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WIG configuration prediction using neural network approach

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Wing In Ground effect (WIG) is a high speed advanced marine vehicle that represents a new era in the waterborne transportation. It operates near water or ground surfaces benefiting from high lift and low drag due to ground proximity. In this paper, the neural network technique is used as a preliminary design tool to predict the main geometrical dimensions, as well as total weight and installed power required to move a new WIG vehicle with given payload at certain speed. The network was carefully trained using available data for existing WIG models and vehicles. The method proved to be quite speedy, handy, and quite suitable for preliminary design purposes.

في هذا البحث تم استخدام تقنية الشبكات العصبية في استنباط أبعاد ومواصفات تصميم جديد لسفينة بحرية من نـــوع الـــويج كما استخدمت الطريقة السالفة الذكر في تقدير الوزن الكلي والقدرة المطلوبة لتـــسيير هـــذه المركبـــة بالـــسرعة والحمولـــة المطلوبتين. ولاستخدام طريقة الشبكات العصبية فانه ينبغي تدريب الشبكة أولا بالمعلومات المتوفرة عن هذا النوع من السفن. من خلال تلك الدراسة تم التوصل الي إثبات قدرة طريقة الشبكات العصبية علي القيام بعملية التصميم الابتدائي لهذه النوعية من المركبات بسرعة وفعالية.

Keywords: WIG craft, Ground effect, WIG design, Neural network

1. Introduction

Marine vehicles are classified according to different criteria. One of these is the lifting force required to vertically support the vehicle as shown in fig. 1. The lifting force is either static (in the form of water buoyancy or pressurized air cushion) or dynamic (planning surfaces, hydrofoils or lifting wings). The most recent member that has joined marine vehicles family is Wing In Ground effect vehicle (WIG).

A Wing-In-Ground-effect vehicle (WIG) is a craft that is especially designed to take advantage of the reduced drag and increased lift due to ground proximity. Therefore a WIG vehicle will always fly close to the water surface.

The payload per power installed is quite remarkable. A hovercraft typically can lift around 5.8 kgs per kilowatt of engines fitted while a WIG craft can lift around 10 kgs per kilowatt of engines fitted; fig. 2. Hence, the main benefits when a craft is operating within ground effect are that speed; payload and fuel economies are considerably more efficient than with traditional boat, plane and helicopter transport.

Large number of different WIG vehicles configurations has been designed and built during the past three decades. [1]. Most of these designs were built for military purposes. Some commercial production already started in the USA [2] and Australia [3]. In 1995, the International Maritime Organization (IMO) recognized and issued regulations concerning WIG vehicles [4]. Data pertaining to WIG design (power, form, speed, etc) are quite few and scattered. No systematic series or model test data are available in the public domain.

Extensive survey for these data is made through published literatures and manufacturers sources. Data obtained included geometrical characteristics, payload, weight and installed power. The aim of this work is to make use of these data in predicting main particulars of a new WIG vehicle. It is suggested here to use artificial neural network technique for this task.

Neural network techniques are very efficient tools in computing problems where many assumptions have to be satisfied in parallel as it happens in image-recognition problems. This can be achieved, in contrast to the classical sequential computers, by using networks of analogue neurons with nonlinear behavior and the neurons are connected with

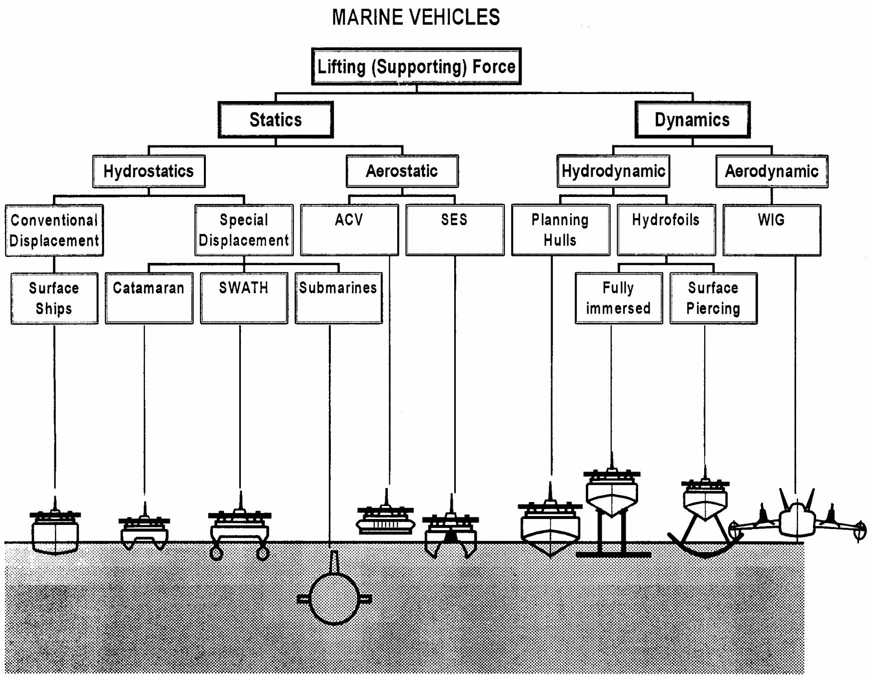

Fig. 1. Marine vehicles classification according to supporting force.

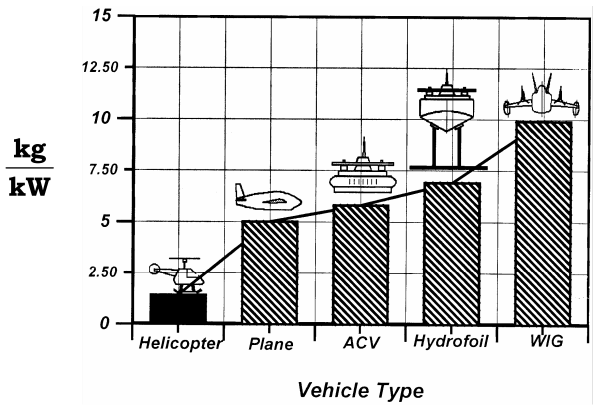

Fig. 2. Payload per installed power ratio for different vehicle types.

links having variable weights. The main benefit of using artificial neural networks is their ability to predict behavior of phenomenon that is random in nature. Recently, neural networks have been applied to a wide range of problems in different disciplines [5-14].

In this paper, the neural network technique is used as a preliminary design tool to predict the main geometrical dimensions, as well as total weight and installed power required to move a new WIG vehicle for a given payload at certain speed. The network was carefully trained using available data for existing WIG models and vehicles.

There are three phases for the used technique: first, the database is prepared and incomplete sets were eliminated. Second, the conditioned data was used to train the network, and finally, the trained neural networks is integrated with a design package as a starting point, which are followed by, detailed selection of other variables and hence assessing the overall performance details.

2. WIG variables (generic WIG model)

Wing In Ground effect vehicle is a complex structure involving a number of systems and subsystems. The vehicle has to meet a number of requirements for operation in different modes; displacement, skimming, takeoff, and cruising modes. Kotb et al. [15] conducted a parametric study on WIG variables. Two parameters combining wing geometry and cruising height were introduced and found to have pronounced effects on WIG performance. Husa [16] prepared a matrix of WIG variables with the purpose of helping in design and selection process of a new WIG craft. To keep the problem within perspective, a WIG vehicle is modeled into a simple generic configuration type. Global WIG variables are considered here while other detailed options of each variable are left for the subsequent and final design phases. Both global and detailed variables are discussed in the sections to follow.

The major component parts of WIG vehicles are: body (or fuselage), lifting surface (or Wings), tail assembly, buoyancy system or floatation system, and power plant.

The fuselage or body of a WIG craft provides an attachment for its wing, tail assembly, floatation system, and power plant. In addition, it provides space for the crew and passengers and houses the various controls and instruments required for cruise. Conventionally, the body or fuselage contributes very little to aerodynamic lift. To fully utilize the body internal volume, the fuselage is divided into three main sections. The middle section, where the crew and payload are located, is short and wide, while the front and rear sections are narrow and tapered towards the ends. The three main dimensions of the body, as shown in fig. 3 are length, width and depth; L, B, and H, respectively.

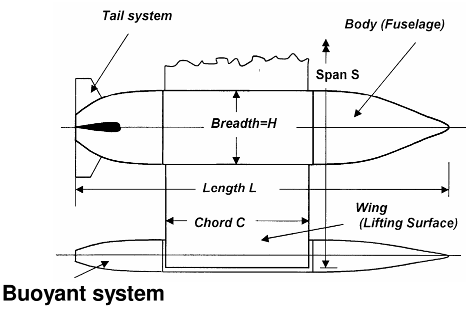

Fig. 3. Generic WIG vehicle.

Wings or lifting surface can take various shapes. The variations in shape include rectangular planform, conventional delta, trapezoid, reverse delta, and forward swept planform. The rectangular planform is the simplest, however it exhibits the least amount of inherent stability and therefore it requires very sizable horizontal tails for sufficient control authority. The trapezoid planform has promise for WIG applications because of its structural simplicity and its ability to be tailored for this application. In this case the Lippish design (reverse delta) is the most favorable layout due to its improved stability.

Wings or lifting surfaces may also be located on the fuselage in different positions. The most basic component of the wing's layout is the vertical position on the body. The three options are high, mid, and low wing. The high wing has the advantages of having the lift distribution less affected by the vehicle body, and easier access to dock facilities. The negative aspects of the high wing include a higher center of gravity, and a less benefit from ground proximity.

The mid wing configuration has the advantages of using the body as a fence, hence, providing a level of control for the root airflow. The configuration however, has structural complications at the wing body regions. The fuselage has also to carry the root bending load in addition to the lifting shear load. This results in a weight and cost increase.

The low wing layout is structurally simple and also provides performance benefits since it can be positioned and optimized for the ground effect flight envelope. The low wing can also provide structural support for any floatations and/or takeoff assist devices. Hence, it allows for the fuselage to remain out of the water.

Wing's cross sectional shape can be selected based on a number of factors. These are lift distribution, pitching moment pressure center shift and aerodynamic behavior near the ground.

The installed power for a WIG vehicle is used mainly for cruising phase. Additional power may be needed for takeoff, hover, or water operation. This additional power may be taken in the form of power takeoff from the main engine, or through a separate system. Propulsion power is provided by conventional diesel engine, turbines, conventional aircraft engines, and converted automotive power plants. To develop the required thrust propellers, ducted propellers, ducted fans ,or turbo fans may be used.

All WIG configurations require some form of displacement buoyancy to keep the craft afloat and stable at low speeds and at rest. This is provided through the use of a conventional hull or flotation system. The buoyant system may be placed half way out on the wings, below the fuselage, or at the wing tips.

Finally, the WIG vehicle variables selected for this study are: body length; *L*, body width, *B*, and height, *H*, lifting surface span, *S*, aspect ratio; AR, payload W_{PL}, cruising speed; *V*, total weight; *W*, and installed power, *P*.

3. Collected database

Extensive survey was made for different existing WIG vehicles, models, and prototype characteristics. The data was tabulated regarding their main dimensions, carrying capacities, cruising speed, gross weight, installed power, and any other relevant information. The payload in the selected database varies in the range from 200kg to 2000kg. Data was filtered and incomplete configurations were eliminated.

4. Neural network technique

The neural network can be defined by the network topology (architecture), its nodes (neuron) characteristics and the learning rules. There are many kinds of network architecture in terms of the way in which the neurons are connected. One of these kinds, is the feed-forward network that is used in this paper.

The architecture of a simple feed-forward network is the three layers network shown in fig. 4. The first one is the input layer, where no computational process happened in each node (neuron) for the input variables. The second layer is the hidden layer that is connected to input nodes with links through weight values that permit the transmission of the input variables. The third one is the output layer that is also linked to the hidden layer through weight connections permitting to transmit the response of each node (neuron) to the output nodes.

Each neuron in the hidden and output layers is responded to the incoming signals by summing the multiplication of the incoming signal by its weight that connects the incoming signal and that neuron, as shown fig. 5, such that:

$$SUM_j = \Sigma\, W_{ij} \times Input_i + Bias. \quad (1)$$

Where:
$Input_i$ = input variable *i*,
W_{ij} = weight value of the connection between input variable *i* and neuron *j* in the hidden layer, and
Bias = is the bias weight value multiplied by one.

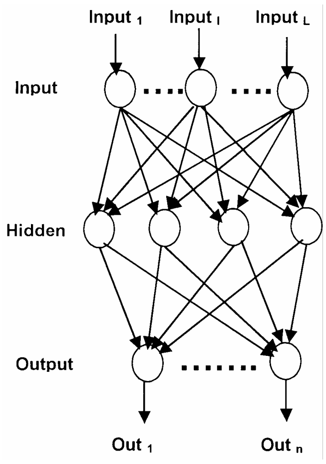

Fig. 4. Simple multi-layer feed-forward network topology.

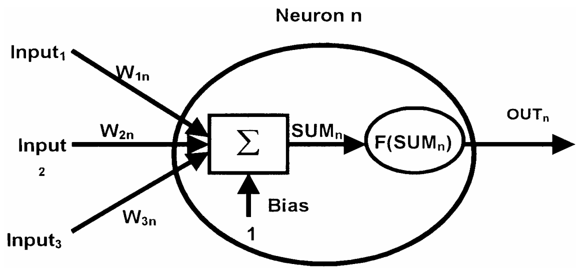

Fig. 5. Summing input variables with bias to process through activation function.

The neuron is activated to these incoming summed signals result through an activation function, *F*, such that:

$$OUT_n = F(SUM_n). \quad (2)$$

This activated value of the neuron is considered as an incoming signal value for the other neurons in the next layer. The activation functions that can be used in the processing calculations can be linear, tangent or sigmoid function.

When a set of inputs is shown to the network, it will self-adjust to produce consistent responses through a process called learning. The learning is the process of adjusting the weights systematically in order to achieve some desired results for a given set of inputs. There are two types of learning; supervised and unsupervised and the former is applied in this study.

In the case of supervised learning, the network is presented with a set of input vectors and desired output vectors. At first, the network uses the input to generate an output that is compared with the desired output. Learning will only take place if there is a significant difference between these values, in which case the weighted interconnection between neurons in the network will be adjusted properly so as to reduce the difference. The most popular supervised learning approach makes use of the multilayer feed forward network architecture. This type of network learns via a process called "back propagation" [17-18]. In this work, the resilient back propagation training algorithm is used to train the multilayer feed forward network [19].

5. Neural network model

Samples of well-correlated data for the WIG vehicles are used for training the neural networks model. The network has two input variables, the payload and speed, and six output variables; namely, length, span, height, aspect ratio, power and weight. The number of hidden units is chosen such that they are equal to the number of training sets. After 15000 epochs, the maximum absolute error that has been achieved for the calculated output variables is less than 0.75%, as shown in fig. 6. This magnitude of error can be considered as good in predicting the principle characteristics of the WIG vehicles. In addition, the trained neural networks model should be capable to extract the principal features for all input data that lies in the range of the training data.

In using the test data to examine the efficiency of network model, the achieved maximum absolute error is 2.8% as shown in fig. 7. The test data that has the maximum error is shown in table 1. It is obvious from this table that all the predicted values for the length, span, height, aspect ratio, power and total weight are considered acceptable with respect to the target ones. Thus, this model can be used efficiently to extract WIG particulars in preliminary design stage.

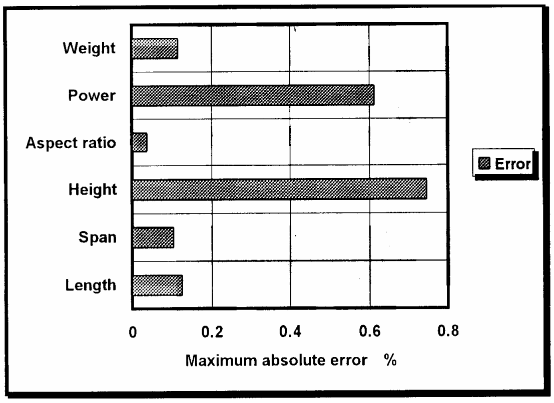

Fig. 6. Percentage of maximum absolute error obtained in training the neural network.

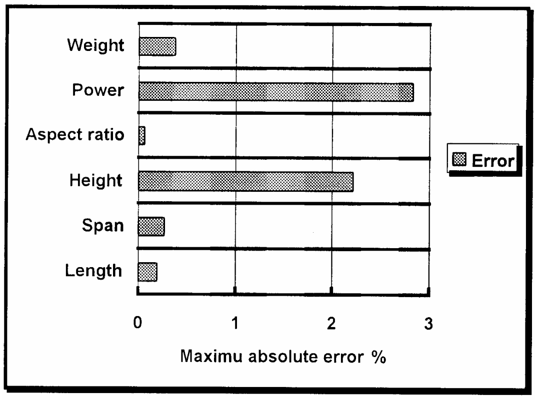

Fig. 7. Percentage of maximum absolute error obtained for test data using neural network.

Table 1
Target and predicted values for the different variable using NNT

Item	Target	Predicted	Error %
Length	7.43	7.427	0.04502
Span	5.7	5.685	0.27157
Height	2.1	2.054	2.20841
Aspect ratio	1.954	1.953	0.03661
Power	39.87	38.741	2.83172
Weight	1072.71	1069.022	0.34379

6. Conclusions

The theory and techniques of neural networks were employed to predict the principal dimensions, as well as weight and installed power required for preliminary design of Wing In Ground effect vehicle. From the work done in the present study, a number of remarks and observations are concluded:

1. The data so far available in the literature for WIG crafts can be fully utilized using Artificial Neural Network, ANN, for preliminary design of a new ones based on the required payload and speed.
2. The back propagation neural networks approach has the ability to predict the main particulars of a WIG vehicle with reasonable accuracy after training the model with the given range of data field.
3. Although these results are promising, the approach needs to be further enhanced for predicting finer details of WIG vehicle other than the global particulars.
4. WIG variables were selected in a global sense with the aim of simplifying the training process of the proposed ANN scheme.
5. The estimated data for geometry, weight, and power can form a good starting point for more and refined detailed design.
6. For each global variable there exist a number of options or sub-options which are left to the designer to suit the operating conditions and to match economic, regulatory or alike constrains.
7. Errors involved in estimating WIG particulars are within accepted engineering practice.
8. The network model used can be retrained using newer updated data when it becomes available.

Finally, the ability of neural networks to accurately learn and predict nonlinear multiple input and output relationships make them a promising technique in interpolation problem in the field of ship design.

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