ResearchGate

See discussions, stats, and author profiles for this publication at: https://www.researchgate.net/publication/44185084

Application of Neural Networks in coastal engineering - An overview

Article · January 2008

Source: OAI

CITATIONS
6

READS
638

4 authors, including:


S. Mandal
National Institute of Oceanography
87 PUBLICATIONS **1,563** CITATIONS

SEE PROFILE


S.G. Patil
RICS School of Built Environment, Amity University Mumbai
19 PUBLICATIONS **136** CITATIONS

SEE PROFILE


Arkal Vittal Hegde
National Institute of Technology Karnataka
203 PUBLICATIONS **600** CITATIONS

SEE PROFILE

Some of the authors of this publication are also working on these related projects:

Project Sliding Stability of Emerged Quarter Circle Breakwater View project

Project stability of semicircular and circular breakwaters, soft computing for coastal engineering View project

All content following this page was uploaded by S.G. Patil on 22 May 2014.

The user has requested enhancement of the downloaded file.

The 12th International Conference of
International Association for Computer Methods and Advances in Geomechanics (IACMAG)
1-6 October, 2008
Goa, India

Application of Neural Networks in Coastal Engineering – an Overview

S. Mandal
Ocean Engineering Division, National Institute of Oceanography, CSIR, Dona Paula, Goa-403 004, India

Sanjay G.Patil, Y.R. Manjunatha and A. V. Hegde
Dept of Applied Mechanics & Hydraulics, National Institute of Technology Karnataka, Surathkal, Srinivasnagar-575025, India.

Keywords: Artificial neural network, Non-linear model, ocean wave parameters and coastal structures.

ABSTRACT: Artificial Neural Network (ANN) is being applied to solve a wide variety of coastal/ocean engineering problems. In practical terms ANNs are non-linear modeling tools and they can be used to model complex relationship between the input and output system. In addition, ANNs have a very high degree of freedom and are very simple to train the system for any number of input values, which makes the network attractive and reliable. ANNs are ideally suited to find many solutions like pattern reorganization, data classification, forecasting future events and time series analysis. This paper gives an overview of application of ANN in the field of coastal engineering.

1 Introduction

In analogy to the biological system ANN is being applied to solve a wide variety of coastal/ocean engineering problems. A neural network is an information processing system modeled on the structure of human brain. The biggest merit is its ability to deal with fuzzy information whose interrelation is ambiguous or whose functional relationship is not clear. A neural network has capability of learning and adjusts with the outside environment. Training the network is a kind of learning process. Method of learning is done with specified examples. A neural network possesses the ability to learn and able to memorize a large amount of various information and then to formalize it. Furthermore, the most precious quality of a neural network is its ability to provide forecasts based on the data it has processed. A neural network is a powerful tool because of its high functioning with fast computation and high memory to solve problems of non-linear interactions that involves complex variables. It is a data oriented modeling technique which finds the good relationship between the input and output system at faster rate of approach. These networks have good capability of learning, and predict better compared to mathematical models. A network has model free solutions, data error tolerance built in dynamism and lack of any exogenous input requirement, which makes the network attractive and reliable. These unique qualities have made neural networks to apply in coastal and ocean engineering field.

Neural networks in coastal engineering applications, namely prediction of sea tides, coastal waves, coastal structural damages, wind-waves, predicting wave induced seabed liquefaction, storm surge prediction, wave tranquility studies and near shore morphology are highlighted in this paper.

2 Feed forward neural network

A neural network model is interconnected by several neurons. Generally, neuron model consists of three layers namely input layer, hidden layer and output layer, called as feed forward neural network as shown in Figure 1. The input parameters are fed at input layer, parameter gets multiplied with the weights and adds with the bias and total value feed through the transfer function or activation function at hidden layer and output is obtained at the output layer. The main aim of the technique is to train the network such that the response to the given set of inputs corresponds as closely as possible to a desired output. This multi layered feed forward networks have the property that they can approximate to arbitrary accuracy of any continuous function defined on a domain provided that the number of internal hidden nodes is sufficient.

Mathematically the feed forward artificial neural network is expressed in the form of

$$y_k(x) = \sum_{i-1}^{M} w_{Kj} \times T_r(z) + b_{ko} \tag{1}$$

$$z = \sum_{i-1}^{D} w_{ji} \times x_i + b_{ji} \tag{2}$$

Where x is the input parameter, w_{ji} and w_{Kj} are the weights for input layer - hidden layer and hidden layer - output layer respectively, b_{ji} and b_{ko} are the bias parameters. *M* is the number of nodes at the hidden layer, *D* is the number of nodes at the input layer and $T_r(z)$ is the transfer function. This transfer function allows a non-linear conversion of summed inputs. Many transfer functions are used to achieve the desired output by researchers such as hardlim, tansig, prelim, logsig, poslin and satlin.

The overall objective of a training algorithm is to reduce the global error, *E* as defined below:

$$E = \frac{1}{p} \sum_{p=1}^{P} E_p \tag{3}$$

Where, *P* is the total number of training patterns, E_p is the error at p^{th} training pattern is given by:

$$E_p = \frac{1}{2} \sum_{k=0}^{N} (O_k - t_k)^2 \tag{4}$$

Where *N* is the total number of output nodes O_k is the output at the k^{th} output node and t_k is the target output at the k^{th} output nodes.

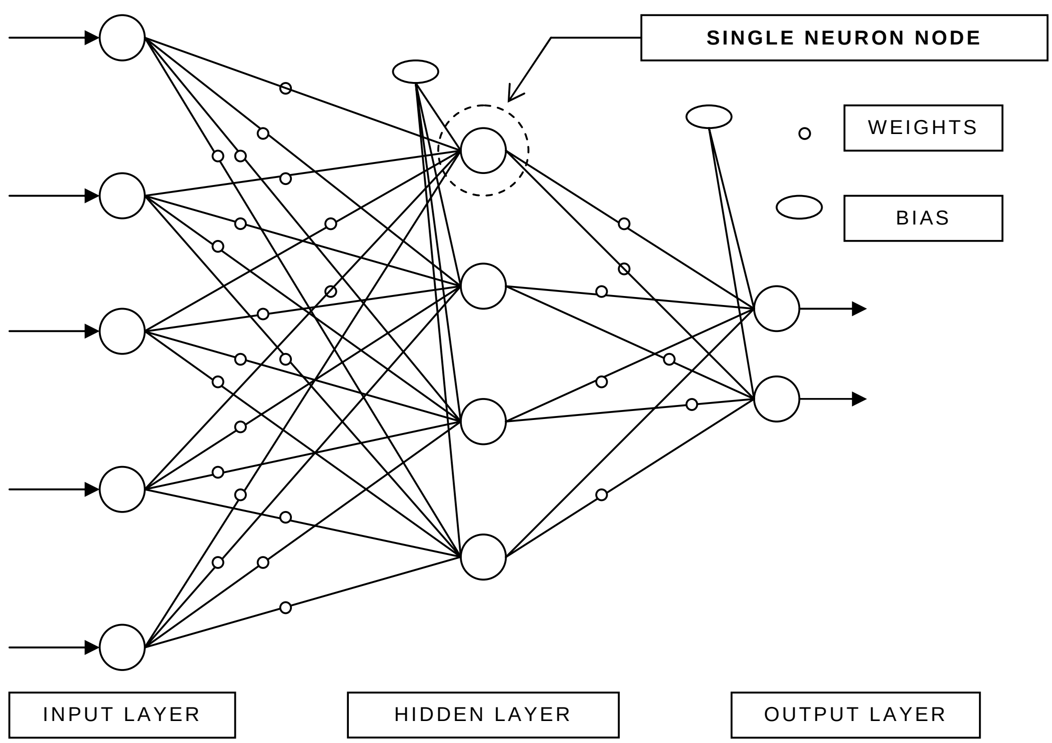

Figure 1. Three-layered feed forward neural network

3 Review of earlier works

Most of the recent works on application of ANNs in coastal engineering are briefly described as given below. However, earlier works on ANNs in ocean engineering overviewed by Jain and Deo (2006) may be referred for completeness in this subject.

3.1 Prediction of ocean wave parameters

Various ocean wave parameters are estimated from theoretical Pierson-Morskowitz (PM) spectra as well as measured ocean wave spectra using back propagation neural network (Mandal et al., 2005). According to them, very high correlation coefficients for significant wave height (Hs), zero crossing wave period (Tz), maximum spectral energy (Emax) and time period for maximum spectral energy (Tp) in training the neural network for PM spectra due to Gaussian distribution justify the use of neural network.

The ANN approach is used to estimate the wave parameters from cyclone generated wind fields (Rao et al., 2005). Estimation of Hs and periods is carried out using back propagation neural network with three updated algorithms, namely Rprop, Quick prop and superSAB. The predicted values using neural networks match well with those estimated using Young's model and a high correlation coefficient of 0.99 is obtained.

The recurrent neural network with updated algorithms is used to forecast ocean waves (Mandal and Prabaharan, 2006). The recurrent neural network of 3, 6 and 12 hourly wave forecasting yields the correlation coefficient (CC) of 0.95, 0.90 and 0.87 respectively. According to them, the wave forecasting using recurrent neural network yields better results compared to previous neural network applications.

The marine structures in Taiwan suffer from typhoon attack every year. The earlier theoretical models are not properly predicting the typhoon waves. According to Chang and Chien, (2006), ANN- multi trend-simulating transfer functions model accurately forecasts wave peak.

It is easy to forecast the waves based on neural network approach (Tsai et al., 2002). They use field data to train the network. They find that the ANN model performs well for both wave forecasting and data supplement using a short term observed wave data.

The feed forward back propagation type of neural network is used to obtain the Hs at specified coastal site from their values sensed by a satellite at deeper locations (Karla et al., 2005). The neural networks provide a useful tool to project deep-water waves sensed by satellite to coastal locations.

The ANN technique is used to predict the Hs and zero crossing wave periods (Tz) (Makarynskyy et al., 2005). They achieved a higher accuracy of simulating the Hs and forecasting Tz using this technique.

A neural network is developed in order to estimate the wave surface density over a wide range of wave frequencies from average wave parameters of Hs, Tz, Spectral width and peakedness parameters (Naithani and Deo, 2005). They compare the neural network predicted values with the measured ones. It shows more satisfactory than those yields by PM, JONSWAP and Scott's spectra.

The Adaptive Network based Fuzzy Inference System (ANFIS) and Coastal Engineering Manual (CEM) methods are used to predict the ocean wave parameters (Kazeminezhad et al., 2005). According to them, the results indicate that ANFIS outperforms CEM method in terms of prediction capability. Here the CEM method over estimates the Hs and under estimates the peak spectral period, while ANFIS results in predictions that are more accurate.

Londhe and Deo (2003) present ANN models in order to obtain distribution of attenuated wave pattern at the entrance of the harbor involving dredged approach channel.

Browne et al. (2007) have carried out near shore swell estimation from a global wind wave model and compared with ANN model.

Further improvement in ocean wave forecasting can be observed as shown in Table 1.

Table 1: Wave height forecast with various methods

Reference	+Hr	CC	RMSE	Method	Inputs
Ozger and Zekai (2007)	+1 +3 +6 +12	0.974 0.960 0.899 0.800	0.282 0.347 0.541 0.741	Fuzzy logic approach	Wind speed and wave height
Ozger and Zekai (2007)	+1 +3 +6 +12	0.972 0.925 0.842 0.690	0.293 0.471 0.666 0.895	ARMAX	Wind speed and wave height
Mandal and Prabaharan (2006)	+3 +6 +12 +24	0.95 0.90 0.87 0.73	- - - -	NARX	Wave height
Zamani and Azimian (2004)	+3 +6 +12 +24	0.911 0.889 0.585 0.356	0.16 0.187 0.311 0.352	MLP	Wave height
Deo and Naidu (1999)	+3 +6 +12 +24	0.81 - 0.78 0.71	- - - -	MLP	Wave height

3.2 Tidal prediction

Prediction of tides is reliably essential for human activities and construction cost in marine environment. The back propagation neural network method is applied for accurate prediction of tides (Mandal et al., 2001). The neural network model predicts the time series of hourly tides using quick learning process called quick prop. The correlation coefficient between predicted tides and measured tides is found to be 0.998. It shows a good agreement between neural network prediction and measured data set.

The harmonic tidal level is conventionally used to predict the tidal levels. The determination of tidal components using the spectral analysis requires a long-term tidal level record (more than one-year data), and for calculating the coefficient of tidal component using least squares method requires a large database of tide measurements. This problem over comes by using neural network with less data set (Lee and Jeng, 2002).

The new method for predicting sea levels by employing self-organizing feature maps is described by Ultsch and Roske (2002). For that purpose, maps are transformed from an unsupervised learning procedure to supervised one. The prediction of sea levels is done by using neural network models and for accuracy and more reliable on neural network prediction results are compared with other six models such as two hydrodynamic model, a statistical model, a nearest neighbor model, persistence model and verbal forecasts. The self-organizing feature maps predict sea levels better than all above-mentioned models.

The functional and sequential learning neural networks are applied for accurate prediction of tides using very short-term observations (Rajasekaran et al., 2005 and 2006). This method does not require harmonic parameters used in conventional method. The comparison between the measured and predicted tidal levels for 3 days and 1 month's prediction using 1 day's observation depicts the correlation coefficients, 0.981 and 0.999, which are higher than the values obtained by Tsai and Lee (1999). It shows that the functional and sequential learning neural networks predict better values as compared to other conventional methods.

The feed forward neural network is used to predict hourly sea level variations for 1/2, 1, 5 and 10 days mean sea level (Makarynskyy et al., 2004). The results show the feasibility of sea level forecasts in terms of correlation coefficient (0.7-0.9), root mean square error (about 10% of tidal range) and scatter index (0.1-0.2).

Chang and Lin (2006) present a tide generating neural network model (TGF-NN) of simulating tides at multi-points considering tide-generating forces. They have compared on the RMS and CC of three year mixed tides at a single point compute with harmonic method, response-orthotide method, the NAO.99b model and the TGF-NN model to show the prediction accuracy of each method. The TGF-NN model is efficient compare to harmonic method to estimate the tides at a single point. Extended application of TGF-NN model to predicting tides at some points neighboring to an original interest point identifies more accurately simulating multi-point tides as compared to that of NAO.99b numerical model.

3.3 Damages of coastal structures

The technique of neural networks effectively applies to predict the stability of rubble mound breakwater (Mase et al., 1995). They consider the parameters of the stability rock slope such as stability number, damage level, permeability of breakwater, number of attacking waves, surf similarity parameter, dimensionless water depth and spectral shape parameters. The damage levels predicted by neural network calibrated using van der Meer's experimental data, agree satisfactorily well with the measured damage levels.

Neural network technique is used to predict the damage ratio of breakwater (Yagci et al., 2005). The accurate estimation of damage levels of breakwater is vital issue in design of breakwater. Network is constructed by considering input parameters like wave stiffness, significant wave period and slope angle. They used fuzzy logy system for mapping the inputs and output. The fuzzy model estimations of damage ratios are close to the predicted values by neural network methods. The employment of Artificial intelligence methods enables consideration of wave period, wave stiffness, breakwater slope and wave height in estimating damage ratio. This application useful especially when there is less number of laboratory data sets.

The ANN is applied to design rubble mound breakwaters (Kim and Park, 2005). They find that the neural network technique gives more accurate results than the conventional empirical model and the extent of accuracy can be affected by the structure of neural network. It is shown that the trained neural network model could be embedded into Monte Carlo simulation technique to estimate the failure probability of breakwater. The neural network integrated reliability analysis gives more advanced results for probability of failure than it is done by empirical model. Mandal et al. (2007) used neural network technique to predict the stability number and damage levels of rubble mound breakwater. It is seen that a good correlation is obtained between network predicted stability number and estimated ones. A comparison of results on stability estimation using ANNs are given in Table 2. This shows that an improvement of stability estimation of stability of breakwater.

Coastal structures like breakwater, groins and gabions are constructed to reduce the coastal erosion. The stability of individual stones on a sloping surface of breakwater is very important because many breakwaters fail due to a defective design. Neural network technique is applied in predicting the stability number and compared it with the estimated stability number by Hudson and Van der Meer (Mandal et al., 2008). The neural network is modeled with parameters, which affects the stability namely Permeability of breakwater, number of attacking waves, significant wave height, mean wave period, damage level, slope angle, berm width and reduced armor weight ratio. It is found that the network predicts lesser armor units compared to empirical formulae which makes the design more economical and safe. The coefficient correlation between the estimated stability number by empirical formulae and predicted stability number by neural networks are close to one.

Table 2: Performance of stability of breakwaters using ANN

Reference	ANN structure/nodes (Input - hidden - output)	Epochs	CC
Mase et al. (1995)	4-8-1	5000	0.92
Kim and Park (2005)	8-12-1	50000	0.95
Mandal et al. (2007)	8-4-1	200	0.99

Gent et al. (2007) develop a neural network model to estimate wave-overtopping discharges for wide range of coastal structures.

3.4 Prediction of seabed liquefaction

Jeng et al. (2004) adopt the concept of genetic algorithm based training of ANN models in an effort to overcome the problems inherent in ANN training procedures while providing accurate results for determining maximum liquefaction depth in a real world application. In the proposed ANN model several important parameters including wave period, water depth, wave height, seabed thickness and degree of saturation are used as the input parameters, and liquefaction depth as output parameter.

3.5 Prediction of storm surge

The storm tidal prediction using conventional methods requires a huge amount of tidal data and many other parameters like central pressure of typhoon, speed of typhoon, heavy rainfall data, coastal topography and local features (Lee, 2006). According to him, neural network technique is used to predict the storm surge with the help of four input parameters such as wind velocity, wind direction, wind pressure and harmonic analysis of tides. It is found that the network predicts better and reliable results of storm surges.

3.6 Prediction of near shore morphology

The ANN model is used to predict the near shore morphology (Bazartseren, 2005). The ANNs are used for deriving certain relations such as sediment transport, seabed and suspended loads. According to him, the neural network with the number of neighboring points and time lags is to be considered for deriving the morphology development tendency. It is attempted to estimate the bed form movement tendencies based on the local neighboring features of bathymetry.

4 Conclusions

Many researchers and scientists have applied neural network techniques in predicting the coastal dynamic processes like wave parameter estimation, tidal prediction, coastal structural design and storm surge. They have achieved better results as compared to that using mathematical models like statistical tools, ARMA model and regression models. It is found that the neural networks are reliable and gives accurate results. The numerical model with various assumptions/ boundary conditions requires a huge amount of data set to predict the future event and this is a time consuming process and become uneconomical. This can be over come by using neural network technique.

5 References

Bazartseren, B. 2005. Applicability of artificial neural networks for investigating short-term developments of near shore morphology, PhD thesis, Lehtuhl Bauinformatil, BTU Cottbus (Germany).

Browne, M., Castelle, B., Strauss, D., Tomlinson, R., Blumenstein, M. and Lane, C. 2007. Near-shore swell estimation from a global wind-wave model: spectral process, linear and artificial neural network, Elsevier J Coastal Engineering, (in press).

Chang, H.K. and Chien, W.A. 2006. A fuzzy neural hybrid system of simulating typhoon waves. Elsevier J Coastal Engineering, 53, 737-748.

Chang, H.K and Lin, L. C. 2006. Multi-point tidal prediction using artificial neural network with tide-generating forces. Elsevier J Coastal Engineering, 53, 857-864.

Deo, M.C., Naidu, Sridhar, C. 1999. Real time wave forecasting using neural networks, Elsevier J Ocean Engineering, 26, 191-203.

Gent, R. A., Boogaardden, Henk, F. P. and Medina, R. 2007. Neural network modeling of wave overtopping at coastal structures, Elsevier J Coastal Engineering, (in press).

Jain, P. and Deo, M.C. 2006. Neural networks in ocean engineering, SAOS Vol. 1 No. 1 pp. 25-35.

Jeng, D. S., Cha, D. and Blumenstein, M. 2004. Neural network for the prediction of wave induced liquefaction potential, Elsevier J Ocean Engineering, 31, 2073-2086.

Karla, R., Deo, M.C., Kumar, R. and Agarwal, V. K. 2005. RBF network for spatial mapping of wave heights. Elsevier J Marine Structures, 18, 289-300.

Karla, R., Deo, M.C., Kumar, R. and Agarwal, V.K. 2005. Artificial neural network to translate offshore satellite wave data to coastal locations. Elsevier J Ocean Engineering, 32, 1917-1932.

Kazeminezhad, M. H., Etemad-shahidi, A. and Mousvi, S. J. 2005. Application of fuzzy inference system in the prediction of wave parameters, Elsevier J Ocean Engineering, 32, 1709-1725.

Kim, D. H. and Park, W. S. 2005. Neural network for design and reliability analysis of rubble mound breakwaters, Elsevier J Ocean Engineering, 32, 1332-1349.

Lee, T. L. 2006. Neural network prediction of a storm surge, Elsevier J Ocean Engineering, 33, 483-494.

Lee, T. L. and Jeng, D. S. 2002. Application of artificial neural networks in tide forecasting, Elsevier J Ocean Engineering, 29, 1003-1022.

Londhe, S. N. and Deo, M.C. 2003. Wave tranquility studies using neural networks. Elsevier J Marine Structures, 16, 419-436.

Makarynskyy, O., Makarynska, D., Kuhn, M. and Featherstone, W.E. 2004 Predicting sea level variations with artificial neural networks at Hillarys Boat Harbour, Elsevier J Estuarine Coastal and Shelf Science, 61, 351-360.

Makarynskyy, O., Piers-Silva, A. A., Markarynska, D. and Ventura-Soares. 2005. Artificial neural networks in wave predictions at the west coast of Portugal, Elsevier J Computers Geosciences, 31, 415-424.

Mandal, S., Rao, S. and Manjunatha, Y. R. 2007. Stability analysis of rubble mound breakwater using ANN, Proc. Indian National Conference on Harbour and Ocean Engineering, INCHOE, NITK, Surathkal, 551-560.

Mandal, S. and Prabaharan, N. 2006. Ocean wave forecasting using recurrent neural network, Elsevier J Ocean Engineering, 33, 1401-1410.

Mandal, S., Rao, S., and Raju, D.H. 2005. Ocean wave parameters estimation using back propagation neural network, Elsevier J Marine Structures, 18, 301-318.

Mandal, S., Rao, S. and Prabhaharan, N. 2001. Wave forecasting using neural networks, Proc. International Conference in Ocean Engineering, ICOE, IIT Madras, 103-108.

Mandal, S., Rao, S. and Manjunatha, Y.R. 2008. Stability prediction of berm breakwater using neural network, Proc. International conference on COPEDEC VII, Dubai (UAE), paper no- 27, 1-11.

Mandal, S. 2001. Tides prediction using back propagation neural networks, Proc. International Conference in Ocean Engineering, ICOE, IIT Madras, 499-504.

Mandal, S. and Prabhaharan, N. 2003. An overview of the numerical and neural network accosts of ocean wave prediction. Proc. International conference COPEDEC, Colombo, (Sri Lanka), 1-9.

Mase, H., Sakamoto, M. and Sakai, T. 1995. Neural network stability of rubble mound breakwaters, ASCE J of Water Port Coastal and Ocean Engineering, 121, 6, 294-299.

Naithani, R. and Deo, M.C. 2005. Estimation of wave spectral shapes using ANN, Elsevier J Advances in Engineering Software, 750-756.

Ozger, M. and Zekai, S. 2007. Prediction of wave parameters by fuzzy logic approach, Elsevier J Ocean Engineering, 34, 460-469.

Rajasekaran, S., Jeng, D. S. and Lee, T. L. 2005. Tidal level forecasting during typhoon surge using functional and sequential learning neural networks, ,ASCE J of waterways, Port, Coastal and Ocean Engineering, 131(6), 321-324.

Rajasekaran, S., Thiruvenkataswamy, K. and Lee, T. L. 2006. Tidal level forecasting using functional and sequential learning neural networks, Elsevier J Applied Mathematical Modeling, 30, 85-103.

Rao, S. and Mandal, S. 2005. Hind casting of storm waves using neural networks, Elsevier J Ocean Engineering, 32, 667-684.

Tsai, C. P. and Lee, T. L. 1999. Back propagation neural network in tidal level forecasting, ASCE J of Waterway Port Coastal and Ocean Engineering, 125, 4, 195-202.

Tsai, C. P., Lin, C. and Shen, J. N. 2002. Neural network for wave forecasting among multi stations, Elsevier J Ocean Engineering, 29, 1683-1695.

Ultsch, A. and Roske, F. 2002. Self-organizing feature maps predicting sea levels, Elsevier J Information Sciences, 91-125.

Yagci, O., Mercan, D. E. Cigizoglu, and Kabdasli, M.S. 2005. Artificial intelligence methods in breakwater damage ratio estimation, Elsevier J Ocean Engineering, 32, 2088-2106.

Zamani, A. and Azimian, A. 2004. On line wave prediction at Caspian Sea by using artificial neural network, 9th Fluid Dynamic conference, Tehran, 48-60.

View publication stats