a significant effect on ship speed and maneuverability, their dependence with ship speed are high as shown in Table 3. On the other hand, headwind and crosswind variables have lower correlation with the ship speed because the data was collected over a period of two months where the meteorological conditions didn't change much. Meanwhile, with a correlation value of 0.7 or higher as an indication of a significant correlation, a stronger correlation can be detected between the rudder angles and the ship speed using a larger sample size. While, at smaller sample size, a moderate correlation can be shown as listed in Table 3.

Another important data preprocessing step is the feature scaling which is made to have a more consistent dataset and make its different attribute values and scales to have equal weights for the training of neural network model. For this study, the data standardization method is used to rescale all data to have a zero mean and a unit standard deviation as suggested in (Gkerekos et al.; Gupta

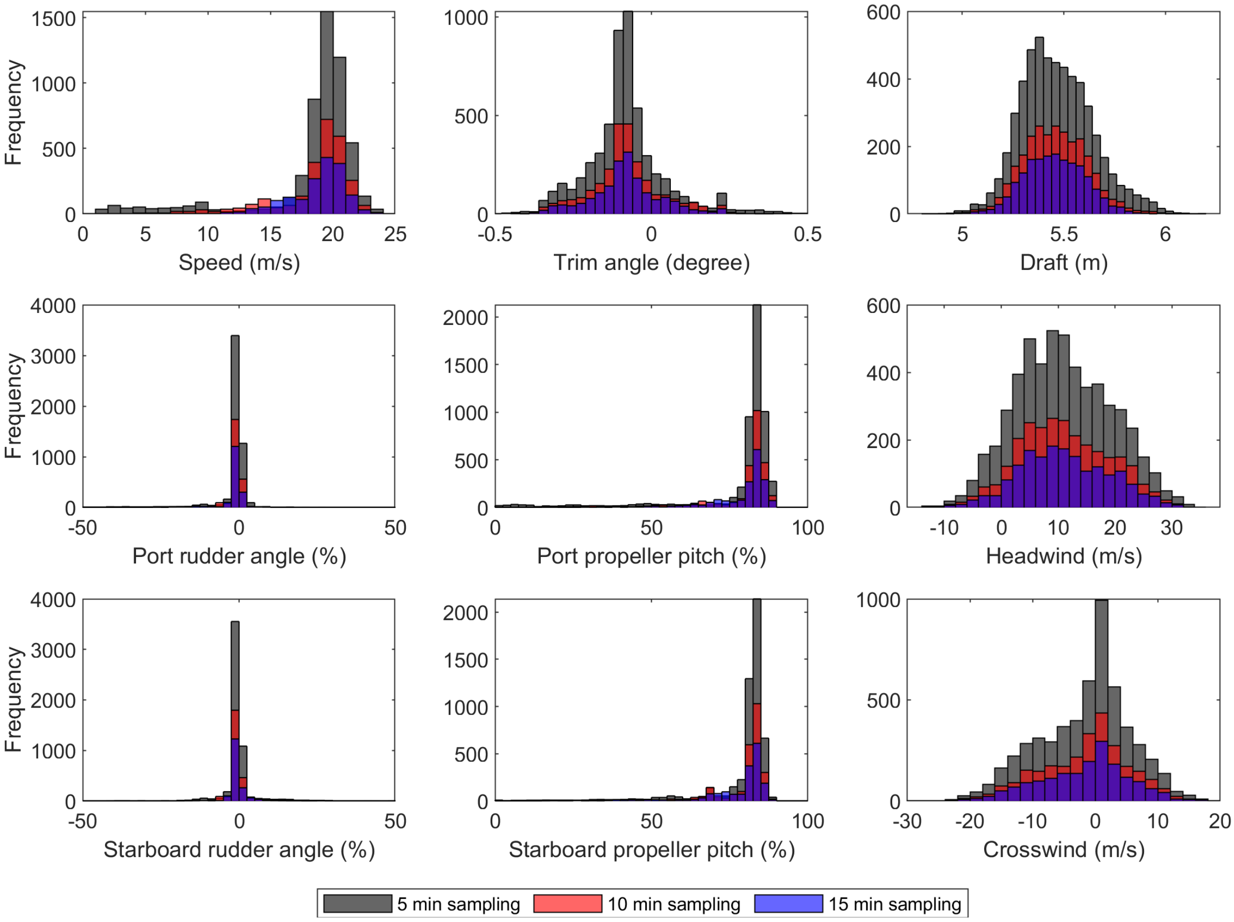


Figure 2: Histograms of ship operational variables using different sampling time

et al., 2022). Afterward, the processed dataset is used in training the neural network model for accurate ship speed prediction as will be discussed later in the following sections.

5. Neural network parameters

The selection of the suitable network structure and parameters is a fundamental issue to provide an accurate prediction. Therefore, this study aims to investigate the effects of different ANN parameters on the prediction performance, especially the number of hidden layers and neurons. For this type of operational data, a shallow ANN model with 1 hidden layer has been considered sufficient for accurate prediction (Petersen et al., 2012; Du et al., 2019). Also, deep networks with large number of hidden layers have been used in several studies utilizing ship operational data (Bui-Duy and Vu-Thi-Minh, 2021). However, by increasing the neural network depth, the overfitting risks and computational complexity are also increasing (Parkes et al.; Gupta et al., 2022). This has been discussed in prior studies where different architectures of neural network with up to 5 hidden layers were compared and it was found that a shallow model with 1 hidden layer (Gupta et al., 2022) or a deep model with 2 hidden layers (Parkes et al.) are sufficient for

Table 3: Distance correlation of ship speed to other operational variables using different sampling periods

Variables	Sampling period		
	5 minute	10 minute	15 minute
Port propeller pitch	0.9282	0.8832	0.8211
Starboard propeller pitch	0.9073	0.8632	0.81
Port rudder angle	0.7779	0.7212	0.6201
Starboard rudder angle	0.6775	0.6099	0.5255
Draft	0.556	0.4011	0.3164
Trim angle	0.2935	0.3108	0.2923
Headwind	0.2777	0.1904	0.1118
Crosswind	0.107	0.0921	0.0728

accurate prediction. Therefore, neural network models with 1 and 2 hidden layers are investigated for ship speed prediction in this study.

Regarding the number of neurons in the hidden layers, several studies have addressed this issue experimentally with a trial and error procedure because there is no general rule to decide the neurons number (Beşikçi et al., 2016; Parkes et al.; Bui-Duy and Vu-Thi-Minh, 2021). For example, a range between 1 and 100 neurons in each layer has been tested for shaft power prediction in (Dalheim and Steen, 2020) and for ship performance monitoring in terms of shaft power and speed in (Gupta et al., 2022). In (Bui-Duy and Vu-Thi-Minh, 2021), the tested number of hidden nodes was between 50 to 200 for a ship fuel consumption model. A larger number of hidden neurons of up to 3500 has been tested for predicting ship fuel consumption and speed. However, using more neurons in the hidden layers increase the probability of overfitting and poor generalization (Du et al., 2019). In some previous studies, the number of neurons in the hidden layers were not specified (Petersen et al., 2012; Simsir et al., 2014; Peng et al., 2020).

Based on the MATLAB (R2019b) Deep Learning Toolbox, different architectures of feed forward neural networks (NN) are investigated in this research for better ship speed prediction as a function of the measured real ship operational data processed in Section 4. The training of different NN architectures is based on the Levenberg-Marquardt algorithm as suggested in (Leifsson et al., 2008; Simsir et al., 2014; Beşikçi et al., 2016) where the network weights are updated during the training using the back-propagation technique to improve the network accuracy. This step is repeated for a number of cycles or epochs which has a default maximum number of 1000. During the training process, a validation check is performed to avoid overfitting and improve the generalization capability of the network. In this check, part of the available dataset is used to calculate a validation error which should decrease during training. An early stopping of the training is initiated when the validation error starts to increase for a specified number of epochs and the network weights are returned to its values at the minimum validation error. After the network training and validation, another part of the dataset is used to test the trained network where a test error is also calculated to compare the performance of different trained networks. Accordingly, the available dataset is randomly divided into 3 sets; training, validation, and test sets, with standard percentages of 70%, 15%, and 15% respectively (Hagan et al., 1997; Parkes et al.; Moreira et al., 2021).

Furthermore, the process of training, validating, and testing of different ANN architectures under investigation is repeated 10 times as suggested in (Gkerekos et al.) and the results are averaged to have more consistent representation of the prediction performance which is evaluated using performance metrics as explained in the next section.

5.1. Performance indicators

The performance of different ANN models can be evaluated through different prediction performance indices which include the mean square error (MSE) which calculates the average of the square of the errors between the measured values of the ship speed y_i and the predicted values $\hat{y}_i$ made by the ANN model for a number of samples n according to the following equation.

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \tag{1}$$

By taking the square root of the MSE, another common error estimation criterion is calculated which is the root mean square error (RMSE) as shown in the following equation.

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{2}$$

A similar error metric to the RMSE, which is the mean absolute error (MAE) that calculates the average of the absolute errors between the measured and predicted values of the ship speed as follows.

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}|y_i - \hat{y}_i| \tag{3}$$

The MAE has more robustness and less sensitivity to the data outliers compared with the MSE. Moreover, in order to represent the quality of the ANN model predictions and show the variability between the real ship speed measurements and the ANN model predictions, the coefficient of determination R^2 can be used and it is computed as follows,

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)}{\sum_{i=1}^{n}(y_i - \bar{y}_i)} \tag{4}$$

where $\bar{y}_i$ is the average value of the response variable (i.e. ship speed). This coefficient's value ranges between 0 and 1 where a higher R^2 indicates a better data fit. On the other hand, the lower the MSE, RMSE, and MAE, the better the model performance.

6. Results & analysis

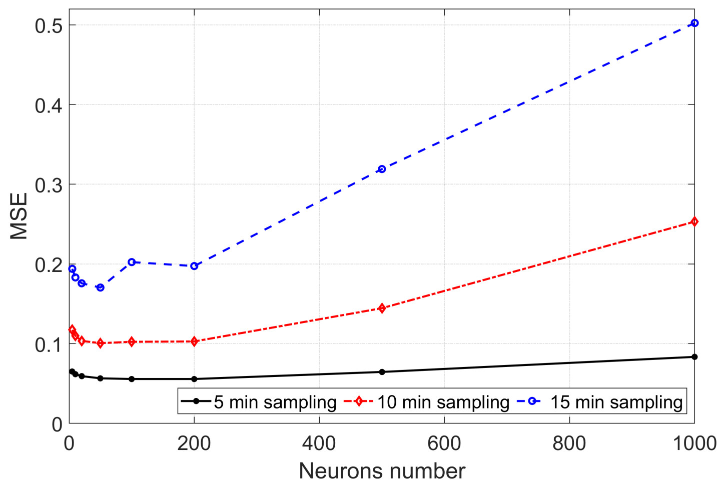
In this section, the performance of different ANN model architectures for predicting the operational ship speed as a function of other ship operational parameters will be evaluated. For 1 hidden layer networks, different number of hidden neurons up to 1000 are examined for different sampling periods of the utilized ship operational dataset. As shown in Figure 3, by reducing the sampling window size of the dataset, more data samples are available for the ANN model which results in better training, lower prediction errors, and higher coefficients of determination. For example, at 200 hidden neurons in the hidden layer, the ANN model predicted better with an R^2 of approximately 94% when the utilized dataset has a 5-min averaging time window compared to an R^2 of approximately 90% and 80% when the ANN model was trained with dataset averaged over 10 and 15-min time windows respectively. Also, the ANN model has lower prediction RMSE by about 26% and 47%, lower MSE by 46% and 72%, and lower MAE by 23% and 42% utilizing the 5-min averaging time window dataset instead of the dataset sampled over 10 and 15 minutes respectively.

Regarding the optimal number of hidden neurons, a slight improvement of the ANN performance indicators can be observed by increasing the number of hidden neurons up to 50 and 100 neurons. The performance then remains nearly stable as more hidden neurons are added to the hidden layer up to 200 neurons. However, by increasing the hidden neurons number of more than 200, the ANN model performance starts to decline with higher errors and overfitting risks as shown in Figure 3. Therefore, for a shallow ANN network with 1 hidden layer, 200 hidden neurons is suitable for accurate prediction. Also, for the deep ANN networks investigation, the number of hidden neurons increases up to only 200 neurons. Moreover, the ship operational dataset sampled over 5-minutes time windows is used for better training and higher prediction accuracy as explained earlier.

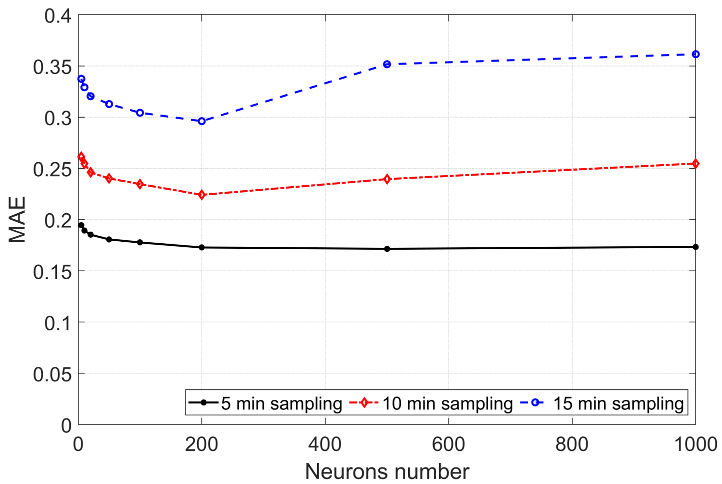
In order to investigate the dependence of the ANN model prediction accuracy on the number of hidden layers, another hidden layer is added to the ANN model while testing different numbers of hidden neurons up to 200 neurons in both hidden layers. As shown in Figure 4, by increasing the number of hidden neurons in the hidden layers, better prediction can be made by the ANN model. Lower MSE, MAE, and RMSE by about 21%, 15%, and 11% can be achieved respectively by increasing the hidden neurons in both layers as shown in Figures 4a, 4b, and 4c. Also, the coefficient of determination can be improved by about 1.4% as shown in Figure 4d with less required number of epochs as shown in Figure 4f which are required to train the ANN model before stopping the training to ensure the network generalization and avoid overfitting. However, more processing time will be required for training the ANN deep network which increases remarkably as a result of using more hidden neurons in the hidden layers as shown in Figure 4e.

Compared with the performance of a single hidden layer with 200 neurons shallow ANN model, adding a second hidden layer with 100 neurons to the first hidden layer with 200 neurons in a deep ANN network architecture can improve the MSE, RMSE, and MAE by about 11%, 6%, and 5% respectively while improving the R^2 by about 1% with less required number of training epochs by about 8%. However, more training time will be required for the deep ANN network which exceeds 20 minutes of training per single epoch. Therefore, to trade-off between complexity and prediction accuracy of the investigated deep ANN model, an ANN model architecture of 100 hidden neurons in each hidden layer is found to be suitable and used in the further investigations.

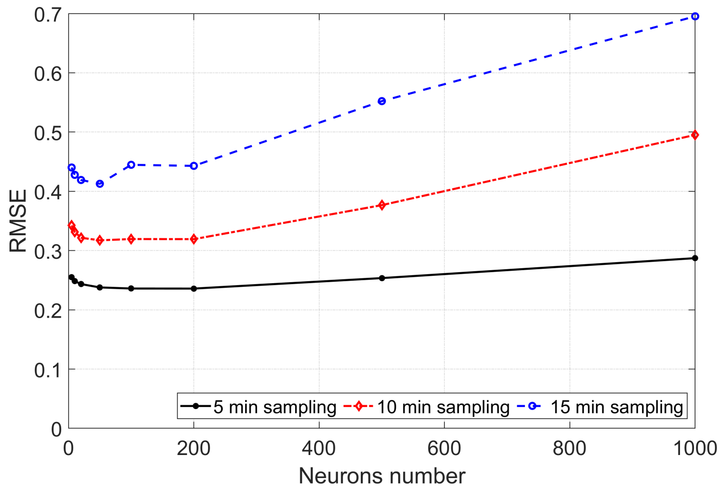
The proposed ANN model with 2 hidden layers and 100 neurons in each layer can predict the ship speed with an R^2 of 95% and a MSE of 0.051, MAE of 0.165, RMSE of 0.225 utilizing the standardized dataset sampled over 5-min time windows which correspond to a MSE of 0.92 kn^2, MAE of 0.7 kn, and RMSE of 0.96 kn. Compared with the performance of the exponential GP model in (Bassam et al., 2022), the proposed ANN model has lower MSE, MAE, and RMSE by



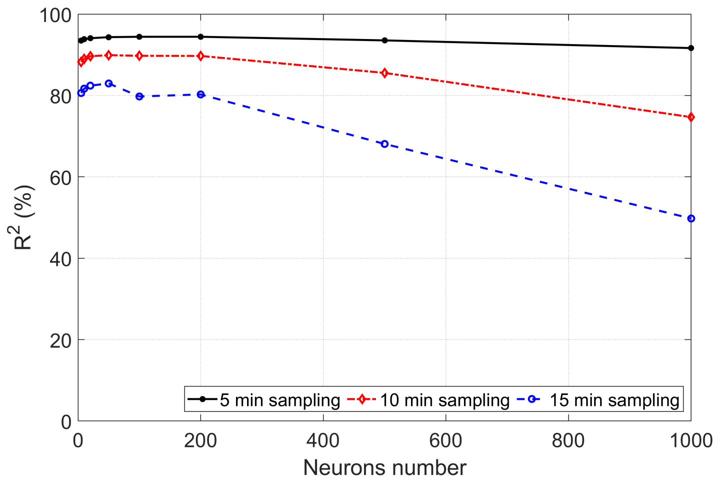
(a) Mean square error



(b) Mean absolute error

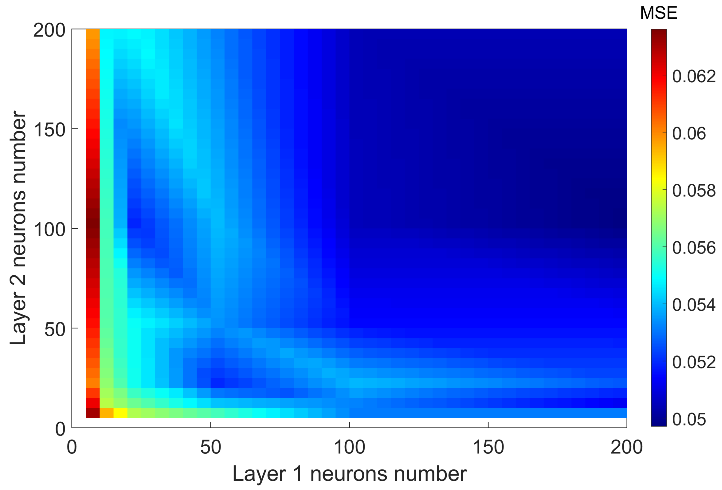


(c) Root mean square error

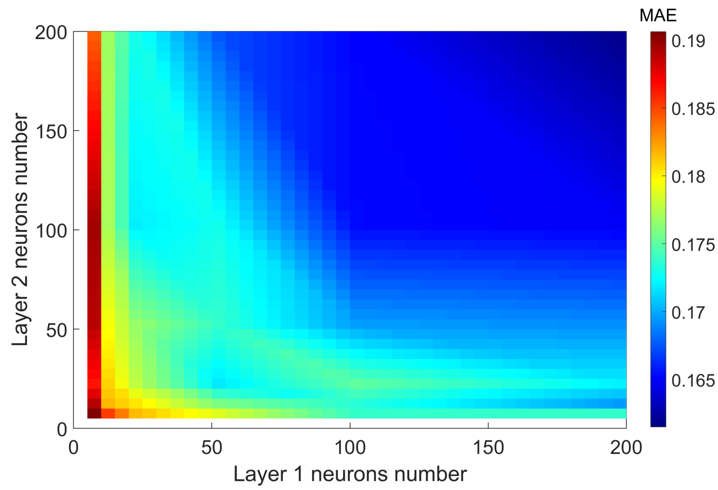


(d) Coefficient of determination

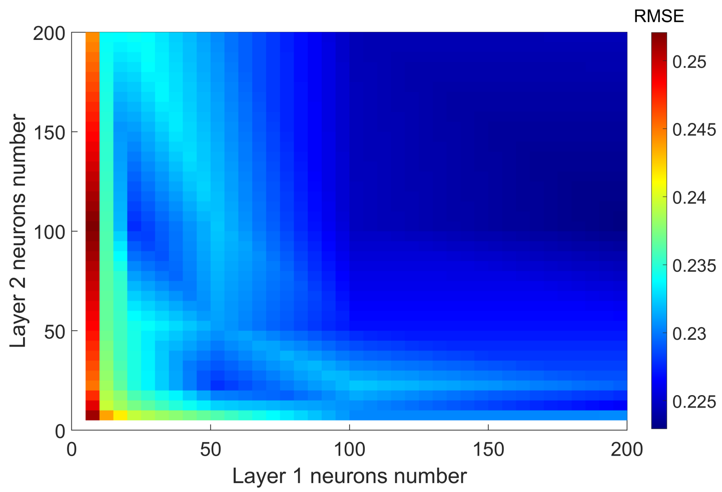
Figure 3: Performance indicators of the single hidden layer network with different hidden neurons number for different sampling periods of the dataset



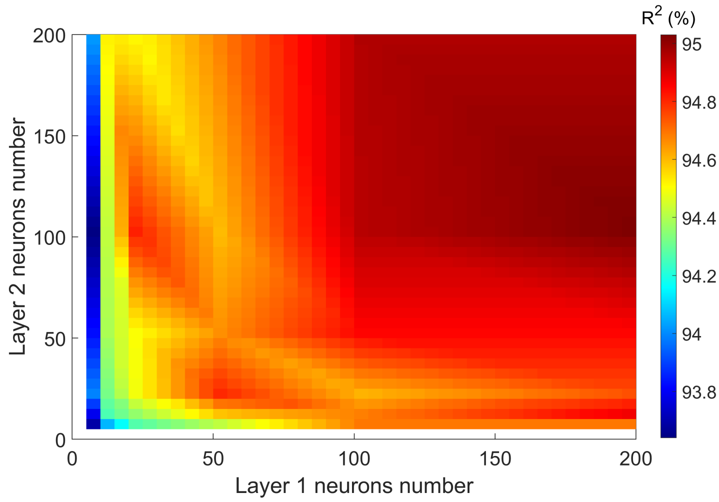
(a) Mean square error



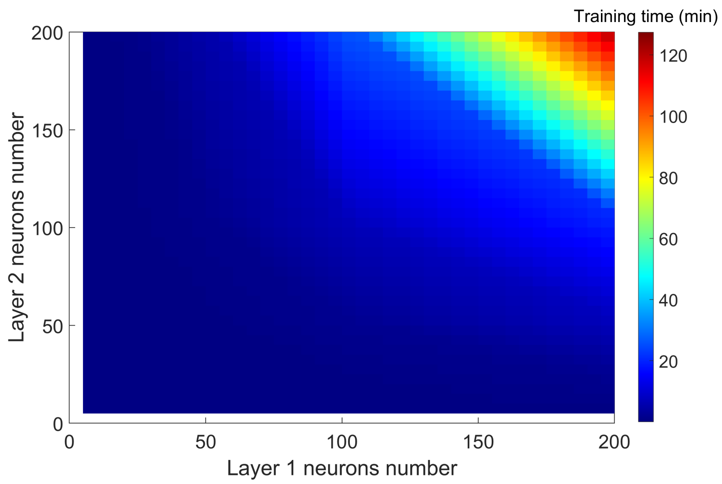
(b) Mean absolute error



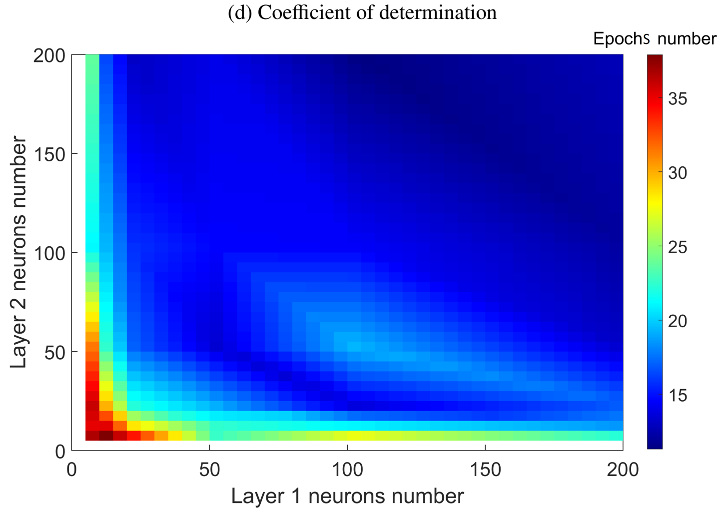
(c) Root mean square error



(d) Coefficient of determination



(e) Average training time per epoch



(f) Number of training epochs

Figure 4: Performance indicators of the deep ANN model of two hidden layers for different number of hidden neurons utilizing the dataset sampled over 5-min time windows

about 41%, 25%, and 22% respectively with a higher R^2 by 4%. Also, the proposed ANN model has better prediction accuracy than the SVM regression model and tree ensemble models with a higher R^2 of about 8% and lower MSE, MAE, and RMSE of more than 56%, 36%, and 34% respectively.

6.1. Sensitivity analysis

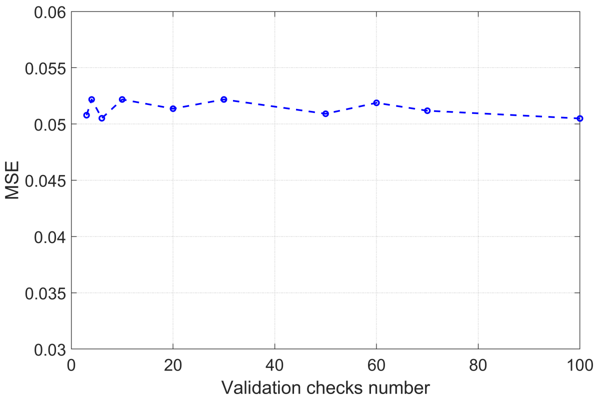
In order to investigate the sensitivity of the deep ANN model performance to the number of training epochs, different values of the performed validation checks are required before stopping the ANN model training. The default value of the maximum validation failures in the Neural Network Training tool in MATLAB is 6. In this analysis, higher and lower values of the validation check number than the default are used for training the proposed deep ANN model of two hidden layers with 100 neurons in each layer to show its impact on the ship speed prediction accuracy and computational time.

As shown in Figure 5f, by increasing the value of the maximum validation checks, more iterations are performed to train the ANN model before it is stopped. Consequently, more training time is required as a result of increasing the training epochs as shown in Figure 5e. However, a negligible prediction accuracy improvement can be obtained. For example, increasing the validation checks from its default value of 6 to 100 will reduce the ANN model prediction errors and improve its coefficient of determination by less than 0.1% as shown in Figures 5a, 5b, 5c, and 5d. Also, using a lower number of validation checks than the default value of 6 results in poorer prediction performance as shown in Figure 5. Therefore, the default validation checks number of 6 is suitable and used in the further investigations.

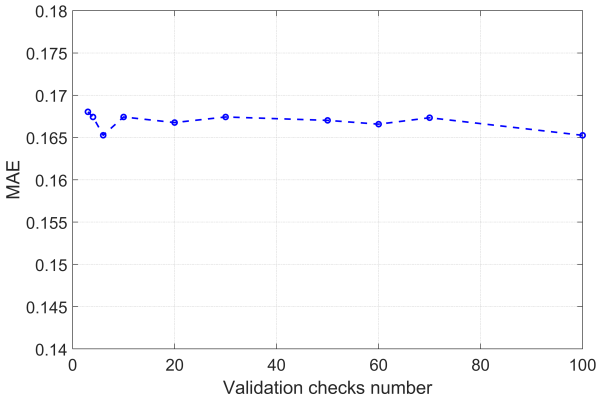
6.2. Computational experiments

In this section, computational studies are performed in order to investigate the generalization capability of the trained deep ANN model for ship speed prediction to demonstrate its usability in voyage planning and optimization. A new unseen dataset of a single voyage of the examined ferry is used as an input to the ANN model to measure its prediction accuracy of the ship speed. As shown in Figure 6, the predicted ship speed by the ANN model is in good agreement with the measured real ship speed with an R^2 of 94.2% and a MSE of 0.043, MAE of 0.152, RMSE of 0.207 utilizing the standardized dataset which correspond to a MSE of 0.8 kn^2, MAE of 0.6 kn, and RMSE of 0.9 kn.

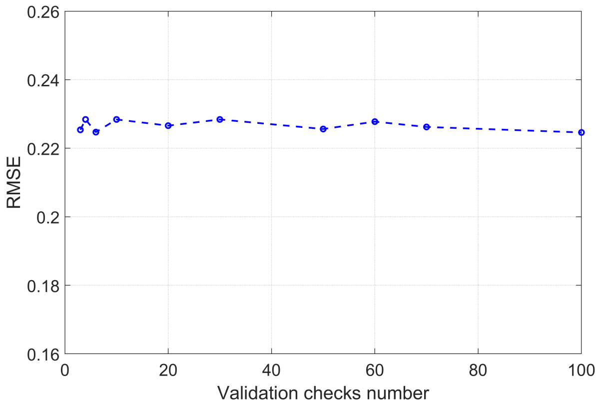
The trained ANN deep network can be also used in voyage optimization studies such as finding the ship optimal sailing speed and investigating different ship energy efficiency measures related to ship speed such as slow steaming. For example, the influence of slow steaming with respect to the ship expected time of arrival can be investigated using the trained ANN network by changing the pitch of ship propellers. As shown in Figure 6, a lower propellers' pitch than the real values by 10% is used as an input to the ANN model to predict the ship speed along with the other real ship operational and environmental parameters of draft, trim, rudders angles, wind speed, and direction. As a result of reducing the propellers pitch 10%, more sailing time of 11 minutes will be required to complete the same ship voyage as illustrated in Figure 6. However, assuming a cubic relation between the ship speed in Figure 6 and the propulsion power, the consumed energy during the voyage is reduced by 14% as a result of reducing the ship speed.



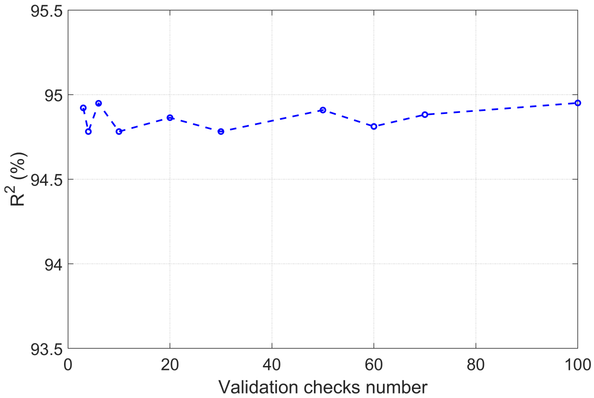
(a) Mean square error



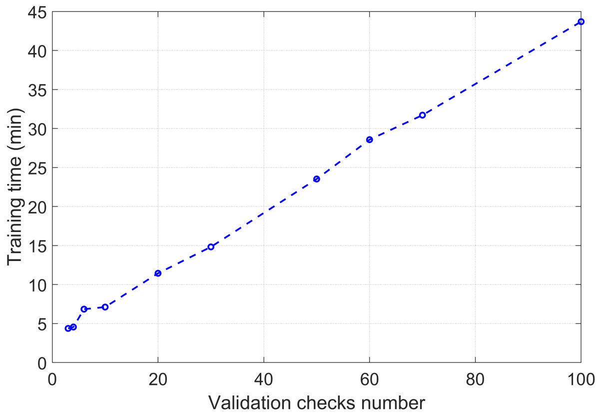
(b) Mean absolute error



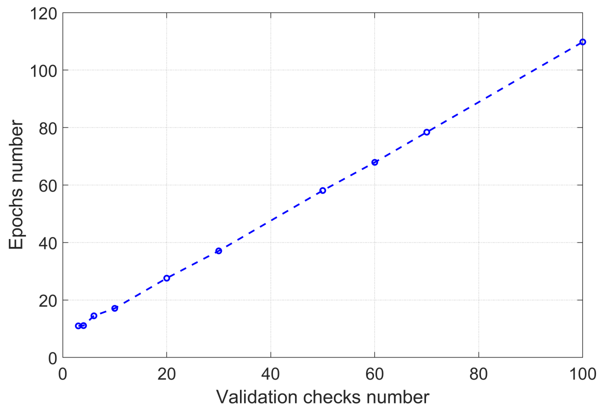
(c) Root mean square error



(d) Coefficient of determination



(e) Average training time per epoch



(f) Number of training epochs

Figure 5: Performance indicators of the deep ANN model of two hidden layers with 100 neurons in each layer at different number of validation check utilizing the dataset sampled over 5-min time windows

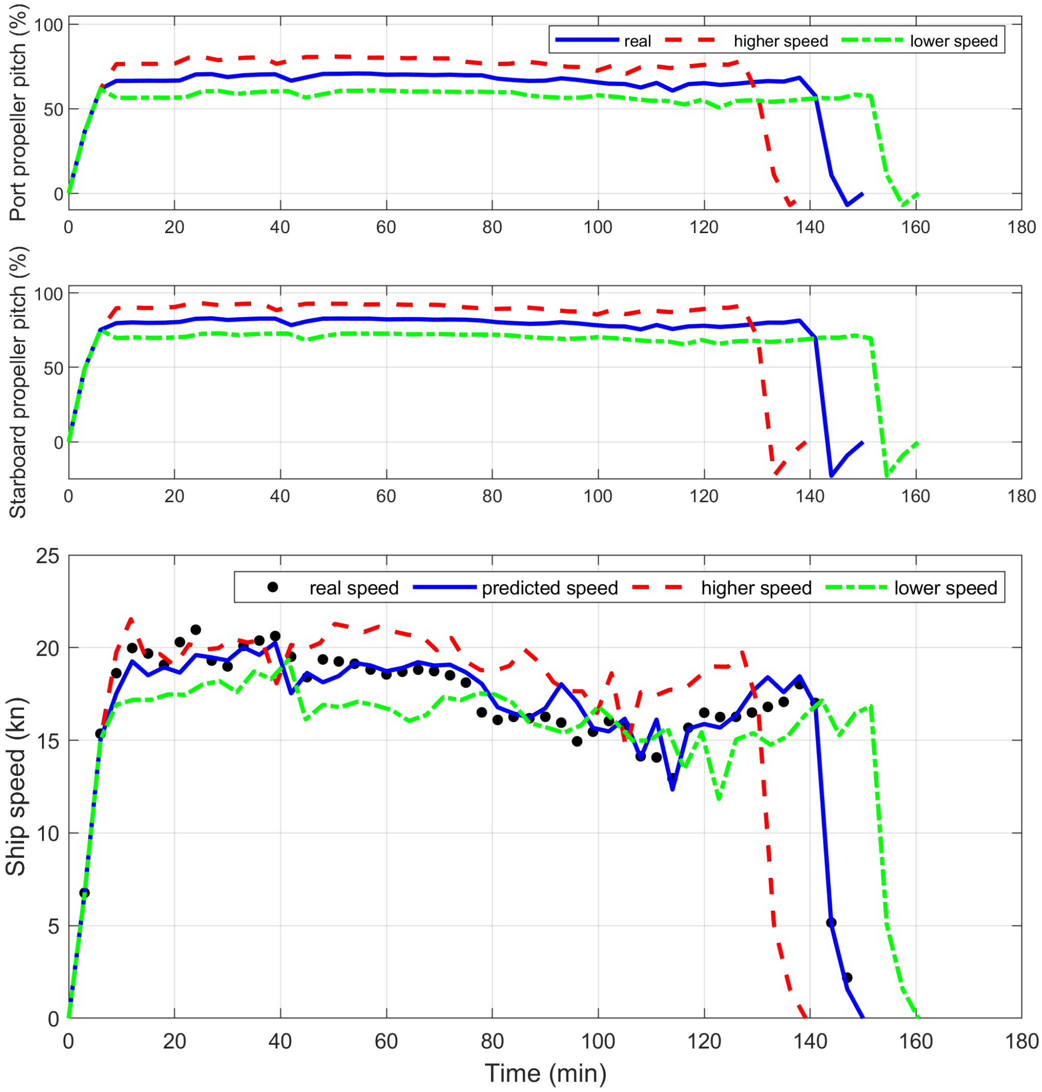


Figure 6: Measured and predicted ship speed using real and different values of propellers pitch

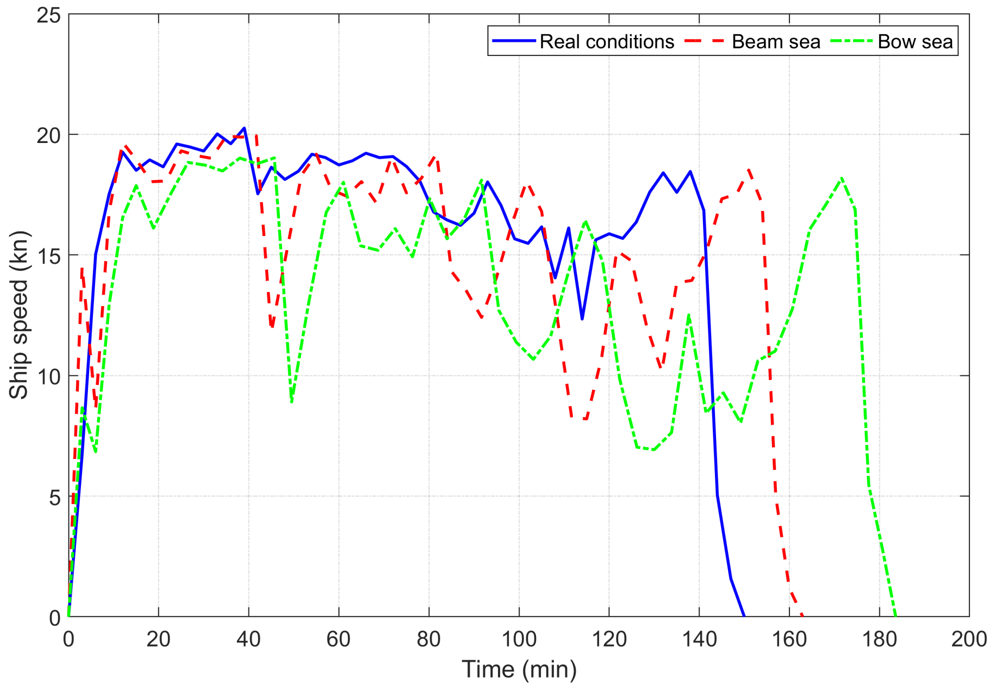


Figure 7: Predicted ship speed at different wind directions

On the other hand, it can be required to reduce the ship sailing time and increase the number of daily voyages depending on the market conditions, freight rates, and fuel prices. The influence of increasing the propellers pitch on ship speed can be also investigated using the trained ANN model. As shown in Figure 6, by increasing the propellers pitch 10% while using other real ship operational and environmental parameters, the required ship sailing time can be reduced by 11 minutes to perform the same voyage. Yet, the consumed energy during the voyage is increased by 17% as a result on increasing the ship speed assuming a cubic relation between the ship speed and propulsion power. However, more accurate prediction of fuel consumption is required for more precise estimation.

The proposed ANN model can be also used to predict the ship speed for a given weather forecast data and identify its impact on a given voyage. In the first case, it is assumed that the ship sails in a beam wind with an angle of 90° while using the real measured wind speed and other real ship operational parameters of draft, trim, rudders angles, and propellers pitch. As a result, less ship speed is obtained due to wind resistance which increases the voyage time as shown in Figure 7. In the second case, while using the real measured wind speed and other real ship operational parameters of draft, trim, rudders angles, and propellers pitch, it is assumed that the ship experiences a bow wind with an angle of 45° which further increases the added resistance and consequently increases the sailing time as as shown in Figure 7. Alternatively, more power can be used to maintain the required service speed which increases fuel consumption.

7. Discussion

Besides the above computational experiments, the trained ANN model can be used to study the effect of changing other ship operational parameters such as ship draft or trim or draft/trim combinations which can be made in future studies. Consequently, ANN models for ship speed prediction can help with the complex decision-making process for voyage planning and execution, speed choice, and monitoring for more efficient ship operation. This can be made by integrating the ANN ship speed prediction model in an optimization model with different objectives of minimizing the fuel consumption, maximizing profit, reducing voyage time, reducing the emissions, etc. It can be also used to provide guidance about the optimal operational parameters for a given navigation or sea condition. Moreover, a ship speed prediction model based on ANN technique can be used to monitor and forecast the ship speed and identify the impact of biofouling on the ship propulsion characteristics.

However, for more reliable and consistent predictions, more data are required for the ANN models' training. For this study, the proposed ANN model has been trained with a high-quality operational dataset but it covers about two months of operation and more than 250 trips of one ferry. Hence, it doesn't include the changing weather patterns during the year. Therefore, a larger and more representative dataset is required. A large dataset over several years will be also required to identify the impact of biofouling on the ship performance. Also, the measured environmental parameters in the utilized dataset includes only the wind speed and direction. Therefore, multiple sources of meteorological data should be used in addition to the recorded sensor data onboard the ship for more information about waves, sea currents and water temperature (Du et al.).

8. Conclusion

The decision-making processes of shipping industry are of growing interest due to the challenge of more energy efficient and environmentally friendly ship operations. This is due to the many operational, commercial, technical, and environmental parameters, constraints, and criteria which are required to be considered and many of them are related, in one way or another, with ship speed. Therefore, the selection, prediction, and optimization of ship speed are of great importance. However, traditional theoretical and experimental methods of studying ship speed can be expensive (i.e. model testing) or have limitations and uncertainties or can require time consuming computational approaches. Therefore, data-driven techniques especially Artificial Neural Networks (ANN) have gained significant momentum due to their advantages, capabilities, and it also driven by the rapidly developing technologies of sensors and communications.

In this study, ANN has been applied to a high-quality and high-frequency real ship operational dataset of a ferry to provide useful insights about the suitable neural network parameters and depth for an accurate ship speed prediction balanced with the computational cost. Different sizes and architectures of shallow and deep ANN models have been investigated and compared in terms of their prediction accuracy of ship speed under real operational conditions and computational complexity. For this investigation, a correlation analysis has been performed to select and extract the most influential parameters on ship speed from the utilized real ship operational dataset. Then, new parameters have been engineered for better representation of the ship operational data.

Also, the extracted and engineered parameters have been resampled, averaged, and standardized for better training of the ANN models. After training, ANN models are validated, tested, and evaluated. Moreover, sensitivity analyses have been performed to show the effect of different data quantity as well as different number of validation checks on the performance of different ANN models.

The results show that an ANN with 2 hidden layers with 100 neurons in each layer can accurately predict the ship speed with an error of less than 1 knot under real operational conditions of the examined ferry. The proposed ANN model also outperformed the SVM and tree ensemble models utilizing the same dataset. These results may be different for other types of ships of different hull types or different operational conditions. However, due to its black-box nature, the proposed methodology in this study of data preprocessing and ANN model training can be used with different ship types and operational conditions without an additional domain knowledge.

The performed sensitivity analysis shows that increasing the number of data samples allows better model training. Also, by increasing the data sample size, the stability of the data correlation analysis can be improved and its estimation uncertainty can be reduced. On the other hand, increasing the number of ANN training epochs has a negligible improvement on the prediction accuracy and increases the computational time and overfitting risks. Moreover, the proposed ANN model has been used successfully to study the effect of changing different operational and environmental parameters on ship speed which can help with decision-making process, voyage planning, optimization, and execution. The proposed ANN model can be also used to identify the impact of biofouling on the ferry operational performance but a large historical dataset would be required.

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