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APPLICABILITY OF ARTIFICIAL NEURAL NETWORKS TO SQUAT PREDICTION OF VERY LARGE AND ULTRA LARGE CONTAINER VESSELS BASED ON MEASUREMENTS ON THE ELBE ESTUARY

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SUMMARY

An artificial neural network approach to squat prediction was implemented and the results were analyzed. Several artificial neural networks were created and trained on data for 15 voyages of very large and ultra large container vessels that were obtained during a measurement campaign concerned with the dynamic response of vessels on approach to and departure from the port of Hamburg. The artificial neural network was able to reproduce the training data with an accuracy better than +/- 0.30 m. Training the network on a partial dataset and testing it on a different voyage resulted in lower accuracy, with values diverging up to 0.50 m.

NOMENCLATURE

AP	Aft perpendicular
BOA	Beam over all (m)
cb	Block coefficient (-)
FP	Fore perpendicular
GNSS	Global Navigation Satellite System
GPS	Global Positioning System
LOA	Length over all (m)
RPM	Revolutions per minute (1/min)
Stw	Speed through water (m/s)
VDR	Voyage data recorder

1 INTRODUCTION

Artificial neural networks are a family of mathematical models within the framework of machine-learning models. They are based on a number of interconnected units, so-called neurons, which can be trained and subsequently used to classify or approximate arbitrarily large datasets. With recent advances in computer hard- and software their use has become near ubiquitous. Examples include, among many others, image recognition, biometrics, disease forecasting [1], prediction of estuarine salinity, stock market prediction [2], load forecasting for power grids [3], autonomous vehicle control and genome sequencing [4].

Ship squat is an effect that is nonlinearly dependent on a number of environmental circumstances. Since artificial neural networks have been used successfully to approximate similarly nonlinear relationships, their application to squat-prediction should be possible.

To achieve high levels of accuracy and reliability with these models a large and comprehensive amount of training data is required. During a measuring campaign for the German Federal Waterways and Shipping Administration (WSV) in cooperation with the Federal Waterways Engineering and Research Institute (BAW) concerning the behavior of large container vessels during their passage of the Elbe estuary Consulting Engineers von Lieberman collected a large amount of data pertaining to these voyages. These data are used as a basis for training several artificial neural networks and for evaluation of their performance as predictors for ship-squat.

2 DATA

2.1 DESCRIPTION OF COLLECTED DATA

During the measurement campaign data for 21 voyages of different types of vessels were collected. The vessels were selected from 7 classes relevant for the current traffic on the Elbe River. For most of these classes, two outbound voyages and one inbound voyage were surveyed. Among these classes were five classes with a vessel length larger than 300 m. This study concentrates on these vessels. Table 1 shows an overview of the classes with major dimensions.

Table 1. Classes of vessels

Class name	LOA [m]	BOA [m]
C335	335	42.8
C347	347	45.2
C366	366	51.2
C396	396	53.6
C400	400	58.6

Due to operational constraints, one outbound and two inbound voyages were observed for the C347-class.
The data collected on each voyage included

- GNSS and GPS position measurements of 6 antennae that were attached to the vessels (4 GNSS antennae, 2 GPS antennae) and recorded positions with a frequency of 2 Hz and 1 Hz respectively
- Salinity and water flow measurements, measured from a convoying vessel with a frequency of about 1 Hz
- VDR recordings of operational parameters (rpm, wind measurements, rate-of-turn etc.)

- Vessel dimensions and hydrodynamic parameters as described in the stability book (draught-dependent measures, derivatives and coefficients)
- Precise determination of actual freshwater draught

After thorough validation tests, all time-dependent variables were interpolated to 2 Hz and an equal timestamp to achieve data consistency and useable time series was applied.
Based on this data collection, additional parameters, such as vessel speed and heading, heel, trim and change of draft and trim were calculated and included in the database.

2.2 SELECTION OF DATA USED FOR NEURAL NETWORK DESIGN

Due to different reception conditions, GNSS post processing did not always result in positions of an adequate quality for a reliable analysis. Possible causes for this include atmospheric effects, local sources of electromagnetic interference or segments of the voyage with limited availability or unfavorable constellations of visible satellites resulting in lower quality observations. Because the measurements were made on a moving vessel, individual measurements could not be repeated to improve the quality. This made it necessary to limit the datasets that were used for training and analysis of the artificial neural networks to a subset of the collected data. Therefore, only database records with 4 or more available antennae of sufficient quality for position and attitude determination were used.

Of similar importance was limiting the data used for training to parameters that were not correlated to the variables that were to be predicted, i.e. squat at the forward and aft perpendiculars. This necessitated exclusion of e.g. the under-keel-clearance that was obtained from the dataset.

To avoid training the network to recognize only certain classes of ships, variables that varied discretely with those classes, e.g. ship length and beam, were also excluded from the training sets. With the perspective of possible future use for immediate squat forecasting aboard the vessel an effort was made to consider only variables that were both readily available to the ships command crew and characteristic for influencing squat behavior.

The variables selected for training were

- Position along river
- Course over Ground
- RPM
- Rudder angle
- Width of swept track
- Speed through water
- Trim angle
- Heel angle
- Water depth
- Water body cross section
- Draft or $c_{B,}$ alternatively

From these variables a number of combinations were tried as input parameters for the network.

Only data sections where all selected variables were recorded were used for inclusion in the input data. Timespans where vessel interaction and mooring took place were excluded from the data as well.

All of the above led to a significant decrease in available data points, resulting in a total of slightly over 500,000 from originally 835,000 data points, amounting to roughly 60% of the recorded data, which formed the basis for network training and analysis. While these are considerably less data than originally collected, it is still a large enough amount to expect artificial neural networks with a good performance as a predictor. Figure 1 shows a sample of the data consisting of the parameters speed through water, trim and squat at FP for a segment of the voyage, plotted against river kilometers. The visible gaps in the data are a result of either vessel encounters or reception problems.

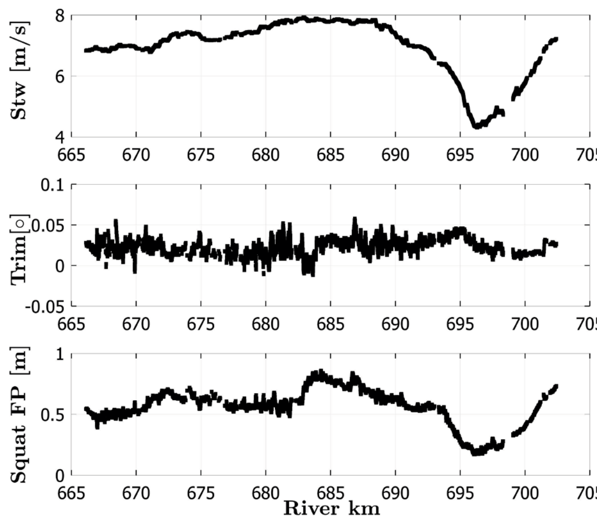

Figure 1. Squat results (sample) obtained during campaign

3 NETWORK ARCHITECTURE, TRAINING AND MODEL SELECTION

3.1 INTRODUCTION TO ARTFICIAL NEURAL NETWORKS

Since a lot of material is available on the basic concepts of artificial neural networks, only a brief introduction is provided. A more in-depth introduction can be found e.g. in [5].
An artificial neural network consists of nodes, so-called neurons, which are usually organized in different layers. Numerical values are passed between these nodes

according to specific rules that define the network architecture. Each node has an activation function that determines its output based on the value of the input. The inputs to a node are assigned weights and bias functions that are changed during the training phase to optimize the network's output to achieve an accurate representation of the training data. The layers are called hidden layers if all inputs and outputs to and from these layers are only to other layers of the network, as opposed to external inputs or outputs of values.

Observed errors between the predicted outcome and the provided training outcome are used to adjust the weights and biases during the next iteration. Several algorithms have been developed for this purpose. After a stopping criterion is reached, training is considered to be finished. If a division of the available data into a training set and a test set was made before training began, the network's performance as a predictor can be estimated by analyzing the error that it produces using the test set.

A commonly used type of artificial neural network is a feed-forward network. In this network architecture, the values resulting from each layer are passed along to the next layer, and each sample of the dataset is treated as independent of previous or following samples.

Another type of network are recurrent neural networks. In this type of network, node values or outputs that were obtained from the network can be fed back into the network or into network layers as additional inputs that augment the samples by conveying information about the state of the network during application to the current or previous samples of the dataset. This makes it possible to use the network for the analysis of time-series, including the analysis of time-lagged effects of input parameters. To further illustrate this distinction, the treatment of RPM in the two network types is given as an example. In the regular feed-forward network, the RPM value for one sample, i.e. the collection of data for one timestep, is passed from the input layer to the hidden layer. In the hidden layer, an output is calculated based on these values and the weights and activation functions of the neurons and passed on to the neurons of the output layer. The neurons of the output layer calculate the final output for this timestep from these values. Intermediate values or the final result of this timestep do not influence the treatment of the next sample. Consequently, in this type of network, squat is only being influenced by the current RPM-value. In a recurrent network, these steps are identical, but in addition to the input based on the measured data, the outputs of the hidden layer or the final results for one timestep can be stored and used as additional input variables for subsequent samples. This way, previous RPM values can influence the result for a later sample. Other network types include e.g. networks where the number of nodes per layer is not fixed but adjusted during training.

3.2 NETWORK ARCHITECTURE

The artificial neural network used in this study was a simple two-layer feed-forward artificial neural network created using Neural Network Toolbox of MATLAB [6]. It consisted of one hidden layer and one output layer. The hidden layer consisted of neurons with a hyperbolic tangent sigmoid transfer function. The number of neurons on the hidden layer was kept constant during training, but several networks with a different number of neurons on the hidden layer were trained as a basis for a comparison between them. The output layer consisted of two output neurons with a linear transfer function. The outputs of these two neurons were selected to be squat at FP and AP, respectively.
The training algorithm used was the MATLAB default Levenberg-Marquardt backpropagation algorithm with validation based early stopping.

3.3 NETWORK TRAINING

For training the neural network, different approaches were used. The first approach involved training of the neural network on a dataset including all voyages. The datasets for each training session were split into three subsets, the training, validation and test set. Splitting was done randomly to create sets with a previously specified sample percentage.
For the second approach, subsets of vessels were created that contained only voyages of vessels belonging to one class. This was done to arrive at conclusions as to whether networks trained on subsets can be used to make predictions about different subsets and if networks that were trained on two voyages for one vessel type could be used to arrive at better predictions for the third voyage than networks trained on datasets including different vessel classes. The datasets were split in a way similar to the divisions for the first approach. Additional testing was performed using data not included in the initial selection.
For all approaches the training data were normalized in a preprocessing stage to span the interval [-1, +1] to improve training performance and avoid numerical errors.

3.4 MODEL SELECTION

In terms of artificial neural networks, model selection describes the process of evaluating which one of several trained artificial neural networks produces the best results with regard to the test data. This includes comparisons between networks of different sizes, the use of different input parameters and different training runs. In this study, several networks with different numbers of neurons in the hidden layer were tested. In addition, different combinations of input variables were used for training. Evaluation of the artificial neural networks was performed by comparing the results of the network with measured squat data. To avoid overfitting the network to the training data, an upper limit for the hidden layer was set at 15 neurons. Using less than 10 neurons resulted in a decrease in accuracy with no apparent improvement in generalization of the network to out-of-sample data. The input parameters were chosen to give as adequate a representation of possible influences as possible. The inclusion of the vessels' position along the river, for instance, was selected to address possible localized phenomena that were not covered by the other variables, such as river bottom structure or influences of river tributaries.The best results on the training set were obtained from a network with 10 hidden nodes and all input parameters mentioned in 2.2.

4 RESULTS

The study yielded mixed results. While on the one hand a good approximation of the observed data was possible using the artificial neural network approach, the use for predictions on different inputs than those used for training resulted in moderate to large errors.

Figure 2 shows a section of the comparison between measured and predicted ship squat at FP for the network that was trained using all but 15% randomly selected data for training. The differences in this section of the data are between 0.05 m and 0.10 m. Figure 3 shows a histogram of the differences between predicted and measured squat at FP for the whole dataset. As can be seen, most differences have a magnitude between +0.30 m and -0.30 m, with the majority lying between +0.10 m and -0.10 m.

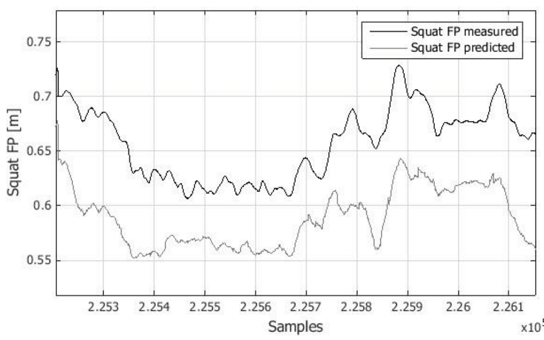

Figure 2. Comparison measured vs. predicted squat FP

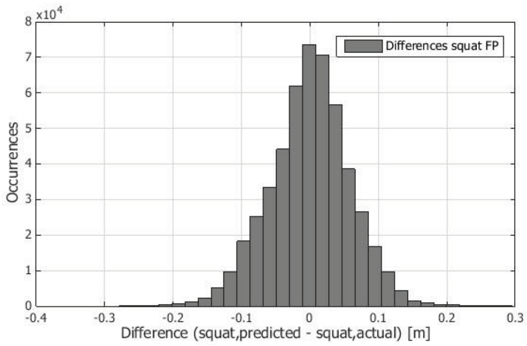

Figure 3. Differences between predicted and measured squat FP

Figure 4 shows the squat prediction of a network trained on data for two voyages of the C400 class for the third voyage of this class in comparison to measured squat data. The differences in this section of the comparison show a wider spread than the differences in figure 1, in a range between 0.00 m and 0.25 m. In Figure 5, the histogram for these differences shows a spread of the differences that is about equal to the spread visible in figure 2, but with a different distribution. While squat is underestimated for only a few data points and only up to -0.15 m, a marked overestimation of the actual squat is evident, with a considerable percentage of values more than 0.20 m up to 0.50 m larger than the observed values. Similar results were obtained for different classes and inter-class comparisons.

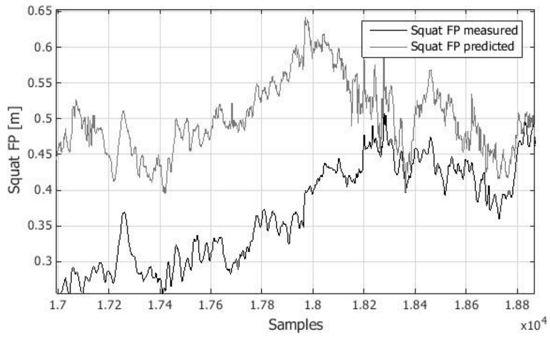

Figure 4. Comparison measured vs. predicted squat FP, C400

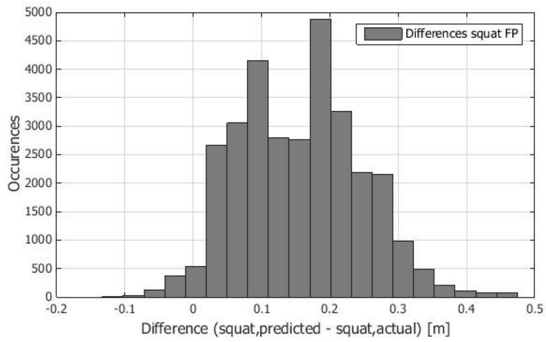

Figure 5. Differences between predicted and measured squat FP, C400

5 DISCUSSION OF RESULTS

One cause for the failure to accurately predict squat for voyages other than those on which the network was trained were parameters with values outside of the range on which the network was trained. For example, vessels with drafts larger or smaller than the drafts included in the training data showed squat behavior that differed markedly from the squat predicted by the network.

Another possible cause for the failure to accurately predict squat may have been a non-optimal choice of input parameters, by neglecting other influences on squat behavior, such as e.g. immersed ship cross-section or different ship specific parameters.

6 OUTLOOK

To further investigate the applicability of artificial neural networks in the context of squat prediction a number of additional approaches to network design should be tried. One approach the authors plan to pursue is the use of recurrent artificial neural networks in order to cover possible time-delayed influences. Additionally, different selections or other combinations of input parameters will be considered and their influence investigated, e.g. the use of Froude-numbers.

Other possible avenues of research include different network architectures with additional layers or only partially connected layers, separate networks for squat prediction at the individual perpendiculars or using several networks for prediction and averaging their outputs.

The inclusion of different types of vessels in the future is also desirable. However, this would be dependent on the procurement of an adequately large database containing possible training data for individual ship types. A first step in this direction could be testing the models on data acquired for bulk-freighters in the context of the squat-study this paper is based upon. However, the cb-values of those ships lie far outside the values that were available for training the container vessel model, which makes a direct applicability of the model for those vessel types rather unlikely.

After a sufficiently accurate artificial neural network model has been found, knowledge discovery techniques for neural networks could be utilized. A first approach could involve gradually reducing the input parameters until a good prediction is still possible, in order to determine the main factors influencing the prediction of squat behavior in the context of these artificial neural networks.

7 CONCLUSIONS

While this study highlighted some of the difficulties of using artificial neural networks for the prediction of ship squat, the authors remain optimistic about the potential of this family of machine learning models. With the artificial neural networks that were created and trained during this study, Squat prediction with an accuracy of 0.5 m could be achieved in a large number of cases. This kind of accuracy must be considered insufficient for practical applications; it is however an encouraging result considering the simplicity of the model used in this study. Further refinement of the network type, architecture and input parameters is expected to improve prediction accuracy.

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