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Predicting the sediment rate of Nakhilo Port using artificial intelligence

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ABSTRACT

In order to predict changes in coastal profile, it is necessary to investigate the sediment transport rate along the coast. Sediment transport is important in the areas of sedimentology, geomorphology, civil engineering and environmental engineering. The study of sediment transport is often performed to determine the location of erosion or deposition, the amount, timing and distance of its occurrence. Forecasting future coastline changes are as a result of the marine structural development. It provides the conditions for appropriate engineering decision-making. It also makes the grounds for sustainable use of the coast. When spot and local forecasts are necessary, models based on time series like support vector regression and Artificial Neural Network as new solutions are taken into consideration. These methods are one of the ways of machine learning. This study was investigated the importance of the offshore sediment transport rate in this research for the desired beach on the west coast of Hormozgan province. The littoral drift (LITDRIFT) model is used to get this type of transfer rate. To estimate evaluation of the longshore sediment transport rate by support vector machine (SVM); it will be needed two categories of data; one for data training and the other to check the machine for testing. The results of estimation of sediment transport rate using support vector regression and artificial neural network method showed the superiority of support vector regression over the neural network in both training and experimental groups of data.

1. Introduction

In coastal engineering, cross shore and longshore sediment transport rate must be calculated to determine shoreline changes. Sediment transport in the Sedimentology, Geomorphology, and Civil Engineering and Environmental Engineering fields are important. The study of sediment transport is often performed to determine the location of sediment deposition (erosion) or sedimentation, amount, time and distance of its event [1]. The instability of beaches and significant shoreline displacement, the erosion of beaches by waves, flows and storms have caused significant damages to offshore installations and structures. The filling the ponds of the ports from the sediments in a short time and similar matters, are among significant problems and difficulties of many countries and regions with maritime boundaries. Therefore, the sediment transfer is one of the most important processes associated with the above dilemmas that is being investigated [2]. Due to the vast shoreline borders in Iran and the existence of various coastal structures, determining the sediment transport rate on these coasts is of great importance. [3]. There is a state of sliding or skipping of the particles that so-called Bed Load transfer and the other which the particles move is in a suspended state that is called Suspended Load transfer, therefore the issue of sediment transport divided into two types: Bed Load and Suspended Load. For each particle of the precipitates, the current must reach the top of the critical incision. To move a particle of non-stick sediment; The fluid velocity must exceed the critical section velocity, when the particle size is very small or when the flow is very slow, the sediment particles are protected by slimy layers and thus there will be no movement. Following the increase in the flow, as the section velocity increases, the effect of this layer becomes lower, the coarsest grain begins to roll and bed load creates [4]. Mohandes et al. used the SVM to predict wind speed and compare its results with the multilayer perceptron (MLP) neural networks. They showed that SVM had better performance than MLP in their studies [5]. Bhattacharya and Solomatine conducted another study on the soil classification using three SVM, ANN and decision tree. in this study, the same results were obtained for all three models [6]. Singh et al. was used to estimate the separation efficiency due to sluice installation in the channels. They also made a comparison to ANN and SVM in their studies. Both of these methods worked in the same way. They also refer to less computational SVM than ANN [7]. The offshore sediment transport can be the result of the sand return to the swells and sinking's of the bay and along the coast. At the other times, there is a widespread displacement of sediment perpendicular to the shore, which will cause sand to move along the beach. Here the focus is on investigating and efficiency of models for predicting sediment transport along the coast [8]. Sediment transport is an evolving science that relies on complex processes. So this research seeks to improve and predict sediment transport rates in coastal areas using soft computing methods [9]. As can be seen, the rate of longshore sediment transport rate has not been predicted by SVM. On the other hand, since the support vector machine has different parameters, the innovation of this research and its distinguishing feature is that it has obtained the optimal values of these parameters for this field. It was estimated of sediment transport rate using support vector regression (SVR) and artificial neural network (ANN). Finally, the results showed a more accurate evaluation of SVR than ANN.

2. Soft Computing

2.1. Support Vector Machine (SVM)

Machine Learning is a scientific discipline that develops and regulates algorithms that according to them, computers can learn. These algorithms allow computers to evolve behavior using experimental data. The history of using machine learning methods in its modern form goes back to World War II (the 1950s) and the invention of modern computers. Machine learning methods, such as genetic algorithms and neural networks, emulated the body structure of alive creature and the human mind. An important breakthrough in machine learning approaches was the introduction of the SVM by Vapnik and his colleagues in the 90s. The support vector machine method has been developed based on the Vapnik statistical learning theory [10]. In SVM to improve model generalizability, Structural Risk Minimization Principles (SRM) is used. However, in other methods, Experimental Risk Minimization principles (ERM) are used. SRM principles have been shown to perform better than ERM [11]. The support vector machine generally is used in two-group or multi-group classification issues and regression. Another criterion in machine learning approaches is based on the type of data available for model development. Generally speaking, based on the kind of data that is used in machine learning the issues are categorized into several sections which are: Supervised Learning, Reinforcement Learning, Unsupervised Learning, Semi-supervised Learning.

2.2. SVM in Data Regression

In the support vector machine in solving the regression problem, the goal is to find a linear function such as $f(x) = (w.x) + b$ which can estimate output values based on input values. In SVM, the Vapnik losses function is used to solve the regression problem. In this losses function, a minimum error of ε is ignorable from the actual value. We define the losses function as follows:

$$L_\varepsilon(y) = |y - f(x)|_\varepsilon = \begin{cases} 0 & if \quad |y-f(x)| \leq \varepsilon \\ |y - f(x)| & otherwise \end{cases} \quad (1)$$

Figure 1 shows the losses function well.

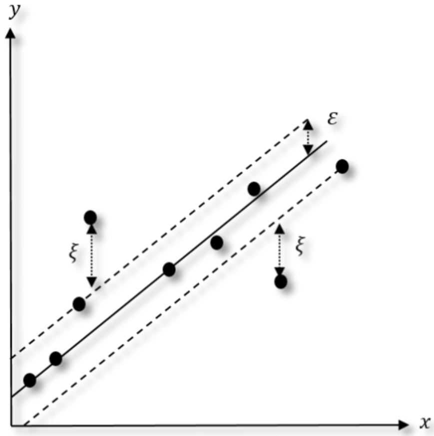

Figure 1. The Losses Function Error

Thus, if the predicted value within the strip is 2ε thick, the losses or harm is zero, but if not, the amount of losses is equal to the difference between the values predicted in ε.

In the learning machine approach to limit model errors, we use structural risk minimization principles. yet, other approaches such as artificial neural networks are on the basis of the principles of Experimental Risk Minimization. It was written the Experimental Risk function in terms of the non-sensible losses function to error ε as follows:

$$R_{emp}(w, b) = \frac{1}{l}\sum_{i=1}^{n}|y - f(x)|_\varepsilon \quad (2)$$

The Experimental Risk function is made up of test samples and if the training dataset is too large; (in other words, the larger the number of training samples) the experimental risk converges to the real risk. But if not, even obtaining a small amount of the experimental risk won't be a guarantee for being small model errors on the samples that it has not yet experienced, (in other words, there is no guarantee of good generalization to the experimental data). In the artificial neural networks to overcome the problem of inappropriate generalization, good architecture should be designed for the network. During the model training, the designed network minimizes the number of errors on training data. The designed network may work well on the test data and even bring the experimental risk to zero, but on the test data, it does not perform well. So, it was selected the appropriate structure which, besides to decrease errors on training data, has good generalization capability [12]. In the support vector machine method to overcome the above problem, minimizing risk is done by minimizing structural risk. In structural risk besides to experimental risk, another operation is defined as the VC dimension. Using the principles of structural risk minimization, it is possible to maximize generalization while minimizing experimental risk. (To maximize generalizability, the VC dimension should also be controlled.) Thus, irrespective of the mathematical basis, the principles of structural risk minimization have been shown, the best function to perform the regression operation on the support vector machine method is to decrease the following function:

Minimize

$$\Phi(w,\xi^*,\xi) = \frac{\|w\|^2}{2} + C\left(\sum \xi_i^* + \sum \xi\right) \qquad (3)$$

Subject to

$$\begin{aligned} &y_i - [(w.x_i) + b] \le \varepsilon + \xi_i \\ &[(w.x_i) + b] - y_i \le \varepsilon + \xi_i^* \\ &\qquad \xi_i, \xi_i^* \ge 0 \end{aligned} \qquad (4)$$

In this relation, the variables of slack are ξ^*, ξ. (Figure 2).

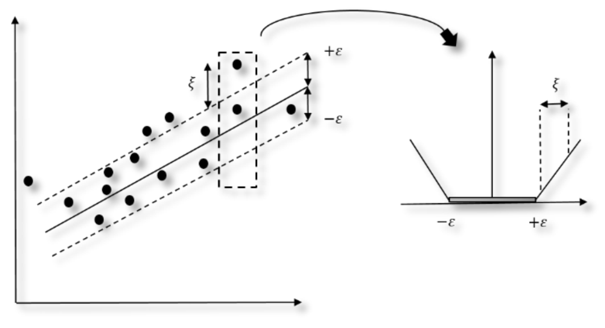

Figure 2. slack Variables

Before presenting the solution to the above optimization problem, it is recalled that, generally the basic foundations of regression in a support vector machine consist of the following three parts [13]:

• The support vector machine estimates a regression function by applying a linear function class.

• The support vector machine performs regression operations with the function that deviation from the actual value in it is less than ε.

• The support vector machine by minimizing structural risk offers the best response.

To solve the optimization problem, the previous relationship is used as its equal in the form of Lagrange function:

$$L(\alpha^*,\alpha) = -\varepsilon \sum_{i=1}^{n}(\alpha_i^* + \alpha_i) + \sum_{i=1}^{n} y_i(\alpha_i^* - \alpha_i) - \frac{1}{2}\sum_{i=1}^{n}\sum_{j=1}^{n}(\alpha_i^* - \alpha_i)(\alpha_j^* - \alpha_j)\,(x_i, x_j) \qquad (5)$$

Where in this relation, the Lagrange coefficients areα^*, α

By maximizing the above function under the following amounts:

$$\alpha \begin{cases} \sum \alpha_i^* = \sum \alpha_i \\ 0 \le \alpha_i^* \le C \\ 0 \le \alpha_i \le C \end{cases} \qquad for \quad i = 1,2,\dots,n \qquad (6)$$

The α, α^* coefficients are calculated. Samples that do not have the corresponding lagrange coefficients are known as support vectors. These data than the measured value have a prediction error greater than ($\pm\varepsilon$), therefore they do not fall into the regression model of intra-band support vectors ($\pm\varepsilon$), thus the value of ε controls the number of support vectors [14].

Once the langrage coefficients are determined, the final answer will be calculated as follows:

$$w_0 = \sum(\alpha_i^* - \alpha_i)x_i \qquad (7)$$

$$\mathrm{f(x)} = \sum(\alpha_i^* - \alpha_i)(x_i - x) + b_0 \qquad (8)$$

In the above relations, ε and C parameters defined by the user. If the uncertainties in the existing data (which may be due to reasons such as unavoidable measured errors and sample shortages occur within ranges of input variables) are great, the larger the value ε leads to a solution that is more independent of these uncertainties. But, very large values of ε leads to a situation where no correct prediction is possible because this will change the state of the support vectors and will affect the results. Although selecting large amounts of ε reduces the number of support vectors, and this reduction is desirable in support vectors (that is the thickness of out-of-band data is reduced to 2ε) but achieving this goal by widening the bandwidth to ε is wrong. If the value of ε is low, a large number of support vectors will be selected which will increase the number of being trained dangerous (That is, although the machine performs well on training samples, it has poor generalizability) [15 and 16]. According to the final answer of relationf(x), it is evident that data with zero Lagrange coefficients have no effect on the final response and only support vectors are used to obtain the regression function. We call his feature sparseness. Since support vectors have a relation with to this feature, it turns out that value ε also controls this feature of the support vector machine [17].

In the regression model, Kernel functions are also used to develop the nonlinear model. Yet various kernel functions have been introduced but it is very difficult to get kernel functions in general. It's mentioned two examples of important kernel functions used in engineering applications are:

- Polynomial Kernel function

$$K(x_i, x) = ((x, x_i) + 1)^d \quad (9)$$

In this relation, d is the degree of a polynomial and its value is defined by the user [18].

- Radial Basis Function (RBF)

$$K(x, x_i) = \exp\left(\frac{-|x-x_i|^2}{2\sigma^2}\right) \quad (10)$$

In this relation, σ is the width factor of Kernel function and is defined by the user [11].

In that case the answer through a process will be as follows:

$$f(x) = w_0.x + b_0 \quad (11)$$

$$w_0.x = \sum(\alpha_i^* - \alpha_i)K(x_i, x) \quad (12)$$

$$b_0 - \frac{1}{2}\sum(\alpha_i^* - \alpha_i)[K(x_r, x_i) + K(x_s, x_i)] \quad (13)$$

As it is evident, selecting the appropriate values for the parameters to be determined by the user forms a very important part of the design of the support vector machine model. The most common way to determine the model design parameters and the parameters of the kernel functions is to use the trial and error process.

2.3. Comparison of SVR and Neural Network

Artificial neural networks (ANNs) are one of the most common and well-known methods of machine learning. Given the widespread and successful use of this method in various engineering issues, a brief comparison between the two methods is presented in this section to better understand the capabilities of the support vector regression method. Given the general principles outlined in the different parts of this chapter, the differences between the two approaches can be illustrated in two important areas. First, because the SRM principles perform better than the ERM, so it is expected that the support vector regression that applies the SRM principles performs better than the artificial neural network that uses the ERM principles. Besides, because the SVR method deals with a convex optimization problem, achieving an overall minimum is guaranteed and there is no risk of stopping the model in the local minimum trap (unlike what exists in artificial neural networks) [19 and 20].

3. Model Used to Investigate Sediment Transport Rate

The accuracy (validity) of the LITDRIFT model available in the MIKE21 software which developed and marketed by DHI has been demonstrated by applying to numerous engineering and research projects and based on actual results as well as comparisons with analytical problems. It is a one-dimensional model and consists of two major parts: the hydrodynamic model and the sediment transport model [21]. The hydrodynamic model can calculate wave's refraction, depth reduction, waves breaking, radiation stress, wave setup, and coastal parallel currents velocity and the sediment transport model also calculates the sediment transport rate by taking into account the simultaneous effect of wave and current. Based on this model, and the theory, the presented relations are about how the current is layered to consider the effect of the simultaneous turbulence of wave and current [22]. In this theory, the depth is divided into two areas near the bed and outside the bed. The software calculates the characteristics of the waves at the breaking point, taking into account the phenomenon of refraction and shallow and wave transfer to shore. Since the depth at which the breaking occurs varies for each wave component, the software determines the depth of the breaking area for the different components of the waves. Then, by applying the appropriate formulas, the sediment transport for each wave and its resulting current is calculated. Finally, by adding sediments from different components of waves to each other, the transverse distribution of sediment transport from sea to coast is determined. It should be noted that the scope of application of the model used in sandy beaches, which is the major factor of waves sediment transport, has been defined. The one-dimensional LITDRIFT model is not used in the areas where the sediments are fine-grained and the equations governing the sand sediment transport is not true, or in areas where sediment transport agent is tidal currents, and due to the geographical location of this part of the beach, there are no significant waves. Because of the fine-grained of the sedimentary materials and is low the rate of collapse velocity of the aggregates and their permanent suspension, there was no major sediment deposition in these areas. so, no significant morphological changes can be identified [18,19].

3.1. The Area of Observation

In this study, longshore sediment transport rate investigates for one of shore of Hormozgan province. Also, it was showed position of the selected shore beach in the overview of Fig 3, as well as the position of the shore beach with details such as the selected buoy in Fig 4.

The details of the shore beach and the location of the buoy are presented in Table 1.

Table1. Details of the shore beach and the location of the buoy

Port	Shore beach	Station location	Measuring range
Nakhilo	W3	E53.375 N26.875	1999 to 2009

According to the historical data of the Ports and Maritime Organization recorded by the mentioned buoys can point out the wave height (Hs), wave angle (α), wave period (T), and particle size (∅).
The statistical characteristics of the recorded data and the investigated littoral sediment transport rate for the shore beach in question are presented in table 2.
The main objective of the present study is to estimate the longshore sediment transport rate, based on data from the Ports and Maritime Organization, using support vector regression. Thus, two categories of data are needed, one related to data training and the other for machine evaluation for testing. The basis of the support vector regression is the use of historical data collected from the studied system conditions. The more scope and variety of the collected data, the more adaptability and comprehensiveness can create. It will be presented the data in Table 2&3 as training and experimental data for using in the support vector machine.

Figure 3. Location of Nakhilo Port

Figure 4. Nakhilo Port

Table 2. Statistical Characteristics of Buoy

Variable	Educational dataset (29654 samples)			
	Minimum	maximum	average	standard deviation
Wave height (meter)	0.014	1.08	0.279	0.156
Wave angle (degree)	185.2	359.8	282.3	19.3
Wave period (second)	1.85	8.7	4.3	1.12
Particle size (m meters)	0.1	0.1	0.1	-
Sediment transport rate (Cubic meters per day)	0.012	5001.7	435.1	862.2

Table 3. Statistical Characteristics of Buoy

Variable	Experimental dataset (3295 samples)			
	Minimum	maximum	average	standard deviation
Wave height (meter)	0.021	0.855	0.277	0.156
Wave angle (degree)	186.8	357.2	282.18	19.14
Wave period (second)	1.85	7.85	4.29	1.11
Particle size (m meters)	0.1	0.1	0.1	-
Sediment transport rate (Cubic meters per day)	0.05	4998.25	432.57	873.29

4. Conclusion and Discussion

Data were collected from the LITDRIFT model as well as support vector regression. In this section, first, the outputs of the LITDRIFT model and then the results are presented to estimate the littoral sediment transport rate.

4.1. Sedimentary Studies

The position of the desired shore beach has examined and the wave climate introduced and finally, by implementing and calibrating the one-dimensional sediment transport model, an estimate of sediment transport rate values was obtained. The computational values applicable along the selected shore beach will be applicable in areas where the coastal line and conditions have a good similarity with specifications of the model calibration location.

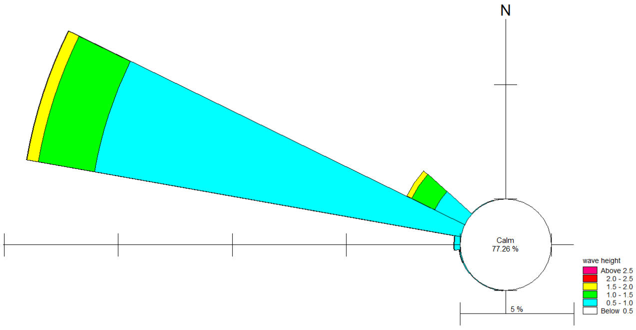

Figure 5. A ten-meter-deep flower wave of shore beach

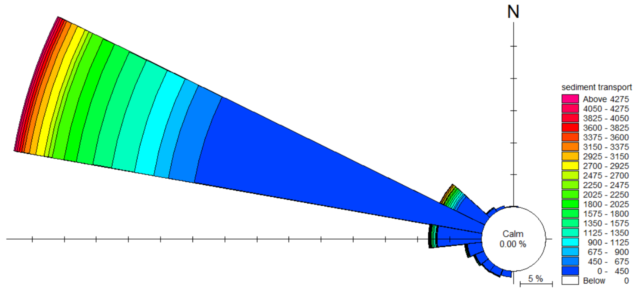

Figure 6. Directional distribution of sediment (cubic meters per year) in the shore beach

4.2. Wave Climatic of West Shore Beach

In order to investigate the wave conditions in the studied shore beach, a flower wave with a depth of 10 m was extracted in the upper area of Nakhilo port as shown in Figure 5. Examination of the rose wave of shore beach shows that in the studied range about 77% of the days, the wave height is less than 0.5 m (calm conditions). The Geographic direction of most waves is from the northwest.

4.3. Model Calibration

Based on the software guide suggested for calculating bed roughness, the following relation can be used:

$$Roughness = 2.5 \,.\, d_{50}$$

d_{50} is particle diameter representing the 50% cumulative percentile value (50% of the particles in the sediment sample are finer than the d50 grain size). But, according to this reference, the above value is not constant and definite and this parameter is one of the most important parameters of the model calibration. Based on the available morphological evidence, one-dimensional mathematical model calibration is considered.

To account for variable grain size and the diameter of sediment particles as one of the effective parameters in calculating the sediment transport rate, in this paper, field data obtained by sediment traps are used.

4.4. LITDRIFT Model Outputs

By implementing the LITDRIFT model, the sediment transport rate in the study area is calculated. The result is shown in Figure 6 as a directional distribution of sediment.

5. Support Vector Regression Results

Support vector regression is used to predict and estimate the longshore sediment transport rate. According to the performance of kernel functions and the description provided in the "SVM in data regression" section; The RBF kernel function is used to predict the sediment transfer rate by this machine and the optimal coefficients obtained by trial and error are equal to C = 9 and σ = 0.28.

To compare and confirm the results obtained by the support vector regression, the values of this machine were compared with the actual sediment transport rate extracted from the Ports and Maritime Organization. Also, ANN is used to compare the support vector regression with another soft computation.

MATLAB software has been used to model coastal sediment transport rates using a multilayer perceptron neural network model. And it was comparing the results of this model with SVR and actual observations. First, the neural network scatter diagram in two training and experiment modes is shown in Figure 7.

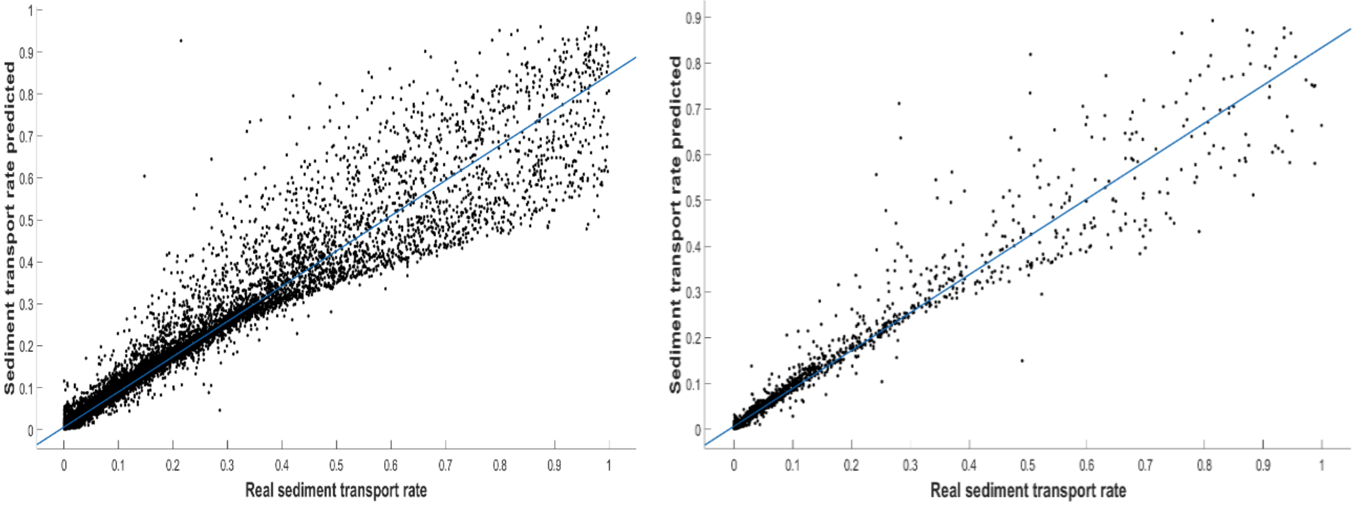

Figure 7. Scatter diagram of real sediment transport rate relative to the values predicted by ANN in training and experiment mode

The scatter diagram of the support vector regression is presented in two training and experiment modes in Figure 8.

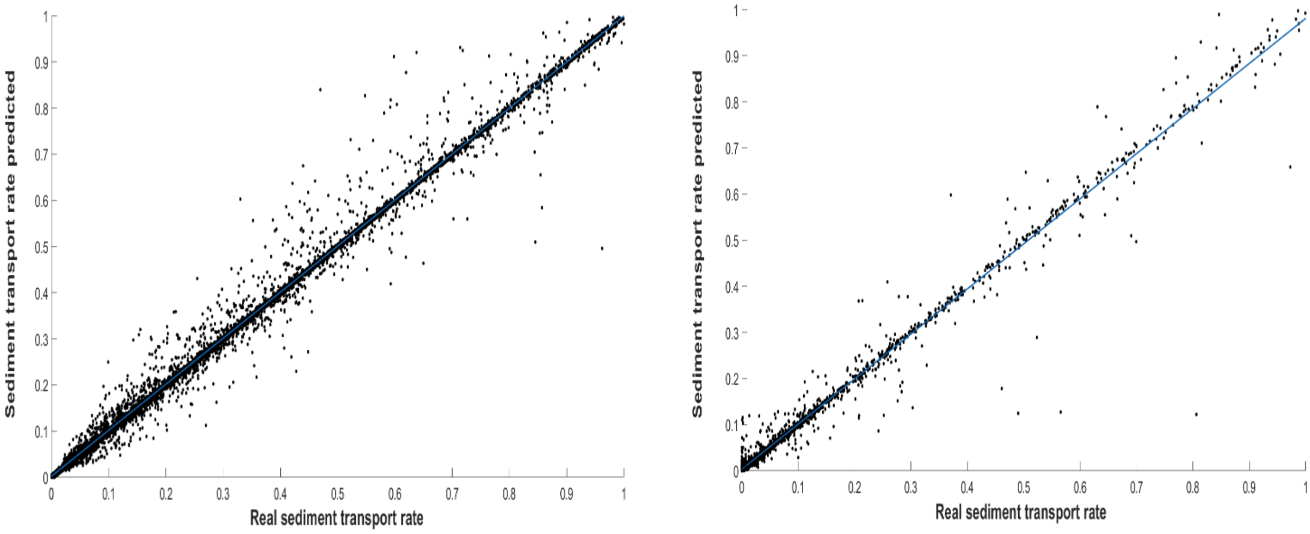

Figure 8. Scatter diagram of the actual sediment transport rate relative to the values predicted by SVR in training and experiment mode

The results of Figures 7 and 8 show the proper fit of the support vector regression than the neural network in predicting the sediment transport rate. Statistical estimations have also been used to investigate more accurately. Detection coefficient (R^2) and root mean square error (RMSE) was used to evaluate the accuracy of littoral sediment transport rate estimation through SVR and ANN. Statistical estimates are presented in Tables 4 and 5 for the two training and experiment modes.

Table 4. Statistical estimation of predicted sediment transport rate in training mode

Statistical estimation / Method	R^2	RMSE
SVR	0.99	0.012
ANN	0.94	0.034

Table 5. Statistical estimation of predicted sediment transport rate in experiment mode

Statistical estimation / Method	R^2	RMSE
SVR	0.98	0.024
ANN	0.94	0.035

It can clear that in training mode, the detection coefficient of the support vector regression method is more accurate than the neural network in estimating longshore sediment transport rate and also has the least root mean square error.
In the experimental mode, the coefficient $\boldsymbol{R^2}$ and RMSE for both SVR and ANN methods show high accuracy of the support vector regression using RBF kernel over artificial neural network.
The Figures 9 and 10 show predictions made by two soft computing methods (SVR and ANN) by comparing the actual values of the longshore sediment transport rate in a bar graph.

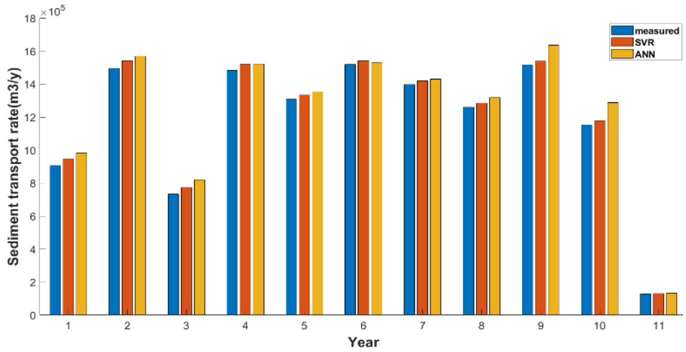

Figure 9. Comparison of 11-year littoral sediment transport rate for training data

In Fig 9, it will be examined the littoral sediment transport rate for 11 years in the training mode. It was compared the results of training from SVR and ANN models with the measured values. The results show a good performance of SVR with RBF kernel function than the ANN ratio. It is evident that the values predicted by the SVR are closer to the actual values. Also the ANN method has predicted higher values over most years than the actual values.

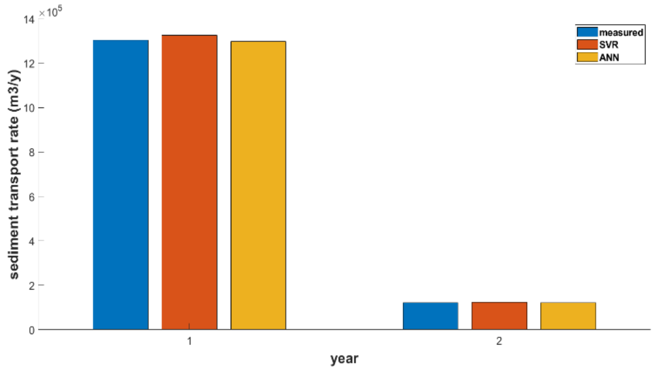

Figure 10. Comparison of 2-year littoral sediment transport rate for the experimental data

It is obvious in Fig 10 that in the experimental mode, as in training mode, the values predicted by the support vector regression are close to the actual values. Also, the values predicted by the ANN show higher values than the real values.

6. Conclusion

This study was divided sediment studies (Sedimentology) into training and experimental groups. It was aimed at identifying sedimentary behavior of one of the shore beaches of Hormozgan province, sediment-prone areas and areas subject to erosion and data. By using vector support regression and kernel RBF function and artificial neural network, this paper was predicted the parallel littoral sediment transport rate. The results of the classification showed better performance of RBF kernel in the support vector regression than the neural network in predicting coastal parallel sediment transport rate. The accuracy of the RBF kernel in training and testing mode was 99% and 98%, respectively, which was about 4% more accurate than the neural network results.
To predict coastal profile changes, it is necessary to investigate the rate of littoral sediment transport along the parallel direction of the coast. The sediment transport rate along the parallel the direction of coast is effective in estimating the rate of sedimentation, descaling, and deformation of the coastal profile. For sediment management in coastal areas, the sediment transport process as well as the morphological changes, the design of protective structures against descaling (erosion) as well as analysis of sedimentation status at the craters of breakwaters and ports are of great importance. Understanding sediment behavior and

predicting future shoreline changes can help coastal engineering and management decisions.

As mentioned earlier, the present study led to the presentation of a method based on soft calculations in estimating sediment transport rates, which can be used in real projects from two perspectives: First, the use of soft computing methods to estimate phenomena such as sediment transport, which on the one hand has many uncertainties and on the other hand has little data, can lead to better estimates of the actual projects. Secondly, support vector machine method has a higher response rate than conventional methods of soft computing such as neural network, which will reduce the cost and time of analysis of the coastal engineering projects.

7. Acknowledgment

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8. References

1- Leeder, M. R. (2009). *Sedimentology and sedimentary basins:* from turbulence to tectonics. John Wiley & Sons.

2- Dezvareh, R. (2019). *Providing a new approach for estimation of wave set-up in Iran coasts*. Research in marine sciences, 4(1), 438-448.

3- Van Rijn, L. C. (1993). *Principles of sediment transport in rivers, estuaries and coastal seas* (Vol. 1006, pp. 11-3). Amsterdam: Aqua publications.

4- Mangor, K. (2004). *Shoreline management guidelines.*

5- Mohandes, M. A., Halawani, T. O., Rehman, S., & Hussain, A. A. (2004). Support vector machines for wind speed prediction. Renewable energy, 29(6), 939-947.

6- Bhattacharya, B., & Solomatine, D. P. (2006). *Machine learning in soil classification*. Neural networks, 19(2), 186-195.

7- Singh, K. K., Pal, M., Ojha, C. S. P., & Singh, V. P. (2008). *Estimation of removal efficiency for settling basins using neural networks and support vector machines*. Journal of Hydrologic Engineering, 13(3), 146-155.

8- Akbarinasab, M., & Paeen Afrakoti, I. (2019). *Application of Soft Computing in Forecasting wave height (Case study: Anzali)*. International Journal of Coastal and Offshore Engineering, 3(1), 31-40.

9- Dezvareh, R. (2019). *Application of Soft Computing in the Design and Optimization of Tuned Liquid Column–Gas Damper for Use in Offshore Wind Turbines.* International Journal of Coastal and Offshore Engineering, 2(4), 47-57.

10- Vapnik, V. (1995). *The nature of statistical learning theory*. New York: Springer-Verlag.

11- Vapnik, V. N. (1999). *Statistical Learning Theory*. John Wiley & Sons, Inc

Kraus, N. C., & Dean, J. L. (1987). *Longshore sediment transport rate distributions measured by trap*. In Coastal sediments (pp. 881-896). ASCE.

12- Kumar, V. S., Anand, N. M., Chandramohan, P., & Naik, G. N. (2003). *Longshore sediment transport rate—measurement and estimation, central west coast of India*. Coastal Engineering, 48(2), 95-109.

13- Dezvareh, R., Bargi, K., & Moradi, Y. (2012). *Assessment of Wave Diffraction behind the Breakwater Using Mild Slope and Boussinesq Theories*. International Journal of Computer Applications in Engineering Sciences, 2(2).

14- Samui, P. (2008). *Support vector machine applied to settlement of shallow foundations on cohesionless soils*. Computers and Geotechnics, 35(3), 419-427.

15- Samui, P., Sitharam, T. G., & Kurup, P. U. (2008). *OCR prediction using support vector machine based on piezocone data*. Journal of Geotechnical and GeoEnvironmental engineering, 134(6), 894-898.

16- Dezvareh, R. (2020). *Upgrading the Seismic Capacity of Pile-Supported Wharfs Using Semi-Active Liquid Column Gas Damper*. Journal of Applied and Computational Mechanics, 6(1), 112-124.

17- Das, S. K., Samui, P., Sabat, A. K., & Sitharam, T. G. (2010). *Prediction of swelling pressure of soil using artificial intelligence techniques*. Environmental Earth Sciences, 61(2), 393-403.

18- Cristianini, N., & Shawe-Taylor, J. (2000). *An introduction to support vector machines and other kernel-based learning methods*. Cambridge university press.

19- Dezvareh, R. (2019). *Evaluation of turbulence on the dynamics of monopile offshore wind turbine under the wave and wind excitations*. Journal of Applied and Computational Mechanics, *5*(4), 704-716.

20- Hashemi, M. R., Ghadampour, Z., & Neill, S. P. (2010). *Using an artificial neural network to model seasonal changes in beach profiles*. Ocean Engineering, 37(14-15), 1345-1356.

21- Singh, A. K., Deo, M. C., & Sanil Kumar, V. (2007, September). *Neural network–genetic programming for sediment transport*. In Proceedings of the Institution of Civil Engineers-Maritime Engineering (Vol. 160, No. 3, pp. 113-119). Thomas Telford Ltd.