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Prediction of main particulars of a chemical tanker at preliminary ship design using artificial neural network

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ABSTRACT
Preliminary ship design is an important part of the ship design and a reliable design tool is needed for this stage. The aim of this study was to develop an artificial neural network (ANN) model to predict main particulars of a chemical tanker at preliminary design stage. Deadweight and vessel speed were used as the input layer; and length overall, length between perpendiculars, breadth, draught and freeboard were used as the output layer. The back-propagation learning algorithm with two different variants was used in the network. After training the ANN, the average of mean absolute percentage error value was obtained 4.552%. It is also observed that the correlation coefficients obtained were 0.99921, 0.99775, 0.99537 and 0.9984 for training, validation, test and all data-sets, respectively. The results showed that initial main particulars of chemical tankers are determined within high accuracy levels as compared to the sample ship data.

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Preliminary ship design; artificial neural network; chemical tanker

1. Introduction

Naval architects have to design the ships in many stages. Ship design can be divided into four main stages namely concept design (feasibility study), preliminary design, contract design and detailed design. The ship design process is traditionally described as an iterative procedure in the form of a design spiral and it was introduced by J. H. Evans (1959) as shown in Figure 1. Concept and preliminary design are also known as preliminary design. First, main particulars of a ship are determined at a preliminary stage. In general, determination of initial main particulars of vessels has traditionally been made using statistical regression equations. In recent years, ratio of DWT/L has been increased and old empirical formulas are inadequate for ship design. Thus, the updating of empirical formulas has become an important issue. This process is both time consuming and unreliable. However, a neural network may be a more favourable option than statistical methods since they have been shown to provide greater flexibility and can create accurate models of complex systems more quickly (Clausen et al. 2001; Mason et al. 2005; Jain and Deo 2006; Lee et al. 2007; Matulja et al. 2010; Papanikolaou 2014).

In recent years, artificial neural network (ANN) has been used for many disciplines. However, there have been little studies reported in ship design and stability by applying neural network. Clausen et al. (2001) have developed a model for the determination of the main particulars of a containership at the preliminary design stage using ANN method. They also used regression analysis, and Bayesian network and all these methods were compared with each other. The loading capacity of the vessel was chosen the input parameter. Length, breadth, speed, draft, depth and displacement were selected as output parameters. The results showed that ANN performance was found to be better compared to the other methods. The average percentage error rate ranges from approximately 4% to 9%. Alkan et al. (2004) developed two different ANN for determining initial stability particulars of fishing vessels. In the first network, vertical centre of gravity (KG) was predicted using block coefficient, beam, depth and length to displacement ratio. In the second network, height of transverse metacentre above keel (KM) and vertical centre of buoyancy (KB) were predicted using length overall (LOA), moulded beam, design draught, moulded depth, block coefficient, prismatic coefficient, waterline area coefficient and displacement at the design waterline. Two hidden layers with seven nodes in the first hidden layer and six nodes in the other were used for this study. Results indicated that both networks developed to predict ship stability give satisfactory results. Matulja et al. (2010) developed an ANN model for the selection of a maximum efficiency ship screw propeller. Blade number, advance speed, delivered power and rate of revolution were used as input parameters since it is common to start the propeller selection from the available engine power at a given rate of revolution. Diameter, pitch ratio, expanded area ratio, thrust and maximum open water efficiency were determined as output parameters. Different neural network architectures and learning parameters were tested in order to find the most reliable model. The results obtained in this study showed that developed ANN is satisfactory model for the preliminary screw propeller selection. Kim et al. (2004) classified surface plates effectively in the preliminary ship design using ANN. Currently in shipyard, the hull surfaces of ship are classified into planar plane, first surface, second surface and third surface according to the shape of sur-

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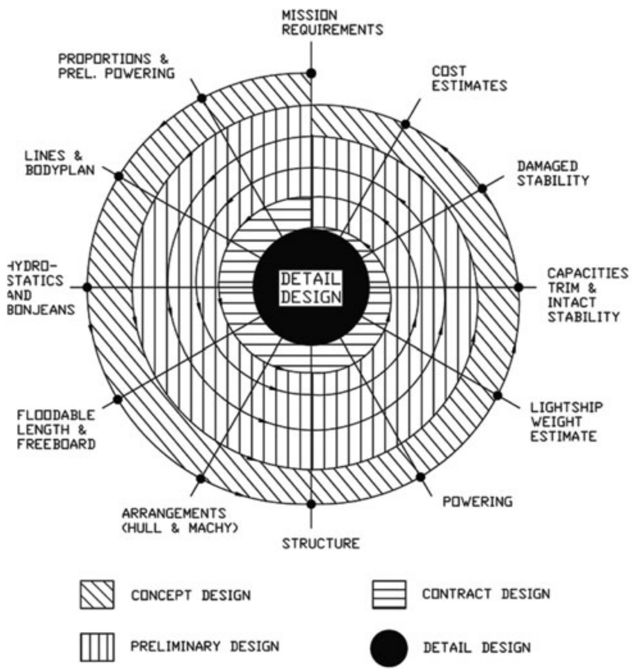

Figure 1. Ship design spiral.

face and required manufacturing curvature. In order to solve classification problem, the pattern classification of neural network was applied in this study. As input pattern, the surfaces are subdivided in the length and width directions. After training, it was found that the proposed ANN method can classify effectively and efficiently the various shape of ship hull.

As seen in the aforementioned studies, there have been little studied reported in ship design by applying neural network. In this study, a reliable model is proposed to ship designers for determining initial main particulars of chemical tankers. Error rates are minimised by testing different optimisation algorithms and neurons.

2. Materials and methods

2.1. Data collection

The speed and load capacity of the ship are important desire for the shipowner. Naval architects start design of the vessel using these parameters. They have to determine the main dimensions including LOA, length between perpendiculars (LBP), breadth (B), draught (T) and freeboard (f) at the preliminary ship design stage.

Table 2. Variability range of parameters of used chemical tanker.

Parameter	Minimum value	Maximum value
Deadweight (ton)	1524	52,725
Speed (kn)	11	16
Overall Length (m)	64.43	195.09
LPP (m)	59.15	187.3
Breadth (m)	10.45	32.2
Draught (m)	4.2	13.3
Freeboard (mm)	707	6412

Due to the complexity and dynamics of ship design, naval architects try to use many types of reliable and adaptive approaches to assist in the design work geared at improving the design quality (Cui et al. 2012). In the present paper, ANN approach was used for ship design. Data to be used for modelling was collected from Veristar (http://www.veristar.com) for chemical tankers built in the last 8 years. One hundred vessels were gathered for this study and Table 1 shows the characteristics of 12 ships. Variability range of parameters was summarised in Table 2.

2.2. Artificial neural network

Artificial intelligence techniques including expert systems, ANNs, fuzzy logic, etc., became attractive worldwide (Helvacioglu and Insel 2008). ANN is an information processing system inspired by biological nervous system. They have been used for many disciplines including medicine, engineering and computer science because of their ability to model nonlinear functions quickly and accurately. In recent years, this method is relatively new tools in the field of naval architecture and marine engineering. They possess characteristics that make them particularly attractive in complex problems, such as the ship design process (Haykin 1994; Alkan et al. 2004; Gougoulidis 2008; Matulja et al. 2010).

An ANN model is composed of the information processing units called neurons, which are fully connected with different weights indicating the strength of the relationships between input and output data (Lee et al. 2016). The ANN has an input layer, an output layer and one or more hidden layers linking them (Haykin 1994). The network topology must be chosen

Table 1. Main dimension of some part of the used data.

Vessel name	Deadweight (ton)	Speed (kn)	LOA (m)	LPP (m)	Breadth (m)	Draught (m)	Freeboard (mm)
KAYA BENER	1524	11	64.43	59.15	10.5	4.4	859
ADELE	3200	11.2	88.22	82.5	13	5.75	1311
TRANSNAV HAZEL	6487	12	100.12	94	18	6.5	3111
PRIA	7534	14	111.5	106	17.6	7.2	2211
HACI FATA ANA	8424	14	123.25	116.07	17.2	7.2	2014
NORDIC AKI	14,701	14.7	134.3	126	22.4	8.9	3214
GT STAR	19,956	16	145.5	137	23.7	9.7	3664
ICDAS-09	19,983	15	149.95	143.3	23	9.2	3217
BOW HERON	33,707	15	174.38	167	27.7	11.02	5014
AGENA	37,583	15	184	176	27.4	11.5	5714
FULL STAR	36,031	14	188.2	178	29	11.4	4614
POER	52,725	15.2	195.09	187.3	32.2	12.5	5317

appropriately so that the model can be simple and reliable. It is also an important problem that network is to memorise instead of learning during training. This means that it is overfitting. The validation data-set can be used to solve this problem. The most popular learning algorithms are the back-propagation and its variants. The fundamental goal of all algorithms is to minimise the global error at training stage. The error equation is often called the objective function. Variants of this error equation are commonly used, including the mean square error (MSE) and the root mean square error (Zurada 1992). Back-propagation training is a gradient descent algorithm. It tries to improve the performance of the neural network by reducing the total error by changing the weights along its gradient with an iterative procedure (López and Iglesias 2013). The Levenberg–Marquardt (LM) algorithm is a variation of Newton's method that is designed for minimising functions that are sums of squares of other nonlinear functions. It can be thought of as a combination of the steepest descent and the Gauss–Newton method (Singh et al. 2007; Zounemat-Kermani 2012). Scaled conjugate gradient (SCG) belongs to the class of conjugate gradient methods, which shows superlinear convergence on most problems. It is designed to avoid time-consuming line search by combining the model-trust region approach used by LM approach with the conjugate gradient approach (Møller 1993; Shaheed 2004).

In the present work, both LM algorithm and SCG algorithm are applied to the multi-layer network-training problem. A typical neural network is shown in Figure 2. In order to implement back-propagation learning algorithm, each iteration of training includes the following procedures.

First, initial values of the weights (w_{0j}, $w_{ij,}$ $etc.$) are assigned randomly. Later, the following equations are used for finding output_j and output_k value:

$$\text{net}_j = w_{0j} + \sum_{i=1}^{n} x_i w_{ij} \tag{1}$$

$$\text{output}_j = f\left(\text{net}_j\right) \tag{2}$$

$$\text{net}_k = w_{0k} + \sum_{j=1}^{m} \text{output}_j w_{jk} \tag{3}$$

$$\text{output}_k = f\left(\text{net}_k\right) \tag{4}$$

where w_{ij} is the weight between the input neurons and the hidden neurons, w_{jk} is the weight between the hidden and the output neurons, x_i is the value of the input, n is the number of inputs of neuron, output_j is the value of the output for hidden nodes, m is the number of neurons of the hidden layer, output_k is the value of the output for output nodes and p is the number of neurons of the output layer, w_{0j} and w_{0k} bias weight.

The final summation is transferred by an activation function f to get the output of node. The logsig function and the purelin function were used as the activation functions in the hidden layer and the output layer, respectively for this study and general definitions are expressed as in following equations:

$$\text{logsig}\,(x) = \frac{1}{1+e^{-x}} \tag{5}$$

$$\text{purelin}\,(x) = x \tag{6}$$

After the output value is determined, the error term for each node is computed. Finally, the new values of the weights are obtained:

$$\delta_k = f'\left(\text{output}_k\right)\left(t_k - o_k\right) \tag{7}$$

$$\delta_j = f'\left(\text{output}_j\right)\sum_{k=1}^{p} w_{jk}\delta_k \tag{8}$$

$$w_{ij}\,(n+1) = w_{ij}\,(n) + \alpha\delta_j\left(\text{output}_j\right) + \beta\left(\Delta w_{ij}\right) \tag{9}$$

$$w_{jk}\,(n+1) = w_{jk}\,(n) + \alpha\delta_k\left(\text{output}_k\right) + \beta\left(\Delta w_{jk}\right) \tag{10}$$

where α is the learning rate and β is the momentum coefficient. The learning rate governs the size of the weight change as per the effect of the weight on the total error. The momentum factor prevents weight oscillations during training iterations and also accelerates the training on flat error surfaces (More and Deo 2003). These procedures are repeated until the desired value of error.

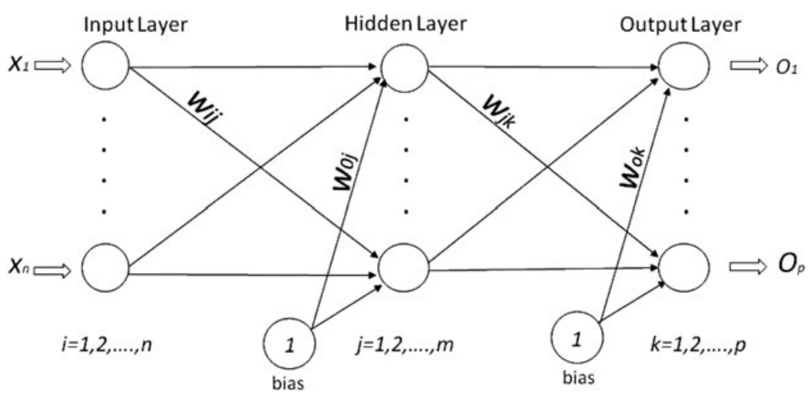

Figure 2. A typical neural network.

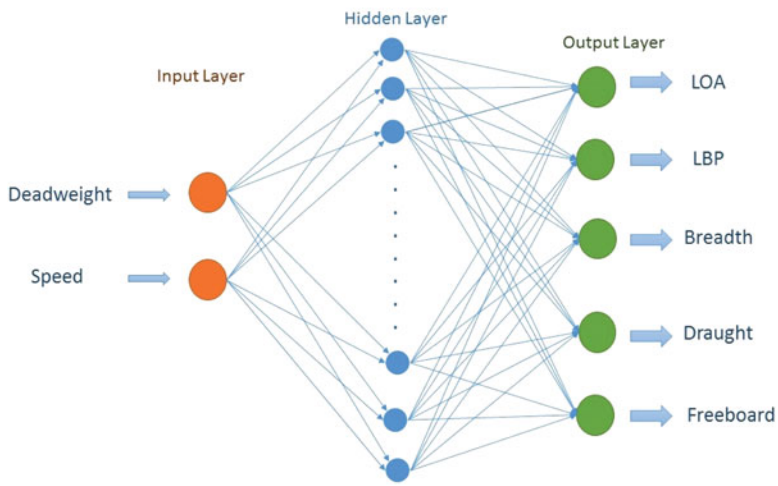

Figure 3. Structure of the ANN model. (This figure is available in colour online.)

3. Implementation

In the present study, ANN was trained and tested by means of the MATLAB software. As mentioned in the previous section, the validation data-set was used to solve overfitting problem and maximum validation failure was set to 100. Back-propagation learning algorithm was applied for the single hidden layer. LM and SCG algorithms have been used for the variants. A set of 100 samples of data was gathered for the present study. Seventy samples were used for training set, 15 samples were used for validation set and remaining 15 samples were used for test set. The training data-set is used only for network training while the test data-set is used for determining network performance. The validation data-set is used to prevent memorisation of the network. In the training process, learning rate and momentum coefficient were taken as 0.4 and 0.6, respectively. Normalised both for inputs and outputs are taken between the values of zero and unity. The logsig function and the purelin function were used as the activation functions in the hidden layer and the output layer.

The performance goal for the training was set to 10^{-6}. The MSE was determined network performance function. The statistical method of mean absolute percentage error (MAPE) value was used for comparisons. These values are expressed by the following equations:

$$\mathrm{MSE} = \frac{1}{n}\sum_{i=1}^{N}(t_i - o_i)^2 \tag{11}$$

$$\mathrm{MAPE} = \frac{1}{n}\sum\left|\frac{t_i - o_i}{o_i}\right| * 100 \tag{12}$$

where t is the target value, o is the output and n is the number of samples. Figure 3 depicts the structure of the ANN model for present study.

4. Results and discussion

The aim of this study was to develop an ANN model to predict main particulars of a chemical tanker at preliminary design stage. Deadweight and vessel speed were used as the input layer; and LOA, LBP, B, T and f were used as the output layer.

Table 3. Performance of different hidden neurons and algorithms.

Number of hidden neuron	LM	SCG
1	7.0554	7.3765
2	6.7576	6.8417
3	6.5236	6.6642
4	6.3535	6.5039
5	6.1656	6.2787
6	5.7338	6.0309
7	5.4308	5.9579
8	5.0613	5.9855
9	5.1615	5.8692
10	4.892	5.9612
11	5.0087	5.9313
12	4.7004	5.9589
13	4.5526	5.6598
14	5.0358	5.888
15	4.9593	5.7342

Table 4. MAPE values of the developed network.

	Train	Validation	Test	All
Overall length	2.272321	3.955429	5.093952	2.948032
LPP	2.597643	3.731425	5.326211	3.176996
Breadth	2.501645	3.606664	3.069288	2.752544
Draught	3.027834	6.279888	6.878408	4.093228
Freeboard	6.802319	14.53806	18.99853	9.792113
Mean value	3.440352	6.422294	7.873278	4.552583

In order to acquire the nearest output values to collected data, different number of neurons (1–15) in the hidden layer was tried. Table 3 gives the MAPE values of all data-set for different hidden neurons and algorithms. It can be observed from this table that the minimum error was found when the numbers of hidden nodes were chosen as 13 at LM algorithm. The error value for 13 hidden neurons in the LM algorithm was found to be 4.5526.

Table 4 shows the MAPE values for the developed network in detail. It can be observed from this table that MAPE values of all data-sets were determined as 2.948032, 3.176996, 2.752544,

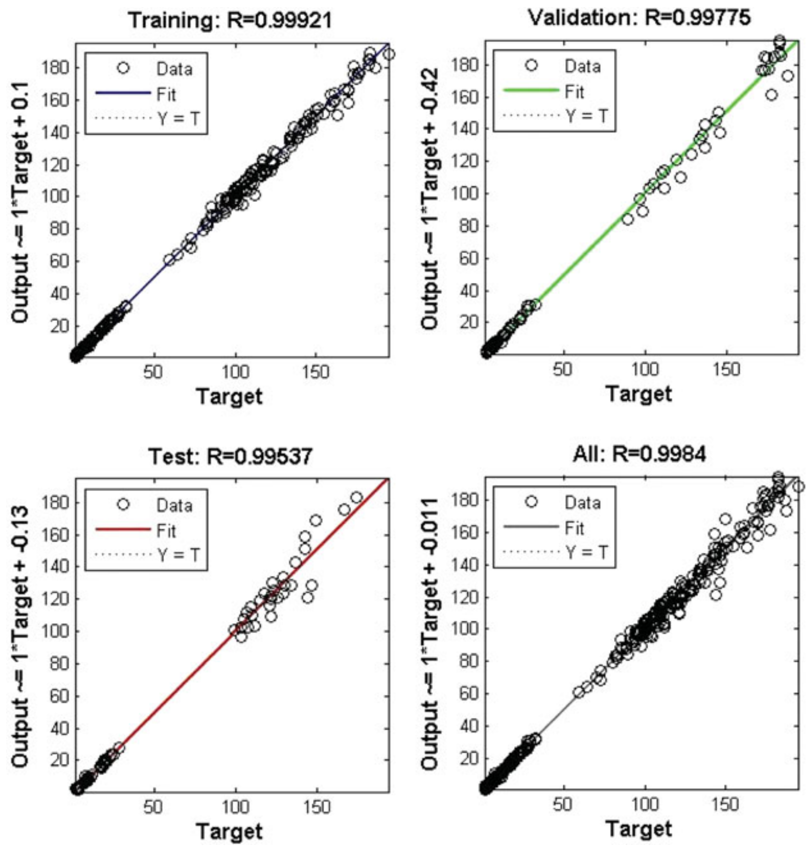

Figure 4. Regression graphics of the developed network. (This figure is available in colour online.)

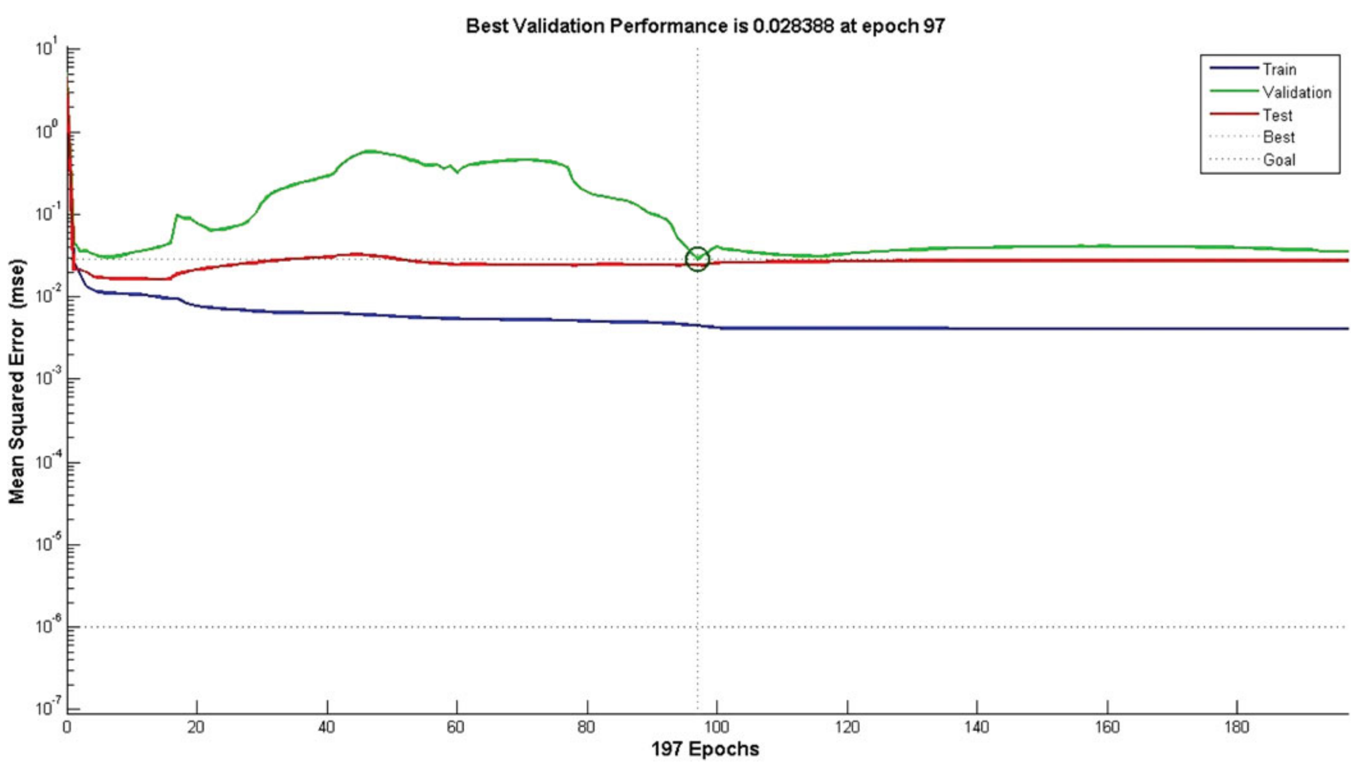

Figure 5. Performance plot of the developed network. (This figure is available in colour online.)

Table 5. Actual and predicted value of outputs.

Data-set	Vessel name	Actual LOA	Predicted LOA	Actual LBP	Predicted LBP	Actual breadth	Predicted breadth	Actual draught	Predicted draught	Actual freeboard	Predicted freeboard
Validation	PALANCA SINGAPORE	133.2	133.975	128.2	124.776	23	21.773	8.6	8.854	3.81	3.079
	T SOCHIA	103	103.344	96.5	97.07	16	16.844	7	6.857	1.712	1.84
	SILVER VALERIE	183	187.607	174	176.477	32.2	31.08	13.26	12.052	5.852	4.387
	INERVA LEO	184	185.506	176.13	176.975	27.4	30.557	11.9	12.173	5.713	5.947
	BIRDIE TRADER	145.5	150.714	137	143.153	23.7	24.37	9.7	9.292	3.664	3.836
Test	AGILITY	114.9	119.459	106.9	111.755	18.6	17.619	8	7.147	2.812	2.184
	ANUKET ABER	122.2	121.828	120.76	115.722	19.05	18.925	7	10.317	3.512	3.58
	BARBARICA	143	150.965	136.8	143.121	23	23.684	8.9	9.415	2.91	3.21
	BOW HERON	174.3	183.131	167	175.356	27.7	27.777	11.02	11.084	5.014	5.583
	CEVDET A	129.7	133.56	123.2	125.66	19.6	19.183	8	8.037	2.4	2.177

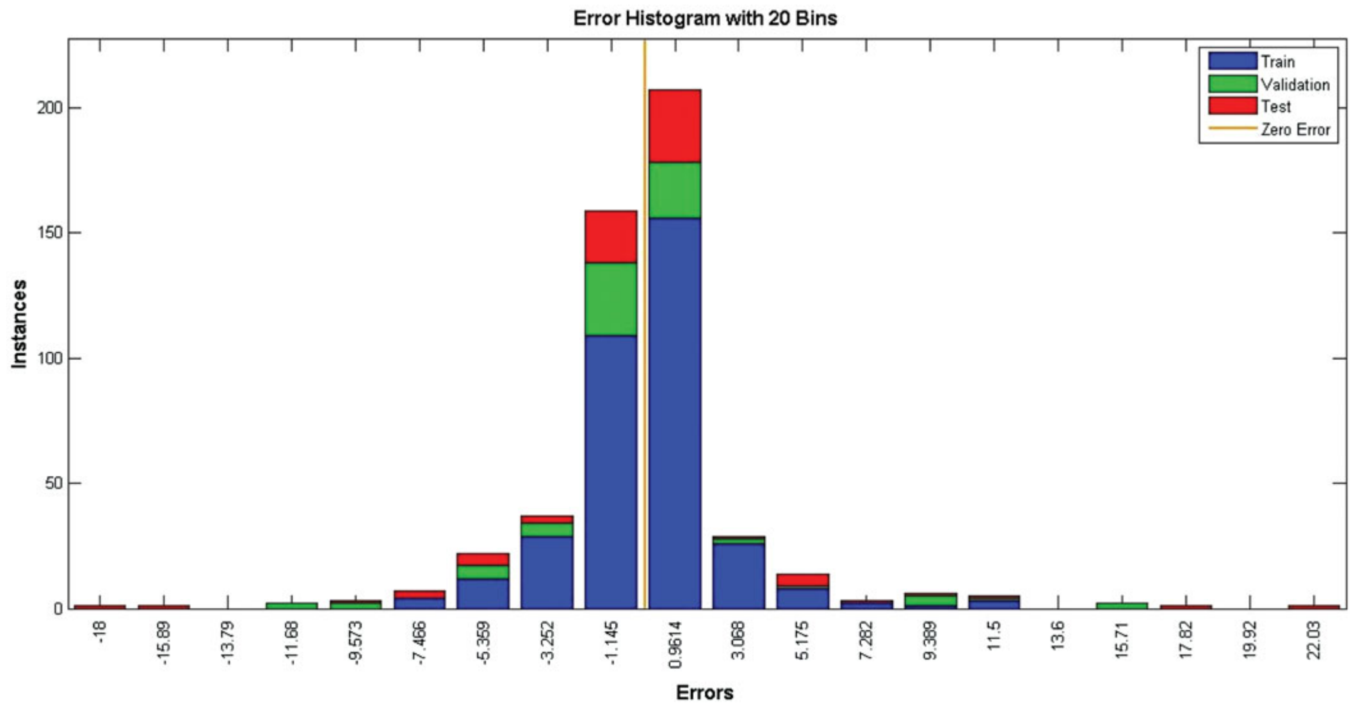

Figure 6. Error histogram of developed ANN model. (This figure is available in colour online.)

4.093228 and 9.792113 for LOA, LBP, B, T and f, respectively. The average of these values was calculated as 4.552583. Among the output parameters, the maximum error occurred at freeboard for all data-sets. The highest MAPE values for LOA, LBP, T and f were calculated as 5.0939%, 5.3262%, 6.8784% and 18.9985% at test data-set. The highest MAPE value of B was found to be 3.6606% at validation data-set. In general, the error has an acceptable error value with a relatively high MAPE value for the freeboard.

The regression graphic between the estimated ANN values and actual ship data is shown in Figure 4. It is observed that the correlation coefficients were obtained as 0.99921, 0.99775, 0.99537 and 0.9984 for training, validation, test and all data-sets, respectively. These results indicated that the actual values and the predicted values are consistent with each other.

Figure 5 illustrates the performance plot of the developed network. After the 97th approach, the validation and test sets exhibited an increasing trend. The training of network was stopped because there was no reduction during the 100 iterations. As a result, the best validation performance was achieved at epoch 97. MSE was calculated as 0.028388.

Table 5 illustrates a part of actual and predicted value of the output parameters, including test and verification data-sets not used for training. It is observed from Table 5 that the actual values of the output parameters are close to predicted value of the output parameters.

Figure 6 shows the error histogram wherein the blue, green and red bars indicate the training data, validation data and testing data, respectively. The error value indicates the difference between the actual and the predicted value. Orange line shows the zero error line. It can be observed from Figure 6 that the largest portion of data coincided with the zero error line. A large part of the errors varied between −3.252 and +3.068.

5. Conclusions

An ANN model to predict main particulars of a chemical tanker at preliminary design stage was obtained. It is found that ANN with LM algorithm including 13 hidden neurons is the best predicted tool. This paper also reveals that results provided good agreement with the actual data. Data collection from a similar built vessels or evaluation of empirical relationships are complex and time-consuming process at the preliminary ship design stage. In addition, this procedure may be inadequate to design innovative ship. Developed ANN model has a very important role to play in meeting the challenge the difficulties described above. The conclusions of this study may be summarised as follows:

- MAPE values of all data-sets were determined as 2.948032, 3.176996, 2.752544, 4.093228 and 9.792113 for LOA, LBP, B, T and f, respectively.
- The average of MAPE values was calculated as 4.552583.
- The correlation coefficients were obtained as 0.99921, 0.99775, 0.99537 and 0.9984 for training, validation, test and all data-sets, respectively.
- The best validation performance was obtained at epoch 97. MSE was calculated as 0.028388.
- A large part of the difference between the actual and the predicted value varied between −3.252 and +3.068.

Disclosure statement

No potential conflict of interest was reported by the authors.

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