Analysis of Key Parameters in Nearshore Current Using Artificial Neural Networks

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Abstract

Design of port and harbor facilities highly depends on the nearshore hydrodynamics. Usually, the significant wave characteristics along with the most severe condition of the nearshore currents based on the field measurements is considered for the design purpose. On the other hand, optimal measurement cost and accurate numerical estimation depends on some key parameters of current velocity. The main objective of present paper is to describe an approach to more accurate and effective prediction of current velocity through key parameterization of observed data based on Root Mean Square (RMS). The procedure has significantly improved by using artificial neural networks due to ANN's capability in high functioning with rapid computation to solve the high nonlinearity and multi-variables systems.

Keywords: Artificial Neural Network (ANN), Feed Forward (FF), Root Mean Square (RMS)

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1. Introduction

Design of port and harbor facilities highly depends on the nearshore hydrodynamics, among them current velocity is one of the most important factors. The knowledge of nearshore currents (including longshore and cross-shore current) plays a crucial role in coastal and offshore engineering, which include calculation of sediment transport in coastal region and current loads on offshore or onshore structures. Prediction of nearshore current velocities based on coastal hydrodynamics is very complex due to involved parameters. Selection of appropriate parameters can be best done with the aid of Artificial Neural Networks (ANNs). This study addresses an efficient tool of ANN to obtain the key parameters in nearshore current. ANNs have been trained to performed complex functions in various fields, including pattern recognition, identification, classification, speech, vision and control systems but their application in environmental prediction at oceans or seas phenomena is a relatively recent approach.

Nowadays coastal engineers are interested in predicting and simulating complex features that are difficult for conventional computers or human beings. ANN has high functioning with fast computation and a considerable memory to solve the problems concerning extremely nonlinear interactions and complex effective variables. Accordingly, ANN has newly been implemented widely in different areas. Some examples of using neural network in marine engineering and science are demonstrated by Vaziri (1997), Deo and Shidhar Naidu (1998), Tsai and Lee (1999), Deo et al. (2002), Lee and Jeng (2002), Lee et al. (2002), Makarynskyy (2004), Lee (2004) and Chang and Chien (2006, in press), etc. In the majority of these studies, the Feed-Forward Back-Propagation method (FFBP) was employed to train the neural networks. This kind of neural networks with multiple-layer networks and nonlinear differentiable transfer functions is popularly used to solve many coastal problems whose solutions that need optimization. The details on ANNs can be obtained from ASCE Task Committee.

2. Mathematical Development

The FFBP is the most popular ANN training method in coastal engineering. A typical feed forward structure is presented in Figure 1. A FFBP distinguishes itself by the presence of one or more hidden layers, whose computation nodes are correspondingly called hidden neurons of hidden units. The function of hidden neurons is to intervene between the external input and the network output in some useful manner. By adding one or more hidden layers, the network is enabled to extract higher order statistics. In a rather loose sense, the network acquires a global perspective despite its local connectivity due to the extra set of synaptic connections and the extra dimension of NN interconnections (Haykin, 1994).

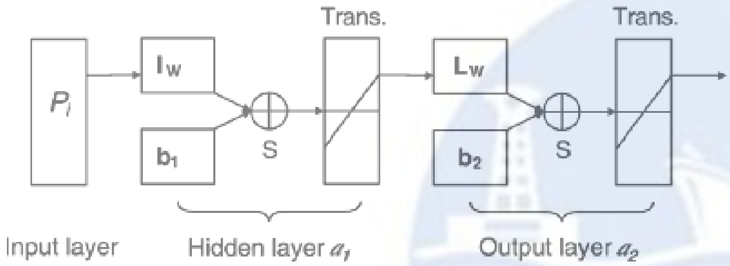

Figure 1. A typical feed forward Back Propagation (FFBP) neural network structure

Input vectors and the corresponding target vectors are used to train a FFBP neural network, until it can approximate a function that associates the input vectors with specific output vectors. Networks with biases, a sigmoid layer and a linear output layer can approximate any function with a finite number of discontinuities (Demuth and Beale, 2000). A properly trained FFBP neural network tends to generate reasonable answers when inputs are provided with it. Therefore, the back-propagation algorithm is an extensively used algorithm in neural networks.

The connections between the input neurons and hidden layer neurons, and those between the hidden perceptions and outputs can be formulated as the following equations:

$$a_1 = f\left(I_w P_i + b_1\right) \tag{1}$$
$$a_2 = f\left(L_w a_1 + b_2\right) \tag{2}$$

where a_1 is the value of the first hidden layer; a_2 is the output value of the network; P_i is the input vector, I_w and b_1 are the matrices of weights and of biases between the input neurons and the hidden layer neurons, respectively; L_w and b_2 are the matrices of weights and biases between the output neurons and the hidden layer neurons, respectively, and f is the hyperbolic tangent sigmoid transfer function which reads as follows:

$$f(x) = 2/(1+e^{-2x}) - 1 \tag{3}$$

The squared difference between the desired response Y and the network response a_2 states the learning error or training error, E, and can be written as:

$$E = \frac{\left\| a_2 - Y \right\|^2}{N} \tag{4}$$

where N is the total number of data and $\|a_2 - Y\|$ is the norm of the vector $a_2 - Y$.

3. Methodology

The data used in this study are field observation of 13 stations at Joetsu-Ogata along the west coast of Japan Sea from December 1998 to March 1999. The data were measured by Wave Hunter Σ, EMC, and ADCP equipments and their sampling duration were 20min per 2hours, 10min per 1hour, and Continuous, respectively. Since the number of input parameters of the networks is large, a sensitivity analysis has been made to minimize the number of input parameters. Thus, the dependent parameters have been omitted and all the aforementioned training process is repeated for new input parameters.

Following parameters of environmental condition at sea were acquired: depth of water (D), number of waves (N), highest wave height (H_{max}), highest wave period (T_{max}), highest one-tenth wave height ($H_{1/10}$), highest one-tenth wave period ($T_{1/10}$), significant wave height (H_s), significant wave period (T_s), mean wave height (H_{mean}), mean wave period (T_{mean}), mean wave direction (θ_{mean}), maximum wave direction (θ_{max}), dominant wave direction (θ_d), average wave direction (θ_a), wave crest length (L), cross-shore wind velocity, longshore wind velocity, east current velocity, north current velocity, longshore current velocity, and cross-shore current velocity. Maximum wave height which had been recorded during the entire observation period at this region was 10.26 meter, the absolute current also was reached to the 78 cm/s, and the severest wind velocity was found to be 14.8 m/s. In each case different combinations of the input parameters have been used in various FFBP ANNs. RMS and correlation between actual and estimated data were used as a criterion for selection of superior ANN.

4. Results and Discussion

Considering Rayleigh distribution for recorded wave height distribution, it can be shown that H_{max}, $H_{1/10}$, and H_{mean} and also T_{max}, $T_{1/10}$, T_{mean} are the functions of H_S and T_S respectively. Therefore, H_S and T_S are selected as representative parameters. Same procedure has been used to decrease the amount of input parameters. Finally it is concluded that the wave characteristics, especially significant wave height (H_s) and average wave direction (θ_{mean}), play a key role in prediction of nearshore current.

Architecture of ANN model for prediction of nearshore current using H_s and θ_{mean} as input parameters, and longshore and cross-shore velocities as output parameters, is illustrated in Figure 2. Results of the output node (cross-shore velocity) versus actual data for afore-mentioned ANN are depicted in Figure 3. As can be seen in this Figure, the results are highly near to the exact match in which demonstrates the high capability of ANN in training and predicting results, together with stating key parameters in nearshore current. Table.1 shows the results of testing all representative parameters in prediction of nearshore current.

Table 1. ANN assessment of wave characteristics on prediction of nearshore current velocities.

No.	Input parameters*	Nodes in input layer	Nodes in first hidden layer	Nodes in second hidden layer	Nodes in output layer	Number of iterations	RMS	Correlation

1	H_s	1	2	3	2	20,000	0.074	0.9025
2	H_s, T_s	2	4	3	2	20,000	0.072	0.9048
3	H_s, θ_{mean}	2	4	3	2	20,000	0.037	0.9760
4	H_s, T_s, θ_{mean}	3	5	4	2	20,000	0.037	0.9759
5	H_s, T_s, N	3	5	4	2	20,000	0.072	0.9086
6	H_s, θ_{mean}, N	3	5	4	2	20,000	0.037	0.9753

*Notes: H_s = significant wave height; T_s = significant wave period; N = number of waves; θ_{mean} = average wave direction.

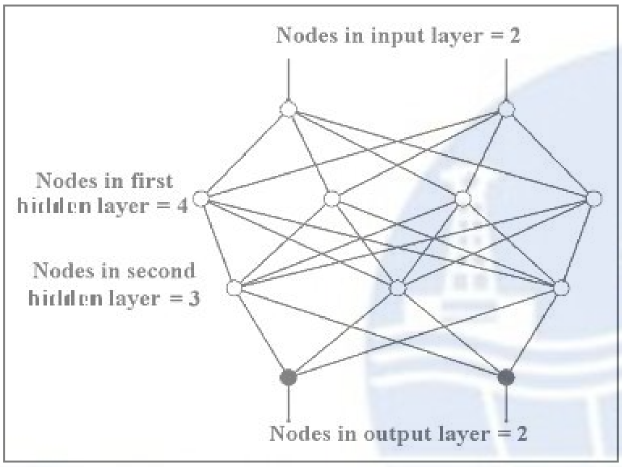

Figure 2. Architecture of ANN model for prediction of nearshore current.
(Input parameters are H_s and θ_{mean}, and output parameters are longshore and cross-shore velocities)

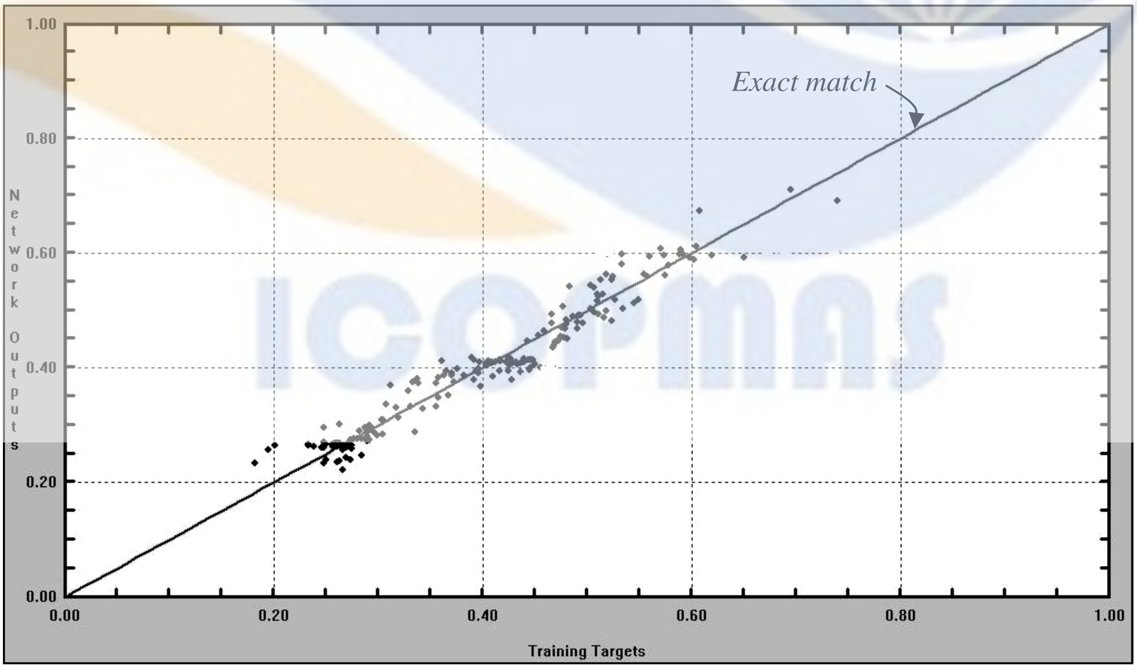

Figure 3. Results of output node (cross-shore velocity) versus actual data

5. Concluding remarks

The procedure has significantly improved by using artificial neural networks due to ANN's capability in high functioning with rapid computation to solve the high nonlinearity and multi-variables systems. After key parameterization procedures, it is stated that wave characteristic parameters, especially significant wave height (H_s) and average wave direction (θ_{mean}), play a key role in prediction of nearshore current velocities.

It is observed that best results are in the stations with a well-trained ANN model. Besides, the stations which are located at nearshore zone have a better estimation of cross-shore and longshore currents, respectively.

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