



PREDICTION OF TOTAL RESISTANCE COEFFICIENTS USING NEURAL NETWORKS

I. Ortigosa¹, R. López¹ and J. García¹

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ABSTRACT

The Holtrop & Mennen method is widely used at the initial design stage of ships for estimating the resistance of the ship (Holtrop and Mennen, 1982). The Holtrop & Mennen method provide a prediction of the total resistance's components. In this work we present a neural network model which performs the same task as the Holtrop & Mennen's method, for two of the total resistance's components. A multilayer perceptron has been therefore trained to learn the relationship between the input (length-displacement ratio, prismatic coefficient, longitudinal position of the centre of buoyancy, after body form and Froude number) and the target variables (form factor and wave-making and wave-breaking resistance per unit weight of displacement). The network architecture with best generalization properties was obtained through an exhaustive validation analysis (Bishop, 1995). The results of this model have been compared against those provided by the Holtrop & Mennen method, and it was found that the quality of the prediction is improved over the entire range of data. The neural network provides an accurate estimation of two total resistance's components with Froude number and hull geometry coefficients as variables.

Key words: Total Resistance's components, Neural Networks, Holtrop & Mennen Method.

¹International Center for Numerical Methods in Engineering (CIMNE), Universidad Politécnica de Cataluña, Campus Norte UPC, 08034 Barcelona, Spain. www.cimne.com E-mail: (inmaortigosa@hotmail.com) (rlopez@cimne.upc.edu) (and julio@cimne.upc.edu).

INTRODUCTION

Prediction of resistance of the ship at the initial design stage is of a great value for evaluating the ship's performance and for estimating the required propulsive power. Essential inputs include the basic hull dimensions and the boat velocity.

The model developed by Holtrop and Mennen at 1982 (Holtrop and Mennen, 1982), is a numerical description of the ship's resistance, subdivided into components of different origin. Each component was expressed as a function of the speed and hull form parameters.

Neural networks have proved to be a very useful tool to data modeling tasks. They can be defined as biologically inspired computational models consisting of a network architecture composed of artificial neurons. One of the most commonly used neural networks is the multilayer perceptron, which is a class of universal approximator (Bishop, 1995).

In this work we present a neural networks approach to two resistance's components prediction. Here a multilayer perceptron has been trained with generated data and experimental data to provide an estimation of the form coefficient and the wave's coefficient as functions of hull geometry coefficients and the Froude number.

THE HOLTROP AND MENNEN'S METHOD

Holtrop and Mennen did a statistical evaluation of model test results, selected from the archive of the Netherlands Ship Model Basin. The evaluation was carried out using multiple regression analysis methods. The objective of this study was to develop a numerical description of the ship's resistance.

Type of ship	L/B	B/T	C_p	$F_n \text{ max}$
Tankers, Bulkcarriers	$5.1 < \frac{L}{B} < 7.1$	$2.4 < \frac{B}{T} < 3.2$	$0.73 < C_p < 0.85$	0.24
General cargo	$5.3 < \frac{L}{B} < 8.0$	$2.4 < \frac{B}{T} < 4.0$	$0.58 < C_p < 0.72$	0.30
Fishing vessels, tugs	$3.9 < \frac{L}{B} < 6.3$	$2.1 < \frac{B}{T} < 3.0$	$0.55 < C_p < 0.65$	0.38
Containers ships, frigates	$6 < \frac{L}{B} < 9.5$	$3.0 < \frac{B}{T} < 4.0$	$0.55 < C_p < 0.67$	0.45
Various	$6.0 < \frac{L}{B} < 7.3$	$3.2 < \frac{B}{T} < 4.0$	$0.56 < C_p < 0.75$	0.30

Table 1. Parameter range for different ship types.



The total resistance of a ship is generally subdivided into components of different origin. The evaluation of each component was performed by applying multiple regression analysis to the results of 1707 resistance measurements, carried out with 147 ship models and the results of 82 trial measurements made on board 46 new ships. A survey of the parameter ranges and ship types is given in Table 1.

The total resistance of a ship has been subdivided into:

$$R_{Total} = R_F \cdot (1+k) + R_{APP} + R_W + R_B + R_{TR} + R_A \quad (1)$$

R_F , Frictional resistance of a ship according to the ITTC-1957 friction formula.

$1+k$, Form factor describing the viscous resistance of the hull form in relation to R_F .

R_{APP} , Resistance of appendages.

R_W , Wave-making and wave-breaking resistance.

R_B , Additional pressure resistance of bulbous bow near the water surface.

R_{TR} , Additional pressure resistance of immersed transom stern.

R_A , Model-ship correlation resistance.

The viscous resistance, $R_F \cdot (1+k)$, represents approximately the 63% of the total resistance, and the wave-making and wave-breaking resistance represents approximately the 27% of the total resistance, for Froude number around 0.30. So we have been working in these components.

$$(1+k) = c_{13} \cdot \left\{ 0.93 + c_{12} \cdot \left(\frac{B}{L_R} \right)^{0.92497} \cdot (0.95 - C_P)^{-0.521448} \cdot (1 - C_P + 0.0225 \cdot lcb)^{0.6906} \right\} \quad (2)$$

$$\frac{L_R}{L} = 1 - C_P + \frac{0.06 \cdot C_P \cdot lcb}{4 \cdot C_P - 1} \quad (3)$$

$$c_{12} = \begin{cases} \left(\frac{T}{L} \right)^{0.2228446} \rightarrow \frac{T}{L} > 0.05 \\ 48.20 \cdot \left(\frac{T}{L} - 0.02 \right)^{2.078} + 0.479948 \rightarrow 0.02 < \frac{T}{L} < 0.05 \\ 0.479948 \rightarrow \frac{T}{L} < 0.02 \end{cases} \quad (4)$$

$$c_{13} = 1 + 0.003 \cdot C_{stern} \quad (5)$$

The C_{sterm} coefficient indicate the afterbody form. For V-shaped sections $C_{sterm} = -10$, for normal sections shape $C_{sterm} = 0$, and for U-shaped sections with Hogner stern $C_{sterm} = 10$.

And lcb is the longitudinal position of the centre of buoyancy forward of 0.51 as a percentage of L .

$$R_W = c_1 \cdot c_2 \cdot c_5 \cdot \nabla \cdot \rho \cdot g \cdot \exp \{ m_1 \cdot F_n^d + m_2 \cdot \cos(\lambda \cdot F_n^{-2}) \} \quad (6)$$

$$c_1 = 2223105 \cdot c_7^{3.78613} \cdot \left(\frac{T}{B} \right)^{1.07961} \cdot (90 - i_E)^{-1.37565} \quad (7)$$

$$i_E = 1 + 89 \cdot \exp \left\{ - \left(\frac{L}{B} \right)^{0.80856} \cdot (1 - C_{WP})^{0.30484} \cdot (1 - C_p - 0.0225 \cdot lcb)^{0.6367} \cdot \left(\frac{L_R}{B} \right)^{0.34574} \cdot \left(100 \cdot \frac{\nabla}{L^3} \right)^{0.16302} \right\} \quad (8)$$

$$\lambda = \begin{cases} 1.446 \cdot C_p - 0.03 \cdot \frac{L}{B} \rightarrow \frac{L}{B} < 12 \\ 1.446 \cdot C_p - 0.36 \rightarrow \frac{L}{B} > 12 \end{cases} \quad (9)$$

$$m_1 = 0.0140407 \cdot \frac{L}{T} - 1.75254 \cdot \frac{\nabla^{1/3}}{L} - 4.79323 \cdot \frac{B}{L} - c_{16} \quad (10)$$

$$c_{16} = \begin{cases} 8.07981 \cdot C_p - 13.8673 \cdot C_p^2 + 6.984388 \cdot C_p^3 \rightarrow C_p < 0.8 \\ 1.73014 - 0.7067 \cdot C_p \rightarrow C_p > 0.8 \end{cases} \quad (11)$$

$$m_2 = c_{15} \cdot C_p^2 \cdot \exp(-0.1 \cdot F_n^{-2}) \quad (12)$$



$$c_{15} = \begin{cases} -1.69385 \rightarrow \frac{L^3}{\nabla} < 512 \\ 0.0 \rightarrow \frac{L^3}{\nabla} > 1727 \\ -1.69385 + \frac{\left(\frac{L}{\nabla^{1/3}} - 8.0\right)}{2.36} \rightarrow 512 < \frac{L^3}{\nabla} < 1727 \end{cases} \quad (13)$$

$$d = -0.9 \quad (14)$$

$$c_3 = \frac{0.56 \cdot A_{BT}^{1.5}}{B \cdot T \cdot \left(0.31 \cdot \sqrt{A_{BT}} + T_F - h_B\right)} \quad (15)$$

In order to make the resistance prediction valid for ships and models of different size, the resistance components have to be expressed as dimensionless quantities depending on their respective scaling parameter. The form factor is a dimensionless quantity and the dimensionless quantity of the wave-making and wave-breaking resistance is the wave coefficient.

$$C_w = \frac{R_w}{\nabla \cdot \rho \cdot g} \quad (16)$$

A possible validation technique for the Holtrop and Mennen's model is to perform a linear regression analysis between the predicted and their corresponding experimental values (Beaver et al., 1994, ITTC-Quality Manual 1999). This analysis leads to a line $y=a+b \cdot x$ with a correlation coefficient R^2 . A perfect prediction would give $a=0$, $b=1$ and $R^2=1$. Figure 1 and 2 illustrates a graphical output provided by this validation analysis. The predicted form factor and the wave coefficient are plotted versus the experimental ones as open circles. A solid line indicates the best linear fit.

The values of the linear regression parameters here are, $a_k=-0.37$; $b_k=1.120$; $R^2=0.636$ for the form factor and $a_w=769$; $b_w=3.862$; $R^2=0.886$ for the wave's coefficient.

The Holtrop and Mennen's method seems to track the experimental coefficients approximately well, and the R^2 values are acceptable. However, these results could be improved.

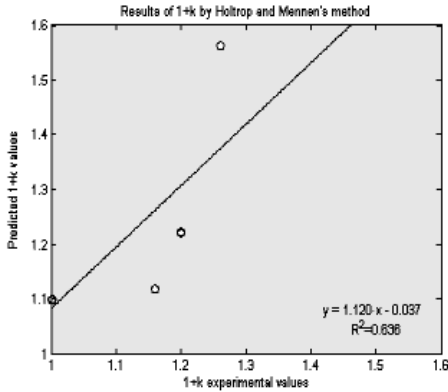


Figure 1. Form factor's linear regression analysis for the Holtrop and Mennen's method.

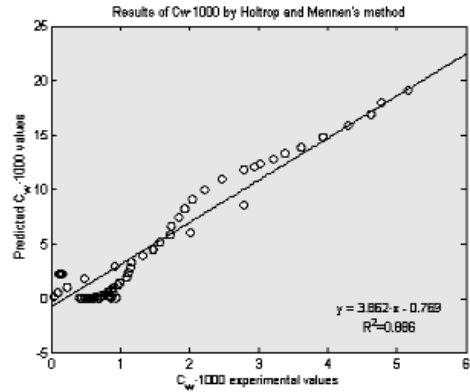


Figure 2. Wave coefficient linear regression analysis for the Holtrop and Mennen's method.

NEURAL NETWORK APPROACH

In this section an empirical model for the form factor and the wave coefficient as functions of hull geometry coefficients and the Froude number is constructed by means of a neural network. The problem is solved with the Flood library (Lopez, 2007).

To training the neural network are necessary data. The calculation is based in the Holtrop and Mennen's method and the original data are not available, so the network has been trained with data generated using the Holtrop and Mennen's method.

The range of the variables considered at the experimental data are:

$$F_n < 0.45; 6.0 < \frac{L}{B} < 9.5$$

$$0.55 < C_p < 0.85; 2.1 < \frac{B}{T} < 4.0$$

To generated the data, has been varied the input data considering the influence of each one in the total resistance. In the most influential variables, the variations have been shorten.

The form factor and the wave coefficient have been calculated with a C++ program, using the Holtrop an Mennen's method for all the possible combinations of the input variables.

A multilayer perceptron is thus trained to learn the relationship between the input ($C_p, C_{stern}, L/B, B/T$ and F_n) and the target variables ($1+k$ and C_W). In that way, the 20664 generated data are divided into a training and a validation subsets, containing the 82% and the 18% of the samples respectively.

Here a multilayer perceptron with a sigmoid hidden layer and two linear output layer is used (Lopez, 2007). The objective functional chosen is the mean squared

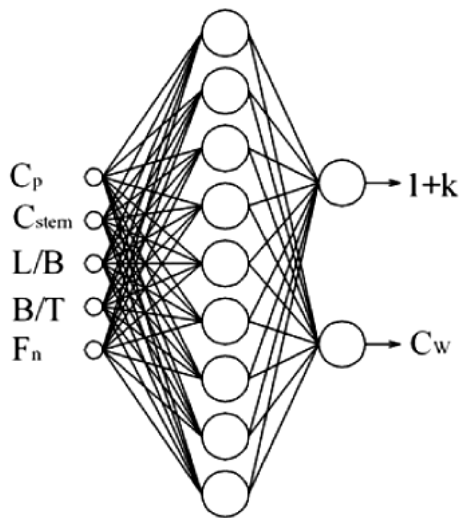


Figure 3. Network architecture for the form factor and wave's coefficient prediction problem.

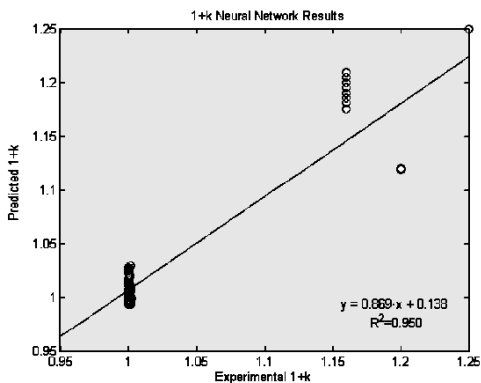


Figure 4. Form factor linear regression analysis for the neural network.

error between the outputs from the neural network and the target values in the data set (Lopez, 2007). The selected training algorithm is a quasi-Newton method with BGFS train direction and Brent optimal train rate (Bishop, 1995).

The neural network must have 5 inputs (C_p , C_{stem} , L/B , B/T and F_n) and two output ($1+k$ and C_w). Here different numbers of neurons in the hidden layer were tested, and the network architecture providing best generalization properties for the validation data set was adopted. The optimal number of neurons in the hidden layer turned out to be 9.

This neural network can be denoted as a 5:9:2 multilayer perceptron, and it is depicted in Figure 3.

Once the optimal network architecture has been found and the generalization properties of the neural network validated, the multilayer perceptron is trained with the experimental data founded in the bibliography (Beaver et al., 1994, ITTC-Quality Manual, 1999), in order to use all the experiments available and to compare the neural network results against the Holtrop and Mennen's method ones.

Figures 4 and 5 shows the linear regression analysis between the experimental and the predicted coefficients provided by the neural network after being trained with the entire experimental data set.

The values of the linear regression parameters here are, $a_k=0.138$; $b_k=0.869$; $R^2=0.950$.

Comparing Figures 1 and 4 we can see that the multilayer perceptron provides better results than the Holtrop and Menne's method.

The values of the linear regression parameters here are $a_w=0.016$; $b_w=0.992$; $R^2=0.998$ for the wave coefficient.

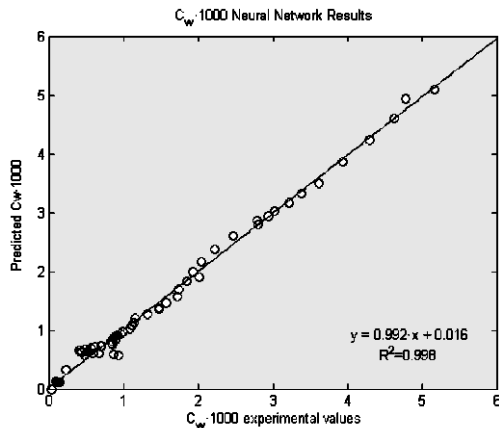


Figure 5. Wave coefficient linear regression analysis for the neural network.

Comparing figures 2 and 5 we can see that the multilayer perceptron provides better results than the Holtrop and Menne's method. Indeed, all the linear regression parameters for the neural network are better than those for the Holtrop and Menne's method.

CONCLUSIONS

The Neural Networks results are compared against those provided by the Holtrop and Mennen's method for estimating the form factor and the wave's coefficient, and it is found that the quality of

the prediction with the neural network is improved over the entire range of data. The Neural Network can be improved, training it with more experimental data.

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PREDICCIÓN DE LOS COEFICIENTES DE RESISTENCIA TOTALES USANDO REDES NEURONALES

RESUMEN

En las fases iniciales de diseño de un barco es de gran valor evaluar el comportamiento del barco para estimar la potencia propulsora necesaria. El modelo desarrollado por Holtrop y Menne en 1982, es una descripción numérica de la resistencia del barco, la cual se subdivide en componentes de origen diferente. Cada componente está expresada en función de los parámetros de forma del casco y de la velocidad.

Se ha demostrado que las redes neuronales son una herramienta muy útil para la modelización de datos. Las redes neuronales se pueden definir como un modelo computacional inspirado en el modelo biológico, que consiste en una arquitectura de red compuesta por neuronas artificiales. Una de las más usadas es el perceptrón multicapa, que es una clase de aproximador universal. En el siguiente trabajo se presenta una red neuronal para el cálculo de dos de las componentes de la resistencia. El perceptrón multicapa ha sido entrenado con datos generados y con datos experimentales, a fin de obtener una estimación del factor de forma y del coeficiente por formación de olas en función de los coeficientes de forma del casco y de la velocidad. La arquitectura de red óptima se ha obtenido mediante un análisis exhaustivo de validación.

EL MÉTODO DE HOLTROP Y MENNEN

El modelo subdivide la resistencia total de un barco en componentes de diferente origen. La evaluación de cada una de las componentes se realizó aplicando múltiples análisis de regresión a 1707 datos experimentales. La resistencia total se expresa como:

$$R_{Total} = R_F \cdot (1+k) + R_{APP} + R_W + R_B + R_{TR} + R_A \quad (1)$$

La resistencia viscosa, R_F , representa aproximadamente el 63% de la resistencia total, y la resistencia por formación de olas representa aproximadamente el 27% de la resistencia total, para números de Froude alrededor de 0.30. El trabajo se ha centrado en estas componentes, ya que son las más significativas.

Los coeficientes que se calculan con la red neuronal son el factor de forma más uno, $(1+k)$ y el coeficiente a dimensional de la resistencia por formación de olas:

$$C_w = \frac{R_w}{\nabla \cdot \rho \cdot g} \quad (2)$$

Validamos el modelo de Holtrop y Mennen realizando una línea de regresión entre valores experimentales que se han encontrado en la bibliografía (Beaver et al., 1994, ITTC-Quality Manual, 1999), y los predichos por el modelo. Esta relación da lugar a una línea de la forma $y=a+b \cdot x$ con un coeficiente de correlación R^2 y una predicción perfecta daría los valores $a=0$, $b=1$ y $R^2=1$. Los valores de los parámetros de la regresión lineal para el factor de forma, $(1+k)$ y para el coeficiente por formación de olas, C_w , son respectivamente $a_k=-0.037$; $b_k=1.120$; $R^2=0.636$ y $a_w=0.769$; $b_w=3.862$; $R^2=0.886$.

Como se puede comprobar el método de Holtrop y Mennen da unos buenos resultados, pero éstos se pueden mejorar.

APROXIMACIÓN CON RED NEURONAL

En esta sección se desarrolla un modelo empírico para el factor de forma y para el coeficiente por formación de olas en función de los coeficientes de forma del casco y del número de Froude, utilizando una red neuronal. El problema se ha resuelto utilizando la librería Flood (López, 2007).

Al no disponer de los datos originales con los que se desarrolló el modelo se han generado unos datos basados en el modelo de Holtrop y Mennen. Las variables de entrada se han ido variando dentro del rango de validez del método

$$F_n < 0.45; 6.0 < \frac{L}{B} < 9.5, 0.55 < C_p < 0.85; 2.1 < \frac{B}{T} < 4.0$$

considerando la influencia de cada una de ellas en la resistencia total.

El factor de forma y el coeficiente por formación de olas se han calculado con un programa C++ utilizando las fórmulas de Holtrop y Mennen, para cada una de las combinaciones de las variables de entrada.

Se ha entrenado un perceptrón multicapa a fin de obtener la relación entre las variables de entrada ($C_p, C_{stern}, L/B, B/T$ y F_n) y las variables de salida ($1+k$ y C_w). El entrenamiento se ha realizado con el 82% de los 20664 datos generados y se ha validado con 12% restante de los datos.

Se ha utilizado un perceptrón multicapa con una capa oculta de neuronas sigmoideas y dos neuronas lineales de salida. El objetivo funcional utilizado es la media cuadrada del error entre las salidas de la red neuronal y los valores de salida de los datos.

La red neuronal ha de tener cinco entradas ($C_p, C_{stern}, L/B, B/T$ y F_n) y dos salidas ($1+k$ y C_w). Se han probado diferentes arquitecturas de red variando el número de neuronas en la capa oculta, y se ha seleccionado la arquitectura que da mejores



propiedades de validación. Para este problema y esta configuración el número óptimo de neuronas en la capa oculta es nueve.

Una vez se ha obtenido la arquitectura óptima de la red y se ha validado, el perceptrón multicapa se ha entrenado con datos experimentales encontrados en la bibliografía (Beaver et al., 1994, ITTC-Quality Manual, 1999), a fin de utilizar todos los datos disponibles y para comparar los resultados de la red neuronal para estos datos con los que da el método de Holtrop y Mennen.

Se ha realizado un análisis de regresión lineal entre los datos experimentales y los coeficientes obtenidos con la red neuronal. Los parámetros de la regresión lineal obtenidos para cada uno de los coeficientes son $a_k=0.138$; $b_k=0.869$; $R^2=0.950$, para el factor de forma y $a_w=0.016$; $b_w=0.992$; $R^2=0.998$, para el coeficiente por formación de olas.

Comparando los parámetros de la regresión lineal obtenidos con la red neuronal y los obtenidos con el método de Holtrop y Mennen, observamos que los de la red neuronal se aproximan más a los parámetros de una regresión perfecta.

CONCLUSIÓN

Los factores de forma y los coeficientes de formación de ola, dados por la red neuronal se han comparado con los dados por el método de Holtrop y Mennen y se ha comprobado que la predicción con la red neuronal, dentro del rango de datos, es mejor que la dada por el método de Holtrop y Mennen.

Un factor favorable en la red neuronal, es que se puede mejorar entrenándola con más datos experimentales.

