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USING ARTIFICIAL NEURAL NETWORKS FOR PREDICTING SHIP FUEL CONSUMPTION

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ABSTRACT

In marine vessel operations, fuel costs are major operating costs which affect the overall profitability of the maritime transport industry. The effective enhancement of using ship fuel will increase ship operation efficiency. Since ship fuel consumption depends on different factors, such as weather, cruising condition, cargo load, and engine condition, it is difficult to assess the fuel consumption pattern for various types of ships. Most traditional statistical methods do not consider these factors when predicting marine vessel fuel consumption. With technological development, different statistical models have been developed for estimating fuel consumption patterns based on ship data. Artificial Neural Networks (ANN) are some of the most effective artificial methods for modelling and validating marine vessel fuel consumption. The application of ANN in maritime transport improves the accuracy of the regression models developed for analysing interactive relationships between various factors. The present review sheds light on consolidating the works carried out in predicting ship fuel consumption using ANN, with an emphasis on topics such as ANN structure, application and prediction algorithms. Future research directions are also proposed and the present review can be a benchmark for mathematical modelling of ship fuel consumption using ANN.

Keywords: Artificial Neural Networks; Fuel management; Marine engine; Ship fuel consumption; Energy efficiencys

INTRODUCTION

In recent years, the maritime transport sector and maritime activities, such as container depots and port activities, have experienced a rise in greenhouse gas (GHG) emissions [1], [2]. This rise can be correlated with the increasing trend in shipping vessel fossil fuel consumption [3]–[5] and serious environmental pollution, including oil spillage [6]–[8]. Consequently, these significant increases in GHG emissions due to the use of fossil fuels are thought to further exacerbate the rise in global average temperature and potentially irreversible ecological impacts related to climate change [9], [10]. Given the fact that a major portion of global cargo is carried by ships, improving the overall energy efficiency of marine transport promises to yield positive results, in terms of GHG emissions relating to fuel consumption [11]–[13]. According to the 2019 data published by the International Maritime Organisation (IMO), emissions from maritime transportation accounts for 2.5% of global GHG emissions. The emissions of these various heat-trapping gases are known to be the main driver behind anthropogenic global warming and changes in global weather patterns, yielding potentially harmful effects on the Earth's ecological systems and human society [14]–[16]. As the main international regulatory body of maritime shipping activities, the IMO has developed the Ship Energy Efficiency Management Plan (SEEMP) and Energy Efficiency Design Index (EEDI) as two crucial measures aimed at lowering GHG emissions and curbing environmental pollution through the more efficient use of fuels in marine vessels [17]–[22].

Consequently, lower emissions of common air pollutants from ships, such as sulphur oxide (SOx) and nitrogen oxide (NOx), as well as major GHG were observed with the introduction of these regulations [23], [24]. Considering the direct relationship between fossil fuel consumption and GHG emissions, several studies have explored different strategies to deliver more efficient ship operations, such as hull cleaning and design [25]–[28], and the incorporation of renewable energy sources including wind energy [29]–[31], solar energy [32]–[35], wave energy [36], [37], and fuel cells [38], [39]. Ship energy management plans provide critical inputs for the continuous monitoring and analysis of marine vessel performance by taking the design and operational measures into account [40]–[42]. Data-driven performance monitoring provides an effective solution to holistic system management including real-time decision making, assessment and evaluation, and cost-effective resource management [43], [44]. Other factors driving the need for better energy efficiency management on marine vessels stem from economics, compliance, and stakeholder requirements [45], [46]. A ship's energy consumption accounts for a significant portion of its operating costs [47]. It has been observed that up to two-thirds of shipping costs and one-quarter of total operating costs depend on fuel consumption [48], [49]. Hence, predicting fuel consumption and energy inputs provides a good measurement of energy efficiency management within marine transport [50], [51]. Besides these proposed strategies, estimation models have been proved effective in identifying the key variables that influence fuel consumption [52], [53]. The availability of estimation models not only provides the total system recognition, but also enhances the capability of monitoring operating conditions and forecasting potential malfunctions [54]–[56]. In general, the characteristics and application of prediction models for ship fuel consumption are illustrated in Fig. 1.

Since fuel costs account for the largest portion of ship operating costs [58], better fuel consumption also means higher energy efficiency and greater profitability for the marine vessel's owner [59]. Therefore, accurately predicting the rate of fuel consumption is a challenging task because there are several external influencing factors. Access to the estimation model has yielded key advantages for fleet owners and companies when optimising fuel consumption and operational costs, by efficiently tracking and analysing the key parameters [60], [61]. Considering these facts, computer-assisted tools would be more appropriate for assisting decision-making [62]. There are several statistical techniques, algorithms, and artificial intelligence methods that are commonly used, and these include polynomial regression (PR), support vector machine (SVM), fuzzy logic, artificial neural network (ANN), and other algorithms [63]–[65]. Among these, PR is the most popular method and it uses polynomial functions to approximate data points. One of the advantages of this method is its simplicity and a high degree of flexibility when applied to a general dataset. In the marine transport and shipping industry, PR is typically used to analyse the hull-propeller's performance loss and reconstruct ship trajectories for automatic identification system data [64]. On the other hand, SVM has gained special interest among the machine learning tools used in classification and regression models. The main objective of SVM is to map input vectors to a higher dimensional space, in which an optimal discriminant hyperplane is constructed. The use of kernel functions is relevant in mapping input data. Within SVM, the ship detection images are divided into small blocks of pixels [66] that can be categorised, based on colour and texture. Using regression models, outliers can then be identified, polluted ship tracks can be regressed [67] and a ship's motion can be predicted [63]. The strong preference for this technique over other learning methods stems from better generalisation that could alleviate overfitting problems.

Grounded in mathematical models, these tools make

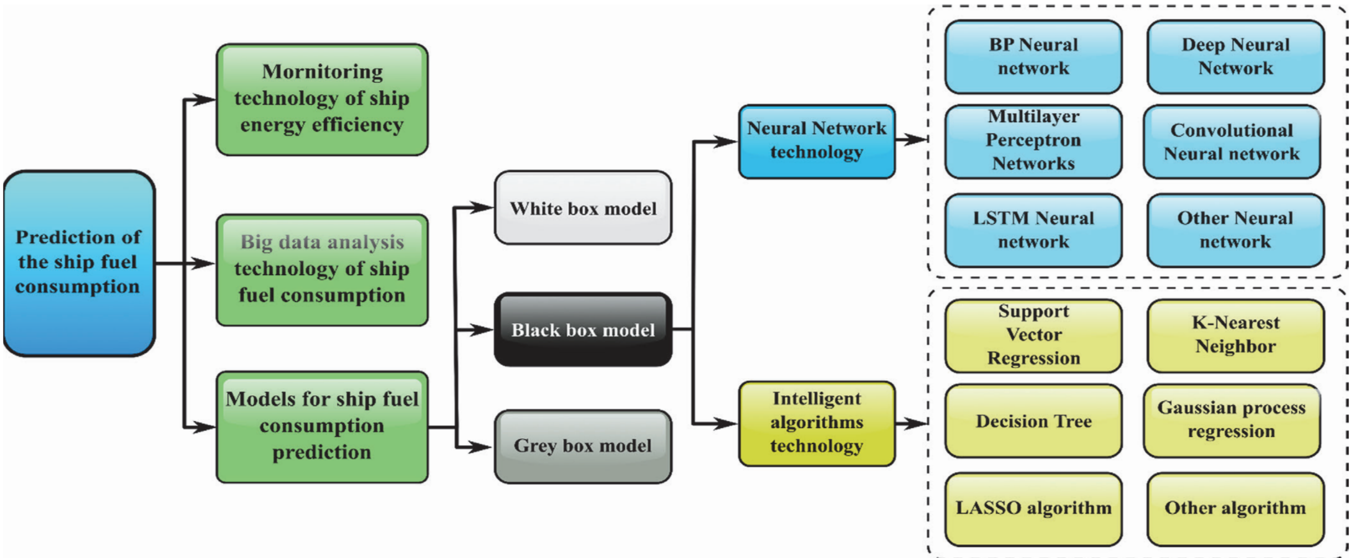

Fig. 1. Topology of models for predicting ship fuel consumption [57]

the connection between the input variables, such as fuel consumption and estimated travel time to the destination, and the outputs, based on command and current operational conditions related to the ship propulsion thrust [68]. In analysing bibliographic references relating to the various techniques of displaying the commanded outputs, Rudzki et al. [69] revealed the inadequacy of the present models that formalise the required heuristic knowledge. According to the authors, the use of ANNs could be applied to attain such models with better predictive power, concerning the estimation of ship fuel consumption and travel time to the destination, for given commanded outputs and operational parameters. ANN is a better approach due to its better accuracy and capability when being applied in practice. In this scenario, the absence of the requirement of mathematical relations between the input and output data gives the ANN technique a key advantage [70]. As a subset of artificial intelligence, ANN enables systems to learn from previous experience and available historical data, and improve on current conditions [71]. Based on recorded system performance, system conditions could then be assessed and further improved upon [72]. First, a model algorithm is run (training mode) on a partial set of data before being fully examined (testing mode) with a full set of data. By combining advanced statistical methods, realistic estimation models can be formulated by applying the train-test process based on the ANN algorithms. Estimating a vessel's fuel consumption with minimal error rates could be useful, while providing ship operators with important insights. For these reasons, ANN is an integral instrument in managing marine vessel operations and energy efficiency [73]. Therefore, the current work reviewed a data analysis framework based on ANN used to predict ship fuel consumption. In addition, the use of ANN to derive a regression model for ship fuel consumption, as well as the performance and accuracy of ANN, were also thoroughly analysed through various inputs and outputs of the ANN model.

ANN STRUCTURE

Machine learning (ML) is a subfield of artificial intelligence that uses algorithms and statistical models to allow computer systems to improve their performance on a given job by learning from data, without being explicitly programmed [74]. The objective of machine learning is to create algorithms that can recognise patterns in data and utilise those patterns to make predictions or conduct actions [75], [76]. ANNs are a type of machine learning algorithm inspired by the anatomy and functioning of the human brain. ANNs are made up of linked layers of nodes, or neurons, which process information and transmit it on to other neurons to be processed [78-79]. ANNs are utilised in a range of applications, including picture and speech recognition, natural language processing, and financial market prediction [79]–[83]. ANNs are a form of supervised learning algorithm that, with training, can learn to recognise patterns in data. During training, the ANN is given a set of inputs as well as the desired outputs [84]. To minimise the difference between the actual output and the required output, the ANN modifies the strength of the connections between its neurons. Once trained, the ANN can be used to make forecasts on previously unknown data [85].

ANNs have proven to be extremely effective in a wide range of machine learning tasks, particularly those involving enormous volumes of data. ANNs are highly versatile and can be used to solve a wide range of problems; they are a strong tool for solving a wide range of challenging issues in machine learning and artificial intelligence [86]–[88]. ANNs can, on the other hand, be difficult to train and demand a large amount of computer power, particularly for deep neural networks with many layers [89]. ANNs are constructed from a collection of small computational units, known as neurons, organised into layers. The neurons in one layer communicate with the neurons in the next layer, establishing a network which is capable of processing complicated information. Each neuron in an ANN gets input from neurons in the previous layer, analyses that information, and generates an output signal that is sent to neurons in the following layer [90]. Each neuron processes its inputs by computing a weighted sum, adding a bias term, and sending the result via a nonlinear activation function. ANNs can simulate complicated nonlinear interactions between inputs and outputs using this nonlinear activation function [91][92]. A neuron's basic mathematical operation can be described as [80]:

$$y = f(\Sigma(w * x) + b). \tag{1}$$

Herein, y denotes the total of all inputs f is the activation function, w is the weight associated with each input x, b is the bias term, and Σ denotes the total of all inputs.

During training, the weights and biases of an ANN are modified to minimise a cost function that assesses the difference between the network's expected and intended outputs [93]. The weights and biases are commonly adjusted using a backpropagation method, which computes the gradient of the cost function with respect to the weights and biases and updates them in the direction of decreasing cost. ANNs have been shown to be extremely effective in applications involving vast amounts of data, such as deep learning [94]. In contrast to the simple linear regression method, which portrays the relationship between input and output variables with a single equation, fuzzy logic-based regression models rely on local functions and provide global approximations in a nonlinear relationship [95]. Consequently, local functions or membership functions are combined into a single expression. Besides this, fuzzy logic models have the capability to capture highly nonlinear and multidimensional interactions among the different factors.

On the contrary, the application of ANN models offers key benefits, including a generalisation and extrapolation capability [96]. Furthermore, ANN models can be constructed without the prior knowledge of the type of function. These systems can be trained by a process called machine learning, through which the performance of simple tasks can be taught and improved over time. There are several basic elements in ANNs, including processing elements (i.e. inputs, outputs, and weights) and activation (neuron/transfer) functions [98-99]. These components closely resemble the makeup of biological neurons which form the basis for the ANN [99]. After inputs are received from one end and processed/summed, the outputs are generated on the other end of the artificial neuron. Within this process, the weight factor for each input is calculated according to the strength of the input signal [100]. The weighted sum of all inputs is processed via a nonlinear function, known as the activation linear function [101]. The activation function can take several forms, including sigmoid, nonlinear, piecewise linear, and step functions. These continuous and monotonically increasing functions are often differentiable and bounded. Based on these models, a computer-assisted decision support system can be constructed to select the ship driveline commanded output to deliver the optimal ship fuel consumption. Besides this, ship logs (which contain ship records such as managing events, ship operation and navigation information) are important sources of historical data which have been used in ANN models to estimate ship fuel consumption [102], [103].

In practice, the ship operators often rely on their knowledge, experience, and instinct when setting the appropriate values for the commanded outputs [104]. As stated earlier, it is impractical to choose one appropriate method that allows for the selection of commanded outputs, based on formalised heuristic knowledge. In certain situations, there is the potential that the chosen settings can be illogical and unsuitable [105]. To minimise the potential risk of such incidences, the availability of a decision support system (Fig.2) is highly desirable, in which the decision support system was constructed based on the following key parts:

- A data acquisition module containing several uncontrollable inputs and one output variable vector based on normalised ANN data;
- An identification module containing the input, based on the normalised ANN output values obtained from the prior module and one matrix-represented output capturing the internal data representation of the ANN used in the estimation of ship fuel consumption;
- An optimisation module containing two input and two output variables. The two-input data include: (i) the output from the preceding module in the form of ANN matrix data, and (ii) the vector value of the weight factors of the two-objective optimisation model. The two outputs correspond with the optimal commanded outputs.

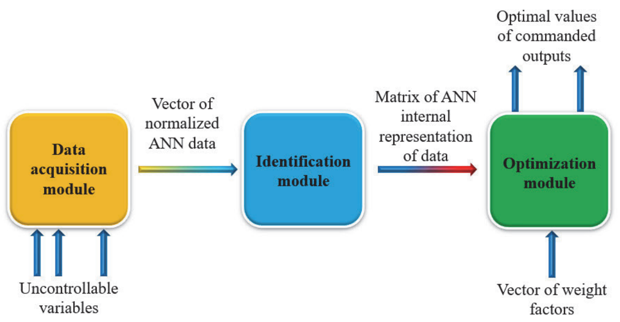

Fig. 2. Structure of decision support system block [105]

The available literature on ship fuel use estimation considers three commonly used models: white-box models (WBMs), black-box models (BBMs), and grey-box models (GBMs) [106], [107]. Based on prior knowledge of the system, a WBM relies on the physical understanding of a system, as well as its identifiable or known structure and parameters in the decision making [70,109]. On the contrary, the use of BBM occurs in the absence of a priori knowledge of the system when making output decisions based on a few key input data [107]. Researchers have found higher accuracy in well-trained BBMs, compared to WBMs. Nevertheless, the training of BBMs often necessitates the collection and input of large amounts of high-quality data [109]. BBMs also fail to provide interpretability and extrapolating capability compared to WBMs [110]. As reported, BBM (which includes Back Propagation Neural Network, Multilayer Perceptron Network, Long Short-term Memory, Convolutional Neural Network, and Deep Neural Network) performs well in terms of ship fuel consumption prediction [96,112]. GBM is a hybrid model constructed on the basis of the system's underlying physical processes, while some parameters can be estimated using input data [70,109]. GBMs leverage the key advantages of the prior two modelling techniques [109]. Referencing several studies, Table 1 provides comparisons between WBMs, BBMs and GBMs, highlighting the advantages of GBMs over the other two methods.

Even though the technique offers several important advantages, GBMs have not been very well studied in the estimation of ship fuel consumption. One of the reasons for the lack of research on GBMs in this context could be that the system is modelled as a piecewise function; whereas, the ship's sailing motion provides the variables in determining the outcomes [122]. Hence, external environmental factors, such as changing wind direction and wave motion, strongly affect the vessel's resistance. Traditional GBM used in the estimation of ship fuel consumption is based on a set of four sub-functions, accounting for each of the weather directions [123]. Besides the common parameters, there are also individual parameters for each of the sub-functions. Considering this fact, the use of derivative-based techniques, such as the Gauss–Newton algorithm and the Levenberg–Marquardt algorithm, is insufficient for providing estimations of all common parameters together. To overcome this obstacle, researchers have come up with sequential parameter estimation procedures at the cost of global optimality [124].

Meng et al. [125] constructed a SPEP, in which the common parameters of the piecewise function were first estimated and then used as fixed variables in other sub-functions (i.e. bow sea, beam sea and following sea). Nevertheless, this approach has not been fully taken advantage of in the collected data. As shown in Fig. 3, only 25% of the data were utilised in the estimation of the common parameters in the sequential parameter estimation procedures. Furthermore, the lack of optimality in the estimation of the common parameters will affect the level of accuracy, when estimating the other parameters included in the remaining sub-functions.

Table 1. Characteristics of WBM, BBM and GBM applied for prediction of fuel consumption for ships

Methods	Advantage	Disadvantage	References
WBM	- Obtained results and system behaviours can be interpreted and predicted. - Data can be extrapolated in addition to the given data. - Historical data are not required.	- Potential uncertainties and assumptions significantly affect the accuracy of predictions. - Required prior knowledge. - Low accuracy.	[109][112][106][113]
BBM	- BBM has higher accuracy than WBM. - Prior knowledge is not required.	- Historical data are required in large amounts. - Model interpretability and extrapolation capacity are poor. - Unreasonable results might be received.	[109][114][115][116] [117][118][119][120]
GBM	- GBM has a higher accuracy than WBM. - Less historical data is required for GBM compared to BBM and WBM. - High model interpretability. - Unreasonable results might be avoided.	- Extrapolation capacity is not high.	[109][121]

Hence, the use of GBMs in the current context of ship fuel consumption estimation is restricted, based on its quality and accuracy [126]. In an attempt to mitigate the shortcomings related to GBMs, a new genetic algorithm-based grey-box model (GA-based GBM) is presented as a possible method for estimating ship fuel consumption [109]. The present GA-based GBM approach differs from conventional GBMs, in that 100% of the collected data are used in the estimation of the common parameters, as shown in Fig. 3. The new approach also allows for the concurrent estimation of all common parameters of the GBM that further enhance the accuracy and reliability of the GBM. Studies by Coraddu et al. [106] and Aldous et al. [127] supported these conclusions. Nevertheless, due to the inclusion of piecewise structures in GBMs subject to the segregated weather directions, it is more difficult to estimate the parameters of GBMs. SPEP has been able to resolve this problem at the expense of the global optimality that inevitably affects the accuracy of GBMs in estimating ship fuel consumption.

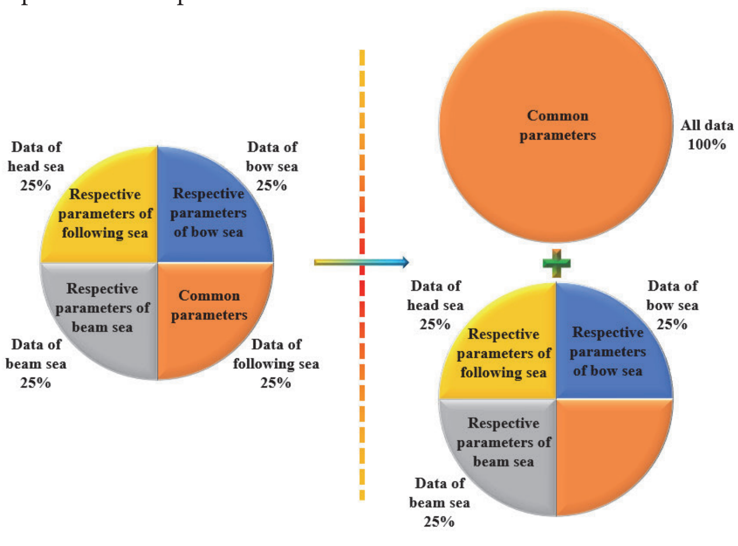

Fig. 3. Data utilisation of GBM based on existing SPEP (Left) and the proposed GA (Right) [109]

Previous studies have been successful in using heuristic and metaheuristic algorithms in solving highly complex problems [129,130]. These methods are potential solutions for the aforementioned problem while taking into account their flexibility. Among the available literature, applications of heuristic and metaheuristic methods in estimating parameters are found in complex (piecewise, nonlinear, etc.) models among various fields. Some examples include the study of evolutionary strategies of biochemical pathways [130], applications of particle swarm optimisation in chemical engineering [131], grasshopper optimization algorithm in engine area [132], [133], simulated annealing algorithms used in the Muskingum routing model [134], and a flower pollination algorithm for solar PV application [135]. Despite the prevalence of heuristic and metaheuristic algorithms in different fields, their use as the main tool in estimating the parameters in ship fuel consumption prediction models has remained relatively limited. They offer a new perspective in the current knowledge gap by proposing a GA-based GBM to be used in the estimation of parameters in the fuel ship consumption model. Compared to existing SPEP-based GBMs, these improved GA-based GBMs have several key advantages.

Furthermore, the GA-based GBM reflects higher reliability in capturing the relationship between ship fuel consumption rate and its determinants. These benefits further strengthen the model application in performing energy efficiency and sustainability analysis in the study of marine vessel operation. From an industrial perspective, the GA-based GBM presented in the current research can be integrated as part of the ship energy efficiency programs, to optimise ship fuel consumption and reduce GHG emissions, because of its better predictive capability.

In the construction of the decision support system, it was found that the following requirements are important: (i) state the input and variables related to the ship driveline system models, (ii) construct models predicting ship fuel consumption and speed based on ANN; and (iii) construct a decision-making model based on multi-objective optimisation [65], [136], [137]. In the development of these models, a ship was identified as a solid object placed at the water-air boundary. Along with the partial immersion position and maintained relative motion, these factors enabled the selection of appropriate variables for both the black box and the decision-making models. Fig. 4 shows the problem captured in the 'black box' form, under the influence of several different factors [105].

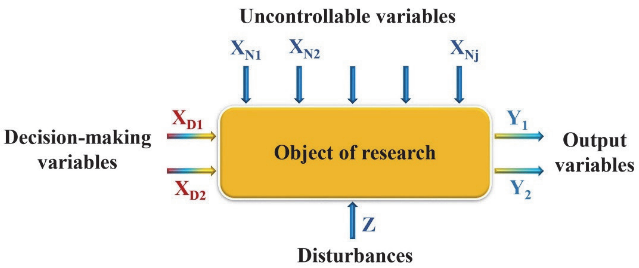

Fig. 4. 'Black box' model [105]

Fig. 4 shows that, in terms of decision-making variables (X_{Di}), the two main selected variables were the combustion engine rotational speed and the CPP pitch. On the other hand, the uncontrollable input variables (X_{Nj}) were identified among a range of factors influencing the ship sailing motion [118]. These factors played an important role in the commanded outputs of the ship driveline system that determined the desired ship motion and speed via the propeller thrust. Last but not least, the model output variables are Y_k, (the combustion engine fuel consumption) [105]. The other factors that were difficult to capture and had minimal variance (with respect to the ship's motion) were denoted as Z or the model disturbances. In formulating the decision-making problem, the distinct variables contained in the black box model were considered. The main problem statement is to determine the values of the decision-making variables X_{Di} subjected to the uncontrollable variables X_{Nj} in order to achieve the anticipated values of the output variables, Y_k. The values obtained for the model output variables Y_k make up the objectives for the optimisation function. The function is set up in order to minimise the ship's fuel consumption. Taking into account the distinguished variables of the black box model, the decision-making problem can be formulated as follows: what should the values of the decision-making variables X_{Di} be for the given values of the uncontrollable variables X_{Nj}, in order to provide the desired values of the output variables, Y_k.

Researchers have constructed models using GBMs, which integrate both partial theoretical structure and input data [138]. WBMs, also known as cause-effect models, can explain the relationship between the different variables and the studied phenomenon, as well as the underlying processes. To quantify these processes, equations were set up based on existing knowledge of the relationships. For dynamic systems, the balance method is the preferred method used in the construction of WBMs [140-141]. In addressing systems containing physical quantities, the balancing of parameters occurs for those that are subjected to the conservation law of momentum and energy. Despite the advantage of the balance method, it is impractical to rely on such a method when modelling both fuel consumption and ship sailing, in implementing a decision-making support model subjected to the commanded output of the ship driveline system. Due to the extraordinary complexity of the equations that are used in describing these relationships and processes, they are impossible to solve. Furthermore, the varying influence of several parameters over the processes and the studied phenomenon also complicate the problem. Even though these equations could be simplified in linear, parabolic or hyperbolic forms, the complexity of the studied processes does not allow for generalisation or linearisation procedures. Besides this, the results obtained from solving these equations through approximation, falls short of being useful in practice. Given these reasons, the need for alternative modelling techniques is highly warranted. In particular, the use of the BBM method could provide important insight into the existing relationships and fundamental processes. In contrast to the WBMs, the use of BBMs does not require the full analysis of the causes when understanding the studied phenomenon. In constructing this type of model, the necessary steps are carried out as follows: performing measurements; analysing the results and identifying the required parameters for the considered issue; examining the validity of the initial conditions; searching for a functional dependency or providing guesses based on the researcher's instinct; fitting the function with the appropriate parameters; comparing the results of measurements and the fitted model [70-142]. In the case of non-conformity, one or several of the following steps or additional measurements can be conducted. Data collection is first carried out using actual measurements or historical records. By the rules of thumb, these data should be grouped into dependent (i.e. those to be estimated) and independent variables (i.e. those to be used in necessary conditions).

ROLE OF ANN AND MACHINE LEARNING IN PREDICTING SHIP FUEL CONSUMPTION

Among the recent advances in research, applications of ANN have been found in several fields, highlighting the latest developments [142]–[147], as well as issues related to the marine industry [148]–[150]. The method based on ANN is known to be a widely applied prediction model. Besikci et al. [151] employed the ANN model to predict fuel consumption by modelling the relationship between engine speed and the outside variables, aiming to predict the fuel consumption of a tanker. Wang et al. [152] used a wavelet neural network (WNN) to optimise the energy efficiency of a ship. By using this developed WNN, engine speed could reach the optimal value under various navigation environments and working conditions; thus, energy efficiency and the ship's sailing were optimised, resulting in optimised fuel consumption of the ship. Arslan et al. [153] and Bal et al. [117] developed decision support systems grounded in ANN prediction models. In these models, there were seven main input variables, including ship speed, main engine rotational speed, mean draft, trim, number of cargos, wind and sea conditions, as depicted in Fig. 5a. These parameters were used as the determinants in predicting the output variable, which was ship fuel consumption. The authors relied on ship noon reports to gather the ship's main operating data. Both studies utilised the Neural Network Toolbox in MATLAB 2010a software to construct the neural network models. In terms of data set, they used data obtained from 7 tanker ships, respectively. 70% of these data were randomly chosen for training, while the rest were utilised to validate the results. The main ANN modelling approach relied on the backpropagation algorithm, which performed learning on a feed-forward neural network consisting of one hidden layer. In these studies, the main learning algorithm was Levenberg–Marquardt, in which hyperbolic tangent sigmoid transfer function was the activation function and the training epochs were limited to 10,000. In comparison with the multiple regression model [118,154], the ANN model performed significantly better, based on the observed correlation of actual and predicted fuel consumption data in both training and validation data groups, as depicted in Fig. 5b and 5c.

Conventional statistical methods have been commonly used in modelling various phenomena. The study by Rudzki et al. [118] provided an assessment of the application of a statistical regression technique in modelling optimal parameters for the ship drive's propulsion. Using multiple regression techniques, a BBM was developed for the decision-making system considered and similar types of data were used in constructing the ANN models utilised in this case [154]. These data are key for explaining the relationship among the different operational parameters (i.e. related to ship propulsion thrust) and the fuel consumption and travel time to the destination subjected to the commanded outputs. As reported in the literature, the Gaussian processes model is a supervised probabilistic machine learning framework, which could be used for regression and classification applications [155]. Therefore, Petersen et al. [116] applied single-input variables with an ANN and a Gaussian process method in predicting ship propulsion efficiency performance. In another study, Li et al. [156] used a neural network in their modelling, analysis, and prediction of ship motion. Utilising another type of neural network, Perera et al. [157,158] was able to capture the compression and expansion of ship performance data. Despite the existence of several ANN studies in the ship and maritime field, they all failed to provide an adequate validation of the entire big data analysis process, as well as the regression models used in predicting ship performance and fuel consumption. In the study conducted by Pedersen et al. [114], a method was proposed for predicting a ship's propulsive power, based on ANN and subject to the external factors affecting the ship resistance and propulsion. These different factors included ship speed, wind speed and direction relative to ship sailing, air and ocean temperature. Based on the hindcast approach, the built model was trained to estimate a ship's propulsive power using input data from three different sources, including onboard measurements, noon reports, and sea state and weather conditions. The authors compiled the data set from 323 different noon report samples. As stated in their methodology, Pedersen et al. [114] only set 5 and 20 hidden layers as the two extremes to train the model. As a result, a 7% accuracy level was achieved when using the ANN model from noon report data in estimating ship fuel consumption. Because the model used 'time' as one of the input variables, it was suggested that the trend line of ship fuel consumption could be identified over time.

In another study, a model was constructed by Du et al. [159,160] to predict a ship's propulsive power. The proposed model was able to capture the synergetic effects of the various

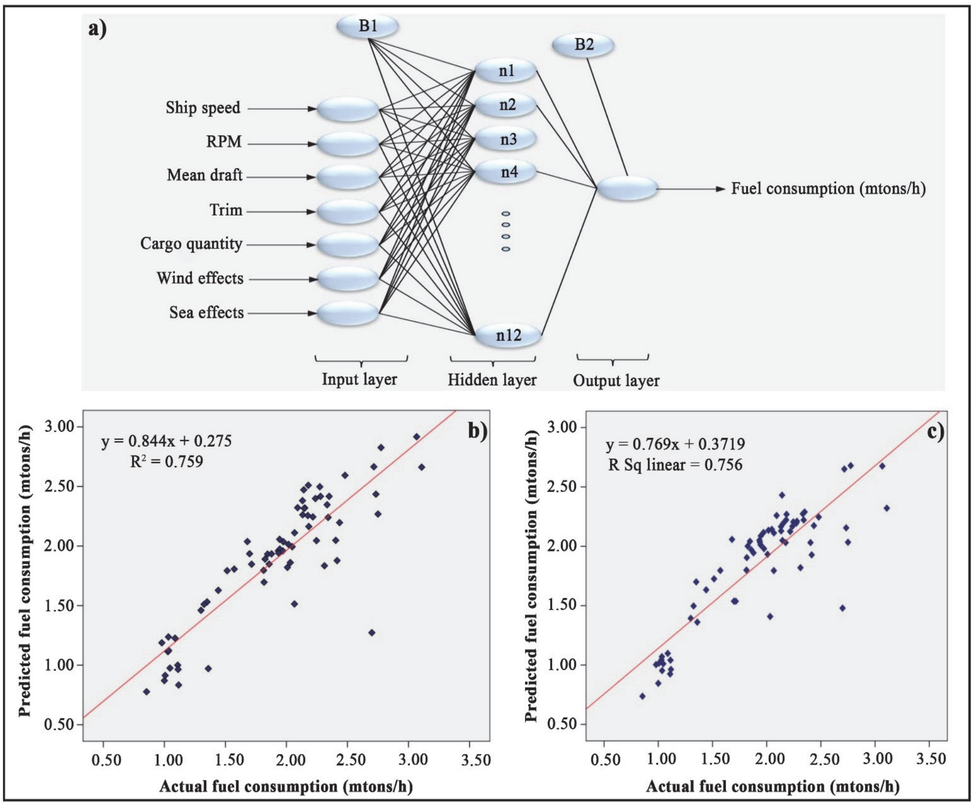

Fig. 5. (a) – ANN structure for predicting fuel consumption of a ship with 7 input data; (b) - Relationships between actual and predicted fuel consumption using ANN model; and (c) - multiple regression model [117]

independent factors affecting ship fuel efficiency. The authors also proposed an ANN-based framework for managing ship fuel consumption which included a two-step procedure. The process began with the estimation of the ship engine rotation speed and then the engine power was subjected to the obtained speed. The calculation of ship fuel consumption was based on a set of estimated parameters. Besides, there are several required variables for the ANN model, such as ship speed, displacement tonnage, wind force, wind wave height, swell height, sea current factor and ship trim [161,162]. Samples of noon reports were collected from 3 different ships, totally 121, 160 and 153 reports, respectively. As a result, the authors concluded that a simple single hidden layer ANN model had the best fit performance among other tested models. In another study, Rudzki et al. [163] developed a two-criteria optimisation algorithm, including both the objective function and the set of acceptable solutions, allowing the rational management of a ship's fuel consumption and navigation time on the basis of the combination ANN and MATLAB package. As a result, they presented the relationship between engine speed and fuel consumption, allowing vessel owners to find the lowest possible operating costs.

As a subject of study, researchers have yet to fully investigate the use of ANN models in predicting ship speed under varying operating conditions. Without the presence of propulsive force, variable speed towing tank experiments could be utilised in estimating the amount of power needed to propel the ship hull. In the analysis of ANN models, the authors have examined those models which take into account the ship resistance or power and their main determinants. In a study by Couser et al. [164], they examined the appropriateness of using ANN for predicting ship resistance compared to conventional statistical methods. In their experiments, the researchers utilised the ANN network as an interpolation strategy in predicting ship residual resistance in various types of catamaran. It was observed that results from ANN models met the accuracy threshold to be applied when making preliminary estimates of ship resistance. In particular, the building of the ANN model was based on a single hidden layer and 15 neurons comprised a hidden layer. The authors arrived at two main conclusions: (i) the added hidden layers did not yield any additional benefits in terms of improving model accuracy and only increased the model complexity and training time; (ii) the availability of specific computer-aided software allowed for the fast training and running of the ANN model in solving the ship resistance problems, relative to traditional statistical techniques.

Using an ANN model, Grabowska et al. [165] followed a similar strategy in their research on ship resistance prediction. In their experiment, the authors applied the parameters from seven available offshore marine vessels to the model parameters obtained from the test results carried out in a towing tank (i.e. a ship model basin used to conduct physical and hydrodynamic tests on ship models). They also compared seven different training algorithms with different hidden layer configurations, to evaluate their performance and identify possible effects of network architecture on the model outcomes. As a result, the Quick Propagation algorithm was selected for additional examination due to the best potential for favourable results, in terms of the correlation between target and output values (i.e. correlation coefficient R2 and absolute validation error). To determine the optimal network design architecture, several cases used 4 to 24 neurons in a hidden layer because the 24-neuron configuration gave the lowest absolute validation error. In this methodology, the study set the required input and output layers according to the input data dimensionality (i.e. the number of input variables in a dataset) and the required output values. Hence, the authors were able to select the number of hidden layer neurons from the geometric mean values obtained from the formula provided by Bishop [166]. Through the automated network architecture design, 24 neurons were identified as the optimal number delivering the highest level of accuracy. In brief, the authors concluded a satisfactory level of accuracy obtained from the constructed network compared to the model test results. However, additional studies on the network architecture are warranted that could offer a potential improvement on the model result. In a different experiment, Mason et al. [167] tested ANN model configurations using the data obtained from the original towing tank tests that had been previously conducted using the method proposed by Holtrop et al. [168]. In the initial test network design configuration, the number of layers was limited to three: the input, hidden and output layer. Utilising a quasi-Newton method, the training runs were set to 50,000 iterations. To lower the potential model errors, 10 retrains were conducted for each tested neural network topology, including 4 inputs, 4 neuron-hidden layers combined with 1 output to 4 inputs, 17 neuron-hidden layers and 1 output. The authors confirmed the effectiveness of the feedforward ANN used in fitting an extra data set containing a fair degree of random and meaningless information.

Consequently, a proposed model containing two hidden layers might be more optimal than one, as depicted in Fig. 6a [169]. Le et al. [169] presented the method of designing a multilayer perceptron artificial neural network (MLP-ANN) and used MLP-ANN to predict ship fuel consumption. They employed data from 100–143 container ships, while sailing time, speed, cargo weight, and capacity were considered as input parameters. As a result, they indicated that MLP-ANN could be used to predict the container ship fuel consumption by fitting lines very close to the actual results, as plotted in Fig. 6b. In another study, Ortigosa et al. [170,171] proposed an ANN model to predict two different ship resistance variables. The authors applied the multilayer perceptron (MLP) in training both synthetically generated and experimental datasets to estimate the different coefficients, including form and wave coefficients subjected to ship hull geometry coefficients and the Froude number. Based on the outlined methodology, an ANN-based empirical model was designed and tested using data produced by the Holtrop and Mennen method [168]. The model aimed to deliver an estimation of the components directly related to the ship resistance. In this case, the authors tested the proposed model using

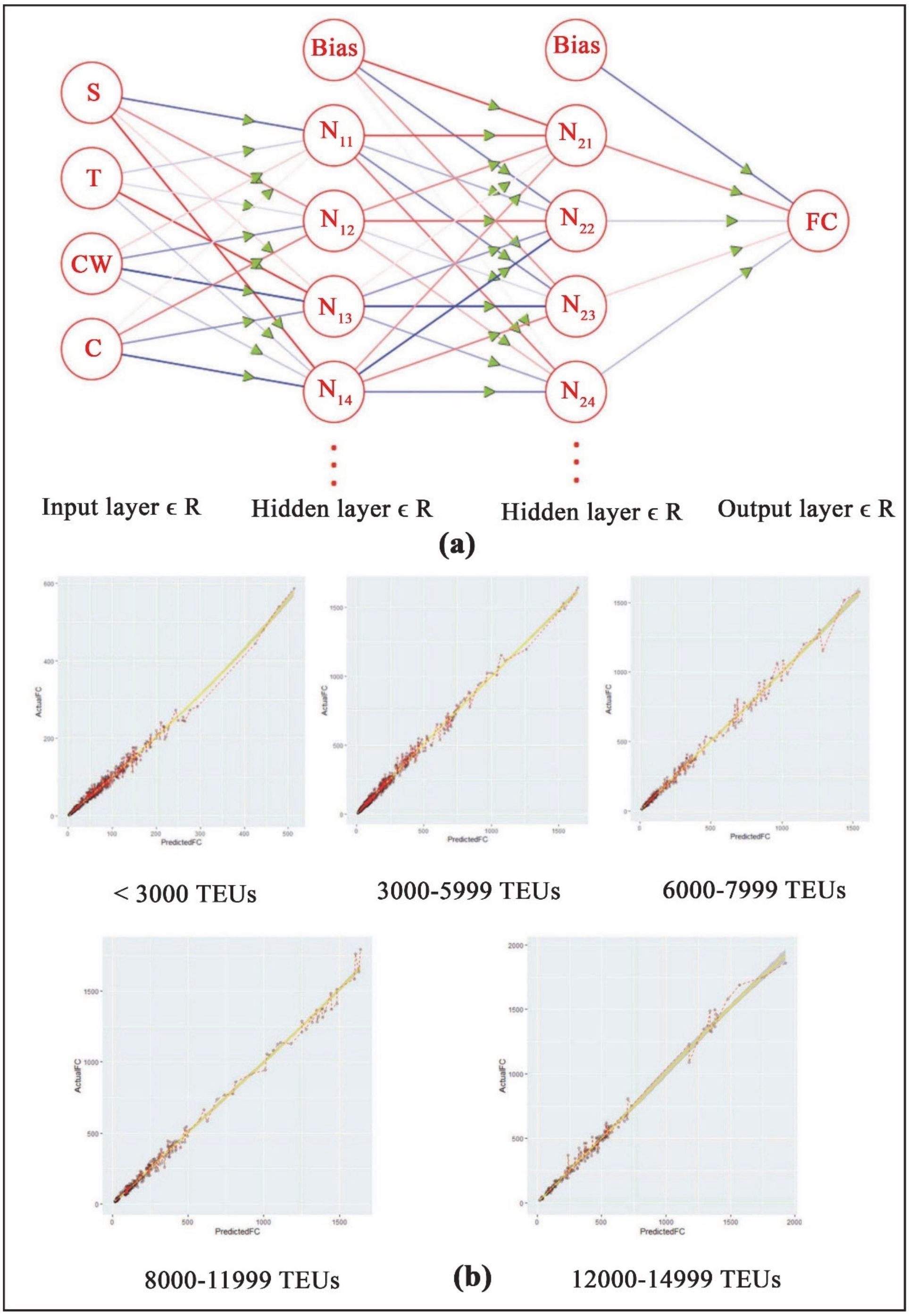

Fig. 6. (a) – ANN model with 2 hidden layers; (b) - Actual and estimated fuel consumption [169]

Comparing the results obtained from the selected ANN model to those produced by the Holtrop and Mennen method, there were overall improvements, in terms of model performance over the whole dataset. In reviewing the available literature on the application of ANN in predicting ship fuel consumption and hull resistance, several conclusions were reached:

(i) Input data used in training the model to predict ship fuel consumption were based on data extracted from actual ship logs, also known as noon reports;

(ii) Most studies relied on design data (geometric parameters of ship hull design) or experimental data obtained from tank tests as input variables for modelling ship resistance;

(iii) There needs to be more information on measurement methods and the types of propellers used in marine driveline systems. The bulk of available references concerning the application of ANNs were found in Bishop [166]. Regarding the strategy in the present research, a detailed experiment was proposed for planning and building sufficient ANN models to estimate ship fuel consumption and desired speed. The specific experiment was tested using various commanded outputs of the marine vessel driveline system while being subjected to a range of different off-shore environmental conditions. However, the collected data from the shipping company was limited, leading to difficulties in predicting to a high accuracy by using ANN. These limitations could be overcome by the integration of ANN with other algorithms, such as expert knowledge [172], the Cognitive Reliability and Error Analysis Method [173], or an Adaptive Neuro-Fuzzy Inference System combined with fuzzy logic theory [174]. In general, the use of ANN for predicting ship fuel consumption is summarised in Table 2.

MLP containing a sigmoid hidden layer and two linear output layers. Subsequently, the quasi-Newton method with Broyden–Fletcher–Goldfarb–Shanno train direction and Brent optimal train rate (as proposed in Bishop [166]) were utilised in training the constructed algorithm. The model was tested with a different number of hidden layer network configurations. In the process, the authors selected the network design that achieved the best optimal generalisation and validation errors. As a result, an ANN network model containing 5 inputs, 9 hidden layer neurons and 2 outputs was selected as the best configuration.

with the consideration of the effects of marine environmental factors. As a result, BPNN (T = 14.7 s) was found to provide shorter runtime than GPR (T = 2236.4 s), while GPR (R^2 = 0.9887) offers higher accuracy than BPNN (R^2 = 0.9817).

Table 2. Various models based on neural network for prediction of ship fuel consumption

Parameters of concern	Data sources	Method	Accuracy	Reference
Engine load, operating parameters, weather conditions	-	ANN	0.9055	[175]
Weather and current conditions, engine speed	Voyage data		-	[176]
Engine load, operating parameters, weather conditions	AMS		0.9709–0.9936	[177]
Weather and current conditions, engine speed	Route software		-	[178]
Weather and current conditions	LAROS system		0.9870	[179]
Weather and current conditions	ACMS, AIS, and weather forecast		0.9960	[103]
Weather and current conditions, engine speed	-	BPNN	R^2 = 0.9817	[180]
Weather and current conditions, engine speed	Ship monitoring system		R^2 = 0.9843	[101]
Weather and current conditions, engine speed	-	MLPN	R^2 = 0.8340	[151]
Weather and current conditions, rudder angle	Sensors		Relative error = 0.02	[181]
Engine speed, shaft power	Sensors	LSTM	RMSE = 2.714	[182]
Weather and current conditions	-		-	[161]
Weather and current conditions, engine speed	Multisource sensors		-	[51]
Weather and current conditions, engine speed	ADLM and CMEMS	DNN	R^2 = 0.8940	[111]
Weather and current conditions, engine speed	Shipping company, and CMEMS		0.95	[183]
Weather and current conditions, engine speed	Ship monitoring system	DBN	MRE = 0.3539	[184]

Big data is well-known as an emerging tool in maritime and intelligent transport applications [186]–[188]. Indeed, ship fuel consumption is associated with a large number of ship parameters such as navigational environment [189], sailing state [112], ship loading [190], hull fouling [191], and applied antifouling coating [192], showing that the related data are diverse, complex and huge [193]. For these reasons, the application of big data could provide a foundation for the establishment of a model for ship fuel consumption [58,197]. In recent years, the use of big data combined with ANN and machine learning techniques was considered as a feasible method to predict the ship fuel consumption more exactly [58,198]. As illustrated in Fig. 8, the following four steps are included in the big data analysis process for ship performance and operational efficiency. They include (1) data denoising, (2) data clustering, (3) data compression and expansion, and (4) regression analysis using a neural network [196].

The input data required for big data analysis include a range of time series data, as well as equipment, navigation, and weather-related data. Upon collection of these data, the data cleaning step, also known as data denoising, is essential in eliminating unnecessary noise, bias, and outliers found in the raw data [197]. Within this step, any abnormalities are extracted from the dataset, once detected. Such types of data are identified as any unusually large differences between two adjacent values or any detectable deviation outside of the normal value range of input or output variables that can be confirmed using the domain knowledge about the variables [198]. In the present research, the authors utilised a smoothing algorithm to clean and refine the raw dataset by minimising any discernibly large differences between two neighbouring data values. Data denoising is then followed by the data clustering step, in which the post-cleaning data are categorised based on the high-frequency operation regions using the Gaussian mixture model [199]. After this initial clustering step, an additional silhouette analysis is conducted to validate the prior classification of data according to the operation regions. The resulting number of clusters is then modified several times, until the highest possible estimated silhouette value is attained. The final number of clusters is identified that corresponds to the highest possible silhouette value. In

The ANN model is found to be cheap in computation; however, it does not seem to have any rule for selecting the feature variables or avoiding the overfitting cases in the training process. For this reason, Wang et al. [185] developed a new model to describe the fuel consumption of a specific ship, in relationship to surrounding environments and ship states. Indeed, they used the LASSO regression algorithm to implement the variable selection of feature variables, such as wind speed and wave height, air pressure and wind force, cargo weight and draft etc., with the aim of evaluating the ship fuel consumption, as illustrated in Fig. 7a. More importantly, they compared the performance of the proposed LASSO model with others like ANN, SVR, and GP in predicting the ship fuel consumption. As a result, the developed LASSO model outperformed the others, as depicted in Fig. 7b. Hu et al. [180] employed the back-propagation neural network (BPNN) and Gaussian process regression (GPR) techniques for the prediction of the fuel consumption of a ship. They found that the two above-mentioned techniques could be used to predict the ship's fuel consumption with high accuracy, especially

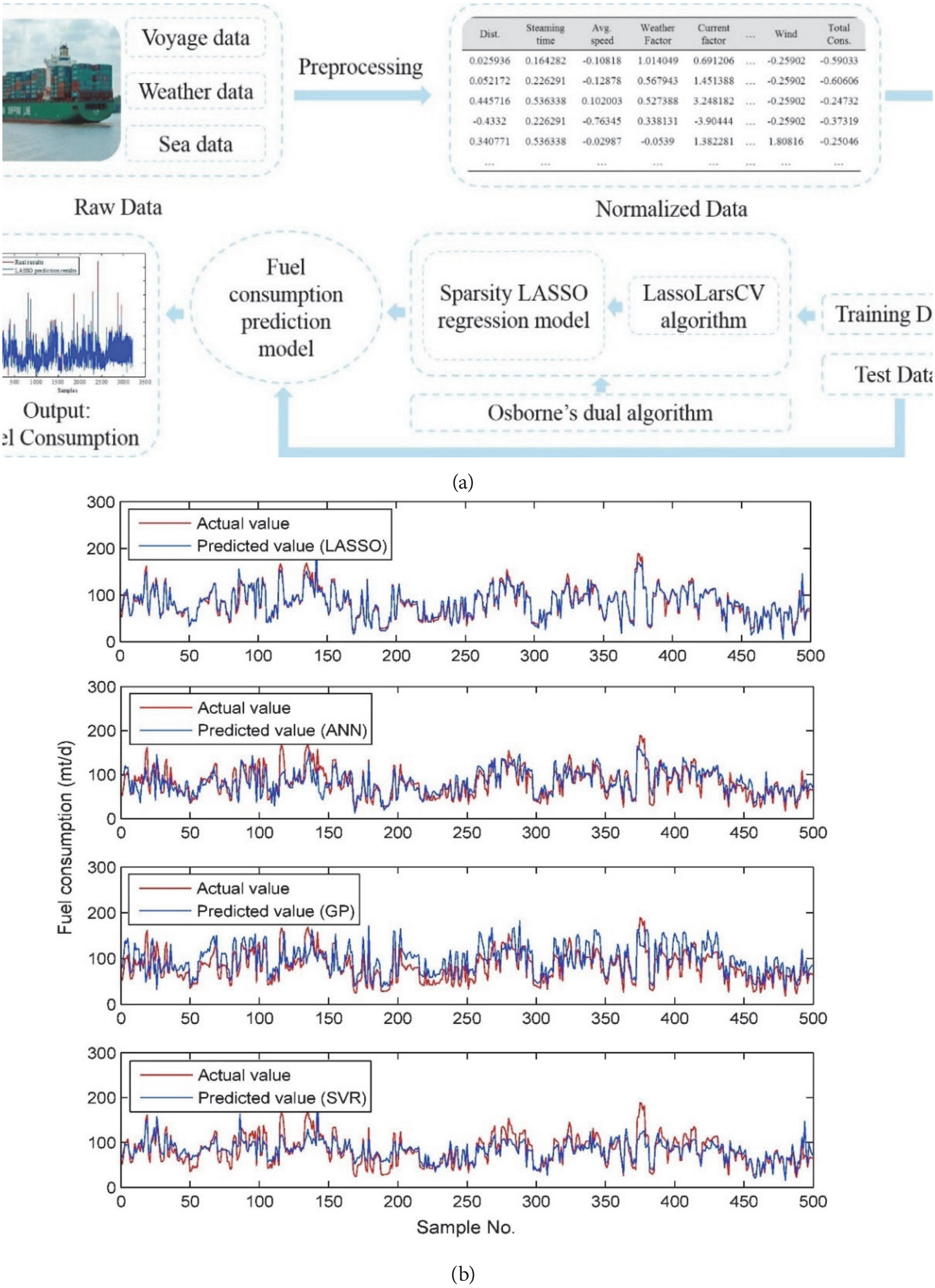

Fig. 7. (a) - Framework for ship fuel consumption based on LASSO regression algorithm; (b) – Comparison of model performance between LASSO and ANN, SVR, and GP [185]

the next phase, compression and expansion processes are performed on the clustered data in order to get them ready for transmission and storage. To ensure minimal data loss, mean squared errors (MSE) are used as a tool to compare the quality of the pre and post-compression datasets. Thus, the MSE between these two datasets is checked against the user-defined

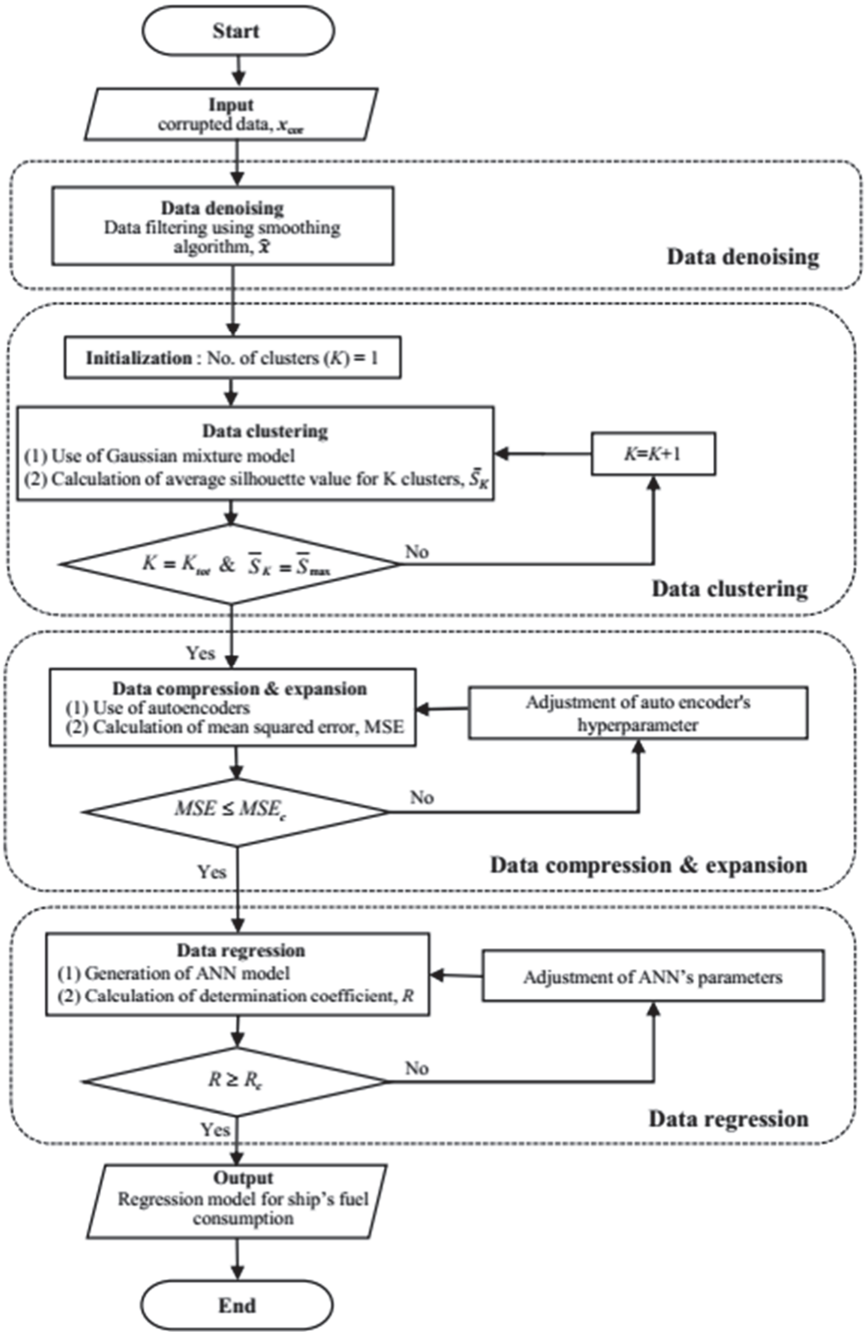

Fig. 8. Big data analysis process for managing ship fuel consumption [196]

MSE. Once the data compression and restoration ratios are examined and the conditions for specific user-defined values are met, the data pre-processing part is complete. Next, the regression analysis is performed using ANN to predict ship fuel consumption. In the process of validating the results, the parameters of the ANN model are modified until the calculated value from the regression function exceeds the user-defined value. The outcome of the analysis provides the regression model for estimating ship fuel consumption.

In recent years, the internet of things (IoT) technology has been applied to the maritime industry with the of improving energy management, ship management, and environmental management [200]. With the integration of IoT technology, the introduction of remote-control systems has allowed for the monitoring of a new generation of smart ships from command centres located on land. With recent advances in IoT technology, the availability of Wi-Fi-enabled sensors mounted on ship equipment and machinery has provided access and continuous collection of a ship's navigational information and operational data [201], [202]. Once collected, this large amount of time-series data must be processed and analysed to reveal insights on ship performance. A big data framework was constructed by Perera et al. [203], which can be used in the pre-processing (e.g. error detection, classification, and data compression) and post-processing (e.g. data expansion, integration verification, and data regeneration) of large volumes of time-series data. In their study, the authors utilised a simple regression model to explain the relationship between the different parameters, despite the lack of verification of the accuracy of fuel consumption data. Because of the high number of dimensions and interactions among variables in most big data analysis, it is important to ensure the accuracy of the final regression model.

CONCLUSIONS AND FUTURE RECOMMENDATIONS

In the present study, a broader literature review has been carried out on developing a prediction model for fuel consumption using ANN. The knowledge gap in the field of research has been addressed. The salient findings of the present review are given below:

1. Most of the present research focuses on machine learning methods to predict fuel consumption with a significant objective of saving energy and reducing emissions.
2. WBMs are suited for conditions with fewer data to process i.e. insufficient voyage data. The workload of the model can be increased by augmenting data sets. So, WBMs can be suited to conditions where the prediction accuracy is not an important factor and voyage data is limited.
3. On the other hand, BBMs can be used effectively and with high accuracy by combining machine learning and

statistics. ANN is one of the most commonly used and accurate methods for BBM. Even though BBMs require highly accurate data, they are preferred for ship fuel prediction applications owing to their reliability.
4. The application of ANN models in predicting ship fuel consumption provides key advantages, including their generalisation and extrapolation capability. From an industrial point of view, the GA-based GBM can be integrated as part of a ship's energy efficiency programs to optimise ship fuel consumption and reduce GHG emissions, as a result of its better predictive capability.
5. The ANN model is cheap, in computation terms; however, it does not have any rule for selecting the feature variables, as well as avoiding the overfitting cases in the training process. As the data collected from the shipping company, for model development, was limited, the accuracy of the prediction model by ANN was affected to a greater extent. These limitations could be overcome by the integration of ANN with other algorithms, such as expert knowledge.

Based on the current status of research into fuel consumption models, the following directions for future research can be proposed:
1. The various alternate sources of marine fuels can be explored. The predictive modelling of data obtained from using alternate fuels can be analysed.
2. The future prediction models may consider additional non-navigational field parameters. Some parameters, such as berth allocation, inventory and market trends, can be added while modelling the system.
3. The fuel consumption models may be integrated with energy efficiency optimisation methods for better results. The developed models can also be used as tools for evaluating the marine vessel fuel consumption study by combining all the factors of cruising.

NOMENCLATURE

ANN	Artificial Neural Networks
GHG	Greenhouse gas
IMO	International Maritime Organisation
LSTM	Long Short Term Memory
BP	Back Propagation
LASSO	Least Absolute Shrinkage and Selection Operator
SEEMP	Ship Energy Efficiency Management Plan
EEDI	Energy Efficiency Design Index
SOx	Sulphur oxide
NOx	Nitrous oxide
PR	Polynomial regression
SVM	Support vector machine
DSS	Decision support system
WBMs	White-box models
BBMs	Black-box models
GBMs	Grey-box models
SPEPs	Sequential parameter estimation procedures
GA-based GBM	Genetic algorithm-based grey-box model
XDi	Decision-making variables
XNj	Uncontrollable input variables
WNN	Wavelet neural network
MLP	Multilayer perceptron
MLP-ANN	Multilayer perceptron artificial neural network
GPR	Gaussian process regression
BPNN	Backpropagation neural network
GMM	Gaussian mixture model
MSE	Mean squared errors
IoT	Internet of things

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