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Artificial neural networks in coastal and ocean engineering

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Artificial neural network (ANN)s have been applied to solve a variety of problems related to the coastal and ocean areas over a period of last one and a half decades. Most of these studies have involved estimation or forecasting of environmental parameters, structural loads and responses. The aim in such studies were to carry out a cause-effect modeling, temporal or spatial mapping, and property integration and resolution. ANN models have been generally found to outperform the traditional empirical, statistical or numerical models to a smaller or larger extent. There are however certain grey areas where the modeling and its usefulness needs to be improved. This paper takes a stock of all such past works and summarizes author's experience in working with ANNs for the benefit of future researchers.

[**Keywords:** Artificial neural networks, Ocean parameters, Ocean predictions]

Introduction

The problems in the field of coastal and ocean engineering can be approached either on the basis of knowledge-based schemes or through data-driven methods. The former calls for modeling a known physical process through analytical, empirical or numerical schemes while the latter essentially analyzes data with little knowledge of the process and incorporates conventional statistical, stochastic schemes or recent approaches of soft computing, artificial intelligence, machine learning and data mining. The artificial neural network (ANN) is one of such modern data driven methods that has been successfully applied in oceanic problems for estimation or forecasting of environmental parameters, structural loads and structure responses by carrying out works like function approximation, optimization, system modeling and pattern matching.

Materials and Methods

An ANN represents an interconnected network of computational elements or neurons that resemble real neurons of a human brain. An artificial neuron follows the action of a biological one engaged in a cognition process. This involves (Fig. 1) combining the weighted input information, adding a bias term to it and passing the sum through a transfer function that determines the strength of such transformed input before sending it to the next neurons. A typical feed-forward type of network shown in Fig. 2 has universal function approximation power and in such architecture the information flows only in one forward direction. It has layers of input, hidden and output neurons. The hidden layers could be ordinarily single or two. Alternative network architectures like recurrent, radial basis, generalized regression, neuro-fuzzy and its variants also exist. Before its actual application an ANN is required to be trained or its weights and bias values need to be fixed and this is done with the help of a mathematical learning scheme and feeding an assumed network topology with examples of input-output pairs. The learning schemes are many and include the common error back-propagation type of iterative method. Theoretical details of ANN may be seen in text books such as Kosko[1], Wassermann[2] and Wu[3].

Mathematically the four-step procedure followed in obtaining the network output is as given below:

1. Sum up weighted inputs, i.e.

$$Nod_j = \sum_{i=1}^{NIN} (W_{ij} x_i) + \beta_j \qquad \dots (1)$$

where, Nod_j = summation for the j^{th} hidden node; NIN = total number of input nodes; W_{ij} = connection weight between i^{th} input and j^{th} hidden node; x_i= normalized input at the i^{th} input node; and β_j = bias value at the j^{th} hidden node.

2. Transform the weighted input:

$$Out_j = 1 \Big/ \left[1 + e^{-Nod_j} \right] \qquad \dots (2)$$

where, Out_j = output from the j^{th} hidden node.

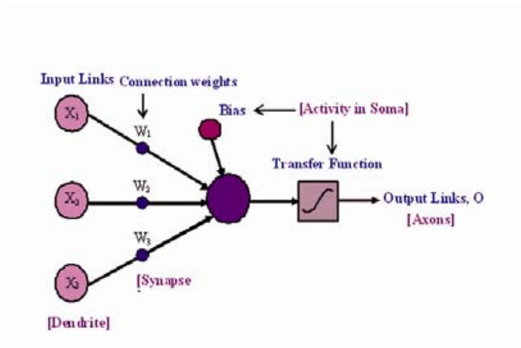

Fig. 1- An artificial neuron.

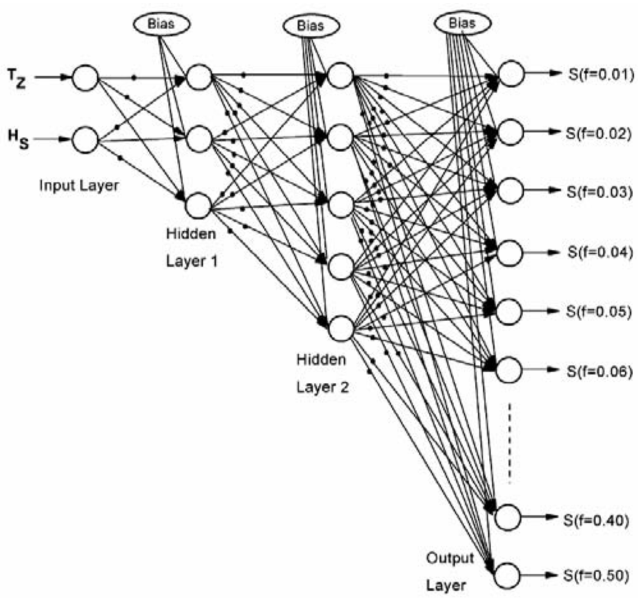

Fig. 2- The feed forward network used in Jain *et al.*[120]

3. Sum up the hidden node outputs :

$$Nod_k = \sum_{j=1}^{NHN} (W_{jk} Out_j) + \theta_k \qquad \ldots (3)$$

where, Nod_k= summation for the k^{th} output node; NHN = total number of hidden nodes; W_{jk} = connection weight between the j^{th} hidden and k^{th} output node; and θ_k = bias at the k^{th} output node.

4. Transform the weighted sum:

$$Out_k = 1/\left[1 + e^{-Nod_j}\right] \qquad \ldots (4)$$

where, Out_k = output at the k^{th} output node.

The objective of any training is to reduce the global error, E; defined below:

$$E = \frac{1}{P} \sum_{1}^{P} E_p \qquad \ldots (5)$$

where P is the total number of training patterns. Ep is given by

$$E_p = \frac{1}{2} \sum_{k=1}^{N} (O_k - t_k)^2 \qquad \ldots (6)$$

where N is the total number of output nodes, O_k is network output at the k-th output node, and t_k is target output at the k-th output node.

In the field of coastal and ocean engineering ANNs have been used to evaluate a cause-effect relationship, temporal relationship and also a spatial one. Further they have been used to carry out resolution or integration of a given property. The performance of the ANNs have been usually checked by more than one error criteria such as the correlation coefficient, root mean square error, mean absolute error, relative absolute error, mean absolute relative error, mean square logarithmic error, inertial root mean square error and error ration of forecasted peak[4].

A review of ANN applications in the field of ocean engineering had been presented in Jain and Deo[5]. This paper takes a lead from it and goes beyond by summarizing author's experiences.

Results and Discussion

Past Applications

The past studies dealing with ANN involved either estimation or forecasting of environmental parameters, or determination of structural loads and responses. The concerned environmental parameters were as follows:

(a) wave height–in both temporal aod spatial mode.[6-41]
(b) wave period and directional characteristics.[35]
(c) wave spectral shapes.[42,43]
(d) wave propagation, wave transmission related.[44- 46]
(e) wave run up.[47- 49]
(f) swell heights.[50]
(g) tidal levels and timings of high and low water.[51-62]
(h) sea levels.[63-70]
(i) other met-ocean parameters.[71-73]
(j) wind speeds.[24, 53, 74]
(k) estuarine characteristics [75]
(i) coastal currents.[76-78]

The determination of structural loads and responses include that of the following:

(a) forces on structures, including wind and wave loadsl.[79-83]
(b) structural damage indicators.[84-92]
(c) ship design parameters.[81, 92-99]

(v) barge motions.[93, 97, 100-104]
(vi) scour depths and soil liquefaction.[105-107]

Authors' experience

A series of studies involving ANNs aimed at carrying out more accurate modeling than the conventional approaches have been made with author as a co-investigator. The various works done can be divided as below:

Estimation and real time prediction of wave heights and periods

The studies under this category include Deo *et al.*[6], Deo and Kiran Kumar[8], Deo *et al.*[9], Agarwal and Deo[10], Deo and Jagdale[12], Agarwal and Deo[23], Kalra *et al.*[38, 39], Kalra and Deo[41], Jain and Deo[29, 108], and Kambekar and Deo[109].

Wave propagation

These studies can be seen in Londhe and Deo[44, 45].

Estimation of wave directional parameters

The corresponding works are due to Deo *et al.*[35]

Evaluation of tidal levels and timings of high and low water

This can be seen in Deo and Choudhary[51].

Real time prediction of wind

The specific work in this category is due to More and Deo[74].

Estimation of pile scour

This is presented in Kambekar and Deo[105].

Estimation of shapes of wave spectra

The works under this category are due to Naithani and Deo[42], Namekar and Deo[43], and Jain *et al.*[120].

Estimation of littoral drift

This has been handled in Singh *et al.*[114, 115].

Real time as well as inverse prediction of wind and coastal currents

This is dealt with in Charhate *et al.*[116, 117].

In-filling of gaps in wave records

Ustoorikar and Deo[119].

Based on the above works a number of observations were made on the use of the technique of ANN for solving oceanic problems. These are descried below:

Applicability

It is necessary to correctly identify the problem for which one wants to apply an ANN. The underlying phenomenon should be truly random and non-linear in nature; otherwise the gains would be only marginal[23]. Before applying ANN it is necessary to check if the traditional methods are good enough or not[10,74,114]. Further, application of ANN should result in substantial gain in accuracy compared with the traditional schemes[38,43]. As far as possible, ANN should be applied where its real prowess would be seen as in cases such as very large number of input or output nodes[41,42,44,45]. Success of ANN in a given application is not guaranteed and one has to try out a large number of architectures, training schemes, control parameters and modes of providing training data[44,45,115]. ANNs are capable of replicating the outcome of a numerical model and that too with a better accuracy in some cases[44,45]. ANNs can be either complimentary[38] or alternative to traditional modeling [42,74,113,120].

Calibration

Many times the use of a simple feed forward network trained using ordinary backpropagation works fine. However model calibration can also substantially improve by adoption of alternative training algorithms and network architectures [39,44,45]. In cases where the training is adaptive the training time would be crucial and in such cases algorithms like the cascade correlation, which generally provide training in a fraction of time compared with ordinary error back propagation, may be resorted to[51]. If the system has a strong memory component then recurrent networks might perform well[121]. Single network may not always fit the entire domain of the training sample and in such cases different networks may be developed over different sub-domains of the sample size[29,38,41] (e. g., monsoon and non-monsoon). Similarly for predictions over multiple future time steps more than one modeling scheme (ANN, stochastic models, genetic programming) may be necessary[121]. It may happen that the network may apparently produce good results but it may not follow the physical process or work as per our understanding of the physics of the phenomenon. This needs to be determined with the help of a parametric study[115] and if need be, recalibration needs to be done. The usefulness of the ANN normally increases with the increasing complexity of the underlying phenomenon[23]. In order to impart more flexibility in network calibration an input of raw variables rather than their dimensional groups may be attempted[113]. ANNs some times may work with less amount of data requirement[121]. The pre-processing of input before its use in network training is not a precondition. But measures such as in-filling of gaps, data division as per the statistics, and use of selected rather than full input sets may improve the accuracy of outcome[29]. The best type of data for use as input in the network training is the observed one (field or laboratory). However in its absence satisfactory training can still be provided with the outcome of a numerical model[44] or even of an empirical model[12]. But in such cases the input-output pairs may be enhanced in number by random simulation, thereby making the training more flexible and increasing the degrees of freedom[12].

General

The ANN may not be used as a black box model and attempts should always be made to decipher the knowledge contained in connection weights, bias as well as the architecture. An insight into the physical process and reasons behind the apparently good performance of ANN should be explored in order to derive full benefit of the ANN modeling[122]. If a single network fails to yield accuracy beyond a certain level then a combination of two in a series form (a two-stage network system) may increase its accuracy level. In such a combination the primary network may first carry out the basic input-output mapping while the secondary one trained using the output of the primary network may provide a fine tuning to it resulting in an improved prediction performance[115]. A similar combination of ANN with another mapping technique like genetic programming may also add significantly to the model performance[114]. On similar lines neuro-fuzzy type of combinations of ANN and fuzzy logic may some times work better due to replacement of the crisp value processing by fuzzy if-then rules. Azmathullah *et al.*[122] found this to be advantageous when a small amount of training data is available.

Future works

There are certain issues for which more research in applied ANN is called for, such as erratically varying input conditions, predictions over large number of time intervals, extrapolation beyond the observed range and extracting domain knowledge from a trained network. It is also recognized that in some applications alternative data driven methods such as genetic programming may appear more attractive[118,119] from considerations such as the use of less human-driven choices of the control parameters, portability as well as transparency of the calibrated model.

Conclusions

Artificial neural networks have been applied widely by now to solve problems related to coastal and ocean engineering. There is however a scope to fully utilize their its potential by targeting certain unresolved issues. Each application of ANN must justify its applicability. Network training can many times be substantially improved by alternative architectures, training schemes and control parameters. Highly innovative methods of training a network can produce remarkable changes in its performance. If this is not done, an impression of failure of ANN in the given application may get wrongly created. A combination of ANN with fuzzy logic and evolutionary approaches may some times work better than a single ANN architecture. Although recently presented alternative data driven methods such as genetic programming, support vector machines, instance based learning, model trees may have some advantages compared with an ANN, a purely non-linear nature and high degrees of freedom still make the ANN a preferred choice as a modeling tool by many investigators.

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