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ORIGINAL RESEARCH

Artificial Intelligence Modeling for Scour Depth Prediction Upstream of Bridge Piers

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Abstract
The failure of river bridges due to scour depth is a significant issue worldwide. The traditional scour depth estimation equations available in the literature are derived from a particular dataset and suitable for a limited range of situations. There is no general formula available in the literature which is applicable to all circumstances. The prediction of scour depth around bridge piers is essential for ensuring the safety and stability of foundations. This paper demonstrates the applicability and efficiency of hybrid artificial intelligence (AI) models, namely adaptive neuro-fuzzy inference system (ANFIS) and genetic algorithm-based artificial neural network (GA-ANN) in the prediction of scour depth upstream of bridge piers. Affecting parameters such as pier length, pier width, flow velocity, flow depth, skew and median sediment size are taken into account to predict scour depth around piers at non-cohesive bed sediments. The hybrid AI model development considered 267 field data compiled from published literature. The results show that the hybrid AI techniques are effective in predicting scour depth around bridge piers with high accuracy and outperform other traditional models. The results of the study also indicate the encouraging performance of the GA-ANN model in accurate estimation of scour depth compared to regression-based formulae as well as ANFIS model. Thus, GA-ANN model can be used as an effective tool for the prediction of scour depth at bridge piers and designing safe bridge pier structure.

Keywords ANFIS · GA-ANN · Scour depth · Bridge pier · Artificial intelligence

Introduction

Scour is the removal of bed material around or near hydraulic structures such as, abutments and piers situated in flowing water [1]. Scour depth is a critical parameter that determines the stability of bridge foundations. It is influenced by several factors, including the velocity of water, the shape of the structure, the soil type, and the water level. It can significantly impact the safety and integrity of bridge structures. Around 60% of bridge failures in the United States are due to the scour [2], which results in financial losses along with loss of lives. To prevent bridge failure caused by scour depth, safe bridge foundation design is required which necessitates accurate prediction of scour depth around bridge piers and abutments. The underestimation of scour depth may lead to bridge failure, while overestimation will increase the construction costs. Thus, it is immensely essential to develop an efficient scour depth estimation model for economic foundation design, ensuring the longevity of the bridge structures and preventing catastrophic failures.

Local scour at piers is a complex phenomenon resulted from the complicated mechanism of flow around the structure [3]. It is affected by many parameters which is difficult to understand and thus experimental investigations to develop general scour depth estimation equations remains incomplete. The empirical equations available in the literature [4–8] are derived using a conventional experimental approach whose predictive accuracy is limited to particular conditions.

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Artificial intelligence (AI) modeling has emerged as a promising approach for predicting scour depth, as it can account for the complex interactions between various factors that influence scour depth. AI models can learn from existing data to make predictions, allowing for accurate and efficient scour depth estimation.

In recent years, researchers have proposed various AI models for predicting scour depth around hydraulic structures, including artificial neural networks (ANNs) [9–15], support vector machine (SVM) [16–20], fuzzy logic system (FLS) [21, 22], genetic algorithms (GA) [23, 24], Gene-expression programming (GEP) [25–29] and Particle swarm optimization (PSO) [30, 31]. These models considered various factors that affect scour depth, such as flow velocity, sediment characteristics, and pier geometry. ANNs are popular for their ability to learn complex relationships between inputs and outputs, while fuzzy logic and genetic algorithms are also effective in handling uncertainty and nonlinearity in the data. The use of AI modeling for scour depth prediction upstream of bridge piers has the potential to significantly improve bridge safety and reduce maintenance costs. By providing accurate predictions of scour depth, AI models can help bridge engineers design more robust structures and develop more effective maintenance plans.

Despite the potential of AI modeling for scour depth prediction, there are still challenges that need to be addressed. These include the lack of high-quality data, the need for reliable and accurate input parameters, and the difficulty in generalizing the model to new conditions. To overcome these challenges, researchers are developing new techniques and approaches for data collection, data preprocessing, and model training. Moreover, the literature survey reveals that there is a lack of comparative study between Adaptive Neuro-Fuzzy Inference System (ANFIS) and genetic algorithm-based artificial neural network (GA-ANN) in predicting bridge pier scour depth.

This paper reviews the state-of-the-art AI modeling techniques for predicting scour depth upstream of bridge piers, focusing on their advantages and limitations. The paper presents two hybrid AI models, namely ANFIS and GA-ANN, for the prediction of scour depth upstream of bridge piers. A performance analysis of the AI-based models is carried out in this study. Finally, sensitivity analysis is conducted to assess the significance of each affecting parameter on pier scour depth. The paper also discusses the challenges and future research directions in this area, with the aim of advancing the development of reliable and accurate AI models for scour depth prediction.

Development of Scour Depth Estimation Model

The development of the scour depth estimation model begins with the collection of data published in the literature. The dataset is then compiled and processed to feed into the AI models. In the next step, the empirical formulae which are based on the parameters of the present dataset are selected. The ANFIS and GA-ANN model development are also described in this section.

Data Collection

Different AI-based research has been carried out in the recent past for estimation of scour depth. The AI techniques and the parameters used in AI modeling for pier scour prediction are shown in Table 1.

In the present study, scour depth around piers is modeled as a function of pier length (l), pier width (b), flow velocity (V), flow depth (h), skew (Θ) and median sediment size (d_{50}). The U.S. Department of Transportation report [32] has been used to compile the dataset for scour depth upstream of the bridge pier with non-cohesive sediments. Table 2 presents the ranges of data values for the 267 field

Table 2 Ranges of the parameters

Variable	Unit	Minimum	Maximum
Pier length	m	0.3	5.5
Pier width	m	2.4	27.4
Flow velocity	m/s	0	4.5
Flow depth	m	0.1	22.5
Skew	deg	0	85
Median sediment Size	mm	0.06	95
Scour depth	m	0	7.7

Table 1 AI-based scour depth modeling techniques

Author	Parameter	AI Technique
Khan et al. [14]	$b, l, g, U, y, d_{50}, \sigma_g$	GEP and ANN
Sharafi et al. [15]	$b, l, g, U, y, r, n, d_{50}, \sigma_g, \rho_s$	ANN, ANFIS and SVM
Khan et al. [21]	b, U, y, d_{50}	ANN and genetic function
Shamshirband et al. [22]	b, l, Fr, U, U_c, y, Re, d_{50}, and $\sigma_{g;}$	PSO
Dang et al. [23]	$b, g, U, U_c, y, Re, d_{50}$	ANN-PSO
Nil and Das [24]	b, U, U_c, y, Fr, d_{50}	SVM

Table 3 Scour depth estimation formulae

Author	Formula
Blench-Inglis [4]	$d_s = 1.53b^{0.25}V_0^{0.5}y_0^{0.5}d_{50}^{-0.125} - y_0$
Laursen and Toch [5]	$d_s = 1.5b^{0.7}y_0^{0.3}$
Lee and Sturm [8]	$\frac{d_s}{b} = 5\log\left(\frac{b}{d_{50}}\right) - 4, \quad 6 <= b/d_{50} <= 25$
	$\frac{d_s}{b} = \frac{1.8}{(0.02b/d_{50} - 0.2) + 1} + 1.3, \quad 25 < b/d_{50}$

measurements of local scour at upstream of a bridge pier, which constitute the dataset considered in the present study.

To enhance the effectiveness of the training process of AI models, dataset is normalized within the range of 0 and 1 using the formula:

X_normalized = $(X - X$_ min$)/(X$_ max $-X$_ min$)$,

where X is the original data, X_min is the minimum value of the data, and X_max is the maximum value of the data. The resulting X_normalized values fall within the range of 0–1. It can help to prevent large values from dominating the analysis and can improve the accuracy of machine learning algorithms. The normalized values of the parameters pier length, pier width, flow velocity, flow depth, skew and median sediment size were used as input parameters to the AI models and that of scour depth was used as target values.

Empirical Formulae

The effectiveness of the developed hybrid AI models is assessed by comparing their performance with empirical formulae [4, 5, 8] presented in Table 3.

In this context, b represents the pier width, y_0 stands for the approach flow depth, V_0 refers to the approach flow velocity, d_{50} denotes the median sediment size, and d_s represents the scour depth.

Adaptive Neuro-fuzzy Inference System

ANFIS is a hybrid intelligent system that combines the learning capabilities of artificial neural networks and the fuzzy logic principles of fuzzy inference systems [33]. It can capture the nonlinear relationships between the input and output variables and provide interpretable results. The ANFIS is composed of five layers, each performing a specific task. The first layer is the input layer, which receives the input data and passes it to the fuzzification layer. The fuzzification layer converts the crisp input variables into fuzzy sets using membership functions. The third layer is the rule layer, which combines the outputs of the fuzzification layer and generates a set of fuzzy if–then rules. The fourth layer is the defuzzification layer, combines the consequent part of the fuzzy rule and generates the crisp output. Finally, the output layer produces the predicted scour depth. A typical architecture of the ANFIS model is shown in Fig. 1.

Consider the fuzzy if–then rule:

If (x is A_i) and (y is B_i) then (z is $f_k = p_k x + q_k y + r_k$).

Considering x and y as two inputs belonging to the fuzzy sets A_i and B_i, respectively and bell-shaped membership function (μ), the fuzzification layer will convert the crisp values as follows:

$$\mu_{A_i}(x) = \frac{1}{1 + \left|\frac{x-c_i}{a_i}\right|^{2b_i}}, \tag{1}$$

where, x is the input, a_i, b_i and c_i are adjustable parameters that govern bell-shaped function. The firing strength is obtained in the second layer by multiplying membership function values, i.e.

$$w_k = \mu_{A_i}(x) * \mu_{B_i}(y). \tag{2}$$

The firing strengths from all the rules are then normalized to obtain the normalized firing strengths:

$$\overline{w}_k = \frac{w_k}{\sum_k w_k}. \tag{3}$$

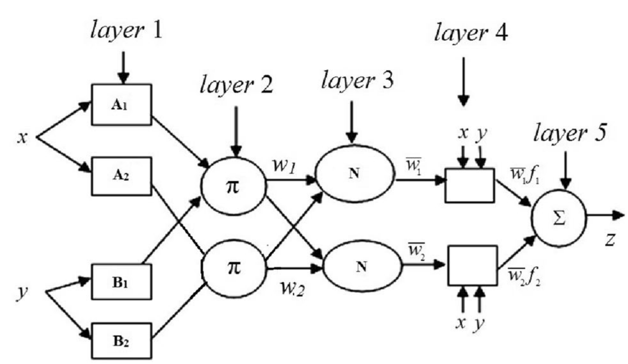

Fig. 1 ANFIS architecture

The normalized firing strengths are used in subsequent layers of ANFIS to determine the output of the layer 4, as shown in (4), which is then added together to get the final result:

$$z_k = \overline{w}_k * f_k = \overline{w}_k \left(p_k x + q_k y + r_k \right), \tag{4}$$

where p, q and r are the adjustable consequent parameters.

ANFIS models are trained using a hybrid learning algorithm that combines the backpropagation algorithm used in artificial neural networks with the least-squares method used in fuzzy inference systems. During the training process, the ANFIS model adjusts the parameters of its membership functions and fuzzy rules to minimize the difference between the predicted output and the actual output of the system.

In recent years, numerous studies have been conducted to investigate the accuracy and reliability of ANFIS in predicting scour depth around hydraulic structures. For instance, Muzzammil and Ayyub [34] developed an ANFIS model to predict the scour depth around bridge piers based on laboratory data. The results showed that the ANFIS model outperformed ANN and traditional regression models in predicting the scour depth around bridge piers. Similarly, an ANFIS model was used to predict the scour depth in long contractions. The results showed that the ANFIS model achieved higher prediction accuracy than SVM and empirical equations [35]. The performance of ANFIS was compared with ANN and empirical formulae for predicting scour depth around bridge piers. The results showed that ANFIS outperformed the other methods in terms of accuracy and reliability [36]. An improved ANFIS-based model proposed in [37] for predicting scour depth at abutment and was found to have a higher level of accuracy than the other models. ANFIS and GEP have been employed in the estimation of scour depth around bridge piers and the results of the study shows that ANFIS is more efficient than the GEP model [38]

The ANFIS framework provides an effective and flexible tool for predicting scour depth around piers. By combining the strengths of ANNs and FLSs, ANFIS can effectively capture the complex, non-linear relationships between input parameters and scour depth. ANFIS can also handle uncertainty and incorporate expert knowledge, making it a powerful tool for predicting scour depth in a variety of scenarios.

Genetic Algorithm-Artificial Neural Network Model

The GA-ANN model for predicting scour depth upstream of the bridge pier is proposed in this study. It is a hybrid intelligent system that combines the benefits of both genetic algorithms and artificial neural networks. GA is a search algorithm that is inspired by the natural selection process and can be used to optimize complex problems. ANN is a data-driven model that can capture complex relationships between input and output variables. The GA-ANN model integrates these two models to optimize the ANN architecture and improve the prediction accuracy.

The GA-ANN model consists of two stages. The first stage is the optimization stage, where the GA algorithm was used to optimize the ANN architecture. The GA algorithm searches for the optimal weights and biases of the ANN by minimizing the error function between the predicted and observed values. The fitness function for the hybrid model was determined as the mean difference between the scour depth values predicted by the model and those obtained through measurements. In the second stage, the optimized ANN was employed to forecast the scour depth around the bridge piers by employing the back-propagation (BP) algorithm which fine-tunes the final weights of the model. The architecture of the GA-ANN model is shown in Fig. 2.

The predictive ability of the genetic algorithm-based model was observed to be remarkably promising in estimating the depth of bridge pier scour [24]. The utilization of the GA approach can be highly effective in predicting the maximum scour depth around the bridge pier [39]. The GA-ANN model is used for the prediction of seasonal groundwater table depth in Uttar Pradesh, India [40]. The hybrid GA-ANN model demonstrated better predictive ability than the traditional GA models. The GA-ANN model also provides superior predictive performance for scour depth, with the highest correlation coefficient and lowest Root Mean Square Error than the Radial basis function network and SVM [41].

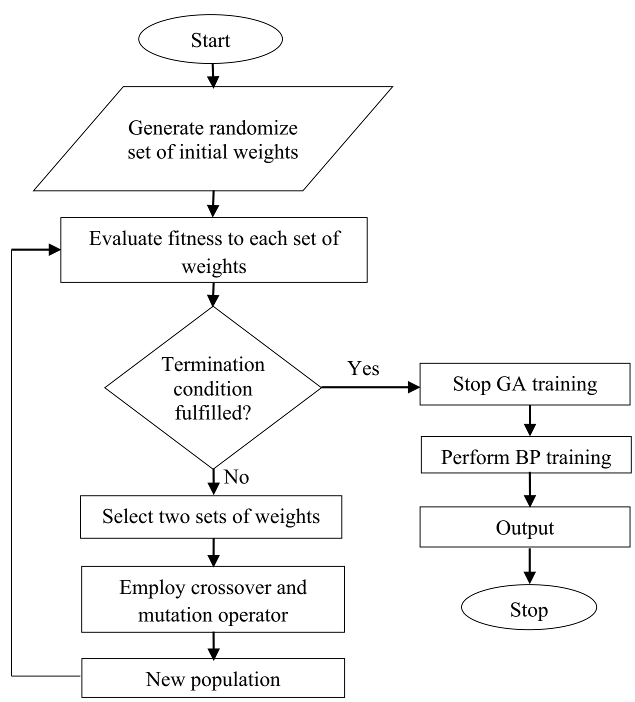

Fig. 2 GA-ANN model

Methodology

The proposed hybrid AI modeling approach comprises three main steps:

Step 1: Data Preparation: The first step is to collect and preprocess the data. The dataset compiled from the literature [32] contains six input parameters viz. pier length, pier width, flow velocity, flow depth, skew and median sediment size and scour depth as an output parameter. The data was cleaned, normalized, and split into training (80%) and testing (20%) sets.

Step 2: Hybrid AI Modeling: The second step is to develop data-driven AI models. Two hybrid AI models, ANFIS and GA-ANN, were used in this study. Both models contain six nodes in the input layer corresponding to six affecting parameters and one node in the output layer. These models were trained using the training dataset to learn the relationship between the input variables and the scour depth. The network parameters i.e. weights are adjusted during the training phase of the ANFIS and GA-ANN to minimize the error between target and predicted values. In addition, the parameters of the membership functions and fuzzy rules of ANFIS are modified during the training process to reach the target values. The trained models were evaluated using the testing dataset.

Step 3: Performance validation: The third step is to validate the performance of hybrid AI models by comparing the results with physical-based models. Three empirical equations available in the literature [4, 5, 8] were used in this study. The physical-based models were evaluated using the compiled dataset and the performance was compared with AI models. Moreover, a comparative analysis of ANFIS and GA-ANN performances was carried out on the testing dataset.

Results and Discussion

To compare the models, both ANFIS and GA-ANN were trained and tested using the same dataset of scour depth upstream of bridge piers. The performance of the models were evaluated using statistical metrics such as, mean absolute error (MAE), root mean square error (RMSE) and coefficient of determination (R^2) between the predicted and target values. The optimal configurations for each model were determined based on the minimum MAE and RMSE values, as well as the maximum R^2 values during testing. The optimal hybrid AI models, as well as the empirical formulae were compared by tabulating their respective performance index values in Table 4.

Table 4 reveals that the hybrid computational models are capable of accurately predicting scour depth, as both the models have significantly smaller MAE and RMSE values with the actual data during the training as well as testing phases, in comparison to the empirical formula. The hybrid models also achieved higher R^2 values than the empirical models, indicating a stronger linear relationship between the predicted and observed scour depth. Moreover, the ANFIS model demonstrated better performance during training, with a smaller error margin of MAE = 0.0021, RMSE = 0.0076, and a higher $R^2 = 0.9853$ than the GA-ANN model, which had MAE = 0.0026, RMSE = 0.0087, and $R^2 = 0.9827$. However, during testing on new data, the GA-ANN model outperformed the ANFIS model. Thus, the study suggests that the GA-ANN model exhibits better performance than ANFIS model in the prediction of scour depth upstream of the bridge pier. The performance of the different models under consideration with respect to errors between estimated and target values are pictorially depicted in Fig. 3.

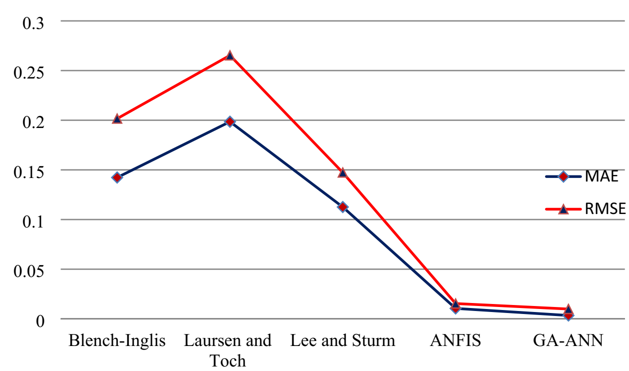

Fig. 3 Performance of scour depth estimation models

Table 4 AI versus traditional models

Method	Training			Testing		
	MAE	RMSE	R^2	MAE	RMSE	R^2
Blench-Inglis [4]	0.1178	0.1839	0.8763	0.1423	0.2016	0.8361
Laursen and Toch [5]	0.1792	0.2482	0.6176	0.1985	0.2653	0.5952
Lee and Sturm [8]	0.0994	0.1251	0.7651	0.1126	0.1473	0.6982
ANFIS	0.0021	0.0076	0.9853	0.0105	0.0154	0.9516
GA-ANN	0.0026	0.0087	0.9827	0.0034	0.0099	0.9767

The optimal results of hybrid AI models, i.e. the model configuration with minimum error and maximum R^2 value during testing along with the corresponding training results are shown in Figs. 4 and 5.

Figures 4 and 5 demonstrate a comparison between the measured scour depth values and the predicted scour depth values. The results indicate that the ANFIS model exhibits lower training error with most of the data points falling near the diagonal line than the GA-ANN model. However, the scatter plots of test cases indicate relatively larger deviations from the diagonal line for the ANFIS model, resulting in a greater testing error compared to the GA-ANN model.

Finally, the sensitivity tests were carried out with best performing model, i.e. GA-ANN model to determine the relative influence of each affecting parameter on scour depth around bridge piers. This was achieved by eliminating one affecting parameter at a time. The results thus obtained are summarizes in Table 5. When performing sensitivity analysis, if the removal of a parameter causes a significant change in performance indices, it indicates that the parameter is highly sensitive. On the other hand, if the change in performance indices is minimal, it suggests that the parameter is less sensitive.

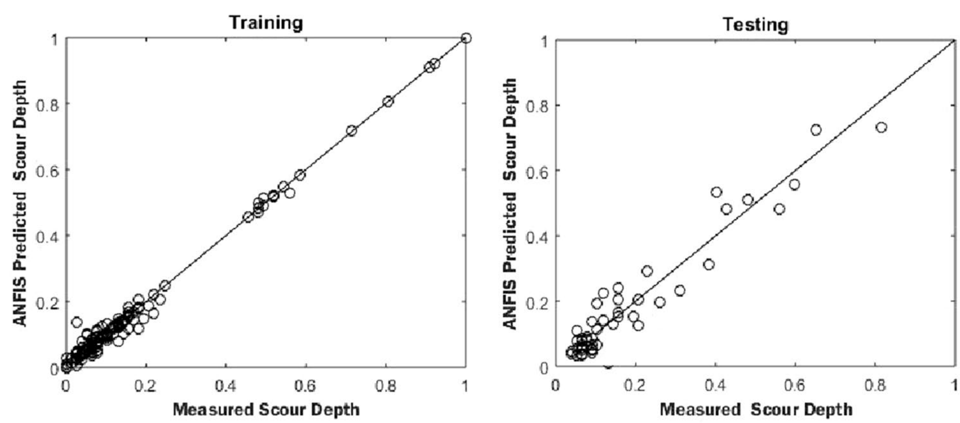

Fig. 4 ANFIS predicted versus measured scour depth

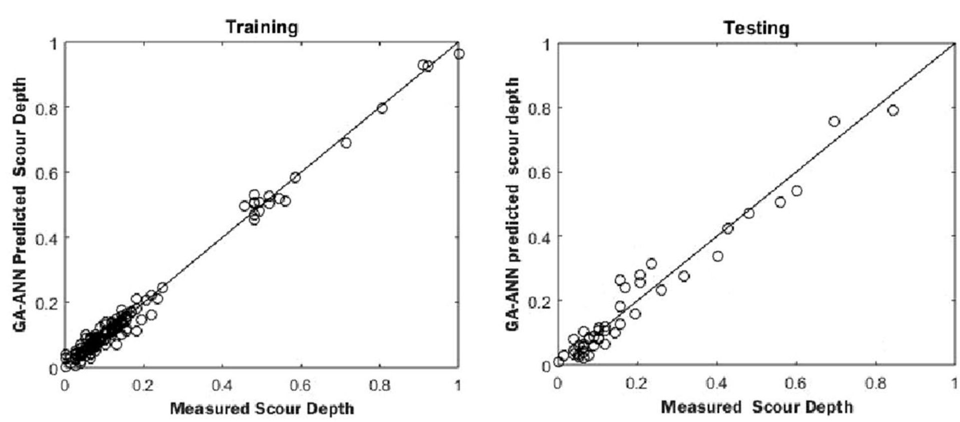

Fig. 5 GA-ANN predicted versus measured scour depth

Table 5 Sensitivity analyses of the affecting parameters

Parameter	Training			Testing		
	MAE	RMSE	R^2	MAE	RMSE	R^2
GA-ANN without l	0.0173	0.0379	0.8895	0.0209	0.0421	0.8806
GA-ANN without b	0.0287	0.0484	0.8739	0.0351	0.0545	0.8673
GA-ANN without d_{50}	0.0101	0.0106	0.9624	0.0112	0.0127	0.9576
GA-ANN without h	0.0160	0.0185	0.9032	0.0187	0.0232	0.9218
GA-ANN without V	0.0156	0.0163	0.9517	0.0175	0.0196	0.9437
GA-ANN without Θ	0.0119	0.0142	0.9586	0.0136	0.0168	0.9541

After conducting a sensitivity analysis, the findings indicated that the model produced the highest error and the lowest coefficient of determination when the pier width was excluded. As a result, the pier width was identified as the parameter with the greatest influence on scour depth and is considered more sensitive compared to the other parameters. Additionally, the results showed that sediment size has the least impact on scour depth.

The findings of the study demonstrate the efficacy of hybrid AI techniques in accurately predicting scour depth around bridge piers, surpassing the performance of traditional models. Additionally, the study highlights the promising performance of the GA-ANN model, which outperforms regression-based formulae and ANFIS models in estimating scour depth with precision. Consequently, the GA-ANN model proves to be a valuable tool for reliably predicting scour depth at bridge piers and facilitating the design of secure bridge pier structures.

Conclusion

The results of the study show that both ANFIS and GA-ANN can be used to accurately predict the scour depth around bridge piers. The models were trained using data from previous experiments and validated using unseen data. The predicted values were compared with the actual values and the results showed that both models had a high degree of accuracy. The AI models have outperformed empirical formula with significantly smaller errors and higher coefficient of determination values. Moreover, the GA-ANN model outperformed the ANFIS in terms of prediction accuracy. The study highlights the significance of the GA-ANN model for predicting scour depth upstream of bridge piers. Accurate predictions of scour depth can help engineers to design safer and more reliable bridges. The use of the hybrid GA-ANN technique can help in designing effective countermeasures to prevent or mitigate the effects of scour. Furthermore, the sensitivity analysis conducted in this study revealed that the pier width is the most significant factors affecting the scour depth. In this study, there has been significant progress in the development of an effective AI tool for estimating scour depth. However, the developed models may still be enhanced by availability of more quality data and adjusting the algorithmic framework of the techniques appropriately. Although the current model efficiently predicts scour depth, it would be beneficial to obtain additional experimental data and observations to create more generalized models. Validating these models with real-world scenarios would be more effective for practical use. Further, the study considered six input parameters, and thus for any alteration on the number of input parameters, the model architecture has to be updated accordingly. The present study is limited in exploring the potential of the GA-ANN model, further comprehensive study can be carried out with other relatively new AI-based models.

Declarations

Conflict of interest The authors declare that they have no conflict of interest.

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