Abstract—The Neuro-Fuzzy model is a method in which a combination of neural network and fuzzy logic to produce a more reliable output. In this method, learning strategies derived from the domain of neural networks theory support the development of a fuzzy inference system (FIS). The depth of scour is an important parameter for determining the minimum depth of foundations as it reduces the lateral capacity of the foundation. It is for this reason that extensive experimental investigation has been conducted in an attempt to understand the complex process of scour and to determine a method of predicting scour depth for various pier situations. In this study, an adaptive neuro-fuzzy inference system (ANFIS) was used. The training and testing data are selected from the experimental and field data of several valuable references. Numerical tests indicate that the ANFIS model leads to reliable results.

Keywords—Neuro-Fuzzy model, Local Scour, Predicting.

I. INTRODUCTION

SCOUR is a kind of erosion around the pier that occurring due to the effect of complex vortex flows. Up to now, a lot of investigations of scour around bridge pier cause to provide the multiple equations for estimation of the maximum depth of scour. Results of these equations are not satisfactory due to non-certainty in scour operation. To date, no generic formula has been developed that can be applied to all pier cases to determine the extent of scour that will develop. An accurate estimate of the maximum local depth of scour around bridge piers is essential for reliable and cost-effective design. ANN is a powerful set of adaptive learning techniques to detect and extract patterns and trends that are too complex to be identified otherwise. Further, ANN has the capability to learn from experience through examples fed to it, generalizing the captured knowledge for future solutions, and self-updating. Learning from experience is accomplished by using a data set to “train” the artificial neurons to recognize the patterns and trends between input and output. The hybrid of ANN and FIS is one of the researching focuses, which can make use of the advantages of both ANN and FIS namely Neuro-Fuzzy (NF) systems. Some specific applications of ANN to hydrology include modeling rainfall-runoff process [1], river flow forecasting [2], and hydrologic time series modeling [3], sediment transport prediction [4], sediment concentration estimation [5], scour depth prediction around bridge piers [6] and groundwater modeling [7].

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II. ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

The adaptive neuro-fuzzy inference system (ANFIS) uses the multi-valued logical system, namely, fuzzy logic, to account for a hidden imprecision in data and to make accurate mapping accordingly. This is done by fuzzification of the input through the membership functions, where a curved relationship maps the input value within the interval of. The fuzzified input leads to an inference, from which the output is produced after defuzzification. The parameters associated with input as well as output membership functions are trained using an algorithm like back propagation and/or least squares. Thus unlike the MLP, where weights are tuned, in ANFIS fuzzy language, the rules or conditional (if–then) statements are determined in order to train the system. Further, while some or all of the neurons can be adjustable or adaptive to the problem requirements, with changeable parameters (during training), the rest remains as the fixed neurons. ANFIS may be advantageous for large data because it maps locally using fuzzy rules and thereby resulting in reduced errors for the current training pattern and minimum interference with the learning already made.

Fig. 1. ANFIS architecture.

III. LOCAL SCOUR

Scour depth around a circular pier in a steady flow over a bed of uniform, spherical and cohesionless sediment depends on numerous groups of variables such as flow, sediment characters, and pier geometry. The basic similitude
requirements for hydraulically modeling the simplest of pier-scour situations are difficult to satisfy. Scour depth at a pier as in Fig. 1, depends on variables characterizing the fluid, flow, bed sediment, and pier. Thus, the parameters influencing the maximum equilibrium scour depth \(Y_s\) for cylinders in uniform non-cohesive sediments are given by

\[
Y_s = f(\rho, \nu, V, y, g, d, \tau_c, D)
\]  

Where \(\rho\)=fluid density; \(\nu\)=kinematics viscosity of water; \(V\)=depth averaged velocity; \(y\)=approach flow depth; \(g\)=acceleration due to gravity; \(d\)=sediment particle diameter; \(\tau_c\)=critical value of \(V\) generating the critical threshold shear stress \(\tau_c\) associated with threshold for movement of particles on bed surface; and \(D\)=pier diameter. Scouring around cylinders in non-cohesive sediment beds has been extensively studied in the last few decades. For non-cohesive soils hundred and five data collected from experimental studies by Federal Highway Administration in three different test flumes housed at the Engineering Research Center at CSU [8]. Three laboratory flumes, designated as the hydrodynamics flume, sedimentation flume, and the river mechanics flume, were simultaneously utilized for conducting the pier scour experiments in non-cohesive sediment mixtures.

![Fig. 2. Flow and a local scour](image)

The first two flumes are sediment recalculating facilities, while the latter does not recalculate sediment. All flumes are housed at the Hydraulics Laboratory of the Engineering Research Center at CSU.

\[
Y_s = f(\rho, \mu, g, V, b, Y, \tau_c, D_{50}, S_o, \sigma)
\]

(2)

Where \(Y_s/b\)=non-dimensional maximum scour depth/D=non-dimensional approach flow depth; \(Fr_p=Fr_p = \frac{V}{\sqrt{gD}}\)=pier Froude number; \(b/D_{50}\)=non-dimensional particle size; \(\tau_c=\frac{\tau}{\rho V^2}\)=non-dimensional bed shear strength; and \(Re_p=Re_p = \frac{\rho V D}{\mu}\)=Pier Reynolds number.

For non-cohesive soils thirty nine field data collected from U.S. Geological Survey [9]. The study site is located at the County Road 87 bridge crossing the South Platte River, 1 mile north of Masters and U.S. Highway 34. The drainage basin (12,119 sq. mi) includes rolling, irrigated farmland and mountainous areas. The bridge, estimated to be at least 40 years old, is 361 ft long, and it has eight concrete piers spaced 40 ft apart. The piers are perpendicular to the bridge and generally aligned with the flow. The piers are square nosed with a width of 0.95 ft and a length of 24 ft.

IV. RESULTS AND DISCUSSIONS

In the ANFIS model, fuzzy subtractive clustering algorithm was used to design an initial rule base. In general, as the number of rules increased, the difference between the predicted and the experimental values decreased and more complex relations can be modeled with a larger number of rules. A crucial point in the rule base design is selecting the number of rules. When fuzzy systems are designed by using fuzzy clustering, each cluster corresponds to a fuzzy rule. Hence, the number of clusters determines the number of rules. We have determined the number of clusters experimentally, by developing various models and studying the rules and their results. Finally, the radius of 0.20 was used for each cluster, and the appropriate number of clusters was 5.

The whole data set was divided into two parts randomly: a training set consisting of 70% data points and a validation or testing set consisting of 30% data points. The performance of all ANFIS configurations was assessed based on three error measures namely, correlation coefficient, \(R\), which presents the degree of association between predicted and true values; root mean square error, \(RMSE\), which is preferred in many iterative prediction, optimization schemes; and mean absolute relative error, \(MARE\). Expressions for these measures are given as follows:

\[
R = \frac{\sum_{i=1}^{N}(Y_m-Y_p)(Y_p-Y_m)}{\sqrt{\sum_{i=1}^{N}(Y_m-Y_m)^2}(Y_p-Y_p)^2}}
\]

\[
RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(Y_m-Y_p)^2}
\]

\[
MARE = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{Y_m-Y_p}{Y_m}\right| \times 100
\]

Where, \(Y_p\) is the predicted scour depth, \(Y_m\) is the observed scour depth, \(Y_p\) is the average of the predicted scour depths, \(Y_m\) is the average of the observed scour depth records and \(N\) is the total number of events considered.

To assess the performance of the ANFIS model, observed scour depth values are plotted against the predicted ones. Fig. 3 illustrates the results with the performance indices between predicted and observed data for the training and testing data sets, respectively. As can be seen from Fig. 3, ANFIS has performed well in predicting the scour depth.

Sensitivity tests were conducted to determine the relative significance of each of the independent parameters (input neurons) on the scour depth (output). The results show that (See Table 1) among the parameters, flow velocity has the most significant effect on equilibrium scour depth.
Table I

<table>
<thead>
<tr>
<th>Dimensional parameters</th>
<th>Non-dimensional parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Method</td>
<td>MARE (%)</td>
</tr>
<tr>
<td>ANFIS</td>
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</tr>
<tr>
<td>ANFIS no V</td>
<td>49.66</td>
</tr>
<tr>
<td>ANFIS no τ</td>
<td>36.08</td>
</tr>
<tr>
<td>ANFIS no Di</td>
<td>34.2</td>
</tr>
<tr>
<td>ANFIS no Y</td>
<td>33.52</td>
</tr>
<tr>
<td>ANFIS no b</td>
<td>49.66</td>
</tr>
</tbody>
</table>

V. CONCLUSION

In this study, the application of ANFIS machine learning approach was evaluated for estimating of the scour depth around bridge piers. Several influencing parameters, such as the flow depth, mean velocity, grain diameter, geometric standard deviation of the grain size distribution, shear stress and pier dimension have been considered in the ANFIS model. The results suggest that the ANFIS method as a superior method can be successfully applied to predict the local scour depth.

REFERENCES