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Prediction of flow through rockfill dams using a neuro-fuzzy computing technique

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Abstract

Rockfill dams are economical and fast tools for flood detention and control purposes. Artificial intelligence approaches may provide user-friendly alternatives to very complex and time-consuming numerical methods such as finite volume and finite element for predicting flow through rockfill dam. Therefore, this paper examines the potential of coactive neuro-fuzzy inference system (CANFIS) for estimation of flow through trapezoidal and rectangular rockfill dams. The results showed that accurate flow predictions can be achieved with a CANFIS with the Takagi–Sugeno–Kang (TSK) fuzzy model and the Bell membership function for both trapezoidal and rectangular rockfill dams. Furthermore, Levenberg-Marquardt and Delta-Bar-Delta were the best algorithms for training the network in order to estimate flow through rectangular and trapezoidal rockfill dams, respectively. Overall, the results of this study suggest the possibility for using CANFIS for prediction of flow through rockfill dam.

Keywords: Flow forecast, Rockfill dam, Coactive neuro-fuzzy inference system

1. Introduction

The flood disaster phenomenon is a complex natural system, which frequently occurs (e.g. [19], [47], [12], [16], [45], [22]). Floods have the greatest damage potential and affect the greatest number of people in comparison with all the other natural disasters worldwide [34].

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Though non-structural measures improve the preparedness to floods and reduce losses, the necessity of structural measures would always remain to reduce the extent of physical damage caused by floods [15]. A rockfill dam is an economical and fast tool for flood detention and control purposes when rock is available [39]. Rock dumps can be used to store water in mining facilities and to build gabion spillways, and groins [43]. The objectives of building rockfill detention dams are flow storage for a specific period and lowering of the outflow hydrograph [38].

In rockfill dams, due to the large size of pores, the flow is inherently turbulent and therefore not amenable to a classic seepage analysis on the basic of Darcy's low, so a non-Darcy flow relationship must be used. In this type of dams, analysis of two-dimensional (2D) flow hydraulic solve by using numerical methods such as finite volume and finite element. Numerical methods are very complex and time-consuming. Also, numerical methods calculation is performed frequently, and so the rate of convergence is slow. Furthermore, the result is affect by the initial values and a local minimum or premature convergence is likely to be obtained, and so the solution is sometimes unstable.

Intelligent computing tools based on fuzzy logic and artificial neural networks (ANNs) have been successfully applied in various problems with superior performances. A new approach of combining these two powerful artificial intelligence tools, known as neuro-fuzzy systems, has increasingly attracted scientists in different fields [44]. This approach is found to be highly adaptive and efficient in investigating non-linear relationships among different variables [46]. The data driven neuro-fuzzy modeling systems are designed to overcome inherent drawbacks of both fuzzy systems and ANNs [18]. Neuro-fuzzy systems are applied in various domains, e.g., control, data analysis, decision support, etc [31].

The drawback of frequently calling the time-consuming and complex numerical methods analysis in the process of optimization can be overcome by computational intelligence methods [48]. In recent years, artificial intelligence technique such as neuro-fuzzy has become increasingly popular in hydrology and water resources among researchers and practicing engineers. For instance; neuro-fuzzy has been used successfully for prediction of suspended sediment ([24], [8], [26], [37]), evaporation and evapotranspiration modeling ([23], [25], [3], [30]), real time reservoir operation ([6], [7], [36]), ground-water vulnerability [10], modeling stage–discharge relationship ([9], [28]), water quality problems [29], estimation of scour depth near pile groups [49], short-term flood forecasting [33], rainfall–runoff modeling ([14], [20]), prediction of water level in reservoir [5], modeling hydrological time series ([32], [13]).

To the knowledge of the authors, no work has been reported in the literature that investigates the accuracy of coactive neuro-fuzzy inference system (CANFIS) model for prediction of flow through rockfill dam. Therefore, the objective of the present study was to evaluate the capabilities of a CANFIS model for prediction of flow through trapezoidal and rectangular rockfill dams. Also, the effect of using different fuzzy models and membership functions on CANFIS model performance was investigated in this paper. The experimental study was carried out for evaluating the accuracy of the method.

2 Data and Method

2.1 Experimental data

Experimental data were needed for evaluating the accuracy of the method. The experiments were conducted in two laboratory flume with 10 and 0.77 m long, 0.3 m wide and 0.5 m height. Diameters of rocks that used in the experiments were 2.5 and 4.5 cm. The particle rocks were sifted through two sieves to get these particle sizes. In each series of the experiments, the height of water in upstream and downstream sides of trapezoidal and rectangular rockfill dams were measured in different discharges (lit s^{-1}). For measuring water level variation along the flume and downstream channel, a number of sensitive digital point gauges were installed. Each point gauge was equipped with memory storage to record water level. In addition, each dam was equipped by a thin galvanized basket to hold rockfill dams in their positions. Overall, the used data set includes 23 patterns of rectangular rockfill dam and 34 patterns of trapezoidal rockfill dam. Schematic views of trapezoidal and rectangular rockfill dams are shown in Figs. 1 and 2, respectively.

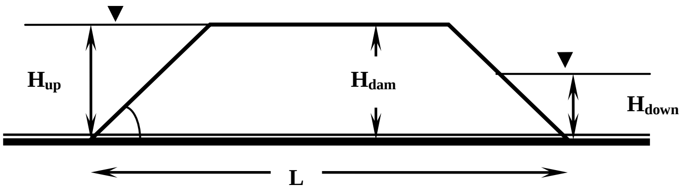

Fig. 1. Sketch of trapezoidal rockfill dam

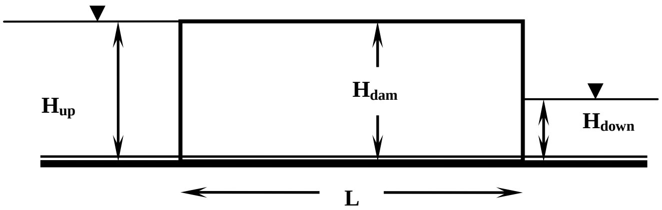

Fig. 2. Sketch of rectangular rockfill dam

2.2. Neuro-Fuzzy Systems (NFS)

Both ANNs and fuzzy logic solely do have certain disadvantages and advantages. Neuro-fuzzy systems have thus been developed by combining the semantic transparency of rule based fuzzy systems with the learning capability of neural networks [27]. A combination of ANNs and fuzzy logic can result in synergy that improves speed, fault tolerance, and adaptiveness [40]. Fuzzy inference systems are also valuable, as they combine the explanatory nature of rules (MF) with the power of neural networks. These kinds of networks solve problems more efficiently than ANNs when the underlying function to model is highly variable or locally extreme [4]. The proposed neuro-fuzzy model is a multilayer neural network-based fuzzy system and the system has a total of five layers. In this connectionist structure, the input and output nodes represent the input states and output response, respectively, and in the hidden layers, there are nodes functioning as membership functions (MF) and rules. This eliminates the disadvantage of a normal feedforward multilayer network, which is difficult for an observer to understand or to modify [42]. A specific approach in neuro-fuzzy development is the adaptive neuro-fuzzy inference system (ANFIS), which has shown significant results in modeling non-linear functions [21].

2.2.1. Coactive neuro-fuzzy inference system

The architecture of ANFIS is a one-output fuzzy inference system based on an adaptive network. CANFIS is a generalized form of ANFIS. CANFIS enables to obtain more than one outputs and has the advantage of non-linear rule formations [17]. The CANFIS model integrates fuzzy inputs with a modular neural network to quickly solve poorly defined problems [41]. The fundamental component of CANFIS is a fuzzy axon, which applies membership functions to the inputs. The output of a fuzzy axon is computed using the following formula:

$$f_j(x,w) = \min \forall_i = \left(MF\left(x_i, w_{ij}\right)\right) \tag{1}$$

where i = input index, j = output index, x_i = input i, w_{ij}=weights (*MF* parameters) corresponding to the j th *MF* of input i and *MF*=membership function of the particular subclass of the fuzzy axon. This system can be viewed as a special three-layer feed forward neural network. The first layer represents input variables, the middle (hidden) layer represents fuzzy rules and the third layer represents output variables [35]. CANFIS architecture is shown in Fig.3.

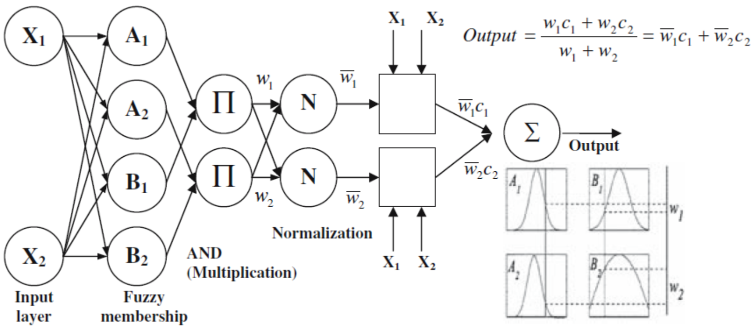

Fig. 3 CANFIS architecture

2.2.1.1 CANFIS Architecture

Consider a CANFIS structure with n inputs and one output. For model initialize, a common rule set with n inputs and m IF-THEN rules as follows [35]

Rule 1: If z_1 is A_{11} and z_2 is A_{12} . . . and z_n is A_{1n} then $u_1 = p_{11}z_1 + p_{12}z_2 + \cdots + p_{1n} z_n + q_1$

Rule 2: If z_1 is A_{21} and z_2 is A_{22} . . . and z_n is A_{2n} then $u_2 = p_{21}z_1 + p_{22}z_2 + \cdots + p_{2n} z_n + q_2$

⋮

Rule m: If z_1 is A_{m1} and z_2 is A_{m2} . . and z_n is A_{mn} then $u_m = p_{m1}z_1 + p_{m2}z_2 + \cdots + p_{mn}z_n + q_m$

The corresponding CANFIS structure is illustrated in Fig.3. All layers in CANFIS structure are either adaptive or fixed. The function of each layer is described as follows:

Layer 1 (*Premise Parameters*): Every node in this layer is a complex-valued membership function (μ_{ij}) with a node function:

$$(1 \le i \le n, 1 \le j \le m) \quad for \quad O_{1,ij} = \left|\mu A_{ij}(z_i)\right| \angle \mu A_{ij}(z_i) \tag{2}$$

Each node in layer 1 is the membership grade of a fuzzy set (A_{ij}) and specifies the degree to which the given input belongs to one of the fuzzy sets.

Layer 2 (Firing Strength): Every node in this layer is product of all the incoming signals. This layer receives input in the form of the product of all the output pairs from the first layer:

$$(1 \le j \le m) \quad for \quad O_{2,j} = w_j = \mu A_{i1}(z_1) \mu A_{i2}(z_2), \ldots, \mu A_{i1n}(z_n) \tag{3}$$

Layer 3 (Normalized Firing Strength): Every node in this layer calculates rational firing strength:

$$O_{3,j} = \overline{w}_j = \frac{w_j}{\sum_{j=1}^{m} w_j} \quad for \quad (1 \le j \le m) \tag{4}$$

Layer 4 (Consequence Parameters): Every node in this layer is multiplication of normalized firing strength from the third layer and output of neural network:

$$O_{4,j} = \overline{w}_j u_j = \overline{w}_j \left(P_{J1} Z_1 + P_{J2} Z_2 + \ldots P_{Jn} Z_{2n} + q_j \right) \quad for \quad (1 \le j \le m) \tag{5}$$

Layer 5 (Overall Output): The node here computes the output of CANFIS network:

$$O_{5,j} = \sum \overline{w}_j u_j \tag{6}$$

A fuzzy set is usually described by its membership function (MF) [1]. Due to smoothness and concise notation, the Gaussian and Bell membership functions are increasingly popular for specifying fuzzy sets. The Bell membership function has one more parameter than the Gaussian membership function, so a non fuzzy set can be approached when the free parameter is tuned. These membership functions are defined as follow [5]:

$$\mu_1(x) = \frac{1}{1 + \left| \frac{(x - c_1)}{a_1} \right|^{2b_1}} \qquad \text{(Bell function)} \quad (7)$$

Where x= input to the node and a_1, b_1 and c_1 = adaptable variables known as premise parameters.

$$\mu(x) = e^{\frac{-1}{2}\left(\frac{x-c}{\sigma}\right)^2} \qquad \text{(Gaussian function)} \quad (8)$$

A Gaussian membership function is determined by c and σ: c represents the centre of the MF; and σ determines the width of the MF

Axons are valuable because their MF can be modified through back propagation during network training to expedite the convergence.

The second major component of CANFIS is a modular network that applies functional rules to the inputs. The number of modular networks matches the number of network outputs and processing elements in each network corresponding to the number of MF. Two fuzzy structures are mainly used: the Tsukamoto model and the Takagi–Sugeno–Kang (TSK) model. Finally, a combiner is used to apply the MF outputs to the modular network outputs. The combined outputs are then channeled through a final output layer, and the error is back propagated to both the MF and the modular network [35].

2.2.1.2 Tsukamoto Fuzzy Model

In the Tsukamoto fuzzy models, the consequent part of each fuzzy if-then rule is specified by a membership function of a step function centered at the constant. As a result, the inferred output of each rule is defined as a crisp value induced by the rule's firing strength. The overall output is taken as the weighted average of each rule's output. This fuzzy model avoids the time consumed by the defuzzification process since it aggregates each rule's output by the method of weighted average [11].

2.2.1.3 Takagi–Sugeno–Kang (TSK) Fuzzy model

The TSK fuzzy model introduced in 1984 by T. Takagi, M. Sugeno, and K. T. Kang [21]. Fuzzy models that assume local model presentations with local function dynamics at the consequent or rule-layer of the models are known as Takagi–Sugeno–Kang (TSK) models. In this model, the output is calculated by performing fuzzy interpolations of simpler functional models in the neighboring fuzzy partitions. The ability of accurate modeling of a system, globally or locally, is the significant advantage of TSK models. Specifically, the accurate global learning ability of TSK models motivates various practical applications of such models in non-linear system estimation. One of the main criteria to categorize existing TSK models is locality of learning. This criterion depends on the model's learning objective function, which is a minimization problem of the global or the local learning errors [44].

In this study the CANFIS architecture used, and the problem is proposed to network models by means of two inputs and one output parameter. The height of water in upstream (H_{up}) and downstream (H_{down}) sides of the dams were selected as the inputs of the models. The flow through the dams was the target outputs of the models. An experimental data set including 23 patterns of rectangular rockfill dam and 34 patterns of trapezoidal rockfill dam were applied. In the CANFIS models developed here, 60% of the available data were used for training, 20% for cross-validation and 20% for testing network. All experimental data were randomly placed in these sets. Before applying the CANFIS to the data, the training, cross-validation and testing subsets were scaled (normalized) to the range of 0–1 using the following equation:

$$X_{norm} = 0.5 + 0.5\left(\frac{X - \overline{X}}{X_{\max} - X_{\min}}\right) \tag{9}$$

where X is the input value, X_{norm} is the scaled input value of the input value X, and X_{max} and X_{min} are the respective maximum and minimum values of the unscaled measured data. In this paper, the Bell and Gaussian membership functions and TSK and Tsukamoto fuzzy models were used. For small to medium-sized data sets, the number of membership functions assigned to each network input, will usually be between 1 and 10. The various algorithms (i.e., Levenberg-Marquardt, Delta-Bar-Delta, Step, Momentum, ConjugateGradient and Quickprop) were applied in order to identify the one which trains a given network more efficiently. Besides, different transfer functions (i.e., Sigmoid, Linear sigmoid, Tanh, Linear Tanh, Linear and Bias) were used in order to identify the one which gives the best results in depicting the non-linearity of the modeled natural system. The best architecture of the network was determined by trial and error. In fact, the optimal network architecture for each model was selected from the one which resulted in minimum errors and best correlation in the data set. The process of designing the networks is managed by NeuroSolution for Excel Release 4.2 software produced by NeuroDimension, Inc.

2.3 Criteria of evaluation

To evaluate the success of CANFIS in learning, several statistical measures could be used for comparison between the flow values calculated by CANFIS method and those obtained by the experimental study. The statistical criteria considered were root mean square error (RMSE), percentage error of estimate (PE), the ratio between average estimated flow values and observed values (RA), coefficient of determination (R^2) and mean absolute error (MAE). The RA shows under (RA<1) or over (RA>1) estimation of the flow. Also, the RMSE and PE are used to determine how much the network has reached to desired output values. The performance evaluation criteria used in this study can be calculated utilizing the following equations:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{n}} \tag{10}$$

$$PE = \left| \frac{\overline{P} - \overline{O}}{\overline{O}} \right| \times 100\% \tag{11}$$

$$RA = \frac{\overline{P}}{\overline{O}} \tag{12}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)^2}{\sum_{i=1}^{n}(O_i - \overline{O})^2} \tag{13}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}(P_i - O_i) \tag{14}$$

Where P_i and O_i are the predicted and observed values, respectively; $\overline{P}$ and $\overline{O}$ are the average of P_i and O_i, and n is the total numbers of data.

3. Results and discussion

3.1. Results of the method for trapezoidal rockfill dam

In the present study, flow through trapezoidal and rectangular rockfill dams was estimated by a CANFIS model. The data used for developing this model was obtained from the experimental study and the prediction capability of the model was analyzed by means of comparison with observed data. In order to assess obtained results, network was run in various manners. Also, the characteristic of type of the fuzzy models and the membership functions were studied. In each simulation, the effect of the different types of the fuzzy models and the membership functions were evaluated. Furthermore, the number of membership functions can determine the performance of a neuro-fuzzy system, in terms of reducing the size of error and generalization [2]. The final architectures of the neuro-fuzzy models found after many trials are given in Table 1 and 2. The RMSE, PE, RA and R^2 statistics of each CANFIS model in the test phase are also provided in these tables.

From the results obtained, CANFIS model appears to be a useful tool for prediction of the flow through rockfill dams.

In trapezoidal rockfill dam, among of the used fuzzy models, the TSK fuzzy model presented a better performance (R^2=0.982, RMSE=0.555 lit s^{-1} and PE=1.199%) compared with the Tsukamoto fuzzy model. The Tanh function as a transfer and the Delta-Bar-Delta algorithm for the network learning were the best architecture as these proved by trial and error for the TSK fuzzy model. Based on Table 1, the TSK fuzzy model had a tendency to underestimate (RA<1) flow through trapezoidal rockfill dam. On the contrary, the Tsukamoto fuzzy model overestimated (RA>1) flow values. Also, different number of membership function in range [1, 10] for each fuzzy model was tested and the number of membership function that gives the minimal output errors are given in Table 1 with respect to type of membership function for each study.

Figures 4 and 5 show the evolution of the MAE according to the number of epochs and membership functions in the TSK fuzzy model. Different numbers of epochs and membership functions were tested for access the best architecture. After many trial and error attempts it was determined that when using 700 epochs and 8 MF, the MAE was the lowest and more or less epochs and MF did not reduce the MAE further.

It can be seen from Table 1 and Fig.4 that the trained CANFIS network with 8 MF per input variable shows the best performance. Furthermore, in the best architecture the Bell membership function had slightly better results than the Gaussian membership function.

Figure 6 shows the plots between the measured and the estimated flow values by the model for training, validation and testing sets in trapezoidal rockfill dam. The selected TSK model provided a best fit model for all the three data sets.

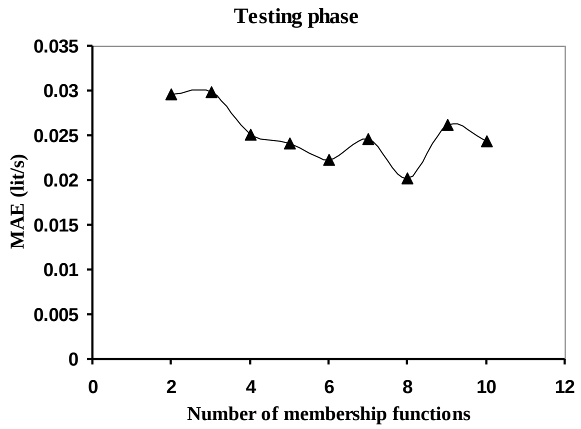

Fig.4 MAE error for CANFIS model with different number of MF in trapezoidal rockfill dam

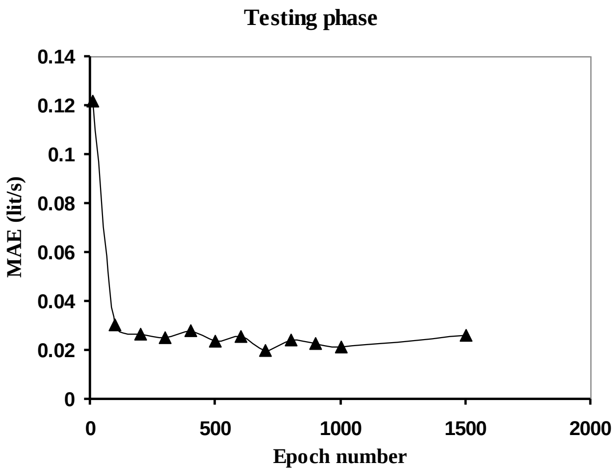

Fig.5 Variation of MAE value for various numbers of epochs for CANFIS model in trapezoidal rockfill dam

Table 1 The final architectures and value of standard statistical indexes of the NF models for the test phase in trapezoidal rockfill dam

Nero-Fuzzy	Transfer function	Learning algorithm	Types of MF	Numbers of MF	Numbers of Epoch	RMSE (lit/s)	PE (%)	RA	R^2
TSK model	Tanh	Delta-Bar-Delta	Bell	8	700	0.555	1.199	0.988	0.982
Tasukamoto model	Linear Sigmoid	ConjugateGradient	Bell	5	600	2.744	16.397	1.639	0.951

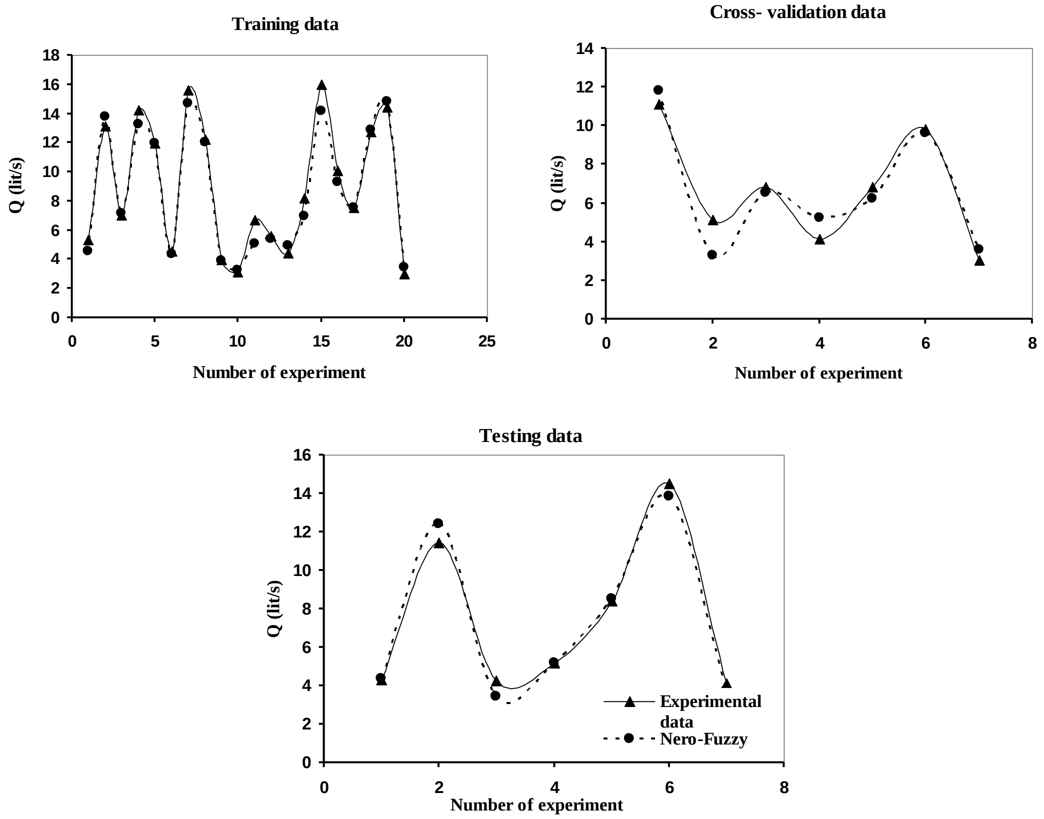

Fig.6 Comparison of the flow predicted by CANFIS model and the observed values in trapezoidal rockfill dam

3.2. Results of the method for rectangular rockfill dam

Obtained results for rectangular rockfill dam for flow prediction are presented in this section. The final architectures of the CANFIS models that were found after many trials are given in Table 2. The statistics values of each CANFIS model in the test phase are also given in this table.

Similar to trapezoidal rockfill dam, comparison of the model performance between the TSK and Tsukamoto fuzzy models indicated that the TSK model was more suitable for flow prediction in rectangular rockfill dam. The TSK fuzzy model presented the best R^2, RMSE and PE statistics of 0.975, 0.965 lit s^{-1} and 4.129%, respectively.

As shown in Table 2, the best overall performance in the TSK fuzzy model was achieved by the network trained with the Levenberg-Marquardt algorithm and the sigmoid function as a transfer function.

The TSK fuzzy model overestimated (RA>1) flow, whilst the Tsukamoto fuzzy model underestimated (RA<1) it (Table. 2). The presented results are briefed for only the Bell membership function as it had slightly better results than the Gaussian membership function.

Figure 7 depicts the MAE versus number of membership functions for the TSK fuzzy model. Different number of membership functions was tried and the best one that gives the minimum MAE was selected. Two Bell membership functions to the CANFIS model were found enough for modeling flow through rectangular rockfill dams.

Moreover, the MAE errors against number of epoch for the TSK fuzzy model are shown in Fig.8. It can be seen that the MAE errors for testing data set more or less reach a minimum after 100 epochs.

Figure 9 shows the observed flow values and the predicted ones by the TSK fuzzy model in rectangular rockfill dam. As can be seen from this figure, it appears the model outputs appropriately correspond with the experimental data.

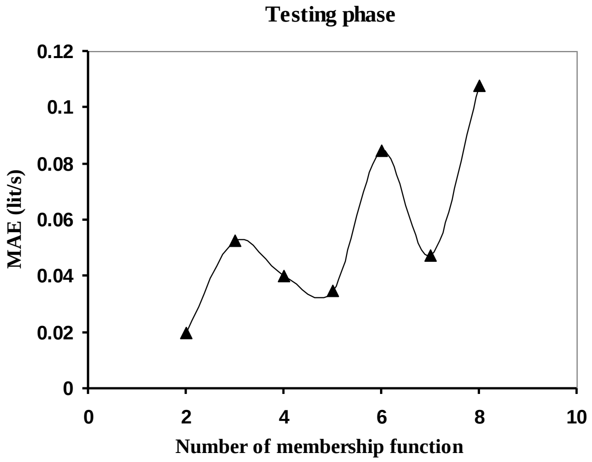

Fig.7 MAE error for CANFIS model with different number of MF in rectangular rockfill dam

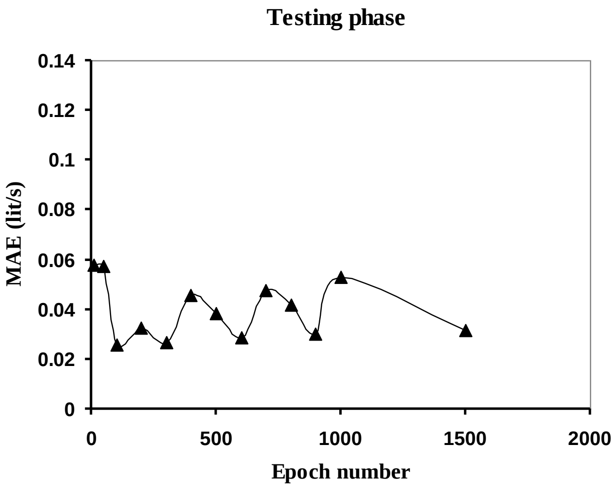

Fig.8 Variation of MAE value for various numbers of epochs for CANFIS model in rectangular rockfill dam

Table 2 The final architectures and value of standard statistical indexes of the NF models for the test phase in rectangular rockfill dam

Nero-Fuzzy	Transfer function	Learning algorithm	Types of MF	Numbers MF	Numbers of Epoch	RMSE (lit/s)	PE (%)	RA	R^2
TSK model	Sigmoid	Levenberg-Marquardt	Bell	2	100	0.965	4.129	1.041	0.975
Tasukamoto model	Bias	ConjugateGradient	Bell	2	200	3.681	19.6240	0.995	0.737

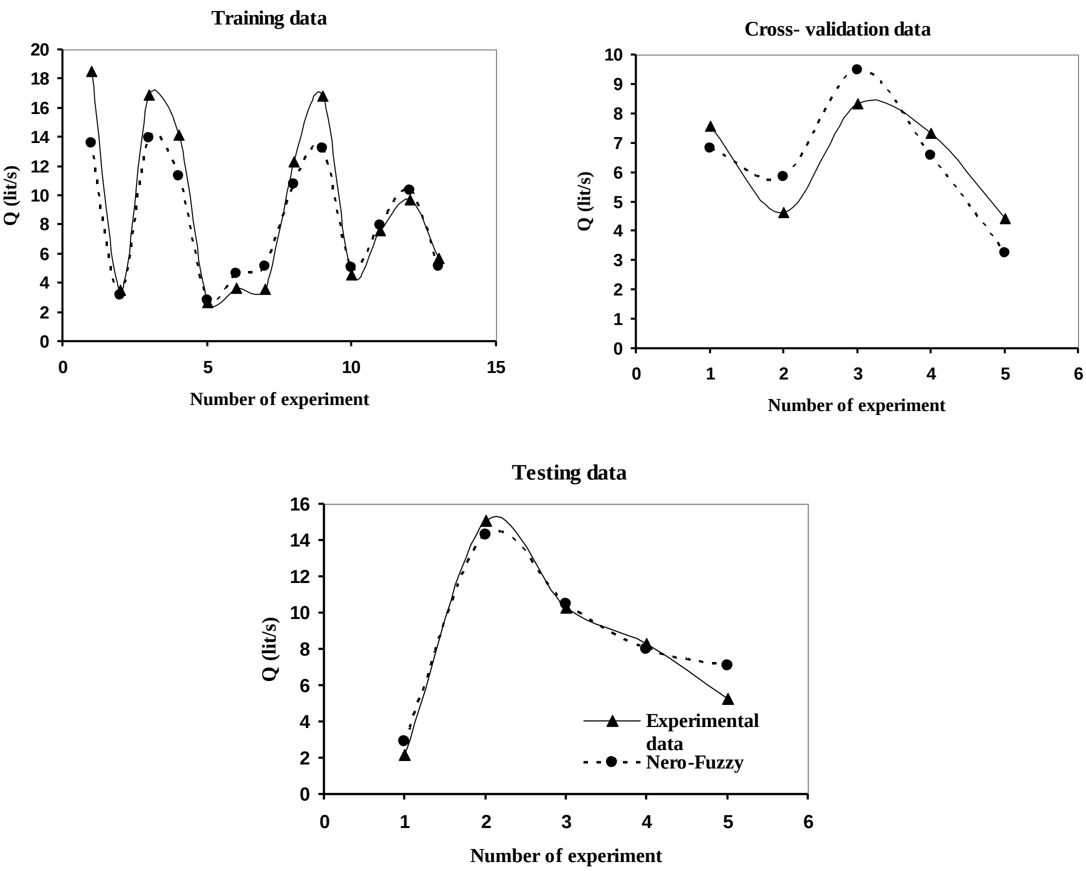

Fig.9 Comparison of the flow predicted by CANFIS model and the observed values in rectangular rockfill dam

4. Conclusions

In the presented article a CANFIS technique was applied for predicting the flow through trapezoidal and rectangular rockfill dams. The TSK and Tsukamoto fuzzy models were developed and their abilities to predict flow through rockfill dams were compared. Input data to each model in CANFIS included height of water in upstream and downstream sides of the dams. The output of the CANFIS was flow through the dams. The results revealed that the TSK fuzzy model was more efficient than the Tsukamoto fuzzy model for prediction of flow through rockfill dams. Moreover, in both types of dams, the Bell function performed better than the Gaussian function. Also, 8 and 2 membership functions provided the best results in trapezoidal and rectangular rockfill dams, respectively.

To sum up, the results of this study indicated that the flow values predicted using the CANFIS model were in good agreement with experimental data, indicating CANFIS model can be employed successfully in estimating flow through rockfill dam.

In general, the findings of this study indicated that intelligence methods such as CANFIS model can be used as an effective tool for prediction of flow through rockfill dam instead of very complex and time-consuming numerical methods.

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