

Estimation of Alongshore Sediment Transport Rate -A Comparison among Semi-Empirical Formulas and an Artificial Neural Network model (ANN)

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ABSTRACT

The rate of alongshore sediment transport in the surf zone is depend on the product of the local wave height and mean alongshore current speed. In this study, measurement of alongshore sediment transport rate had carried out in the surf zone of Noor coastal area, in the southern part of the Caspian Sea during September to June 2012. Further, alongshore sediment transport rate had estimated by different famous semi-empirical formulas. Further, an Artificial Neural Network (ANN) model is trained using three dominant parameters of sediment transport formulas including wave breaking height (H_b), surf zone width (W), and alongshore current velocity (V). ANN models are able to show hidden laws of natural phenomena such as sediment transport process. The results of ANN and some sediment transport rate formulas were compared with mean variables which can be used in developing sediment transport rate formulas. The Results show that, the estimated value of alongshore sediment transport rate by C.E.R.C, Walton and Bruno (W.B) and Kamphuis (K) formulas and ANN model was $737.8 \left(\frac{m^3}{day}\right)$, $670.3 \left(\frac{m^3}{day}\right)$ and $593.3 \left(\frac{m^3}{day}\right)$ and $592.4 \left(\frac{m^3}{day}\right)$ Respectively. Also according to the results, the calculated R^2 values in estimation of alongshore sediment transport rate for ANN method and C.E.R.C, W.B, and K, were 0.99, 0.98, 0.75, and 0.84 and RMSE 4.7×10^{-4} , 8.4×10^{-4} , 9.1×10^{-2} , and 1.4×10^{-3} , respectively. The results, the Study also show that the formulas based on physical laws of sediment transport rate, such as C.E.R.C, W.B, and K formulas that were developed based on power concept, are more accurate than Galvin and Van Deer Meer formulas for estimating sediment transport rate in the Caspian Sea coastal areas.

1. Introduction

The total alongshore sediment transport rate (LSTR) is one of the most commonly required quantities in coastal engineering needed in problems such as infilling of dredged channels, dispersion of beach fills and placed dredged material, and the morphodynamic response of coastal areas to engineering works [2].

Measurement of the LSTR in the surf zone is one of the great challenges in coastal engineering and sciences. Transport rate data collected with along with the waves and currents that caused the transport are needed to improve basic understanding of sand movement also to develop engineering predictive techniques for estimating transport rates beach evolution [18].

For these purposes, it is desirable to make simultaneous measurements of the transport rate at a point across the surf zone to get its cross-shore or lateral distribution. Point measurements are needed, because the transport rate are depending up on the characteristics of the local waves, currents, also bottom material, and beach morphology. the lateral and vertical distributions of the long shore sand transport rate are needed for relating changes in the beach morphology to the imposed hydraulic forces, and for designing structures this may intercept sand transported alongshore. Total longshore transport is easily computed from the lateral distribution by integration over the active zone of transport [2]. many formulae were proposed for to predict LSTR, in which normally represented in term of the incident wave climate and beach characteristics [34].

The most widely formula for estimation of LSTR is commonly known as the C.E.R.C Equation [30]. This method is based on the principle the LSTR, including bed load and suspended load that is a proportional to alongshore wave power P per unit length of beach; $LSTR = K P$, with K =calibration coefficient. The C.E.R.C formula was calibrated using field data from sand beaches. The effects of particle diameter and bed slope were studied systematically by Kamphuis (1991), resulting in a more refined equation for LSTR. The last equation was found to be in best agreement between computed and measured transport rates. Equations (C.E.R.C and Kamphuis) were used in the present study as well [26].

Transported sediment rate sometimes only results in local rearrangement of sand into bars and troughs, or into a series of rhythmic embayment cut into the beach [10]. Littoral transport is to move sedimentary material in the littoral zone, which is, the zone close to the shoreline. Littoral transport is classified as cross-shore

transport or as alongshore transport. It may result from to interact winds, waves, currents, tides, sediments and other phenomena in the littoral zone. Transport can be described by the product of instantaneous concentration and the instantaneous velocity [14].

To place the role of the streamer trap in perspective, a review is first given of methods usually employed to measure the LSTR in the surf zone. The advantages and disadvantages of each method are looked. The streamer trap is described in detail and sample field results are given. The paper concludes by describing some applications of the trap made in environments except the surf zone, and plans for further testing and development [19].

A few predicting model such as Artificial Neural Networks (ANNs) were previously applied to coastal studies [6], wave prediction [15, 22], ripple and beach bar behavior and location [29, 36], coastal water level prediction [8, 12, 23, 27], wind-wave analysis [5, 11], head-bay geometry [13], tidal prediction [24], breakwater design [28, 35] and estimation of suspended sediment concentrations [7, 31]. The streamer can be used to measure sediment transport rate when a current is present, too. Kraus et al. (1989) used similar traps to carry out 10-15 minutes daily measurement of sediment transport for a 6 days' period [19].

Bakhtyar et al., (2008) by Neural Fuzzy inference system estimate the sediment transport rate in Arge coast of India [1]. Also, Hashemi et al (2011) stated that the ANN could predict the seasonal changes in Tremadoc Bay coast profiles [9]. In another studies, Kabiri - samani et al (2011) by using of Artificial Neural Network (ANN) and Fuzzy Logic (FL) evaluated the sediment transport rate methods in coastal zone of Iran and concluded that ANN, FL and Gradient descent method have better efficiencies from the others [14]. In addition, Boveiri and Musaddad (2012) calculated the sediment transport rate in the Caspian Sea and reported that the highest transport rate was $3927.45 \text{ m}^3/\text{day}$ during cold season in Anzali port and the lowest transport rate is $122.53 \text{ m}^3/\text{day}$ during warm season in Noshahr port [4].

A trap, called the streamer trap, which was developed to allow direct point measurement of the lateral and vertical distributions of the transport rate in the near shore zone under low wave energy conditions was used in this study. Emphasis will be given to measure of the LSTR in the surf zone. The main and this study is to compare the performances of semi-empirical formulas and an artificial neural network ANN, model in predicting of LSTR in the Noor coastal area in the southern part of the Caspian Sea. For this purpose, a daily observation of alongshore sediment transport rates is performed and used as reference for evaluating the accuracy of the semi-empirical formulas and the proposed ANN model.

2. Material and methods

2.1. Study Areas

A segment of beach by 2.4 km in length at Noor's coastal area, in the southern part of the Caspian Sea, in the North of Iran, was selected for this study. The beach is straight and open and lies between $36^{\circ} 52' 5.20''$ and $37^{\circ} 17' 40.93''$ N latitudes and $50^{\circ} 32' 17.16''$ and $53^{\circ} 27' 37.18''$ E longitudes. These measurements were carried out from September to June 2012. The mentioned stations were far apart 0.6 km in distance. The 0.6km coastal stretch of Izadshahar city on the East and Royan City on the West forms the study area (Fig 1). Sediment samples were collected at 0, 5, and 10 meter depths using by grain size of shoreline of Caspian Sea.



Fig 1: An illustration of the sampling stations in the Caspian Sea shoreline

2.2. Research Method

In order to conduct the present study observation obtained parameters from September to July 2012 including: wave breaking height ($H_{(s,b)}$), wave period (T), wave breaking angle (α_b), surf zone width (W), was measured. Sediment samples collected at each trap location during September to the end of July 2012 were used for the sieve analysis to estimate the median grain size. Measurement was alongshore current velocity in the surf zone (V) by using current meter and bed slope was mathematical formula slope measuring water depth and horizontal distance between the shoreline and the depth of 1 m.

2.3. The Streamer Trap method

The streamer trap was used for measuring the sand transport rate in the surf zone. The name of the trap derives from the long rectangular bags of sieve cloth that stream out with the current and capture sediment, while letting water pass through. The streamer trap was originally designed to measure alongshore sand transport in the surf zone [20] and the present discussion will mainly focus on that application. The basic idea of streamer trap was developed during a series of field experiments in Japan [20]. It was later

learned that a similar type of portable trap, the Helley-Smith trap is used by geologists in the United States for measuring bed load transport in rivers [3].

The mentioned method does not widely known in the coastal engineering community, however. But, given the present small capability to measure sand transport in the surf zone, simple devices such as the streamer trap and Helley-Smith trap are worthy of serious consideration by coastal engineers and scientists.

The streamer is made from commercially available polyester monofilament sieve cloth. Polyester cloth does not stretch or degrade in seawater. The cloth is available from scientific distributors in square mesh sizes ranging from 0.074 to 1.68 mm (Fig 2).

A sieve cloth allows water to flow through, but captures sediment particles of nominal diameter greater than the mesh opening. Streamers in use at C.E.R.C are made of 0.105 mm mesh cloth. In the United States, the cloth can be purchased in bolts 102 cm (40 in.) wide and is bought by the linear foot (30.5 cm) [20].



Fig2: Streamer trap rack at study

2.4. Trap Design

Two streamers were made each width of cloth by setting mouth dimensions at 25 cm wide by 15 cm high (Fig2). The frame holding the streamer was made of P.V.C. The rectangular section, on to which the streamer mouth is sewn, is found 4 cm forward of the four mounting rods, to place the mouth up current and away from flow disturbance and scour created at the legs of the rack holding the streamers. The bottom-most streamer frames its can generate scour, Factors controlling scour include the long shore current speed, wave height, water depth, turbulence, grain size, and duration of sampling interval. The dependence of scour on these factors has yet to be investigated.

2.5. Trap Operation

To conduct a cycle of sampling, streamers are mounted in the rack and the trap is carried out to a mentioned location in the surf zone. At the start signal, the trap is positioned so the streamer mouths face into the alongshore current, and the rack legs are thrust into the bed. The streamers immediately unfurl to full-

length when their mouths are pointed into the current. If the current is weak or intermittent, the streamers wrap around the legs of the rack caused oscillatory water motion caused by the passage of waves.

In a reasonably steady current, however, the streamers expand fully behind the trap without tangling. The operator stands down current and shoreward of the trap to monitor the streamers and to keep the rack legs fully inserted in the bed. It is dangerous to stand seaward of a trap as a large wave may throw the operator into it. The trap is more stable under wave action than a standing human. Traps in operation in the surf zone are shown in Figure 3. The streamer trap presents a fairly small cross-sectional area to the current and waves.

The weight of the steel rack, small cross-sectional area of rack members and streamers, and the implanted legs combine to produce stability. But, it was found that if all streamers are mounted on a rack deployed in waves higher than roughly 50 cm, the trap tended to tip in to direct forward wave motion.

The tendency of tip in higher waves and deeper water is Decrease if less than the maximum possible a streamer is mounted. In this configuration the trap has acted well with one operator in breaking wave heights up to 1 m and more. At the end of the sampling interval, usual 5 to 10 minute, the trap is brought to shore and the streamers are removed from the rack. Most of the collected sediment is found to lie at the back of the streamer. Sediment clinging to the sides can be washed down to the back, either with a jet of water, or by immersing the streamer in a large bucket and gently lifting it up and down. The streamer is opened by untying the nylon cord, allowing the trapped sediment to be washed into a container.

Collected sediment was easily transferred from streamer to container. In experiments performed by C.E.R.C, sediment sample transfer and weighing operations are done on the beach. Trapped sediment is washed out of the streamer and on to a square of pre-wetted sieve cloth placed in a plastic cooking colander to allow drainage of water. The wet sediment and prepared wet cloth are weighed on a portable electronic balance. Dry weight of sediment samples consisting mainly of cohesion less sand can be accurately estimated from the weight of wet sediment in sieve cloth [10]. Selected samples are retained for further analysis in the laboratory and for calibrating between wet and dry sample weight [20].



Fig3: Photograph showing traps employed in the surf zone

2.6. Transport Rate Analysis

As opposed to instantaneous samplers, pumps, and acoustic or optical sensors which measures and concentration, the streamers measure a sand flux, i.e., the weight of sand passing through the nozzle of a certain cross-sectional area in the sampling interval. If the sampling is performed in a unidirectional flow, as was the case in these experiments, no sand is lost once it has entered the streamer, and the flux can be directly associated with the current to develop predictive empirical relations. The transport rate was calculated according to the following procedures. The flux of sand F at streamer k is given by:

$$F(k) = \frac{S(k)}{\Delta h \Delta w \Delta t} \quad (1)$$

Where; F is sand flux ($\text{kg} \cdot (\text{m}^2 \cdot \text{sec})^{-1}$), k is streamer number, 'raising in order from the bottom ($k = 1$) to the last streamer ($k = N$), S is dry weight of sand (kg), Δh is height of streamer nozzle (0.15 m), Δw is width of streamer nozzle (0.25 m), Δt is Sampling time interval (sec).

The flux between adjacent streamers, $F_E(k)$, can be estimated by linear interpolation using adjacent measured values:

$$F_E(k) = 0.15 [F(k) + F(k+1)] \quad (2)$$

2.7. Alongshore Sediment Transport Rate (LSTR)

The LSTR was calculated from the empirical equation relating the alongshore energy flux in the breaker zone to the alongshore transport rate (Komar and Inman, 1970). the simplest and most commonly used methods

for calculating LSTR is the Coastal Engineering Research Center (CERC) formula (Shore Protection Manual, 1984), Kamphuis (1991) and Walton & Bruno (1989) (table. 1). (refer to Appendix)

Table1.Semi-empirical formula

Name	Formula	Year
CERC	$Q_t = 2.9 \times 10^6 H_{sb}^{2.5} \sin \alpha_b$	1984
KAMPHUIS	$Q_{Lst,m} = 6.4 \times 10^4 H_{sb}^2 T_p^{1.5} m_b^{0.75} D_{50}^{-0.25} \sin^{0.6}(2\alpha_b)$	1991
Walton & Bruno	$Q = \frac{KA\rho g H_b WVC_f}{0.78(\frac{5\pi}{2})(\frac{v}{v_0})_{LH}}$	1989

2.8. Artificial Neural Network (ANN)

2.8.1. Concepts of ANN

ANNs is a fairly new nonlinear statistical technique that can be used to solve problems that are not suitable for conventional statistical methods. ANNs are based on the present understanding of the biological nervous system, which consists of some data processing parts called neurons or nodes that are grouped in layers. The input layer neurons get input data or information and send the values to the next layer of processing get across connections. This process is continued until the output layer is reached. Such network in which data flows in one direction (forward) is known as a feed-forward network. The application of ANN models was the topic of many recent literatures, (such as, Lingireddy and Brion, 2005) [25].

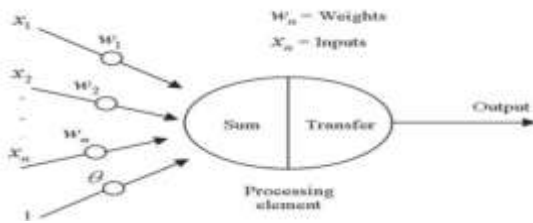


Fig 4: basic concepts of artificial neuron

Figure 4 shows the basic an artificial neuron. In this figure, various inputs to the network are represented by the symbol x_n . Another input in the figure is called a bias, θ , and it is always equal to one. Each of these inputs is multiplied by a connection weight. These weights are represented by w_n . In the simplest case, these products are simply summed, fed through a

transfer function, σ , to generate a result, and then output. In mathematical form, a neuron with n number of inputs is shown in Eq. (9).

$$Output = \sigma(\sum_{i=1}^n w_i \times x_i + \theta) \quad (9)$$

2.8.2. Training of ANN

Determining ANN weights is called learning or training, and is similar to calibrating a mathematical model. The ANNs are trained with a training an input data and known output data. At the beginning of training, the weights are initialized either with a random values or based on previous experiences. Next, the weights are systematically changed by the learning algorithm such that for a given input the difference between the ANN output and output is lowered.

Many learning examples are repeatedly presented to the network, and the process is ended when output and observed value difference is less than a specified value. This process requires that the neural network computes the error derivative of the weights (EW). In other words, it must calculate how the error changes as each weight is resin or decreased slightly. The back propagation algorithm is the most widely used method for determining the EW. The algorithm involves calculating the derivatives of the network training error about the weights by the application of chain rule and gradient descent optimization to adjust the weights to lower the error. The equations on this algorithm are available in ANN text books (such as. Lingireddy, Brion 2005) [25].

In ANNs modeling process, large attribute values might cause numerical problems because the neurons in ANN are combined sigmoid function as excitation function. There are two main advantages to normalize features before applying ANN to prediction. One advantage is to avoid attributes in greater numeric ranges dominating those in smaller numeric ranges, and another advantage is to avoid numerical difficulties during the calculation. It is recommended to linearly

scale each attribute to the range [0.1, 0.9], $[-1, +1]$ or [0, 1]. In the modeling process, the data sets of alongshore current velocity, surf zone width, breaking wave height and sediment transport rate were standardized to the range between 0 and 1 as follow:

$$N_i = \frac{x_i - x_{min}}{x_{max} - x_{min}} \quad (10)$$

Where N_i is the normalized value, x_i is the original data, and x_{min} , x_{max} are the minimum and maximum of the original data, respectively.

2.8.3. Performance evaluation

Four different types of standard statistical criterion were considered as statistical performance evaluation. The root mean squared error (*RMSE*), efficiency coefficients (*CE*), mean absolute error (*MAE*) and mean relative error (*MRE*) was used. The four performance evaluation criteria used in this study can be calculated utilizing Eqs.11 to 14.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (P_i - O_i)^2} \quad (11)$$

$$CE = 1 - \frac{\sum_{i=1}^n (O_i - P_i)^2}{\sum_{i=1}^n (O_i - \bar{O}_m)^2} \quad (12)$$

$$MAE = \frac{1}{n} |P_i - O_i| \quad (13)$$

$$MRE = \frac{1}{n} \sum_{i=1}^n \left| \frac{P_i - O_i}{\bar{O}_m} \right| \times 100 \quad (14)$$

Where O_i and P_i are, respectively the observed and the predicted sediment transport rate, $\bar{O}_m$ is the average observed sediment transport rate and n is the number of observations.

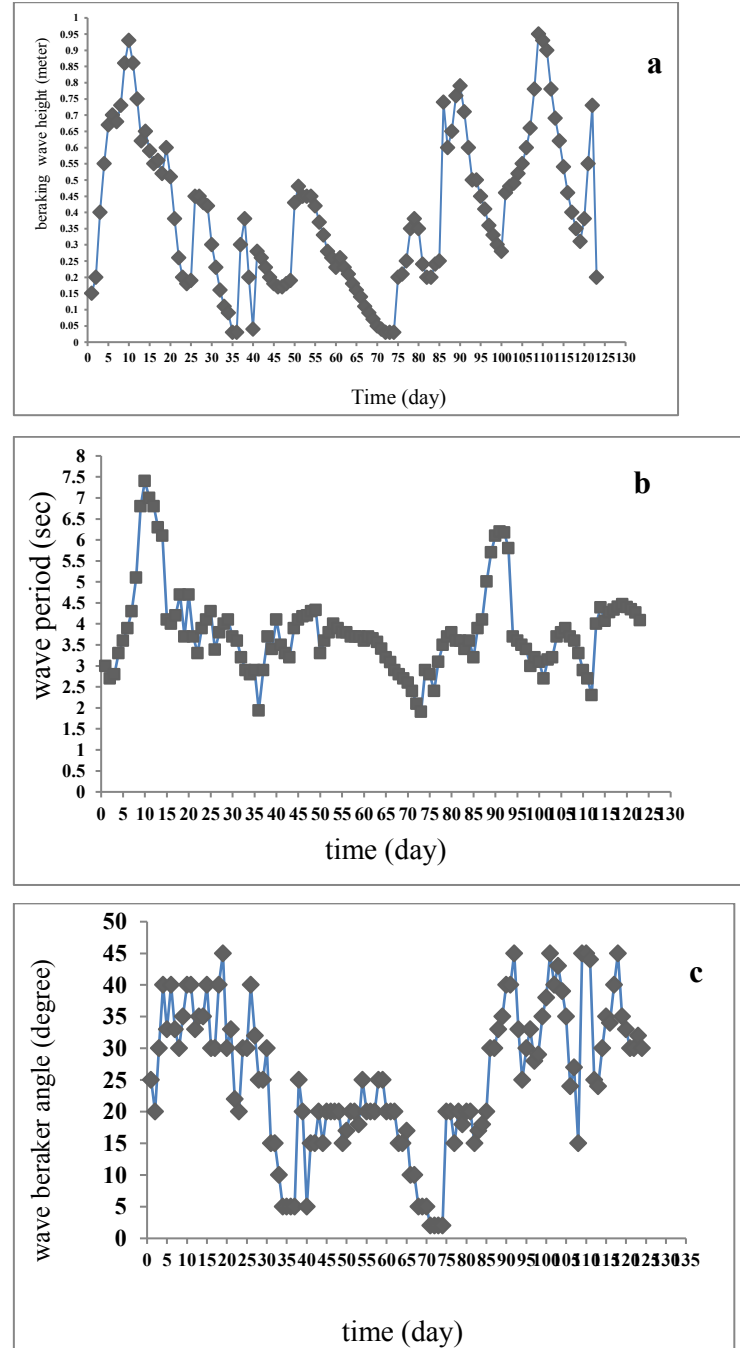
1. Results and discussions

1.1. Breaker characteristics

The daily variations of breaking significant wave height, wave period, and breaker angle calculated from the wave measurements along are shown in Fig. 5. The breaking wave height varied from 0.01 to 1.8 m with an average value of 0.47 m during September to June 2012. The wave period mostly varied from 1.91 to 7.4 with an average value of 4.65 s, and the average wave-breaking angle was 27.8 degree. The breaking waves

approached the coast predominantly from the south (positive values). The average surf zone width was about 84 m. The daily statistical variables of wave characteristics (height, period and angle), surf zone width, alongshore current velocity, beach slope, and grain size data are shown in Table 1.

Table 1.



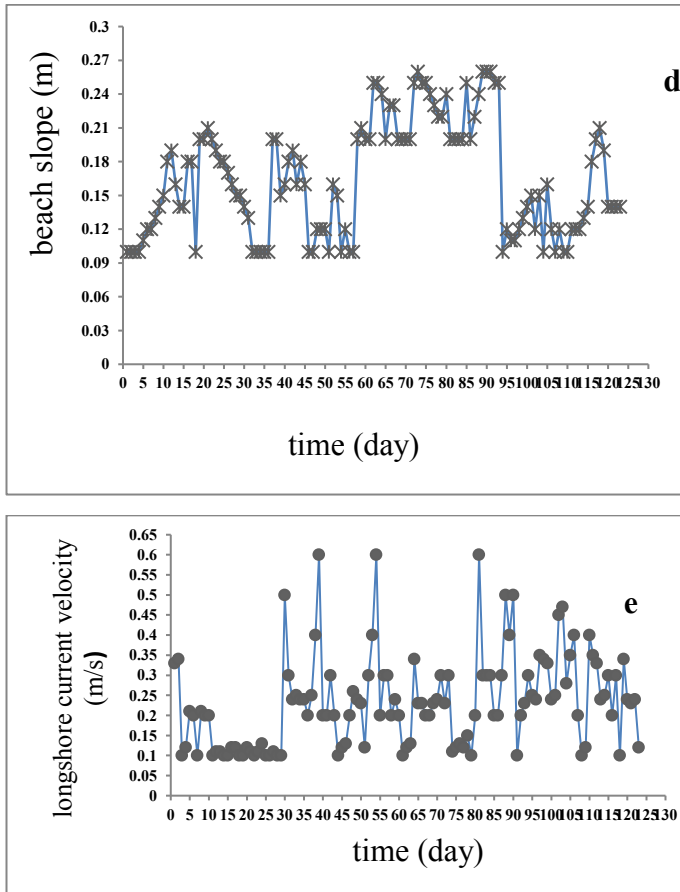


Fig 5: Variation of (a) breaker height, (b) breaker period, (c) breaker angle, (d) beach slope, and (e) alongshore current velocity from September to June 2012.

Table 1. The daily statistical variables of the observation data in the study area

Parameter	N	Max	Min	Mean	Sta.dev	C.V
H(m)	123	0.87	0.01	0.3	0.18	0.6
T(sec)	123	7	2.3	4.6	0.9	0.2
(degree) α	123	45	5	27.8	11.5	0.41
W(m)	123	170	30	83.3	31.6	0.38
V(m/s)	123	0.5	0.1	0.2	0.09	0.45
m	123	0.26	0.08	0.14	0.045	0.32
D(ϕ)	123	5.12	0.2	1.22	1.25	1.02

3.2.Sediment size distribution

The variations of median size (d_{50}) and d_{90} of the sediment at each trap location are shown in Table2. As an expected, d_{50} increased from the water surface to the seabed at each trap location. In general, the

sediments consist of fine sand ($d_{50}=0.12$ to 0.2 mm) to medium sand ($d_{50}=0.2$ to 0.25 mm).

Table2. Sediment size article of the observation data in the study area

Deep(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

1.1.Longshore Sediment Transport Rates Measured by Streamer Traps

The measured LSTRs123 observation in this study by the streamer traps and the rates predicted by the employed formulas are compared in Table 3. The ACES (Automated Coastal Engineering System; LEENKNECHT et al., 1992) prediction applies the same C.E.R.C-formula except that the wave group velocity is calculated by solitary wave theory instead of linear wave theory. The use of solitary approximation results in a prediction that is 25% greater than the C.E.R.C prediction and is not considered appropriate by Bodge and Kraus (1991). Conclusions from streamer trap are summarized in figure 6:

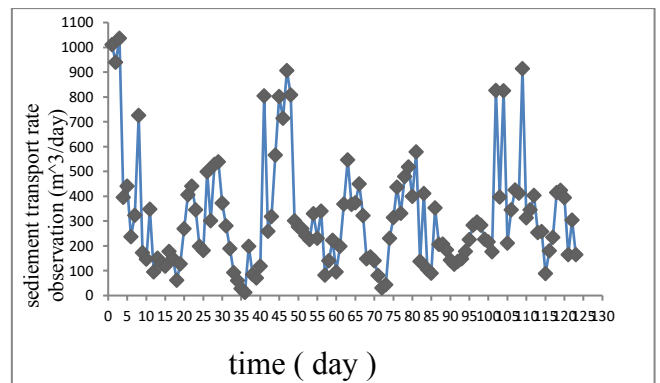


Fig6: collected sediment transport data in Noor coastal zone by streamer traps

Tabel3: The estimated value sediment transport rates by the observation method

Name	Q(kg.(year) ⁻¹)	Q(kg.(day) ⁻¹)
Sediment transport rate	334340	916

3.4. Prediction of longshore sediment transport rate

To determine the LSTR in the study area; the long-term observations of shoreline changes, sediment properties, wave characterizes measurement campaigns were performed. The LSTRs are obtained from three different methods (e.g. C.E.R.C (USACE, 1984) Formula, Kamphuis (1991) Formula, Walton and Bruno (1989) Formula).

According to the calculations for the research area, the gross and the net LSTRs were obtained as shown in Table 4 statistical evolution reuse C.E.R.C, W.B and Kamphuis formulas are shown in Table 5.

Table 4: The daily and yearly alongshore sediment transport rates predicted by different methods

Formula	$Q(m^3 \cdot (year)^{-1})$	$Q(m^3 \cdot (day)^{-1})$
C.E.R.C (USACE, 1984)	350400	960
Kamphuis (1991)	359890	986
Walton and Bruno, 1989	315360	864

For the current study, C.E.R.C formula used to be the most frequently applied expression which yields to the new models that include more coastal parameters. It is recommended that to use C.E.R.C formula in storm conditions where the wave heights exceed 4 m [34]. But, in Noor coastal region according to the wave climate studies, the average wave height was 0.3 m. Thus, C.E.R.C equation overestimates LSTRs obtained from Kamphuis (1991), W. B, and ANN by factor of 0.97 and 1.1, and 0.98 respectively. It is recommended to use Kamphuis (1991) formula in low-wave energy conditions with breaker heights of less than 1 m [34]. The recommended value corresponds to the study area's wave condition. Thus,

Kamphuis (1991) equation overestimates LSTRs obtained from C.E.R.C, W.B, and ANN by factor of 1.03 and 1.14, and 1.01, respectively.

3.5. Application of ANN for estimation of alongshore sediment transport rate

3.5.1. Data used in training the ANN model

Important parameters in most sediment transport formulas area alongshore current velocity (V), surf zone width (W) and breaking wave height (H_b) in this study, observed data by obtained from streamer trap was used. Measured V , W , H_b values were used as an input data to the model and sediment transport rate (Q_s) as an output of model. A total of 123 samples were used for training the model and 87 samples, 36 samples of total measured data randomly selected to validation and testing the model.

3.5.2 ANN model development

To choose the best network for forecasting, different models were built with various nodes and middle layers. In Learn Rate Control (LRC) feature, 0.001 and 0.15 were used as the minimum and maximum limit for auto control of learning rate. The input combinations to estimate total sediment load are: 1) H , W and V 2) H and α ; and 3) H , T , α , D_{50} and m . The first combination includes breaking wave height, long shore current velocity and surf zone width most of sediment transport rate using W.B formula. Other two combinations include parameter used C.E.R.C and Kamphuis formulas. After try-and-error tests, the best network found in this study is the one with 3 layers including one input layer, one middle layer, and one output layer. The best model consists of 3 input including H , W and V , 14 middle nodes, and an output node which should have a sigmoid transfer function. The sigmoid function represented by $1/(1+e^{-x})$ and set the output single strength between 0 and 1. The correlation coefficient and $RMSE$ of this model

were 0.98 and 0.017 for the training data set and 0.96 and 0.015 for the test data set, respectively. The final architecture of the ANN model is given in Table 6.

The ANN model (3-14-1) which was trained using three important parameters of sediment transport rate formulas has slightly more accurate results than other models with four inputs. The accuracy of the chosen ANN model (3-14-1) in comparison with other models of 3 inputs, especially those ones with more than one hidden layer, has insignificant difference. According to the intricacy and longer time needed for training of models with more than one hidden layer, the selection of ANN model (3-14-1) is reasonable. The comparison of the measured data and estimated total sediment load using ANN for training and testing procedures are shown in Figs. 7.

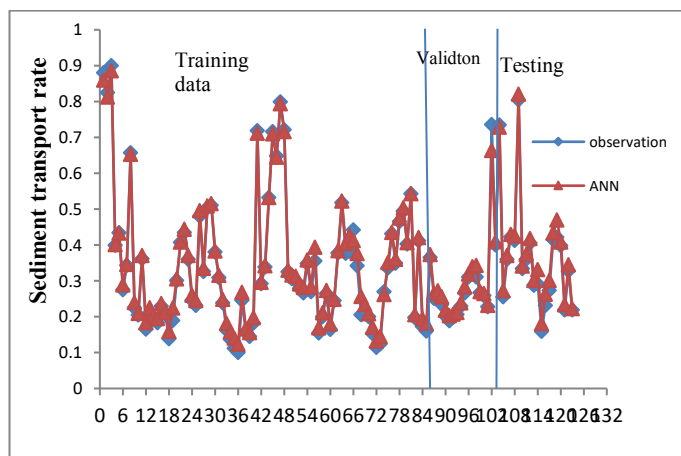


Fig 7: Comparison of observed and simulated sediment transport rate form ANN (3-14-1)

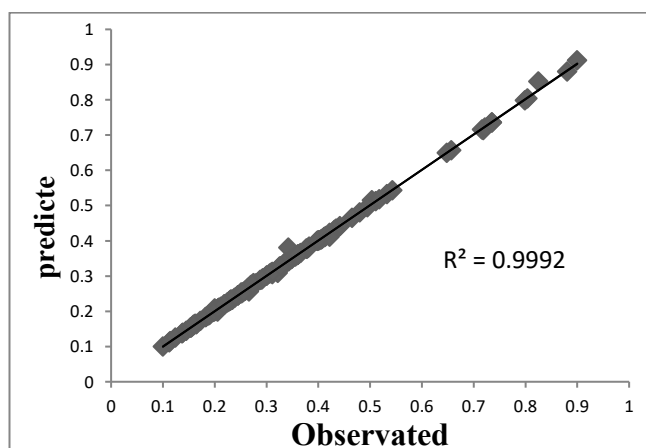


Fig 8: The scatter plot of observed and predicted sediment transport rates forecasts of the ANN (3-14-1)

The daily statistical variables of the breaking wave height (H), wave period (T), wave breaker angle (α), surf zone width (W), long shore current (V), beach slope (m), grain size (D), sediment transport rate observation ($Q_{\text{observation}}$), and sediment transport rate forecast ANN (Q_{ANN}) data. Table.7. In this table, S_x , C_v and C_{sx} denote the standard deviation, variation and skewness coefficients, respectively.

4. Comparison the results of ANN and sediment transport rate formulas

123 sets of observed data with accurate wave properties, surf zone width and alongshore current velocity information, not used in the training and verification of Ann in previous section, are used to compare the results of Ann model and sediment transport formulas. Field data including breaking wave height, period wave, breaker wave angle, surf zone width, long shore current velocity, sediment particle size distribution, beach slope and sediment transport rate. These data were measured by observation filed using streamer trap.

Figure 9 shows the comparisons between computed results from three sediment transport rate formulas and the computed results from the Ann.

In summary, the ANN model was trained using three important parameters H , W , and V which can be further used to estimate sediment transport rate in Caspian Sea data. But, the accuracy of an ANN model is data sensitive, and should not be applied to the conditions outside the data range used in training the ANN model without verification.

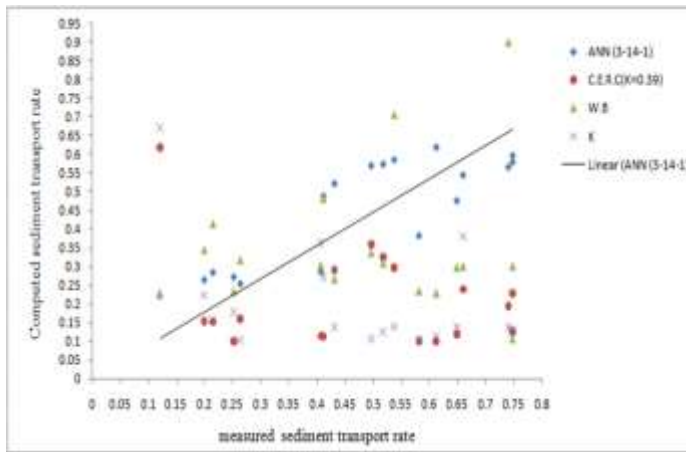


Fig 9: Comparison of ANN the formulas results with observed data

Fig. 10 shows the predicted Q_p compared with observed Q_s using C.E.R.C, Kamphuis, W.B formulas, and ANN method. The R^2 , $RMSE$, CE , MRE and MAE statistical criteria were used to calculation the results of the different models (Table 8).

5.CONCLUSIONS

In the presented study, the accuracy of empirical formula and ANN was evaluated in prediction of daily sediment transport rate. The LSTRs measured by the streamer sediment traps along the low-wave energy coast are lower than the rates predicted by the various empirical formulas. The commonly used C.E.R.C-formula, Kamphuis Formula, W.B predictions are unrealistically high for the studied low-energy settings. The linear relationship between the energy flux factor and LSTR contained 0n the C.E.R.C formula is supported by the streamer trap measurements. But, an order-of-extent lower empirical coefficient, 0.08 rather than 0.78 recommended by Shore Protection Manual (1984), is suggested by the trap data for low-energy coast.

The LSTR predicted by the Kamphuis (1991) formula was 3 times lower than the C.E.R.C prediction and closer to the measured values. The relationships between LSTR with the wave period, beach slope, and sediment grain size established in the Kamphuis (1991) formula are approved by the present study. It is

essential to reconcile the different measurement techniques of, sampling. Further studies on the comparability of the field techniques are recommended. Relationship among the different key measurements (Table 3) needs to be explored to further under-stand their compatibility ANN model is used for estimating sediment transport rate in sea in this study. 87 samples were used for training the ANN model and 36 samples were used to verify the model. Inputs for training the model include breaking wave height (H), surf zone width (W) and alongshore current (V). The results showed that the artificial neural network alongshore sediment transport rate in Noor coastal zone calculate. It is obvious R^2 , RMSE, MAE, CE and MRE form ANN method, 0.96, 0.015, 1.7×10^{-4} , 0.93, and 3.5×10^{-2} respectively.

6. References

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