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Probabilistic Neural Network for Predicting the Stability numbers of Breakwater Armor Blocks

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Summary

The stability numbers determining the Armor units are very important to design breakwaters, because armor units are designed for defending breakwaters from repeated wave loads. This study presents a probabilistic neural network (PNN) for predicting the stability number of armor blocks of breakwaters. PNN used the experimental data of van der Meer as train and test data. The estimated results of PNN were compared with those of empirical formula and previous artificial neural network (ANN) model. The comparison results showed the efficiency of the proposed method in the prediction of the stability numbers in spite of data incompleteness and incoherence. The proposed method was proved to an effective tool for designers of rubble mound breakwaters to support their decision process and to improve design efficiency.

Introduction

Armor units are designed for defending breakwaters from repeated wave loads. Because armor units are decided by the stability numbers, these numbers are very important to design rubble mound breakwaters. The stability of rubble mound breakwaters is usually analyzed by the well-known empirical formulae by Hudson [1] and van der Meer [2]. Those formulae are used to determine the individual weight of armor blocks of breakwaters. Although those formulae were derived from a number of experimental data, they show too much disagreement between the measured stability numbers and the predicted ones. The uncertainties in the empirical formulae inevitably increase the factor of safety and eventually, the construction cost. Therefore, a number of studies have been carried out to develop an advanced empirical formula for breakwater stability.

Recently, Mase et al. [3] examined the applicability of a neural network to analyze stability of rubble-mound breakwater and compared between predicted stability numbers by neural network and measured ones of van der Meer [2] and Smith et al. [4]. The neural network technique seems to make a breakthrough in the design of rubble mound breakwaters. Actually, the stability numbers predicted by the neural network agree better than those by van der Meer's [2]. The stability number, however, still needs to be improved. Kim, D. H. et al. [5] presented several network models to predict the stability number of armor blocks of breakwaters. The same

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training data set is used for the neural networks but the structures of neural network and the number of nodes at input and hidden layer differ from those of Mase's neural networks. Even if the neural network technique shows better performance than the empirical model based approach in breakwater design, it can be adapted to new data through a re-training process and needs more efforts to determine the architecture of network and more computational time in training the network. Moreover, the estimated results from neural network are not probabilistic but deterministic. The probabilistic neural network (PNN), therefore, could be an effective and reasonable alternative, because PNN needs less time to determine the architecture of the network and to train the network. Moreover the PNN provides the probabilistic viewpoints as well as deterministic classification results.

PNN has been widely used for pattern recognition problems such as texture recognition, image recognition, medical/biochemical field, signal processing [6], civil/geotechnical engineering [7], and so on.

In this study, a PNN method is proposed to predict the stability number of armor blocks of breakwaters. Training and test patterns for PNN are prepared using the data sets from the experimental data of van der Meer [8]. The predicted stability numbers are compared with those measured by laboratory. The results show that PNN can effectively predict the stability numbers in spite of data complexity, incompleteness, and incoherence, and it can be an effective tool for designers of rubble mound breakwaters to support their decision process and to improve design efficiency.

Empirical Formula for Stability Number

van der Meer [8] proposed a stability model by analyzing a large number of irregular wave tests on rock stability. He first surveyed the influential design parameters which should be included in the empirical model such as the significant wave height (H_s), the mean wave period (T_m), the relative density of stone ($\Delta = \rho_s/\rho_w - 1$), the nominal diameter of stone (D_{n50}), the permeability of breakwater (P), the number of wave attack (N_w), the slope angle (α), and so on. The stability formula using these parameters was given by

$$N_s = \begin{cases} 6.2P^{0.18}(\frac{S_d}{\sqrt{N_w}})^{0.2}\frac{1}{\sqrt{\xi_m}} & \xi_m < \xi_c \\ 1.0P^{-0.13}(\frac{S_d}{\sqrt{N_w}})^{0.2}\sqrt{\cot\alpha\,\xi_m^P} & \xi_m \geq \xi_c \end{cases} \tag{1}$$

where N_s is the stability number; S_d is the damage level defined by using the eroded area (A) of the breakwater cross-section; ξ_m is the surf similarity parameter; and ξ_c is the transition condition of surf similarity.

Figure 1 shows the predicted stability numbers together with the measured ones for van der Meer's 641 data [8]. As can be seen in the figure, the degree of agreement between the measured stability numbers and the predicted ones is not so good.

The scattering of the predicted stability numbers from the measured ones cannot be negligible. Due to the uncertainty of the prediction results, the unnecessary increase both in the factor of safety and in the construction cost is inevitable. Hence, a new prediction model with higher accuracy is certainly required

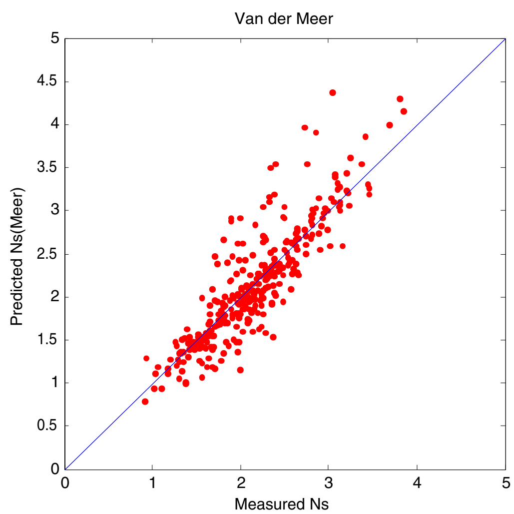

Figure 1: Stability numbers predicted by van der Meer

Probabilistic Neural Network

The objective of this paper is to develop a PNN-based estimation method for predicting stability numbers of breakwater.

In order to apply the PNN to the prediction of stability numbers, the rule base which implicitly tells the input (design condition) output (stability number) relationship should first be composed by using the so-called training patterns. About two thirds of the experimental data by van der Meer [8] were used as training patterns, and the others as test patterns to evaluate the performance of the PNN. In the van der Meer's 641data, there are only two cases for the number of wave attack; 1000 and 3000 wave attacks. In general, it is not easy to have nonlinear mapping function using only two cases of data in function mapping problems. Therefore, two PNNs were separately constructed; PNN_1 is for 1000 attacks and composed of 326 experimental data sets. PNN_2 is for 3000 attacks and composed of 315 experimental data sets. The measured stability numbers that were defined as output whose definitions are respectively set to 207 and 201 classes (the ranges of the measured stability numbers was from 0.7907 to 4.3848). In order to make the training pattern be an adequate representation of the class distinctions, PNN_1 and PNN_2 were constructed using 207 and 201 training patterns out of 326 and 315 experimental data sets, respectively, which correspond to 1000 and 3000 wave attacks.

Five design parameters including the permeability of breakwater (P), the damage level (S_d), the surf similarity parameter (ξ_m), the dimensionless water depth (h/H_s), and the spectral shape (SS) were used as the input set for PNN and a smoothing value of all the variable $\sigma = 0.1$ and all the input data are normalized to 0.1~0.9 to give an equal weighting factor before implementing the data to the network. In which, in cases of impermeability core, permeability core, and homogeneity structure, the permeability of breakwater (P) was assumed to be respectively 0.1, 0.5, and 0.6. In cases of Pierson Moskowitz, narrow, and wide spectrum, the spectral shapes (SS) were used to be respectively 1, 2, and 3.

Results

To verify the prediction/classification capability of the PNN, the predicted stability numbers by PNN_1 and PNN_2 for all input patterns including training patterns are compared with those by measurements (target values).

To compare the performance of each model in a more reasonable way, the agreement index (I_a) and correlation coefficient (CC) were used as follows [9]

$$I_a = 1 - \frac{\sum\limits_{i=1}^{n} (e_i - m_i)^2}{\sum\limits_{i=1}^{n} [\,|e_i - \bar{m}| + |m_i - \bar{m}|]^2} \tag{2}$$

In Equation (2), e_i and m_i denote the estimated and the measured stability numbers respectively; $\bar{m}$ is the average of measured stability numbers; T is the transpose matrix. If I_a is close to one, the predicted set agrees well to the measured set.

In case all the experimental data including trained patterns are used as testing patterns, the results are shown in Table 1. PNN models seem to be the best predictor in this example.

Table 1: Performance of stability with all patterns including training patterns.

	VM_1	VM_2	ANN_1	ANN_2	PNN_1	PNN_2
Ia	0.926	0.927	0.959	0.963	0.991	0.990
CC	0.875	0.877	0.925	0.930	0.982	0.981

To evaluate the generalized capability of the ANN and PNN, they were tested only by untrained patterns. The results are shown in Table 2. In which, the results by ANN and PNN models show slight deterioration compared to those in Table 1. However, the comparison results show that PNN can effectively predict the stability numbers.

To optimize the construction of PNN, $I_a$of models were compared according to the number of training patterns. Performance of models according to the number of training patterns is shown in Table 3.

Table 2: Performance of stability models with only untrained patterns.

	ANN_1	ANN_2	PNN_1	PNN_2
Ia	0.928	0.926	0.955	0.954
CC	0.904	0.896	0.913	0.913

Table 3: Performance of models according to the number of training patterns.

Model	Training patterns	Test patterns	Ia	CC
PNN_1	207	119	0.955	0.913
	182	144	0.937	0.880
	146	180	0.931	0.872
PNN_2	201	114	0.954	0.913
	178	137	0.944	0.896
	140	195	0.935	0.883

Conclusion

In this study, we applied PNN to predict the stability number of breakwater and assessed the performance of the PNN. Through the trend according to the number of training patterns, we can find the optimum condition of construction of the PNN. It was shown that PNN gives more advanced results than the empirical model and ANN in estimating the stability number of breakwaters. Also PNN technique has another merits in that it can provides the probabilistic viewpoint as well as deterministic classification results in considering the uncertainties in the design of rubble mound breakwaters.

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