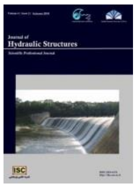
Journal of Hydraulic Structures
J. Hydraul. Struct., 2023; 9(3):88-102
DOI: 10.22055/jhs.2023.45445.1276



Predicting the geometry of stable alluvial channels: combination of data mining and meta-heuristic optimization

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Abstract

One of the important topics in river engineering is the design of stable alluvial channel geometry in the regime mode (dynamic balance between erosion and sedimentation) including the width, depth and slope. In this research, the ANFIS and ANFIS-PSO models were used to model the geometry parameters of stable channels. To achieve this objective, we utilized a comprehensive dataset comprising 410 data series sourced from 15 different channels, encompassing various types such as straight and meandering, as well as natural and laboratory. In each measurement, information on the flow rate (Q), average particle diameter (d), shear stress (τ), top width of the channel (W), average depth of flow (h) and longitudinal slope of the channel (S) was collected. Randomly, 70% of the data was used for training, and the remaining 30% was used for validation of the ANFIS and ANFIS-PSO models. Totally, 42 models were derived from the combination of 7 input data sets (Q, d, and τ) and employed both ANFIS and ANFIS-PSO, models to estimate the W, h, and S as the three types of outputs. In modeling of the W and h parameters, the best input was the Q, which the R2, CRM and NRMSE for all data with the ANFIS model were equal to 0.954, -0.029, 0.567 and with the ANFIS-PSO model were 0.912, -0.042, and 0.487, respectively. Also, to estimate the S, the modeling results had error. In general, the modeling results with the ANFIS-PSO model were more accurate than the results of the ANFIS model.

Keywords: Stable Channel, Geometry, ANFIS, ANFIS-PSO.

Received: 01 December 2023; Accepted: 29 December 2023

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1. Introduction

It is imperative to manage and mitigate the risks associated with flooding. For more than a century, the design of stable channel geometry in regime mode, including the width, depth and slope has been the focus of river engineers. A stable channel (similar to a river in regime mode) doesn't imply that the channel bed and walls are indestructible and unchanging over time. Rather, it means a slight change in the average geometric dimensions of the channel over several years (the presence of dynamic balance in the average dimensions of the channel with time). In other words, the regime river is in a dynamic balance and adjusts its channel pattern, cross-section, slope and roughness in such a way that the river's ability to carry sediment is in balance with the incoming sediment load. The regime rivers maintain their stability and resistance against erosion and sedimentation resulting from water flow and sediment [1].

The dimensions that the channel attains after a period of erosion and sedimentation and under which its dimensions do not change with the passage of time are called the stable dimensions of the channel (including the width, depth and slope) [2]. For the design of stable channels, field, laboratory, experimental, analytical, numerical, and simulation methods are used [3]. Due to the high cost of field and laboratory research and spending a long time to do it, and due to the influence of natural factors during data collection, conducting this research is not cost-effective. On the other hand, these methods are only used in the same test conditions [4].

The experimental methods are developed by observing actual rivers and deriving their hydraulic characteristics and geometry based on statistical relationships and has no theoretical basis. By studying different rivers, these methods establish connections between hydraulic and geometric factors (e.g., velocity, width, depth, and slope of the channel) and independent variables such as discharge and bed sediment size [5].

The main drawback of the experimental relationships was that they yielded accurate results only for rivers that closely matched the data used to develop the relationships. For rivers with differing geographical and morphological conditions, these relationships often result in inaccurate findings or numerous errors. Therefore, the researchers decided to provide relations that can be generalized to the conditions of other rivers, and in this way, the analytical relations were developed. Analytical or theoretical methods (such as continuity equation, flow resistance, secondary flow, and sediment transport equation) are methods that calculate the geometry of the channel in such a way that some characteristics are optimized using the principles of fluid mechanics [6].

Due to the complex flow and sediment behavior in channels and the lack of necessary information, relying solely on theoretical analyses is inadequate to fully investigate and explain these natural phenomena. Additionally, the large number of influential parameters in the channel's hydraulic geometry poses challenges in obtaining the optimal value using traditional mathematical and computational methods. On the other hand, sometimes it is not possible to obtain a specific relationship based on the effective parameters as the objective function. For this reason, in order to solve the problems of hydraulic geometry of the channel using the limit assumptions, researchers often enter relative parameters (width to depth ratio) and assume constant some parameters (such as the slope and angle of the sides) and some simplifying assumptions (rectangular cross section), reducing the number of parameters so that they can determine the optimal value of the objective function using the numerical methods and simulation [7].

The numerical methods [8] despite being used in different conditions, due to the inherent complexity and influence of the complex physics of this process, were not considered as much as simulation methods with data mining. Simulation methods using artificial intelligence as predictors have greatly simplified the complex calculations needed to estimate stable channel geometric parameters and analyze hydraulic and hydrological phenomena in recent years [9, 10, 11, 12]. Many models have been developed to predict parameters [13, 14, 15]. One of the models that have been used in various research is the Adaptive Neuro Fuzzy Inference System (ANFIS) [16]. The ANFIS model, which is a combination of fuzzy systems and artificial neural network, has fewer problems than other models [17]. In recent years, the use of meta-heuristic algorithms in order to increase the accuracy of data mining models has been of great interest [18]. The PSO algorithm is one of the algorithms that has a great ability to solve optimization problems [19]. The performance of the ANFIS model can be improved by combining it with the PSO meta-heuristic optimization algorithm in data mining [20].

The behavior and hydraulic geometry of the trapezoidal compound channel have been investigated using MIKE21software for steady and unsteady overbank flow. The results of modeling in steady flow conditions showed less difference with real values than in unsteady flow conditions. [21]. The performance of multiple standalone and hybrid Machine Learning (ML) techniques was investigated for predicting flow velocity in a vegetative alluvial channel. Among the proposed methods, AR-M5P provides the highest prediction [22].

Totally, in the field of stable or regime channels, the use of the meta-heuristic method in order to predict stable channel geometry has been considered in a few researches. Therefore, based on the literature review and research gaps in the field of stable channel design, this study aims to assess the effectiveness of the ANFIS and ANFIS-PSO models in determining stable channel geometry.

2. Materials and methods

2.1. Used data

To conduct this study, a comprehensive compilation of laboratory and field data is essential. The sources of these data included technical reports and journal articles that provided a diverse range of observations from various types of channels. These channels included both straight and meandering channels, as well as naturally straight canal sections and laboratory channels [23]. The breadth of the data used in this study was significant and encompassed several orders of magnitude for each parameter of interest. In total, 410 data were used to compare the actual values of the top width, average flow depth and longitudinal slope of stable channels with the estimated values of the ANFIS and ANFIS-PSO models. The boxplot of parameters is depicted in Fig. 1. The visual representation provides a clear overview of the distribution and variability of the data.

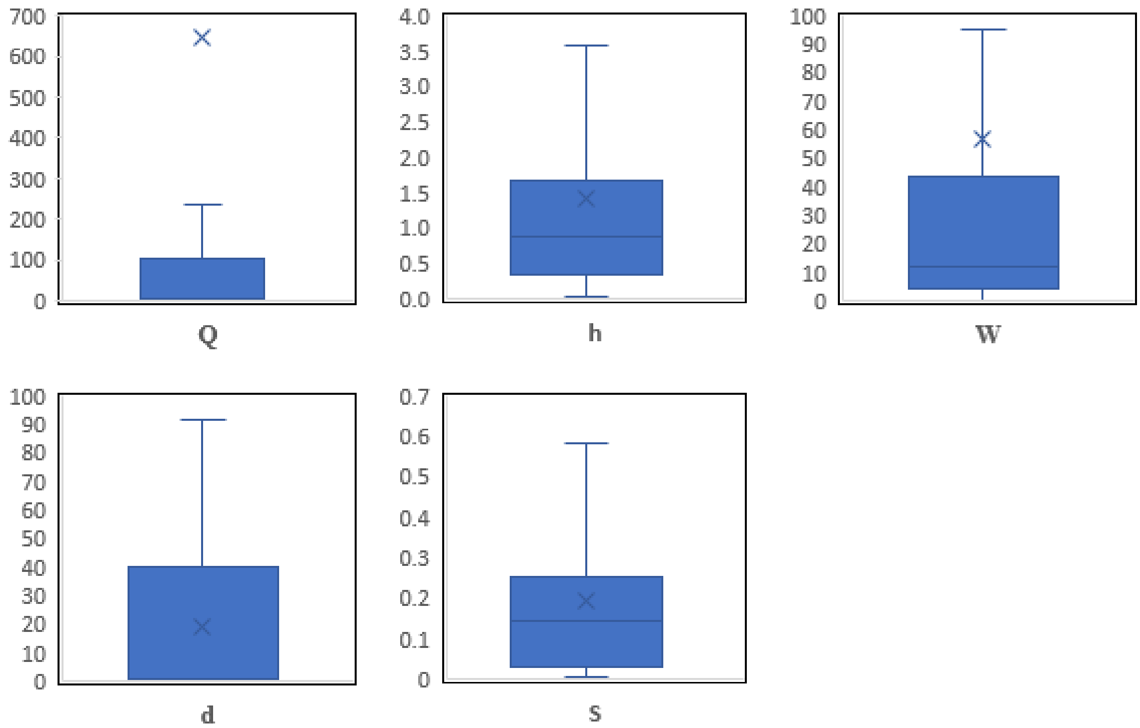

Figure 1. The boxplot of parameters

However, it is important to acknowledge the potential for errors in the measurement of regime channel characteristics. Accurate measurement of the channel slope, in particular, may be challenging to obtain, as the slope is not always constant. The compilation and analysis of laboratory and field data from various sources provides a robust foundation for this study. The diverse range of observations from different types of channels, as well as the extensive range of data used, allowed for a comprehensive analysis of the parameters of interest. However, it is crucial to recognize the potential for errors in the measurement of channel characteristics, particularly in the case of channel slopes. This acknowledgement of the potential limitations in the data is essential to ensuring the accuracy and reliability of the study's findings.

2-2- Adaptive Neuro Fuzzy Inference System (ANFIS)

The Neuro-fuzzy system, which is a combination of neural network with fuzzy logic, was first introduced by Jang [24]. This model implements a Sugno fuzzy system in a neural structure and uses a combination of the Error Back-Propagation and the Least Square Error training methods for the training process. Membership functions in Fuzzy Logic and neurons in the Neural Network are important. First, the membership functions are defined for the input parameters, and then the membership value of each input parameter is determined for different fuzzy intervals. The main weakness of the fuzzy inference system is determining the optimal membership functions, which is solved in the ANFIS by using the learning ability of the neural network.

The structure of the ANFIS consists of five layers, and the functions of different layers are described below:

- Layer 1: Each node in this layer is equivalent to a fuzzy set. The output of each node in this layer is equal to the degree of membership of the input variable in this set.
- Layer 2: In each node in this layer, the input signals are multiplied and an output is produced.
- Layer 3: The output of this layer is normalized from the previous layer.
- Layer 4: The nodes of this layer are adaptive nodes with nodal functions.
- Layer 5: Each node in this layer calculates the final output value (the number of nodes is equal to the number of outputs).

Each node has a function with adjustable or fixed parameters. During the training phase, the membership function parameters are adjusted and calculated using the gradient vector. This process aims to establish a suitable criterion for determining the efficacy of the parameter modeling. After creating the gradient vector, optimization models are used to optimize parameters and minimize errors.

2-3- Particle Swarm Optimization Algorithm (PSO)

The PSO algorithm [25] has a continuous origin, and then its discrete and multi-objective versions were presented. In the field of Swarm Intelligence, it is classified into two components: self-organization and information flow. Self-organization is a set of rules that all particles must follow. As natural signs of Swarm Intelligence, we can see the cooperation of social insects such as ants, bees, termites and the performance of collective animals such as birds and fish.

The steps of PSO are as follows: 1- Creating a random population and evaluating it. 2- Determining the best particle and the best personal memory. 3- Update speed and position for all particles. 4- Determining the best particle and the best personal memory of each particle. 5- Return to step 3 if the termination conditions are not met. 6- The end.

In the PSO, there are a series of hypothetical living organisms (particles) that are distributed in the search space. Each particle calculates the value of the objective function in the position in which it is placed. Then, by combining the information of its current location and the best location it has been in so far and the information of the best creatures in the group, it chooses the direction of movement. These steps are repeated several times. In other words, the movement is influenced by the speeds caused by inertia, personal experience, and the best collective experience. Assuming the existence of the D-dimension space and the i-th particle in this space, it is shown as Xi and the velocity vector is shown as Vi. The best position found by the i-th particle is denoted as $\mathrm{P}_{\mathrm{best}_\mathrm{i}}$ and the best position found by the best particle among all particles is denoted by $\mathrm{G}_{\mathrm{best}_\mathrm{i}}$. The speed and position of each particle is calculated and updated in each iteration using relations 1 and 2:

$$\mathrm{V_i(t) = W.V_i(t-1) + \rho_1\left(X_{Pbest_i} - X_i(t)\right) + \rho_2\left(X_{Gbest_i} - X_i(t)\right)} \tag{1}$$

$$\mathrm{X_i(t) = X_i(t-1) + V_i(t)} \tag{2}$$

Where, $\rho_1 = C_1R_1$ and $\rho_2 = C_2R_2$. Also, C1 and C2 are constant training coefficients, R1 and R2 are two random numbers with a uniform distribution between zero and one, and W is a weight. Indices t and t-1 are related to the current and previous iterations of the algorithm, respectively.

2.4. The ANFIS-PSO integrated model

In data mining methods such as ANFIS, for the training process, an optimization problem is solved in order to adjust the turns of the ANFIS algorithm by the inverse modeling method. Mainly, in different software, the Levenberg-Marquardt algorithm is used, which is a heuristic algorithm and does not have the ability to get out of the local optimal trap. However, a method such as ANFIS-PSO replaces the meta-heuristic PSO algorithm with the Levenberg -Marquardt algorithm. In simpler terms, the weights of membership functions in the composite model are optimized using the PSO algorithm. This optimization aims to minimize the difference between observed and predicted values [26]. The flowchart of ANFIS-PSO model is shown in Fig. 2.

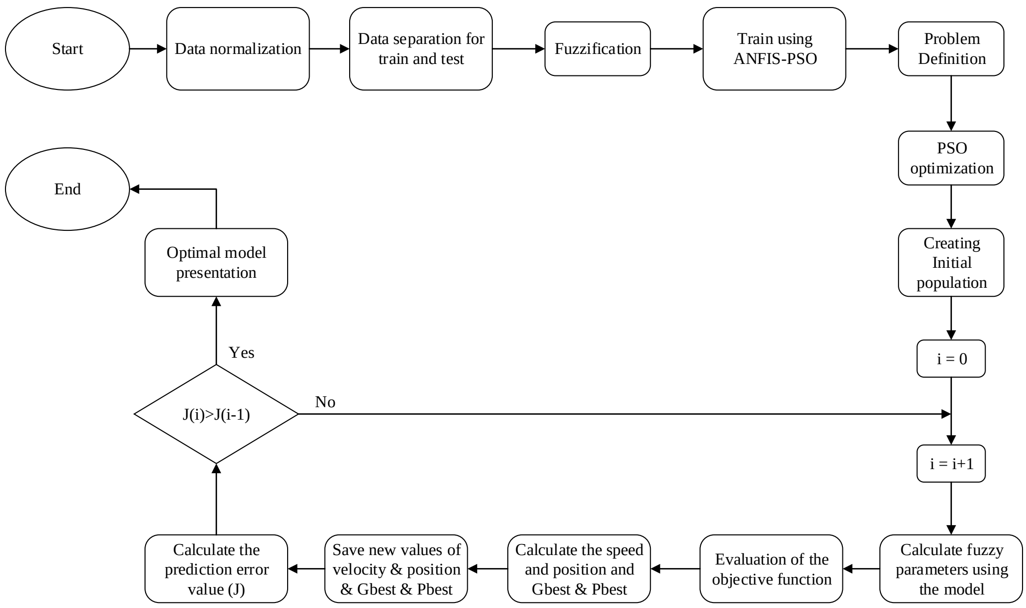

Figure 2. The flowchart of ANFIS-PSO model

2.5. Modeling the geometry parameters of stable channels with ANFIS and ANFIS-PSO models

In the MATLAB software, the ANFIS model can be implemented both by the graphical interface (anfisedit command) and by writing the function code and its requirements in the M-File. The graphical interface has limitations, such as the inability to integrate with the PSO algorithm. Therefore, in this research, two main programs were coded for modeling with ANFIS and ANFIS-PSO. In each of these two programs, four stages of data loading, initial network creation, network training and network performance evaluation are passed.

2.5.1. Data Loading

In the data loading stage, the stages of determination, randomization, normalization and division of input and output variables were implemented for both the ANFIS and ANFIS-PSO models:

Determination of input and output variables: Among the parameters affecting the geometry of stable channels are flow rate (Q), average particle diameter (d), shear stress (τ), channel top width (W), average flow depth (h) and channel longitudinal slope (S). In this research, a total of 42 models were derived from the combination of 7 input data sets (flow rate, average particle diameter, and shear stress) and 2 models (ANFIS and ANFIS-PSO). The models were used to estimate the upper width of the channel, the average flow depth, and the longitudinal slope of the channel as three types of outputs.

To ensure accurate modeling results and avoid biases caused by potential connections between vectors, the input and output variables were randomized. This involved disrupting the initial order of the data and introducing them to the model in a random manner. Normalization of input and output variables: Entering data in raw form reduces the accuracy and speed of the network. To avoid such conditions and also in order to equalize the value of data for the network, its inputs were placed within the range of the transfer function used in the network design and became so-called normal (standard). This prevents the weights from shrinking too much and prevents early saturation of the network. For normalization of input and output variables, the *mapminmax* built-in command was used.

Division of input and output variables: Usually, the data are divided into two sets of train and test for calibration and validation, respectively. The train and test sets should represent the same population. The training data (TrainInputs and TrainTargets) were used to find the relationship between the observed inputs and outputs of the model (TrainOutputs). In the training phase, by modifying the membership degree parameters based on the acceptable error rate, the model parameters were close to the real values. Usually, about 60-80% of input data is considered training data. In this research, 70% of the total data was selected as training data. The remaining 30% of the data was used as test data to evaluate the network performance. Thus, after training the network, test input data (TestInputs) is introduced to the model and test output data (TestOutputs) are predicted to estimate the target outputs (TestTargets). In the test mode, the accuracy of the model can be evaluated.

2.5.2 Initial Network Creation

For this purpose, in the MATLAB software, three methods can be used: Grid Partitioning, Subtractive Clustering, and Fuzzy C_Means clustering. In this study, the Sugno type Fuzzy C_Means clustering (FCM) method was used for both models.

2.5.3. Network Training

For this purpose, in the MATLAB software, two methods of the Error Back-Propagation and the Hybrid can be used. In this study, the Error Back-Propagation method was used in ANFIS model. Also, for the training of the ANFIS-PSO model network, three programs were implemented in order to get the fuzzy parameters, the training objective function, and the set of fuzzy parameters.

2.5.4. Network Performance Evaluation

After the training of the system and choosing its parameters, it is necessary to verify or check the validity of the model. Since the data used in system training is not necessarily a complete representative of comprehensive training, the model validation stage is of particular importance. Therefore, another part of the existing input-output data set, which was not used for training, was used as input data to the system in order to ensure the accuracy and validity of the prepared model to predict the output values of the corresponding input data.

2.6. Evaluation criteria

In order to check the accuracy of the results of the models, three statistical criteria including Determination Coefficient (R^2), Coefficient of Residual Mass (CRM) and Normalized Root Mean Square Error (NRMSE) were used to check correlation, over-estimation or underestimation, and error values, respectively.

$$R^2 = \left(\frac{\sum_{k=1}^{n}(O_i - \bar{O})(P_i - \bar{P})}{\sum_{k=1}^{n}(O_i - \bar{O})^2 \sum_{k=1}^{n}(P_i - \bar{P})^2}\right)^2 \quad (3)$$

$$CRM = \frac{\sum_{i=1}^{n} O_i - \sum_{i=1}^{n} P_i}{\sum_{i=1}^{n} O_i} \quad (4)$$

$$NRMSE = \frac{\left(\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}\right)^{0.5}}{\bar{O}} \quad (5)$$

In the above relationships: Oi are the measured values, Pi: the predicted values, n: the number of observations, $\bar{O}$ and $\bar{P}$ are the average of the measured and predicted values, respectively. R^2 is the square of Pearson's correlation coefficient and describes the ratio of the total variance in the observed data to the data simulated by the model. This index changes from zero to one. Larger values indicate better matching of the simulated data. The negative and positive values of the CRM standard indicate overestimation and underestimation in the model results, respectively. Also, the NRMSE index must be close to zero to make a proper estimate [27].

3. Results and Discussion

The ANFIS and ANFIS-PSO models were executed seven times for each of the three outputs. This comprised three executions with one input, three with two inputs, and one with three inputs. The executions utilized the FCM network creation method and the Error Back-Propagation training algorithm. Out of a total of 410 data series, 287 were randomly assigned to training and 123 were to test.

3.1. Results of modeling channel top width (W)

Tables 1 and 2 show the values of R^2, CRM and NRMSE statistical criteria by training, test and overall stages for modeling W using the ANFIS and ANFIS-PSO models.

Table 1. Evaluation of modeling W with ANFIS model

Input(s)	Train			Test			All		
	R^2	CRM	NRMSE	R^2	CRM	NRMSE	R^2	CRM	NRMSE
Q	0.99	-0.009	0.317	0.78	-0.014	1.342	0.92	-0.010	0.765
d	0.04	-3.070	2.272	0.04	0.112	2.870	0.04	0.036	2.502
τ	0.25	3.169	2.033	0.16	0.212	2.625	0.21	0.070	2.276
Qd	0.97	-0.039	0.435	0.84	-0.533	2.763	0.86	-0.164	1.328
Qτ	0.43	9.137	171.990	0.28	16.674	178.576	0.37	11.570	174.517
dτ	0.52	4.752	1.738	0.35	-2.053	13.151	0.14	-0. 359	4.542
Qdτ	0.99	0.004	0.254	0.48	-1.366	8.287	0.44	-0.466	5.202

Table 2. Evaluation of modeling W with ANFIS-PSO model

Input(s)	Train			Test			All		
	R^2	CRM	NRMSE	R^2	CRM	NRMSE	R^2	CRM	NRMSE
Q	0.98	0.008	0.335	0.89	-0.139	1.016	0.95	-0.029	0.567
d	0.11	0.003	2.054	0.01	0.558	2.464	0.04	0.272	2.521
τ	0.25	0.058	2.345	0.07	0.107	2.233	0.20	0.073	2.311
Qd	0.95	0.017	0.548	0.95	0.096	0.497	0.95	0.012	0.552
Qτ	0.99	-0.001	0.332	0.85	0.039	0.780	0.95	0.033	0.553
dτ	0.28	-0.020	2.171	0.19	-0.630	2.264	0.25	-0.142	2.236
Qdτ	0.98	0.004	0.354	0.94	-0.056	0.545	0.98	-0.008	0.393

In the single-input models, based on the evaluation criteria, the highest prediction accuracy for both the ANFIS and ANFIS-PSO models was achieved when using flow rate (Q) as the input. Comparing the results of the two models demonstrates that the best results are achieved when utilizing the ANFIS-PSO model. In this case, the R^2, CRM and NRMSE with the ANFIS-PSO model, were equal to 0.954, -0.029, and 0.567, respectively, which indicates the highest correlation, slightly over-estimation, and the lowest error. In other words, among the three parameters affecting the W, the Q was the most important. Fig. 3 shows the correlation plots of the single-input ANFIS-PSO model of Q for all data as the best model for modeling the W. Fig. 3 shows the matching of target and output data, the closeness of target and output values to the y=x chart, the low deviation of error values from zero, and the closeness of the error distribution (histogram) to a normal distribution.

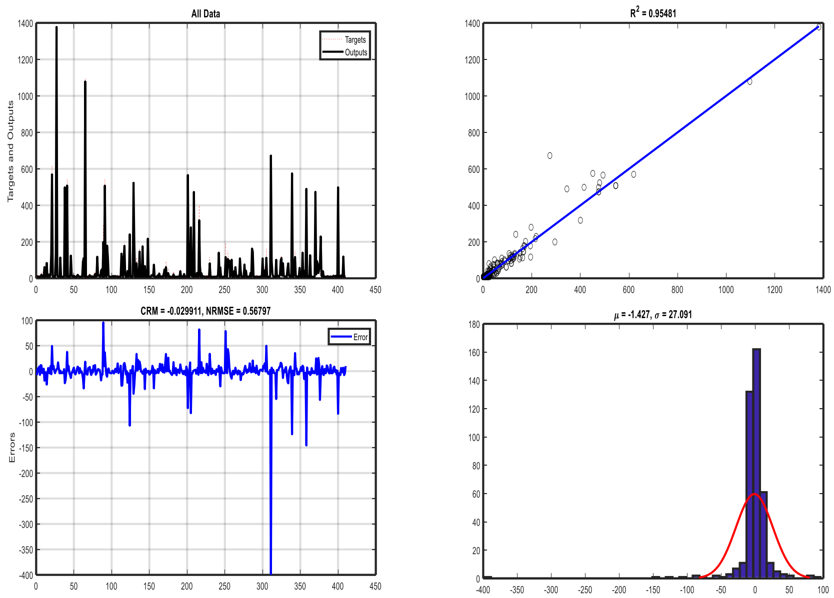

Figure 3. Correlation diagrams of the single-input Q model as the best model for modeling W using the ANFIS-PSO model

In the two-input models, according to the evaluation criteria, the highest prediction accuracy in both ANFIS and ANFIS-PSO models was related to the use of Qd as input. Comparing the results of two models shows that better results are obtained by using the ANFIS-PSO model. In this case, the R^2, CRM and NRMSE with the ANFIS-PSO model, were equal to 0.953, 0.012, and 0.552, respectively, which indicates the highest correlation, slightly under-estimation, and the lowest error. When comparing the values of single-input models with two-input models, there was a slight decrease in modeling accuracy. Therefore, the best parameter for modeling the top width of the channel is the flow rate.

In the three-input model, according to the evaluation criteria in both ANFIS and ANFIS-PSO models, the modeling accuracy has decreased and the results are not suitable. Therefore, the results indicate that utilizing three inputs is not suitable and may lead to erroneous modeling results. The best mode for modeling the upper channel width parameter (W) is to use a single flow rate (Q) input.

3.2. Results of modeling average flow depth (h)

Tables 3 and 4 show the values of R^2, CRM and NRMSE statistical criteria for training, testing and overall stages in modeling h using the ANFIS and ANFIS-PSO models.

Table 3- Evaluation of modeling h with ANFIS model

Input(s)	Train			Test			All		
	R^2	CRM	NRMSE	R^2	CRM	NRMSE	R^2	CRM	NRMSE
Q	0.92	-0.0009	0.485	0.59	-0.0007	0.942	0.84	-0.0008	0.675
d	0.03	-3.442	1.571	0.02	-0.190	1.725	0.03	-0.050	1.613
τ	0.32	-1.801	1.260	0.25	-0.127	1.652	0.29	-0.035	1.375
Qd	0.97	0.0005	0.304	0.51	-0.103	1.242	0.78	-0.034	0.794
Qτ	0.40	1.955	32.666	0.50	3.865	31.313	0.43	2.591	32.259
dτ	0.36	9.243	1.407	0.27	-0.015	1.039	0.34	-0.004	1.326
Qdτ	0.30	858.072	13982.934	0.08	4.592	56.128	0.24	626.373	12175.722

Table 4- Evaluation of modeling h with ANFIS-PSO model

Input(s)	Train			Test			All		
	R^2	CRM	NRMSE	R^2	CRM	NRMSE	R^2	CRM	NRMSE
Q	0.94	-0.038	0.390	0.85	-0.053	0.684	0.91	-0.042	0.487
d	0.07	-0.001	1.408	0.01	0.022	1.999	0.03	0.005	1.611
τ	0.35	0.012	1.240	0.32	0.008	1.641	0.32	0.011	1.351
Qd	0.91	0.014	0.417	0.87	-0.073	1.271	0.84	-0.017	0.912
Qτ	0.90	-0.030	0.521	0.78	-0.221	1.265	0.81	-0.082	0.775
dτ	0.26	0.010	1.519	0.13	-0.076	1.09	0.24	-0.013	1.428
Qdτ	0.92	-0.020	0.434	0.94	0.025	0.503	0.92	-0.004	0.462

In the single-input models, according to the evaluation criteria, the highest prediction accuracy in both ANFIS and ANFIS-PSO models was related to the use of flow rate (Q) as input. Comparing the results of two models shows that better results are obtained by using the ANFIS-PSO model. In this case, the R^2, CRM and NRMSE with the ANFIS-PSO model, were equal to 0.912, -0.042, and 0.487, respectively, which indicates the highest correlation, slightly over-estimation, and the lowest error. In short, among the three parameters that impact h, Q was identified as the most influential. Fig. 4 shows the correlation plots of the single-input ANFIS-PSO model of Q for all data as the best model for modeling the h. In Fig. 4, you can observe the matching of target and output data, the closeness of target and output values to the y=x chart, the low deviation of error values from zero, and the closeness of the error distribution (histogram) to a normal distribution.

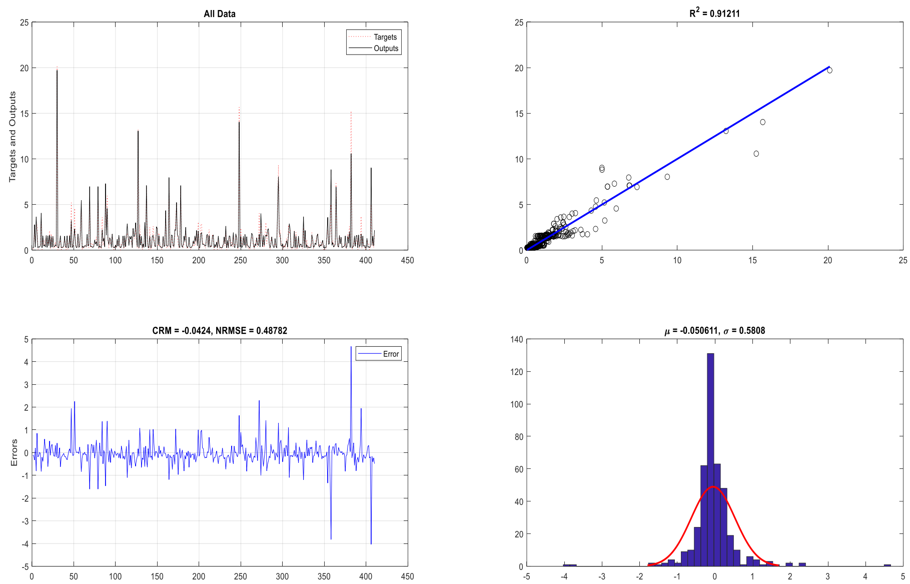

Figure 4. Correlation diagrams of the single-input Q model as the best model for modeling h using the ANFIS-PSO model

In the two-input models, according to the evaluation criteria, the highest prediction accuracy in both ANFIS and ANFIS-PSO models was related to the use of Qd as input. Comparing the results of two models shows that better results are obtained by using the ANFIS-PSO model. In this case, the R^2, CRM and NRMSE with the ANFIS-PSO model, were equal to 0.842, -0.017, and 0.912, respectively, which indicates the highest correlation, slightly over-estimation, and the lowest error. Comparing the values of single-input and two-input models showed a slight decrease in modeling accuracy. Therefore, the best parameter for modeling the average flow depth is the flow rate.

In the three-input model, according to the evaluation criteria in both ANFIS and ANFIS-PSO models, the modeling accuracy has decreased and the results are not suitable. Therefore, the results indicate that using three inputs is not appropriate, and it may lead to erroneous modeling results. The optimal approach for modeling (h) is to utilize a single (Q) input.

3.3. Results of modeling longitudinal slope of the channel (S)

Tables 5 and 6 show the values of R^2, CRM and NRMSE statistical criteria by training, test and overall stages for modeling S using the ANFIS and ANFIS-PSO models.

Table 5- Evaluation of modeling S with ANFIS model

Input(s)	Train			Test			All		
	R^2	CRM	NRMSE	R^2	CRM	NRMSE	R^2	CRM	NRMSE
Q	0.06	5.645	1.141	0.03	0.081	1.364	0.05	0.026	1.224
d	0.41	-2.341	0.902	0.41	0.002	1.100	0.41	0.0006	0.967
τ	0.07	7.962	1.2	0.03	-0.068	1.264	0.06	-0.020	1.219
Qd	0.28	8.717	1.153	0.08	0.046	1.121	0.19	0.015	1.146
Qτ	0.10	0.0007	1.233	0.02	1.227	8.899	0.01	0.351	4.763
dτ	0.21	-5.667	1.072	0.07	0.034	1.422	0.13	0.010	1.201
Qdτ	0.01	0.204	6.492	0.02	3.972	27.901	0.01	1.438	17.479

Table 6- Evaluation of modeling S with ANFIS-PSO model

Input(s)	Train			Test			All		
	R^2	CRM	NRMSE	R^2	CRM	NRMSE	R^2	CRM	NRMSE
Q	0.01	0.011	1.250	0.02	-0.086	1.157	0.04	-0.016	1.226
d	0.18	-0.012	1.072	0.04	0.132	1.356	0.12	0.034	1.178
τ	0.11	0.013	1.194	0.08	-0.123	1.162	0.10	-0.023	1.190
Qd	0.45	-0.012	0.999	0.33	-0.086	0.958	0.40	-0.035	0.986
Qτ	0.17	-0.049	1.094	0.09	0.100	1.277	0.13	0.0002	1.166
dτ	0.60	0.056	0.765	0.18	-0.087	1.390	0.42	0.015	0.971
Qdτ	0.34	0.006	1.028	0.32	0.038	1.009	0.33	0.015	1.023

Based on the evaluation criteria, the prediction accuracy of S with both ANFIS and ANFIS-PSO models is inadequate, leading to modeling errors.

Shaghaghi et al. [12, 28] showed that discharge has a great effect on predicting channel width and also the combination of average diameter and shear stress creates a large error in predicting channel width, which is consistent with the results of this research. But they showed that the combination of three input parameters predicts the depth of the channel with acceptable accuracy, which is not consistent with the findings of this research.

Khosravi et al. [5] showed that the Shields parameter is very effective in predicting the depth, which is not consistent with the results of this research. Also, they showed that discharge has the least effect on predicting the depth and top width of the channel, which is not only consistent with this research but also numerous other studies such as [29, 30, 31]. Since the data utilized in their study pertains to three specific rivers, this discrepancy in findings between their research and that of [5] may be attributed to the specific characteristics of the rivers analyzed. Abdelhaleem et al. [32] showed that the discharge parameter increases the prediction accuracy, but the effective parameters may be different in different rivers. In some studies, the use of all parameters has increased the prediction accuracy [33, 5], which is not in line with the results of the current research. However, in other research, it has been observed that the use of a smaller number of inputs, which makes the modeling less complex, has provided better results [34, 35], which is consistent with the results of this research.

Gholami et al. [36, 11] showed that the cross-sectional profile and shape of channels can be predicted with great accuracy using artificial intelligence. Also, Qasem et al. [37] and Shaghaghi et al. [12] showed that the use of meta-heuristic methods as an optimization algorithm can increase the efficiency of artificial intelligence models in predicting parameters, which is similar to this research. Sharafati et al. [38], Qasem et al. [37], and Basser et al. [39] conducted comparative studies on different meta-heuristic methods. These studies showed that ANFIS-PSO is a reliable technique for predicting hydraulic parameters of flow and sediment, which aligns with the findings of this research.

The ANFIS-PSO method has demonstrated satisfactory learning and prediction capabilities as a soft computing approach. Moreover, the results have shown its ability to overcome the main limitations of artificial neural networks. This includes addressing the need to define network structure and dealing with the challenge of converging to local optima. This suggests that ANFIS-PSO has the potential to be a valuable tool in the field of soft computing. The ANFIS-PSO model used in this study showed a significant improvement in accurately predicting stable channel geometry. As a result, ANFIS-PSO can be considered a promising alternative to other complex models for stable channel design. One of the main advantages of ANFIS-PSO, as opposed to classical ANFIS, is its swift execution coupled with high accuracy. Nonetheless, a notable challenge emerges when adding more membership functions, resulting in increased computational time. PSO effectively addresses this challenge by using an evolutionary algorithm (compared to the traditional ANFIS model), resulting in reduced computational time costs.

4. Conclusion

In this research, the width, depth, and slope of the stable channel were modeled as a function of flow rate, average particle diameter, and shear stress using the ANFIS and ANFIS-PSO methods. In order to provide an acceptable simulation, a wide range of field and laboratory data on the characteristics of stable channels were used. In general, the modeling results with the ANFIS-PSO model were more accurate than the results of the ANFIS model. The optimal modeling approach involved using a single input, whereas employing three inputs would lead to errors in the results. When estimating the parameters of the width (W) and depth (h) in single-input and two-input modes, the most effective inputs were the Q parameter for single-input and the Qd parameter for two-input mode, respectively. The inputs used in this research, including Q, d, and τ, were found to be unsuitable for estimating S, and as a result, S cannot be accurately modeled. Hence, alternative inputs or models should be considered for modeling S. Overall, the findings indicate that artificial intelligence methods with strong simulation capabilities can enhance predictive accuracy.

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