The Development of a Combined Method to Quickly Assess Ship Speed and Fuel Consumption at Different Powertrain Load and Sea Conditions

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ABSTRACT: Decision support systems (DSS) recently have been increasingly in use during ships operation. They require realistic input data regarding different aspects of navigation. To address the optimal weather routing of a ship, which is one of the most promising field of DSS application, it is necessary to accurately predict an actually attainable speed of a ship and corresponding fuel consumption at given loading conditions and predicted weather conditions. In this paper, authors present a combined calculation method to predict those values. First, a deterministic modeling is applied and then an artificial neural network (ANN) is structured and trained to quickly mimic the calculations. The sensitivity of the ANN to adopted settings is analyzed as well. The research results confirm a more than satisfactory quality of reproduction of speed and fuel consumption data as the ANN response meet the calculation results with high accuracy. The ANN-based approach, however, requires a significantly shorter time of execution. The directions of future research are outlined.

1 INTRODUCTION

A growing demand for optimization tools utilized in decision support systems (DSS) in marine navigation may be clearly seen in last decade. The persistently relatively high level of bunker oil prices has encouraged ship operators to search for weather routing solutions that are capable to adjust a ship voyage plan according to a weather forecast and a set of predefined goals. The latter typically include time of passage and fuel consumption mitigation. Thus, modeling of speed and a demand for bunker oil becomes issues worthy investigation.

Scientific efforts both undertaken to examine an interesting and important complex phenomena and, not less importantly, to address a practical problem of a ship resistance, speed and power demand modeling, are not new. A variety of approaches have been implemented over time, including modeling of physical phenomena governing the resistance [14, 27], statistical analysis of relatively numerous group of existing ships [9], some semi-empirical methods [21], Computational Fluid Dynamics utilization [31] and model testes carried out in numerous towing tanks worldwide. Another promising research direction here assumes utilization of Artificial Neural Networks (ANN) to benefit from their capability to deal with multi-input nonlinear systems [6, 20, 22]. Such approach finds its place in marine applications for more than a decade, still being in a phase of dynamic development. ANNs have been already tested for numerous characteristics modeling like for instance cargo carrying capacity of ships [22], hydrodynamic coefficients [22], a ship response to wave excitation [20], a ship stability [6], her structural issues [6, 17], maneuvering capabilities [10] and others. The

resistance and propulsion problems remain within the scope of trial application of ANNs as well [6].

Modelling accurately the ship behavior at sea, accounting for all components of resistance, degraded performance of the propulsion system in unsteady environment, and their effect on ship speed and fuel consumption is a complex task which may lead to poor predictions. Therefore, the ANN-based approach may be handy from the operational point of view. There are some scientific works dealing with ANNs aiming at towing tank resistance results reproduction [7] or marine propeller geometry related phenomena [19]. Some others are even closer to the pending problem we focus in this research. In [26] authors train an ANN on the basis of noon reports that record a ship speed and fuel consumption. The ANN model input variables were speed, displacement, wind force, wind wave height, swell height, sea current factor and trim, though such set of data allows only for a rough estimation of speed and fuel consumption that ought to be referred rather as an average value for a day period. Very similar approach is presented in [13] where some data are measured by sensors and recorded to be supplemented by noon reports. Authors of the study [1] also use quite sparse data recorded by a ship machinery sensors and they finally announce the need for further enhancement of the scope of measurements. Realistic navigation data set obtained from ship operations simulated by a weather routing software are used in [18] to train an ANN for the prediction of a ship speed and fuel consumption.

Taking into account the state-of-the-art, two main observations could be made. First of all the utilization of ANN is promising and more and more frequently applied, worthy to be examined with no doubt. Secondly, the problem of accurate and reliable ship speed and fuel consumption prediction is still challenging and not fully solved. Having the gap identified, we studied the prospect of application the ANN aiming at accurate and quick assessment of a ship speed and fuel consumption with the view on future application in weather routing DSS.

The rest of this paper is organized as follows. Section 2 elaborates on the method adopted to compute predictions of the ship speed and fuel consumption in a variety of conditions and on the ANN development. In Section 3 the obtained deterministic data are utilized to train the ANN, then the accuracy of predictions by the ANN is examined, finally a verification is applied. Section 4 provides discussion on the results, while Section 5 concludes.

2 METHODS

The method applied in this research comprises of two components. Firstly, a deterministic approach is utilized to obtain a set of predictions of the ship speed and fuel consumption in a variety of conditions. That part of the work stems from modeling of physical phenomena related to the ship resistance and propulsion characteristics. The second component of the proposed method includes development of the ANN, its training and evaluation of the outcome.

2.1 Resistance-thrust balance method

Ship performance at sea depends on the amount and distribution of cargo onboard, the meteocean conditions in which it operates, and the command of the engine. The input variables are divided in three categories:

- Loading conditions summarized by the displacement (Δ) and the trim (δT);
- Weather conditions including both waves (significant wave height H_s, peak period T_P and mean relative wave direction χ_m) and wind (relative speed V_{Wrel} and mean wind direction θ_{Wrel});
- Navigation condition given as the revolutions of the main engine (RPM).

The latter assumes the presence of a fixed pitch propeller (FPP) and that the ship speed is controlled by actuating on the RPM of the main engine [30]. Each of the input variables assumes a range of suitable values, where number and resolution is chosen in a trade-off between improving the model accuracy and limiting the computational effort. The attainable speed and fuel consumption are computed for 1.5 million of combinations.

The resistance that the ship must experience at a given speed depends, besides on its form, on the loading and weather conditions being faced. The total resistance obtained as a sum of still water resistance [10], added resistance in waves and wind resistance [12, 28]. The numerical approaches proposed in the literature for the estimation of wave added resistance are often relatively accurate for restricted range of wave directions and frequencies, while tendentially unreliable in others. For this reason a combination of a far-field method [23] for the radiation component in head/bow seas and a semi-empirical approach [16] in following/quartering seas and for the diffraction component is adopted.

A preliminary information required is the specific fuel consumption (SFC) of the engine at different working conditions, namely different combinations of power and revolutions. Manufacturers publicize typically these kind of information only for a limited number of settings, not sufficient to cover all the operative conditions expectable at sea. The SFC is than assessed numerically by an engine model developed in [24] and the appropriate match with the propeller is consequently obtained as described in [25].

For a given value of RPM, and known loading and weather conditions, the following iterative procedure is adopted:
1. assuming an initial value for the ship speed V_S, in this case the design speed;
2. computing the total resistance;
3. computing the brake power and RPM required to achieve this speed;
4. if the latter differs from the given value of RPM, varying the V_S and returning to point 2. until convergence;
5. verifying if the engine can operate at the required settings;
6. obtaining the SFC from the engine model, dividing it by the ship speed and multiplying by the power to get the fuel consumption per nautical mile.

The presented deterministic approach, though feasible, could be hardly found time-effective since

the required effort is 242 minutes to calculate 4.1 million different combinations on Dell server with Intel Xeon 6130 2.1GHz processor and 64GB RAM running Windows Server 2016 operating system. As the number of governing variables is significant and the range of their values is wide, the resultant number of combinations makes the sole application of the deterministic approach impractical in terms of weather routing applications. Thus, the ANN is expected to help.

2.2 *Artificial Neural Network development*

In complex systems, especially in presence on numerous nonlinearities in their characteristics, artificial intelligence techniques find their application. Artificial neural networks (ANN) seem to notice a rapid growth in application among other AI approaches.

There are many different kinds of ANNs. Usually feedforward, convolutional and recurrent ANNs are distinguished [2, 4]. The simplest of them is a feedforward ANN. Convolutional ANNs are applied in more demanding scenarios like image and speech recognition [3]. In recurrent ANNs the presence of loops causes that the input may not determine the output, as it will also depend on the initial state of the ANN. Thus, recurrent ANNs can be used as associative memories [2]. In the case of approximating a multidimensional function the feed forward ANN is sufficient [11, 15]. The size of feedforward ANN to accurately mimic a function is also determined [11]. Choosing the right ANN kind and structure is a key issue to obtain satisfactory results.

Another important issue is to choose the right implementation of an ANN. Of course it is possible to make your own implementation of an ANN, however using a ready one gives an advantage to apply standards and easily exchange data. There are commercial packages including ANNs like e.g. Matlab. On the other hand there are more and more reliable open source solutions. One of them is TensorFlow and Keras [5], which were chosen by the authors for this project. TensorFlow with Keras is versatile and scalable environment supported with Python language. In this environment many different kinds and structures of ANN may be defined, trained and utilized. The scalability means that small cases might be solved on a desktop PC and when they grow the same environment is accessible on servers or in the cloud. Thus, migration to more effective platforms and applying multiprocessing is relatively easy and does not require thorough reorganization of the entire project.

The deterministic calculation procedure described in chapter 2.1 is a multivariable function. The input variable are the journey environmental conditions, ship loading conditions and the engine RPM. The results are the ship speed and fuel consumption. As proved in [15] and [8] a feedforward ANN is enough to approximate a function. To replace our function with an ANN it was necessary to generate a vast set of results using deterministic calculation procedure for the entire spectrum of input parameters. This set was then used to train the ANN. The Keras software was utilized to develop the ANN for that purpose. This feedforward network was named the base ANN and it was intended as the reference network in further undertaken verification process. The base ANN layers settings are presented in Table 1.

Table 1. Number of neurons in each layer of the base ANN

Layer (disregarding layers used for data input and result output)	Number of neurons
1	32
2	64
3	64

The activation function applied in the base ANN was 'relu' type (a rectified linear unit) which is one of the commonly used in ANN application. The mean absolute error was selected as an evaluation function remaining an essential element of the ANN training. All examined ANNs, including the base one, were trained within 50 epochs.

The verification process refers to the uncertainty resulting from adoption of the ANN settings. The validation process aims at assessing of uncertainty with the use of experimental data. In this study only verification was performed as the validation is unfeasible at the present stage of the project execution. Collecting of experimental data is planned at the next stage of the project. Therefore, the sensitivity of prediction accuracy to the following settings was verified:

- the evaluation function utilized during training process;
- the type of activation function;
- number of neurons in each of three layers of the ANN.

The mean error and the standard deviation of prediction were utilized to compare performance of the ANN being modified with regard to each of the listed settings. The results of such verification are presented in section 3.

3 RESULTS AND VERIFICATION

The method described in section 2 was applied to a container vessel. The main particulars of the vessel and the ranges of considered operational variables are summarized in Table 2.

Table 2. Particulars of the considered ship

Length between perpendiculars	175 m
Breadth	25.4 m
Nominal service speed	25 kn
Draft	[8; 9] m
Trim (negative trim by the stern)	[-0.75; 0.25] m

The vessel was assumed to sail in a variety of conditions ranging from calm sea up to stormy weather. The environmental data applied in this study are shown in Table 3. The applied main engine settings with regard to the engine speed covered a feasible range of revolutions per minute (RPM). We assumed the RPM $\in [61; 144]$ min^{-1}.

Table 3. Environmental conditions applied in the research

Significant wave height Hs	[0; 10] m
Wave peak period Tp	[0; 18.5] s
Relative wave angle	[0; 180] deg
Wind speed	[0; 25] m/s
Relative wind direction	[0; 180] deg

The deterministic modeling of the ship speed and related fuel consumption provides a set of data that are pretty difficult for graphical presentation due to the number of input variables. Namely, for each considered loading condition of the vessel, there are six values of governing variables that influence the resultant speed and fuel consumption. Therefore three-dimensional visualization may be shown only for some parameters fixed, like presented in Fig. 1.

Figure 2. Visualization of the base ANN prediction accuracy for the ship speed.

Figure 1. Modeled speed and fuel consumption for the wave direction 180 deg, Tp=10.37 s, draft=9 m and trim=0 m

The full set of the deterministic modeling output data was gathered in multidimensional matrices that were subsequently used by the ANN as the training data set, with respect to random fraction excluded from input to be later utilized for the purpose of evaluation, as described in section 2. The obtained results of the ANN prediction were compared to that share of data left. The visual presentation of the prediction accuracy may be presented in a common way as a projection and a histogram that are shown in Fig. 2 for speed and in Fig. 3. for fuel consumption. The closer results pattern follows the diagonal straight line the more accurate prediction is.
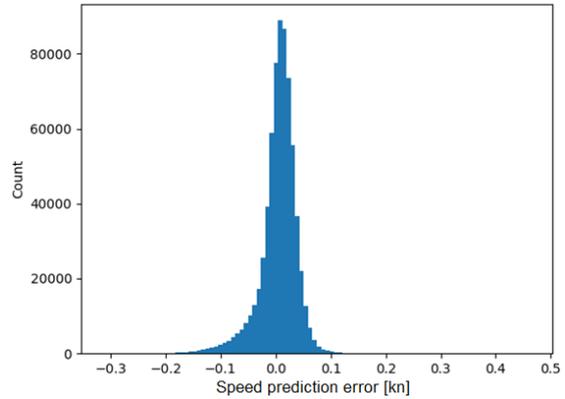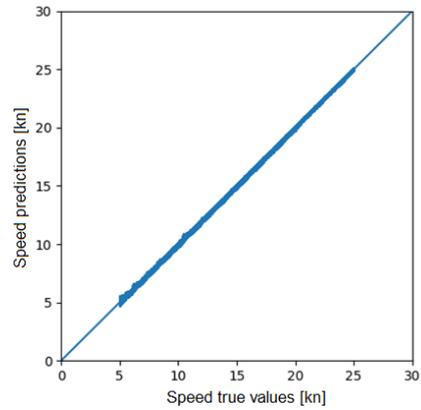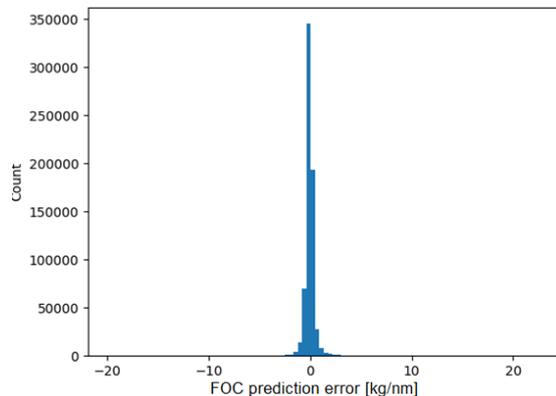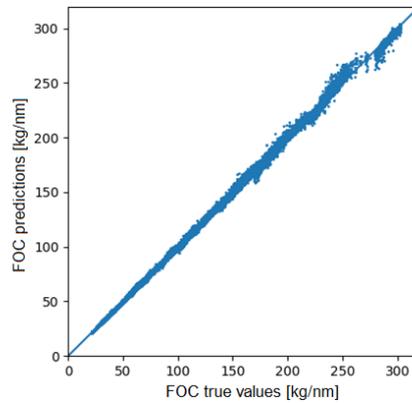

Figure 3. Visualization of the base ANN prediction accuracy for the ship fuel consumption.

440

The obtained results characterized by the mean error of prediction and its standard deviation are listed in Table 4.

Table 4. Accuracy of prediction performed by the base ANN

Predicted characteristics	Speed	Fuel consumption
Mean error	0.006 kts	-0.022 kg/nm
Standard deviation	0.034 kts	0.548 kg/nm

As the base ANN achieved a high level of accuracy the crucial question shall be raised what is the sensitivity of the predictions to different possible settings of the ANN. This problem is address within the verification procedure as described in section 2.

First, the evaluation function was modified. The mean squared error method was set instead of the mean absolute error that was utilized in the base ANN. The result of this modification is shown in Fig. 4.
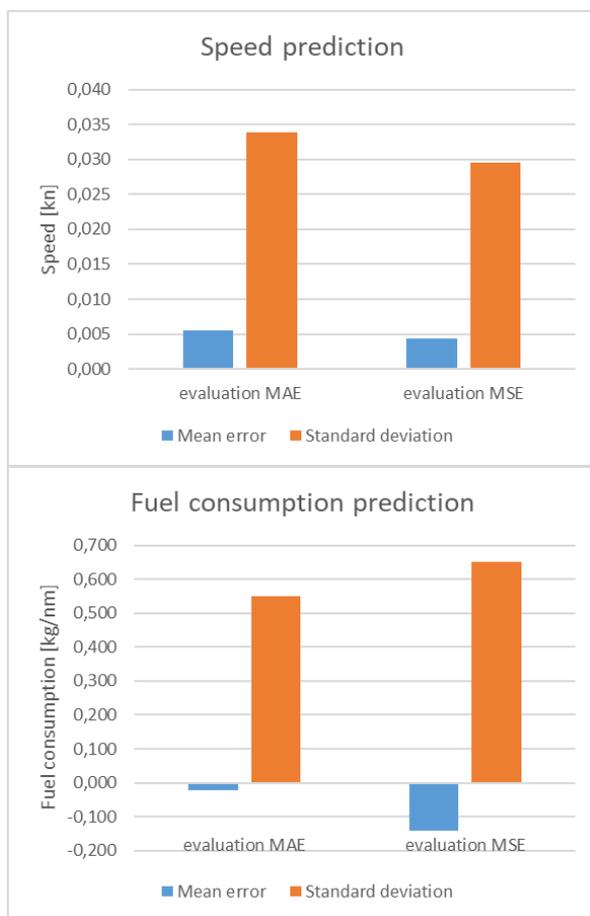

Figure 4. Influence of the evaluation function selection (MAE - mean absolute error; MSE - mean squared error)

The second setting modified in order to reveal the sensitivity of predictions was the type of the activation function. The setting was changed from the rectified linear unit ('relu') to the sigmoidal activation. The effects of the applied modification are shown in Fig. 5.
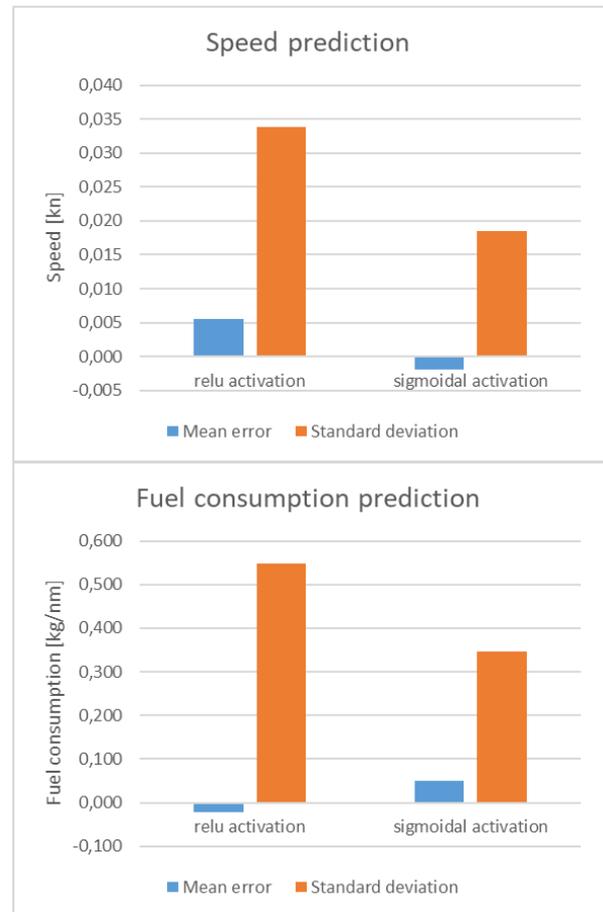

Figure 5. Influence of the activation function selection

The last, though the most thoroughly examined setting applied to the ANN refers to the number of neurons in each layer. The base ANN consisted of three layers, disregarding layers used for data input and result output. The number of neurons was set to 32, 64, 64 for the layers 1, 2 and 3 respectively (as indicated in Table 1). The number of neurons seemed to be massive so for the sake of verification we decreased it dividing those figures by 2, 4 and 8. Eventually, we structured the ANNs with:

− 32 / 64 / 64 neurons;
− 16 / 32 / 32 neurons;
− 8 / 16 / 16 neurons;
− and 4 / 8 / 8 neurons;

where the notation refers to 1st layer / 2nd layer / 3rd layer of the tested ANN. Thus we trained four networks with the use of exactly the same input data set observing potential deterioration of the prediction accuracy that might have been noticed for a dropping number of neurons.

The ANN with the largest number of neurons is the base ANN performing at the accuracy level presented earlier in Fig. 2 and Fig. 3. The network with the littlest number of neurons, counting only up to 1/8th of the base ANN, predicted speed and fuel consumption with the accuracy visualized in Fig. 6 and in fig. 7.
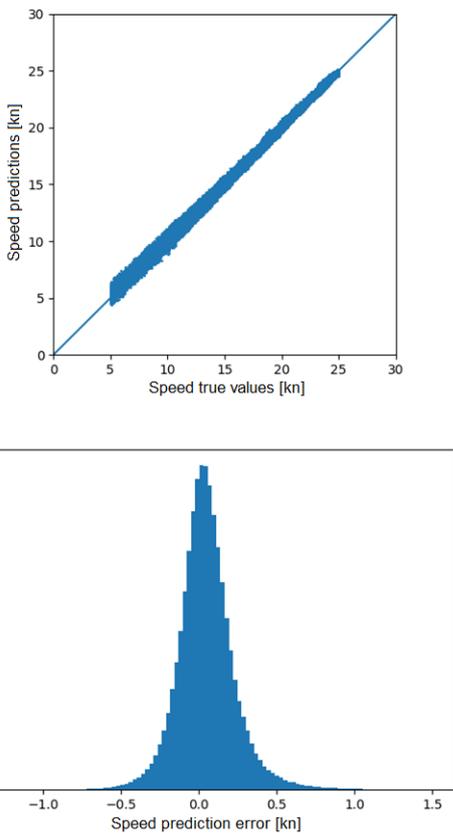
Figure 6. Visualization of the ANN prediction accuracy for the ship speed for the smallest examined number of neurons, e.g. 4 in 1st layer, 8 in 2nd layer and 3rd layer
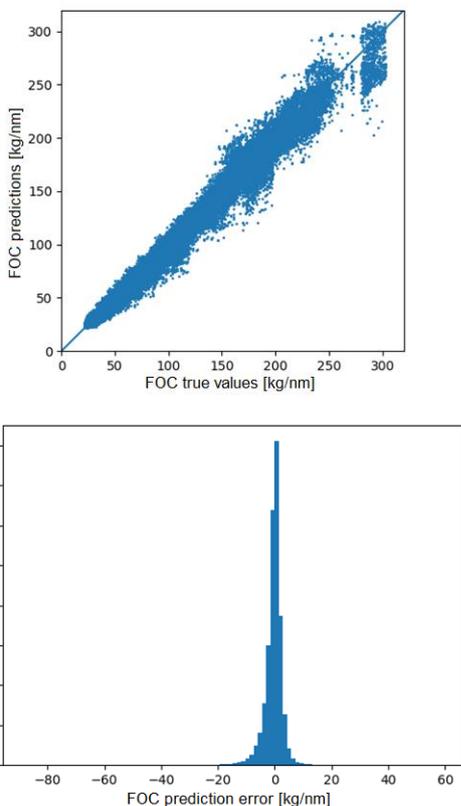

Figure 7. Visualization of the ANN prediction accuracy for the ship fuel consumption for the smallest examined number of neurons, e.g. 4 in 1st layer, 8 in 2nd layer and 3rd layer

The performance of all four examined ANNs with regard to their accuracy indicators is shown in Fig. 8. The observed trend of the rising standard deviation of both predictions (i.e. speed and fuel) with the decreasing number of neurons is dot-line plotted.
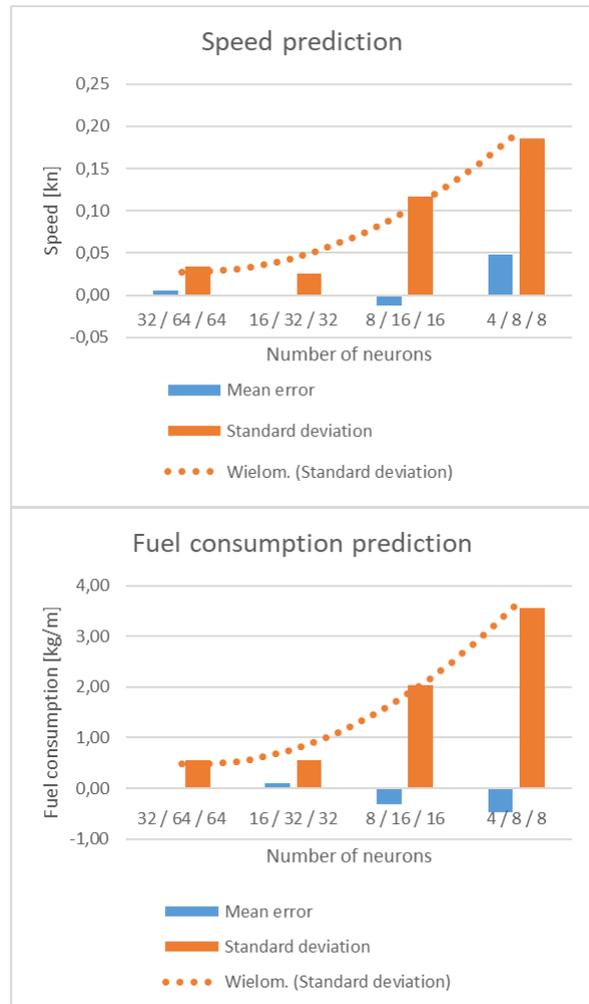

Figure 8. Influence of the number of neurons in each layer (notation: 1st layer / 2nd layer / 3rd layer)

4 DISCUSSION

The obtained results revealed the capability of the ANN to reproduce deterministic input data with an exceptional accuracy. The mean errors were negligible for both the ship speed and the fuel consumption. The standard deviation of the prediction outcome remained more than satisfactory, ranging up to 0.034 knots of speed and up to 0.55 kg/nm of fuel for the base ANN. From the practical point of view the input characteristics were perfectly captured.

Both examined types of the evaluation function applied during training performed similarly well. The mean absolute error (MAE) function produced slightly lower value of the fuel consumption mean error while the mean squared error function (MSE) a bit overcame MAE in terms of the mean error of speed prediction. The standard deviations of the predictions were similar.

The application of the sigmoidal activation function produced a noticeably lower values of the

standard deviation both of the speed prediction and the fuel consumption prediction than the 'relu' activation function. The resultant mean error of the predictions did not vary significantly and in both cases remained close to zero. Thus, we may find the sigmoidal activation performing better out of two examined types.

The most significant impact on the obtained prediction results brought up the modification of the number of neurons. Initially the reduction by factor two did not cause any vital changes in the ANN performance. However, the reduction of the neurons number by the factor four caused the rapid rise in the standard deviations of predictions. They grew about four times in terms of both the speed and the fuel consumption predictions. The further reduction of the number of neurons resulted in peaking the standard deviations of predictions.

However, it ought to be emphasized that the input data characteristics are very regular, thus predictable. The astonishing accuracy was obtained for the input data set coming from the deterministic model, not from real operation measurements, so data were smoothly patterned without any random errors. The validation against real data has not been performed yet at the present stage of the ROUTING (ERA-NET Cofund MarTERA-1) project [29].

5 CONCLUSIONS AND FUTURE WORKS

The research being a part of ROUTING project focused of the capability of the Artificial Neural Network to reproduce the ship speed characteristics and the fuel consumption in a variety of conditions, with the view on application as a prediction tool in a weather routing software. The obtained accuracy of predictions was very high and from the practical future utilization point of view it may be assessed as more than satisfactory.

The conducted verification revealed that both examined evaluation function, i.e. mean absolute error (MAE) and mean squared error (MSE) perform very similar without a clear domination of any of them. The choice of the activation function influences the obtained predictions results to a greater extent. The sigmoidal activation function noticeably overcomes the 'relu' function performance. However, the greatest impact on the predictions accuracy related to the number of neurons used in the ANN. The too excessive reduction of that number reduced the accuracy. Therefore, according to the preliminary results of the study, the most productive settings of the ANN are as follows:
− the mean absolute error evaluation function;
− the sigmoidal activation function;
− the numbers of neurons set to 16 in 1st layer, 32 in 2nd layer and 32 in 3rd layer of the ANN.

The first attempt described here confirmed a potential of the ANN based approach, so the preliminary results justify further research efforts on the ANN utilization for the ship speed and fuel consumption prediction. Moreover, ANNs seem to be very promising due to their capability to learn on data acquired from sensors installed onboard a real ship under actual operation. Combining data from deterministic calculations with data collected during ship voyages and using them to train the ANN may lead to a complex solution that can evolve with time covering a wide range of operational conditions. Once designing the automatic training process, the ANN is expected to become even more accurate when the set of acquired data grows after completed voyages.

However, the actual performance of the ANN has not been yet tested with the use of real data containing intrinsic uncertainties and even sometimes errors due to a variety of reasons. Thus, the future works are required to research on additional settings of the ANN that remain untouched in this study, like for instance the number of epochs and their mutual interaction with the number of neurons, and the performance of the ANN trained on real data acquired in the course of measurements under the ship operation. The results obtained so far encourage the continuation of the research.

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