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Prediction of Sediment Transport in Sewer using a Combination of Adaptive-Neuro Fuzzy Inference Systems and Genetic Algorithm

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1. Introduction

In order to use the sediment transport criterion in sedimentary threshold conditions, some data such as the size of particles, density, sediment concentration, and flow depth are required for establishing an equation forecasting the sediment transport rate as the bed load of suspended load. Sediment transport in the sedimentary threshold state has two types, including suspended load and bed load. To use the existing self-cleansing equations, the transport state (bed load or suspended load) should be specified. Ota and Perrusquía (2013) studied the dimensionless shear stress to evaluate particles with the size of d moving on a rough bed with (k<d). In their study, they measured the influence of variations of flow rate on sediment transport rate. In the last decade, different neural network and artificial intelligence techniques were used by many researchers to forecast and pattern-cognition of complex, non-linear phenomena in various sciences. In addition, neuro-fuzzy models and different artificial neural networks have been recently utilized for solving various hydraulic and hydrology problems. Jain et al. (1999) and Bae et al. (2007) approximated the flow entering into a reservoir using different neural network algorithms. The load of suspended sediments was predicted by means of neuro-fuzzy models by Kisi (2005). In this study, the least required velocity (Froude number) to prevent from sedimentation on the bed of sewer canals was predicted for the first time by different soft computation approaches including adaptive neuro-fuzzy inference system and a hybrid method based on the adaptive neuro-fuzzy inference system (ANFIS), and the genetic algorithm. Also, the results of the soft calculations in predicting the Froude number of the three-phase flow required to prevent sediment deposition into the sewer canals were compared with the laboratory measurements. Reviewing previous studies on sediment transport in sewage canals, it was revealed that the modeling of the three-phase sediment transport mechanism within circular channels has not been performed by this hybrid ANFIS-Genetic algorithm. In this paper, the minimum velocity (Froude number) required to prevent the sedimentation of residual solids entering sewer canals is modeled by the hybrid artificial intelligence method, which illustrates the innovation of the research topic.

2. Experimental Model

In this paper, to validate the numerical models, the measurements conducted by Ab. Ghani (1993), Ota and Nalluri (1999) and Vongvisessomjai et al. (2010) were employed. They measured the values of the flow Froude number (Fr), volumetric concentration of sediments (Cv), the ratio of the mean diameter of sediment particles to the hydraulic radius (d/R), the ratio of the pipe (channel) diameter to the flow cross-section (D^2/A), the ratio of the hydraulic radius to the pipe diameter (R/D), the number of the dimensionless particle ($d_{50}(g(s-1)/\nu^2)^{1/3}$) ($D_{gr}$), the ratio of the mean diameter of particles to the pipe diameter (d/D) and the sediment load general strength factor (strength factor of sedimentary flow) (λ_s). In other words, they studied the influence of the mentioned parameters on changes of the Froude number (Fr).

3. Materials and Methods

Structure of Adaptive neuro-fuzzy Inference system. In this study, an adaptive neural fuzzy inference system is used to predict the required Froude number to prevent sediment deposition in the canal bed. The system is presented as a modeling framework combining fuzzy logic and artificial neural network. This hybrid model is proposed to overcome the weaknesses in both fuzzy logic and artificial neural network methods. In fact, inspired by fuzzy systems, basic knowledge is shown in a set of constraints to reduce the optimization search space, whereas the structured network is inspired by the artificial neural network using back propagation. In this model, the artificial neural network is used to regulate membership functions.

Genetic Algorithm. The genetic algorithm has provided a powerful method for the heuristic development of large-scale hybrid optimization problems. A genetic algorithm encodes the problem as a set of strings containing fine

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particles, and then, applies changes to the strings to stimulate the process of gradual evolution. Compared to local search algorithms, in general searches where there is only one acceptable solution, the genetic algorithm considers a community of individuals. Working with a set of people makes it possible to study the different structures and characteristics of different people leading to identifying and discovering more efficient solutions. In this study, the genetic algorithm chooses strings that are proportional to the value and eliminates those strands that are less proportional to the population under study. Each community member that is an approximation of the final answer is coded as a string of letters or mergers. These strands are called chromosomes. The most common display mode is zero and one digits. Other modes of use of the three digits, real numbers, and integers are also implemented.

ANFIS-Genetic algorithm hybrid method. After the recall, the dataset is categorized into two parts: training and testing. At this point, the data are divided into two categories of 50% and 50% and are used for training and testing the model, respectively. After the classifications, the fuzzy inference system is produced. To this end, three are two methods including grid partitioning and subtractive clustering. Moreover, the number of memberships and the type of input and output membership functions should be specified. In this study, the Gaussian membership function is utilized. The number of membership functions determined through the trial and error process is considered to be 3. Generating the fuzzy inference system, the network learning algorithm must be determined. Generally, two hybrid and back propagation algorithms which are well-known algorithms are used to train the adaptive neural fuzzy inference system. Therefore, in this study the performance of the hybrid algorithm is compared with the genetic algorithm as a well-known evolutionary algorithm suggested by researchers for future studies. After training the adaptive neuro-fuzzy inference system, the prediction accuracy is evaluated using the test data and if the satisfactory results are obtained, the modeling process is terminated, otherwise, this process is repeated from the fuzzy inference production stage until reaching the acceptable response.

4. Conclusion

If the flow within the sewage channel is semi-fill and the flow which the sediment transport in it is in the form of the bed load enters the channel with insufficient velocity to prevent from the sedimentation, the sedimentary bed is formed. It might be assumed that the velocity reduction is a reason for decreasing the sediment transport capacity of the flow which leads to more sedimentation and possibly obstruction. However, the experimental findings indicate that the presence of the sedimentary bed allows the flow to have much more sediment transport capacity in the form of bed load. In this study, using a meta-heuristic approach developed through the combination of the ANFIS model and the genetic algorithm, the three-phase flow in sewage canals was modeled. For the models with one input parameter, the model which was the function of the ratio of the mean diameter of particles to the pipe diameter (d/D) estimated the Froude number of the three-phase flow with higher accuracy. For this model, the values of the RMSE and MAPE indices in the testing mode were calculated to be 1.057 and 19.134, respectively. Also, for the models with two input parameters, this model approximated the values of Cv and d/R. For this model, the values of MAPE and RMSE in the training model were 5.529 and 0.315, respectively. For the superior model which estimated the flow Froude number with three input parameters, the values of MAPE, RMSE and SI in the testing mode were computed to be 7.789, 0.403, and 0.102, respectively. Moreover, for the model which estimated the values of the target function with four input parameters, the values of RMSE and SI for Model No.65 in the testing mode are calculated to be 0.510 and 0.129, respectively. In addition, for the superior model with five input parameters, the values of MAPE and RMSE in the testing mode are 11.980 and 0.579, respectively. Moreover, the model estimating the Froude number values by means of the combination of six input parameters calculated the values of R^2 in the training and testing model are 0.906 and 0.900, respectively. Based on the results of different models, for the model which simulated the three-phase flow characteristics using a combination of seven input parameters, about 69 percent of the results have an error less than 14%.