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PREDICTION OF SCOUR DEPTH AROUND BRIDGE PIERS USING ADAPTIVE NEURO-FUZZY INFERENCE SYSTEMS (ANFIS)

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In this study, the application of a machine learning model, namely the adaptive neuro-fuzzy inference system (ANFIS) is proposed to estimate the scour depth around bridge piers. In particular, various complexity architectures are sequentially developed, trained and validated using appropriate training and validation subsets obtained from the USGS database. The raw data are pre-processed to remove incomplete records and randomly split into the training and validation data sets which are both representative of the same space. The model has five parameters, namely the effective pier width (b), the approach velocity (U), the approach depth (y), the mean grain diameter (D_{50}) and the skew to flow. Simulations are conducted with data groups (bed material type, pier type and shape) and different number and combinations of input variables, to produce reduced complexity and easily interpretable models. Analysis and comparison of the results indicate that the developed ANFIS model has high accuracy and outstanding generalization ability for prediction of scour parameters. The optimal ANFIS models are identified utilizing appropriate error metrics. The effective pier width (as opposed to skew to flow) is amongst the most relevant input parameters for the estimation. The developed models can be used as a scour prediction tool performing satisfactorily even in the presence of scarce available data, while empirical rules can be also derived for the reduced order models.

INTRODUCTION

Earth's surface is continuously shaped due to the action of geophysical flows. Erosion due to the flow of water in river systems has been identified as a key problem in preserving ecological health but also a threat to our built environment and critical infrastructure, worldwide. The impact of climate change on erosion and sediment transport by rivers has been a key challenge in a global scale. It has been estimated that the most common cause for bridge failure is due to scour of the bridge pier's foundation during significant floods. More than half (an estimated 53 percent) of over 500 bridge failures in the United States between 1989 and 2000 are attributed to scour of their foundations [1]. A United States Federal Highway Administration (FHWA) national study of 383 bridge failures showed that 25 percent involved pier damage and 75 percent involved abutment damage, caused by catastrophic floods [2]. A second more extensive study in 1978 indicated local scour at bridge piers to be a problem about equal to abutment scour problems [3]. In financial aspects, the 1993 flood in the upper Mississippi basin caused 23 bridge failures with an estimated damage of $15 million, while the 1994 "Alberto storm" flooding in Georgia caused approximately $150 million. Bridge scour also costs millions of pounds in the United Kingdom, for maintenance operations.

Indisputably bridge pier scour is a significant problem that requires appropriate attention. Even though the flow past bridge piers has been investigated both experimentally and numerically, and the mechanisms of scouring are relatively well understood, there still lacks a tool that can offer fast and reliable predictions. Most of the existing formulas for prediction of bridge pier scour depth are empirical in nature, based on a limited range of data or for piers of specific shape. Additionally, the accuracy of available data may be prone to a spectrum of errors, ranging from following different methodology prone to observation errors to variable instrumentation.

Different from traditional physically based, analytical or empirical approaches, this study investigates the utility of a robust machine learning approach, namely an artificial neuro-fuzzy inference system (ANFIS), trained and tested with a range of appropriate field data to predict bridge pier scour depth. In the following, a brief literature review is offered, leading to the potential utility of a neuro-fuzzy approach, which is demonstrated using appropriate performance metrics via an exhaustive search for the best model structure. Finally, the major findings are further discussed, while essential suggestions are offered regarding the choice of parameters that practitioners and hydraulic or bridge engineers need monitor to get reliable estimates of incurred scour.

LITERATURE REVIEW

Local scour at piers has been studied extensively in the laboratory, mostly for simple piers geometries. As a result of these numerous laboratory studies, many equations primarily for live-bed scour in non-cohesive, sandy bed streams have been developed.

There exist two types of scour depending on the condition of sediment transport in the approach flow: a) clear-water scour, where bed material is removed from the scour hole until an equilibrium geometry is reached, but not replenished by the approaching flow; and b) live-bed scour, where the scour hole is continually supplied with sediment by the approaching flow. Many studies investigated the relationship between the maximum bridge piers scour depth under clear-water scour conditions [4-8]. Most of the derived equations (e.g. see [9]), have the about the same functional representation incorporating flow intensity, flow depth, sediment size, sediment gradation and pier shape and alignment. On the other hand, more studies are focused on live-bed scour conditions [8].

Regarding pier geometry, most of the experimental research has focused on circular piers, which are the most commonly employed. The main problem with these formulas is that the existing equations are based on laboratory data, which do not accurately simulate the prototype conditions, with most of the formulas yielding conservative results and overestimating scour depth [9]. This is because the conventional analysis of data may fail to capture the underlying mechanisms of a number of parameters influencing scour depth.

The Adaptive Neuro-Fuzzy Inference System (ANFIS) has been used in many water resources problems such as reservoir operation, modeling of hydrological time series, wave prediction studies and other related fields. Over the last decades, soft-computing methods have been extensively utilized and are successfully employed for the prediction of sediment load. In a previous study [10], the authors constructed several ANFIS structures and compared them with ANN models of about the same structural complexity, for the prediction of dislodgement events of a coarse particle resting on a packed bed surface. Generally the ANFIS models demonstrated superior performance compared to other machine learning techniques such as artificial neural networks (ANN) [11, 12, 13].

Numerous studies have been conducted in the past, producing a vast amount of bridge pier scour formulas, which however may return predictions that can vary significantly, resulting in structural uncertainties or conservative bridge designs. A range of Machine Learning methods developed over the last few decades, offer an alternative way to efficiently and reliably estimate the scour parameters. Here the use of adaptive neuro-fuzzy inference system, is proposed to predict bridge pier scour based on appropriate input. The search for the best architecture and model parameters using a set of input-output pairs is offered below and a discussion on the utility of the method follows.

METHODOLOGY

Estimation of depth of local scour depth around bridge pier is a vital issue in the bridge design. Many studies have been carried out in this field, and numerous formulas have been proposed representative of a range of conditions. ANNs and ANFIS could be used as alternative methods in overcoming the variation of physical modelling [14], thus they have been widely applied in various fields of water resources and hydraulics engineering. In this project, the ability of ANFIS to predict scour depth around bridge piers for a wide range of physical parameters and its performance are evaluated. Firstly, a search is conducted for a sufficient ANFIS structural complexity, by adjusting the fuzzy inference system settings. Both are being considered. This is done following a trial and error approach for the best performing model, by sequentially changing the number and types of membership functions. The fittest ANFIS architecture, using a range of appropriate performance indices, will be employed for the following runs. A subsequent set of simulations targets at identifying which of the various possible groupings of data input, offers the best performance. This will be examined for a decreasing set of input parameters (from four to only two), to observe is sufficient prediction can be achieved with a limited set of available or desirable input and for which combination of input data.

ANFIS framework

Adaptive Neuro-Fuzzy Inference Systems (ANFIS) combine the advantages of both Artificial Neural Networks (ANN) and Fuzzy Inference Systems (FIS). They demonstrate inherent learning abilities due to the neural network training algorithm incorporated for the tuning of the nonlinear parameters while they also have a rule based structure to perform fuzzy reasoning and extract the nonlinear dynamics of the studied phenomenon [10].

To present the ANFIS structure, a first order Sugeno fuzzy inference system with two fuzzy If-Then rules, two inputs (x, y), an output $f_k(x, y)$, could be expressed as follows (Sugeno, 1985):

Rule 1: If x is A_1 and y is B_1, Then $f_1 = p_{1,1}\, x + p_{1,2}\, y + r_1$

Rule 2: If x is A_2 and y is B_2, Then $f_2 = p_{2,1}\, x + p_{2,2}\, y + r_2$

where A_i, B_i are values of membership functions for x, y respectively, in the premise part and $p_{k,i}$ and r_k are the linear parameters of the consequent part, for each input parameter i and rule k. An example of two inputs ANFIS architecture is shown in **Figure** 1, in which a circle represents a fixed node, whereas a square represents an adaptive node. Typically an ANFIS model consists of five layers and an overview of each of these layers is offered in [10].

There exists no general rule in defining a priori the optimal architecture for ANFIS since it is highly dependent on the nature and dynamic complexity of the studied phenomenon. In general a complex structure with many nodes attains high accuracy (small training error) but poor generalization ability (higher testing error). However, a simple, relative to the dynamics of the studied model, architecture, might generalize well but exhibit a low accuracy. Thus, a trial and error method approach, where a range of different shapes, numbers and types of membership functions, as well as various parameters used as input data, should be followed towards identifying the optimal ANFIS architecture [10].

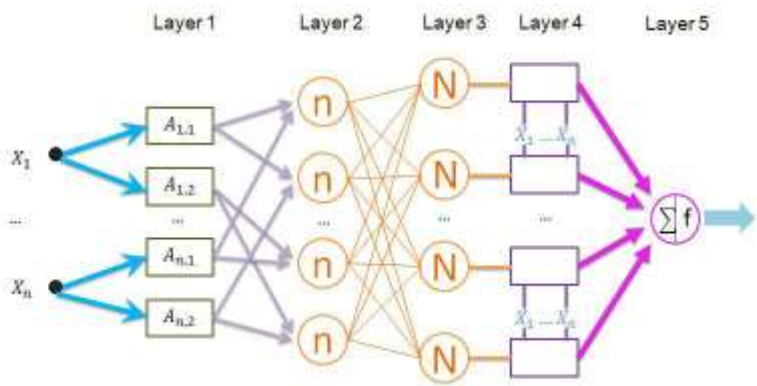


Figure 1. Generic example of an ANFIS architecture

Data preparation and classification

For this study, the pier scour data used to train and test the various ANFIS architectures are retrieved from the National Bridge Scour Database of the United States Geological Survey (USGS). These include a total 508 data sets reflecting a range of cases characteristic of pier scour, along with pier and sediment features, flow conditions, site information, date and time. In particular these are the effective pier width (b), the skew to flow (α), the approach velocity (U), the approach depth (y), the bed material type (cohesive or coarse), the sediment fraction sizes (mainly D_{50}, but also D_{16}, D_{84} and D_{95}) and the scour depth (d). Data pre-processing involves removing any data set with incomplete information, which reduces the initial data set to 486 data sets. This set is split in half and used in the following for training and validation of the range of developed ANFIS models. The resulting classification of all data sets into characteristic sub-sets as well as their size (number of data points in each) is shown in Table 1.

Table 1. Classification of the initial data set into subsets of characteristic size

<table>
<tr><td>All data sets</td><td colspan="6">486</td></tr>
<tr><td rowspan="2">Bed material type</td><td colspan="5">Non-cohesive</td><td>Unknown</td></tr>
<tr><td colspan="5">367</td><td>119</td></tr>
<tr><td rowspan="2">Pier type</td><td colspan="4">Single</td><td>Group</td><td rowspan="4"></td></tr>
<tr><td colspan="4">325</td><td>42</td></tr>
<tr><td rowspan="2">Pier shape</td><td>Round</td><td>Sharp</td><td>Square</td><td>Cylindrical</td><td rowspan="2"></td></tr>
<tr><td>151</td><td>95</td><td>71</td><td>8</td></tr>
</table>

Table 2. Input and output range of values for variables with non-cohesive data sets

Non-cohesive bed material	Effective pier width (ft)	Approach velocity (ft/s)	Approach depth (ft)	Grain size D_{50} (mm)	Normalized skew to flow
Training	[0.95 18.1]	[0.5 12]	[0.4 73.9]	[0.0115 95]	[0 0.9444]
Validation	[0.95 17.9]	[0.8 14.7]	[0.5 73.4]	[0.01 95]	[0 0.7378]

The effective pier width, the approach velocity, the approach depth, the mean grain diameter and the skew to flow are chosen as input variables, while the scour depth as the output. All data points were used to train and validate the best-fit ANFIS model. Then these data were classified into different groups based on bed material type, pier type and pier shape and were applied to the ANFIS model for further results. Under each classification, data sets were randomly divided into two groups, one for training and the other for validation. The statistical parameters and range of the two sets were examined to ensure both are representative of about the same physical space for the variables of interest (Table 2).

SIMULATION RESULTS

All models are developed in an appropriate scientific programming language (Matlab) using the fuzzy logic toolbox. The performance of the developed systems is evaluated using appropriate error indices, such as the root mean square error (RMSE) and the mean average error (MAE), as shown in Eq. 1 and Eq. 2 below:

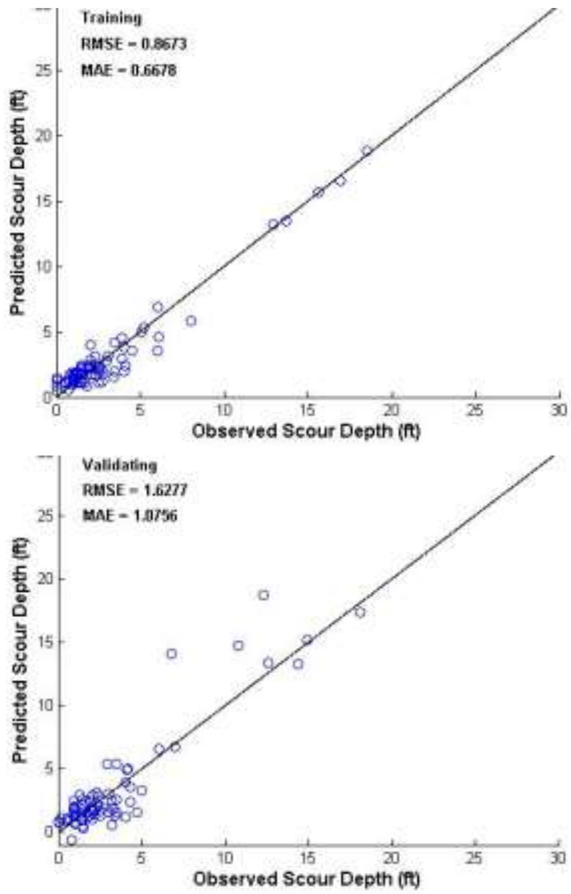
$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} (o_i - t_i)^2}{N}} \tag{1}$$

$$\mathrm{MAE} = \frac{\sum_{i=1}^{N} \left| o_i - t_i \right|}{N} \tag{2}$$

Generally, the lowest the error metrics for a certain model using both the training and validation subsets the better its predictive ability. In case, the training error is low but the validation error is high then the model is over-trained and fails to generalize, having a low predictive ability for unseen data. Employing such models should be avoided.

First, all data and input parameters are utilized in search of the best performing ANFIS structure. This involves running models with various types of membership functions and the number of membership functions for each input parameter. It is readily realized that using 3 or more membership functions not only results in overtraining, but also is exponentially more costly in time required to train the model (e.g. the time required for training the model with 4 membership functions per input was 100 times greater than for the model employing only 3). Thus using 2 membership functions per input and testing for different types of membership function ranging from triangular to sigmoid the Gaussian is found to obtain the best accuracy, with good generalization ability.

For the model employing all input parameters, namely the effective pier width (*b*), the approach velocity (*U*), the approach depth (*y*), the mean grain diameter (D_{50}) and the skew to flow, its performance is tested using data from a single subgroup, until all data groupings are tested. The best model performance was achieved for the subgroup containing only round piers, shown in Figure 2. It can be observed that the predicted data match the observed data quite well.



a)

b)

Figure 2. Plot of observed and predicted scour depth training the model with all input parameters with the subset of single round pier data: a) performance for the training subset (77 data points) and b) performance for the validation data set (74 data points). Note the line of perfect agreement is shown with the straight line (diagonal).

DISCUSSION

In addition to identifying the optimal full model (with 2 Gaussian membership functions per input, and all 5 input parameters), trained with all the data as well with subgroups of characteristic data alone (total of 24 models), a search was done to find the best performing models for gradually reduced number of inputs. Assuming a certain number of input parameters all possible input combinations were tested. This would lead to reduced complexity models, where only the most relevant input with high information content is retained to enable prediction. The advantage over other methods in the topical literature of bridge pier scour is that the relevant parameters are not determined a-priori. For this search 23 new models were generated, trained and validated. A comprehensive comparison of all the best performing models for each examined category is shown in Table 3.

Table 3. Input and output range of values for variables with non-cohesive data sets

	Training RMSE	Validation RMSE
5 inputs (single round pier data)	0.87	1.63
5 inputs (all data)	1.76	2.07
4 inputs (without skew to flow)	1.82	2.03
3 inputs (without D_{50} & skew to flow)	1.87	2.04
2 inputs (pier width & approach depth)	1.93	2.39
1 input (pier width)	2.44	2.54

Overall, the best performing model has 5 input parameters with 2 Gaussian membership functions per input and has been trained with the single round pier data alone. Comparing this with the model trained with all the data, there is a reduction in the model's accuracy, which may be attributed to the data not being as accurately describing the underlying dynamics well or that there may be greater errors associated with obtaining such group of data.

It can be further noted that as expected there is a reduction in the accuracy of the models, as their input is reduced. This is particularly true if the input parameter was of high value and information content for the prediction. Only if one of the parameters is not contributing relevant information, then the error metrics will not improve, as occurs in the case of the model trained without the skew to flow parameter. Actually there is a small improvement in the validation RMSE (from 2.07 for all data to 2.03 for the case where the skew to flow input parameter is removed). This is the only of the examined cases where a reduced structure model demonstrates better predictive ability.

Comparing the case of 4 and 3 inputs the model performance is quite the same, rendering the model relatively insensitive to the size of bed material, as the validation RMSE only improves by 0.01. However, the value of this performance metric, increases further by 0.35 and 0.50 for 2 and 1 input respectively. This is only a small deterioration in performance and the results are still accurate.

It can be observed that the optimal reduced order models incorporate bridge pier's width and approach depth as the most relevant input parameters. This is in accordance with simple models proposed in the literature. For example the 1 input model, is based on the pier's width, which is of the same functional form as the formulas suggested by Neil [15] for circular piers and R&E for uniform sediment, $y = K\, b$, with K being a coefficient ranging typically from 1.5 to 2.3. Likewise, for the 2 input model, it is the flow depth and pier width that determine the pier scour. This is similar to the formula proposed by Breusers et al. [16].

It is envisaged that such machine learning methods employing physically relevant input for the energy performed towards scouring the bridge pier as described by Valyrakis [17], could potentially lead to improved predictions.

CONCLUSIONS

In this project, the prediction of scour depth around bridge piers is investigated using ANFIS. A wide range of models is developed, trained with appropriate data and validated using appropriate error indices. Comparison between these models allows identifying the best performing models with good generalisation ability. The results are satisfactory even for the reduced order architectures and functionally in agreement with other models proposed in the literature.

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