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Optimizing ANFIS for sediment transport in open channels using different evolutionary algorithms

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ABSTRACT

Flow through open channels can contain solids. The deposition of solids occasionally occurs due to insufficient flow velocity to transfer the solid particles, causing many problems with transfer systems. Therefore, a method to determine the limiting velocity (i.e. Fr) is required. In this paper, three alternative, hybrid evolutionary algorithm methods, including differential evolution (DE), genetic algorithm (GA) and particle swarm optimization (PSO) based on the adaptive network-based fuzzy inference system are presented: ANFIS-GA, ANFIS-DE and ANFIS-PSO. In these methods, evolutionary algorithms optimize the membership functions, and ANFIS adjusts the premises and consequent parameters to optimize prediction performance. The performance of the proposed methods is compared with that of the general ANFIS using three different datasets comprising a wide range of data. The results show that the hybrid models (ANFIS-GA, ANFIS-DE and ANFIS-PSO) are more accurate than general ANFIS in training with a hybrid algorithm (hybrid of back propagation and least squares). Among the evolutionary algorithms, ANFIS-PSO performed the best (R^2=0.976, RMSE=0.26, MARE=0.057, BIAS=-0.004 and SI=0.059).

1. Introduction

Solid particles that deposit in entry flow through open channel systems can eventually become consolidated or cemented, especially during dry weather flow (DWF). In DWF, the lowest discharge passes through the channel. The flow velocity is below the minimum velocity required to sediment transport without deposition (limiting velocity), causing solid deposits on the channel bottom. Solid deposition on the channel bottom besides increasing bed roughness cause reduced cross-sectional area. Consequent to material deposition due to changes in velocity and shear stress distribution, reduced transmission capacity is expected.

Conventional methods of determining the limiting velocity employ constant velocity or shear stress by applying practical engineering experience obtained from project to project. Constant velocity and shear stress were presented comprehensively by Vongvisessomjai et al. (2010). These methods do not consider sediment and flow characteristics, therefore the limiting velocity, which is often presented as underestimated or overestimated, leads to sediment deposits or uneconomical plans, respectively (Bonakdari and Ebtehaj 2014a; Safarzadeh and Mohajeri 2016). Hence, many experimental and analytical studies have been conducted to investigate the factors influencing limiting velocity estimation (Nalluri and Ab Ghani 1996; Ota and Nalluri 2003; Banasiak 2008; Vongvisessomjai et al. 2010; Bonakdari and Ebtehaj 2014b) and several regression-based equations have been recommended. Since understanding the mechanism of sediment transport in open channels due to its complex three-dimensional nature is difficult, existing equations cannot provide precise estimates of limiting velocity (Ebtehaj et al. 2014). Soft Computing (SC) performs well in different engineering fields, such as Multi-reservoir real-time operation rules (Akbari-Alashti et al. 2014); sediment transport in sewer systems (Ebtehaj and Bonakdari 2013; 2016a); wastewater treatment (Amiri et al. 2015); Scour depth (Khan and Azamathulla 2012; Najafzadeh et al. 2014); side weir discharge capacity (Parsaie and Haghiabi 2014; Ebtehaj et al. 2015); and longitudinal velocity field (Zaji and Bonakdari 2015). Fuzzy systems are one of the most widely applied methods that yield good prediction results. Azamathulla et al. (2012) predicted sediment transport in clean sewers using adaptive neuro fuzzy inference systems (ANFIS). The authors compared the results of ANFIS with a non-linear regression (NLR) equation and found that ANFIS is more accurate than NLR. Reservoir water level was estimated using ANFIS by Valizadeh and El-Shafie (2013). To improve the ANFIS ability, they used a certain membership function for each input parameter. A performance evaluation of the developed ANFIS indicated its higher accuracy over general ANFIS. Akrami et al. (2014) predicted rainfall using ANFIS. To eliminate prediction error due to noisy data, the authors combined a wavelet transform with ANFIS (Wavelet-ANFIS). The results showed that Wavelet-ANFIS performed better than ANFIS.

Combining evolutionary algorithms with other SC methods in engineering problems leads to increased accuracy. Kisi (2010) modeled suspended sediment concentration by combining differential evolution (DE) and artificial neural networks (ANN). A comparison of ANN-DE with general ANN and ANFIS showed the superior performance of ANN-DE in forecasting suspended sediment concentration. Afshar et al. (2013) evaluated the performance of multi-objective particle swarm optimization (MOPSO) in automatic calibration of water quality and hydrodynamic parameters. The results indicated that MOPSO provides a wide range of all potential calibration solutions for better decision-making. Tayfur et al. (2013)

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surveyed sediment load prediction by a hybrid genetic algorithm and artificial neural network (ANN-GA) method. They found that ANN-GA is able to predict total sediment load with good accuracy. Sahay and Srivastava (2014) forecasted monsoon floods in rivers using a combination of GA, ANN and wavelet transform. To process the time series and optimize ANN's initial parameter, they used a wavelet transform and GA, respectively.

Ebtehaj and Bonakdari (2014a) evaluated the performance of ANFIS in forecasting sediment transport. The authors suggested the application of evolutionary algorithms rather than back propagation and hybrid algorithms, and compared them. Thus, in this paper, the performance of evolutionary algorithms, i.e. differential evolution (DE), genetic algorithm (GA) and particle swarm optimization (PSO) based on ANFIS (ANFIS-DE, ANFIS-GA and ANFIS-PSO) in predicting sediment transport in pipe channels using three datasets is surveyed. using dimensional analysis, the effective parameters on limiting velocity (Fr) prediction are placed in 5 groups and 6 proposed models. As a result, the performance of all models is evaluated using ANFIS, ANFIS-DE, ANFIS-GA and ANFIS-PSO.

2. The concept of ANFIS

2.1. ANFIS structure

In this paper, in order to predict the limiting velocity to prevent sediment deposition on the channel bed, a neuro fuzzy system is used. The neuro fuzzy system is a modeling framework in the form of a hybrid artificial neural network (ANN) and fuzz logic (FL). The hybrid model is presented to overcome the limitations in both FL and ANN methods. In fact, inspired by fuzzy systems, basic knowledge in a collection of constraints showed a reduction in the optimization search space. Meanwhile, a structured network is inspired by ANN back propagation. In this method, ANN tunes the membership functions (MFs) (Singh et al. 2012). There are also non-linear membership functions in the neuro fuzzy method, which lead to notable reduction in the implementation cost of a simple design based on rules and memory consumption. Thus, it is clear that a hybrid of neural networks and fuzzy systems reduces the limitations of each of two methods, hence a data mining technique is proposed to solve complex engineering problems. Adaptive neuro fuzzy inference system (ANFIS) is one of the known methods of simultaneously combining neural networks and fuzzy systems. This method is used to identify the performance of nonlinear systems with input and output datasets defined for the model. ANFIS is a structured, fuzzy inference system (FIS) model. Two of the most prominent FIS used in ANFIS are Mamdani (Mamdani and Assilan 1975) and Takagi-Sugeno-Kang (TSK) (Takagi and Sugeno 1985; Jang 1992). TSK is simpler because there is less need for rules and it uses known training methods like back propagation. Two of the algorithms by default in ANFIS training are back propagation and hybrid (hybrid of back propagation and least squares).

A schematic ANFIS structure for a network with two inputs (x, y) and one output (f) is presented in Fig. 1. The considered rules with two IF-THEN rules for FIS of TSK-type can be expressed as follows:

Rule 1
$$\begin{aligned}&IF \quad x \ is \ A_1, \quad and \ y \ is \ B_1,\\ &Then \quad f_1 = p_1 x + q_1 y + r_1\end{aligned} \tag{1}$$

Rule 2
$$\begin{aligned}&IF \quad x \ is \ A_2, \quad and \ y \ is \ B_2\\ &Then \quad f_2 = p_2 x + q_2 y + r_2\end{aligned} \tag{2}$$

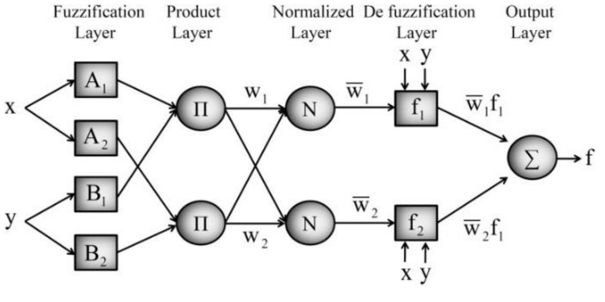

Fig. 1. ANFIS architecture for 2 inputs and 1 output.

The number of nodes in the first layer with the use of entire nodes and the number of membership functions (n) for each input is determined. However, the number of nodes in other layers (layers 2 to 4) depends on the rule (R) in each fuzzy rule base. The ANFIS layer structure is as follows:

The first layer (fuzification layer): The Xi input comprising the membership degree label of fuzzy set A_{ij}, shows the membership degree of each fuzzy collection. The node function of this layer can be expressed as follows:

$$O_{ij}^{1} = \mu_{ij}(X_i) \quad i = 1,2,..., number\ of\ inputs, \quad j = 1,2,...,n \tag{3}$$

where μ_{ij} is the j^{th} MF for the X_i input and O_{ij}^1 is the output of node ij. Due to the satisfactory performance of Gaussian membership functions in various engineering applications (Zanganeh et al. 2009; Güneri et al. 2011; Abdi et al. 2012; Karasakal et al. 2013; Bosque et al. 2014; Premkumar and Manikandan 2015), the membership function used in this study is a Gaussian-shaped MF. This function has smoothness and concise notation as well. The Gaussian MF mathematical relationship is as follows:

$$\mu(X) = exp\left(-\frac{X-a}{b}\right)^2 \tag{4}$$

where a and b are the parameter set.

The second layer (produce layer): the nodes in this layer (k), which are provided as circular nodes (Π), generate output using the received input.

$$\begin{aligned}&O_k^2 = W_k = \mu_{e1}(X_1)\mu_{e2}(X_2)..\mu_{ek}(X_k)\\ &k = 1,2,...,R \quad e1...e2 = 1,2,...n\end{aligned} \tag{5}$$

The third layer (normalized layer): in this layer, the k^{th} node determines the relative firing strength of the k^{th} rule to the firing strengths of all rules as follows:

$$O_k^3 = \overline{W}_k = \frac{W_k}{W_1 + W_2 + ... + W_R} \quad k = 1,2,...,R \tag{6}$$

The fourth layer (de-fuzzification layer): Each node in this layer is an FIS weighted output performed as follows:

$$O_k^4 = \overline{W}_k f_k \tag{7}$$

where W_k and f_k are the output layer of de-fuzzification and k^{th} TSK-FIS, respectively. The m TSK-FIS number rules are as follows:

$$f_k = \sum_{i=1}^{m} p_{i_{ei}} + r_k \tag{8}$$

where $p_{i,ei}$ and r_k comprise the parameter set. The parameters of this layer are referred to as consequent parameters.

$$O_i^5 = Y = \sum_{k=1}^{n} \overline{w}_k f_k = \frac{\sum w_k f_k}{\sum w_k} \tag{9}$$

where Y represents all network outputs. To evaluate ANFIS performance, mean squared error (MSE) indicators are used, which are calculated as follows:

$$MSE = \frac{1}{n}\sum_{i=1}^{n}(Fr_{Actual} - Fr_{Predicted})^2 \tag{10}$$

where n is the pattern number, Fr_{Actual} is the observed Fr in the experimental tests and $Fr_{Predicted}$ is the Fr predicted by ANFIS.

Fig. 2 shows a flowchart of ANFIS. Firstly, the datasets are classified into two parts: training and testing. In this study, 70% and 30% of data were used for training and testing of the model, respectively. FIS generation is done following categorization. There

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are two methods, namely grid partitioning and subtractive clustering to carry out FIS generation. In this study, grid partitioning (Ebtehaj and Bonakdari 2014a) is used owing to better performance. At this stage, the numbers and types of input and output MFs should be determined. In this study, the Gaussian membership function (Eq. 4) is used as an MF. The number of MFs is determined by trial and error and considered equal to 3. The training network algorithm should be determined following FIS generation. For ANFIS training, back propagation and hybrid (back propagation algorithm with least squares) are normally used (Sobhani *et al*. 2010; Bilgehan 2011; Behera and Guruprasad 2012). Ebtehaj and Bonakdari (2014a) indicated that hybrid algorithm performance is better than back propagation. Therefore, in this study the performance of a hybrid algorithm is compared with evolutionary algorithms, namely genetic algorithm (GA), Particle Swarm Optimization (PSO) and Differential Evolution (DE), as suggested by researchers for future studies. After training ANFIS, the prediction accuracy is assessed using test datasets and if satisfactory results are achieved, the modeling process ends; otherwise the FIS generation process is repeated to reach an acceptable solution.

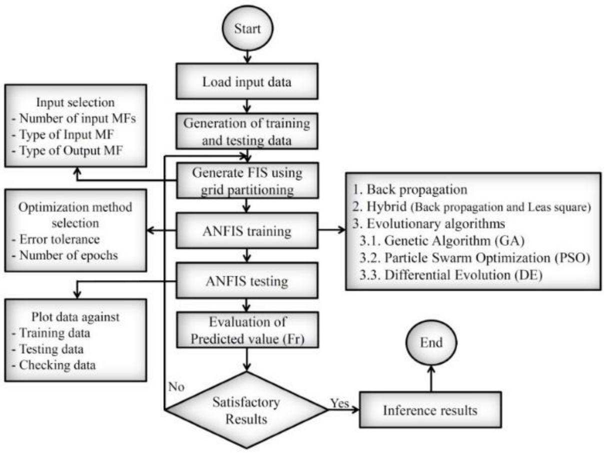

Fig. 2. General ANFIS flowchart.

2.2. Learning algorithms
2.2.1. Genetic Algorithm (GA)

Genetic algorithm (GA) is a stochastic optimization method that has performed successfully for various engineering issues. GA is capable of solving problems that gradient-based methods cannot solve well, such as nonlinear, stochastic and non-differentiable problems (Ocak. 2013). In conventional optimization approaches, in order to achieve the optimum solution, every point is generated using deterministic computations in each iteration and sequence of point approaches. In GA, the points of a population for each iteration are generated randomly and the best population point has a desire to the optimum solution that is similar to the final result (Goldberg 1989; Melanie 1996).

One of the most important steps in using GA to investigate an optimization problem is to provide an optimized potential solution to the problem as an individual or gene sequence known as chromosomes. The most common way of encoding problems as binary strings is to use zero and one strings. The basic steps in a genetic algorithm are presented in Fig. 3.

GA includes three essential components. The first part concerns creating an initial population using the m^{th} individual that was randomly selected. The initial population produces the first generation. The second part consists of entering the m^{th} individual and generating the output; evaluating each is based on the objective function known as a fitness function (Fig. 3). The evaluation determines the demands expected of each individual in order to achieve the ultimate goal. Finally, the third component is responsible for the new generation. A new generation is created based on the fittest individual from the previous generation.

Evaluating the process of producing generation N and generation N + 1 based on the N generation continues until the desired function is achieved. Offspring generation, which is based on the fittest individual related to the previous generation, is known as breeding. The breeding process consists of three basic steps in GA: reproduction, crossover and mutation.

Reproduction is done by two genetic operators, namely crossover and mutation. Crossover is a process in which the parent's genes change, but mutation is where genes randomly modify in the parent chromosome. Both of these operations have significant impact on the search space and a lack of appropriate values may not provide good results. Crossover and mutation represent searching the new solution area and the behavior of a random jump into unknown areas in the search space, respectively (Holland 1992). The genetic evolution algorithm process for different generations continues until a termination condition is fulfilled. The best gene call is decoded in the last generation in order to achieve the desired, optimum solution to the problem.

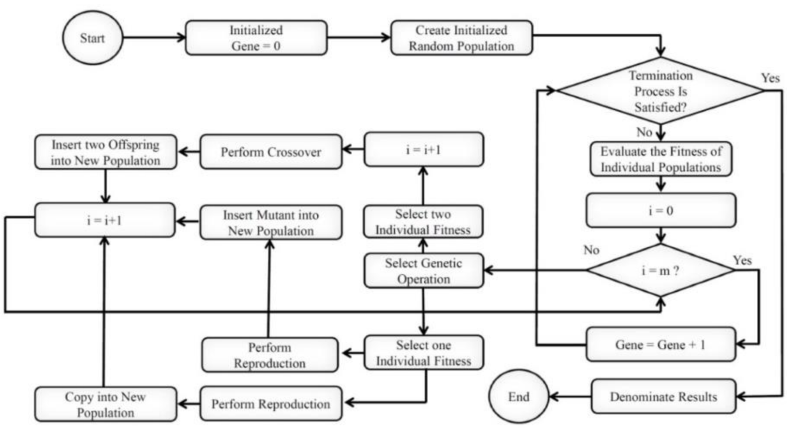

Fig. 3. GA flowchart

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2.2.2. Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is a smart method group (swarm) presented by Eberhart and Kennedy (1995). It is inspired by the social behavior of birds and fish. PSO is a population-base search method, in which every particle could be a candidate for the optimum solution. Particles change their positions in a multi-dimensional search space to achieve an optimal condition or limited circumstance calculation.

Empirical observations show good performance in the optimization methods field (Naka et al. 2002; Mendes et al. 2004; Yu and Li 2004). Thus, this method has been widely used in engineering optimization problems (Eberhart and Hu 1999; Yoshida et al. 2000; Ciuprina et al. 2002; Ratnaweera et al. 2004; Heo et al. 2006; Del Valle et al. 2008; Pedersen and Chipperfield 2010; Mousa et al. 2012; Ebtehaj and Bonakdari 2016b). A PSO algorithm flowchart is presented in Fig. 4. The first step is to determine the initial particle swarm, P(k), so that the $x_{is}(k)$ position of each particle ($P_i \in P(k)$) in hyperspace is equal to k = 0. The second stage is to evaluate the F function performance for each particle using the particle position ($x_i(k)$).

$$if \quad F(x_i(k)) < pbest_i \quad then \quad \begin{cases} pbest_i = F(x_i(k)) \\ x_{pbest_i} = x_i(k) \end{cases} \tag{11}$$

In the third stage, the best particle performance of each individual is evaluated as follows:

$$if \quad F(x_i(k)) < gbest_i \quad then \quad \begin{cases} gbest_i = F(x_i(k)) \\ x_{gbest_i} = x_i(k) \end{cases} \tag{12}$$

In the fourth stage, for each individual, the velocity vector is changed using the following equation:

$$v_i(k) = wv_i(k-1) + r_1C_1(x_{pbest_i} - x_i(k)) + r_2C_2(x_{gbest_i} - x_i(k)) \tag{13}$$

where r and C are random parameters. The r_1 and r_2 parameters are in the range of (0, 1) while C_1 and C_2 are positive constant values. Ebtehaj and Bonakdari (2016b) concluded that the best result is achieved when the sum of these two parameters is not more than 4 $(C_1 + C_2 \le 4)$.

The w parameter is known as the weight parameter in the above equation. Careful selection of these parameters leads to a balance between local and global swarm performance, which reduces the iteration number. The value of the w parameter using the equation proposed by Shi and Eberhart (1998, 1999) is calculated as follows:

$$w = w_{max} - \frac{w_{max} - w_{min}}{iter_{max}}.iter \tag{14}$$

where w_{min} and w_{max} are the initial and final weights, respectively.

Also, itr_{max} is the maximum iteration value and itr is the iteration number.

In the fifth step, every particle transforms to its new location using the following equation:

$$x_i(k) = x_i(k-1) + v_i(k) \tag{15}$$

2.2.3. Differential Optimization (DE)

Differential Evolution (DE) belongs to evolutionary algorithm ancestors presented by Storn and Price (1997). DE is a random population-based algorithm. The difference between this method and other evolutionary algorithms is the use of differential mutation. In a desired solving population with n-dimensional space, fixed vector numbers are created randomly. To understand the different search spaces and reach the minimum objective function, evolution over time is needed.

A mutation function in DE (*F:* $I^\mu \rightarrow I^\mu$) consists of producing a mutated vector (*μ*) using the following equation:

$$\vec{v}_i = \vec{a}_{r1} + F(\vec{a}_{r2} - \vec{a}_{r3}) \quad i = 1,2,...,\mu \tag{16}$$

where r_1, r_2, $r_3 \in [1, 2,... \mu]$ are selected randomly. These parameters differ from each other and index *i*. $F \in [0\ 2]$ is a constant parameter affecting the differential variation between two vectors. Larger *F* or population size (*μ*) quantities tend to increase the capacity of the global search algorithm because a new area is known to the search space.

The crossover operator in DE (*CR:* $I^\mu \rightarrow I^\mu$) mutates the vectors $(\vec{v}_i = [\vec{v}_{1i}, \vec{v}_{2i}, ..., \vec{v}_{di}])$ with a target function $(\vec{a}_i = [\vec{a}_{1i}, \vec{a}_{2i}, ..., \vec{a}_{di}])$ (an answer to the previous population parent) to produce a trial vector combination $(\vec{a}'_i = [\vec{a}'_{1i}, \vec{a}'_{2i}, ..., \vec{a}'_{di}])$ using the following equation:

$$a'_{ji} = \begin{cases} v_{ji} \ \ if \ \ (randb(j) \le CR) \ or \ j = rnbr(i) & j = 1,2,...,d \\ a_{ji} \ \ if \ \ (randb(j) > CR) \ and \ j \ne rnbr(i) & i = 1,2,...,\mu \end{cases} \tag{17}$$

where $randb(j) \in [0\ 1]$ is the j^{th} assessment of a uniform random generator and $rnbr(i) \in 1,2,\ldots,d$ is the random selection index. $CR \in [0\ 1]$ is the crossover parameter that increases the variety of individuals in populations. Larger *CR* values cause increased child vectors (a_i') similar to mutated vectors (v_i'). Thus, the algorithm convergence speed is increased. According to Eq. 17, each objective function has a target function rule. If *CR* is considered zero, vectors of parents and children differ from at least one variable (Eq. 17).

The selection operator in DE (*s:* $I\mu \rightarrow I\mu$) selects the best costly target function (a_i') and associated trial vector (a_i') as a part of the population for the next generation.

$$\begin{aligned} &If \ \ \Phi(\vec{a}'_i(g)) < \Phi(\vec{a}_i(g)), then \ \vec{a}_i(g+1)) = \vec{a}'_i(g)) \\ &else \qquad\qquad\qquad\quad \vec{a}_i(g+1)) = \vec{a}_i(g+1)) = \vec{a}_i(g)) \end{aligned} \tag{18}$$

where *g* is the current generation. The DE flowchart with the main operators is presented in Fig. 5.

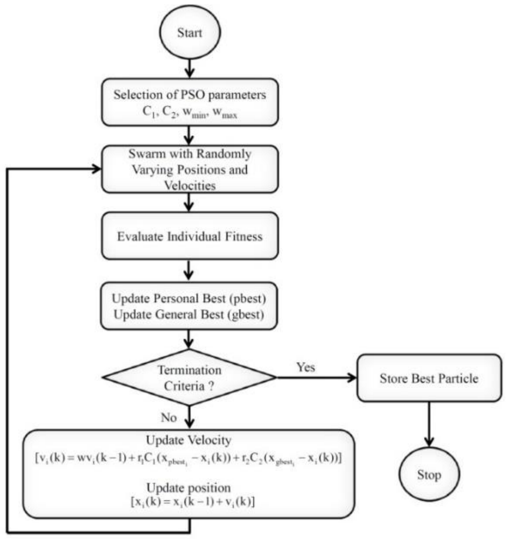

Fig. 4. PSO flowchart.

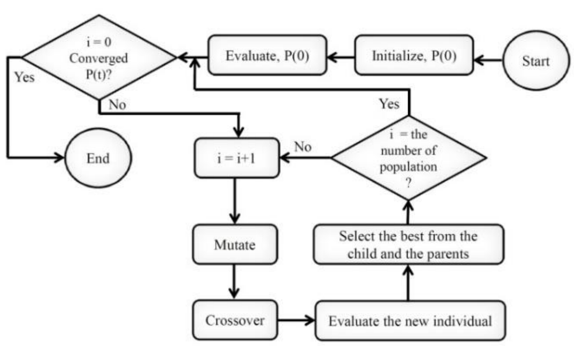

Fig. 5. DE flowchart.

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3. Methodology

To determine the minimum velocity required to avoid sediment deposition in open channels (limiting velocity), factors affecting flow velocity should be determined first. Experimental studies in the field of sediment transport with non-deposition condition consider parameters such as flow depth, volumetric sediment concentration, particle size and pipe diameter as effective parameters in determining the limiting velocity. Since each of the parameters includes different dimensions, the dimensionless parameters are used to determine the limiting velocity. Several studies have considered (Nalluri and Ab Ghani 1996; Ab Ghani and Azamathulla 2010; Azamathulla et al. 2012; Ebtehaj et al. 2013) limiting velocity parameters in assessing the functional relationship below:

$$Fr = V/\sqrt{g(s-1)d} = f(C_V, D_{gr}, d/D, d/R, R/D, D^2/A, \lambda_s) \tag{19}$$

where Fr is the densimetric Froude number, V is the limiting velocity, g is the gravitational acceleration, s is the specific gravity of sediment (=ρ/ρ_s), C_V is the volumetric sediment concentration, D_{gr}(=$d(g(s-1)/v^2)^{1/3}$) is the dimensionless particle number, d is the median particle diameter, D is the pipe diameter, R is the hydraulic radius, A is the cross sectional area of the flow, and λ_s is the overall friction factor of sediment.

Ebtehaj and Bonakdari (2014a) classified the dimensionless parameters provided in Eq.19 in 5 different categories: movement (Fr), transport (C_V), sediment (D_{gr}, d/D), transport mode (d/R, D^2/A, R/D) and flow resistance (λ_s). Because there is only one parameter in the transport and flow resistance groups, this parameter is considered fixed. Sediment and transport have two and three different parameters, respectively; therefore, to consider the effect of all groups in Fr parameter estimation related to the movement group, six different models are presented as follows:

Model 1: Fr = f (C_V, D_{gr}, d/R, λ_s)
Model 2: Fr = f (C_V, D_{gr}, D^2/A, λ_s)
Model 3: Fr = f (C_V, D_{gr}, R/D, λ_s)
Model 4: Fr = f (C_V, d/D, d/R, λ_s)
Model 5: Fr = f (C_V, d/D, D^2/A, λ_s
Model 6: Fr = f (C_V, d/D, R/D, λ_s)

In this study, to predict the Fr parameter of the movement group in order to sediment transfer in non-deposition condition, three different data sets, including by Ab Ghani (1993), Ota and Nalluri (1999) and Vongvisessomjai et al. (2010), with a total of 218 different data are used. This data was obtained in different experimental conditions (pipe diameter, sediment and flow characteristics). Details of the experiments were presented in previous studies (i.e., Ebtehaj and Bonakdari 2014a, 2014b, 2016b).

For modeling, the data were divided into two categories in this study: 70 % of data (150) for training and 30% (68) for testing model performance. The control parameters for each evolutionary algorithm employed in this study are GA, DE and PSO (Table 1).

Table 1. Control parameter of evolutionary algorithms

	Parameters	Value
PSO	Number of iterations	5000
	Number of Particles	50
	Initial inertia weight w_{min}	0.9
	Final inertia weight w_{max}	0.3
	Cognitive acceleration C_1	2
	Social acceleration C_2	2
DE	Number of dimensions (D)	4
	Population size (NP)	20
	Mutation constant (F)	0.5
	Crossover constant (CR)	0.9
	parameters; boundaries Vj(U)	12
	parameters; boundaries Vj(L)	-12
GA	Population size	30
	Number of generations	60
	Crossover rate	0.8
	Mutation rate	0.2
	Selection Method	Roulette wheel selection

3.1. Statistical measure

The employed statistical indices to performance evaluation of densimetric Froude number are as follows:

$$R^2 = \left[\frac{\sum_{i=1}^{n}\left(Fr_{Expi} - \overline{Fr_{Exp}}\right)\left(Fr_{Modeli} - \overline{Fr_{Model}}\right)}{\sqrt{\sum_{i=1}^{n}\left(Fr_{Expi} - \overline{Fr_{Exp}}\right)^2 \sum_{i=1}^{n}\left(Fr_{Modeli} - \overline{Fr_{Model}}\right)^2}} \right]^2 \tag{20}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(Fr_{Expi} - Fr_{Modeli}\right)^2} \tag{21}$$

$$MARE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|Fr_{Expi} - Fr_{Modeli}\right|}{Fr_{Expi}} \tag{22}$$

$$SI = \frac{RMSE}{\overline{Fr_{Model}}} \tag{23}$$

$$BIAS = \frac{1}{n}\sum_{i=1}^{n}\left(Fr_{Expi} - Fr_{Modeli}\right) \tag{24}$$

4. Results and discussion

Fig. 6 shows the performance of the three hybrids, ANFIS-DE, ANFIS-GA and ANFIS-PSO as well as general ANFIS in estimating the limiting velocity, which is expressed as a dimensionless parameter, Fr, for 6 models proposed in the study. For each of the three hybrid models proposed using an evolutionary algorithm, model 1 produced good results. The values estimated by the three methods often had less than 10 % relative error. But clearly, the hybrid algorithm in ANFIS performance training did not do as well as other methods, with a relative error of more than 10% as under and overestimation was used. Results obtained from Table 2 show that the statistical indicators for six different models in both testing and training datasets and using evolutionary algorithms for all indexes leads to better estimation.

Compared to model 1, model 2 showed a completely different situation. Evidently, the performance of all models diminished. Since the only difference between this model and model 1 is using the D^2/A parameter instead of the d/R parameter, it can be concluded that with fixed parameters, including transport (C_V), flow resistance (λ_s) and sediment (D_{gr}), using parameter D^2/A rather than d/R leads to at least 10% increase in relative error with all methods. However, the relative error increase in the ANFIS-DE and ANFIS-GA methods is about 15%. Therefore, the second model in any method presented in this study is uncertain. The performance comparison between evolutionary and hybrid algorithms for the presented input combination in model 2 as obtained from Table 2 indicates the superiority of evolutionary algorithms.

Similar to model 2, model 3 may not perform so well. Nonetheless, the best performance among the parameters related to the transport mode is attained when parameter d/R is used as the group representative. The prediction progress of this model is quite different than the second. In Model 3, most estimates are lower than the experimental data values. Therefore, using the model with the input combinations suggested in model 3 leads to high sediment deposition on the channel bed.

The models' quantitative performance indicates that except for the ANFIS-PSO method, which increased the estimation accuracy less than the ANFIS model, ANFIS-DE and ANFIS-GA performed better than the ANFIS model. Using the DE and GA algorithms in ANFIS training decreased the relative error by about 12% compared to the hybrid algorithm. In comparing models 4 and 2, the parameters related to sediment from D_{gr} to d/D changed and other groups' parameters remained fixed.

Fig. 6 shows that the performance of model 1 is as good as model 4, and all estimated values had less than 10% relative error. Table 2 shows that all methods, namely ANFIS, ANFIS-DE, ANFIS-GA and ANFIS-PSO, performed better than model 1. In fact, selecting the sediment parameter using d/D leads to better results than d/R. But it is noteworthy that there is no significant difference in the index values of both models. Model 5, much like model 1, did not perform well; as a result, using d/D instead of d/R did not significantly change the outcomes, but there was improvement overall. The performance of model 6 compared to model 3 is similar to that of model 5 compared with 2. Using the d/D parameter related to sediment leads to better model performance than D_{gr}.

The comparison between the presented models and results obtained from Table 2 indicate the superior performance of model 4 among all methods. However, there were no significant differences between the hybrid methods, but the ANFIS-PSO Model 4 (R^2=0.976, RMSE=0.26, MARE=0.057, BIAS=-0.004 and SI=0.059) exhibited the best performance among the methods.

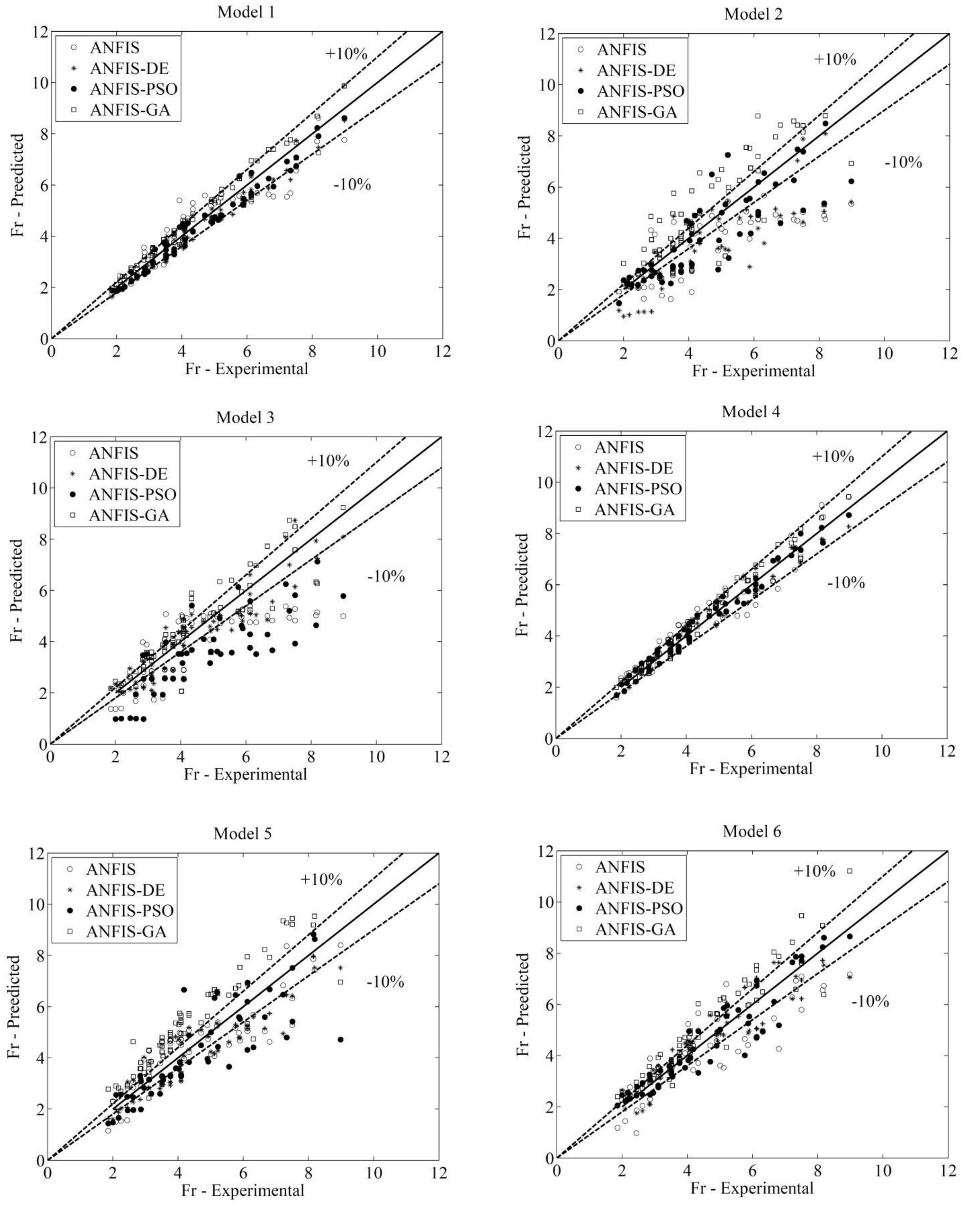

Fig. 6. Scatter plot of Fr prediction (testing).

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Table 3 presents the DR values (relative predicted Fr to observed Fr) of different methods and model 4 in this study. In this table, the differences of 0.05, 0.10, 0.15 and 0.20 to the value of the unit is provided for all methods (DR ±0.05, DR ±0.1, DR ±0.15, DR ±0.2). For the values with a difference of 0.05 to the unit (DR ± 5 %), ANFIS and two evolutionary methods, namely ANFIS-DE and ANFIS-GA showed approximately the same results; but it is clear that ANFIS-PSO had superior performance to the other methods.

Immense difference between the gross evolutionary ANFIS and general ANFIS was observed. Hence, the performance of the general ANFIS method was verified with values having difference of 0.1 to the unit (DR ± 10%). It can be concluded from Table 3 that all methods presented in this study had the maximum difference of 0.15 to DR = 1 (DR ± 15 %), which is 0.2 for general ANFIS.

Table 3. DR values for different ANFIS methods (Model 4).

Method (Model 4)	(DR±5%)	(DR±10%)	(DR±15%)	(DR±20%)
ANFIS	0.27	0.53	0.87	1
ANFIS-DE	0.29	0.82	1	1
ANFIS-PSO	0.4	0.9	1	1
ANFIS-GA	0.25	0.86	1	1

Table 2. Performance evaluation of ANFIS methods in prediction of Fr (All models)

	Models		R^2	RMSE	MARE	BIAS	SI
Train	Model 1	ANFIS	0.933	0.579	0.120	-0.051	0.146
		ANFIS-PSO	0.976	0.342	0.062	0.058	0.089
		ANFIS-DE	0.972	0.370	0.074	0.008	0.095
		ANFIS-GA	0.977	0.399	0.088	-0.201	0.102
	Model 2	ANFIS	0.707	1.136	0.260	-0.031	0.289
		ANFIS-PSO	0.905	0.638	0.099	0.002	0.164
		ANFIS-DE	0.840	0.831	0.167	-0.086	0.213
		ANFIS-GA	0.869	0.997	0.231	-0.527	0.256
	Model 3	ANFIS	0.637	1.255	0.282	-0.099	0.314
		ANFIS-PSO	0.874	0.736	0.160	-0.028	0.187
		ANFIS-DE	0.906	0.637	0.121	0.059	0.163
		ANFIS-GA	0.836	0.996	0.196	-0.457	0.255
	Model 4	ANFIS	0.963	0.406	0.094	-0.027	0.103
		ANFIS-PSO	0.984	0.262	0.060	-0.012	0.067
		ANFIS-DE	0.973	0.341	0.072	0.033	0.087
		ANFIS-GA	0.986	0.318	0.071	-0.185	0.082
	Model 5	ANFIS	0.665	1.198	0.267	-0.027	0.305
		ANFIS-PSO	0.899	0.659	0.102	-0.003	0.169
		ANFIS-DE	0.913	0.632	0.125	0.001	0.162
		ANFIS-GA	0.878	0.887	0.186	-0.424	0.227
	Model 6	ANFIS	0.733	1.080	0.221	0.153	0.288
		ANFIS-PSO	0.962	0.404	0.088	0.000	0.103
		ANFIS-DE	0.916	0.613	0.105	0.041	0.157
		ANFIS-GA	0.927	0.689	0.143	-0.343	0.177
Test	Model 1	ANFIS	0.882	0.590	0.099	0.072	0.137
		ANFIS-PSO	0.966	0.356	0.073	0.173	0.085
		ANFIS-DE	0.963	0.392	0.076	0.216	0.089
		ANFIS-GA	0.965	0.402	0.082	-0.249	0.092
	Model 2	ANFIS	0.611	1.375	0.240	0.895	0.394
		ANFIS-PSO	0.728	1.027	0.173	0.518	0.266
		ANFIS-DE	0.720	1.248	0.232	0.881	0.285
		ANFIS-GA	0.711	1.155	0.205	-0.525	0.263
	Model 3	ANFIS	0.572	1.340	0.254	0.762	0.370
		ANFIS-PSO	0.702	1.564	0.237	1.262	0.501
		ANFIS-DE	0.869	0.663	0.128	0.264	0.151
		ANFIS-GA	0.829	0.762	0.122	-0.235	0.174
	Model 4	ANFIS	0.929	0.452	0.091	-0.077	0.101
		ANFIS-PSO	0.976	0.260	0.057	-0.004	0.059
		ANFIS-DE	0.965	0.323	0.065	0.076	0.074
		ANFIS-GA	0.972	0.346	0.069	-0.175	0.079
	Model 5	ANFIS	0.463	1.223	0.229	0.023	0.280
		ANFIS-PSO	0.722	0.981	0.147	0.376	0.245
		ANFIS-DE	0.868	0.801	0.154	0.507	0.183
		ANFIS-GA	0.841	1.165	0.253	-0.882	0.266
	Model 6	ANFIS	0.538	1.201	0.179	0.348	0.297
		ANFIS-PSO	0.905	0.536	0.088	0.095	0.125
		ANFIS-DE	0.869	0.606	0.112	-0.023	0.138
		ANFIS-GA	0.899	0.785	0.138	-0.477	0.179

5. Conclusions

Sediment transport capacity is reduced by solid deposition in open channel flow. Therefore, an approach of estimating minimum velocity to prevent sediment deposition is required. This study presented three different evolutionary algorithms, i.e. differential evolution (DE), genetic algorithm (GA) and particle swarm optimization (PSO) based on adaptive neuro fuzzy inference systems (ANFIS), as new methods for estimating the limiting velocity (Fr). The new methods are ANFIS-DE, ANFIS-GA and ANFIS-PSO. To estimate Fr, previously conducted studies and dimensional analysis were used, and different dimensionless parameters were identified in 5 groups: movement, transport, sediment, transport mode and flow resistance. Studies have shown that the d/D parameter in sediment and the d/R parameter in transport mode perform the best in their groups. Therefore, the best model was chosen as Fr = f (C_V, d/R, d/D, λ_s). Comparing the proposed procedure performance with general ANFIS represents the ascending performance of ANFIS when using evolutionary algorithms in hybrid algorithms. Among the proposed methods, ANFIS-PSO (R^2 = 0.976, RMSE = 0.26, MARE = 0.057, BIAS = -0.004 and SI = 0.059) performed the best. Therefore, using evolutionary algorithms as an optimization algorithm method is useful to hybrid performance.

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