Adaptive Neuro-Fuzzy Inference System for Prediction of Bed-Load Sediment Transport in the Swash Zone

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Abstract
Fluid and sediment interactions occurring in the swash zone determine the erosion or accretion of the beach and act as boundary conditions for morphodynamic models. Therefore, it is necessary to predict the sediment transport in this area. In this paper, the abilities of Fuzzy Inference System (FIS) and Adaptive-Network-Based Fuzzy Inference System (ANFIS) methods are used to predict and modeling bed-load sediment transport in the swash zone. The ANFIS and FIS are established using the free stream velocity time series and antecedent sediment data. Statistic measures were used to evaluate the performance of the models. The cross-shore sediment transport rate and swash velocity time series for the swash experiments of Masselink and Hughes (1998) were used as case studies. Based on comparison of the results, it is found that the ANFIS-based predictions are slightly superior to the FIS-based predictions. Also, results indicate that using neuro-fuzzy approach in sediment transport modeling have a sufficient prediction accuracy.
Keywords: ANFIS, Sediment transport, Shields parameter, Swash zone.

Introduction
1. Introduction
The swash zone constitutes the area of the beach where the incident waves dissipating or reflecting their remaining energy after traveling towards shore. On the other hand, swash zone is a turn-point of sedimentation between offshore and onshore and maximum sediment transport loads have been observed in this region. Recently considerable attention has been committed to the contentious issue of swash motion, since the sedimentation process in this region is a paramount boundary condition for beach evolution.

To date, mathematical expressions describing sediment movement in the swash zone on the basis of the fundamental physics have not been established, due to the enormous complexity of the phenomenon (Van Rijn, 1993). Most existing models for coastal sediment transport have been developed by adapting and modifying the results for sediment transport in rivers. However, the driving forces in the swash zone region are different from that in river, as both waves and currents are involved. A precise evaluation of swash zone hydrodynamic processes is required to obtain reliable formulations for estimating the sediment transport rate. Many different formulations are available for estimating cross-shore sediment transport in the swash zone.

Sediment transport in the swash zone may be considered an exciting of the sediments by energetic swash and a net transport due to mean long-shore currents. Some researchers have found it useful to consider two separated phases of the swash cycle with different transport efficiencies. That is, sediment transport rates during the propagation of waves up the beach face (up-rush) and during the return flow down the slope (backwash) can be considered, individually (Masselink and Hughes, 1998). In an ample study involving field measurements and model estimation, Masselink and Hughes (1998) found that the Meyer-Peter and Muller (1948) equation required different empirical constants for linking measured velocities and sediment transport rates in up-rush and backwash, respectively. The up-rush coefficients were for formulation approximately two times the backwash coefficients. If we focus on the cross-shore direction, the sediment balance between the swash phases will give the overall erosion and accretion of the beach face (Puleo et al. 2000). The swash zone sediment transport and foreshore evolution has been analyzed in several studies (Larson et al., 2004; Miles et al., 2006). The sediment transport models described, do include some aspects of a detailed deterministic approach and have a certain validity range. The major shortcoming of these empirical formulas is that these formulas are not able to provide

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reasonable prediction in the field transport rate.

Recently, fuzzy inference systems have been recognized as a potentially valuable tool for modeling complex non-linear systems. A fuzzy inference system employing fuzzy IF-THEN rules can model the qualitative aspects of human knowledge and reasoning processes without precise qualitative analysis. The fuzzy modeling or fuzzy identification, first explored systematically by Takagi and Sugeno (1989), has numerous practical applications in control, prediction and inference. They have been applied in several engineering problems, e.g., flood forecast (Stuber et al., 2000), real time flash flood forecasting (Khondker et al., 1998), rainfall-runoff models (Minns and Hal, 1996) and scour depth (Bateni and Jeng, 2007).

In this paper, a FIS and an Adaptive-Network-Based Fuzzy Inference System, which can serve as a basis for consulting a set of fuzzy IF-THEN rules with appropriate membership functions to generate the stipulated input-output pairs, is used to predict and modeling Shields parameter and bed-load sediment transport in the swash zone. To verify the applicability of these models, the cross-shore sediment transport rate and swash velocity time series for swash experiment of Masselink and Hughes (1998) were chosen as a case study. In Section 2, the concepts of FIS and ANFIS models will be outlined. Then, the techniques that have been developed to estimate the cross-shore sediment transport rate in the swash zone will be presented in Section 3. A presentation of study area and data set and the results of FIS and ANFIS models are presented and discussed in Section 4. Finally, numerous conclusions will be drawn in Section 5.

Adaptive-Network- Based Fuzzy Inference System

Fuzzy logic is based on the fuzzy set theory that establishes a soft boundary between different levels of subjects where membership is defined by degree. Fuzzy logic is an extension of Boolean logic that allows intermediate values between True and False. The fuzzy models can be used as a means of capturing humans' expert knowledge about the process, in terms of fuzzy (IF-THEN) rules. The fuzzy inference system can initialize and learn linguistic and semi-linguistic (Sugeno) rules – therefore it can be considered as direct transfer knowledge, which is the main advantage of fuzzy inference systems over classical learning systems and Neural Networks. This suggests that the fuzzy process models can be initialized by expert knowledge and can be adapted by the use of process data. Often the rules of the fuzzy system are designed a priori and the parameters of the membership functions are adapted in the learning process from input-output data sets. Basically, a fuzzy inference system is composed of five functional blocks (Jang, 1993):

1. A *rule base* containing a number of fuzzy IF–THEN rules. In general, a fuzzy IF–THEN rule involves two parts. The first is IF part and the second is THEN part which are called premise and consequent, respectively.
2. A *database* which defines the membership functions of the fuzzy sets used in the fuzzy rules.
3. A *decision-making* unit which performs the inference operations on the rules.
4. A *fuzzification inference* which transforms the crisp inputs into degree of match with linguistic values.
5. A *defuzzification interface* which transforms the fuzzy results of the inference into a crisp output.

Several types of FIS have been proposed in the literature (Lee, 1990), upon the differences between the specification of the consequent part and the defuzzification schemes. Takagi and Sugeno FIS (Sugeno, 1985) is the most common one. In this study, we tends to incorporate the Sugeno fuzzy model presented by Takagi and Sugeno (1989) to propose a systematic scheme for the development of fuzzy rules using the input/output data sets.

There is no systematic way to determine what type and shape of membership functions of premise variables have the best performance in a defined FIS. An efficient way for doing this is using an Artificial Neural Networks (ANNs) model trained by input–output data. This approach is called ANFIS, which is explained in this section. In the Neural Network section, implementing the training methods a relation for obtaining information regarding the sets of data for fuzzy modeling is presented. Thereafter, the membership function parameters are designated in a manner that assigns the best fuzzy inference system to a set of variables. This system of training works is similar to Neural Networks.

ANFIS is a multilayer feed forward network which searches for fuzzy decision rules that perform well on any given task. The fuzzy decision rules are implemented as MFs and the model learns the best fitting parameters of the MFs. Even though ANFIS is a five-layer neural network, only two of these layers have adjustable weights. The first layer is composed of n MFs, each implementing a fuzzy decision rule. Any type of distributions can be modeled by MFs and the set of parameters to minimize is determined accordingly. The second layer computes every possible conjunction of the n decisions rules. The third layer normalizes the conjunctives MFs in order to rescale the inputs. The fourth layer is a standard perception and associates every normalized MF with an output (weights are called consequent parameters). Finally, the fifth layer sums the evidences. The output is a real number.

ANFIS uses back-propagation learning to determine premise parameters and least mean squares estimation to determine the consequent parameters. This is referred to as hybrid learning. A step in the learning procedure has got two passes: in the first or forward pass, the input patterns are propagated, and the optimal consequent parameters are estimated by an iterative least mean square procedure, while the premise parameters are assumed to be fixed for the current cycle through the training set. In the second or backward pass the patterns are propagated again, and in this epoch, back propagation is used to modify the premise parameters, while the consequent parameters remain fixed. This procedure is then iterated until the error criterion is satisfied.

The modeling method used by ANFIS is similar to most conventional methods. First the model architecture with specified parameters (related to input, input membership functions, rules and output membership functions) is assumed. Then, a series of input/output data applicable for ANFIS training is collected. Thereafter, ANFIS trains the fuzzy inference system using the available training data and modifies the membership function parameters with an assigned error limit to converge the data acquired from the model to actual values.

Estimation of Bed-Load Sediment Transport Rate in the Swash Zone

To date, due to the complexity of velocity and sediment concentration, empirical formulas based on numerous experiments on steady flow for defining the amount of sediment transport (Nielsen, 1992). Most of these formulas are based on relations between the bed effective shear stress and the dimensionless rate of sediment as follows:

$$\phi \propto (\theta-\theta_{cr})\sqrt{\theta} \qquad \phi = \frac{Q}{d\sqrt{(s-1)gd}} \tag{1}$$

where θ is the Shields parameter; ϕ is the dimensionless sediment transport rate; s is the specific weight of the sediment; d is the sediment diameter; and θ_{cr} is the critical shear stress to initiate sediment movement. The bed-load formula Meyer-Peter and Muller (1948) is as follows:

$$\phi_B = \begin{cases} 0 & for\ \theta \ge \theta_{cr} \\ C(\theta-\theta_{cr})^n & for\ \theta \ge \theta_{cr} \end{cases} \tag{2}$$

where C is the empirical constant. The studies devoted to sediment transport in the swash zone use the Meyer-Peter relations to evaluate the amount of transported sediment. Since, physically the up-rush and backwash flows are different, it seems logical that the sediment transport processes in these area also be different. Masselink and Hughes (1998) have shown that the Meyer-Peter formulas require empirical multipliers to relate the measures velocities with the sediment transport for the two phases (up-rush and backwash) of flow in the swash zone.

Masselink and Hughes (1998) show that Bagnold's energetics-based bed-load sediment transport equations were validated using their field data. Their findings have been confirmed by Nielsen (2002) as follows:

$$\phi(t) = \begin{cases} 0 & for\ \theta_{2.5} < 0.05 \\ C(\theta_{2.5}-0.05)\sqrt{\theta_{2.5}}\,sign(u_*(t)) & for\ \theta_{2.5} > 0.05 \end{cases} \tag{3}$$

$$\theta_{2.5} = \frac{\frac{1}{2}f_{2.5}}{(s-1)gd_{50}}\left[A_{rms}\omega_P\right]^n \times \left[\cos\varphi_\tau u_\infty(t)\sin\varphi_\tau \frac{u_\infty(t+\delta_t)-u_\infty(t-\delta_t)}{2\omega_P\delta_t}\right]^{2-n} \times sign(u_*(t)),\ n\in[0;1] \tag{4}$$

$$u_*(t) = \sqrt{\frac{1}{2}f_{2.5}}\left[\cos\varphi_\tau u_\infty(t)+\sin\varphi_\tau \frac{u_\infty(t+\delta_t)-u_\infty(t-\delta_t)}{2\omega_P\delta_t}\right] \tag{5}$$

$$f_{2.5} = \exp\left[5.5\left(\frac{2.5d_{50}}{A_{rms}}\right)^{0.2} - 6.3\right] \tag{6}$$

where d_{50} is the sediment diameter; ω_P is the angular frequency ; A_{rms} is the near bed semi-excursion; $\theta_{2.5}$ is the Shields parameter corresponding to a bed roughness of $2.5d_{50}$; $u_\infty(t)$ is the instantaneous free stream velocity; δ_t is the time step and $f_{2.5}$ is the wave friction factor corresponding to a bed roughness of $2.5d_{50}$; and φ_τ is the phase lead of the bed shear stress compared with the free stream velocity at the peak frequency. With the two different relations for up-rush and backwash are as follows:

$$C_{uprush} = 19.9 \pm 4.1$$
$$C_{bachwash} = 8.9 \pm 1.7 \qquad (7)$$

Note that the quasi-steady Shields parameter corresponding to quadratic drag

$$[\theta_{2.5}(t)]_{quasi-steady} = \frac{f_{2.5}}{2(s-1)gd_{50}} |u_\infty(t)| u_\infty(t) \qquad (8)$$

Eq. (3) gets with $\varphi_\tau = 0$. Nielsen (2002) presented two mechanisms for the sediment transport during up-rush (*i*) The existence of higher shear stresses during up-rush; and (*ii*) The existence of prefloating sediment from the.

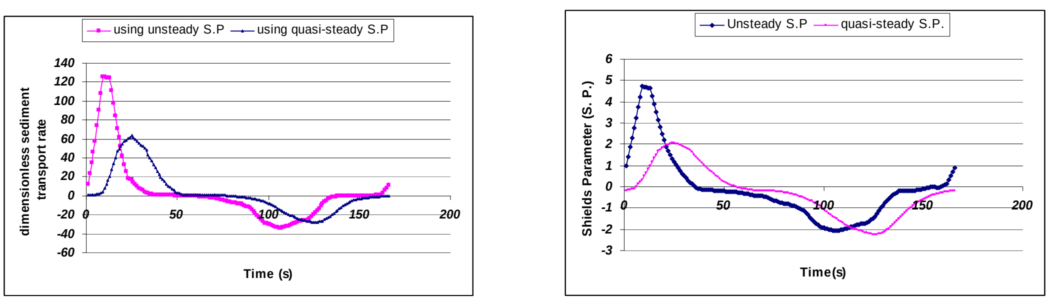
It should be noted that some mechanisms have not been considered in this formulation. For example, the observed lag between the instantaneous bed shear stress and the rate of sediment transport has not been considered. Therefore a complete knowledge of sediment transport in the swash zone is not available.

Nielsen (1992) modeled the shear stress of the bed by the time series of free level velocity in terms of the boundary layer. He postulated that the total amount of sediment transport during up-rush and backwash is well estimated by the model without the need for incorporating different multipliers for up-rush and backwash and suggested that the range in *C*-values is 9.7 ± 0.2. It should be noted that although the total amount of sediment transport is the same, the timing of sediment transport rate has not yet been accurately modeled due to the very unsteady nature of the swash zone and the existence of prefloated sediments.

The skill and predictive capability of FIS and ANFIS models developed for calculating the bed-load sediment transport in the swash zone is evaluate by comparison to data on sediment transport in the present study.

Case Study

The data implemented in this study are the swash velocity time series, corresponding quasi-steady Shields parameter, unsteady Shields parameter, dimensionless sediment transport rates using the quasi-steady Shields parameter and the two different *C*-values for up-rush and downrush, and dimensionless sediment transport rates using the unsteady Shields parameter and optimal *C*-value (9.7) for the swash experiments of Masselink and Hughes (1998). The swash velocity is between 1.98 to -1.90 *m/sec* (cf. Fig. 1).



Dimensionless sediment transport rate **Shields parameter (S.P.) and swash velocity**

Figure 1- Data set (Nielsen, 2002)

The data set were divided in 3 parts: The first part is used in FIS development and also as the training data in ANFIS modeling, the second one as the checking data in ANFIS modeling and the third one as the testing data for evaluation of developed FIS and ANFIS models. The training data set was used to train the ANFIS, whereas the testing data set was used to verify the accuracy and the effectiveness of the trained ANFIS model for the prediction of sediment transport. As a general rule, the model error for a set of checking data decreases from the start of the training process to the point of over-fitting. After this step the error of the model for checking data increases unexpectedly. That is to say, checking data cause the over-fitting of the model to decrease. If there is an apparent discrepancy between the training and checking data, by evaluating the checking data error in the training step, the inefficiency of the checking data for the model evaluation will be revealed. The hybrid-learning rule is used to train the model according to input/output data pairs.

The statistical parameters of swash velocity time series, the Shields parameters, and the dimensionless sediment transport rates data are shown in Table 1. It can be seen that the velocity, Shields parameters, and sediment data do not show a significantly high skewed distribution. This is confirmed by the low ratio between standard deviation and mean. The maximum–mean ratio (x_{max}/x_{mean}) for sediment series in the training period is as high as 5.

Table 1- The daily statistical parameters of data set (input/output)

Data set	Data Type	x_{mean}	Standard Deviation(SD)	SD/x_{mean}	x_{max}	x_{min}
Training	swash velocity	1.10	0.66	0.59	1.98	-0.04
Training	quasi-steady Shields parameter	0.75	0.81	1.07	2.07	-0.2
Training	unsteady Shields parameter	0.99	1.66	1.66	4.72	-0.46
Training	dimensionless sediment transport rates using eq.(8)	21.42	23.10	1.07	63.63	0.65
Training	dimensionless sediment transport rates using eq.(4)	25.28	39.91	1.57	125.97	-2.43
Testing	swash velocity	-1.27	0.56	-0.44	-0.02	-1.90
Testing	quasi-steady Shields parameter	-1.3	0.70	-0.53	-0.16	-2.26
Testing	unsteady Shields parameter	-0.89	0.90	-1.01	0.87	-2.07
Testing	dimensionless sediment transport rates using eq.(8)	-13.62	9.81	-0.72	-0.64	-27.92
Testing	dimensionless sediment transport rates using eq.(4)	-12.7	14.48	-1.13	11.03	-34.41

To calculate the performance of the FIS and ANFIS methods, using subtractive clustering method and training data including swash velocity time series as input variable and unsteady Shields parameter, quasi-steady Shields parameter, dimensionless sediment transport rates using the quasi-steady Shields parameter and the two different *C*-values for up-rush and downrush, dimensionless sediment transport rates using the unsteady Shields parameter and optimal *C*-value as output variables, a FIS is developed for estimation. Acceptable values for the radius of each cluster are usually between 0.2 and 0.4. Developed FIS is then used as an initial FIS for ANFIS modeling. ANFIS optimizes the premise and resulting parameters of initial FIS using neural network technique.
Using training data set, the coefficient of efficiency (E) is computed. E ranges from minus infinity (poor Model) to 1.0 (perfect model), and can be calculated as:

$$E = 1.0 - \frac{\sum_{i=1}^{N}(O_i - P_i)^2}{\sum_{i=1}^{N}(O_i - \overline{O}_m)^2} \qquad (9)$$

where O_i is an observed value; P_i is a predicted value; N is the number of observations; and $\overline{O}_m$ is the observed mean value. For training data, E is evaluated as equal to 0.91 which is close to 1.0, implying the successful training of the ANFIS model. After developing FIS and ANFIS models, testing data are used to verify the truthfulness of the predicted values of Shields parameters and sediment transport rates. The data set of swash experiments of Masselink and Hughes (1998) is used as training, testing, and checking data.

Many various membership functions such as trapezoidal, triangular, Gaussian function, etc. can be applied to determine the membership grades. In this study, the generated Gaussian membership function given below was used:

$$\mu_{A_i}(x) = a_i \exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \qquad (10)$$

where $\mu_{A_i}(x)$ is the membership functions; x is the crisp inputs to the node i; and $\{a_i, b_i, c_i\}$ is the membership functions' parameter set that changes the shape of membership function from "1" to "0". These parameters are referred to as the premise parameters.

For statistical comparison of predicted and observed Shields parameters and dimensionless sediment transport rate, bias, coefficient of determination and Scatter Index are used. The bias is shown by Mean Error (*ME*) and the Scatter Index (*SI*) is defined as the Root Mean Square Error (*RMSE*) normalized by the mean of observed values of the reference quantity as follows

$$bias = \frac{1}{N}\sum_{i=1}^{N}(P_i - O_i) \qquad (11)$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \qquad (12)$$

$$SI = \frac{RMSE}{average\, observed\, value} \times 100 \qquad (13)$$

$$R^2 = \frac{\sum_{i=1}^{N} \left(O_i - \overline{O}_m\right)\left(P_i - \overline{P}_m\right)}{\left(\sum_{i=1}^{N} \left(O_i - \overline{O}_m\right)^2\right)^{0.5} \left(\sum_{i=1}^{N} \left(P_i - \overline{P}_m\right)^2\right)^{0.5}} \quad (14)$$

where R^2 is the coefficient of determination and $\overline{P}_m$ is the predicted mean value.

Tables 2 and 3 report the statistics error of calculated quasi-steady Shields parameter and unsteady Shields parameter using developed FIS and ANFIS models and also the average values of predicted and observed Shields parameter. It can be seen that the FIS-based and ANFIS-based predictions are biased. In addition, both FIS and ANFIS methods over predicts the quasi-steady Shields parameter (*bias*=0.25 and 0.11 for FIS and ANFIS, respectively for testing data) and under predicts unsteady Shields parameter (*bias*=-0.15 and -0.09 for FIS and ANFIS, respectively for testing data) in the studied case. In addition, the scatter index for predicted using FIS method (*SI*=25.5% and 22.8% for testing data) is larger than that of predicted using ANFIS method in same condition (*SI*=18.4% and 17.3 % for testing data). In addition, the values of the efficiency (*E*) and determination coefficients (R^2) of the ANFIS model are higher than the FIS model. Comparison of calculated *SI* shows that the accuracy of the developed ANFIS models is better than that of the developed FIS models in both Shields parameters prediction.

Table 2- Statistics of observed and predicted quasi-steady Shields parameter by FIS and ANFIS methods

Shields Parameters	Methods		Average observed values	Average predicted values	*SI* (%)	*bias*	R^2	*E*
quasi-steady Shields parameter	FIS	Training data	0.75	0.85	21.6	0.10	0.91	0.86
		Testing data	-1.3	-1.05	25.5	0.25	0.88	0.86
	ANFIS	Training data	0.75	0.82	16.2	0.06	0.92	0.91
		Testing data	-1.3	-1.19	18.4	0.11	0.90	0.88

Table 3- Statistics of observed and predicted unsteady Shields parameter and by FIS and ANFIS methods

Shields Parameters	Methods		Average observed values	Average predicted values	*SI* (%)	*bias*	R^2	*E*
unsteady Shields parameter	FIS	Training data	0.99	0.89	18.9	-0.10	0.91	0.88
		Testing data	-0.89	-1.04	22.8	-0.15	0.91	0.87
	ANFIS	Training data	0.99	0.93	15.7	-0.06	0.93	0.91
		Testing data	-0.89	-0.98	17.3	-0.09	0.92	0.90

As shown in Tables 2 and 3, the average measured quasi-steady Shields parameter for testing data was found to be 1.23 times the value calculated using FIS method and 1.08 times the value calculated by ANFIS method. The average measured unsteady Shields parameter for testing data was found to be 0.86 times the value predicted using FIS method and 0.91 times the value predicted by ANFIS method.

Comparison of the observed and predicted quasi-steady and unsteady Shields parameters with developed ANFIS model are illustrated in Fig. 2. As seen in this figure, ANFIS has performed well in predicting the Shields parameters.

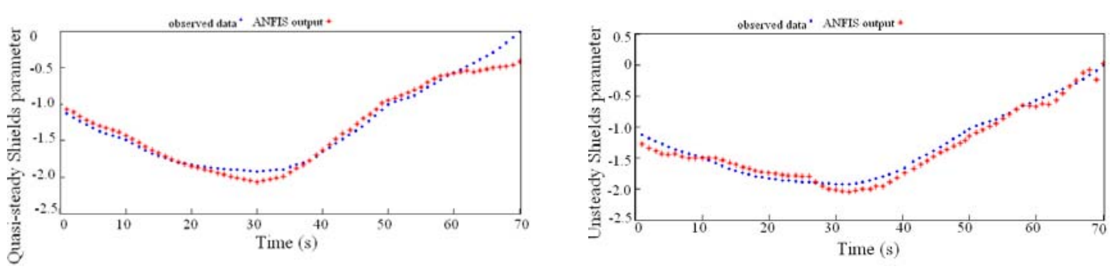


Figure 2- Observed and predicted quasi-steady Shields parameter (left) and unsteady Shields parameter (right) with developed ANFIS model

Tables 4 presents the error statistics of calculated dimensionless sediment transport rates using the two different *C*-values for up-rush and downrush and the quasi-steady Shields parameter and also the average values of predicted and observed dimensionless sediment transport rates. The error statistics of calculated dimensionless sediment transport rates using the unsteady Shields parameter and optimal *C*-value are given in Table 5. As seen in Tables 4 and 5, both FIS and ANFIS methods under predicts the dimensionless sediment transport rates using the quasi-steady Shields parameter (*bias*=-2.36 and -1.65 for FIS and ANFIS, respectively for testing data) and over predicts the dimensionless sediment transport rates using the unsteady Shields parameter (*bias*=3.48 and 2.56 for FIS and ANFIS, respectively for testing data) in the studied case. In addition, the scatter index for predicted using FIS method (*SI*=32.2% and 23.1% for testing data) is larger than that of predicted using ANFIS method in same condition (*SI*=26.3% and 19.6 % for testing data). Furthermore, the values of the efficiency (*E*) and determination coefficients (R^2) of the ANFIS model are higher than the FIS model. The results suggest that the ANFIS method is superior to the FIS method in the modeling and forecasting of the sediment transport rate.

Table 4- Statistics of observed and predicted dimensionless sediment transport rates using the two different C-values for up-rush and downrush by FIS and ANFIS

Dimensionless sediment transport rates	Methods		Average observed values	Average predicted values	*SI* (%)	*bias*	R^2	*E*
Dimensionless sediment transport rates using the two different *C*-values for up-rush and downrush	FIS	Training data	25.28	22.12	20.2	-3.16	0.91	0.88
		Testing data	-12.7	-15.06	23.1	-2.36	0.89	0.87
	ANFIS	Training data	25.28	23.03	17.1	-2.25	0.92	0.91
		Testing data	-12.7	-14.35	19.6	-1.65	0.90	0.89

Table 5- Statistics of observed and predicted dimensionless sediment transport rates using unsteady Shields parameter by FIS and ANFIS methods

Dimensionless sediment transport rates	Methods		Average observed values	Average predicted values	*SI* (%)	*bias*	R^2	*E*
Dimensionless sediment transport rates using unsteady Shields parameter	FIS	Training data	21.42	25.48	29.5	4.06	0.89	0.87
		Testing data	-13.62	-10.14	32.2	3.48	0.88	0.86
	ANFIS	Training data	21.42	24.86	24.5	3.44	0.92	0.90
		Testing data	-13.62	-11.06	26.3	2.56	0.90	0.89

It can be seen from Tables 4 and 5 that the average measured dimensionless sediment transport rates for testing data using the unsteady Shields parameter was found to be 1.12 times the value calculated using FIS method and 1.09 times the value calculated by ANFIS method. The average measured dimensionless sediment transport rates for testing data using the two different *C*-values for up-rush and downrush was found to be 0.84 times the value calculated using FIS method and 0.88 times the value calculated by ANFIS method.

The trained FIS was then used to predict the dimensionless sediment transport rates using data pairs of testing data, not used in training procedure. These predicted values are compared with observed data to see how well the ANFIS model performs. Figs. 3 and 4 illustrate the observed and predicted dimensionless sediment transport rates using quasi-steady and unsteady Shields parameter developed ANFIS, FIS models. These Figs. nicely demonstrate that ANFIS model performance is, in general, accurate and good, where all predicted points are quite near the observed points.

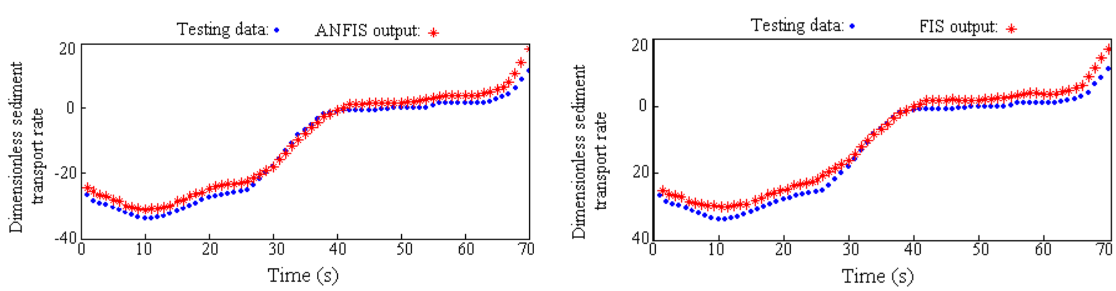


Figure 3- Plotting of estimation performances using unsteady Shields parameter with (left) ANFIS and (right) FIS

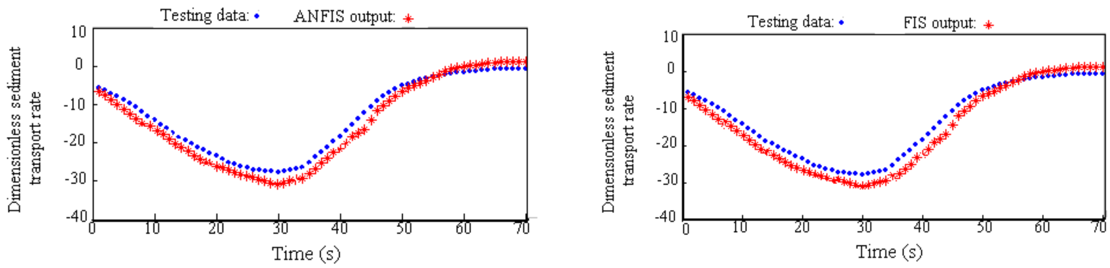


Figure 4- Plotting of estimation performances quasi-steady Shields parameter with (left) ANFIS and (right) FIS

Concluding Remarks

This study indicates the ability of neuro-fuzzy and fuzzy inference approach to model the swash velocity-sediment transport rates relationship. Four FIS models were developed to predict quasi-steady Shields parameter, unsteady Shields parameter, dimensionless sediment transport rates using the quasi-steady Shields parameter and the two different C-values for up-rush and downrush. For verification of our findings, the data set of swash experiments of Masselink and Hughes (1998) set and subtractive clustering method was used to evaluate the FIS model. Developed FIS models were then used as an initial FIS for ANFIS modeling.

Results indicate that using FIS and neuro-fuzzy approach in the swash zone sediment transport modeling have a high prediction accuracy and reliability without the need for incorporating different multipliers for up-rush and backwash. Also, the errors of ANFIS models in predicting parameters are less than those of the FIS models. The ANFIS model is more flexible than the FIS model considered, with more options of incorporating the fuzzy nature of the real-world system. We conclude that the constructed ANFIS models, through the subtractive fuzzy clustering, can efficiently deal with enormous and complex input–output patterns, and has a great ability to learn and build up a neuro-fuzzy inference system for prediction, and the forecasting results provide a useful guidance or reference for cross-shore sediment transport.

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