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Determination of the Most Important Parameters on Scour at Coastal Structures

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ORIGINAL ARTICLE

ABSTRACT: Scour at coastal structures is one of the major problems that may lead to their failure. Therefore, predicting accurate scour depth at coastal structures is important. Extensive laboratory studies have been conducted predicting the maximum scour depth. These studies have developed their formulas using the limited set of effective input parameters. This study presents an alternative to the conventionally regression-based equations in the form of genetic programming (GP) in order to predict the maximum scour depth at coastal structures under the action of breaking waves. To determine the effective parameters, different models with various combinations of input parameters were considered. Parameters such as reflection coefficient, relative water depth at the toe of the structure, the serf similarity parameter, Shields parameter and breaking wave steepness and the wave breaking depth were found to be best inputs. 46 data sets compiled from published literatures were used to train and test the networks or evolve the models. Statistical parameters including the root mean square error, determination coefficient, scatter index and BIAS are used to measure their performance. The results indicate that relative water depth at the toe of the structure plays a crucial role in the scour process.

Keywords: Coastal structures; breaking waves; Genetic programming; Scour depth; Regression-based equations.

INTRODUCTION

Coastal structures such as breakwaters and seawalls are built to protect the shore from the force of the waves and provide calm water condition for loading, unloading and repairing the ships. Scour, one of the significant problems for the coastal structures stability according to Oumeraci (1994) and Lilly and Hughes (1993) reports, results from the interaction between structure, bed and incident waves. An understanding of this process is of important for the optimum design of breakwaters. Being so complicated, it is so difficult to establish a general empirical model to predict the ultimate scour depth. However, many investigators had conducted laboratory studies on this subject. In addition to these studies, different methods such as numerical methods have been developed for this purpose. Empirical investigators such as Herbich et al. (1981), Xie (1985), Fowler (1992), Sumer and Fredsoe (2000), Sanchez and Archilla (2000), Sutherland (2006), Lee and Mizutani (2008) and Ching-Piao Tsai et al. (2009) , among others, produced empirical equations for predicting maximum scour depth in front of the toe of coastal structures. These formulas are simple and fast ones. However, their low accuracy and limited application are their problems. Investigators such as Arneborg et al. (1995), Gislason et al. (2000) and Chen Bing (2007) employed numerical models for scour depth prediction. These numerical models are time consuming and require high-speed computers. However, they show higher accuracy. Since most of the seawalls and sloped breakwaters are under the action of breaking waves, understanding the mechanism of interaction between breaking waves and these structures, and also developing an applicable model for prediction the maximum scour depth is of important.

Sutherland et al. (2006) conducted experimental investigation into scour at the toe of the sloped seawall under the action of breaking waves. They deduced that scour depth is highly dependent on the form of wave breaking onto the seawall. Moreover, they pointed out when waves plunge directly onto the wall generate jets of water that may penetrate to the seabed and cause a local scour hole just adjacent to the seawall. Therefore, they introduced serf similarity parameter as the most significant one.

Ching-Piao Tsai et al. (2009) conducted experimental studies of toe scour of seawall on a steep seabed with slope of 1:5 under the action of breaking waves. Their experimental results indicate that depth of toe scour increased as steepness of the incoming wave increased, but an increase in the water depth at the toe makes it decrease. Moreover, they introduced the breaker type in front of the seawall as another significant parameter in scour depth. They deduced that the scour depth due to a plunging breaker is larger than that of a spilling breaker or non-breaking wave in front of the seawall.

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The objective of this paper is on the determination of effective parameters on the process of scour at coastal structures under the action of breaking waves by training and testing different ANN and GP evolved models with various input parameters, and the application of Artificial Neural Networks and Genetic Programming Models to predict maximum scour depth at coastal structures. Comparing the performance of GP and ANN in prediction of scour depth, also has discussed in this paper.

Genetic programming:

GP is a branch of the genetic algorithm belonging to the family of evolutionary algorithms, first proposed by Koza (1992) and (Goldberg (1989). The GP is similar to Genetic Algorithm (GA); however, it employs a “parse tree” structure for the search of its solutions, whereas the GA employs bite strips. The technique is truly a “bottom up” process, as there is no assumption made on the structure of the relationship between the independent and dependent variables but an appropriate relationship is identified for any given data sets. The relationship can be logical statements; or it is normally a mathematical expression, which may be in some familiar mathematical format; or it may assemble mathematical functions in a completely unfamiliar format. The GP implementation of relationships has two components: (i) a parse tree, which is a functional set of basic operators emulating the role of RNA and (ii) the actual components of the functions and their parameters (referred to as the terminal set), which emulate the role of proteins or chromosomes in biological systems. When these two components work hand in hand, only then efficient emulation of evolutionary processes become possible. The relationship between the independent and dependent variables are often referred to as the “model”, the “program” or the “solution” but whatever the terminology ,the identified relationship in a particular GP modeling is continually evolving and never fixed. GP finds the best solution for a problem by implementing following steps :(John Koza (1999))

i) Initialize a population of individuals known as chromosomes at random.

ii) The fitness value of each model is evaluated using the values of independent and dependent variables with respect to a target value.

iii) Select the fittest individuals for being modified. There are various selection methods including (i) ranking, in which individual models are ranked and selected according to their fitness value and (ii) selection by tournament, in which the population is regarded as a “gene pool” of models and a certain number of models are picked up randomly and are then compared according to their fitness; a set number of winners are picked based on their fitness values.

iv) Modify a selected individual with a relatively high fitness using a genetic operator. Applying operators like crossover and mutation to the winners, “children” or “offspring” are produced, in which crossovers are responsible for maintaining identical features from one generation to another but mutation causes random changes in the parse tree, although data mutation is also possible. This completes the operations at the initial generation.

v) Repeat steps 2-4 until a termination criterion is met. In this case, the best solution is printed.

There are now various software applications for implementing GP models and Fig.1 presents a typical implementation procedure. This study was carried out by using Genexpro software application. The modeling algorithms of GeneXproTools are based on Gene Expression Programming (GEP), an extremely fast and powerful learning algorithm. This application provides tools to post-process the identified model and refine it if necessary.

In this study, the GP was used for predicting the maximum scour depth in front of the toe of coastal structures under the action of breaking waves. The mathematical form of such a relation can be shown as follows:

$$\frac{S_{max}}{H_0} = f\left(Cr,\ \frac{h_{Breaking}}{L_0},\ \frac{h_{toe}}{L_0},\ \frac{H_{Breaking}}{L_0},\ Ir,\ \theta,\ \frac{U_m - U_{cr}}{W}\right) \quad (1)$$

Where $\frac{S_{max}}{H_0}$ is the maximum scour depth to deep-water wave height (relative scout depth),Cr = the reflection coefficient, $\frac{h_{Breaking}}{L_0}$ = the relative breaking depth, $\frac{h_{toe}}{L_0}$ =relative water depth at the toe, $\frac{H_{Breaking}}{L_0}$ = relative breaking wave height, Ir is the serf similarity parameter which determines the type of wave breaking, θ is the Shields parameter and $\frac{U_m - U_{cr}}{W}$is the criterion initiation of bed sediment suspension under waves proposed by Xie (1981).

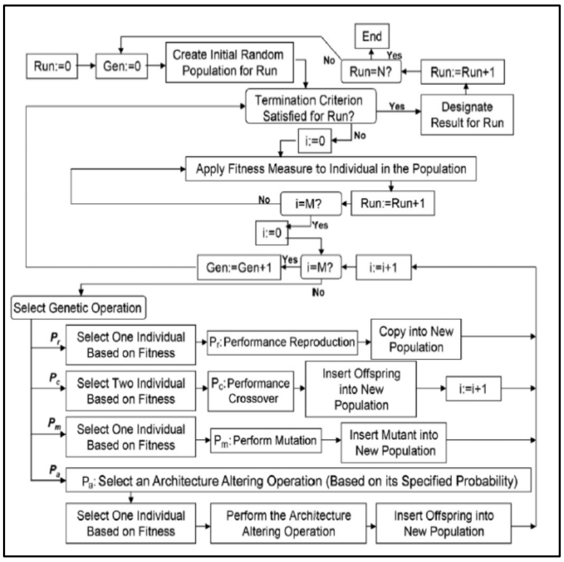

Figure1. Flowchart of Genetic Programming (Koza, www.genetic-programming.com).

The used data sets

A combination of Sutherland et al. (2006) and Ching-Piao Tsai et al. (2009) data sets was used in order to develop the models with Artificial neural networks (ANN) and genetic programming (GP). These data sets contain experimental results of the maximum scour depth at coastal structures under the action of breaking waves. Overall, 46 data sets were extracted from these literatures.70 percentage of data used for training and the remaining 30% were used for testing. As mentioned in previous parts, various input parameters have considered in order developing the best model. Table.1 shows the ranges of different parameters of the data sets.

Table 1. Range of different train and test data used for the prediction of scour depth

Parameters	Train Range	Test Range	Minimum	Average	Maximum
Cr	0.223-0.863	0.256-0.842	0.223	0.4828	0.863
$\frac{h_{Breaking}}{L_0}$	0.012-0.094	0.012-0.094	0.012	0.0500	0.094
$\frac{h_{toe}}{L_0}$	0.006-0.150	0.006-0.150	0.006	0.0587	0.150
$\frac{H_{Breaking}}{L_0}$	0.009-0.087	0.009-0.087	0.009	0.0474	0.087
Ir	0.001-4.761	0.001-4.761	0.001	1.269	4.761
$Shields\ parameter\ (\theta)$	0.074-2.981	0.156-2.834	0.074	1.3463	2.981
$\frac{S_{max}}{H_0}$	0.017-0.9	0.031-0.814	0.017	0.3816	0.900

For quantitative evaluation of the models performance, different statistical measures including the determination coefficient (R^2), root mean square error (RMSE), BIAS and Scatter index (SI) were calculated as below:

Where X_i is the observed parameter and Y_i is the corresponding simulated parameter, $\bar{X}$ is the mean value of the observed parameters and $\bar{Y}$ is the mean value of the predicted parameters and N is the number of measurements.

$$R^2 = \frac{\sum_i((X_i-\bar{X})\times(Y_i-\bar{Y}))}{\sqrt{\sum_i(X_i-\bar{X})^2\times\sum_i(Y_i-\bar{Y})^2}} \quad (2)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Y_i-X_i)^2}{N}} \quad (3)$$

$$BIAS = \frac{\sum_{i=1}^{N}\sum(Y_i-X_i)}{N} \quad (4)$$

$$SI = \frac{RMSE}{\bar{X}} \quad (5)$$

Results of the GP:

As discussed in previous sections, in order to evolve a model with GP, the function set and the Characteristics of the employed Genetic Programming must be introduced. In this study, a function set, composed of the operators that have been used in previous investigations, used to achieve the best model evolved by genetic programming.

Table 2. Characteristics of employed Genetic Programming

Linking function	Addition
Number of chromosomes	30
Head size	8
the number of genes	4
Mutation rate	0.044
Inversion rate	0.1
One-point recombination rate	0.3
Gene transposition rate	0.1
Fitness function error type	Root mean square error
SF1	$\{+\,;\,-\,;\times;/;\sqrt{};\ \boldsymbol{e^x};\ \boldsymbol{x^2};\ \boldsymbol{sinh}\,;\sqrt[3]{}\ ;\ \boldsymbol{tan\,x}\}$

To evolve the model with most effective input parameters, a sensitivity analysis was done in order to investigate the significance of each input parameter given in Eq.1. Table 3 compares the GP evolved models, with one of the input parameters neglected in each case. It should be noticed that although some parameters make the performance of the evolved models less accurate, they simulate the important mechanism. Therefore, using them as input parameters can help us to understand the scour mechanism better.

Moreover, Table 3 shows the error indices for the testing and training data sets. As shown in the Table 3, the $\frac{h_{Breaking}}{L_0}$ and $\frac{H_{Breaking}}{L_0}$ have the lowest influence on the performance of evolved models. However, since they are effective parameters in simulating the scour mechanism under the breaking wave action, they must not be neglected. Moreover, the results of the sensitivity analysis indicate that relative water depth at the toe of the structure ($\frac{h_{toe}}{L_0}$), reflection coefficient (Cr) and Serf Similarity Parameter (Ir) are the most effective parameters in predicting the maximum scour depth under the action of breaking waves. Furthermore, the results of the Table 3 show that the characteristics of the breaking wave such as breaking depth and breaking wave height have less influence on the process of the scour at coastal structures rather than other input parameters. However, they are considered in final evolved model because of its fundamental concept, as discussed in analysis of parameters section. In order to compare the GP evolved models performance clearly, the error indices are plotted in Fig.4 for various models number. This figure, which is in the accordance of mentioned results, illustrate that models 3, 1 and 5 are the less accurate in comparison with the others. Therefore, as mentioned above, it concluded that neglected parameters in these models such $\frac{h_{toe}}{L_0}$, $Cr\ and\ Ir$ play a key role in simulating the scour process.

Table 3. The sensitivity analysis of independent parameters by genetic programming for all data sets

Model number	Input parameters						Function Set	Test		Train	
	Cr	$\frac{h_{Breaking}}{L_0}$	$\frac{h_{toe}}{L_0}$	$\frac{H_{Breaking}}{L_0}$	Ir	θ	SF1	R^2	$RMSE$	R^2	$RMSE$
1	-	*	*	*	*	*	*	0.790	0.092	0.755	0.108
2	*	-	*	*	*	*	*	0.839	0.082	0.681	0.121
3	*	*	-	*	*	*	*	0.727	0.106	0.711	0.118
4	*	*	*	-	*	*	*	0.870	0.072	0.811	0.095
5	*	*	*	*	-	*	*	0.803	0.090	0.803	0.100
6	*	*	*	*	*	-	*	0.830	0.082	0.752	0.111

CONCLUSIONS

In this study, the application of the GP as the new soft computing methodologies to predict the maximum scour depth due to breaking waves investigated. The results of sensitivity analysis by GP models showed that the relative water depth at the toe ($\frac{h_{toe}}{L_0}$) and reflection coefficient (Cr) are the most important ones. Moreover, the GP methodology can better simulate the effective parameters; in a way that serf similarity parameter is among the third important parameters and also it is verified by the concepts presented in Section 4. Therefore, the most important findings of this study are as follows:

1. Introducing the effective parameters on the scour process due to breaking waves with physical justifications.
2. Using the GP approach for determination the importance of effective parameters.

Introducing the relative water depth at the toe and reflection coefficient as the most important input parameters.

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