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SURROGATE MODEL BASED ON ARTIFICIAL NEURAL NETWORK FOR THE FAST PREDICTION OF HYDRODYNAMIC RESISTANCE FOR BULBOUS BOW VESSELS

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Abstract

In recent years, machine learning tools have demonstrated their potential for accurate predictions. In the field of naval hydrodynamics, Computational Fluid Dynamics (CFD) tools are widely used to calculate ship resistance during the design stage. These tools are time-costly and require powerful computational resources. The estimation of ship resistance is a key factor for the operation of a vessel, and it should be obtained in early stages of design. Nowadays, numerical tools allow the study of different hull parameters before building the full-scale ship or an experimental model, saving time and money. Potential-flow-based tools give a relatively fast prediction when waves are dominating. However, potential solvers do not give accurate predictions when friction forces are significant. Viscous solvers are more suitable for this case, although they require much higher calculation time. The hull design of a bulbous bow vessel demands testing different bulb configurations to minimize ship resistance. This can be accomplished with viscous solvers, which are highly costly in computational resources due to the big number of models to be tested. This work proposes the creation of a surrogate model using Artificial Neural Networks (ANN) for the prediction of the ship resistance for different configurations of the bulb. The ANN is trained using a large database of different bulb configurations, and their corresponding computed ship resistance obtained with a CFD solver. Results show that the surrogate model can predict the ship resistance to high degree of accuracy and significantly faster than performing the corresponding CFD simulation.

Keywords: Bulbous bow, ship resistance, surrogate model, Artificial Neural Network (ANN), Machine Learning, CFD.

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1 INTRODUCTION

The estimation of the power consumption of a vessel is a key factor that will determine the size of a ship engine, thus fuel consumption, gas emissions and operating costs. Traditionally, towing tank tests have been performed to estimate the ship resistance of scaled models of vessels, that were extrapolated to full scale with several methods. These tests were expensive and time consuming, which led to the creation of some prediction models of ship resistance based on statistical data for different ship types, such as Holtrop and Mennen's [1], van Oortmerssen's methods [2], among others. These models, usually developed on behalf of towing tank facilities, allowed a relatively accurate prediction of ship resistance for some ship types within a range of ship variables.

The development in technology allowed great advances in numerical methods, and computational fluid dynamics (CFD) prompted in the field of marine hydrodynamics. The use of CFD meant that a design could be numerically tested without the need of performing expensive experimental tests, as well as providing the possibility of making design variations on the model since traditional tests require to build different models for such a purpose, increasing experimental costs ([3]–[5]). Increasing computing capabilities have made CFD analysis an attractive alternative to estimate resistance prediction, especially for optimization purposes, reducing analysis time from days to several hours. Although numerical solutions are mostly used nowadays, traditional experimental tests have not been totally replaced, since there is still a need for validation of these numerical tests, as many authors show in their works ([6]–[9]).

Numerical tools require the creation of a virtual hull, that will be used to create the calculation mesh for the CFD solver. This virtual hull, usually created with Computer Aided Design (CAD) software with solid bodies or surfaces, provides the option of easily parametrizing the hull model. This is highly advantageous when performing multiple studies for optimization purposes. Different tools and methods are found in the literature to create variations of the model parameters; Free From Deformation (FFD) and Bezier curves being among the most popular methods ([10]–[14]). FFD is used in this work to parametrize the CAD model.

Although CFD analysis provide many options in ship design, they have a clear disadvantage when a huge number of analyses is required: they are very time consuming. For this reason, several authors have tried to develop faster prediction methods such as surrogate models, which are based on different approaches [14]. Recent developments in Machine Learning (ML) techniques have attracted researchers' attention to obtain surrogate models that accurately infer the desired results in shorter time. In the field of marine engineering, ML tools are being used to design vessels and estimate their hydrodynamic resistance and fuel consumption ([15]–[18]), as well as added resistance and seakeeping behavior. Among these ML techniques, Artificial Neural Network (ANN) is the most used, showing promising results ([19]–[22]).

This paper presents a method to obtain a surrogate model based on ANN for the fast prediction hydrodynamic ship resistance of a vessel with different bulb shapes. The advantage of this method, compared with traditional numerical simulations, resides in a reduced calculation time from hours to seconds. Next section of this work shows the methodology to obtain training data with a parametric numerical model. Section 3 shows the implementation of the ANN, and section 4 comprehends results and conclusions.

2 NUMERICAL SET-UP

2.1 Parametric Modelling

The bulbous bow of a ship has complex surfaces with curvature in several directions that are usually difficult to model. These surfaces must be smooth enough to avoid hydrodynamic interferences that could lead to increased ship resistance. KRISO containership (KCS), a well-studied ship model with an existing bulbous bow, has been selected as a case for this study. The main features of the vessel are shown in Table 1, and the definition of the bulb parameters is shown in Figure 1.

To carry out a reasonable number of simulations with different bulb shapes, the bulb has been parametrized by using Free Form Deformation (FFD). This technique allows local deformation of a part of the hull, restricted to the desired surfaces or influence area to be changed. Deformation is achieved by moving 3 control points affecting the bulb shape, which define the bulb length, beam, and depth (Figure 2). The points named length and stem can move in the length direction in a specified range, the movement of the width points being dependent of the former. Only stem point moves in depth direction, over the line that the stem of the ship would have if no bulb was placed. Width points are moved in beam direction according to a specified range.

Parameter	Value
Length (L)	7.7 m
Length between particulars (L_{pp})	7.28 m
Beam (B)	1.02 m
Draft (D)	0.342 m
Bulb length (L_b)	0.248 m
Bulb beam (B_b)	0.152 m
Bulb depth (D_b)	0.304 m
Froude number (Fn)	0.2599

Table 1: Main features of the KCS model.

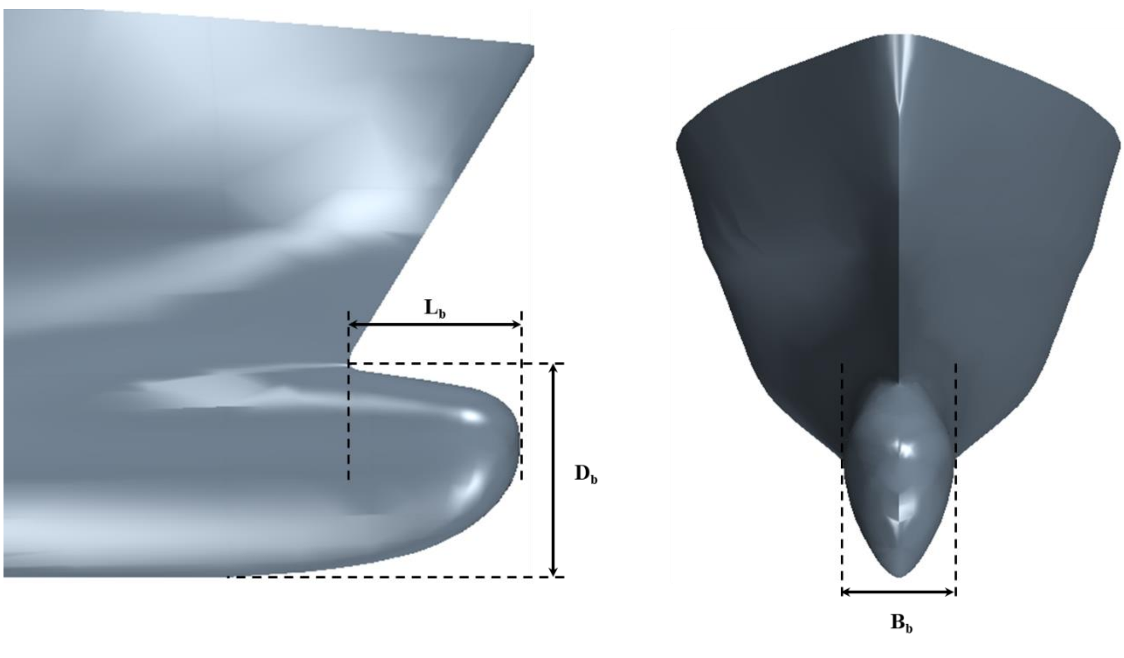

Figure 1: Definition of bulb parameters.

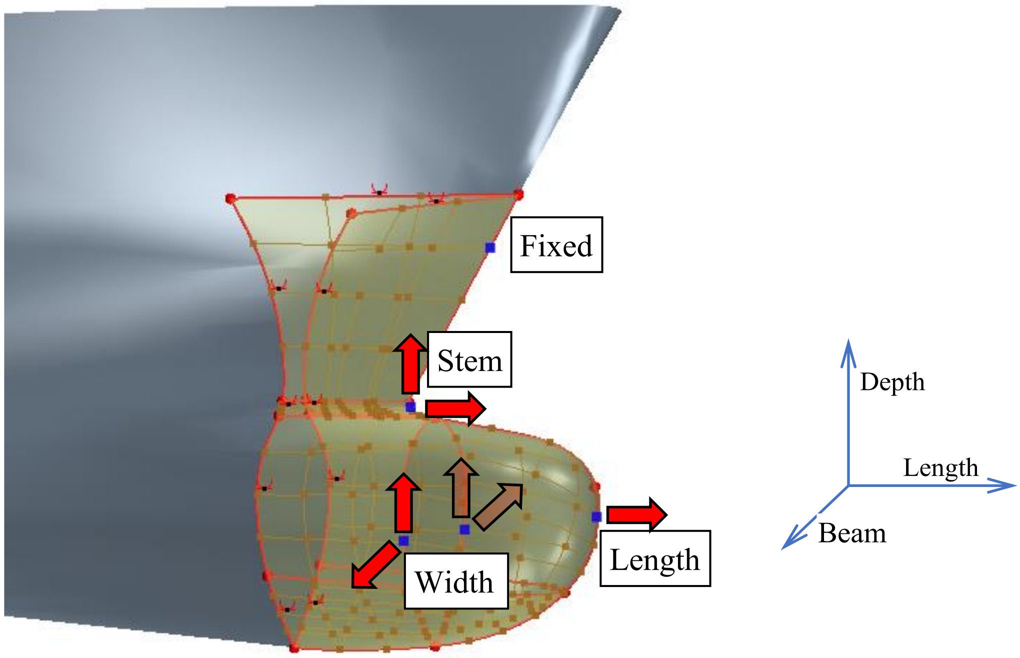

Figure 2: Position of the control points and area of the hull affected by FFD. Red arrows show the direction of the movement of each point in relation with the axis of the ship (right).

2.2 Computational domain

Hydrodynamic ship resistance has been calculated with the software STARCCM+. The scale factor of the model is 36. The domain mesh, shown in Figure 3, contains nearly a million cells, varying with the dimensions of the different ships. The Volume of Fluid Method, Reynolds-averaged Navier-Stokes (RANS), and turbulence model k-ω are the main solvers and methods used for the equations of fluid dynamics. Dynamic fluid body interaction (DFBI) is also used, allowing heave and pitch for the ship model to obtain more accurate results. Damping is used in the walls to avoid wave reflections.

ITTC [23] recommendations for hydrodynamic simulations with Computational Fluid Dynamics (CFD) have been followed for the numerical set up. The domain size has dimensions that set 1.5 L_{pp} in the tank inlet in front of the ship, 3 L_{pp} in the tank outlet behind the ship, 2.5 L_{pp} to the sides and below the hull and 1 L_{pp} in the vertical direction above the hull. Symmetry has been used to reduce calculation time, which varied from 6 h to more than 30 h for a time step of 0.4 s, depending on the features of the vessel. Mesh refinements are applied to the surfaces of the hull and nearby areas, specially at the bow region and the bulb, as well as in the free surface to properly capture generated waves.

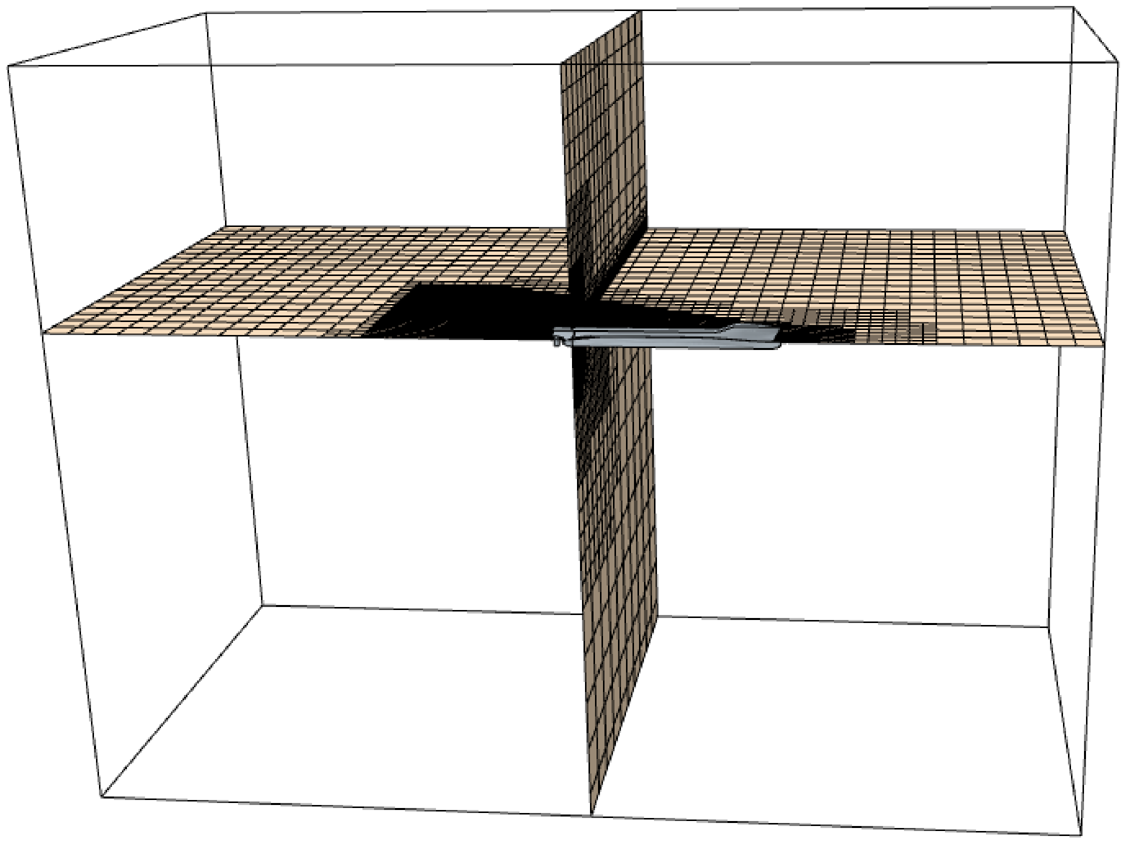

Figure 3: Domain mesh for the calculation of hydrodynamic ship resistance.

3 SURROGATE MODEL BASED ON ANN

Artificial Neural Networks (ANN) have been used to obtain a surrogate model that infers hull hydrodynamic resistance based on the bulb parameters (see Figure 4). Multi-Layer Perceptron (MLP) has been selected for the architecture of the ANN. To generate, and to train the ANNs, the GPU-Tensorflow library has been used. GPU capabilities provide faster results than those obtained with traditional CPU ([24]–[26]).

For this study, the configuration adopted for the ANN is based on common configurations existing in the literature [24]. Different neural networks have been tested, varying 3 layers of 10, 20 and 30 neurons, including Adam and RMSprop optimizers, activation functions (ReLU, Sigmoid), different number of epochs (50-200) and seeding.

The input values are the parameters of the bulb defined in Section 2 (see Figure 2). The output value is the hydrodynamic ship resistance. Simulations performed with the numerical solver provide the points that conform the data set. The more points provided to the network, the better the prediction will be. However, the problem studied here requires several hours of calculation time per simulation, making it unfeasible to have a large data set.

Mean absolute error (MAE) has been used to assess the neural networks, the most suitable ANN being that with the lowest MAE. This error is calculated from equation (1), where t_i is the value from the numerical simulation and p_i is the ANN predicted value.

$$MAE = \frac{\sum_{i=1}^{n} |t_i - p_i|}{n} \tag{1}$$

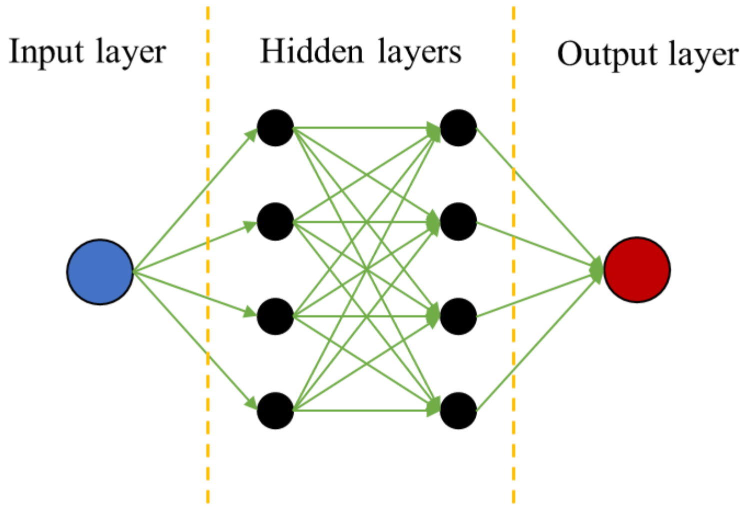

Figure 4: Graphical representation of an Artificial Neural Network (ANN).

4 RESULTS AND CONCLUSIONS

A total number of 40 vessels with different bulb shape has been numerically tested. The resistance to motion of the original KRISO containership has been initially calculated and compared with benchmark experimental data [27]. Table 2 shows the comparison between both results, with an error that is below 2 %. Thus, the numerical set up is validated to perform other simulations with similar features. In addition, wave patterns of the resistance simulation, shown in Figure 5, present a reasonable distribution over the free surface.

Experiment (N)	Simulation (N)	Difference (%)
85.269	83.711	1.82

Table 2: Validation of the numerical software with experimental results.

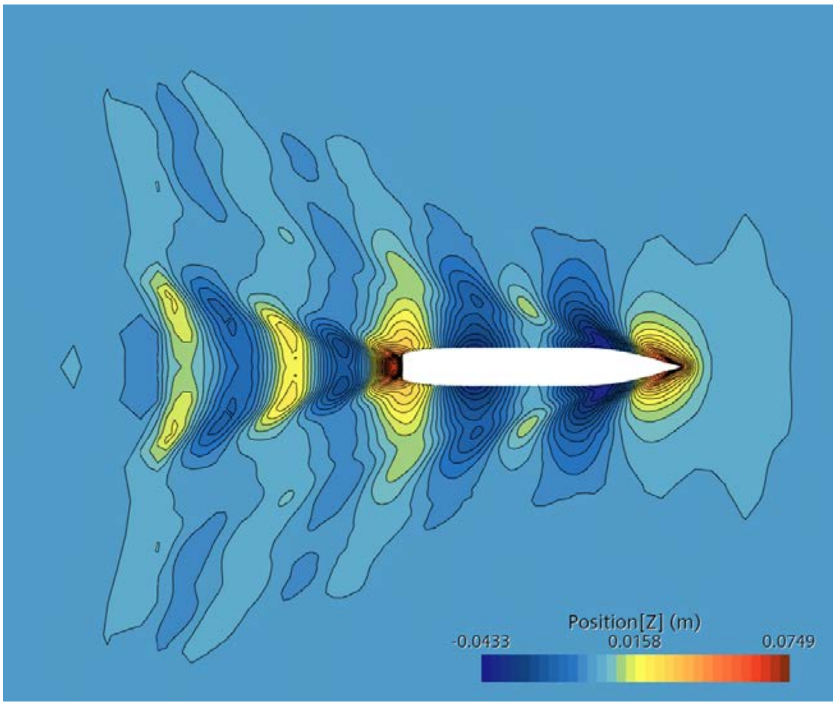

Figure 5: Wave pattern of the KCS hull in the numerical simulation.

The results from the neural network showed that the best ANN configuration has 3 layers of 30 neurons each, ReLU activation function, RMSprop optimizer and 200 epochs.

Figure 6 compares the results obtained through the numerical simulations, which are used to train the ANN, with those predicted with the ANN. The deviation of the ANN predicted results provide an average error of 8 %, varying for the different designs. As shown in the figure, the network usually predicts with better accuracy values below 100 N. This is reasonable considering the relatively low number of input data used to train the ANN, which was mainly concentrated in the range of 80-100 N.

The trained Artificial Neural Network provides relatively accurate results if compared with the numerical simulations, with the advantage of reducing the calculation time from several hours to less than a second. The use of ANN for the estimation of ship resistance with different bulb shapes has shown to be effective and will be further developed.

As shown in Figure 7, the error decreases with the number of iterations. It is expected to obtain even lower errors with a larger dataset, and that will be assessed in future work.

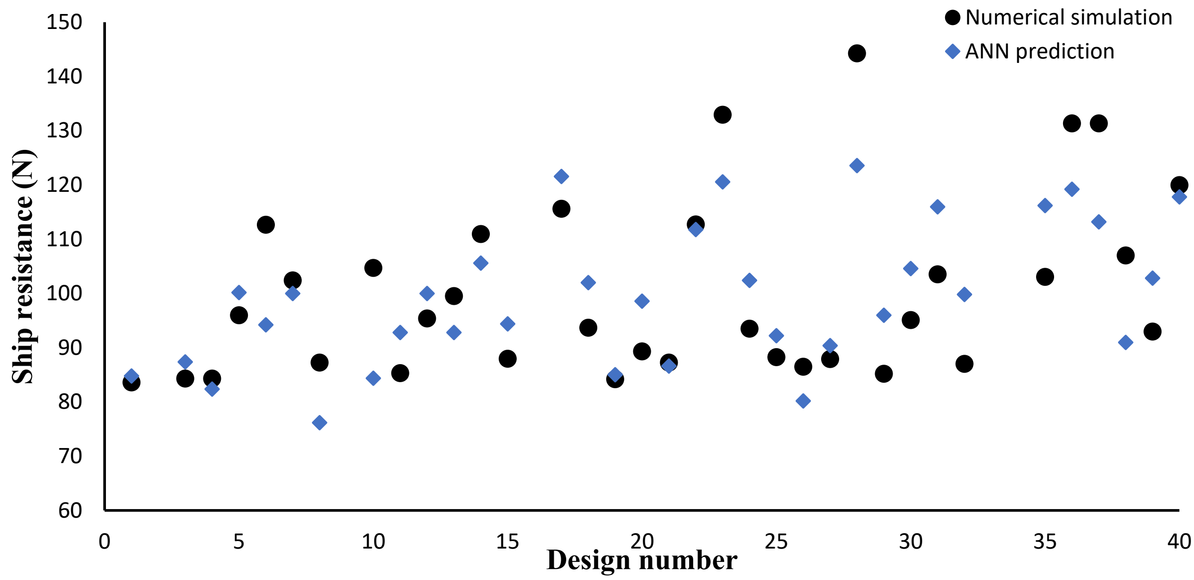

Figure 6: Comparison between results from numerical simulations and ANN predictions.

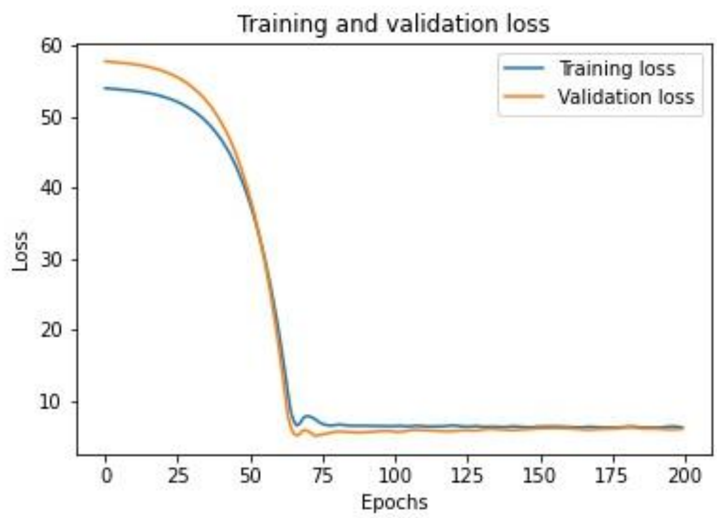

Figure 7: Error decrease for training and validation results over epochs.

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