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ANALYSIS OF BEACH EROSION BY STORM USING ARTIFICIAL NEURAL NETWORK

Y.H. Park[1] and J.-H.Yi [1]

ABSTRACT: Beach erosion by storm condition is so severe and it causes major unbalance on sand budget along the coastline. Beach erosion including overwash is complicated and difficult to analyze. The beach erosion of overwash using the artificial neural network is compared with the empirical equation developed by robust regression and experiment data in this study. Error-back propagation method is used for training artificial neural networks. The eroded volume of sand is well estimated by the artificial neural network without understanding mechanism of beach process. The study focused on onshore and offshore sediment transport by overwash on storm wave condition.

Keywords: Analysis, beach, erosion, storm, artificial neural network.

INTRODUCTION

The beach was mainly damaged by storm and it might cause permanent retreat of coastline. However, only some related research has been conducted in a laboratory experiment and a field measurement due to danger and difficulty. Overwash on storm conditions was suspected to cause beach erosion along the Texas coast and the experiment study for overwash was carried by the first author at Texas A&M University (Park, 2006). Donnelly *et al*. (2006) conducted experiments for overwash in a midscale wave tank and analyzed seven different profiles from the result. Park and Edge (2010) mentioned that the deposition rate of eroded sand by overwash behind beach face is higher on storm conditions.

The field measurements for overwash were conducted by Park and Edge (2011) and they were conducted immediately before and after landfall of storms around Sabine Pass, Texas. They found that the northeast Texas coast has been eroded mainly by overwash of long period swells generated by remote storms. Though there were only two landfalls of storms in 2004 and 2005 during the period 1991-2005, the retreat of coastline was extreme. The highway along the northeast Texas coast was closed by destruction of repeated beach erosion.

The mechanism of sediment transport including erosion and deposition has been studied but it has not understood completely yet. The Artificial Neural Network (ANN) is a black box model and it can estimate result without understanding the mechanism of sedimentation. It has already been applied to estimate metocean data such as wave, tide, and storm surge in coastal engineering but the applicability on beach erosion has been studied in a few cases. Lee (2004) applied an ANN to predict long-term tidal variations. Kim and Park (2005) analyzed rubble mound breakwaters using an ANN and the results became references in design and stability. Chang and Chien (2006) simulated typhoon waves quickly using an ANN instead of a numerical model which needed much computation time. Though Lee (2006) predicted storm surge using ANN, it contained meteorological tide. Van Gent et al. (2007) predicted wave overtopping discharges using ANN and they were verified with experimental data of the European project CLASH.

The purpose of this study is to estimate the volume of sand by overwash in the direction of onshore and offshore.

LABORATORY EXPERIMENT

The experimental data which were used in this study came from the laboratory experiments for overwash were conducted at Texas A&M University (Park, 2006). Their intensive analyses were introduced in Park and Edge (2010). Most of experiments were carried out in short (327 s) and some of them did in long term (30, 60, and 180 min). The size of wave tank is 40 m long, 1.5 m wide, and 3.0 m deep (Figure 1). Sand berm is installed on the top of the beach face and its size is 5 m long, 1.5 m wide, and 0.45 m high. The uniform size of sand was used; d_{50} is 0.15 mm and specific gravity is 2.65. The initial and final beach profiles were measured by laser equipment. The sixteen cases of experiments were conducted in the combination of two slopes (1:4 and 1:5), two wave height (0.14 and 0.17 m), and four wave period (1.4, 1.6, 1.8, and 2.0 sec) in regular waves (Table 1).

[1] Coastal Development & Ocean Energy, Korea Institute of Ocean Science & Technology, Ansan, Gyonggi-Do, 426-744, KOREA

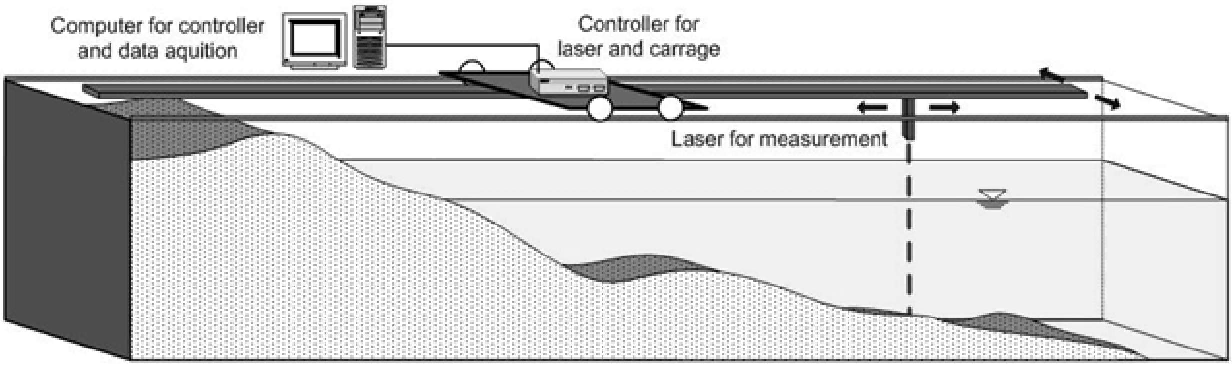

Fig. 1 Measurement of beach profile using laser equipment in a laboratory test.

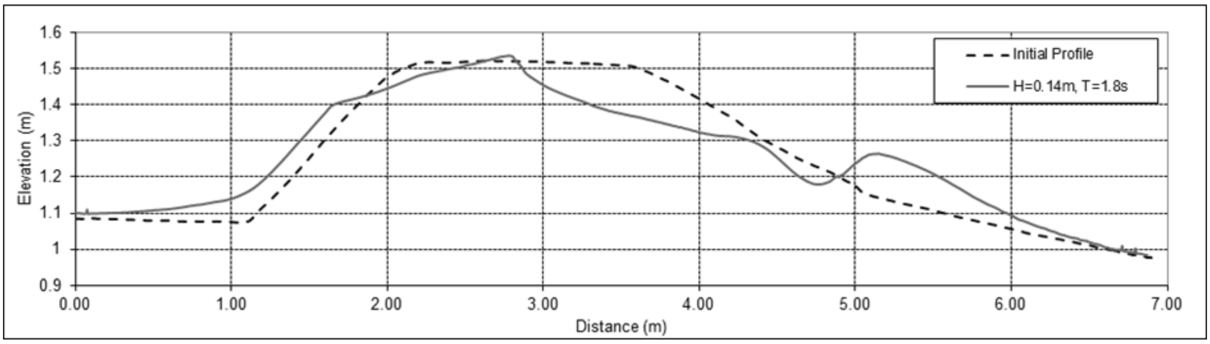

Fig. 2 Measurement of beach profile using laser equipment in a laboratory test.

Table 1 The conditions of test cases in experiments at Texas A&M University

Slope	Wave height (m)	Wave period (sec)	Sand transport (m^3/m)	
			Onshore	Offshore
1:4	0.14	1.4	0.0230	0.115
		1.6	0.0550	0.129
		1.8	0.0876	0.089
		2.0	0.1201	0.121
	0.17	1.4	0.0490	0.099
		1.6	0.0670	0.111
		1.8	0.1040	0.089
		2.0	0.1180	0.105
1:5	0.14	1.4	0.0100	0.090
		1.6	0.0210	0.116
		1.8	0.0490	0.061
		2.0	0.0361	0.101
	0.17	1.4	0.0250	0.081
		1.6	0.0312	0.120
		1.8	0.0222	0.092
		2.0	0.0700	0.079

The experimental conditions and results were shown in Table 1 and the section was divided into onshore and offshore. The volumes of sand transported onshore and offshore were calculated at each test. The empirical equation for regular waves was developed by the robust regression R-squared was 0.8791.

The experimental results showed that the volume of sediment transport by overwash was increased at steep slope, higher wave, and longer period. The volume of sand in onshore direction could be considered as a permanent loss of sediment in the balance of sand budget in a beach. The transported sand in offshore direction might return to the beach by deposition activity. These two experiment results (Table 1 and 2) aimed at sediment transport on storm conditions but they had difference. The experiment at Texas A&M University was conducted to understand beach erosion by overwash and the experimental data in Tsai et al. (2000) were analyzed in a sloping beach. The beach erosion was generally occurred with overwash but it was accompanied with overwash at landfall of storm.

NEURAL NETWORK METHOD

In this study, a popular artificial neural networks (ANN) model called a multi-layer perceptron or a back-propagation neural networks is used for perfection of sand transport by beach erosion. This ANN model consists of an input layer, hidden layers, and an output layer as in Fig. 3. The input layer contains the slope gradient, wave height and wave period, and the output layer consists of the onshore sand transport. It is noteworthy that the offshore sand transport is not included in this study because the comparison results by Park and Edge produced only onshore sand transport values as well. The input and output relationship of the ANN can be nonlinear as well as linear, and its characteristics are determined by the weights assigned to the connections between the nodes in two adjacent layers. Changing the weights will change the input and output behavior of the network. Systematic way of determining the weights to achieve a desired input and output relationship is referred as training or learning. In this study, the standard back-propagation algorithm is used.

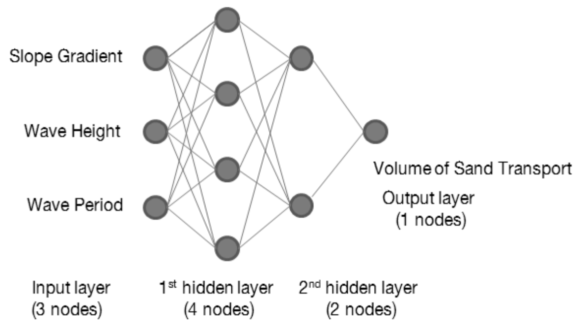

Fig. 3. ANN for Predicting Volume of Sand Transport

Figs. 4 and 5 show the results by this study and Park and Edge (2010), and it can be found that the result by ANN gives a better relationship between measured and predicted volume of sand transportation. The R-squared value was 0.879 by Park and Edge, and it is enhanced as 0.99 by using ANN method.

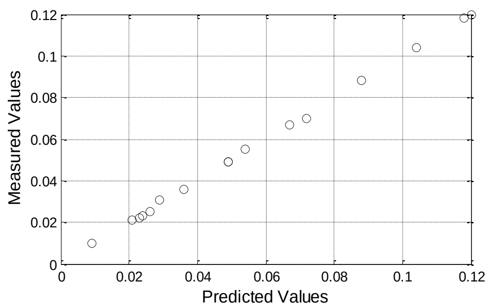

Fig. 4 Prediction results by ANN (in this study)

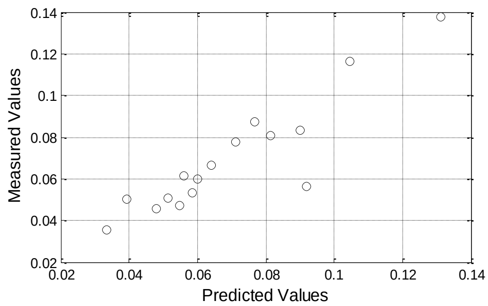

Fig. 5 Prediction results by Park and Edge (2010)

It should be noted that the results in Fig. 4 shows the results by training not by testing. The testing is not conducted herein because the number of training data set is very limited and all available data are used for training. Tsai *et al*. (2000) studied sediment experiments to predict geometric parameters using an artificial network (Table 2). The experiments were conducted in a large wave tank by Saville in 1956-7 and Caldwell in 1962 and their data were analyzed by Kraus and Larson (1988). They selected 5 geometric parameters of a submerged sand bar such as distance, depth, and volume. Fifteen of eighteen cases were used for training in the ANN method and rest of them was for verification processes. Because more inputs do not imply the better outputs in a neural network, the number of inputs should be calibrated carefully. In their case, five inputs was optimal number to minimize the prediction error with the experimental data. Five inputs were wave height in deep water, wave period, bottom slope, d_{50} particle size, and settling velocity.

Yang *et al*. (2009) studied the estimation of bed load by ANN in rivers. They selected four inputs in ANN and they were flow velocity, slope of energy, flow depth, and d_{50}. Hashemi *et al*. (2010) analyzed the beach profiles at 19 stations using an ANN from 1997 to 2004. He mentioned that the inputs should be in the range of inputs and the inputs out of the range need to be verified.

Table 2 The storm-built bar profiles. H_0, T, X_c, V_{bar} were wave height in deep water, wave period, distance of bar from a beach, and volume of bar, respectively (Tsai et al., 2000)

Cases	H_0 (m)	T (sec)	X_c (m)	V_{bar} (m/m)
CE100	1.08	11.33	39	18.50
CE300	1.40	11.33	41	30.10
CE400	1.72	5.60	44	28.60
CE500	1.64	3.75	56	33.30
CE700	1.12	16.00	40	24.50
CE401	1.72	5.60	37	19.60
CE501	1.65	3.75	44	22.10
CE911	1.25	7.87	36	11.30
PI1-8	0.85	3.00	20	1.60
PI2-1	1.76	6.00	70	7.50
PI3-1	1.04	9.10	36	12.40
PI3-2	1.10	6.00	39	15.30
PI3-4	1.61	3.10	66	24.90
PI4-2	1.06	4.50	57	4.50
PI5-2	0.80	3.10	73	6.50
PI6-1	1.78	5.00	40	36.50
PI6-2	1.10	7.50	21	25.30
UH-1	1.50	6.00	14	48.70

CONCLUSIONS

The estimation of beach erosion by overwash was analyzed by an artificial neural network and the results were compared with those of the equation by Robust regression. Artificial neural network showed better result and the volume of erosion was well estimated. It was a good way to calculate the volume of sediment quickly using an artificial neural network on storm conditions.

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