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Predictions of oil/chemical tanker main design parameters using computational intelligence techniques

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ABSTRACT

Ship design and construction are complicated and expensive processes. In the pre-design stage, before the construction according to some special rules, determination of the main ship parameters is very important. In this study, instead of traditional methods, the oil/chemical tanker main design parameters are estimated by 18 computational intelligence methods. Therefore, all the data of 114 tankers in operation are used in the experiments in order to estimate a parameter from the remaining ones. Main result of this article is to show that, except for the speed parameter, the main parameters of tankers can be estimated sufficiently well for pre-design stage without having to apply conventional but arduous ship modeling experiments.

1. Introduction

Hydrodynamic model tests are the most conventional methods in Naval Architecture to obtain ship main dimensions and main engine power, coupled to resistance-propulsion characteristics, accurately. During model test, geometric model of ship, scaled down to required a size, is towed along towing tank at specified speeds to measure data for ship resistance, propulsion, engine power calculations. But, model production takes time and is costly due to labor and material needs. In this case, to obtain required data for ships with different dimensions in each time a model ship should be produced and repeated tests should be conducted. Nonetheless, in this study prediction of main design parameters and main engine power for ships outside of present data cluster using Computational Intelligent Techniques, instead of experimental method, is presented.

The most important stage before the production of a chemical tanker construction is the pre-design stage. In the pre-design, with respect to the capacity of goods, the main parameters of the tankers, namely, length, height, draught, breadth, main engine power and speed must be determined as correctly, rapidly and inexpensively as possible. The parameters in focus are calculated using the parameters above mentioned as main design parameters. An error in the calculation of the main parameters consequently results in situations difficult to return or costly to compensate. In order to estimate the main engine power, conventional methods imposed model pool experimental data and/or highly professional software results are used. The convenient methods, especially the experiments, can take enormous times. To overcome, recent machine learning techniques have been investigated.

Of parameters utilized at initial design stage, length between perpendiculars (L_{BP}), breadth (B), draught (T) and deadweight ton (DWT) have influence on stability, strength, capacity, construction and operational costs, moreover, ship speed (V) and main engine power (P) have influence on techno-economic aspects such as, hydrodynamic characteristics, resistance/propulsion, seakeeping and they all affect performance of ships. Thus, at the initial design stage, it is crucial that, these parameters should be determined accurately. For instance, hull weight increases with increasing (L_{BP}), resulting an increase in total construction cost. Or, increase in B value causes higher resistance and power. Or, decrease in T results in longitudinal strength challenges. Considering these facts, predicting and determining the relation of coupled parameters which have importance at initial design stage and the ship speed and engine power are more of an issue.

The study of Alkan et al. [1], in which two fishing vessel data were used in several algorithms in order to calculate the ship geom-

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etry and stability, can be regarded as a pioneer for a realistic neural network in this field.

Amasyali et al. [2] and Bal et al. [3] made main power engine estimations with an acceptable rate of success, in their studies. These previous works have given light to the idea that the pre-design parameters for the chemical tankers, despite their enormous difference in size with motorboats can be estimated by computational intelligence methods as well. In this study various algorithms have been used, not just a few, but all of the parameters have been estimated well.

Recent studies related to artificial neural network and machine learning methods find practice in naval architecture and ocean engineering fields: In particular, identification of ship motion characteristics using ship hydrodynamics, fault optimization of propeller and shaft systems, intelligent ship autopilot design [4–10], prediction of immersed ship form underwater acoustic noise and ship classification [11–15] and prediction, simulation and fault analysis of ship propulsion powers [16–18].

In this study, different Computational Intelligence Techniques are applied for determining principal parameters of current oil/chemical tankers which have lengths of 53–182 m.

This article is organized as follows. In the following chapter, definition of ship parameters are given. The third chapter defines some properties of the data set. In the fourth chapter, artificial intelligence methods deployed in this study are explained briefly. In the last two chapters, the experimental results and a summary of ideas that may be deduced from this study are given, respectively.

2. Tanker' main dimensions and used tanker data sets

Tanker' profile and front view are given in Fig. 1. Main dimensions and related tanker parameters are defined as follows.

- (*BL*) **Baseline**: The horizontal line parallel to the design waterline (*DWL*), which cuts the midship section at the lowest point of the ship. The vertical heights are usually measured from the baseline.
- (*AP*) **After Perpendicular**: The vertical line at the point of intersection of the *LWL* and the centerline of the rudderstock.
- (*FP*) **Forward Perpendicular**: The vertical line at the point of intersection of the *LWL* and the forward end of the immersed part of the ship's hull.
- (*LWL*) **Load Water Line**: The water line at which the ship will float when loaded to its designed draught.
- ($L = L_{BP}$) **Length Between Perpendiculars**: The distance measured parallel to the base at the level of the load waterline from the after perpendicular to the forward perpendicular.
- (*T*) **Draught**: The vertical distance from the waterline at any point on the hull to the bottom of the ship.
- (*B*) **Breadth**: The distance from the inside of plating on one side to a similar point on the other side measured at the broadest part of the ship.
- (*V*) **Ship Speed (Knot)**: The distance in miles taken in a hour.
- (*DWT*) **DeadWeight Ton**: Total amount of weight that a ship can carry (cargo, fuel, lubricating oil, fresh water, stores, passengers and baggage, crew and their effects).
- (*P*) **Main Engine Power(kW)**: This is measured at the flywheel of an engine.

In this study, 114 real oil/chemical tanker data (obtained from www.veristar.com web site and www.gisbir.com – Turkish shipbuilders association web site) are used. Each tanker's main parameters L_{BP}, DWT, B, T, V, P are estimated by using computational methods. The parameters' cross-correlation are given in Table 1. The scatter plot of the data used is given by Fig. 2. Table 1 and Fig. 2 are examined together, and the highest correlation observed is between B and L_{BP}. Moreover, the average highest and lowest correlation between the remaining main parameters belong to T and V, respectively.

Table 1
Cross-correlation of pre-design parameters.

	L_{BP}	B	T	V	P
DWT	0.9265	0.9547	0.9318	0.5018	0.8872
L_{BP}		0.9724	0.9615	0.6808	0.9627
B			0.9670	0.6156	0.9367
T				0.6510	0.9373
V					0.7418

3. Computational Intelligence Techniques

In this study, several regression algorithms from different software packages are used. Table 2 illustrates list of methods used and related software packages. WEKA is available at www.cs.waikato.ac.nz/ml/weka. Regression Toolbox is available at www.control.hut.fi/Hyotyniemi/publications/report125/RegrToolbox, PLSToolbox is available at www.eigenvector.com. Matlab Neural Network Toolbox version 7.0 is used. The notation used in the methods are:

The regression approximation addresses the problem of estimating a function $y = f(x)$ based on a given data set $G = \{(x_i, d_i)\}_{i=1}^{N}$ where $x_i = [x_{i1}, x_{i2}, \ldots, x_{im}]$ is input vector, d_i is the desired value, y_i estimated value, f is the estimation function, w is the weight vector, N is the number of observations and m is the number of features.

3.1. Least Median Square (LMS)

LMS algorithm uses the estimation of the gradient vector from the given data set. Successive corrections to the weight vector in the direction of the negative of the gradient vector are made iteratively until reaching the minimum median square error.

3.2. Simple Linear Regression (SLR)

It is the process of fitting straight lines (models) between each attribute and output. In Eq. (1, the values of w and w_0 are estimated by the method of least squares.

$$y = wx + w_0 \tag{1}$$

The model having lowest squared error is selected as the final model among each parameter model.

3.3. Linear Regression (LR)

The final model is linear regression of a subsample of the attributes. The subsample is selected by iteratively removing the one with the smallest standardized coefficient until no improvement is observed in the estimate of the error given by the Akaike information criterion [22].

$$y = w_0 + w_i x_i + \varepsilon \tag{2}$$

The AIC value, with the assumption of eventual normally distributed errors, is calculated as follows,

$$AIC = 2k + N \ln\left(\frac{RSS}{N}\right) \tag{3}$$

where k is the number of parameters in the model, RSS is the Residual of Sum of the Squares.

3.4. Multi-layer Perceptron with Adaptive Learning Rate (GDA)

In this technique, backpropagation is often used. The backpropagation used in this article is derived from a Least Mean