Estimating Maneuvering and Seakeeping Characteristics with Neural Networks

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Maneuvering and seakeeping are two very important naval architecture research areas. There are several methods to determine a vessel’s behavior, but most of them are time-consuming, apply linear techniques or introduce several simplifications. This paper proposes to apply feed-forward neural networks to predict maneuvering behavior in the design phase or following changes on a new design. The feed-forward neural network is trained using sea maneuvering trials data of similar vessels. In order to prove this hypothesis, the method is applied to a set of 47 maneuvering trials from two different vessels, obtaining a standard error of 6.61%, which compares favorably with conventional methods.

Keywords: Maneuvering, Feed-forward Neural Networks, Non-linear Modeling, Turning Circle, Steady Turning Diameter

I. INTRODUCTION

Today, in order to have a successful ship design, maneuvering and seakeeping performances have to be taken into account from her initial sizing up to delivery to the owner. Nowadays, ships are no longer just a platform to carry goods or where people travel because there is no other mean to do it. Instead, some vessels are applied in several tasks that may require for them to be a stable platform, which lead to the development of several standards such as acceleration limits for launching a craft or operating a helicopter, among others. Simultaneously, bearing in mind the safety of navigation, the International Maritime Organization (IMO) released the “Interim Standards for Ship Maneuverability” in 1993 [2], with their final adoption in 2002 [3].

Both for seakeeping and maneuvering prediction there are several methods such as the strip theory [4] and the classical maneuvering theories [5]. Nevertheless, most of the classical methods are very time consuming and, in many cases, it is very difficult to use them to model non-linearities.

On the other hand, in order to have a simple and quick method to solve seakeeping and maneuvering problems, feed-forward Neural Networks can be used. There are some references that present neural networks applications in this field of expertise. Recursive Neural Networks (RNN) have been used to simulate submarine manoeuvres [6] and to simulate turning and zig-zag manoeuvres of surface ships both using model tests and real data from sea trials to train the network, as presented in [7], [8] and [9], where errors between 5 and 10% were obtained.

Differently from previous works, the aim of this paper is to use neural networks as a design tool, or as a control tool during construction once the model tests have already been done. In fact, neural-networks can be trained with data gathered during sea trials or model tests and then used to predict the vessels’ performance.

This work starts with a review of the classical methods applied to ship motion prediction and the presentation on how neural networks can be applied to determine them. Secondly, a specific application to maneuvering prediction is discussed, characterizing the neural network architecture and the variables used in the determination of tactical diameters. Next the results of the steady turning diameter study are presented and compared with some values calculated using the classical method with empirical expressions to estimate stability derivatives. Finally some conclusions are reached and future development is discussed.

II. MOTION PREDICTION

Traditionally, it is considered that a vessel moves in waves around three Cartesian axis with six degrees of freedom coupled with each other, i.e. surge (x), sway (y), heave (z), roll (φ), pitch (θ) and yaw (ψ) [1]. These motions are excited by external sources, such as waves, wind, etc, or by the operator of the ship himself, by acting on her propulsion or appendages such as the rudder. In the first case, it is said that it is a seakeeping problem, while in the second case it is a maneuvering problem.

![Fig. 1. Vessel motion around Cartesian axis (6-degrees of freedom)](image-url)
The equations of motion can be expressed analytically as in (1):

\[
\sum_{j=1}^{6} \left[ (I_{j} + A_{j}) \ddot{s}_{j} + B_{j} \dot{s}_{j} + C_{j} s_{j} \right] = F_{j} \quad \text{where } j = 1, \ldots, 6
\]

where the excitation forces \( F_{j} \) are related to the inertia forces \( (I_{j}) \), added mass \( (A_{j}) \), damping \( (B_{j}) \) and stiffness \( (C_{j}) \) for each motion coupling (\( j \) and \( k \) stand for the different degrees of freedom).

Using these equations, it is possible to derive transfer functions between excitation forces and the ship’s response to them, commonly known as RAO (Response Amplitude Operator).

Unfortunately, it is very difficult and time consuming to obtain good RAO estimates for real ships. Strip theory has been used extensively to solve seakeeping problems, but besides being very time consuming, it requires many simplifications, such as the assumption that some of the degrees of freedom are un-coupled and that the system can be linearized [4].

Maneuvering problems for surface ships are usually solved applying the classical method based on considering only two coupled motions, yaw and sway, and small motion deviations. Expression (2) represents the linearized equations of motion for yaw moment \( (N) \) and sway force \( (Y) \) obtained by the above:

\[
\begin{align*}
\left[ (m - Y) \ddot{Y} - Y_{r} \dot{r} - Y_{v} (mU - Y_{f}) r = Y(t) \\
- N_{v} \ddot{v} + (I_{r} - N_{r}) \dot{r} - N_{v} \dot{v} - N_{r} r = N(t)
\end{align*}
\]

where \( m \) - constant mass of the ship; 
\( v \) - sway velocity; 
\( r \) - yaw angular velocity; 
\( U \) - ship’s velocity; 
\( I_{r} \) - second moment of area about the z axis; 
\( Y_{f} \) - force against sway; 
\( Y_{v} \) - added mass due to sway acceleration; 
\( Y_{r} \) - sway force due to yaw velocity; 
\( Y_{r} \) - sway force due to yaw acceleration; 
\( N_{v} \) - yaw moment due to sway; 
\( N_{v} \) - yaw moment due to sway acceleration; 
\( N_{r} \) - moment against yaw; 
\( N_{r} \) - added mass due to yaw.

However this approach is not able to model several non-linear problems such as tight turns, maneuvering in extreme astern seas, or maneuvering in shallow waters. To obtain better results in some problems, some authors ([10] and [11]) propose a non-linear theory using Taylor’s expansions up to third order terms. Further, there are other theoretical developments that can be followed in the ITTC maneuvering reports, such as reference [12], whose review is beyond the scope of this paper.

Alternatively, there are several model trials to determine the stability derivatives of a vessel that characterizes her maneuverability, or tank tests with self propelled models in order to find the response of the vessel to a set of waves. However, in these tests it is required to bear in mind model-ship correlation errors (scale-effects) that are out of the scope of this study.

All in all, though these methods provide, in most cases, accurate data, it is accepted that they are time consuming, of difficult application and not able to model some non-linear phenomena. Hence, it would be very useful, especially during the design process, to have a fast and reliable way of estimating the performance of different ship configurations, avoiding the effort required by the traditional methods mentioned.

In this paper, we show that neural networks are able to fulfill these requirements. It will be shown that this method may be used to find the response of a ship to certain maneuvers, based on data of the same vessel or different vessels, thus determining the vessel behavior without explicitly solving the equations of motion.

Further, we show that the diameter of steady turning circle of a vessel can be determined with the same accuracy, or even better, using this approach than with the traditional methods and empirical expressions to determine the stability derivatives of the vessel.

In particular, this problem was selected for its simplicity and because no external forces are present, being able to evaluate the method by itself without any uncontrolled error sources.

### III. CLASSICAL THEORY APPLICATION

The turning circle test is one of the trials specified by IMO in reference [2], which aims to check the turning ability of a ship. In this context, the diameter of steady turning circle can be defined by the diameter described by the ship motion following application of the rudder, once the speed and drift stabilize after an initial period of transient motion.
Perpendiculars of the vessel, where by providing pairs of input-output values. The training process of the neural network will use this data to adjust the values of the connections between elements (weights), in order to match the pre-defined targets.

A neural network architecture was defined in order to determine the diameter of steady turning circle from an input vector formed by 15 different variables, and is presented in fig. 3.

This architecture was selected among others, with more neurons in the hidden layer, since it provided the best fit for the data that is going to be presented.

To implement it, the software “Enterprise Miner” from SAS 8.1 has been used. To train the data, it was decided that 70% of the data would be used for training and the other 30% for validation. The validation set was used to determine error that, in fact, makes the error estimates slightly optimistic. However, since at this time the amount of data available is rather limited, this was considered an acceptable compromise.

As far as the input variables are concerned, at this stage of the work development, it was decided to introduced almost all data known for each trial namely: displacement (∆), length (L), beam (B), draught (T), trim (t), block coefficient (C_b), rudder angle (δ), rudder area (A_R), longitudinal rudder position (L_R), number of rudders (1 in all cases), longitudinal position of the center of gravity (LCG), vessel speed (U), metacentric height (GM), side to which the vessel turns (A_Z), and the wind force applied to the areas above water line (F_W).

The first six variables are the ones normally used in the empirical expressions to determine stability derivatives, though there are other formulations, which use some other parameters, such as the fullness forward and fullness aft. The next four are the rudder parameters, followed by the longitudinal position of the center of gravity used to determine the rudder’s yaw moment influence.

Next, there are some variables that aim making the model able to represent more accurately the maneuvering trials:

\[ R = \frac{Y'_1 N' - N'_1 Y'}{N'_1 Y'_2 - N'_2 Y'} \]  

where \( R \) is the turning radius, \( L \) the length between perpendiculars of the vessel, \( \delta \) the rudder angle.

The other coefficients have been non-dimensionalised, and may be determined considering that each one of the stability derivatives can be determined by adding different components, such as the ones that account for the ship’s bare hull including trim effects (\( \tau \)), rudder (\( \phi \)) and other appendages (\( \phi \)), as presented in expression (4).

\[
\begin{align*}
Y' &= \left( Y' \tau \right)_{\text{bare hull}} + s Y' + \rho Y' \\
N' &= \left( N' \tau \right)_{\text{bare hull}} + s N' + \rho N' \\
Y' &= \left( Y' \tau \right)_{\text{bare hull}} + s Y' + \rho Y' \\
N' &= \left( N' \tau \right)_{\text{bare hull}} + s N' + \rho N'
\end{align*}
\]  

In the literature there are several regression techniques available to determine the bare hull coefficients, such as the ones presented in [13], as well as others to determine the different appendages effects. Since the sea trials data that are available for comparison are from warships maneuvering trials or similar, it has been found that the formula presented in [1], with the trim corrections taken from [14] produces good results.

As far as the rudder effects are concerned, the values may be determined by estimating the rudder lift coefficient from rudder force values determined using empirical formula developed in Hasslar towing test tank as a function of the number of rudders, number of shafts and their position relative to each other, as in [1].

One of the characteristics of this formulation is that all the stability derivatives calculations are speed independent. This is considered to be correct for moderate Froude numbers [15].

IV. NEURAL NETWORK APPLICATION

Artificial Neural Networks are a mathematical model, inspired by the observation of biological nervous systems. Basically, a neural network consists of a number of units (called neurons) that receive inputs from other units, process them, and pass the results on to other units. A neural network may have many units that may operate in parallel, thus performing complex operations. Although there are many different types of neural network, the most widely used are the feed-forward multi-layer perceptrons, or MLP. These consist of three or more layers: the input vector, hidden layer(s) and the output layer. Each one is formed by a set of processing units connected by their inputs to all units of the previous layer.

The network can be trained to perform a particular function by providing pairs of input-output values. The training process
Metacentric Height - It is possible to verify in model tests that when a model is prevented from rolling as it turns, a much larger diameter is observed. Nevertheless, the change may not be significant in most vessels.

Side to which the vessel turns - This parameter has been added due to the fact that some ships have a significant tendency to produce a tighter diameter when turning to one of her sides. This characteristic may be of no relevance for most of the ships, namely for this particular application. Nevertheless, for a specific neural network trained only for one ship this parameter has to be considered.

Wind force applied to the areas above waterline - About this parameter, reference [3] states that wind, waves and current can significantly affect trial results, hence, this parameter is used to introduce the wind effects. Nevertheless, the available data did not provide significant wind values to study its real influence.

V. EXPERIMENTAL DATA

The data used in this paper is from five sets of full-scale maneuvering trials for two different vessels, including 56 turning circle maneuvers, done during the 90’s decade. The evaluation of these trials was done by the Navigation Division of the Portuguese Hydrographic Institute.

These tests were selected among several others due to both ships having only one rudder, but on the other hand having quite different dimensions. Therefore, if this method could predict the steady turning diameter for both vessels, the hypothesis of applying neural networks in maneuvering assessment would be proven.

First, an analysis was done on the available data, and it was found that nine of those tests were not reliable due to the large difference between their diameter and diameters obtained in similar tests. Hence, 47 trials were retained: 11 of them are from a hydrographic vessel (Vessel A) and the remaining 36 from a warship (Vessel B).

This set of data includes trials done at different speeds, load conditions and for several rudder angles, where Froude number varies from 0.1 up to 0.5 (0.1 ≤ Fn ≤ 0.5) and the relation between diameter and vessel length varies between 3.5 up to 14 (3.5 ≤ D/L ≤ 14).

VI. DIFFERENT METHODS COMPARISON

For the maneuvering trials described above both procedures presented in chapters III and IV have been applied to predict the steady turning circle diameters.

As previously discussed, the aim of this work is not to simulate the maneuver; rather, it is to develop a simple tool for previous stages of design and to be able to follow changes in maneuvering characteristics during construction, caused by design changes.

The errors obtained are presented in table 1. The table shows the averages and maximum errors obtained for all the trials, for the trials of vessel A and B separately.

<table>
<thead>
<tr>
<th></th>
<th>Neural Network</th>
<th>Classical Theory</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Average Error %</td>
<td>Max. Error %</td>
</tr>
<tr>
<td>All Trials</td>
<td>6.61</td>
<td>20.52</td>
</tr>
<tr>
<td>Vessel A</td>
<td>6.77</td>
<td>16.71</td>
</tr>
<tr>
<td>Vessel B</td>
<td>6.56</td>
<td>20.52</td>
</tr>
</tbody>
</table>

From the table, both the average and maximum errors estimations using the classical theory application are larger than the ones obtained using the neural network implementation.

In figures 4 and 5 the errors for each run are plotted against Froude number (Fn) and non-dimensional diameter (D/L).

Comparing the errors against Froude number, as far as the classical theory application is concerned the highest errors are for a large Fn. Nevertheless, since the errors vary for all Fn values, it is not possible to conclude that neural networks are
better in predicting the steady turning diameter than the classical theory as a function of $Fn$ difference, at least in this interval.

On the other hand, for most of the turns with low values of $D/L$, the neural networks seem to be able to predict more accurately the steady turning diameter.

In fact, vessel’s behavior in tight maneuvers is non-linear and therefore, classical theory, which is linear, is not able to predict them accurately. In contrast, the neural network implementation was able to predict with the same accuracy independently of $D/L$ relation. After all, neural networks are known for having an amazing ability to track non-linear behavior.

**VII. Conclusion**

The results of the steady turning diameter estimated using the neural networks application are as good as, or even better, than the results obtained using the classical maneuvering theory with the empirical expressions selected.

In fact, for the non-linear tight maneuvers the neural network accuracy is always better than the classical method. Furthermore, in both linear and non-linear regimes the neural network developed is the same, which is an advantage against having two methods, one for each regime.

All in all, the hypothesis of using neural networks for maneuvering prediction was validated. Nevertheless, further research must be done so as to prove that neural networks can be used both for maneuvering and seakeeping predictions.

**VIII. Future Work**

As stated in the conclusion chapter, there are several tasks that require attention and that will be dealt with:

1. gather new data and analyze it using the neural network application;
2. analyze each variable and include the environmental conditions as an input variable;
3. transform the method in order to predict other maneuvering trials;
4. validate the method against sea trials of a new vessel design;
5. implement the method as a bridge support tool for navigation safety;
6. apply the method to multi-hull maneuvering problems;
7. apply the method to seakeeping problems.

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**REFERENCES**