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ORIGINAL ARTICLE

Analyzing bank profile shape of alluvial stable channels using robust optimization and evolutionary ANFIS methods

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Abstract

In natural rivers and artificial channels in addition to the channel dimensions (widening, reduction in slope and depth in the channel banks), formed shape profile in the case that the sediment on the banks with no movement (thresholds state) is of considerable importance for engineers. To determine the bank shape profiles, various theoretical, empirical and statistical relations have been provided based on physical and numerical models by different researchers. In this study, a simple model of adaptive neuro-fuzzy inference systems (ANFIS) is combined with two algorithms of differential evolution (DE) and singular value decomposition value (SVD) and the performance of these models to predict the stable shape profiles of the channels is evaluated and compared. In this paper, the main goal is to assess extensively the effect of hybrid models based on optimized algorithms (ANFIS-DE) and multi-objective evolutionary algorithm (ANFIS-DE/SVD) in improvement of performance of ANFIS and ANFIS-DE models, respectively. Accordingly, the results assessment show that all three ANFIS, ANFIS-DE and ANFIS-DE/SVD models are perfectly able to predict shape profiles in accordance with the observed profiles for the threshold channels. Using optimized and evolutionary algorithms has a positive impact on the performance of simple model of ANFIS. As compared to the simple ANFIS model, ANFIS-DE approximately 10.1% and ANFIS-DE/SVD model 7.2% is improved compared to the ANFIS-DE model. The accuracy of ANFIS-DE/SVD model showed better performance as well about 18.6% compared to the simple ANFIS model. Therefore, it can be said that not only DE optimization algorithms have a significant impact on increasing the performance of a simple ANFIS model but also using evolutionary algorithms (ANFIS-DE/SVD) reduce the ANFIS-DE model error accordingly. Polynomial equations of bank profiles proposed by hybrid ANFIS models in the present study can be used in design and implementation of cross section of stable channels.

Keywords Threshold channel · Bank profile shape · ANFIS · Evolutionary algorithms

Introduction

The process of channels widening until you reach equilibrium or stable state is continued in the channels, and the final state of this process causes the threshold channel (Yu and Knight 1998). In this case, the bank sediments are on the threshold and the bed particles are moving. This case is a simple model of most natural rivers and channels. Therefore, identification of the type of shape profile created on the banks like as specified channel geometric dimensions of stable channels is important. Concerning to the determination of slope, depth and water surface width in stable state or regime of channels, extensive research has been done (Lee and Julien 2006; Afzalimehr et al. 2010; Métivier et al. 2016; Gholami et al. 2017a; Shaghaghi et al. 2017; Joshi et al. 2018). But there is little research to determine the type of bank profiles. The first study in this regard is the approach of Glover and Florey (1951), which is an adaptation of tractive force approach related to US Bureau of Reclamation (USBR). Lateral diffusion term caused by the turbulence in his equations is ignored and cosine curve proposed for the

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banks. Parker (1978) justified the non-uniform shear stress distribution on the banks and channel bed by considering the lift force on the channel banks. In this case, initial cosine curve profile is modified. Ikeda et al. (1988) considered the main factor in holding stable state of the channels as lateral momentum transfer channels caused by turbulence that is lead to a reduction in the shear stress distribution from bed to the banks. The exponential shape is proposed for the channel banks in this case. Pizzuto (1990) stated that the channel widening and erosion in the channel banks are continued until to attain an equilibrium state. The exponential function was introduced in this case, but in following by flatting the channel bed the profiles shape of banks will be cosine curve. Diplas and Vigilar (1992) proposed the fifth-degree polynomial with a numerical solution of diffusion equations for fluid flow and balance forces equation for bank particles. Vigilar and Diplas (1997) by providing a numerical model considered the transition of momentum caused by the turbulence as a function of the flat bed width of the channel. They presented the three-degree polynomial function for shape profile of stable channel. Cao and Knight (1997) explained the non-moving particles in the banks by using the combination of the entropy concept with continuity equations and sediment transport relationships and proposed the parabolic curve for the bank profiles. Babaeyan-Koopaei and Valentine (1998) were one of the researchers that carried out several experimental studies on measuring the stable channel shape and dimensions. A hyperbolic function was fitted on their experimental results. For other experimental studies it can be noted to Stebbings (1963), Mikhailova et al. (1980), Ikeda (1981) and Diplas (1990) studies. Dey (2001) by providing a simple numerical code considered the momentum transformation as a function of transverse distance from the channel center which is described by a power law. Khodashenas (2016) examined extensive experimental research on the threshold channel at different flow discharges. By comparing the results with predecessor's model, results stated that the most conformity was seen with the Vigilar and Diplas (1998) results and the best shape for the banks is introduced as polynomial. Most mentioned studies are based on laboratory methods and numerical codes which are very time-consuming and costly. Gholami et al. (2018b) for the first time investigated the ability of artificial intelligence (AI) method in prediction of banks shape profile of threshold channels based on different observed datasets using robust gene expression programming (GEP) model. They presented a reliable relationship in estimating vertical boundary levels of channel banks with acceptable accordance with observed values.

Today, the application and development of the artificial intelligence (AI) method have been common in many sciences (Gholami et al. 2016a, b, 2019; Diop et al. 2018; Ebtehaj et al. 2016, 2018, 2019; Singh et al. 2017; Ghorbani et al. 2018; Li et al. 2018; Sanikhani et al. 2018; Sulaiman et al. 2018; Tao et al. 2018a, b; Yaseen et al. 2018a). Among these methods, fuzzy models of Takagi–Sugeno–Kang (TSK) as an adaptive neuro-fuzzy inference system (ANFIS) are known (Manu and Thalla 2017). To increase the speed and performance of ANFIS models, using optimization algorithms (Hosseini et al. 2016; Gholami et al. 2017b; Bonakdari and Zaji 2018; Karaboga and Kaya 2018) and evolutionary models (multi-objective optimization) (Dariane and Azimi 2016; Ahmadianfar et al. 2017; Saba et al. 2017; Karkevandi-Talkhooncheh et al. 2017; Nouiri 2017) has been very common. Regarding the use of AI methods in prediction of the stable channel geometry dimensions (width, depth and slope), it can be noted to Madvar et al. (2011), Taher-Shamsi et al. (2013), Bonakdari and Gholami (2016), Gholami et al. (2017a), Shaghaghi et al. (2017, 2018a, b). All of them referred to high ability of AI models in prediction of stable channels geometry. However, regarding application of AI methods (especially different ANFIS models) in estimation of cross-sectional banks shape profile of stable channels, it can be pointed out to recent contributions of authors. Accordingly, Gholami et al. (2018c) assessed the ability of evolutionary algorithm of particle swarm optimization (PSO) algorithm and genetic algorithm (GA) combined with ANFIS model. Their results showed the ANFIS-PSO/GA has an acceptable agreement with observed data with the relative error index of 0.1557 in prediction of vertical boundary level of stable channel shape profile. Gholami et al. (2018a) evaluated the ability of ANFIS-DE/SVD in prediction of the vertical boundary level of the stable channel. They referred to the high accuracy of this type of evolutionary algorithms combined with ANFIS model. DE algorithm has ability to choose the optimal non-linear coefficient of Gaussian membership function. On the other hands, the SVD can calculate the ANFIS consequent part's linear coefficients. Therefore, the examination of these algorithms in detail compared to each other in combination with ANFIS model is of great importance and necessary to choose them as alternatives to classic ANFIS model.

Therefore, the aim of this study is to evaluate the performance of classic ANFIS model, ANFIS optimized using differential evolution (DE) (ANFIS-DE) and ANFIS optimized multi-objective evolutionary algorithm using SVD (ANFIS-DE/SVD) compared to each other in estimation of banks shape profile of stable channels. Indeed, based on the previous literature studies that we conducted, the main goal of the present paper is evaluating the impact of hybridization in classic ANFIS method, extensively to choose the optimal and efficient method in measuring cross-sectional shape of stable channels. In this study, the question of "whether improvements of ANFIS models using different optimization and evolutionary methods in better prediction of the shape profiles of stable channel banks are effective or not?"

is answered. At first, the experimental studies of the coordinates of the points located on the boundary of the stable channel at four different discharges in the laboratory are measured by the authors. Then, using these data the models of ANFIS, ANFIS-DE and ANFIS-DE/SVD are trained and tested. The performance of these models in prediction of bank shape profiles is evaluated and compared with each other (ANFIS-DE compared to ANFIS and ANFIS-DE/SVD compared to ANFIS-DE), and also the best model is presented. Furthermore, the capability of these hybrid models is assessed in different flow discharge values and the proposed shape profile is presented accordingly.

Experimental work

In this study, four laboratory sets by the authors in hydraulic laboratory of the Department of Civil and Geological of the University of Saskatchewan, Canada, to measure the two parameters of depth or vertical level of points (y) located on the channel boundary and the transverse distance of the points from the channel axis (x) are done in an equilibrium channel state. The used flume of the channels has dimensions of $20\times1.22\times0.6$ m in length × width × height directions. The channel bottom is filled of uniform sand with $d_{50}=0.053$ mm. Cross-sectional shape is in two triangular and trapezoidal modes. Experiments are done in four different discharges of 1.157, 2.18, 2.57 and 6.2 l/s. Laboratory sets specification is shown in Table 1. A magnetic flow meter is used to measure the flow discharges. Deal of conducting the experiments is like that in each runs the desired discharge passed through the channel and to achieve the equilibrium state in the channel cross section and plan the discharge is kept constant. The passed through water is drained from the channel and channel geometry and coordinate points specifications in the stable channel boundary are measured at different cross sections. Two levels of channel water and bed using a point gages at different transverse distances of 8, 9, and 11 m from the channel entrance are measured. Also point gauge measurements by a laser gauge are checked. In this experiment, the flow parameters at stable state in two different cross sections: channel upstream end points with zero bed load, and the downstream channel end points with a maximum bed load on the channel bed (wider cross section) which is measured. In this study, the results of measured dimensions and shape of the stable channel related to the first mode (upstream end points) are used. A view of a laboratory flume is shown in Fig. 1. The channel shape in stable state is a particular importance in the formation of banks profile geometric forms. Figure 2 shows two bank profiles characteristic. In this figure, x and y are the transverse and vertical distance from the central axis of the channel bed (m), h is the flow depth in the channel centerline, and T shows the water surface width, respectively. The bank profile characteristics are dimensionless as follows:

$$y^* = y/h \text{ and } x^* = x/h,\ T^* = T/h.$$

where x^*, y^* and T^* are dimensionless values of x, y, and T.

Table 1 Different experiment characteristics

Test no.	Discharge (Q) (l/s)	d_{50} (mm)	S	h (cm)	Cross section's shape
1	1.157	0.53	0.0023	37	Triangular
2	2.57	0.53	0.0023	61.3	Triangular
3	6.2	0.53	0.0023	80	Triangular
4	2.18	0.53	0.0023	61.2	Compound channel

Evolutionary Pareto design of ANFIS

Gholami et al. (2018a) applied DE and SVD model in hybrid with ANFIS model. They expressed the rules of these methods extensively and detailed. In this section, how to optimize the ANFIS networks to model the thresholds channel bank profile by combining this method with differential evolution (DE) as an evolutionary algorithm and singular value decomposition (SVD) as a powerful numerical method is expressed in summary.

Modeling using ANFIS

ANFIS network includes a set of IF–THEN fuzzy rules of fuzzy systems of TSK (Takagi and Sugeno 1985). This network is capable of modeling to establish a mapping between inputs of multi-inputs with one output (multi-inputs–single outputs) as well. In an identification problem, the main goal is to find the function $\hat{f}$ as using leads to a good accuracy estimation of actual f function. In fact, this function using an input vector $X = \{x_1, x_2, \ldots, x_n\}$ estimates the function $\hat{f}$ as obtained y as closely as possible to be close to

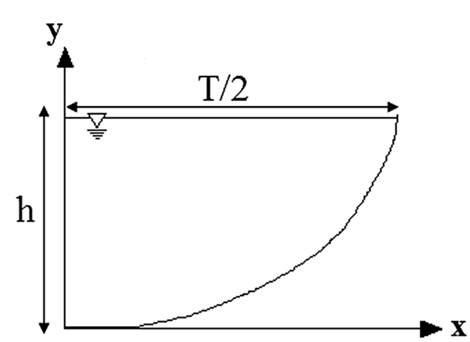


Fig. 1 Geometry definition sketch of bank profile in stable channel

Fig. 2 A view of studied laboratory flume

the actual value using mean square error (MSE) (Gholami et al. 2018a). TSK fuzzy rules of the ANFIS models can be expressed as follows:

$$\text{Rule}_l : \text{ IF } x_1 \text{ is } A_l^{(j_1)} \text{ AND } x_2 \text{ is } A_l^{(j_2)} \text{ AND} \ldots x_n \text{ is } A_l^{(j_n)} \\ \text{THEN } y = \sum_{i=1}^{n} w_i^l x_i + w_0^l \tag{1}$$

where $j_i \in \{1, 2, \ldots, r\}$ and $W^l = \{w_1^l, w_2^l, \ldots, w_n^l, w_0^l\}$ are parameter sets related to the consequent part of each TSK-type fuzzy rules. The fuzzy sets due to the good performance Gaussian membership function (Azimi et al. 2016; Khoshbin et al. 2016) are considered as a Gaussian shape in the range of $[-\alpha_i, +\beta_i]$ $(i = 1, 2, \ldots, n)$ (Gholami et al. 2018a). Each fuzzy set $A^{(j)}(j = \{1, 2, \ldots, r\})$ which has a Gaussian shape is defined as follows:

$$\mu_{A^{(j)}}(x_i) = \exp\left(\left(-\frac{x_i - c_j}{2\sigma_j}\right)^2\right) \tag{2}$$

where σ_j and c_j are variances and centers (respectively) related to parameters antecedent part. These parameters should be adjusted to gain the optimized results. It is clear that the number of parameters in the antecedent part of ANFIS is equal to the multiplication of the input vector (n) in the number of fuzzy sets in each antecedent (nr) (Gholami et al. 2018a). By Mamdani algebraic product concept, the degree of TSK-type fuzzy IF–THEN rules could be assessed (Gholami et al. 2018a).

The $\mu_{A_l^{(j_i)}}(x_i)$ is the membership function degree of x_i concerning their linguistic value of lth fuzzy rules $\left(A_l^{(j_i)}\right)$. A singleton fuzzifier regarding product inference engine and accumulation of individual contribution of each fuzzy rules results in following fuzzy system form:

$$f(X) = \frac{\sum_{l=1}^{N} y_l \left(\prod_{i=1}^{n} \mu_{A_l^{(j_i)}}(x_i)\right)}{\sum_{l=1}^{N} \left(\prod_{i=1}^{n} \mu_{A_l^{(j_i)}}(x_i)\right)} \tag{3}$$

The above relationship is a set including the number N of fuzzy rules as Eq. (1). The above equation can be rewritten in linear form as follows:

$$f(X) = \sum_{l=1}^{N} p_l(X) y_l + D \tag{4}$$

where D is the difference of predicted value ($f(X)$) and corresponding real value (y). It is evident that for a set of pair data of multi-inputs–single output (x_i, y_i) $(i = 1, 2, \ldots, m)$, Eq. (4) is rewritten as matrix form:

$$Y = PW + D \tag{5}$$

where $W = [w_1, w_2, \ldots, w_s]^{\mathrm{T}} \in R^s$, $S = N(n+1)$, and $P = [p_1, p_2, \ldots, p_s]^{\mathrm{T}} \in R^{m \times S}$.

Since the number of data pairs used in the model training process is usually more than all the coefficients in the conclusion part of TSK-type fuzzy rules, the rules are sufficiently small. These conditions lead to a least-square approximation process to estimate the unknowns $W = [w_1, w_2, \ldots, w_s]^{\mathrm{T}}$, as the difference between the actual and predicted values (D) is minimized (Gholami et al. 2018a). Correction of coefficients in the conclusion part of fuzzy rules similar to those described above leads to better estimation of data pairs for multi-inputs–single output (x_i, y_i) $(i = 1, 2, \ldots, m)$ which reduce the vector D as much as possible that shows the difference between estimated and actual values. Using direct methods to solve main normal equations shows too much sensitivity to round-off and, more importantly, is prone singularity. Therefore, to avoid this, in this study, singular value decomposition (SVD) as a powerful and widely used numerical method to calculate the linear coefficients corresponding to the conclusion part of TSK-type fuzzy rules to avoid the risk of singularity in Eq. (5) is used. In addition, in this study using a combination of SVD and differential evolution (DE), ANFIS network optimization design for modeling of thresholds channel bank profile is done. Details about the combination of SVD and DE methods are expressed in following.

Application of DE in optimize design of ANFIS

In this study, to have an optimal design parameters membership function of the network ANFIS algorithm DE (Storn and price 1997) is used. The used membership function in this study is in the Gaussian form (Eq. 2) (Gholami et al. 2018a). Coefficients set that should be optimized in this function to model the thresholds channel bank profile with the least amount of errors are as $\{c, \sigma\}$. An overview of the algorithm DE and operators in this algorithm was expressed in Gholami et al. (2018a).

Overview of DE

Differential evolution (DE) which is introduced by Storn and price (1997) is a population-based evolutionary algorithm for universal optimization of continuous search domain. Accordingly, using mechanisms defined for algorithm that includes operators crossover (or recombination), selection and mutation proceeds in development and optimization of random respond vector is considered (Gholami et al. 2018a). In following, the basic control variables related to the algorithms include population size (NP) crossover constant (CR) and mutation scale factor (F) which expressed distinctly.

Mutation DE algorithm by adding differences between vectors of two populations to a third vector, the new vectors parameter is generated. This function is known as mutation. Then, to obtain a trial vector, mutated vector parameters with an estimated vector (target vector) are combined; for each target vector, a mutant vector is defined as follows:

$$v_{i,G+1} = x_{r1,G} + F * (x_{r2,G} - x_{r3,G}) \tag{6}$$

$x_{i,G} = 1, 2, \ldots, \mathrm{NP}$ (NP is population size which is constant during search process).

In the above equation, coefficients r_1, r_2, r_3 are defined members of the population for the problem which are selected randomly as any one of them is similar to each other. In the above equation, the parameter F is scaling factor. This factor controls the differential variation related to $(x_{r2,G} - x_{r3,G})$. DE mutation operator is presented in Fig. 3.

Crossover In this function, parent and mutant vectors are combined and trial vector (u_{ji}, $G+1$) which are defined as follows is created:

$$u_{ji,G+1} = \begin{cases} u_{ji,G+1} & \text{if } (\mathrm{rnd}_j \le \mathrm{CR}) \text{ or } j = rn_i \ (j = 1, 2, 3, \ldots, D) \\ x_{ji,G+1} & \text{if } (\mathrm{rnd}_j > \mathrm{CR}) \text{ and } j \ne rn_i \ (j = 1, 2, 3, \ldots, D) \end{cases} \tag{7}$$

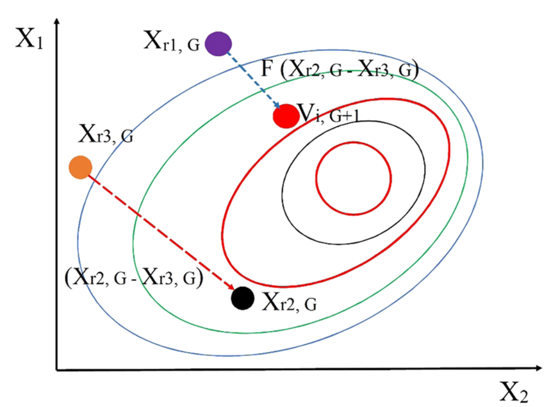


Fig. 3 Mutation operation in DE

where CR $\in [0,1]$ is the crossover constant, $\text{rnd}_j \in [0,1]$ is a random value, D is dimensions of a vector, and $\text{rn}_i \in (1,2,3,\ldots,D)$ is the randomly chosen index.

Selection This operator evaluates the trial vector generated by the crossover and mutation operators. In fact, the performance of target and trial vector is compared and vectored with better performance is selected. If the target function value of the vector trial is less, the vector in the target vector is copied and used in the next generation. Otherwise, target vector is transferred to the next generation.

$$x_{i,G+1} = \begin{cases} u_{i,G+1} & \text{if } f(u_{i,G+1}) \le f(x_{i,G}) \\ x_{i,G+1} & \text{Otherwise} \end{cases} \tag{8}$$

Mutation scale factor distribution control

To achieve an optimal design of the system ANFIS, it is needed to determine the amount of DE algorithm operators. NP and F values should be determined. NP value using trial and is considered 80, but the mutation scale factor (F) using trial and error is difficult. In this study, the amount of the operator using the distance F from the optimal solution is obtained. As parents vector positions in large amounts, so that of Pareto front indicates its great distance from the optimum population. Thus, according to far distance from optimal solution, more search solution to achieve optimized solution of mutation scale factor (F) is required and its value is closer to 1. Due to the near condition to optimal solution and limited space search, Pareto front in the lower layer decreases toward zero. Diagram, Pareto front schematic figure to determine the mutation scale factor (F) is as Fig. 4 (Gholami et al. 2018a).

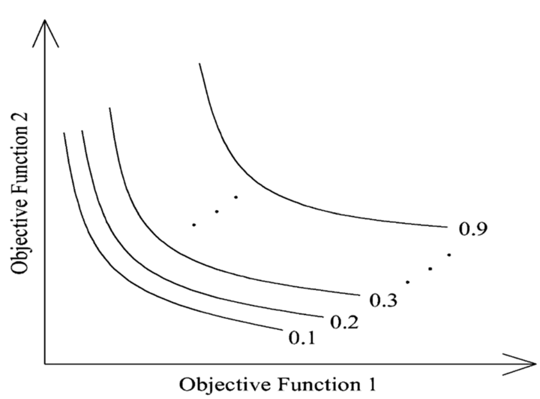


Fig. 4 Mutation scale factor (F) based on proximity to optimal solution in Pareto front (Azimi et al. 2016)

Application of SVD in ANFIS design

In this study, the optimum design and estimation of linear parameters of the conclusion part of fuzzy sets, the SVD (Golub and Reinsch 1970) is used. This method to solve the least-square problem that singularity is there in the governing equations is used (Azimi et al. 2016). SVD of the matrix $P \in R^{M\times S}$ is consist of the factorization of it and produces three different matrices including a diagonal matrix that has nonnegative components to prevent of singular values $Q \in R^{S\times S}$, a column-orthogonal matrix $U \in R^{M\times S}$ and orthogonal matrix $V \in R^{S\times S}$ is (refer to Gholami et al. 2018a for more explanations).

Bank profile of threshold channel modeling by ANFIS-DE/SVD

In this study, to model and optimal estimation of the bank profile of threshold channel using the method presented in this study (ANFIS-DE/SVD), the Pareto curve is used. By defining functions training error (TE) and predicting error (PE) as objective functions, the optimal point regarding the model performance in both mentioned target function is evaluated and optimal point selected. To select an optimal point, nearest to ideal point (NIP) (Khalkhali et al. 2016) method is used. The TE, PE, and Trd points presented in Fig. 5 represent the point with the largest prediction error, the point with the most training error showing the optimal point (respectively). In fact, the main goal is to find the point Trd that simultaneously in both training and prediction model mode show good performance which is selected as the optimal point. Also, Fig. 6 shows the graph of Gaussian membership function (MF), for each inputs of the present

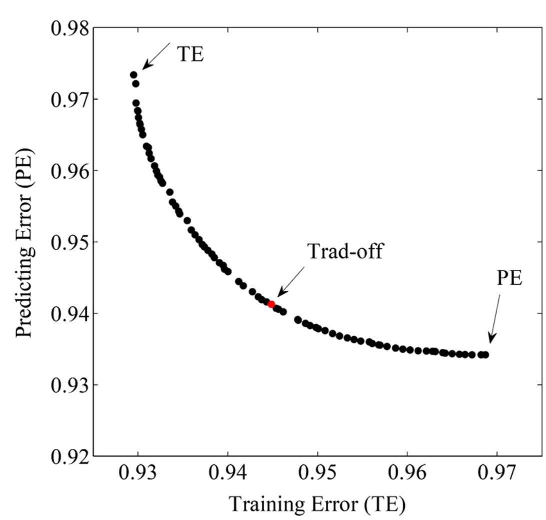


Fig. 5 Pareto curve of training error and prediction error

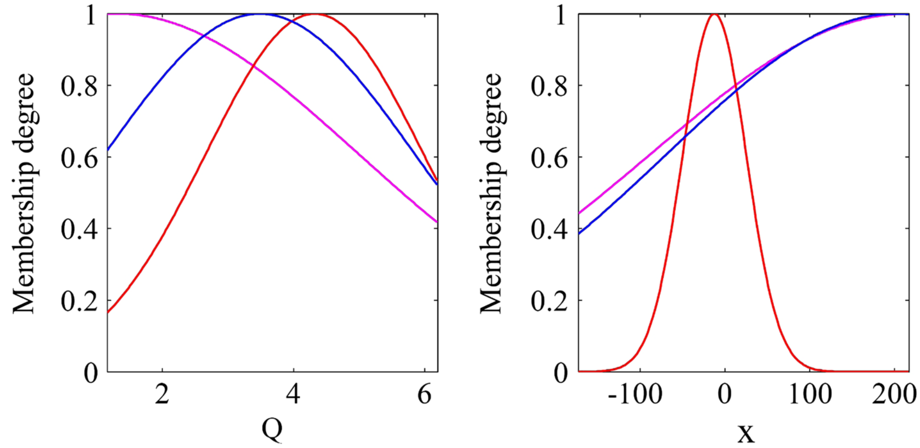


Fig. 6 Optimal membership function form of the trade-off design point

Table 2 Optimal parameters of Gaussian membership functions in trade-off point

	Q	X
σ	3.69	303.04
	1.67	37.42
	2.37	270.76
C	1.32	214.92
	4.32	− 12.21
	3.48	201.70

problem (Q, x). The values of these functions using a combination of DE and SVD method with ANFIS for the optimal point are obtained. Optimal values for each input are presented in Table 2. Axes x and y in the figure represent the amount of input parameters (Q or x) and the respective membership degree. Also according to the figure, it is observed that the number of membership functions in this study, for each input is equal to 3.

Statistical error criteria for models performance

In the present study to assess and evaluate the performance of ANFIS, ANFIS-DE and ANFIS-DE/SVD models, various statistical indices are used. Three indices of absolute error mean error (ME), mean absolute error (MAE) and root-mean-squared error (RMSE) and relative error mean absolute percentage error (MARE) and other statistical parameters BIAS and ρ according to Eqs. (9–16) are used (Khosravi et al. 2018; Yaseen et al. 2018b).

$$\mathrm{ME} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i) \tag{9}$$

$$\mathrm{MAE} = \frac{1}{n}\sum_{i=1}^{n}\left|y_i - \hat{y}_i\right| \tag{10}$$

$$\mathrm{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{11}$$

$$\mathrm{MARE} = \frac{1}{n}\sum_{i=1}^{n}\left(\frac{\left|y_i - \hat{y}_i\right|}{y_i}\right) \tag{12}$$

$$R = \frac{\sum_{i=1}^{n}(y_i - \bar{y}_i).(\hat{y}_i - \bar{\hat{y}}_i)}{\sqrt{\sum_{i=1}^{n}(y_i - \bar{y}_i)^2 \sum_{i=1}^{N}(\hat{y}_i - \bar{\hat{y}}_i)^2}} \tag{13}$$

$$\mathrm{BIAS} = \frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)}{n} \tag{14}$$

$$\mathrm{SI} = \frac{\mathrm{RMSE}}{\frac{1}{n}\sum_{i=1}^{n} y_i} \tag{15}$$

$$\rho = \frac{\mathrm{SI}}{1 + R} \tag{16}$$

In the above equations, y_i, $\hat{y}_i$ and predicted values and $\bar{y}_i$, $\bar{\hat{y}}_i$ average of these values are observed, respectively, and n is the number of parameters. Error indices MAE, RMSE, MAE and MARE represent the difference between the model and the observed values with the same unit and scale. The value close to zero of these indices presents a more accurate and less difference between the models with observed data (Kisi and Yaseen 2019). BIAS index shows the performance models in estimation of the values as negative and positive values indicate underestimation and overestimation of the model. SI index values are dimensionless index of RMSE. Error functions showed only the error between observed data and the model error values and there is no correlation between them. Therefore, using an index that simultaneously shows the error value and the correlation between the values appears appropriate index. Hence, this study investigates the index ρ as an ideal index to compare the models (Gandomi and Roke 2013; Gholami et al. 2017c, d).

Results and discussion

Figure 7 shows the regression plots for the predicted y^* values by ANFIS, ANFIS-DE and ANFIS-DE/SVD models compared to the corresponding observed values in two train and test mode. In addition, various error index values for each model are estimated and also bar graph to compare the models is drawn in this figure. It can be seen from

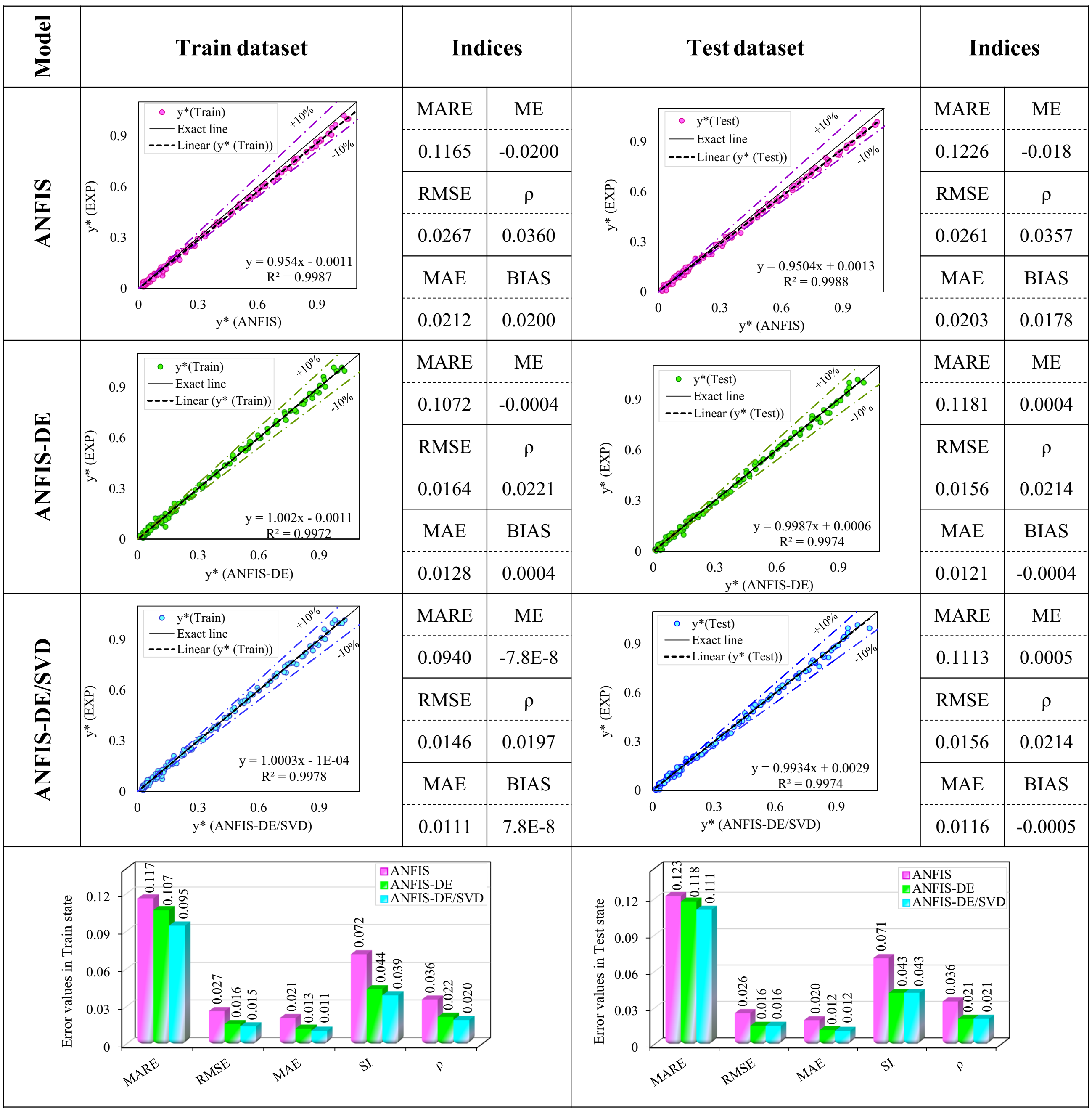


Fig. 7 Scatter plots of the y^* value predicted by the ANFIS, ANFIS-DE and ANFIS-DE/SVD models compared to the corresponding laboratory values and error index bar graphs

the graphs that in ANFIS model data are far from the exact line and the fitted line with a large gap is located on the right side. Also, it can be seen in the bar graph that the MARE index value in the ANFIS model is higher than the rest ANFIS-DE and ANFIS-DE/SVD models which using two DE and DE/SVD algorithms, the simple ANFIS model accuracy is increased (respectively, about 8.6% and 14% in the train mode). According to R^2 values close to 1, in all three models it can be realized that models are capable of predicting the coordinates of points on the stable channel boundaries. ρ index that combines the two indices R and SI is able to express the correlation between the data with error between them (Gandomi and Roke 2013). It is clear from the values of this index that value of this index in the ANFIS-DE/SVD model is less than the other two models that represent the less error of this model in prediction. In this model, the impartial value close to zero of index ME ($-7.8E-8$) (which represents the actual difference between the predicted and observed data) than the other two models has also considerable differences. Moreover, in comparison with ANFIS-DE compared to ANFIS, it can be seen that almost all error indexes in ANFIS-DE are more less than these indexes in ANFIS model which represents the more efficiency of ANFIS-DE. Also, the high performance of ANFIS-DE/SVD compared to ANFIS-DE model is confirmed according to error indexes values. Therefore, it can be pointed out to high effect of optimized (ANFIS-DE) and evolutionary algorithms (ANFIS-DE/SVD) to improve the performance of ANFIS and ANFIS-DE models, respectively.

The positive and negative values of BIAS index indicate the model underestimation and overestimation, respectively, which can be seen from the positive values of this index in ANFIS model confirming the model overestimation. Overestimation of ANFIS model can be seen in large amounts of predicted y^* value and can be said that this model predicts the coordinate in the points near the water surface much greater than the observed data. The comparison of the water surface profiles predicted by the three models and the impact of flow discharge parameter (Q) is discussed in the subsequent sections. SI is the dimensionless index of RMSE (squared difference between predicted and experimental) that lacks accuracy of this model in large y^* leading to an increase in this index (and larger bar length in the bar graph) in ANFIS model to the two other. Using DE optimization algorithm improves the ANFIS model performance, and the use of evolutionary algorithms DE/SVD also has a considerable impact on the performance of the model ANFIS-DE. It can be said in this paper that ANFIS-DE/SVD model with the lowest values of relative error (0.0940) than the ANFIS (0.1165) and ANFIS-DE (0.1072) is selected as the superior model. Therefore, it can be said that the proposed ANFIS-DE and ANFIS-DE/SVD can be used as alternative to classic ANFIS model in accurate estimation of stable channels shape and dimensions. These models can accurately detect the erosion and sedimentation processes of profiles formed on channel banks after reaching stable state or threshold motion of sediments in banks. Furthermore, it seems that the proposed hybrid methods can detect the widening free water surface during stability state due to overestimation of classic ANFIS model in these areas. So, using these hybrid models it can be confidently assured in implementation and execution of stable channels in urban watersheds.

In Fig. 8, stable bank profiles predicted by the three ANFIS model with experimental model with different itemizations of results have been compared at different discharges. Also, the bar graphs of error index for these three models are plotted in Fig. 9 in two different modes as the model performance at each four different discharges and the error resulted from the model is shown at each discharge. It can be seen from Fig. 9 that by increasing flow discharge almost in all three models, the less error index values are seen; especially in the model ANFIS-DE/SVD, the MARE value equal to 0.188 in discharge of 1.157 l/s reaches to 0.088 in discharge of 6.2 l/s (reduction about 53%). The highest and lowest amount of errors in all three models is in the minimum and maximum flow discharge, respectively (1.157 l/s and 6.2 l/s). A notable point in the graphs is that ANFIS-DE and ANFIS-DE/SVD models at high discharge rates have the lowest error which can be mentioned as an advantage of the hybrid models presented in this research. Therefore, the proposed hybrid models can well predict and detect the complicated flow pattern in high discharge values in field open channel compared to classic ANFIS model. These hybrid models are able to detect the widening free water surface, gradually increasing flow depth and decreasing transverse slope of banks with high adaption with observed values. These processes are occurred by channel to adjust its pattern in plan and cross-sectional shapes during to reach stable state in alluvial natural channels (Yalin 1992; Ackert 2000). In Table 3, the error index value for the models at different discharges and also for the entire discharges (average) has been estimated in test mode. It can be seen from the table data that although at two discharges of 1.157 and 2.57 l/s, respectively, ANFIS-DE and ANFIS models have the lowest error indices, but in both discharges of 2.18 and 6.2 l/s, the error index in the ANFIS-DE/SVD model is the lowest amount. So that, it can be seen that the ANFIS-DE/SVD model can accurately estimate the widening in water surface almost similar to observed values better than classic ANFIS model which is physical justification of proposed hybrid models in this paper as before mentioned. Thus, using two-objective evolutionary algorithm of SVD significantly increases the efficiency and accuracy of ANFIS-DE and also ANFIS models. Also, both hybrid models of ANFIS-DE and ANFIS-DE/SVD are capable of predicting the flow pattern in stable channels after stability with hig adaption

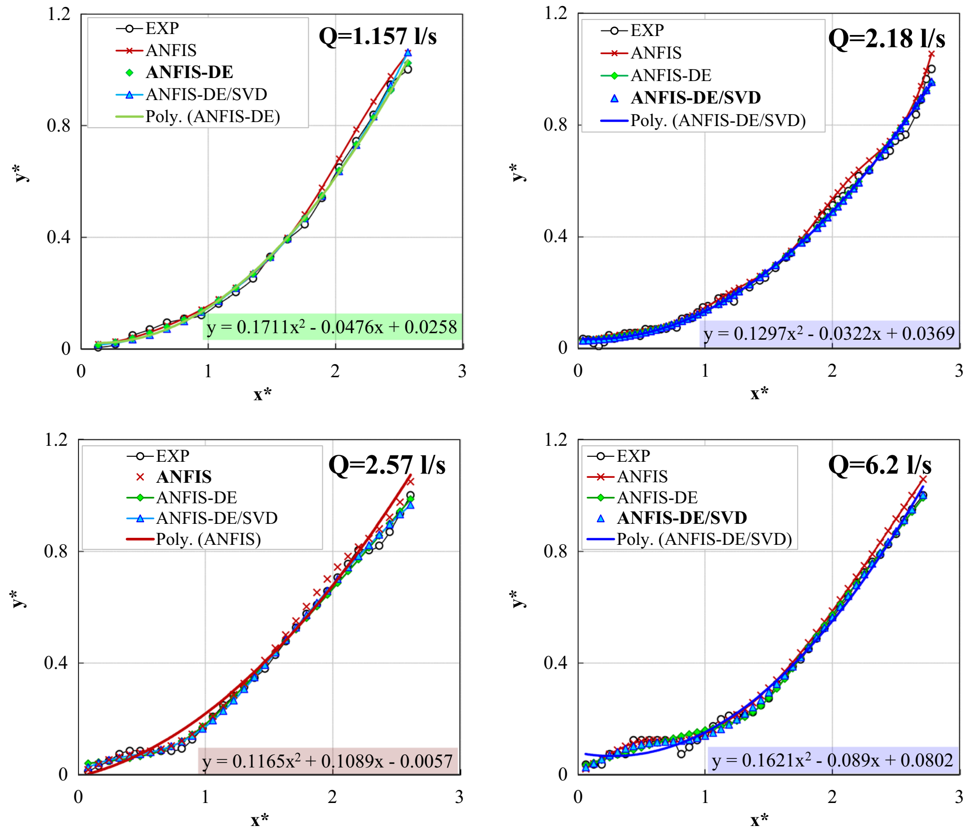


Fig. 8 Stable channel bank profiles predicted by the three models of ANFIS, ANFIS-DE and ANFIS-DE/SVD in comparison with laboratory values at different discharges and their fitted curves

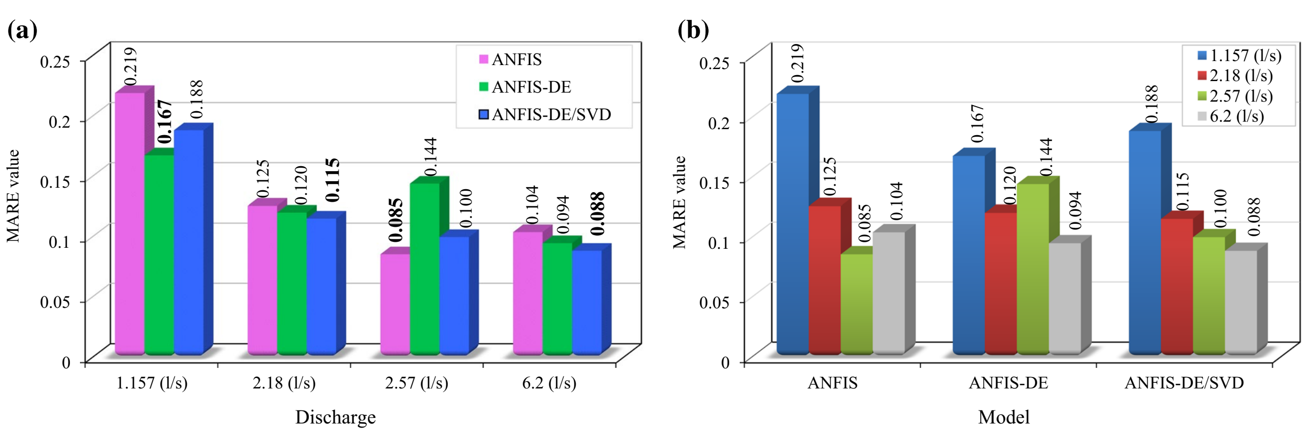


Fig. 9 Bar graphs error index MARE **a** at each discharge for three ANFIS, ANFIS-DE and ANFIS-DE/SVD models and **b** evaluation of the model performance at each model at four different discharge

with observed values. On the other hands, also in the lowest discharge (1.157 l/s), the ANFIS-DE model compliance with experimental data was evident that is more accurate than ANFIS model; therefore, using optimization algorithms of DE has a significant role in improvement of performance of ANFIS model. ANFIS-DE/SVD model difference with experimental data at discharge of 1.157 l/s in the level close to water surface is clear that by increasing the flow discharge the model accuracy is increased and at discharge of 6.2 l/s is perfectly compliance with experimental values. By increasing the flow discharge to 2.57 l/s, although ANFIS model error is less than the other two, but the compliance of values predicted by the ANFIS-DE and ANFIS-DE/SVD models at the levels close to water surface with experimental values is more. It can be said that ANFIS-DE and ANFIS-DE/SVD models are well able to predict the water surface widening by increasing discharge through the channel as mentioned before. Cross-sectional shape over time is important in stable

Table 3 Evaluation and comparison of the model ANFIS, ANFIS-DE and ANFIS-DE/SVD at different discharges and in total (average) using various statistical indices (test mode)

Discharge (l/s)	Models	MARE	RMSE	MAE	ME
1.157	ANFIS	0.220	0.0007	0.0215	−0.018
	ANFIS-DE	0.167	0.00017	0.0120	−0.0012
	ANFIS-DE/SVD	0.188	0.00035	0.0140	−0.003
2.18	ANFIS	0.125	8.5E−5	0.0049	−0.0035
	ANFIS-DE	0.1198	7.1E−5	0.005	−0.00014
	ANFIS-DE/SVD	0.115	6.5E−5	0.0050	0.0001
2.57	ANFIS	0.085	0.00074	0.0217	−0.020
	ANFIS-DE	0.144	0.00030	0.1410	−0.00037
	ANFIS-DE/SVD	0.099	0.00024	0.0123	−0.0010
6.2	ANFIS	0.104	0.0007	0.022	−0.018
	ANFIS-DE	0.0944	0.00031	0.0124	−6E−6
	ANFIS-DE/SVD	0.088	0.00023	0.011	−0.0005
Total	ANFIS	0.1226	0.0261	0.020	−0.018
	ANFIS-DE	0.1200	0.0156	0.0121	0.00037
	ANFIS-DE/SVD	0.1113	0.0156	0.0106	0.00026

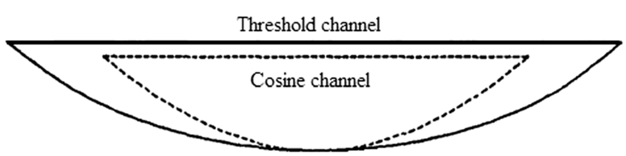
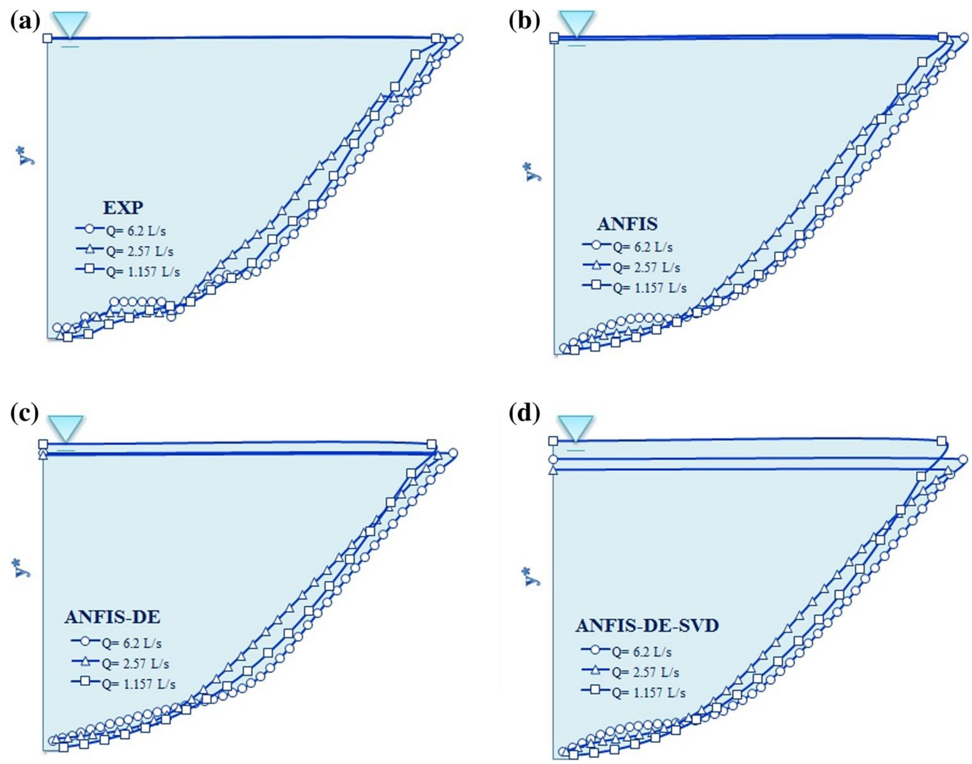


Fig. 10 Comparison of threshold channel and cosine channel profiles (Vigilar and Diplas 1997)

channels as all the predecessors know the general mode for threshold channels like Fig. 10. Accordingly, it has been suggested by researchers that the lateral momentum transfer term induced by turbulence is often applied in their equations which is proposed the shear stress distribution as non-uniform (Cao and Knight 1997; Vigilar and Diplas 1997; Dey 2001). Opposing to classic cosine mode, in the early years by researchers described the theory of stable channels and ignores the lateral diffusion term in their equations with no movement of sediments (Glover and Florey 1951; Parker 1978). In "threshold channel" mode, by increasing flow discharge, the water surface width is increased (widening) and transverse bank slope is gradually decreased associated with sediments movement through the bed and threshold motion of sediments in banks (Yu and Knight 1998). This model is a simple form of natural channel. Therefore, a model that can predict the formed trend of threshold channel well and be far from the original classic mode (cosine channel) is of particular importance. In the highest flow discharge rates (6.2 l/s), ANFIS-DE/SVD model always has the most accuracy than the rest of the models and discharges. Error reduction in ANFIS-DE/SVD model compared to ANFIS-DE and error reduction in ANFIS-DE model compared to ANFIS are evident in all discharges. So that, the hybrid models proposed in this paper can well estimate the physical processes of alluvial channels in which the flow is comfortable (Ackert 2000). Hence, it can be said that using evolutionary algorithm has a significant impact on improvement of performance of classic ANFIS model. And in respond to the mentioned question "Is evolutionary and optimization algorithms in improvement of the performance of ANFIS model is effective or not?" Replied yes these algorithms (especially the optimization algorithm DE) had a positive impact on improving the model performance. As the performance of ANFIS-DE model compared to simple ANFIS about 10.1%, and the ANFIS-DE/SVD compared to ANFIS-DE model almost 7.2% improved also ANFIS-DE/SVD model accuracy to simple ANFIS model 18.6% gets better. It can be said that in addition to the use of optimization algorithms DE having a significant impact on increasing the performance of a simple ANFIS model, using evolutionary algorithms ANFIS-DE/SVD causes a reduction in ANFIS-DE model error. It can be seen from the index values for total discharge in Table 3 that the accuracy of the ANFIS-DE/SVD model is more than two ANFIS and ANFIS-DE models. Also, in the graphs of Fig. 8, the equation of the fitted line is drawn for the superior model at each discharge value. The equation of the lines is second-degree polynomial that is in compliance with the results of Vigilar and Diplas (1998) and Dey (2001). Dey (2001) and Khodashenas (2016) considered the polynomial equation as the best and most logical fit for stable channel shape profiles that the lower degree reflects the more accuracy of the model: Diplas and Vigilar (1992) fifth-degree polynomial, then Vigilar and Diplas (1998) third-degree polynomials and in the present study second-degree polynomial as the best fit is suggested. Furthermore, the hybrid ANFIS-DE/SVD models presented in this study as the most accurate model than predecessor models are selected and introduced. Therefore, the hybrid models proposed in this paper can be used to implement and design of stable channels. However, the proposed models are considered and trained based on certain hydraulic conditions according to this paper. Therefore, the application of obtained results in this paper can be applied with some cautions and limitations for other stream geometries, other substrate conditions (cohesive/cohesiveless), other geological conditions in the field and various flow conditions (Hey and Thorne 1986; Gomez 1993; Dade 2000; Davidson and Hey 2011; Kaless et al. 2014; Pfeiffer et al. 2017).

In Fig. 11, the wall of the stable bank for each model in different discharges for better comparison is drawn. It

Fig. 11 Stable bank walls at different flow discharges predicted by **a** experimental model, **b** ANFIS, **c** ANFIS-DE and **d** ANFIS-DE/SVD models



is clear from the figures that in each model by increasing flow discharge, water level widening is well evident that by all models is predicted and have a good conformity with the corresponding experimental values. More conformity of ANFIS model compared to two hybrid models is well observed. But the widening and reduction in the bank slope of the channel to reach stable state cause a reduction in flow depth that at high discharges by two ANFIS-DE and ANFIS-DE/SVD models which is well simulated. In this mode, the ANFIS-DE model compared to the simple ANFIS model and ANFIS-DE/SVD to ANFIS-DE performing more successful. Notable point at high discharges is clear prediction of this depth reduction by the ANFIS-DE/SVD model that it is known as an advantage of hybrid ANFIS-DE/SVD model.

Conclusions

Channel dimensions during the stable state formation that no movement of sediment in flow or a mobile bed of particles and threshold banks particles is done have a particular importance. In addition to dimensions, a model that can predict the reasonably shape profile by considering the conditions and governing rules on the threshold channels in design and implementation of stable channel cross section has many applications. In this study, models ANFIS, ANFIS evolved with the use of DE and hybrid ANFIS-DE/SVD model by defining two objective functions and using of Pareto curve to predict the shape profile formed in the stable channel banks are designed and evaluated. Furthermore, the main goal of this paper was to extensively examine the performance of different evolutionary algorithms in hybrid with ANFIS model in estimation of the bank profile shapes of stable channels. Review of the results shows that in different flow discharges, all three models are capable of predicting the stable channel profiles accurately and are in good conformity with experimental data. However in general, using evolutionary DE and SVD algorithms causes an improvement in the performance of the classic ANFIS model and the prediction error by these hybrid models is reduced about 20% in estimation of boundary vertical levels of stable bank profiles. Accordingly, by using DE algorithm and simultaneous DE/SVD algorithm in hybrid with ANFIS model, the ANFIS-DE and ANFIS-DE/SVD models performance improves about 10% and 18.6% compared to classic ANFIS model. Moreover, also using DE/SVD causes to increase the efficiency of ANFIS-DE/SVD model equal to 7.2% compared to ANFIS-DE model. Therefore, it can be pointed out to high ability of hybrid models in estimation of bank profile shapes and can be used as alternative to classic ANFIS model in design and implementation of stable channels. In high discharges, the hybrid ANFIS-DE/SVD model is capable well of predicting the water surface widening, reducing the slope and depth of the channel which are the advantages of this model compared to the classic ANFIS model. However, it should be attention and cautions to limitation of these models in estimation of cross-sectional bank profile shapes of stable channel in other hydraulic, geometry and geomorphologic conditions different with available observed conditions in this paper. Following the research, other clustering and sampling algorithms [fuzzy *C*-means clustering (ANFIS-FCM) and ANFIS-SC] in prediction of dimensions and shape of stable channels are recommended.

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