Indian Journal of Science and Technology, *Vol 9(29), DOI: 10.17485/ijst/2016/v9i29/89933, August 2016*
ISSN (Print) : 0974-6846
ISSN (Online) : 0974-5645

Extreme Learning Machine for Prediction of Wind Force and Moment Coefficients on Marine Vessels

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Abstract

Background/Objectives: To develop a universal method for wind force and moment coefficient prediction on marine vessels independent of ship types. The marine vessels' equation of motion includes hydrodynamics forces, moments and environmental disturbances. One of the environmental forces and moment acting on the ship originate from wind and play a vital role in offshore operations. Till date, wind loads are determined by statistical and regression analysis. In this paper, an extreme learning machine is used as a technique to predict the wind force and moment coefficients. **Findings:** This approach is novel and is common for any ship shapes. The performance of the proposed method is much more accurate and simplified compared with the existing tools. The result matches precisely with the experimental data. **Applications/ Improvement:** This method shall be an effective tool in calculation of wind loads on marine structures which is extremely critical in marine operations and ship maneuvering and positioning.

Keywords: Extreme Learning Machine (ELM), Neural Network, Wind Force and Moment Coefficient

1. Introduction

There has been a considerable increase in the offshore activities in the recent times. This needs an efficient dynamic positioning system for safe operation of the ships. The ship is considered as a rigid-body and its equation of motion consist of hydrodynamic forces, moments and environmental disturbances. The hydrodynamic forces is composed of radiation-induced forces and damping forces[1]. The environmental forces and moments are due to wind, wave and currents. Wind exerts a significant force on marine vessels and the true distribution and magnitude of wind forces on the marine vessels is time-varying and unpredictable. In addition to the static structure, resonances due to excitation close to the natural frequencies of the structure significantly. An exhaustive analysis of wind forces and moments should be carried on a scaled model, to make the ship control system robust especially in harsh environmental situation. Data obtained from reliable and adequate scaled model tests are required to calculate the forces and moments acting on ships of complex shape. These tests are to be carried out on a properly scaled model of the full scale shape of the ship. This process is accurate but it's expensive and tedious.

In addition there are different numerical methods to estimate the wind forces (surge and sway) and moment (yaw) acting on ships without direct scaled model testing. However these methods involve numerical statistical study with the data, to determine expression for estimation of wind forces and moments. Beside there is no common feature among these methods and its heavily depended upon the shapes and structure of the ships. In order to overcome these difficulties and to identify a universal method, we propose an extreme learning machine in this paper.

The extreme learning machine for Single hidden Layer Feed forward neural Network (SLFN) tends to provide better generalization performance at a faster learning

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rate. The performance of the network is verified by comparing the predicted coefficients with measured coefficient from experimental tests of Blendermann[2].

2. Background

In this section, brief comparisons over the different numerical and statistical methods used for wind force and moment coefficient calculation are reviewed. Wind forces and moments action on marine vessel shown in Figure 1 is determined by,

$$X_{wind} = \frac{1}{2} C_X(\gamma_r)\rho_a V_r^2 A_T(N) \quad (2.1)$$

$$Y_{wind} = \frac{1}{2} C_Y(\gamma_r)\rho_a V_r^2 A_L(N) \quad (2.2)$$

$$N_{wind} = \frac{1}{2} C_N(\gamma_r)\rho_a V_r^2 A_L L(N_m) \quad (2.3)$$

where X_{wind}, Y_{wind} and N_{wind} are the wind forces in surge and sway direction and the moment in yaw direction, C_X and C_Y are the empirical force coefficients, $\rho_a\left(\frac{kg}{m^2}\right)$ is the density of air, V_r is the wind velocity in knots, $A_T(m^2)$ and $A_L(m^2)$ are the transverse and lateral projected area, and $L(m)$ is the overall length of the ship.

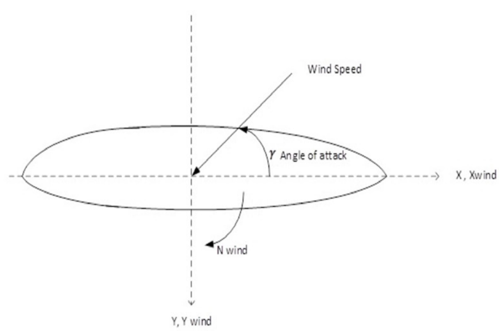


Figure 1. Co-ordinates, wind Forces and moments.

Isherwood[3] pioneered development of numerical methods by performing a multiple regression analysis based on earlier experimental results. For more information, one may refer to[9]. Later, Gould[4] devised a mathematical procedure to calculate the ahead force, side force and yawing moment on ships due to wind. These methods are non-parametric, require a wind tunnel test on a scale model, or estimate the wind loads by a reference to known values of a similar vessel.

Thirdly, Blendermann[2] formulated a statistical analysis of the wind load exerted on marine vessels and developed a semi-empirical loading function to relate the characteristics of the wind to the marine vessels. There are[5,6] force and moment coefficients for various wind direction is expressed in terms of fore and side projected areas of ship as below:

$$C_X = \frac{X_{wind}}{(q.A_T)}, C_Y = \frac{Y_{wind}}{(q.A_L)}, C_N \frac{X_{wind}}{(q.A_L.L)} \quad (2.7)$$

Where $q = \frac{p_a}{V_T^2}$ represents the dynamic pressure of the true wind.

Blendermann also provided a method for the prediction of wind force on ships where the air flow is non-uniform with experimental data. The non-uniform of air flow is considered for an effective dynamic pressure.

Wind loads for Very Large Crude Carriers (VLCCs) can be computed by applying the OCIMF 1977 formulas[7]. This method is valid for class of vessels in the 150,000 to 500,000 dwt. The non-dimensional force and moment coefficients C_X, C_Y and C_N are given as a function of γ_r. For ships that are symmetrical with respect to the *xz* and *yz* planes,

$$C_X(\gamma_r) = c_x \cos\gamma_r, C_Y(\gamma_r) = c_y \sin\gamma_r, C_N(\gamma_r) = c_n \sin(2\gamma_r) \quad (2.8)$$

Where

$$c_x \in \{-1.0, -0.8\}, c_y \in \{-1.0, -0.7\}, c_n \in \{-1.0, -0.05\}$$

Indicated that the magnitude of wind forces on the various components of marine vessels; depend greatly on the character of the wind at sea[8]. A preliminary attempt at defining the wind field at sea is also represented mainly for offshore structures. Experimental results of different offshore structures are carried out in wind tunnel and analysis of the drag coefficients based on the structures has been detailed.

Details of different methods for estimating wind forces and moment coefficients on ships are explained. Two methods, Blendermann and Isherwood are used to estimate the drag coefficients of a container ship in loaded and in ballast condition. Table 1 shows the dimension and particulars of the container ship. The results are shown in Figures 2-4 for loaded container ship and Figures 5-7 for empty container ship.

Table 1. Dimension and Particulars of the container ship

	Loaded	In Ballast
Total Length (m)	210.75	210.75
Beam (m)	30.5	30.5
Lateral projected area (m^2)	375L 11	2947.30
Draft (m)	11.6	9.6
Height of ship centre in lateral side (m)	10.08	8.67
Distance of lateral centre from midship (m)	3.87 (forward)	2.14 (forward)
Transverse area (m^2)	801.97	857.06

Figure 2 and Figure 5 represents longitudinal force coefficients. For wind angles above 150 and below 60, Isherwood method tends to overestimate the Blendermann experimental results.

Figure 3 and Figure 6 represents side force coefficients. For wind angles between 30 and 150, Isherwood method deviates more from the Blendermann results. We can also observe that there is some difference between loaded container and the container in the ballast condition. Figure 4 and Figure 7 is the yaw moment coefficient. In both loaded and ballast condition, the Isherwood method differs from the Blendermann method drastically. The coefficient calculated by Isherwood method is no were close to that of Blendermann. The conclusion is that there is no uniformity in any of the above described methods. The differences between the estimates obtained from Isherwood and Blendermann methods shall be due the limitations in the range of experiments. For different conditions, different methods perform better and so there is no unique method to determine the wind force and moment coefficient irrespective for the type of marine vessel.

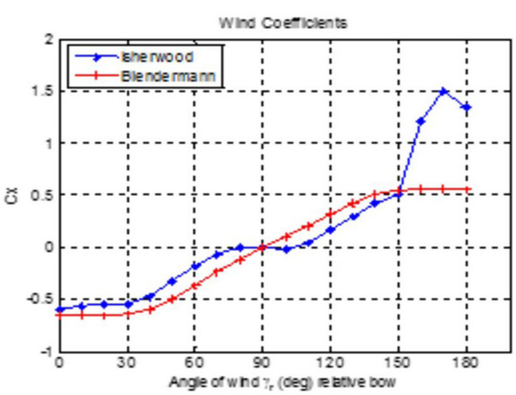


Figure 2. Longitudinal force coefficient, loaded container.

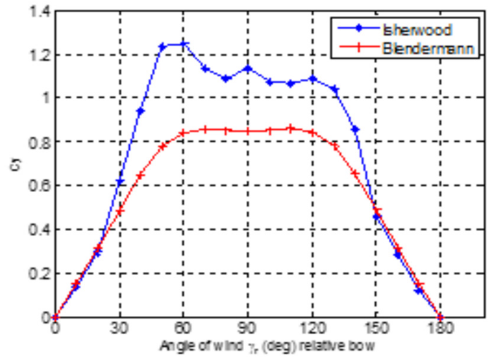


Figure 3. Slide force coefficient, loaded container

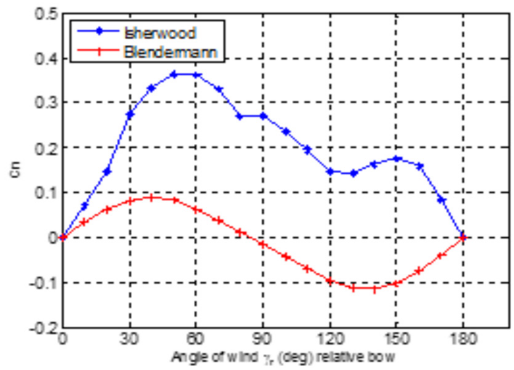


Figure 4. Yaw moment coefficient, loaded container

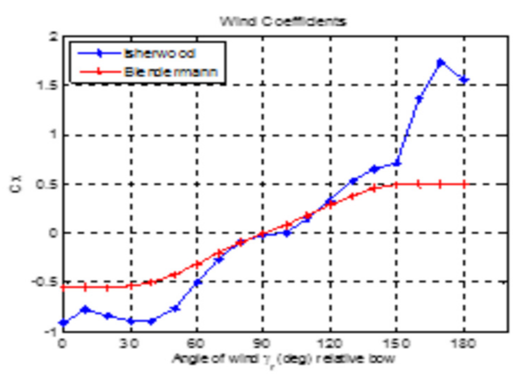


Figure 5. Longitudinal force coefficient for container in ballast

A neural network technique that can estimate wind force and moment coefficients on ships[9]. Experimental results of 19 ships from Blendermann[2] are used to train the network. A universal expression that is independent of ship types is proposed and results obtained show that the prediction by the network agrees very closely to the Blendermann experimental result. There are no details on the learning time of the network, training and testing errors.

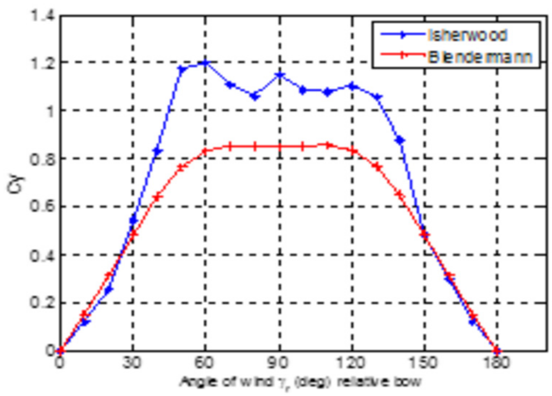


Figure 6. Slide force coefficient, container in ballast

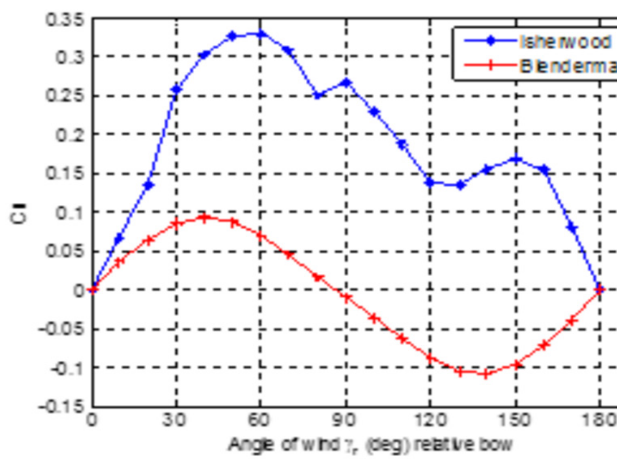


Figure 7. Yaw moment coefficient, container in ballast

3. Methodology and Problem Formulation

The neural network used in[9], is a feed forward neural network, using the back-propagation method. From literatures, we know that feed forward neural network has the ability to approximate any complex nonlinear structures and provide models for a very large scale system which are difficult to handle in conventional parametric methods. However, the learning speed of feed forward neural networks[10] is in general far slower than often required by the applications. The important factors for this is, 1. The slow gradient descent based learning algorithm which may easily converge to local minimum and 2. All the network parameters are to be tuned iteratively introducing dependency between different layers of parameters. This clearly identifies that the feed forward neural network used in[9], has greater chances of converging to a local minimum and also require numerous iterative learning in order to obtain better performance. So if the training sample is too large, the network might take several hours to converge. To overcome this, Extreme Learning Machine (ELM) is proposed for prediction of wind forces and moment coefficients. The ELM randomly selects hidden nodes and determines the output weights analytically. The learning speed of ELM is thousand times[10] faster than he traditional feed forward network and is able to obtain better generalization. It also provides smaller training error and smaller norm of weights. As the expression of wind force and moment coefficients Isherwood[3], is a linear fit as seen in (2.4), (2.5) and (2.6). This linear relation between the output and the vessels parameters makes it much more realizable in ELM.

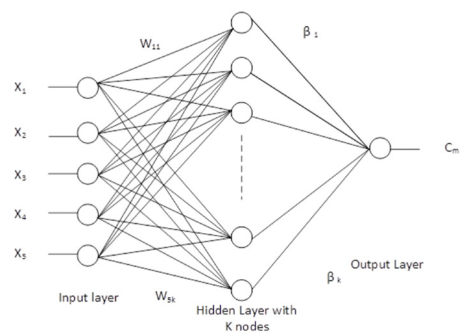


Figure 8. ELM neural network with linear nodes

The architecture of the proposed SLFN ELM is shown in Figure 8. Where the output layer has one linear node, hidden layer has K nodes and the input layer has five nodes.

From the Figure 8, the input data vector X_n and output data C_m can be expressed as below:

$$X_n = \left(X_1, X_2, X_3, X_4, X_5, X_6\right)^T \tag{3.1}$$

$$C_m = \sum_{k=1}^{k} \beta_k h_k \tag{3.2}$$

Where $X_1 = \frac{A_L}{L^2}$, $X_2 = \frac{A_r}{B^2}$, $X_3 = \frac{L}{B}$, $X_4 = \frac{C}{L}$,

$X_5 = \gamma_r$ and m=1,2,3 refer to longitudinal force coefficient, side force coefficient and yaw moment coefficients and K is the number of hidden neurons.

The activation function g(y) is chosen to be Gaussian function as follows,

$$g(y) = \exp\left(\frac{-y^2}{2\sigma^2}\right) \quad (3.3)$$

Where the Gaussian width is chosen randomly based on the number inputs.

The input to each hidden layer neuron is as follows,

$$y_i = \sum_{j=1}^{n} W_{tf} \quad (3.4)$$

Where $W_{if} = \left(X_j - \mu_i\right)$ is the radial distance between the input and centre of hidden neurons μ_i. The hidden layer output at k[th] neuron as follows,

$$h_k = \exp\left(\frac{-y_i^2}{2\sigma^2}\right) \quad (3.5)$$

and the Hidden layer Output matrix H is as follows,

$H = [h_1, h2.... h_k]^T$ (3.6)

It is seen from[10,11] that ELM is treated as a linear network and the output weight matrix is computed using the generalized Moore-Penrose inverse of the hidden layer output matrix as follows,

$$\beta = H^{+}C \quad (3.7)$$

Where H^+ is the generalized Moore-Penrose inverse of the matrix H, β is the output weight matrix and C is the desired output data.

4. Design of ELM SLFN

We have implemented three number of networks as shown in Figure 8, where network one predicts Longitudinal force coefficient, network two predicts side force coefficient and network three predicts yaw moment coefficient respectively. The training data used in this network is normalized between [-1, 1]. The centre of hidden neurons is selected randomly from the normalized input of the training data. Upon selection of μ_i there is in fact no necessity to tune it further and the Hidden Layer output H actually remains the same once random values are assigned for μ_i in the beginning of learning[10]. The upper bound on the number of hidden neurons is the number of

Table 2. Ship particulars used for validating ELM

	LOA	B(m)	D(m)	$A_L(m^2)$	$A_T(m^2)$	C(m)
Gas Tanker (loaded)	274	47.2	10.95	7537.41	801.97	-3.87
Gas tanker (ballest)	274	47.2	8.04	8313.74	1827.12	-2.53
Tanker (loaded)	351.4	55.4	23.5	3401.47	1131.79	-24.45
Tanker (ballast)	351.4	55.4	10.625	7839.63	1803.93	-8.32

Table 4. Training and Testing Error

Itr. No	Network1 Train M.E	(C_x) Test M.E	Network1 Train M.E	(C_y) Test M.E	Network 1 Train M.E	(C_N) Test M.E
1	0.0686	0.0678	0.0445	0.0445	0.0396	0.0422
2	0.0662	0.0637	0.0479	0.0577	0.0371	0.0399
3	0.0616	0.0633	0.0451	0.059	0.0413	0.0405
4	0.0653	0.0602	0.0509	0.0469	0.0395	0.0362
5	0.0677	0.0719	0.0465	0.0545	0.0398	0.0472
6	0.0686	0.0797	0.0423	0.0621	0.0379	0.043
7	0.0681	0.0873	0.038	0.056	0.0383	0.0303
8	0.0655	0.0893	0.0476	0.0477	0.0392	0.0402
9	0.0714	0.0734	0.0419	0.0612	0.0388	0.0392
10	0.0614	0.0831	0.0482	0.0482	0.0382	0.0346
Mean	0.0664	0.0074	0.0453	0.0538	0.039	0.0393

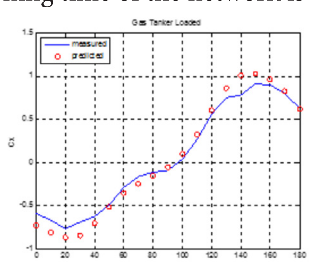
distinct training samples, that is $N \le K$, where N is the total number of training samples (Xn, Cm). The experimental data of 4 ships[2] used to validate the performance of the network is listed in Table 2. The experimental data of 20 ships[2] used to train the network is listed in Table 3.

5. Results and Discussion

A total of **1162** samples are used to train the network. The number of hidden neurons used on all three networks is K=150. To illustrate the performance of the ELM in prediction of wind force and moment coefficient, comparisons between the predicted output of the network and Blendermann[4] experimental results are shown in Figures 9-12. Figure 13 shows the training error for the three networks. Each of the three networks are trained repeatedly for 10 iteration and the mean square training error and testing error of each iteration for the three networks is shown in Table 4 is Training and Testing Error.

From Figures 9-12, we can see that the prediction of wind force and moment coefficient by the proposed ELM SLFN is far efficient that the feed forward neural network proposed in[9]. The network has obtained better generalization of training data. For the gas tanker and tanker in both loaded and in ballast condition as shown in Figures 9-12, the longitudinal and side force coefficients and yaw moment coefficient follows the measured experimental results closely. From Figure 13 and Table 4, we can observe that the training error is on average for the three networks are bounded below 0.07.

The learning time of the network is 4.08 seconds.



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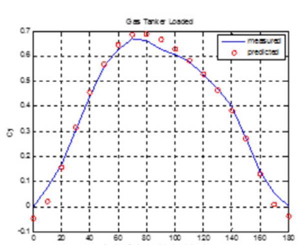

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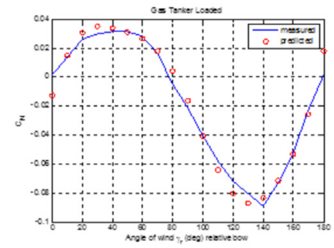
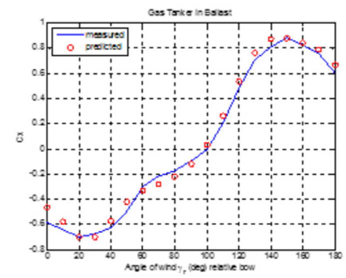


(c)

Figure 9. (a), (b) and (c) shows C_X, C_Y and C_N for the gas tanker in loaded condition.



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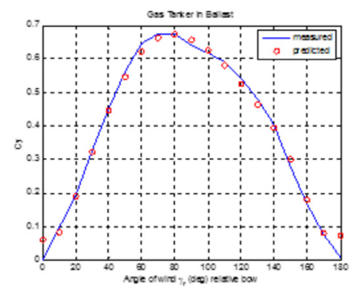

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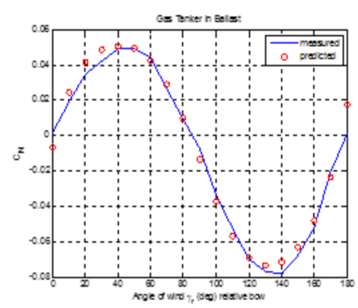

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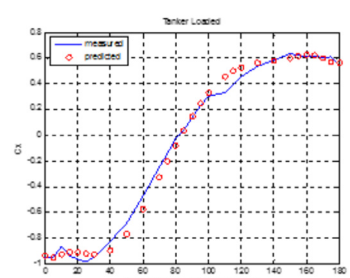
Figure 10. (a), (b) and (c) shows C_X, C_Y and C_N for the gas tanker in ballast condition.



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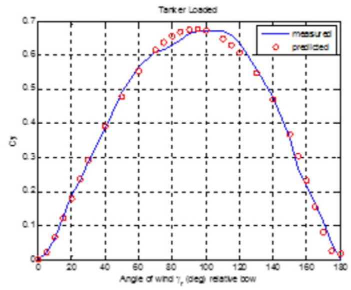

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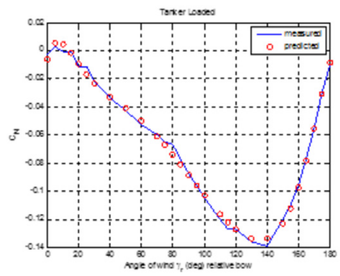

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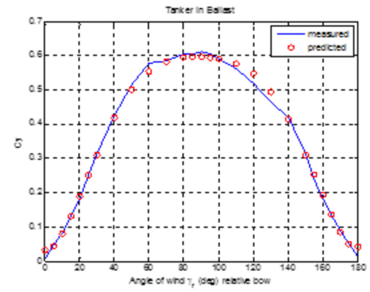
Figure 11. (c)Figure 11. (a), (b) and (c) shows C_X, side force C_Y and C_N for the tanker in loaded condition.



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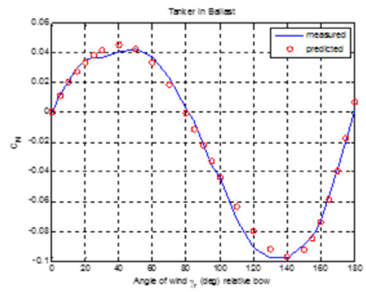

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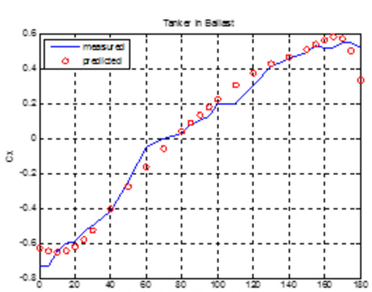
Figure 12. (a), (b) and (c) shows CX, CY and CN for the Tanker in Ballast Condition.

6. Conclusion

In this paper, an Extreme Learning Machine for SLFN to predict the wind force and moment coefficients has been developed. We observed from the results that the prediction of the network is very much matching the experimental results from Blendermann[4] with significantly minimum mean square error. The network has shown faster learning rate and much more accurate generalization than the feed forward back propagation proposed in[9]. This technique provides a universal expression to determine the wind force and moment efficiently irrespective of the geometry and shape of the vessel. This avoids the tedious and expensive numerical, regression analysis of wind tunnel test data in calculation of drag coefficients as discussed in section 2. The paper has demonstrated that ELM can be used an as effective alternative



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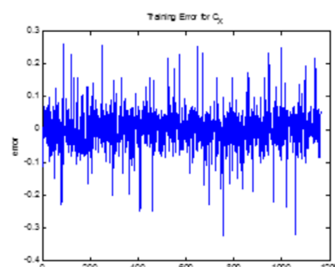

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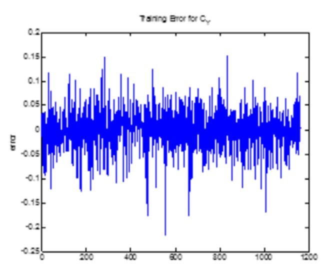

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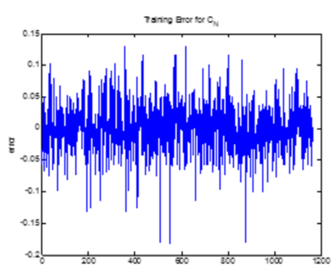

(c)

Figure 13. (a), (b) and (c) shows the training error of the network prediction CX, CY and CN.

to wind tunnel test for calculation of wind force and moment coefficients.

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