Artificial Neural Networks for Hull Resistance Prediction

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Abstract

The applicability of artificial neural networks to the problem of ship resistance prediction as an alternative to more traditional statistical regression models has been investigated. In this work, an artificial neural network has been used as an interpolation tool to predict the residuary resistance of a systematic series of catamaran forms. It has been found that an artificial neural network is able to produce results of sufficient accuracy to be useful for preliminary prediction of vessel resistance, with the major benefits of: being relatively simple to set up; being easily retrained with new data; and that Froude number may be easily included as an independent variable.

Nomenclature

A	Static wetted surface area
B	Demihull maximum beam on waterline
C_{F}	Coefficient of frictional resistance [ITTC-57 Correlation line]
C_{R}	Coefficient of residuary resistance
C_{T}	Coefficient of total resistance
C_{W}	Coefficient of wave resistance
C_{WP}	Coefficient of wave pattern resistance
F_n	Froude Number, $[v/\sqrt{gL}\,]$
g	Acceleration due to gravity
L	Vessel length between perpendiculars
$L/\nabla^{\frac{1}{3}}$	Slenderness ratio
R_e	Reynolds Number, $[vL/\nu]$
S	Catamaran demihull centreline separation
T	Demihull draught
v	Vessel velocity
∇	Demihull volume of displacement
ν	Fluid kinematic viscosity
ρ	Fluid density

(ITTC Resistance Coefficients = resistance/$\frac{1}{2}\rho A v^2$)

1 Introduction

The aim of this research was to determine whether artificial neural networks can be used as an alternative to traditional statistical regression techniques for the interpolation of vessel resistance from tank test results.

For some time, artificial neural networks have been used in many diverse fields as function approximation tools, producing results comparable with (or better than) regression models and other statistical methods, see for example *Negnevitsky (2001)* or *Neocleous and Schizas (1995).* One of their key advantages is their ability to easily model complex, non-linear systems, a feature which is not true of statistical regression methods where an appropriate non-linear function must first be found.

Table 1: Hull model notation and main parameters

	B/T		
$L/\nabla^{\frac{1}{3}}$	1.5	2.0	2.5
6.3	—	3b	—
7.4	4a	4b	4c
8.5	5a	5b	5c
9.5	6a	6b	6c

In the field of Naval Architecture, interpolation and prediction of hull resistance from model experiments and tank testing has traditionally used statistical regression methods. However, this is a problem that is also well suited to the application of artificial neural networks. Specifically, artificial neural networks may offer a more favourable solution than statistical methods due to greater flexibility and the ease with which they can be applied to complex non-linear systems, see for example *Jain et al. (1996)*.

An advantage of artificial neural networks over statistical methods is their ability to adapt to new data. Once an artificial neural network architecture has been designed, it can quickly be retrained as new data becomes available. In addition, the same artificial neural network topology can be trained with other data for different vessel types. Retraining the artificial neural network with additional data is generally simpler and quicker than recomputing a statistical model.

Finally, the difficulty of using statistical approaches for prediction escalates quickly as the number of inputs (independent variables) or non-linear nature of the data increases, whereas the difficulty of developing a neural network increases less dramatically with the complexity of the system.

A disadvantage of artificial neural networks is the lack of a single approximation equation: the result is an artificial neural network topology and set of weights. This means that the prediction can only be calculated on a computer with suitable artificial neural network software. In practice this is not really a big disadvantage because regression equations can also only really be developed and implemented with suitable software.

It is also true that it is usually a goal for statistical regression models to be based on an equation which has some physical significance. In some cases the physical significance of the regression equation is subject to interpretation. However, an artificial neural network does not represent a physically meaningful model of the data, which could be considered a disadvantage.

1.1 Resistance data

The resistance data used for this investigation was from a series of resistance experiments carried out on a systematic series of hull forms tested in both monohull and catamaran configurations. These experiments together with the resistance data are described in full in *Molland et al. (1994, 1995)* and *Insel and Molland (1992)*. A typical body plan of these hulls is shown in Figure 1 and the range of hull parameters tested is summarised in Table 1. A total of ten hull forms were tested, covering a slenderness ratio range of $L/\nabla^{\frac{1}{3}} = 6.3$ to 9.5 and a Breadth:Draught ratio range of $B/T = 1.5$ to 2.5. In addition, all models were tested as monohulls and in catamaran configurations at Separation:Length ratios of $S/L = 0.2$, 0.3, 0.4 and 0.5. Most configurations were tested in the Froude number range $F_n = 0.2$ to 1.0. However, for models 3b and 4b (see Table 1), at the closer demihull catamaran configurations, the upper F_n tested was reduced due to excessive spray between the demihulls.

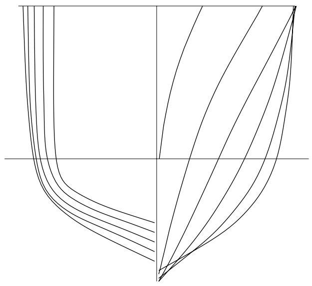

Figure 1: Typical hullform tested ($B/T = 2.0$)

In the present work, only modelling and function approximation of residuary resistance (C_{R}) was considered – see Equation 1. Additional data such as wave pattern resistance coefficient (C_{WP}), running trim and sinkage were also measured during the experiments and these could be modelled using the same artificial neural network topology retrained with the relevant data.

$$C_{\mathrm{R}} = C_{\mathrm{T}} - C_{\mathrm{F}} \tag{1}$$

where C_{F} is calculated from the ITTC-57 correlation line: $C_{\mathrm{F}} = \frac{0.075}{(\log R_e - 2)^2}$

2 Development of artificial neural network architecture and training

2.1 Selection of input parameters and output values

One of the key factors in the development of a successful predictive tool (irrespective of whether the method is statistical regression or an artificial neural network) is the selection of appropriate input parameters (or independent variables); it is important to include only those parameters that have a significant influence on the value of the predicted result.

The principal parameters that were varied in the catamaran systematic series were: $L/\nabla^{\frac{1}{3}}$, L/B, B/T and S/L, and the hulls were tank tested over a range of F_n. In the original analysis of the tank results *(Molland et al. 1994)*, a very high degree of correlation between the effects of $L/\nabla^{\frac{1}{3}}$ and L/B was observed. For this reason, it was decided that the only input parameters that should be used were: $L/\nabla^{\frac{1}{3}}$, B/T, S/L and F_n.

One problem often found with statistical regression methods is the highly non-linear relationship between resistance and Froude number (illustrated by the typical resistance curve in Figure 2). This can cause difficulty in obtaining a regression equation with Froude number as an independent variable or, as is more often the case, quite a large number of independent regression equations are developed for individual Froude numbers. A benefit which will be seen with artificial neural networks is their ability to model the non-linear relationship between resistance and Froude number and thus only require one artificial neural network instead of different ones for each individual Froude number.

Some regression methods have attempted to include F_n explicitly as an independent variable. However, it is often still not possible to have a single equation because of the complex nature of the variation of C_{R} with F_n. For example, *Holtrop (1977)* includes F_n as an independent variable but requires two equations: one for slow speeds, below the resistance hump, and a second for higher speeds.

2.2 Development of the artificial neural network architecture

Selection of a suitable artificial neural network architecture is probably the hardest part of the problem and critical to obtaining a useful artificial neural network. It is analogous to selecting the

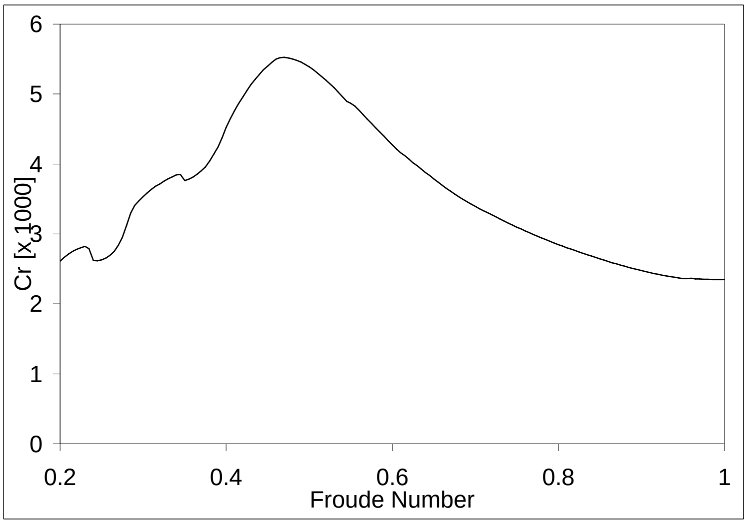

Figure 2: Typical residuary resistance coefficient curve

form and independent variables of a regression equation. One of the advantages of the artificial neural network approach is that it is easy to automate searching for an optimum architecture, either by using a simple exhaustive search or by using some sort of heuristic search methodology.

Alyuda's NeuroIntelligence software *(Alyuda 2004)* was used for the artificial neural network calculations. This proved to be a very powerful tool for carrying out the artificial neural network design and analysis.

During the development of the artificial neural network design, the available input data was split into three, mutually exclusive, sets described below. In all cases, a 70%, 15%, 15% split between the training, validation and test sets was used.

Training set: used to train the artificial neural network, i.e. to adjust the artificial neural network weights to maximise the artificial neural network's predictive ability and minimise its forecasting error.

Validation set: used to tune the artificial neural network topology or parameters other than weights. Also used for automatic comparison of alternative artificial neural networks.

Test set: used *only* to test the accuracy of the predictions made by the artificial neural network on new data.

The accuracy of the artificial neural networks can be measured in several ways:

Test error: the mean absolute artificial neural network error on the test set. The lower the value, the better the artificial neural network is at predicting the test set.

Fitness: in the work presented here, the fitness is based on the inverse of the test error, thus the greater the fitness, the better the artificial neural network.

R-squared: a standard statistical measure. R-Squared = 1 implies a perfect fit.

Correlation coefficient, r: the correlation between the test set and the predicted values from the artificial neural network. r = 1 implies a perfect fit.

Akaike's criterion: a measure of the error on the test set compared with the complexity of the system; systems with greater complexity are penalised. The greater the number, the better the artificial neural network.

Of the measures available for comparing the accuracy of the alternative artificial neural networks, the fitness score based on test error was found to be the most sensitive and was used to select the best artificial neural network architecture. Akaike's criterion was also found to be a useful quantity for comparing artificial neural networks with a single hidden layer and both R-Squared and the correlation coefficient tended to be maximised for the artificial neural networks with the highest fitness scores based on test error and Akaike's criterion.

The accuracy of the predicted results from the artificial neural networks was also assessed in a qualitative manner by visual inspection of the resistance curves predicted by the artificial neural networks and their ability to interpolate results for input values between those actually tank tested.

The training algorithm used to train the artificial neural network was found to have quite an important influence on its accuracy and the speed with which the training converged (or whether it converged at all). In general, the artificial neural network starts with random weights and the training process adjusts these weights with the aim of producing an accurate prediction of the training data. Because this is a semi-random process (due to the initial values of the weights), it is important to retrain the artificial neural network several times with different starting values for the weights. It is also important to allow sufficient iterations of the training regime to allow the artificial neural network to converge. The required computational effort increases considerably as the number of neurons in the artificial neural network, the number of retrainings and the number of allowed training iterations increase. Because of limited computational resources a compromise is required between these factors. It is for these reasons that it is not possible to perform an exhaustive search of all possible artificial neural network architectures and that there can be considerable scatter in the fitness results for alternative artificial neural network architectures.

2.3 Fitting single resistance curve

In order to determine how well an artificial neural network could fit a typical C_{R} vs. F_n curve (Figure 2), a simplified problem with only one hull model was investigated. This data set had only one input variable (F_n). Artificial neural networks with up to two hidden layers were investigated, the number of neurons in these layers was systematically varied.

Initially, a wide range of neurons in a single hidden layer artificial neural network was investigated. It was found that a minimum of six neurons in the hidden layer were required to provide a reasonable approximation to the shape of the C_{R} curve, whilst around 10 to 20 neurons provided the most accurate fit.

Figure 3 shows how the various fitness criteria varied for the single hidden layer artificial neural network as the number of hidden layer neurons was increased. In this figure, the fitness is based on the inverse of the test error. Hence, the greater the fitness, the better the artificial neural network was able to predict the training set. The number of hidden layer neurons was varied between one and 50.

Figure 4 shows the effect of varying the number of hidden layer neurons on the predicted resistance curve compared with the actual C_{R} curve. It can be seen that the accuracy of the fit increases quickly with increasing number of hidden layer neurons. This is because the artificial neural network has a greater number of degrees of freedom and is better able to model the non-linear nature of the resistance curve. As the number of neurons was increased further, the accuracy of the network was found to deteriorate. This was because although the training set

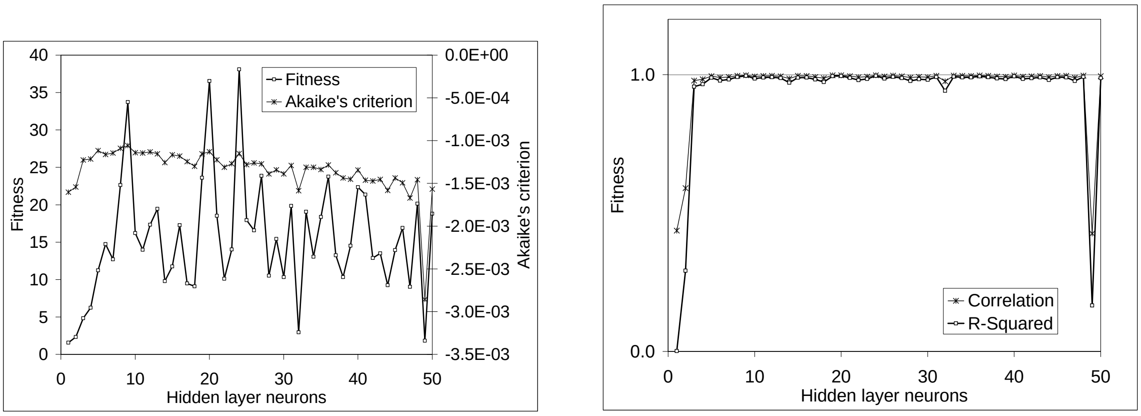

Figure 3: Influence of number of hidden layer neurons on artificial neural network accuracy (fitness score) for an artificial neural network with a single hidden layer

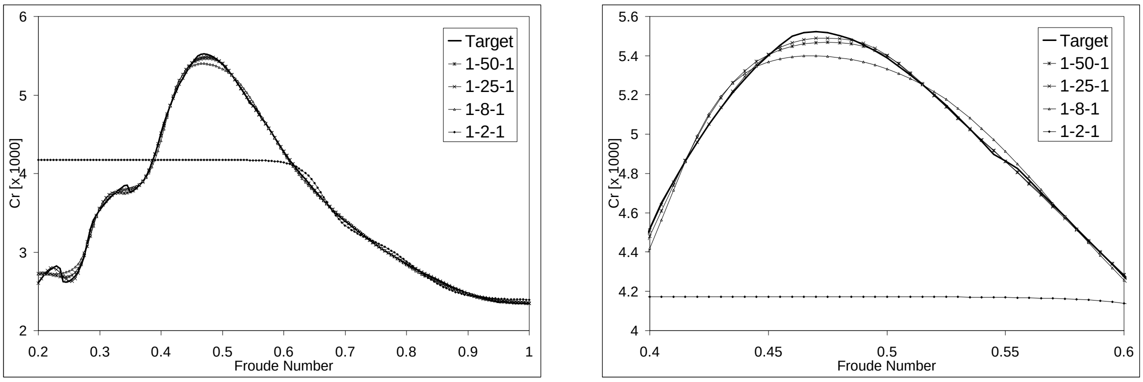

Figure 4: Influence of number of hidden layer neurons on artificial neural network accuracy (prediction of resistance curve) for an artificial neural network with a single hidden layer

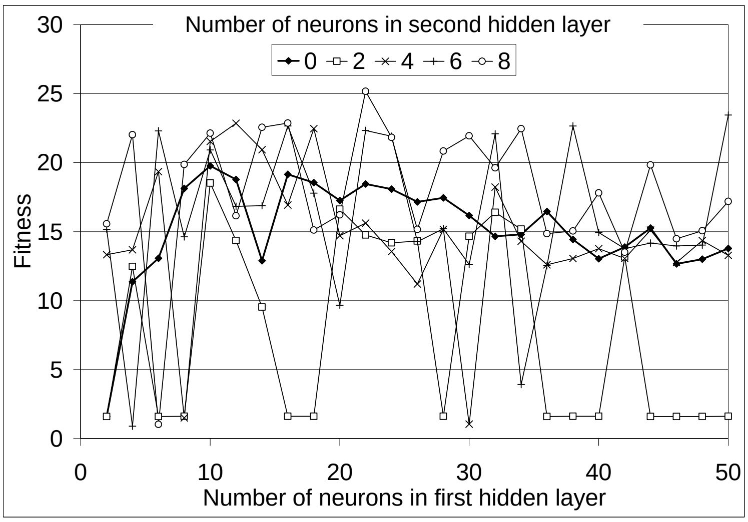

Figure 5: Influence of number of hidden layer neurons on artificial neural network accuracy (fitness score) for artificial neural networks with single and two hidden layers

was modelled more accurately, a degree of over fitting had occurred and the test set was not well predicted (see Section 2.5 for further discussion of over fitting.)

2.4 Number of hidden layers and hidden layer neurons

Some investigations into artificial neural networks with two hidden layers were performed, but the results were somewhat inconclusive. Figure 5 shows the effect of increasing the number of hidden layers to two. Fitness curves are plotted against the number of neurons in the first hidden layer for different numbers of neurons in the second layer. The number of neurons in the first layer was varied between two and 50, whilst the number in the second layer was varied between two and eight. (The artificial neural network with a single hidden layer is shown in the bold line, with the solid diamonds, whilst the artificial neural networks with two hidden layers are shown by the lighter lines with open symbols or crosses.) It can be seen that adding a second hidden layer did not significantly improve the artificial neural network's performance and increasing the number of neurons in the second hidden layer had little effect. In fact, for the artificial neural network with two neurons in the second hidden layer, there are many cases where the training failed to converge. The only cases where two hidden layers were possibly more effective was where there were few (less than ten) neurons in the first hidden layer. The large degree of scatter in the fitness values has been discussed at the end of Section 2.2.

The observations of *Neocleous and Schizas (1995)*, which indicate that rarely are multiple hidden layers effective in terms of both accuracy and speed of training, are borne out.

It is for the reasons described above that an artificial neural network architecture with a single hidden layer was selected.

A search of the available literature suggested many (sometimes conflicting) rules of thumb for determining the number of neurons in the hidden layer. It became apparent that there is no general rule by which a suitable number of hidden layer neurons can be chosen and that the optimum number is very specific to the problem being solved.

For example, Kolmogorov's theorem *Brattka (2003)* suggests that the optimum number of hidden layer neurons is $2n+1$, where n is the number of inputs to the artificial neural network. However, the number of hidden layer neurons suggested by the NeuroIntelligence software is half this number. For this particular problem, it is thought that the high degree of non-linearity in the C_{R} vs. F_n curve requires quite a large number of neurons. The non-linear relationship between C_{R} and F_n is in contrast to the relationship between the other independent variables ($L/\nabla^{\frac{1}{3}}$, B/T and S/L) which were only varied over a range of three to five values, and were often nearly linear functions. The relatively large number of hidden layer neurons required to fit the C_{R} vs. F_n curve may cause over-fitting to the remaining independent variables. This is discussed further in the following section.

2.5 Over-fitting

Both statistical methods and artificial neural networks can suffer from over-fitting. Over-fitting occurs as the number of degrees of freedom, or unknowns, approaches the number of training data points. If over-fitting occurs, the training data is predicted very well, but new input data is often poorly predicted.

The method used to overcome this is to divide the data into mutually exclusive training and testing sets. The training set is used to train the artificial neural network (or solve the regression equation) and the test set is used to test the accuracy of the fit. Since the test set is not used in the training, any over-fitting to the training set will lead to a poorer result when using the test set and a lower fitness score for that particular artificial neural network. As mentioned in Section 2.2, an additional validation set is also sometimes used.

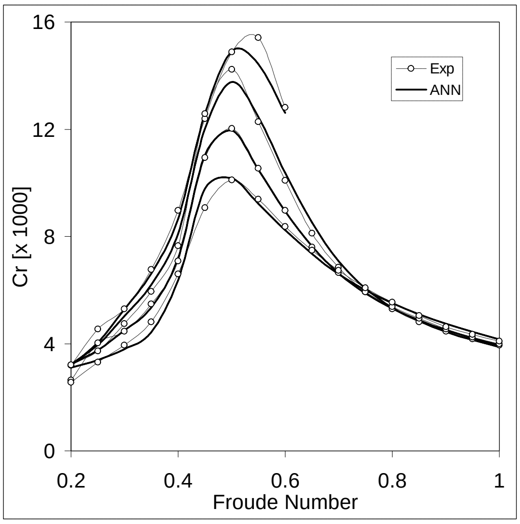

Figure 6: Model 3b

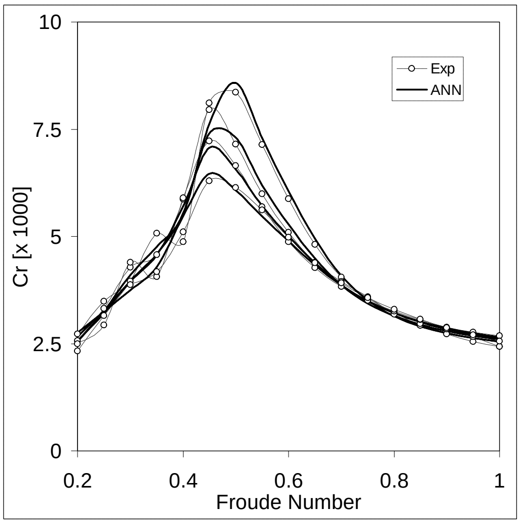

Figure 7: Model 4a

In the problem presented in this paper, the data is highly non-linear with respect to Froude number but is quadratic with B/T (three points tested) and cubic with $L/\nabla^{\frac{1}{3}}$ and S/L (four points tested). Hence, for a statistical regression model, one might choose a function which includes four or five (or more) non-linear functions of F_n but probably only a linear function of B/T and perhaps up to a quadratic function of $L/\nabla^{\frac{1}{3}}$ and S/L; a total of around 13 unknowns. With an artificial neural network, it is not possible to be so specific about how the function varies with each independent variable. It is simply a matter of choosing a suitable number of neurons. However, the number of neurons must be sufficient to have a good fit with respect to F_n but this can lead to an over-fitting with respect to B/T, $L/\nabla^{\frac{1}{3}}$ and S/L. Hence with the artificial neural network problem, over-fitting can only be avoided by having a sufficiently large test set. The trade-off is that increasing the size of the test set reduces the quantity of data in the training set and hence (in general) the accuracy of the fit.

2.6 Artificial neural networks for catamaran systematic series resistance data

Further investigations into suitable artificial neural network architectures for modelling the resistance data of the whole systematic series indicated that it was not necessary to increase the number of hidden layers or neurons compared with the artificial neural network used to predict the resistance curve for a single vessel. This is thought to be because the artificial neural network has sufficient degrees of freedom to model the relatively linear variation with the other independent variables: $L/\nabla^{\frac{1}{3}}$, S/L and B/T. The final artificial neural network architecture selected had a single hidden layer with 15 neurons.

3 Results

Results from the artificial neural network described in the previous section are presented in Figures 6 to 15. These figures compare the resistance data from experiments (used as the training data for the artificial neural network) with the predictions from the artificial neural network. (The results from experiments are shown as open circles and the predicted data from the artificial neural network as a solid line.) In each figure, the results for the four catamaran configurations tested are presented, the closest spacing ($S/L = 0.2$) causing the greatest resistance hump and the widest spacing ($S/L = 0.5$) causing the smallest. It can be seen that there is generally very good agreement for all the hulls and conditions tested.

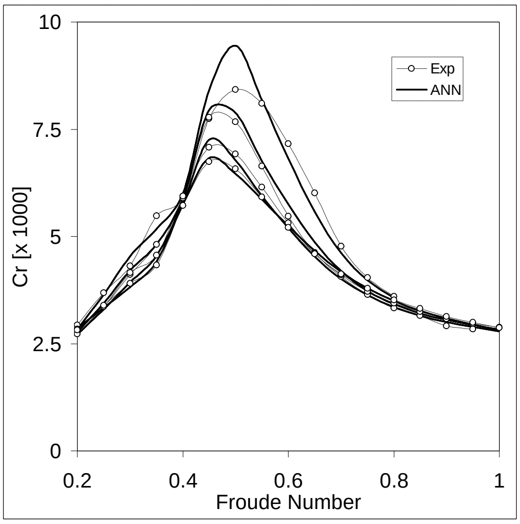

Figure 8: Model 4b

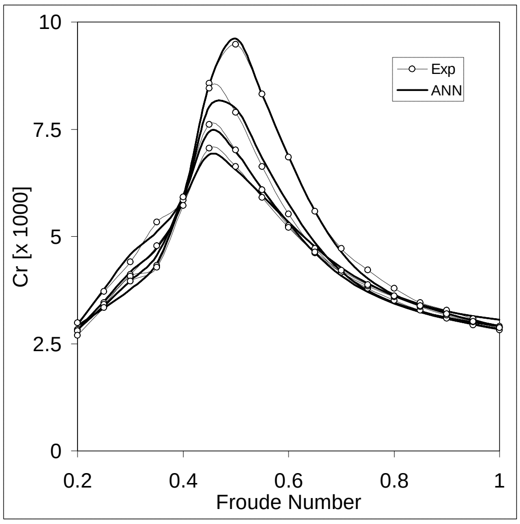

Figure 9: Model 4c

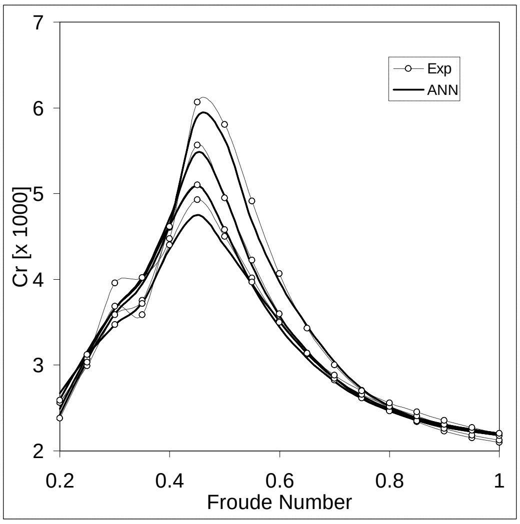

Figure 10: Model 5a

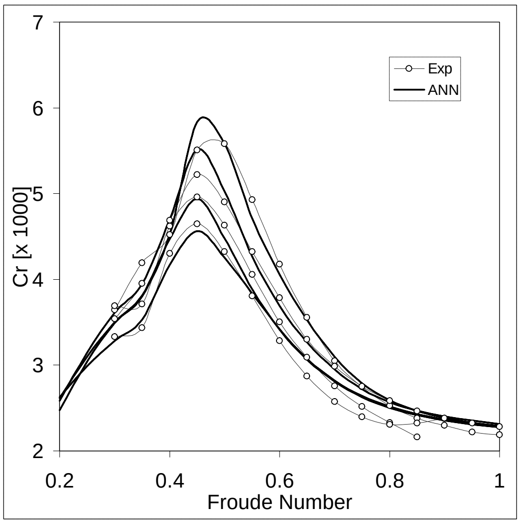

Figure 11: Model 5b

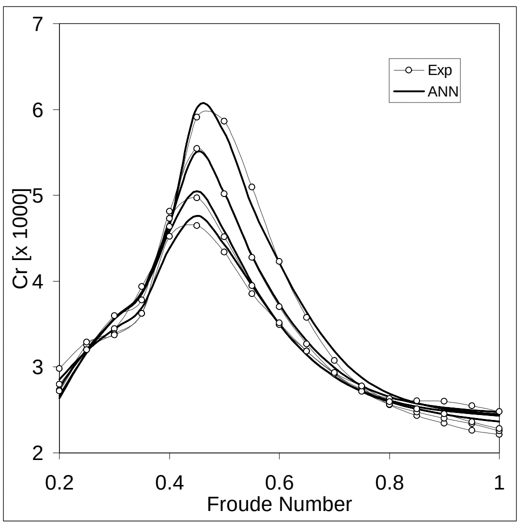

Figure 12: Model 5c

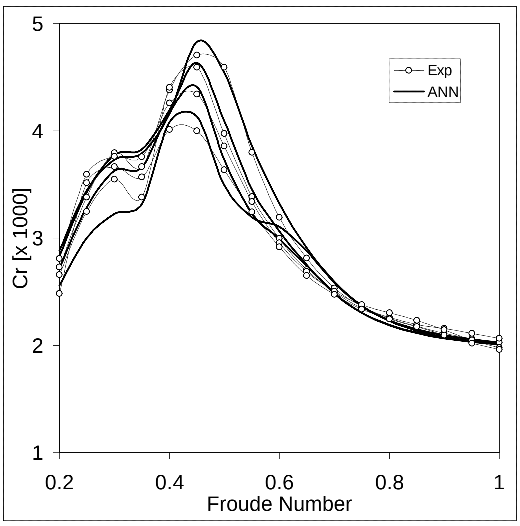

Figure 13: Model 6a

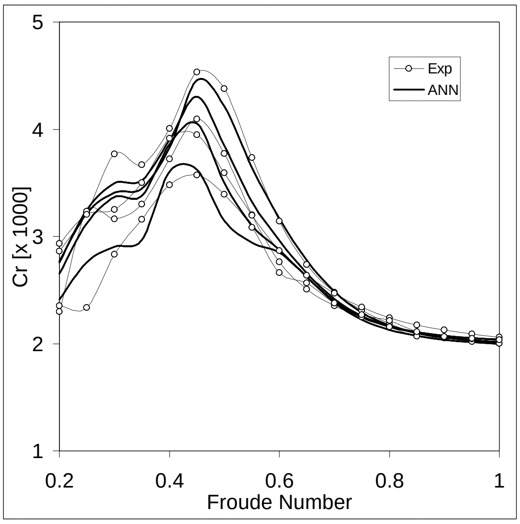

Figure 14: Model 6b

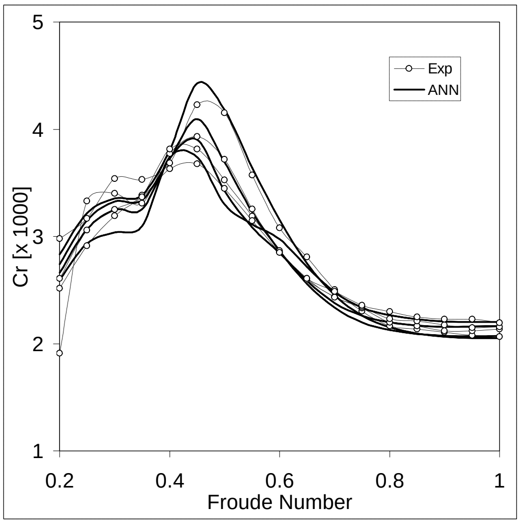

Figure 15: Model 6c

3.1 Interpolation and extrapolation

In order to assess the real usefulness of the artificial neural network, it has been used to interpolate data between the tested values of S/L, B/T and $L/\nabla^{\frac{1}{3}}$. The input parameter values have also been extended beyond the range of the original training set to examine the ability of the artificial neural network to extrapolate data – something which can be quite dangerous with statistical regression formulae.

Figure 16 shows the C_{R} variation with S/L for a catamaran with demihulls with $L/\nabla^{\frac{1}{3}} = 8.0$ and $B/T = 2.0$. Figure 17 shows the effect on C_{R} of varying demihull $L/\nabla^{\frac{1}{3}}$ for a catamaran with $S/L = 0.3$ and demihull $B/T = 2.0$. Finally, Figure 18 shows the effect of B/T variation for a catamaran with $S/L = 0.3$ and demihull $L/\nabla^{\frac{1}{3}} = 8.0$. It can be seen that, in all cases, the artificial neural network produces smooth response surfaces which behave well even when extrapolating beyond the range of the training data.

4 Conclusions

It has been shown that artificial neural networks are able to provide good approximations to hull resistance data and that a single artificial neural network may be used with Froude number as an independent variable over a wide speed range.

An artificial neural network with a single hidden layer and 15 neurons in the hidden layer was found to adequately model the residuary resistance of a systematic series of catamarans where slenderness, Breadth:Draught and Separation:Length ratios were varied for a geosim hull form. Further, the artificial neural network was sufficiently well behaved so as to allow extrapolation outside the range of test data for all independent variables. The single hidden layer architecture is recommended, since addition of further hidden layers did not appear to improve the accuracy of the artificial neural network and only added to the artificial neural network's complexity and required training time; in some cases preventing the training algorithm from converging.

The use of automated artificial neural network software makes it very quick and easy to produce and train an artificial neural network capable of modelling hull resistance problems. This is considerably easier and quicker than traditional statistical methods. Whilst it is important to choose a reasonable artificial neural network architecture, the exact number of neurons in the hidden layer is not too critical.

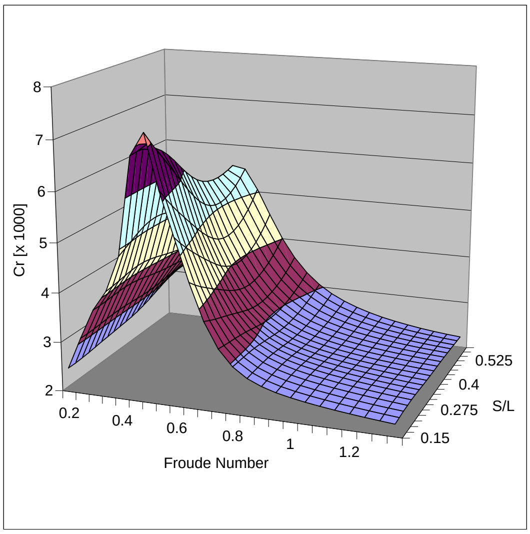

Figure 16: Effect of catamaran S/L for a demihull with $L/\nabla^{\frac{1}{3}} = 8.0$ and $B/T = 2.0$

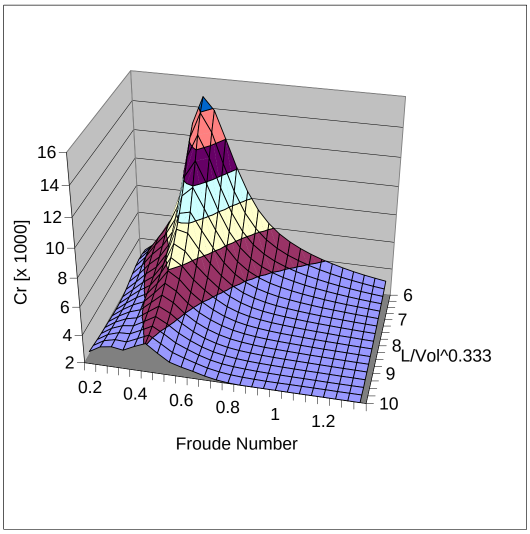

Figure 17: Effect of demihull $L/\nabla^{\frac{1}{3}}$ for a catamaran with $S/L = 0.3$ and demihull $B/T = 2.0$

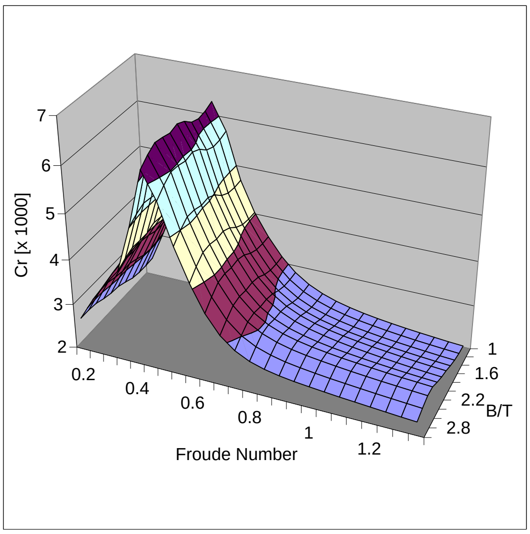

Figure 18: Effect of demihull B/T for a catamaran with $S/L = 0.3$ and demihull $L/\nabla^{\frac{1}{3}} = 8.0$

5 Further work

The artificial neural network approach makes it very easy to either generate a new artificial neural network for another systematic series or to add more data to the existing one. It is simply a matter of retraining it with the additional data. This will be done to produce artificial neural networks to predict C_{WP}, trim and sinkage data also measured by *Molland et al. (1994)*.

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