PREDICTION OF HYDRODYNAMIC COEFFICIENTS OF OFFSHORE STRUCTURES USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Artificial neural networks developed by researchers in cognitive sciences and artificial intelligence are used in many engineering problems. The main benefit of using artificial neural networks is their ability to predict behavior of phenomenon that is random in nature. In this paper, back propagation neural network is used to determine hydrodynamic force coefficients (added mass, drag and lift coefficients) for an articulated offshore tower subjected to non-uniform flow. The neural network is first trained with a set of experimental data obtained from test results of an articulated tower model oscillated sinusoidally in still water. The capability of the back propagation neural network to predict new coefficients was then tested against a separate set of experimental data. The results show that application of artificial neural networks in predicting hydrodynamic force coefficients has a considerable potential regarding accuracy.

Keywords: Artificial neural networks, Offshore structures, Hydrodynamic coefficients.

1. INTRODUCTION

The forces due to waves and current effects past members of offshore structures whose diameter is small relative to the wave length generally have two components at right angles to each other. One of these fluid-induced forces is the in-line force which is parallel to the flow propagation and the other is the vortex-induced transverse forces. Many studies have been done to predict these forces in different flow and structure conditions, see Sheppard and Omar (1992) for review on these studies. The in-line force is calculated by Morison equation which is composed of an inertia and a drag term linearly added together. The vortex-induced transverse force is commonly expressed by a formula similar to the drag force-type formula which involves a lift coefficient, C_L. Calculation of these forces depends on the suitable inertia, drag and lift coefficients (C_m, C_D and C_L). With unsuitable coefficients these equations achieve simplicity but limit accuracy and applicability. According to previous studies (see Sheppard and Omar, 1992) these coefficients are found to be a function of either Reynolds number, R_e, or Keulegan-Carpenter number, KC, or the frequency parameter, $\beta (\beta = R_e/KC)$. Therefore, for a successful prediction of the total wave forces on structural members of offshore structures, the hydrodynamic coefficients, C_m and C_D and the lift coefficient C_L, must be known for the range of application of R_e and KC. The values of these coefficients are generally obtained through model testing which covers a certain range of R_e and KC.

Ever since Morison, et al, (1950) presented their force equation for unsteady fluid-structure interaction, many experimental studies have been carried out to obtain the hydrodynamic coefficients (C_m and C_D). Same has been done for vortex-induced transverse force to obtain the lift coefficient (C_L). For over a third of a century, many hydrodynamic force coefficients for different ranges of R_e and KC have been available. In an attempt by the offshore industry to make use of this data, and in the same time to isolate the ranges of R_e and KC that are not covered, Horton (1992), through a joint industry project, collected the available experimental data on force coefficients for making a data base and presented their ranges of K_e and KC as shown in Figure (1) (reproduced here with his permission). As shown in this figure there are many gaps which do not have any data. Of course when values of force coefficients are needed in the ranges where no data is available interpolation should be used. Successful interpolation is achieved if the data is well correlated. However, attempts to correlate these coefficients for the ranges covered have been discouraging and a satisfactory correlation of these coefficients has not been achieved. This is due to the random nature of these hydrodynamic forces and the scatter in the data.

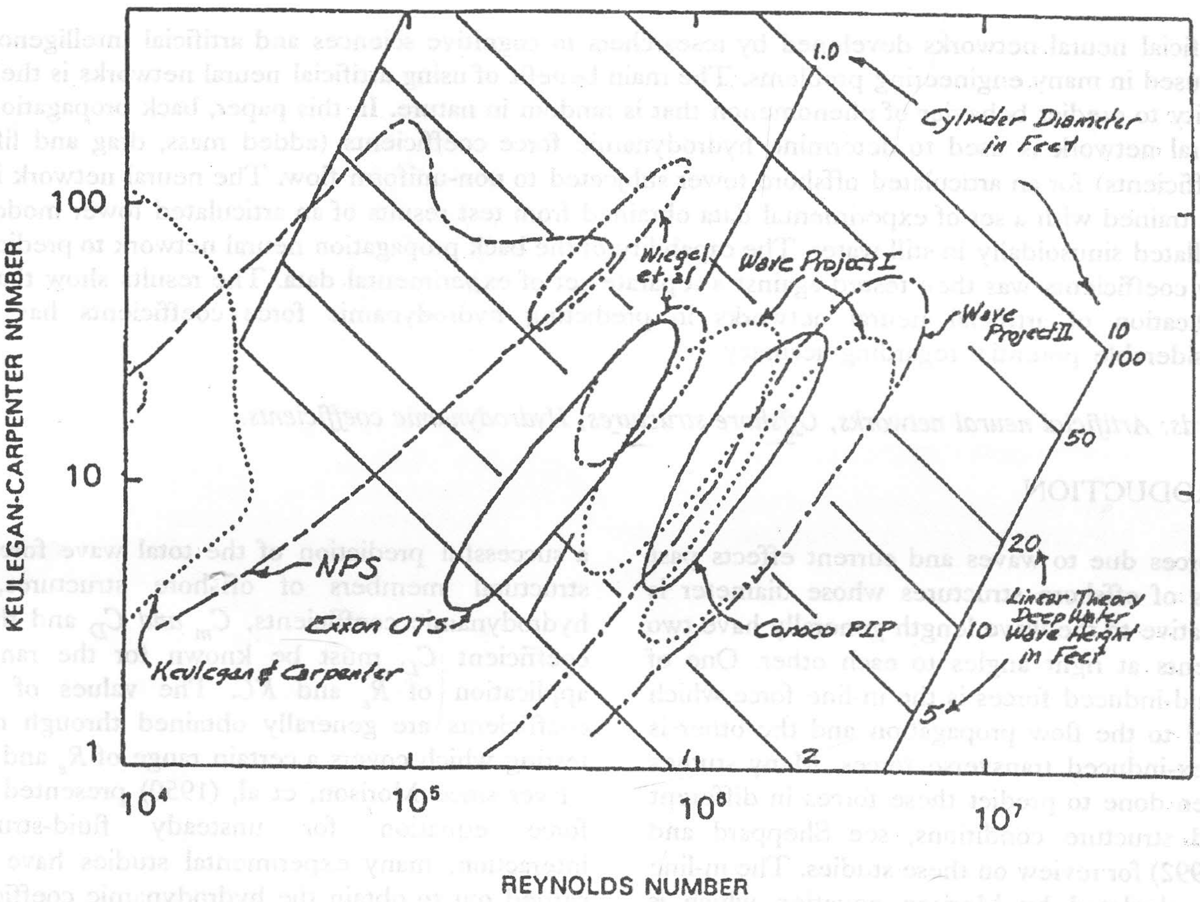


Figure 1. Correlation space-plot of well known sea test hydrodynamic force experiments.

In view of an ever increasing data base and in order to show the consistency and the scatter in this data of force coefficients, Sheppard and Omar (1992) gathered the available experimental data for C_m, C_D and classified them according to the flow and structure conditions. Such classification should make correlation of these coefficients using available methods such as regression analysis and curve fitting to data points for individual variations, either analytically or graphically much better. However, a more rational method recently developed could be used for the selection of hydrodynamic coefficients at any values of the ranges of a data base even those where no data exists. Such a method is the artificial neural networks which is a computational model that can be loosely described as sets of simple processors called neurons or nodes and dense interconnections between them, (see Rumelhart et al., 1986a).

Artificial neural networks (ANN) are inspired by the neural architecture and operation of the human brain. Now they find applications in almost all branches of science. This is because it can be used to address problems that are intractable, with high coupled nonlinear system, or cumbersome with traditional methods. These intelligent capabilities of the neural networks can be achieved by using a number of parallel operating processors interconnected in certain form. The knowledge of a specific system is stored in the neural networks to determine the parameters of the networks which influence the properties of the actual system with no assumption being made. Thus, a broad spectrum of applications found their course based on the characteristics of the neural networks.

In order to use artificial neural networks for prediction of force coefficients, they have to be trained with measured force coefficients that comprise the training set. Once the network is trained, it will be able to predict the output (force coefficients) for an untrained input (e.g., values of R_e and KC and/or β). However, the networks cannot make a correct extrapolation. Therefore, the data of the training set must cover the range of application or the input data must be within the range of that used to train the networks.

In this paper, the readily available experimental data sets (C_m, C_D and C_L), carried out by Omar (1992) for an articulated offshore tower, provide the data base for this study. Different values of R_e and KC and β were used as input parameters to back-propagation neural networks. Two different sets of experimental data were used to train two different neural networks models. The first networks model contains the R_e and KC as input parameters, and the C_m and C_D coefficients as output. In a similar manner, the second networks model includes KC and β as input parameters while the C_L coefficient as output only. Then the capability of these neural networks models to identify force coefficients was tested with a separate set of experimental data.

2. BASICS OF BACK PROPAGATION NEURAL NETWORK

Many kinds of the architecture of a network, in terms of the way in which the neurons are connected, have been proposed. Of these kinds, the back propagation neural networks are consideredthe most popular networks in pattern mapping applications. The elementary back propagation neural networks architecture, three-layer with feed forward connection shown in Figure (2), is considered in this study. It has the capability to "learn" system characteristics through nonlinear mapping.

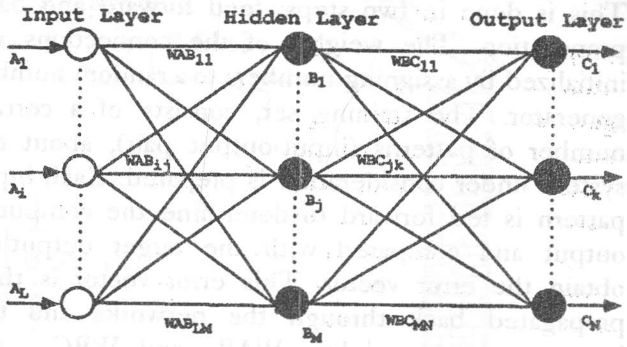


Figure 2. Back propagation neural netowrk topology.

The first layer is the input layer where no operations are performed in each unit. The second and third layers are called hidden and output layers in which each unit perform certain function. The activation value of each unit in the input layer is passed through links to the hidden layer units. Each value is multiplied by the connection strength, which is called the weight WAB_{ij}, and these multiplied values incoming to the hidden units are summed as follows

$$X_J = \sum_{I=1}^{M} WAB_{IJ} A_I \tag{1}$$

The results is placed through an activation function, often using the segmoid function f(X), where

$$B_J = f(X_j) = \frac{1}{1+e^{-X_j}} = \frac{1}{1+e^{-\sum_{I=1}^{M} WAB_{IJ} A_I}} \tag{2}$$

This activation value of the hidden unit B_j is considered as an input value for the output units and the same procedure is repeated to get the output activation values C_k, such that,

$$Y_K = \sum_{J=1}^{N} WBC_{JK} \, B_J \qquad (3)$$

$$C_K = f(Y_K) = \frac{1}{1+e^{-Y_k}} = \frac{1}{1+e^{-\sum_{J=1}^{N} WBC_{JK} B_J}} \qquad (4)$$

The network is trained to recognize the system characteristics through a supervised training scheme. This is done in two steps: feed forward and back propagation. The weights of the connections are initialized by assigning numbers to a random number generator. The training set, consists of a certain number of patterns (input-output pair), about the system under consideration is prepared. Each input pattern is fed forward to determine the computed output and compared with the target output to obtain the error vector. This error vector is then propagated back through the networks and the interconnection weights, WAB_{ij} and WBC_{jk}, are adjusted at each layer using the generalized delta rule (GDR), see Rumelhart et al. (1986b). Afterwards, the next training pattern is fed forward to obtain a new error vector, and the process is repeated for the remaining training patterns. The whole training process is repeated until the magnitude of weights is converged and the error of computed outputs is reduced to an acceptable limit, see Simpson (1990).

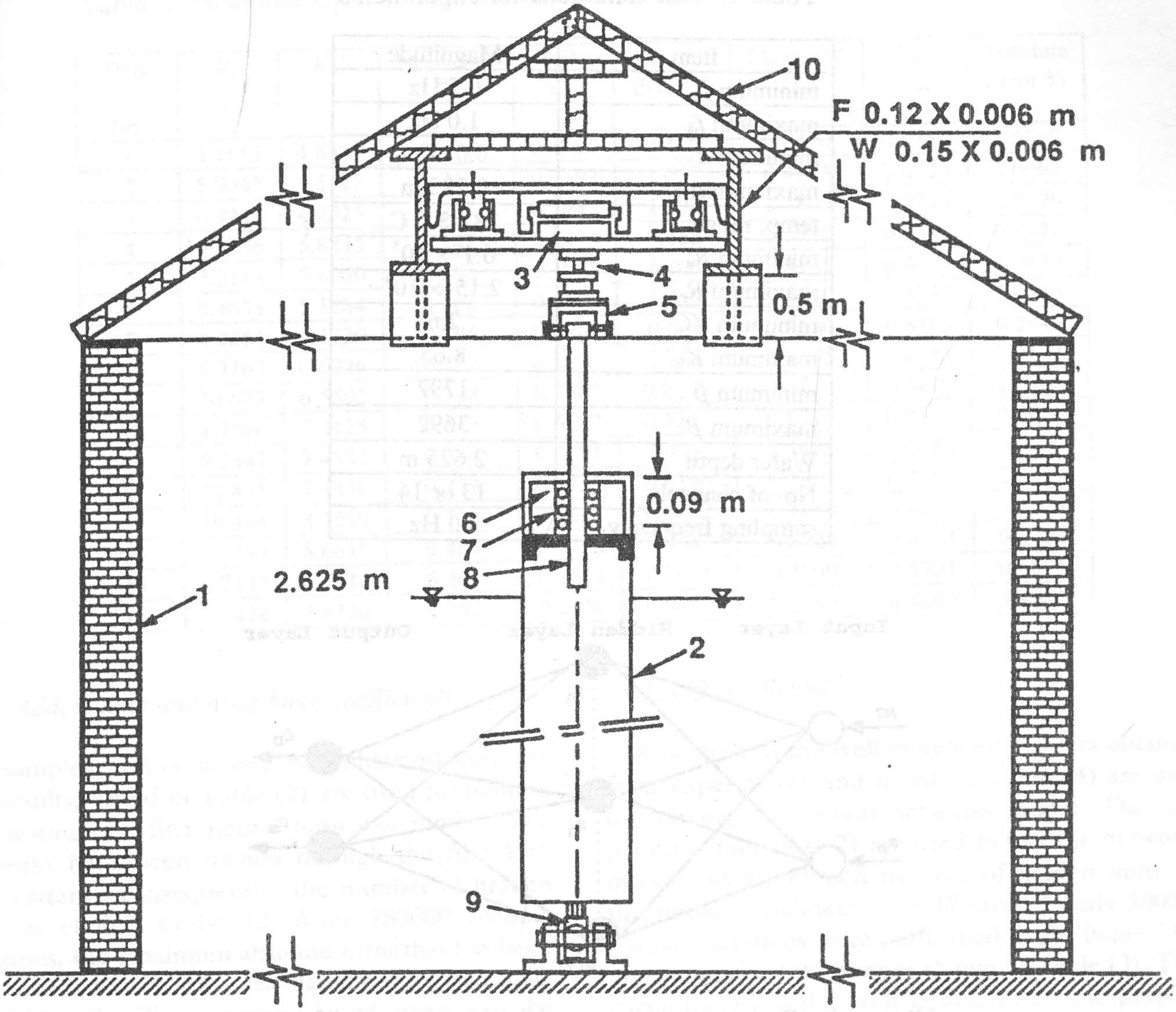
The input and output values within the training set should be normalized between zero and one. In addition, the number of units in the hidden layer should be equal to N-1, where N is the number of training patterns, to alleviate the local minima problem (Kwon et. al. 1996). Once the network is trained, it will be able to predict the output for an untrained input. It should be noted that the networks cannot make a correct extrapolation. Therefore, the data of the training set, that is used to learn the system characteristics, must cover the range of application. A FORTRAN computer program is implemented for encoding the back propagation neural networks algorithm to predict the hydrodynamic force coefficients.

3. EXPERIMENTAL DATA

The readily available data sets that provide the data base for this study is the test model results of an articulated offshore tower (Omar, 1992). The experimental program for the data used in this paper represents the results of 276 tests carried out at the university of Florida. This data is for R_e range between $6.1x10^3$ and $1.3x10^5$ and KC between 2.6 and 9.5. A summary of the test conditions is shown in Table (1). In these experiments, the test model is a circular cylinder with an outside diameter of 0.1524 m. and length of 3.05 m. in 2.625 m. water depth. Among the instrumentation installed on the test tower is an X-Y force transducer to measure the instantaneous in-line and vortex-induced transverse forces simultaneously. Such transducer was inserted between the top of the tower and the table of the linear drive motor that drives the cylinder sinusoidally in still water, see Figure (3). To negate the need to measure forces at the base, a pin-joint was placed between the tower and the X-Y force transducer at the top. The velocity and acceleration were computed from the time derivatives of the measured in-line motion monitored by an LDT transducer. Data has been reduced to extract the forces coefficients (C_m, C_D and C_L) and each coefficient is correlated as a function for two dimensionless parameters independent of each other (R_e and KC). This reduces the scatter usually found in other investigators' data. Reader should refer to (Omar, 1992) for details of the model experiments setup.

4. APPLICATION OF NEURAL NETWORK

Values of C_m C_D, and C_L reduced from test results has been used to examine the proposed scheme with two neural networks models. The first back propagation neural networks model is used to predict the added mass and drag coefficients. R_e and KC are considered as the input parameters, while C_m and C_D, are the desired output parameters as shown in Figure (4a). On the other hand, the second networks model is structured with two input and one output parameters to predict the lift coefficient C_L. The input parameters are the frequency number, β, and KC and the lift coefficient, C_L, only is considered as the output parameter as shown in Figure (4b).



1	Tank
2	Articulated Tower (3 X 0.15 m ϕ)
3	Linear Motor Drive
4	Force Transducer
5	Trandsucer Coupling
6	Upper Cylinder Bearing Guide
7	Linear Bushing Bearing
8	Vertical Sliding Shaft
9	Universal Joint
10	Lumber Frame Cover

Figure 3. Schematic diagram of constrained experimental setup.

Table 1. Test conditions for experiments.

Item	Magnitude
minimum f_d	0.5 Hz
maximum f_d	1.0 Hz
minimum a	0.085 m
maximum a	0.283 m
temp. range	28 - 31° C
minimum R_e	6.1×10^3
maximum R_e	2.15×10^4
minimum KC	2.6
maximum KC	8.65
minimum β	1792
maximum β	3692
Water depth	2.625 m
No. of channels	13 or 14
sampling frequency	40 Hz

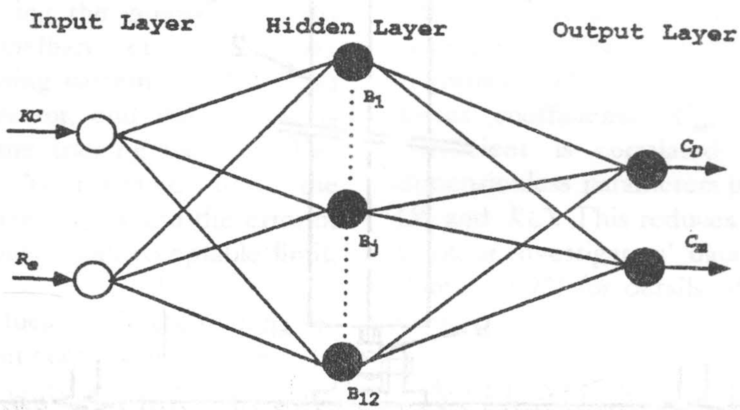


Figure 4a. Back propagation neural network model I.

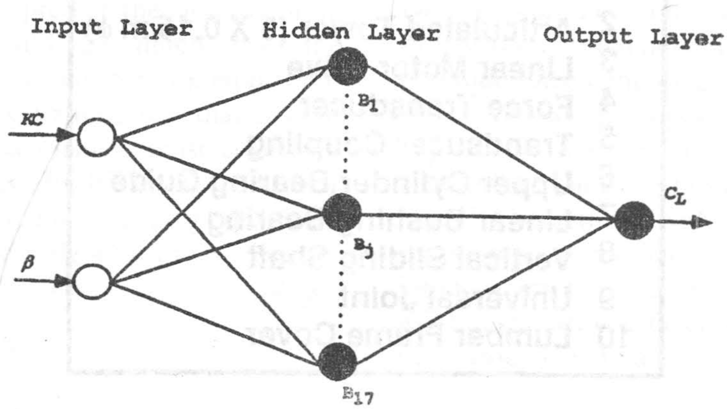


Figure 4b. Back propagation neural network model II.

Table 2. Measured C_D and C_m used for training and testing neural netork model I.

Data No.	R_e 10^{-4}	KC	Measured C_D	Cal. C_D	Absolute Error %	Measured C_m	Cal. C_m	Absolute Error %
1	3.1855	4.8959	0.496	0.4967	0.156	0.8470	0.8382	1.0369
2	5.9645	4.1113	0.242	0.2392	1.037	0.4385	0.4314	1.6068
3	6.9248	4.2525	0.201	0.2042	1.602	0.3805	0.3878	1.9398
4	5.8186	5.8845	0.247	0.2434	1.455	0.5770	0.5819	0.8472
5	7.2183	5.8060	0.185	0.1932	4.465	0.4765	0.4699	1.3849
6	8.4031	5.1784	0.162	0.1596	1.498	0.3690	0.3732	1.1210
7	4.2054	6.4729	0.496	0.4963	0.065	0.8380	0.8363	0.2043
8	8.3167	6.6926	0.237	0.2290	3.361	0.4695	0.4683	0.2574
9	10.678	6.5592	0.218	0.2162	0.8103	0.3570	0.3478	2.5740
10	4.7546	7.3125	0.519	0.5163	0.5233	0.8315	0.8348	0.4056
11	9.2347	7.4537	0.264	0.2731	3.429	0.4685	0.4682	0.0630
12	10.435	7.3438	0.272	0.2721	0.0396	0.3965	0.4056	2.3130
13	10.364	8.3559	0.315	0.3127	0.7367	0.4655	0.4636	0.3920
14	3.6797	5.6648	0.484	0.4794	0.9583	0.8320	0.8364	0.5303
15	6.7475	6.7946	0.268	0.2684	0.1651	0.5740	0.5701	0.6805
16	7.5478	7.6106	0.292	0.2976	1.9413	0.5745	0.5660	1.4802

4.1. *Added mass and drag force coefficients*

16 samples well correlated data obtained from the test results, listed in Table (2), are used for training and testing the first neural networks model. The networks have been trained through the first 13th data patterns, consequently, the number of hidden units is chosen to be 12. After 280000 training iterations, the maximum absolute error that has been achieved is 4.5%, for the calculated output, as shown in Table (2). This magnitude of error can be considered as good as enough in predicting the hydrodynamic coefficients. In addition, the trained neural networks model should be capable to extract the features of the coefficients behavior for all input data which lies in the range of the training data. The rest of data (14 to 16th data patterns) is chosen to test the model. It is clear from Table [2] and Figures (5) and (6) that the differences between the model output and the measured data are small too. Thus, this model can be used to extract the added mass and drag force coefficients of the articulated tower in nonuniform water flow within the input training data range of R_e and KC.

4.2. *Lift coefficient*

18 samples of the well correlated C_L data obtained from experiments and listed in Table (3) are used for training the second networks model. The data patterns from 19 to 21 are used to test the network model and the chosen number of hidden units for this network architecture is 17 units. Nearly 500000 training iterations were performed to get below 10% maximum absolute error as shown in Table (3). This is considered as the error limitation for the purpose of this study. However, such error could be reduced if error criteria (tolerance) is reduced. But this will be on the expense of the number of iterations and CPU time for computing. Testing the networks model using the 19-21st data patterns shows that the differences between the model outputs and the experimental data are small compared with that obtained using the training data, see Table [3] and Fig. 7. Therefore, this model can also be used to extract the lift coefficient for the articulated tower within the range of input training data of β and KC.

Table 3. Measured C_L data used for training and testing neural network model II.

Data pattern No.	β 10^{-3}	KC	Measured C_L	Cal. C_L	Absolute Error %
1	1.3284	3.4033	0.3135	0.3147	0.3787
2	1.6207	3.2566	0.2185	0.2218	1.5018
3	2.0693	3.4277	0.8711	0.8372	3.8932
4	2.7321	3.5744	0.3229	0.3233	0.1142
5	1.3276	4.1615	0.3286	0.3336	1.5286
6	1.6209	4.0937	0.1864	0.1696	8.9898
7	2.0692	4.1182	0.6138	0.6188	0.8108
8	2.7320	4.5734	0.2285	0.2273	0.5208
9	1.3276	5.5833	0.2203	0.2313	5.0010
10	2.4642	5.5296	0.4222	0.4285	1.4987
11	2.4642	5.8809	0.4812	0.4822	0.2087
12	1.3759	6.2842	0.2537	0.2384	6.0837
13	1.6016	6.5988	0.1776	0.1768	0.4222
14	2.1964	6.9563	0.0977	0.0988	1.1026
15	1.3759	7.1212	0.2358	0.2239	5.0355
16	1.3595	7.8975	0.1933	0.1980	2.4658
17	1.6017	7.2495	0.1563	0.1714	9.7264
18	1.6017	8.6518	0.1409	0.1370	2.8054
19	1.8169	4.2513	0.1385	0.1444	4.3114
20	1.3758	5.4440	0.1881	0.2013	7.0571
21	2.1964	6.9563	0.0977	0.0988	1.1026

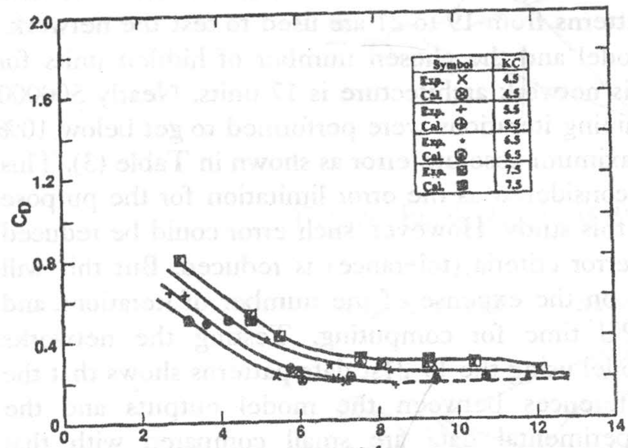


Figure 5. Drag coefficient C_D for harmonically oscillated articulated offshore tower.

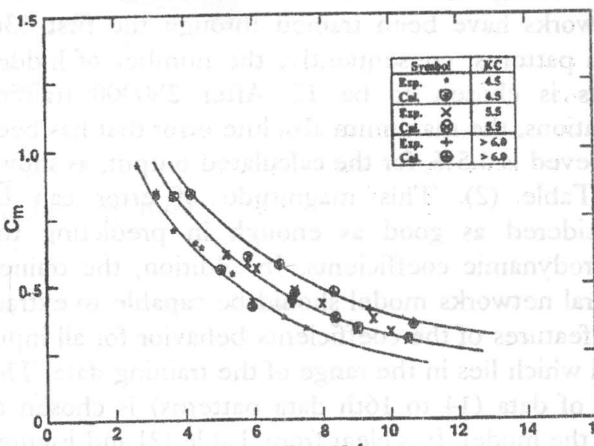


Figure 6. Interia coefficient C_M for harmonicall oscillated articulated offshore tower.

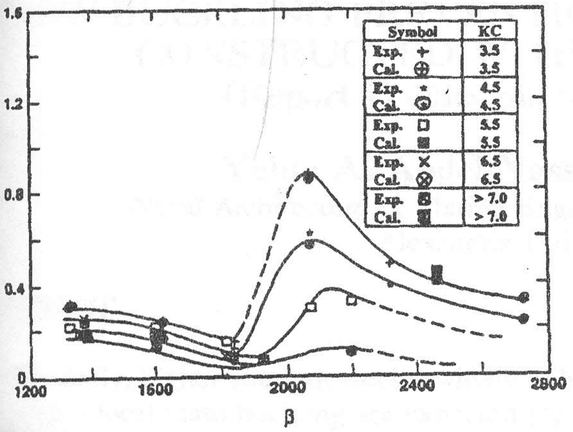


Figure 7. Lift coefficient C_L for harmonically oscillated articulated offshore tower.

5. CONCLUSIONS

A method has been presented to predict hydrodynamic forces coefficients. The back propagation neural networks approach has the ability to predict the force coefficients with reasonable accuracy after learning the model with the desired range of data field. Using the back propagation neural networks, the values of the added mass, drag and lift coefficients, C_m , C_D , and C_L, for an articulated offshore tower are predicted with good accuracy. Results of using such a networks model showed that using well correlated data creates distinct patterns corresponding to different ranges of R_e, KC and β.

Although these results are promising, the approach needs to be further investigated for predicting the hydrodynamic forces rather than their coefficients. Back-propagation algorithm has the ability to handle the more difficult classification problems that may results from those tests.

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