Application of ANFIS and LR in prediction of scour depth in bridges

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ABSTRACT

This study uses the Adaptive Network-based Fuzzy Inference System (ANFIS) as a modeling tool to predict the scour depth in bridges. Experiments involved different sediment sizes, flow rates, and time evolution with and without *Epipremnum aureum* for predicting the effects of scouring on integral bridge piers. A total of 2500 data were taken at the maximum location of scour, and 17,500 scour data were taken at every pile for each time interval. Single row and double row pile integral bridge piers with pile group model were embedded in the two floodplains. The input data and its corresponding scour depth in bridges as output data were recorded at all testing stages. Results from ANFIS were compared with the classical linear regression (LR). ANFIS’s results were highly accurate, precise, and satisfactory.

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1. Introduction

In many countries, bridges have been built across canals and rivers as traffic volume has increased due to economic development. Bridges that are built with the new modern system are more cost-effective. If the total length of a bridge is less than 60 m, then its overall cost is lower if appropriately designed with fewer expansion joints. This advantage makes integral bridges an alternative solution. Many of these types of bridges have been constructed in Malaysia over the past few years. However, the effects of natural hazards, local weather, as well as environmental conditions are relatively unknown for this new system. An example is effect of floods on bridges. In 1920s, there were reports of surface run-off due to flood that exceeded the capacities of most rivers in Malaysia. Flash floods have become a concern in urban areas recently. Therefore, investigation on the effect of flood on integral bridges is important.

One of the most important effects of floods on integral bridges is scouring. Scouring occurs due to the erosive behavior of flowing water on the bed and banks of alluvial channels. Flow near a bridge pier or abutment is accompanied by an enhanced sediment-carrying capacity. This may occur even when there is no transport of sediment away from the structure. Scouring can cause catastrophic hazard by reducing support. There are reports of many bridge failures over the past years. The Federal Highway Administration (FHWA) results reports that 383 bridges collapsed due to catastrophic floods. Pier damage observed in 25% and 72% involved abutment damage [9], Brice and Bledgett [8] showed that local scour at bridge piers and abutment scour are equally critical. Pattern of flow near bridge piers is very complex, specifically around the scour hole [12]. The occurrence of a complex vortex system at the vicinity of the bridge piers is the key factor in development of the scour hole. As the flow impacts the pier nose, a down-flow is created in front of the pier. The down flow impinges the stream bed, causes the scour hole in front of the pier, and eventually forms a complex vortex system. In addition, wake vortices are formed due to downstream flow separation of the pier, which behave as little tornados causing the bed material to lift and create an independent scour hole downstream of the pier [22].

Zarrati et al. [33], Akib et al. [2], Fayyadh et al. [3] and [13] studied the effect of time on local scour. Ataie-Ashtiani and Beheshti [4] tested the problem regarding the interaction of two widths (pier and piles) set at different elevations from the riverbed. They recommended the width-weighting method because of the great scouring that exists closer to the riverbed at the base of the pier. Local scour depth prediction near bridge piers and abutment-like structures has attracted considerable research interest, and a number of prediction methods exist at present [2,3]. However, the high costs involved in testing procedures necessitate the search for inexpensive new effective tools for prediction of scour depth in bridges with modeling. This involves the use of classical and/or modern models for scour depth in bridges with an emphasis on effective parameters.

Fuzzy inference systems (FIS) and neuro-fuzzy/fuzzy-neural systems have been used successfully for modeling in many engineering applications as well as in agricultural [26], water science [20,24], soil science [31] and stability of structures [7]. ANNs have been established and acknowledged as a powerful tool in pattern...
recognition, signal processing, and control and complex mapping because of their excellent learning capacity and their high tolerance to error [18].

Fuzzy logic, which was first introduced by [32], is a self-learning technique that provides a mathematical tool to convert linguistic evaluation variables based on expert knowledge into an automatic evaluation strategy. Fuzzy-neural systems are part of an intelligent system which combines significant characteristics of ANNs and a fuzzy inference system (FIS) to construct powerful tools for computing. The Adaptive Network-based Fuzzy Inference System (ANFIS) uses artificial neural network theory in order to determine the properties (fuzzy membership functions and fuzzy rules) of data samples in learning a fuzzy inference system.

In ANFIS, a fuzzy inference system is implemented through a feed-forward network and a hybrid learning method including back propagation theory from ANNs, the recursive least square (RLS) method, and clustering techniques to construct the FIS. In other words, ANFIS combines fuzzy logic and ANNs by utilizing the mathematical properties of ANNs in tuning a rule-based fuzzy inference system that approximates how the human brain processes information. ANFIS has shown significant promise in modeling nonlinear systems where it is able to learn features of the data set and adjusts accordingly the system characteristics to a given error criterion [16]. ANNs have been used for learning the mathematical mapping between input and output variables of nonlinear systems [5].

Some studies have examined how to apply ANN to estimate local scour. Trent et al. [30] applied ANN to estimate local pier scour and sediment transport in open channels. Biglari and Sturm [6] pointed out that local scour around piers is observed as a result of bridge failure. Abutments have motivated many examinations into scour prediction as well as reliable design methods. Liriano and Day [23] compared current prediction equations for culvert outlets with results obtained from two ANN models. They concluded that the ANN model is better than other empirical relationships that are currently in use in the laboratory and in the field.

There are also a number of models to predict pier scour which employ ANN and other soft computing applications structures [5,28]. Kambekar and Deo [17] developed different neural network models to predict scour depth and found that the neural network provides a better alternative to statistical curve fitting. Choi and Cheong [11] applied an ANN model to predict the scour depth around bridge piers in both laboratory and field studies. Lee et al. [21] applied neural networks to predict scour depths around bridge piers. Adaptive neuro fuzzy inference systems (ANFIS) have been recently shown to yield effective estimates of scour around hydraulic structures. Kaya [19] developed an ANN model to study the observed pattern of local scour at bridge piers using an FHWA data set composed of 380 measurements at 56 bridges in 13 states.

Scour prediction in bridges is rather difficult to measure. Physical modeling demands high costs to model the prototype and requires extensive work in the laboratory. For the first time, this paper presents and compares the results of scour prediction in bridge using ANFIS and LR; to date, no such work has been carried out in this area. The proposed model can adequately predict the scour depth in bridge.

2. Material and methods

This research includes experimental work and numerical modeling. The present study conducted experimental work at the Hydraulics Laboratory of the University of Malaya. Experimental investigations were conducted in a flume of 16 m length, 0.60 m width, and 0.6 m depth of a fixed slope (Fig. 1).

The flow velocity components were measured by a three axis electronic current velocity meter with an accuracy of ±1 cm/s and depth of scouring around piers and piles was measured and recorded by digital point gauge.

Scour depths were measured as a function of discharge and sediment size for two types of hydraulic structures (double-row pile integral bridge and single-row pile integral bridge). Scour depths at abutments, piers, and combined piles for integral bridge were measured. All experiments involved similar time intervals for scour reading until a final reading of 24 h. Scour depth measurements were purposely taken at intervals of 1 min for 10 times, followed by readings at intervals of 10 min for 10 times, 5 times for every 1 h and 40 min, and the final reading after 24 h. A total of 2500 data values were taken to measure the maximum scour depth after 24 h. A total of 17,500 scour data values were taken at every pile for each time interval for different sediment sizes, flow rates, and time evolution with and without Epipremnum aureum.

The procedure for each type of structure was repeated with five discharges (Table 1), three types of sediment sizes (Table 2), and by adding E. aureum to discover the impact of vegetation on the reduction of the scour rates.

According to Chiew and Melville [10] the scour depth (d_s) was not affected by the non-uniformity of the bed material, if \( \sigma_s < 1.4 \) (\( \sigma_s \) is the standard deviation of grain size). Moreover, the clear-water condition, \( V/V_c < 1 \) (V is the velocity of the approaching flow and \( V_c \) is the critical velocity for incipient motion for bed sediment movement), was satisfied in all experiments to reach the maximum scour depth.

2.1. Integral bridge detail

The integral bridge model is a complex structure consisting of abutment and piles. The model was made from Perspex material. Cylindrical Perspex pipes with diameter of 15 mm were used as pier models in single-row pile integral bridge and 10 mm for double-row pile integral bridge. According to Chiew and Melville [10], the pier diameter (D) should not be more than 10% of the channel width (W). The application of small scale integral bridge model with the scale of 1:45 was used in this study. Piles were embedded in 2 m long floodplains at both sides of the flume.

Vertical depth scales were used to measure the scour depth at the abutments and piles. Fig. 2 shows the integral bridge model with one row of pile used in this study. Fig. 3 shows the integral bridge model with two rows of pile used in this study.

Fig. 1. Flume in hydraulics laboratory.
The bed of the flume was embedded in floodplain of river sand layer of about 0.15 m in depth. Single row and double row pile integral bridge piers with pile group model made from Perspex material were embedded in the two floodplains (Fig. 4).

Laboratory works involved different flow rates for sand sizes $d_{50} = 0.8 \text{ mm}$, $d_{50} = 0.26 \text{ mm}$, and $d_{50} = 0.13 \text{ mm}$ (course, fine, and very fine, respectively). Three uniform sediments with median particle size, $d_{50} = 0.8 \text{ mm}$, $d_{50} = 0.26 \text{ mm}$, and $d_{50} = 0.13 \text{ mm}$, were carefully compacted and leveled. Initial readings were taken as a control experiment before the compound channel was flooded with water. Five discharges and flow depths were created by adjusting the valve on the main inlet pipe. For scour countermeasure experiments, approximately 250 $E. aureum$ leaves together with stems were counted and planted in the floodplains (Fig. 4). Throughout the experiments, the developments of scour at abutments and piles were monitored. The flow velocity and depth of scouring were measured and recorded using a 3 Axis Electronic Current Velocity Meter and digital point gauge.

Small-scale models in this study are used for investigating channel-control integral bridge scour issues. Froude number is the primary similitude criterion for models of fixed-bed open-channel flows. Oliveto and Hager [27] presented a research to clarify the minimum laboratory dimensions required to apply Froude similitude, effect of sloping abutments on scour advance, extension of scour formula to spur dikes and effect of unsteady flow on scour development. They concluded that the effect of the densimetric particle Froude number is significant since it determines scour depth and allows expressing suitable length and time scalings.

Dynamic similitude between model and prototype requires that there must be an exact geometric similitude and the ratio of dynamic pressures at corresponding points be a constant. Second requirement expressed as a kinematic similitude which is the streamlines must be geometrically similar. Geometric similitude extends to the actual surface roughness of model and prototype. For dynamic pressures to be in the same ratio at corresponding points in model and prototype, the ratios of various types of forces must be the same at corresponding points. For dynamic similitude, the Reynolds and Froude numbers must be the same in both model and prototype.

Integral bridge structures have forces due to gravity and inertial forces that are greater than viscous and turbulent shear forces. Geometric similitude and the same value for Froude’s Number in the model and prototype produce a good approximation to dynamic similitude, that is (Eq. (1)).

$$\frac{V_m}{g_m} = \frac{V_p}{g_p}$$

(1)

where $V_m$ is velocity of model, $V_p$ is velocity of prototype, $g_m$ is gravitational acceleration of model, and $g_p$ is gravitational acceleration of prototype.

Since gravity is the same, the velocity ratio varies as the square root of the scale ratio (Eqs. (2) and (3)).

$$R = \frac{l_p}{l_m}$$

(2)

$$V_p = V_m \sqrt{R}$$

(3)

where $R$ is scale ratio, $l_p$ is length of prototype, and $l_m$ is length of model.

The corresponding times for events to take place (as time for passage of a particle through a transition) are related (Eq. (4)), thus,

$$t_m = \frac{l_m}{V_m}, t_p = \frac{l_p}{V_p}.$$  Then $t_p = \frac{t_m l_p}{l_m V_p} = t_m \sqrt{R}.$

(4)

where $t_p$ is time of prototype, and $t_m$ is time of model.

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<th>Table 1</th>
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<tr>
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</tr>
<tr>
<td>Type 3</td>
<td>2.65</td>
</tr>
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</table>

Fig. 2. One row integral bridge model.
The discharge ratio (Eq. (5)),

\[
\frac{Q_p}{Q_m} = \left( \frac{p}{m} \right)^{5/2}
\]

where \(Q_p\) is discharge of prototype, and \(Q_m\) is discharge of model.

Geometric similitude is needed for vegetation experiment in order to relate the scale effect for model and prototype. Small size of \(E.\text{ aureum}\) was used in the experimental works. The plant has the capability to grow its height and size of roots, stems and leaves depending on the supporting structure surrounding it. The matured leaves can grow up to 18 in. in length [14]. The \(E.\text{ aureum}\) used in this study was scaled from matured real life plant at Darul Ehsan Club, Kuala Lumpur (Fig. 5). For practical application, a new research in determining the size of supporting structure that affect the growth of \(E.\text{ aureum}\) is proposed in the future work. The results could be used to relate the experimental work with the field study on integral bridge scour.

2.2. Numerical method

2.2.1. Data availability

An extensive data set was gathered from the Hydraulic Laboratory, Department of Civil Engineering, University of Malaya. The data used in this paper are based on the parameters presented in Table 3.

The available data set covers 2500 data taken at the maximum location of scour; 17,500 scour data were taken at every pile for each time interval. Each instance is represented by a 10-dimensional real-valued vector. The input parameters are shown in Table 3 with the corresponding scour prediction in bridge.

2.2.2. System modeling

System modeling alters the parameters of an adaptive intelligent system (ANN, ANFIS) to suit an unknown actual/engineering system transfer function. A schematic of the system modeling problem utilizing the adaptive intelligent system is shown in Fig. 6. As shown, the parameters of the estimated intelligent system are tuned using proper learning methods to ensure accurate estimation of the actual system. In other words, performance function, typically the mean squared error (MSE) between intelligent system’s output and actual response, is minimized.

The objective function in system modeling problems (Eq. (6)) is expressed as follows:

\[
\text{MSE} = \frac{1}{T} \sum_{k=1}^{T} (y(k) - y(k))^2
\]
where \( y(k) \) is the noisy output of the actual system (measured or observed), \( \hat{y}(k) \) is the adaptive intelligent system output, and \( L \) is the number of instances. Some cases are noise free where \( y(k) \) is equal to \( d(k) \), which is the desired output. When noise is present, \( \hat{y}(k) \) is the estimation of desired or semi-desired output.

### 2.2.3. Fuzzy expert system

Human reasoning is able to process uncertainties and vague concepts; however, it cannot express them precisely. Fuzzy logic allows the modeling of uncertainties and human thinking, reasoning, and perception [1]. Based on Boolean logic, we apply two concepts, either ‘true’ or ‘false’, represented by 1 and 0, respectively. Fuzzy logic, an extension of Boolean logic, allows intermediate values between these two values where the classical theory of binary membership in a set is extended to incorporate memberships between 0 and 1. This allows each proposition to be either true or false to a certain degree. With \( X \) as the space of objects and \( x \) as an element of \( X \), a classical set \( A \subseteq X \) is defined as a collection of elements \( x \in X \), such that \( x \) can either belong or not belong to the set \( A \). Eq. (7) describes set \( A \).

\[
A = \{ x \mid x \in X \} \tag{7}
\]

A fuzzy set \( A \) in \( X \) is defined by Eq. (8).

\[
A = \{(x, \mu_A(x)) \mid x \in X\} \tag{8}
\]

where \( \mu_A(x) \) is the membership function for the fuzzy set \( A \). Here, \( A \) is a linguistic term (label) that is determined by the fuzzy set. The membership function maps each element of \( x \) to a membership grade between zero and one \((\mu_A(x) \in [0, 1])\). For example, this set can present \( x \) as ‘medium’, which is a linguistic term that can be described by a fuzzy set with soft boundaries. Fig. 7 shows two sets, one based on Boolean logic and the other on fuzzy logic.

### 2.2.4. Fuzzy inference system (FIS)

Fuzzy systems provide the means of representing expert knowledge in terms of if–then rules, which is the basic unit for capturing of knowledge in a fuzzy system. Similar to a conventional rule in artificial intelligence, a fuzzy rule has two components: an ‘IF’ part and a ‘THEN’ part, which are also referred to as antecedent and consequent, respectively. The main structure of the fuzzy rule is shown in Eq. (9):

\[
\text{IF } \text{< Antecedent > } \text{THEN } \text{< Consequent >} \tag{9}
\]

The antecedent of a fuzzy rule can conditionally be satisfied to a degree. Similar to conventional rules, the antecedent of a fuzzy rule may combine multiple simple conditions into a complex string using AND, OR, and NOT logic operators. The consequence of a fuzzy rule can be classified into two main categories:

(a) Fuzzy consequent (Eq. (10)) where \( C \) is a fuzzy set.

(b) Functional consequent (Eq. (11)) where \( p, q \) and \( r \) are constant.
IF \( x \) is \( A \) and \( y \) is \( B \) THEN \( f \) is \( C \) \hspace{1cm} (10)

IF \( x \) is \( A \) and \( y \) is \( B \) THEN \( f = px + qy + r \) \hspace{1cm} (11)

Fuzzy inference systems incorporate an expert’s experience into the system design and are composed of four blocks (Fig. 8).

A FIS comprises a ‘fuzzifier’ that transforms the ‘crisp’ inputs into fuzzy inputs by membership functions that represent fuzzy sets of input vectors. It also contains a knowledge-base that includes the information given by the expert in the form of linguistic fuzzy rules. An inference-system (engine) uses them together by a method of reasoning and a ‘defuzzifier’ that transforms the fuzzy results of the inference into a crisp output using a ‘defuzzification’ method [15]. The knowledge base comprises two components: a database, which is the membership functions of the fuzzy sets used in the fuzzy rules, and a rule base, which comprises a collection of linguistic rules that are combined by a specific operator. The two common types of FIS vary according to differences between the specifications of the consequent part of fuzzy rules (Eqs. (10) and (11)). The first fuzzy system uses the inference method proposed by Mamdani and Assilian [25], which the rule consequent defined by fuzzy sets and has the structure of Eq. (10). The second fuzzy system proposed by Takagi and Sugeno [29] (TSK) contains an inference engine where the conclusion of a fuzzy rule is made up of a weighted linear combination of the crisp inputs rather than a fuzzy set. The TSK system has the structure shown in Eq. (11). The TSK models are suitable for approximating large non-linear systems.

The knowledge base containing the database and rule base of a FIS can be constructed from an expert’s knowledge. In this way, fuzzy models can help in extracting expert knowledge at an appropriate level. Fuzzy systems can also be constructed from data, which alleviates the problem of knowledge acquisition. Various techniques have been used to analyze data with the best possible accuracy. There are two common approaches for constructing a FIS using available data. In the first approach, the rules of the fuzzy system are often designated a priori, and the parameters of the membership functions are adapted during the learning process from input to output data using an evolutionary algorithm. In the second approach, the fuzzy system can be generated using hybrid neural nets. The neural net defines the shape of the membership functions of the premises; this architecture and learning procedure is called an Adaptive Network-based Fuzzy Inference System [16].

2.2.5. Adaptive Network-based Fuzzy Inference System (ANFIS)

ANFIS is a multilayer feed-forward network in which each node performs a particular function on incoming signals and has a set of parameters pertaining to this node [16]. Similar to ANN, ANFIS is capable of mapping unseen inputs to their outputs by learning the rules from previously seen data. A simple structure of this type of network having just two inputs of \( x \) and \( y \) and one output of are shown in Fig. 9.

As can be seen from Fig. 9, ANFIS contains five layers in its architecture: a fuzzify layer, a product layer, a normalized layer, a defuzzifier layer, and a total output layer. Assuming just two membership functions for each of the input data \( x \) and \( y \), the general form of a first-order TSK type of fuzzy if–then rule is given by Eq. (12). Here, we re-write rule \( i \) of the ANFIS as:

\[
\text{Rule } i: \quad \text{IF } x \text{ is } A_i \text{ and } y \text{ is } B_i \text{ THEN } \\
\hat{f}_i = px + qy + r_i \quad i = 1, 2, 3, \ldots \; n \tag{12}
\]

where \( n \) is the number of rules and \( pi, qi \) and \( ri \) are the parameters determined during the training process. At the first stage of the learning process, the membership function \( \mu \) of each of the linguistic labels \( A_i \) and \( B_i \) are calculated as follows (Eqs. (13) and (14)):

\[
Q_i = \mu_{A_i}(x), \quad i = 1, 2, 3, \ldots \; n \tag{13}
\]
\( Q_i^1 = \mu_{q_i}(y), \quad i = 1, 2, 3, \ldots, n \) (14)

At the second layer, the product layer, the previously calculated membership degrees of linguistic variables are multiplied as shown in Eq. (15):

\( Q_i^2 = w_i = \mu_{q_i}(x)\mu_{q_i}(y) \quad i = 1, 2, 3, \ldots, n \) (15)

The third layer, the normalized layer, calculates the ratio of each weight to the total weights (Eq. (16)):

\( Q_i^3 = \bar{w}_i = \frac{w_i}{\sum_{i=1}^{n} w_i} \quad i = 1, 2, 3, \ldots, n \) (16)

The fourth layer is the defuzzification layer with adaptive nodes. Their outputs depend on the parameters pertaining to these nodes; the learning rule specifies how these parameters are altered to minimize the measure of prescribed error [16]. The relationship for these nodes is as follows (Eq. (17)):

\( Q_i^4 = \bar{w}_i f_i = \bar{w}_i(p_i x + q_i y + r_i) \quad i = 1, 2, 3, \ldots, n \) (17)

Finally, in the 5th layer, the summation of all incoming signals is performed, where the output of the system is the final result (Eq. (18)):

\( Q_i^5 = \sum_{i=1}^{n} \bar{w}_i f_i \quad i = 1, 2, 3, \ldots, n \) (18)

3. Results and discussion

3.1. Experimental results

Experimental work was conducted to study the effects of scour in relation to time, velocity, flow intensity, flow shallowness, two types of bridge structure (integral bridge with one row pile and integral bridge with two rows of piles), different sand sizes, and vegetation. Scour results presented in this section were clustered into effects of time, sediment coarseness, flow intensity, flow shallowness, vegetation, strain, and displacement on scour. A brief of Table 4 and 5, respectively.

Fig. 10 demonstrate that the process of scouring was asymptotic and shows the significance of time for scouring action at the single- and double-row pile integral bridge with E. aureum.

3.2. Numerical results

3.2.1. Developing the ANFIS model for the prediction of scour depth in bridges

First, the data were normalized. To normalize the data, a Gaussian normalization technique was used. Then, 70% of the normalized data were randomly chosen as training data and the remainder 30% as testing data. A total of 14 ANFIS models with different input parameters were implemented as shown in Fig. 7. To implement ANFIS, MATLAB programming language version R2010a was used.

The Genfis2 function based on subtractive clustering method was used to generate the FIS structures. Finding the best structure with the appropriate membership function parameters involved two processes: learning and testing. Through the learning process, the membership functions of the inputs were generated using subtractive clustering. Then, the membership function parameters were tuned using a back propagation algorithm in combination with a recursive least squares method followed by the testing step where the generalization capability of the generated model was checked. To decrease the Mean Square Error (MSE) obtained by this method, the number of membership functions was gradually increased by lowering the range of influence of cluster centers in a step-by-step and trial and error manner.

Linear regression (LR) is a simple and effective scheme used for predicting domains with numeric attributes. The linear models function as building blocks for more complex learning tasks. Linear regression analysis is carried out to establish a relationship between the output and input data for the proposed ANFIS modeling.

To evaluate the comparative methods, the MSE and Correlation Coefficient/Pearson Coefficient (R) values are used. MSE is a risk function which corresponds to the expected value of the squared error loss or quadratic loss, and R is the degree of success in reducing standard deviation (SD). It is widely used in the sciences as a measure of the strength of linear dependence between two variables. Eq. (19) presents the MSE and R.

\[ R^2 = 1 - \frac{\sum_{k=1}^{L} (y(k) - \bar{y}(k))^2}{\sum_{k=1}^{L} (y(k) - \bar{y}_{\text{ave}})^2} \] (19)

### Table 4

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### Table 5

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<th>D (mm)</th>
<th>d50/D</th>
<th>y</th>
<th>y/D</th>
<th>Time (min)</th>
<th>d/d50</th>
<th>V/Vc</th>
</tr>
</thead>
<tbody>
<tr>
<td>Double row</td>
<td>31</td>
<td>0.8</td>
<td>8</td>
<td>10</td>
<td>0.8</td>
<td>26</td>
<td>2.6</td>
<td>1440</td>
<td>12.5</td>
<td>0.598</td>
</tr>
<tr>
<td>Double row</td>
<td>36</td>
<td>0.26</td>
<td>12</td>
<td>10</td>
<td>1.2</td>
<td>26</td>
<td>2.6</td>
<td>1440</td>
<td>38.5</td>
<td>0.757</td>
</tr>
<tr>
<td>Double row</td>
<td>41</td>
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<td>28</td>
<td>10</td>
<td>2.8</td>
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<td>2.6</td>
<td>1440</td>
<td>76.9</td>
<td>0.748</td>
</tr>
<tr>
<td>Double row (veg)</td>
<td>46</td>
<td>0.8</td>
<td>3</td>
<td>10</td>
<td>0.3</td>
<td>37</td>
<td>3.7</td>
<td>1440</td>
<td>12.5</td>
<td>0.315</td>
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<tr>
<td>Double row (veg)</td>
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<td>0.26</td>
<td>5</td>
<td>10</td>
<td>0.45</td>
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<td>3.7</td>
<td>1440</td>
<td>38.5</td>
<td>0.403</td>
</tr>
<tr>
<td>Double row (veg)</td>
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<td>0.13</td>
<td>5</td>
<td>10</td>
<td>0.5</td>
<td>37</td>
<td>3.7</td>
<td>1440</td>
<td>76.9</td>
<td>0.401</td>
</tr>
</tbody>
</table>
where \( \hat{y}(k) \), \( y(k) \) and \( y_{ave} \) are the output predicted by ANFIS, actual (observed) output, and averaged actual output, respectively, and \( L \) is the total number of training/testing instances. Table 6 summarizes the MSE and \( R \) results obtained using the proposed method and the linear regression separately for training and testing data.

As noted, the MSE values from ANFIS are approximately four times smaller than values from classical linear regression. Furthermore, the \( R \) value from ANFIS for test data is 0.9348. Fig. 12 shows scour depth in bridges prediction performance provided by linear regression and ANFIS for the test data. The horizontal and vertical axes present the actual and predicted data, respectively. Precise modeling should result in a direct linear relation between the actual and predicted data. Fig. 12 reveals that the proposed ANFIS method is highly accurate and precise compared to the classical linear regression for the scour depth in bridges prediction.

The relation between input variables and output variable can be visualized with the modeled fuzzy surfaces shown in Fig. 13. The Graphical User Interface (GUI) tool allows for examining of the output surface of a FIS model. GUI provides a visual impression of the possible combinations of the two input variables and the output in 3-D. This is a fast visual method to analyze the scour depth in bridges. The FIS gives a mathematical solution to determine the scour depth in bridges based on data such as \( \text{(time \( t \)) vs. (flood level \( y \))} \) and \( \text{(mean velocity of flow at the armour peak \( V_a \)) vs. (depth-size factor \( K_{yb} \))} \).

The input–output surfaces shown in the figures above are nonlinear and monotonic surfaces that illustrate how the ANFIS model will respond to varying values on ‘strain in tie section’ prediction.

### Table 6

<table>
<thead>
<tr>
<th>Methods</th>
<th>Training set</th>
<th>Testing set</th>
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<tr>
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<td>0.0864</td>
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</tbody>
</table>

Fig. 10. Influence of time on local scour at piles for single- and double-row piles integral bridge.

Fig. 11. Influence of time on local scour at piles for single- and double-row piles integral bridge with *Epipremnum aureum*.

**Table 6**

Comparison of MSE and \( R \) values from ANFIS and linear regression.
4. Conclusion

The experimental results show that scour depth increased as the discharge, water level, and velocity increased. Scour depth developed asymptotically towards the maximum depth of scour under clear water conditions. Scour was more severe for double-row pile integral bridges compared to single-row pile integral bridges in most cases. Water tended to flow faster between the two rows. *E. aureum* was proven to be the scour countermeasure for single- and double-row pile integral bridges in most cases. Scouring was greater for single-row pile integral bridges with loading compared to double-row pile integral bridges with loading. The applications of ANFIS and LR models for scour depth in bridges have been demonstrated in this study. ANFIS showed relatively higher accuracy and precision compared to LR. The MSE from ANFIS is approximately four times less for training and testing and therefore is more accurate than those from classical LR. Comparison of performance of strain in scour depth in bridges prediction ability of both ANFIS and LR for the test data shows that the proposed ANFIS method is more accurate than the classical LR for scour depth in bridges prediction.

Acknowledgements

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