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Application of Adaptive Neuro-Fuzzy Inference System to Estimate Alongshore Sediment Transport Rate (A Real Case Study: Southern Shorelines of Caspian Sea)

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ABSTRACT

Many empirical models have been introduced by scientists during the recent decades for estimating longshore sediment transport rate, but these approaches have been calibrated and applied under limited conditions of the bed profile and specific range of the bed sediment size. The existing empirical relations are linear or exponential regressions based on the observation and measurements data, and there's a great potential to build more accurate models to predict sediment transport phenomena using soft computation approach. This paper presents a novel case study application of the adaptive Neuro-fuzzy inference system (ANFIS) as a superior modeling technique for estimation of the longshore sediment transport rate in the southern shorelines of the Caspian Sea. The results will be compared with the top three popular existing empirical equations. Daily grab samples from four stations were collected from March 2012 through June 2012. The trained ANFIS model outperformed the existing regression-type empirical equations for the estimation of the alongshore sediment transport rate due to the adaptive structure of the ANFIS model to better fit complex systems.

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1. Introduction

Sediment transport along the shore is one of the most important coastal processes that largely specify the coastal morphology, control and erosion, sedimentation, and sustainability. The alongshore current has an important role in sediment transport in the surf zone. This current is generated by obliquely incident breaking waves. Although the rate of transport and the direction of the sediment transport in certain parts of the coast are variable according to wave parameters, it indicates the annual sediment transport net rate and annual total alongshore sediment transport.

Several popular semi-empirical methods have been proposed to estimate the alongshore sediment transport rate (LSTR), including Bijker (1971), CERC Shore Protection Manual (1984), Kraus et al. (1989), Walton and Bruno (1989), and Kamphuis (1991), Watanabe (1999), Bayram et al. (2001), van Rijn (2002), and Kumar et al. (2003) [1–9]. The alongshore sediment transport is episodic and unpredictable because of coastal wind events that occur at irregular intervals [10–12]. Furthermore, the wave energy and angle with respect to the coastline, have the greatest influence on the alongshore sediment transport rate [13–15].

Soft computing techniques are a useful tool to increase the performance of the modeling. More recent studies have used power machine learning approaches such as artificial neural networks (ANN) and adaptive Neuro-fuzzy inference systems (ANFIS) to estimate the alongshore sediment transport rate [10,12,16–21].

In this study, the ANFIS model is developed for estimation of alongshore sediment transport rate in Noor coastal zone (Caspian Sea southern coasts) using wave parameters including height, period, and breaking wave angle as model input and the sediment transport rate as model output. The prediction accuracy of the trained ANFIS model is compared with the top three popular existing semi-empirical formulas, including the CERC (1984), Walton and Bruno (1989), and Kamphuis (1991) methods for estimation of the LSTR [2,4,5].

2. Methodology

2.1. Study area

The present study is carried out in the Noor coastal zone (located in the *Caspian Sea southern*) with length segment 2.4 km located in latitude N 36 ° 52 ‘5/20 to 37°17 ‘40/93” and longitude E 53° 27’27/18” to 50°32’17/16” in four stations from March 2012 through June 2012. The data recording stations were situated on the coastline in spanning around 600m in proper intervals, and sampling was performed daily at given time for each site and then measured data were averaged, and relevant data were obtained (Fig.1).

2.2. Sampling method

In order to carry out the present study, the important parameters including the breaking wave height (H_b), the breaker angle (α_b), the wave period (T), wave approaching the coast angle (β), surf zone width (W) were measured and recorded using field observations from 20 March 2012 through 21 July 2012 at four stations. The height of the breaking wave varied between 0.01 to 0.91 m, and the period of the wave varied from 2.3 to 7 s, the average breaker angle value was 23.5°, the wave approaching the coast angle was 93.5° and the average surf zone width was 84 m. The measurement of alongshore current velocity (*V*) was calculated using currethe nt meter (model 1205, Germany), and coastal slope (*S*) at each station with mathethe matical formula of slop with measuring water depth and horizthe ontal distance between coastline and depth of one meter. The sampling from sediment across the zone to analyze the sediment grain size distribution (*D*) on the coastline and in depths of 0 m, 5 m, and 10 m using grapple were taken and delivered to laborthe atory. After washing and drying with shaker and various sieves, according to Britain standard (BSI; 1967, 1986), the grain size distribution (Table 1) was carried out (Fig. 2).

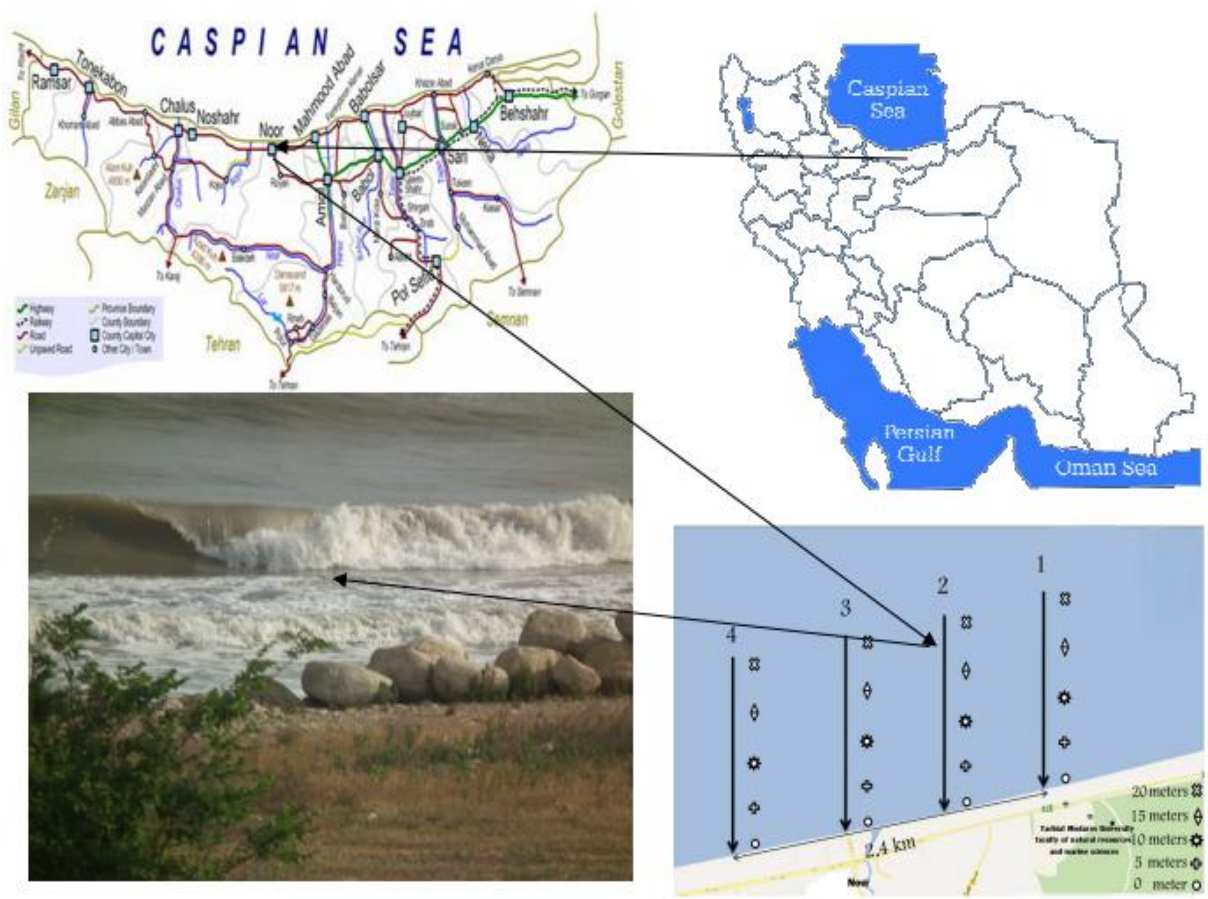
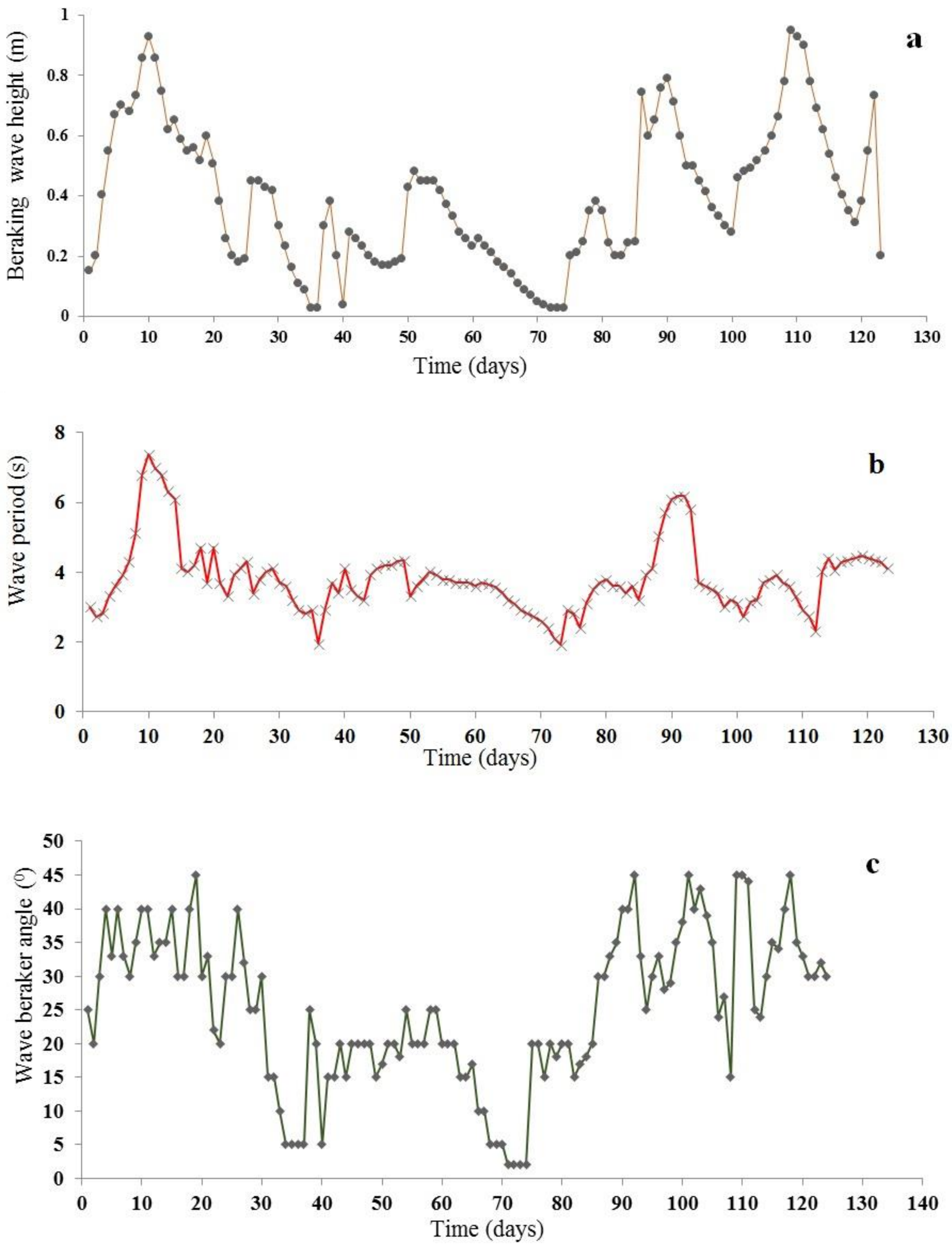


Fig. 1. Illustration of the Study area (Noor coastal zone located in the Caspian Sea southern).

The alongshore current velocity in the surf zone is not uniform. Then, this velocity is calculated with dye injection method and in terms of distance and time traveled from dye injection point to the coastline. The measurement of breaking wave height is made with field observations and according to US Army Coastal Engineering Manual [22]. Obtain the wave period, the time interval between two consecutive waves is measured with a chronometer, and the average of three values obtained from this method is considered as wave's period. The breaker angle related to the coastline was measured with observation and using a protractor [22].

Table 1
The Statistical characteristics of grain diameter in various depths (μm) in cothe ast of Caspian Sea, Noor City.

Depth (m)	$D_{10}(\mu m)$	$D_{50}(\mu m)$	$D_{90}(\mu m)$
0	154.3	219.2	590.3
5	92.15	173.7	283.6
10	60.02	117.0	577.0



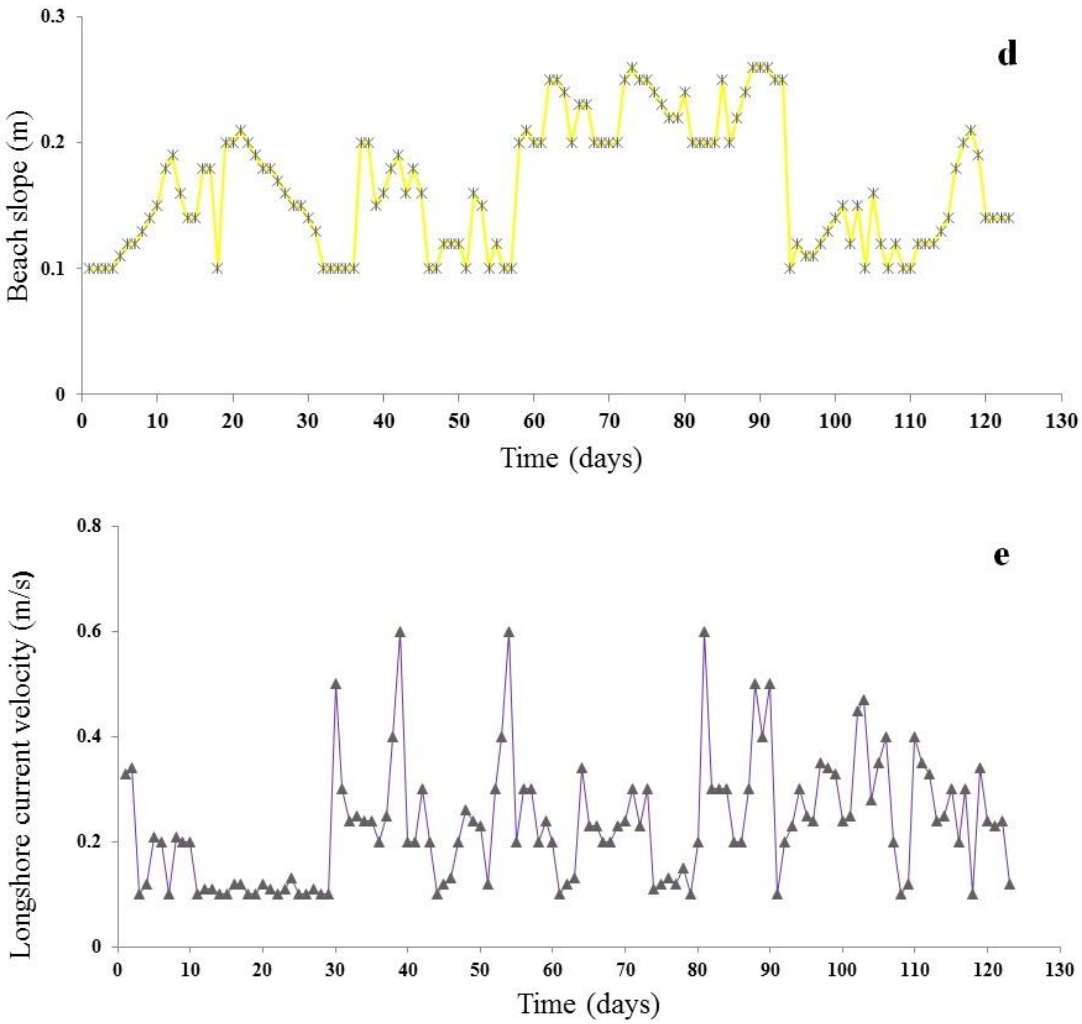


Fig. 2. The measured parameters (A): wave period, (B): breaking wave height, (C): width surf zone, (D): current longshore velocity, (E): coastal slope, (F): wave approaching the coast angle.

2.3. Measurement of longshore sediment transport rate (LSTR)

In order to begin sediment sampling, the trap is installed on a line spanning the surf zone, such that the trap opening is toward the current and it is installed in the bed and sampling was carried out for an hour. Then, the trap is transported to the coast and the sediment trapped is discharged in suitable containers, and was delivered to the laboratory for purposes of drying (for 24 hours at temperature 105°C) and sediment distribution. The LSTR is calculated by Kraus et al. method in final report DUCK 85 (Fig. 3) [23].

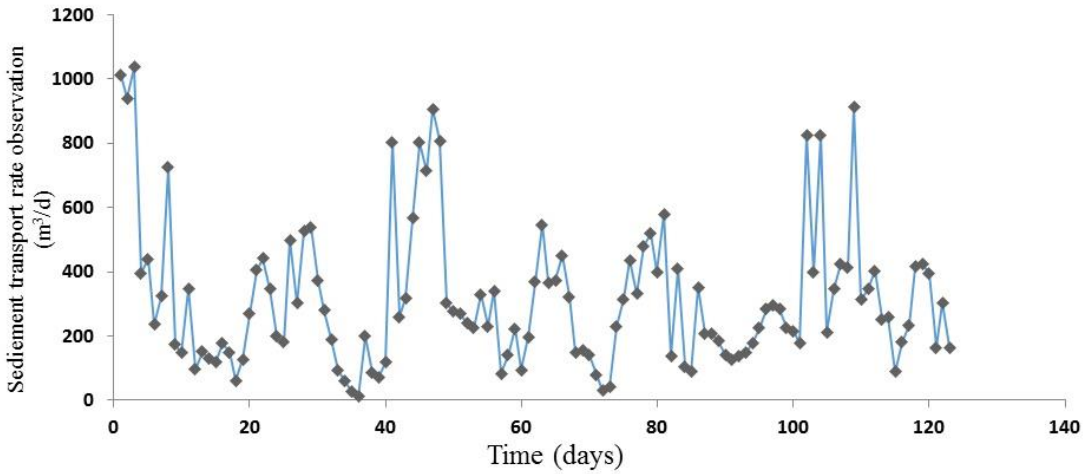


Fig. 3. The observed values of sediment transport rate using the trap in Noor coast.

2.4. Alongshore sediment transport rate

The current along the shore is caused by obliquely incident breaking waves and has a significant role in sediment transport in a region of the seabed relatively close to a shore. The alongshore current is one of the key parameters in most coastal engineering studies. In stormy conditions, transport of sediment happens for a relatively short time in the surf zone. In mild wave conditions, the least transport rate of sediment occurs for an extended period, often in the swash zone. Since, hydrodynamic processes are entirely different in two points, indicate that single parametric model in two conditions, may not be well performed.

The three different sediment transport zone include:

A) Initial breaker zone,

B) Surf zone,

C) Swash zone.

The coastal breaking waves that occur in the surf zone are specified with the reversible transformation from organized wave travel and scales including disturbance, vorticity, waves with low frequencies and currents [24]. The greatest transport is occurred by overtopping waves in the initial breaker zone. This breaking type carries the most suspended sediments available by mid currents.

2.4.1. The coastal engineering research center (CERC) formula

The Coastal Engineering Research Center [2] approach is one of the most common and simplest models for calculating LSTR, which is given by Eq.1:

$$Q = KA\frac{\rho g^2}{64\pi}TH_b^2\sin 2\alpha_b \qquad (1)$$

where Q = the alongshore transport rate volume, K = 0.39, which is the constant dimensionless relating sand transport to alongshore energy flux, $A = 1/[\rho_s - \rho)g(1 - p)]$, ρ_s = the sediment mass density, ρ = seawater mass density (1025 kg/m^3), p = sediment porosity, T = wave period (s), H_b =breaking wave height (m), and α_b = breaker angle with respect to coastline [2]. LSTR is proportional to energy flux in this model (energy flux factor alongshore in breaker condition,$P_{1b} = (E_w C_g) sin\alpha\ cos\alpha$, where P_{1b} is the energy factor alongshore in the breaker point; E_w denotes the wave energy and C_g indicates group velocity of the wave). The previous researches of this work are [25,26]. For more information, refer to [27].

2.4.2. Walton and Bruno formula

The breaker height, the width of the surf zone, and the average current velocity of the alongshore in the surf zone were considered by Walton and Bruno [4] for calculation of LSTR:

$$Q = \frac{KA\rho g H_b WVC_f}{0.87(\frac{5\pi}{2})(\frac{v}{v_0})_{LH}} \tag{2}$$

where $C_f = 0.005$, which is the friction coefficient, W = the width of the surf zone in m, V= the measured current velocity of the longshore (m/s), and $(v/v_o)_{LH}$ = theoretical dimensionless longshore current velocity with the mixing parameter as 0.4 [28]. This model is chosen based on parameters that are easily measured, and consequently it is ,expected that in this field, the study of model performance evaluation is well carried out [4].

2.4.3. Kamphuis formula

The Kamphuis formulas include the effects of the wave period, the coastal slope and the size of the grain [5]:

$$Q = 6.4 \times 10^4 H_b^2 T^{1.5} m_b^{0.75} D^{-0.25} sin^{0.6}(2\alpha_b) \tag{3}$$

where Q = the alongshore sediment transport rate (m^3/year); H_b = the height of the breaking wave; T= the period of the wave, α_b = the breaker angle; m_b= the coastal slope; and D = the grain size.

2.4.4. Analysis of the sediment transport rate

The traps are used to measure sediment flux, for example, sand weight and sand discharged from the nozzle in certain cross section at the time of sampling. If sampling is used unidirectional current that is the case here, the flux can directly obtain with developed current using predicted formulas [3]. The sediment flux in column K is given as:

$$F(K) = \frac{S(K)}{\Delta h \Delta w \Delta t} \tag{4}$$

where F = sediment flux ($Kg/m^2.s$); K= number of traps, increasing in bed ($K=1$) and decreasing in column ($K=N$); S = Dried sediment weight (in kg); Δh= Nozzle column height (0.15 m in this study); Δw =Trap nozzle width (0.25 m in this study); Δt =Sampling time interval (in s).

2.4.5. Adaptive Neuro-fuzzy inference system (ANFIS)

The networks based on adaptive Neuro-fuzzy inference system suggest a useful approach from network to solve the problems of an approximate function. The fuzzy set theory is designed for systems that can deal with complicated processes, effectively. The elements of a fuzzy set can be mapped individually using membership values to the theory of function. The elements of the fuzzy theory can be extended to actual values in the interval [0, 1]. Dividing data as training, and validation and testing are necessary for the fuzzy inference system (FIS) and ANFIS models.

The aim of using validation data is to evaluate and validate the model. If there is a noticeable difference between training and validation data, the deficiency of evaluated model will be revealed. For estimation of developed sediment transport, the wave period, breaker angle, and breaking wave height were used as input data and LSTR as output data. To analyze the performance of the ANFIS model, subtractive clustering method was used to divide data into clustering groups. The acceptable values for the radius of each cluster are varied between 0.15 to 0.40.

In this study, the structure of ANFIS model is: (a) Sugeno one fuzzy order model, it leads to rules IF-THEN in linear equations, (b) an operator with norms T for the fuzzy approach as an algebraic product, and (c) membership functions that are organized regarding Gaussian functions [29].

The different numbers of membership function (Trapezoidal, Triangular, Gaussian, etc.) are used to determine the degree of the membership function. The Gaussian membership function is used as:

$$\mu_{Ai}(x) = \exp[-\left(\frac{x-c_i}{a_i}\right)^2] \tag{5}$$

where, $\mu_{Ai}(x)$ = membership function; x= new inputs to i^{th} node ; $\{a_i, c_i\}$ membership function parameters which are set of membership function variations. These parameters are considered as assumed parameters.

2.4.6. Error statistical indices for evaluation and comparison of results

The criteria used to measure model performance, including the coefficient of efficiency (CE), the root mean square error (RMSE), and the correlation coefficient (R^2) is determined as follows:

$$CE = 1 - \frac{\sum_{i=1}^{n}(O_i - P_i)}{\sum_{i=1}^{n}(O_i - \bar{O}_m)} \tag{6}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \tag{7}$$

$$R^2 = \frac{\sum_{i=1}^{N}(O_i - \bar{O}_m)(P_i - \bar{P}_m)}{\left(\sum_{i=1}^{N}(O_i - \bar{O}_m)^2\right)^{0.5}\left(\sum_{i=1}^{N}(P_i - \bar{P}_m)^2\right)^{0.5}} \tag{8}$$

where, R^2= The Correlation coefficient, $\overline{P}_m$ = predicted values average, P_i= predicted value, Q_i= observational value. The root mean square error (*RMSE*) is varied between 0 and 1, the closer the 0 indicates the high prediction accuracy. The scattering index is in % and indicates the scattering of predicted data relative to actual values, and 0 indicates the lack of scattering in the prediction. Also, the correlation values (*R*) is varied between -1 to 1 and 1 indicates the prediction without error. *CE* ranges from negative infinite (poor model) to 1 (good model).

3. Results and discussion

The statistical results obtained from systematic observations of parameters (Table 2).

Table. 2
Statistical parameters of measured data in Noor coast.

Parameter	Number	Maximum	Minimum	Mean	Standard Deviation	Variation Coefficient
H(m)	123	0.87	0.01	0.3	0.18	0.6
T(sec)	123	7	2.3	4.56	0.9	0.2
$\alpha(deg)$	123	45	5	27.8	11.5	0.41
W(m)	123	170	30	84	31.6	0.38
V(m/s)	123	0.5	0.1	0.2	0.09	0.45
S	123	0.26	0.08	0.14	0.045	0.32
D(Φ)	123	5.12	0.2	1.22	1.25	1.02

The performance of LSTR calculated by CERC, Walton, and Bruno, and Kamphuis formula and ANFIS approach were evaluated. The performance evaluation criteria are shown in Table 3.

Table. 3
Obtained statistical indices values from the empirical formula and ANFIS approach.

Formula	Type	N	RMSE	R^2	CE
CERC	training	87	8.4×10^{-3}	0.59	0.39
	validation	18	2.3×10^{-2}	0.58	0.38
	testing	18	1.4×10^{-2}	0.58	0.38
Walton and Bruno	training	87	5.6×10^{-3}	0.75	0.29
	validation	18	4.3×10^{-3}	0.73	0.24
	testing	18	7×10^{-3}	0.79	0.23
Kamphuis	training	87	1.1×10^{-1}	0.6	0.32
	validation	18	6.7×10^{-2}	0.54	0.38
	testing	18	7.6×10^{-2}	0.56	0.35
ANFIS	training	87	7.3×10^{-3}	0.98	0.99
	validation	18	3.2×10^{-3}	0.83	0.99
	testing	36	5.6×10^{-3}	0.88	0.99

By using the measurement of the scattering index, the root means square error (RMSE) is calculated according to Eq. 9:

$$\sigma_{rms} = \left[\frac{\sum_1^n[\log(q_c) - \log(q_m)]^2}{n-1}\right]^{0.5} \quad (9)$$

where n= number of data; q_c = LSTR calculated by emthe pirical formula; q_m = LSTR measured.

The correlation coefficient (R) between calculated and measured LSTR values is obtained. The RMSE between calculated and measured LSTR values by CERC formula is 1.8 and correlation coefficient (R) is 0.25. The smaller RMSE means less scattering. Kamphuis (1986) using results obtained by CERC formula, observed the grain sizes between 0.2 to 0.6 mm. In this study, the grain size means varied between 0.03 to 0.9 mm, but standard deviation between measured and calculated LSTR by CERC formula is more [24]. Wang (2002) showed that the estimated value from the semi-empirical method is more than measured ones [30,31]. The RMSE between measured and calculated LSTR by Walton and Bruno formula is 1.7, and the correlation coefficient (R) is 0.73. The RMSE between measured and calculated LSTR values by Kamphuis formula is 0.89 and correlation coefficient (R) is 0.76.

In Neuro-fuzzy modeling and for training models, it was tried for various combinations of the input parameters (i.e., breaking wave height, wave period, alongshore current velocity, coastal slope, surf zone width, grain size distribution). For this purpose, the combination training (error back propagation, least squares of errors) and Sugeno one-order system were used. In models with large R^2, the real behavior of LSTR is very close to linear behavior. With various results from investigations, a combination consisting of the breaking wave height, wave period as input parameters and LSTR as output parameter is considered. In Table 3, the results of statistical errors from training and testing in the ANFIS model in two prediction and observation modes are listed. In Table 3, the calculated statistical errors from LSTR in two prediction and observation modes by ANFIS model and measured LSTR by sediment trap are given. On average, the measured LSTR parameter for data training is equal to 0.96 times of the predicted one. The comparison of the predicted and measured LSTR for ANFIS model in training and predicted steps were illustrated in Figs 4, 5, 6.

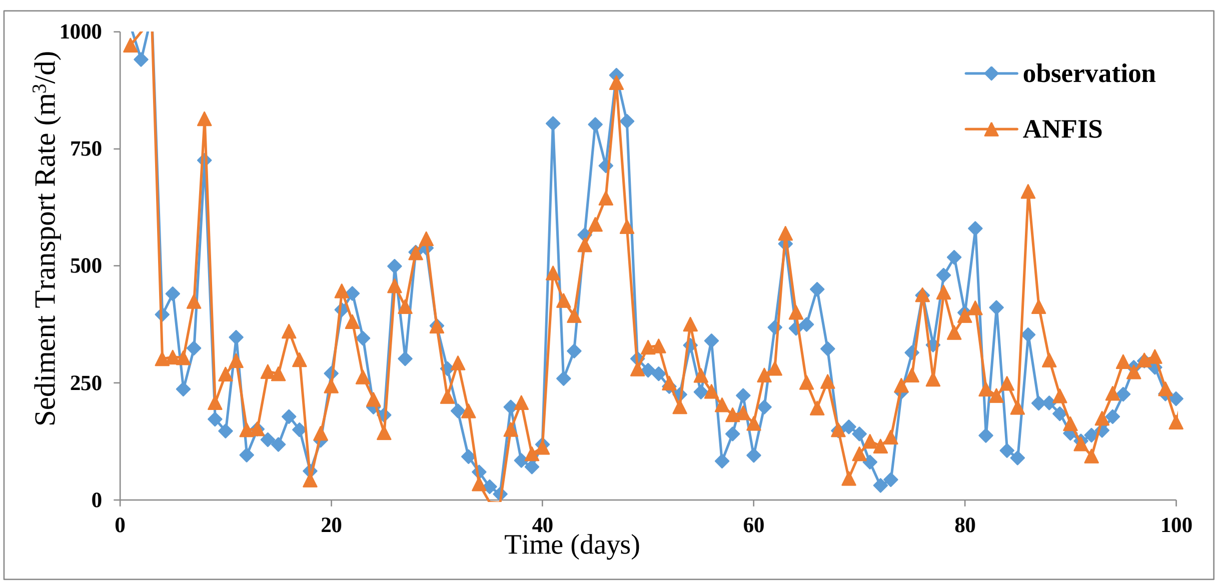


Fig. 4. The predicted and observed parameters of LSTR by using developed ANFIS model (training).

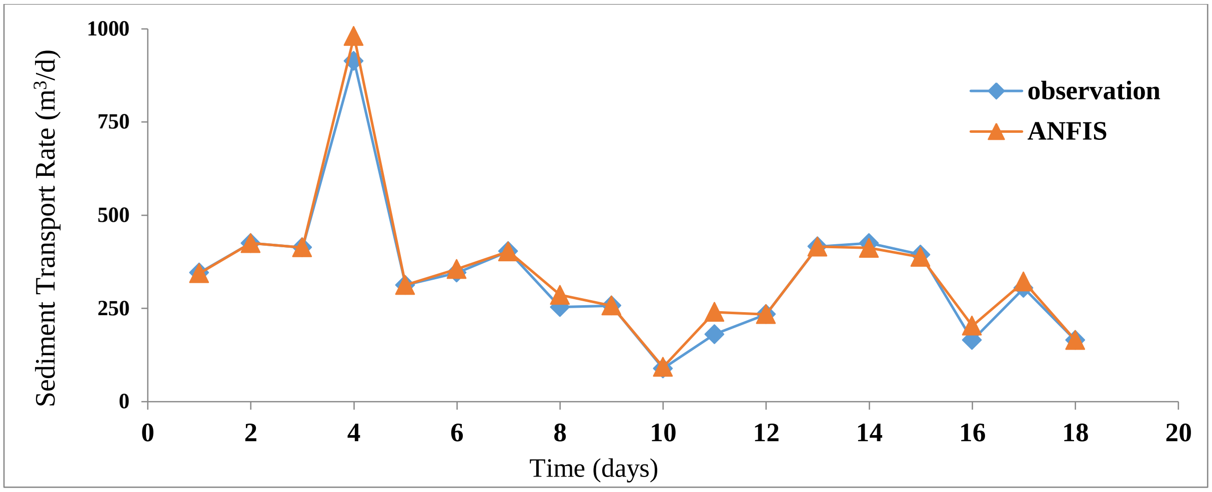


Fig .5. The predicted and observed parameters of LSTR by using established ANFIS model (prediction).

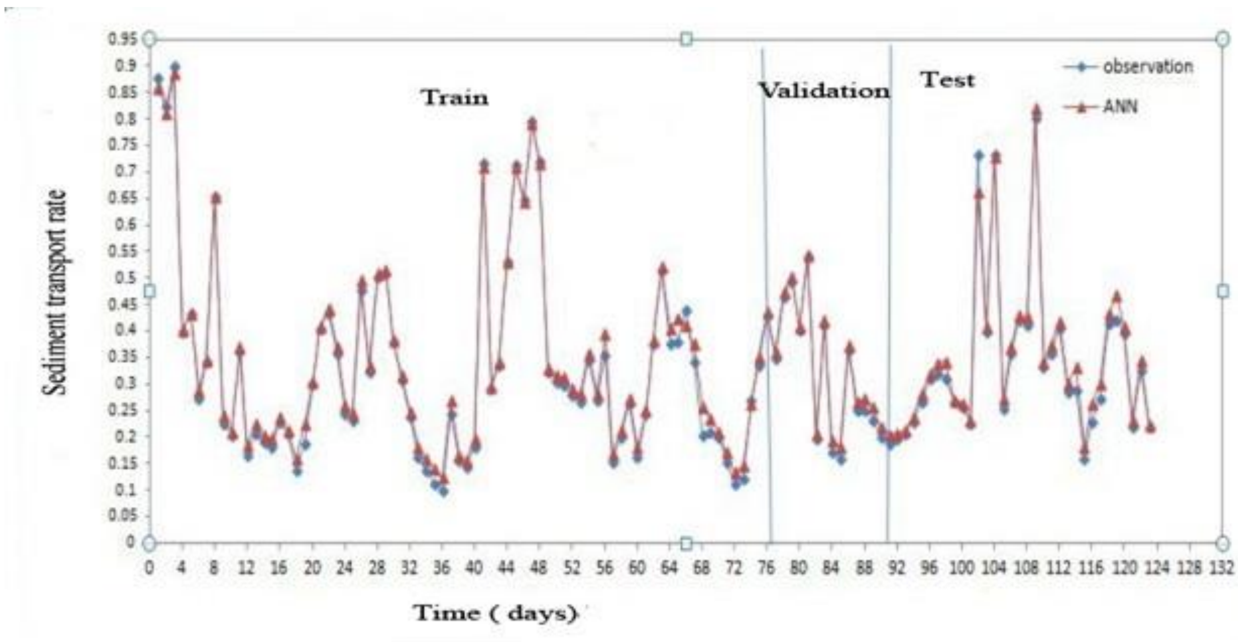


Fig. 6. The fitting of observational and estimated data of the network in the training, validation and test phase.

The results showed that if epoch number is equal to 1000 and membership function is equal to 2 and from two bell-shaped functions and Gaussian function, the former function provides the best solution. The scattering index for the prediction of LSTR using Kamphuis formula (SI=85.5 %) is greater than the predicted value by Walton and Bruno (SI=72.3 %) and CERC (SI=80.6 %) formula. The Kamphuis formulas also provide less correlation between predicted and measured values. The LSTR measured average is 50 % values obtained from CERC formula, 56 % from Walton and Bruno formula and 45 % from Kamphuis formula. The difference between measured and calculated values is as follows: error in the measurement of bed load, current difference in depth and surface and using the developed semi-empirical formula for high energy costs with short waves conditions (in this study mean wave height is 0.46 m).

For evaluating the performance of CERC, Walton and Bruno and Kamphuis formula, the models are trained and then are used for the estimation of LSTR using data sets. Therefore, we expect that the breaking wave height in sediment transport is greater than to other parameters (i.e., wave period and breaker angle, consistent with semi-empirical formula). The results suggest that the ANFIS approach in the modeling and estimation of LSTR is very better than other semi-empirical approaches tested for these data sets. There is an equilibrium between wave height, wave period, breaker angle, and by using ANFIS model, we can appropriate estimate with measured data. This model is a useful tool for estimation of LSTR from wave parameters.

4. Conclusion

The applications of the soft computing have been widely considered in the field of water engineering [30,32–37]. The estimation of sediment transport is a complicated process [38]. In the present case study, the applicability of the powerful ANFIS model as a superior tool for prediction of the sediment transport rate along the shorelines of the southern Caspian Sea has been studied. The accuracy of the ANFIS model compared with the empirical formulas using criteria including bias, root mean squared error (RMSE), scattering index (SI) and correlation coefficient (R) has been analyzed.

The results indicated that the ANFIS model outperformed the semi-empirical models for the estimation of the alongshore sediment transport rate in the southern shorelines of the Caspian Sea. The scattering indices of Kamphuis, Walton, and Bruno, and the CERC empirical models for the estimation of LSTR respectively are 85.5 %, 72.3 %, and 80.6 %, while the scattering indices of ANFIS model for evaluation of LSTR is 27.32 %. However, it can be suggested that other machine learning approaches such as the artificial neural networks, gene expression programming, time series, fuzzy logic, and wavelet analysis could be used and their results compared with ANFIS in the next studies.

Acknowledgments

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