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PREDICTION OF DAILY TIDAL LEVELS ALONG THE CENTRAL COAST OF EASTERN RED SEA USING ARTIFICIAL NEURAL NETWORKS

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ABSTRACT: Accurate tidal prediction is essential for the design and construction of coastal and marine structures. In this study, an Artificial Neural Network (ANN) approach uses four algorithms (Radial Basis Function, General Regression, Multilayer Perceptron, and Cascade Correlation) were developed to estimate the tidal levels along the central coast of eastern Red Sea. A genetic algorithm was used to determine the adequate ANN structure and the optimal values of the parameters for the different algorithms of the ANNs. The obtained results confirm that the General Regression Neural Network (GRNN) model outperforms the other techniques. Moreover, the results verify that the GRNN model provides improvements in root mean square errors of 117.15%, 122.85%, 121.43%, and 127.15% over the Multilayer Perceptron Neural Network (MPNN) with three layers, MPNN with four layers, Cascade Correlation Neural Network (CCNN), and Radial Basis Function Neural Network (RBFNN), respectively for training and 19.26%, 20.50%, 11.8%, and 23.61% for testing. This investigation further indicates that the GRNN model can be useful as a supervised learning-based tool for predicting tidal levels.

Keywords: Tidal Level, Red Sea, Prediction, Artificial Neural Network, Genetic algorithm.

1. INTRODUCTION

Tide is a phenomenon used to describe the periodic motion of water due to the differential gravitational forces of mostly the moon and sun upon the differential parts of the rotating earth [1]. Tide prediction plays an important role in the exploitation and utilization of sea resources, especially in the prevention and reduction of sea disasters. Accurate tidal level prediction is a crucial issue for the design of coastal and offshore constructions and coastal development [2].

Numerous models for tidal level forecasting have been carried out previously. In recent years, soft computing techniques, especially Artificial Neural Networks (ANNs), have become increasingly popular in sea-level data analysis and prediction attributes to their merits, such as nonlinearity, adaptivity, arbitrary approximation capability, and parallel information processing mechanism [3]. A fundamental principle in data modeling is to incorporate useful a priori information regarding the underlying data-generating mechanism into the modeling process [4, 5]. The topology of the neural prediction model is substantially important for predictive efficiency [6].

Various research works have been conducted to make the best use of soft computing techniques to analyze and predict tidal levels. Vaziri [7] compared the ability of ANNs with multiplicative autoregressive integrated moving average modeling. Deo and Chaudhari [8] used the three algorithms (back-propagation, cascade correlation, and conjugate gradient) of ANNs for predicting tides, and they found that the algorithm of cascade correlation involves the lowest training time and is suitable for adaptive training purposes. Also, Tsai and Lee [9] employed the Back-Propagation Neural Network (BPNN) along with a gradient descent method to predict tides at Taichung harbor and Mirtuor coast. Lee and Jeng [10] extended the diurnal and semi-diurnal tides to mixed tides, which are more likely to occur in the field. However, their model is only applicable for instant prediction and not for long-term prediction. Lee, Tsai, Jeng, and Shieh [11] and Lee [12] applied ANNs to predict the different types of tides and found that the technique can be effective. Steidley, Sadovski, Tissot, Bachnak, and Bowles [13] also utilized an ANN to improve the predictions of water levels where the performance of the tide charts is particularly poor. Rajasekaran, Lee, and Jeng [14] developed functional and sequential learning neural networks to predict tidal levels with a typhoon surge effect. Moreover, Rajasekaran, Thiruvenkatasamy, and Lee [15] constructed functional networks and sequential learning neural networks based on historical tidal observations. Makarynska and

Makarynskyy [16] used a Feed-Forward Neural Network with a Resilient Back-Propagation learning algorithm to predict tide levels. Rajasekaran, Gayathri, and Lee [17] also employed a promising Support Vector Regression (SVR) technique for storm surge predictions. Pashova and Popova [18] utilized the statistical parameters of tidal levels for daily mean sea-level prediction. A variable-structure radial basis function neural network constructed by sequential learning was proposed for tidal predictions [19]. Shetty and Dwarakish [20] predicted tide levels using the BPNN with the Levenberg Marquardt (LM) algorithm, and they concluded that ANNs can be used to predict tides at Karwar, West Coast of India successfully using short-term hourly tide level data. Mlybari, Elbisy, Alshahri, and Albarakati [21] used the Support Vector Machines (SVM) with different kernel functions and the BPNN to predict daily tides level along the Jeddah coast, Saudi Arabia, and they demonstrated that the SVM is better than the BPNN and has better generalization performance. Salim, Nayak, Mohanthy, Sasamal, Dadhwal, Dutt, and Rao [22] predicted tide levels using the BPNN and Non-linear Autoregressive with an Exogenous input network. Furthermore, Meena and Agrawal [23] also employed the ANN model with different learning algorithms for forecasting tidal levels using the limited measured data, and they found that the BPNN with the LM algorithm provides good correlations as compared to other algorithms. Okwuashi and Ndehedehe [24] used the SVM as an alternative model to the conventional least-squares model for predicting tide levels.

This study aims to measure the accuracy of an ANN approach and uses different algorithms (Radial Basis Function, General Regression, Multilayer Perceptron, and Cascade Correlation) to predict daily tidal levels. To this end, a GA is used to determine the adequate ANN structure and optimal values of the parameters for the different algorithms of ANNs. The rest of this paper is organized as follows: Section 2 describes the study area and data and introduces the methodology, Section 3 demonstrates the results and discusses them, and Section 4 concludes the paper.

2. MATERIALS AND METHODS

2.1 Study Area and Data

The Red Sea is a narrow seawater body in the Indian Ocean, lying between Asia and Africa and has an area of approximately 438,000 km^2. It is approximately 2300 km long and 360 km wide at the widest part. The average depth is nearly 490 m. The maximum recorded depth in the central axis of the Red Sea is 2920 m, while a figure of 3040 m has also been reported [25]. In the south, the Red Sea connects to the ocean body through the Bab el Mandeb Strait and the Gulf of Aden. In the north, the Red Sea is leading to the Gulf of Suez and the Gulf of Aqaba. The Jeddah coast lies in the central Red Sea between 21.55° N and 21.85° N and 38.9° E and 39.3° E (Fig.1).

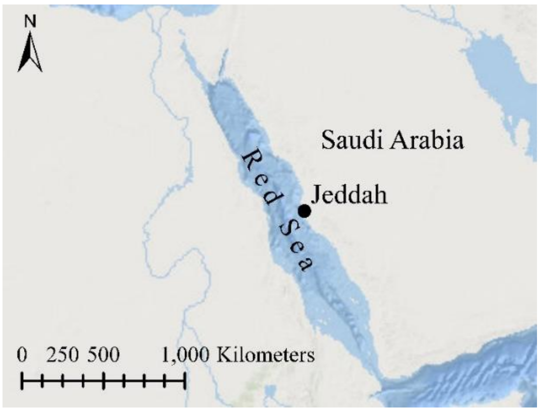

Fig.1 Location of the study area.

The sea-level change data refer to hourly observed sea-level changes during the years 2014 to 2016. The data were obtained from the Saudi Aramco Company (Hydrographic Unit, Surveying Services Div., Protect Support and Controls Department) by a pressure type recorder (OSK LP2) during the years 2003 and 2004 at a depth of 3 m at Jeddah. The data return is greater than 95% with gaps filled by linear interpolation. The sea-level station (Jeddah station (21° 25' 52" *N* and 39° 09' 17" *E*) is situated at the entrance of the Obhur creek, a finger of the Red Sea extending inland. The creek serves as an ideal location for sea-level gauge installation as it is protected from the direct effects of wind and waves. The accuracy of the device is ± 0.5 cm. The timing error on the records is minimal (of the order of a few minutes per 45 days of chart length).

2.2 Methods for Daily Tidal Levels Prediction

Neural networks provide a random mapping between an input and an output vector by mimicking the biological cognition process of our brain. The network "learns" by adjusting the interconnections (called weights) between layers. When the network is adequately trained, it can generalize relevant output for a set of input data. A valuable property of neural networks is that of generalization, whereby a trained neural network can provide a correct matching in the form of output data for a set of previously unseen input data. Learning typically occurs by example through training, where the training algorithm iteratively adjusts the connection weights (synapses).

MPNN consists of an input layer one or more internal layers of hidden neurons and an output layer, which are fully interconnected. The network is repeatedly exposed to a set of training data, and errors were calculated based on the resulting outputs. These errors were used to adjust the weights and biases. This process will eventually lead to optimum and bias values that can mimic the model. There are several issues involved in designing and training, such as the number of hidden layers and the number of neurons in each layer and the size of the training data set. The learning rules used are the conjugate gradient algorithm to adjust weight values using the gradient during the backward propagation of errors through the network. The transfer functions (sigmoid and linear) were used as an activation function for the hidden layers and the output layer.

The CCNN is similar to the MP neural network and consists of three layers. The CCNN was developed by Fahlman in 1990. Cascade correlation neural networks [26] are "self-organizing" networks. The network begins with only input and output neurons. During the training process, neurons were selected from a pool of candidates and added to the hidden layer. The transfer functions (sigmoid and linear) were used as activation functions for the hidden layers and the output layer, respectively.

A RBFNN is a type of multilayer and feed-forward neural network [27]. This is a function approximation model that can be trained by examples to implement the desired input-output mapping. Due to their excellent non-linear approximation properties, RBF neural networks can model complex mappings, in which perceptron neural networks can only model utilizing multiple intermediary layers [28]. The structure of the RBFNN is similar to the multilayer forward network type, and it is a forward network that is made up of the input, hidden, and output layers. The input layer sends information to the hidden layer. The hidden layer that has RBFs is activated depending on the Gaussian activation function that relies on two-parameter centers and radii, which determine the structural behavior of the RBFNN. The output layer calculates the linear sum of values of the hidden neuron multiplied by the third parameter of the RBFNN, which is the weight [29].

In 1991, the GRNN was first proposed by Specht based on a standard statistical approach called kernel regression [30]. The GRNN is a kind of radial basis network that is often used for any regression problem [31]. The GRNN has four layers (input, hidden, pattern or summation, and decision layers). In the input layer, there is one neuron for each predictor variable. The input neurons standardize the range of the values by subtracting the median and dividing the interquartile range. The input neurons then feed the values to each of the neurons in the hidden layer. The hidden layer has one neuron for each case in the training data set. A hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the RBF kernel function using the sigma (σ) value (s) that determines the spread of the RBF function. The resulting value is passed to the neurons in the pattern layer. There are two neurons (denominator and numerator summation units) in the pattern layer. The decision layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value. When the GRNN is trained, it memorizes every unique pattern. This is the reason why it is a single-pass network and does not require any back-propagation algorithm. After training the GRNN with adequate training patterns, it will be able to generalize new inputs.

2.2 Data Normalization and Criteria for ANN Performance

A certain amount of data processing is required before presenting the training patterns to the network. In this study, a linear scaling was used. A linear normalization function within the values of zero to one is as $\boldsymbol{S} = (\boldsymbol{V} - \boldsymbol{V_{min}})/(\boldsymbol{Vmin_{max}})$, where S is the normalized value of variable V, and V_{min} and V_{max} are the variable minimum and maximum values, respectively.

The ANN model's performance was assessed in terms of the mean squared error (*MSE*), mean absolute error (*MAE*), mean absolute percentage error (*MAPE*), normalized mean square error (*NMSE*), root mean square error (*RMSE*), and correlation coefficient (R).

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

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|P_i - O_i| \tag{2}$$

$$MAPE = \left[\frac{1}{N}\sum_{i=1}^{N}\left|\frac{(P_i - O_i)}{P_i}\right|\right] \times 100 \tag{3}$$

$$NMSE = \frac{1}{N}\sum_{i=1}^{N}\frac{(P_i - O_i)^2}{\bar{P}\bar{O}} \tag{4}$$

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(P_i - O_i)^2} \tag{5}$$

$$R = \frac{\sum_{i=1}^{N}\left(P_i - \bar{P}\right)\left(O_i - \bar{O}\right)}{\sqrt{\sum_{i=1}^{N}\left(P_i - \bar{P}\right)^2 \sum_{i=1}^{N}\left(O_i - \bar{O}\right)^2}} \tag{6}$$

where O_i is the observed value, P_i is the predicted value, N is the number of observations, $\bar{\boldsymbol{O}}$

is the mean value of the observations, and $\bar{P}$ is the mean value of the predictions.

3. RESULTS AND DISCUSSION

In this study, the inputs to be used in constructing the ANN models are the previous daily tidal level observations. Evaluating the model with a different number of previous daily tidal level values led to the conclusion that the best result could be achieved when using only seven previous tidal level values. Adding more of the previous data to the inputs did not change the result. Following routine procedures for the selection of the best ANN suited to the daily tidal level data, different activation function options, and network architectures were compared [18, 31]. Several trains were performed to determine the number of hidden layers and the number of neurons in the hidden layers giving the best testing performance for the RBFNN, GRNN, MPNN, and CCNN. A Genetic Algorithm (GA) was utilized to adjust the optimum structures for the ANN models. Table 1 shows the training parameters of the ANN models. The sigmoid transfer function was used for the hidden layer of the ANN models to consider the nonlinearity of tidal levels. For the output layer, the activation function is the linear function. Once the activation function and the architecture are chosen, the final training process can begin. An optimization of the networks' architectures was performed by analyzing the results during the training and the testing of the different ANN networks. The optimal training algorithm for each case was also determined. The model accuracies were evaluated using the *MSE*, *MAE*, *MAPE*, *NMSE*, *RMSE*, and *R* criteria. Table 2 summarizes the achieved results for the RBFNN, GRNN, MPNN, and CCNN and shows the *MSE*, *MAE*, *MAPE*, *NMSE*, *RMSE*, and *R*, which were obtained from the data subsets utilized in the training and in the testing procedures in every model.

During the training stage of different ANNs, we noticed that all of them approximate well the data subset pattern. The training data subset is fitted better by the different neural network algorithms by comparing the results for the testing stage.

For the exploration of an MPNN having optimum generalization ability, the MPNN model with different architectures (one and two hidden layers) was used. Among the MPNN with one and two hidden layers employed for this problem, the three-layer MPNN was found to be superior to the four-layer MPNN in the prediction of the daily tidal levels. Table 2 presents the model results for different MPNN architectures. This result confirmed the inferences made by Elbisy [32].

Table 1 Model parameters of the ANN models used for the training and testing.

Models	Parameters
MPNN (3 layers)	Training method: conjugate gradient algorithm; transfer function: sigmoid for the hidden layer and linear for the output layer; the number of hidden neurons = 8
MPNN (4 layers)	Training method: conjugate gradient algorithm; transfer function: sigmoid for the hidden layer and linear for the output layer; the number of hidden neurons in the first layer = 18; the number of hidden neurons in the second layer = 4
CCNN	Transfer function: sigmoid for the hidden layer and linear for the output layer; the number of hidden neurons = 11
GRNN	Kernel function: Gaussian; sigma (σ) = 0.0001:10
RBFNN	Transfer function: Gaussian activation for the hidden layer and linear for the output layer; radius = 0.26952: 392.819; lambda = 0.0144 : 7.32216

Table 2 Performance of the ANN models.

Methods	Type of Data	*NMSE* (m)	*MSE* (m^2)	*MAE* (m)	*RMSE* (m)	*MAPE* (%)	*R*
MPNN (three layers)	Training data	0.0136	0.0002	0.0086	0.0152	2.9372	0.993
	Test data	0.0414	0.0004	0.0148	0.0192	4.2607	0.992
MPNN (four layers)	Training data	0.0145	0.0002	0.0091	0.0156	3.1336	0.993
	Test data	0.0426	0.0004	0.0153	0.0194	4.3333	0.993
CCNN	Training data	0.0143	0.0003	0.0097	0.0155	3.3140	0.995
	Test data	0.0366	0.0003	0.0136	0.0180	3.5949	0.989
GRNN	Training data	0.0029	0.0001	0.0031	0.0070	1.0146	0.998
	Test data	0.0292	0.0003	0.0107	0.0161	3.2024	0.996
RBFNN	Training data	0.0150	0.0003	0.0099	0.0159	3.7717	0.992
	Test data	0.0447	0.0004	0.0174	0.0199	4.6815	0.992

Table 2 shows that all the models have lower *NMSE*, *MSE*, *MSE*, *MAE*, *RMSE*, and *MAPE* values in the training subset compared with the testing subset. Higher *R* values were obtained, which varied from 0.989 to 0.998 for the four- ANN models. Comparing the results between different training algorithms, we found that the GRNN gave the minimum *NMSE*, *MSE*, *MSE*, *MAE*, *RMSE*, and *MAPE* and the maximum *R* during the training. Moreover, the best test results were obtained for the GRNN with 0.0292 m, 0.0003 m^2, 0.0107 m, 0.0161 m, 3.2024%, and 0.996 for the *NMSE*, *MSE*, *MSE*, *MAE*, *RMSE*, *MAPE*, and *R*, respectively. The choice of neural network for the prediction of the daily tidal levels should be given to the one that has the smallest training and testing errors as a global estimator. In this investigation, the GRNN exhibited higher accurate performance in the training and testing subsets. The majority of the error values of the GRNN, the difference between the tidal-level measurements and the predicted tidal level values fall within the −2 cm and +2 cm range with *RMSE* falling within a 0.7–1 cm range. Figs. 2, 3, and 4 graphically exhibit the achieved results for the GRNN. In contrast to the obtained results for the GRNN network, the RBFNN exhibited the lowest accuracy.

The results show that the use of the GRNN significantly reduces the overall errors in the predictions of daily tidal levels. The variation in tidal-level between the observed data and the results of the GRNN model has the same trend. For training, the *RMSE* of the GRNN was an improvement of 117.15%, 122.85%, 121.43%, and 127.15% over the MPNN (3 layers), MPNN (4 layers), CCNN, and RBFNN, respectively, and 19.26%, 20.50%, 11.8%, and 23.61% for testing.

4. CONCLUSION

Tidal level prediction is an important issue for the design and construction of coastal and marine structures. For the exploration of an effective method to predict tidal levels along the central coast of the eastern Red Sea, four ANN models (RBFNN, GRNN, MPNN, and CCNN) were introduced. The different ANNs perform satisfactorily due to their main advantage of being a universal function approximators for even non-linear functions. The results indicate that the GRNN model performs the best for predicting tidal levels, and RBF is the poorest. When compared with the other models, the GRNN yielded an *RMSE* that was 117.15%, 122.85%, 121.43%, and 127.15% lower than those of the MPNN (three layers), MPNN (four layers), CCNN, and RBFNN, respectively, with respect to the training data; and 19.26%, 20.50%, 11.8%, and 23.61% lower with the respect to the test data. In this study, the results indicate that the GRNN model could be a suitable tool that can be utilized for tidal level predictions.

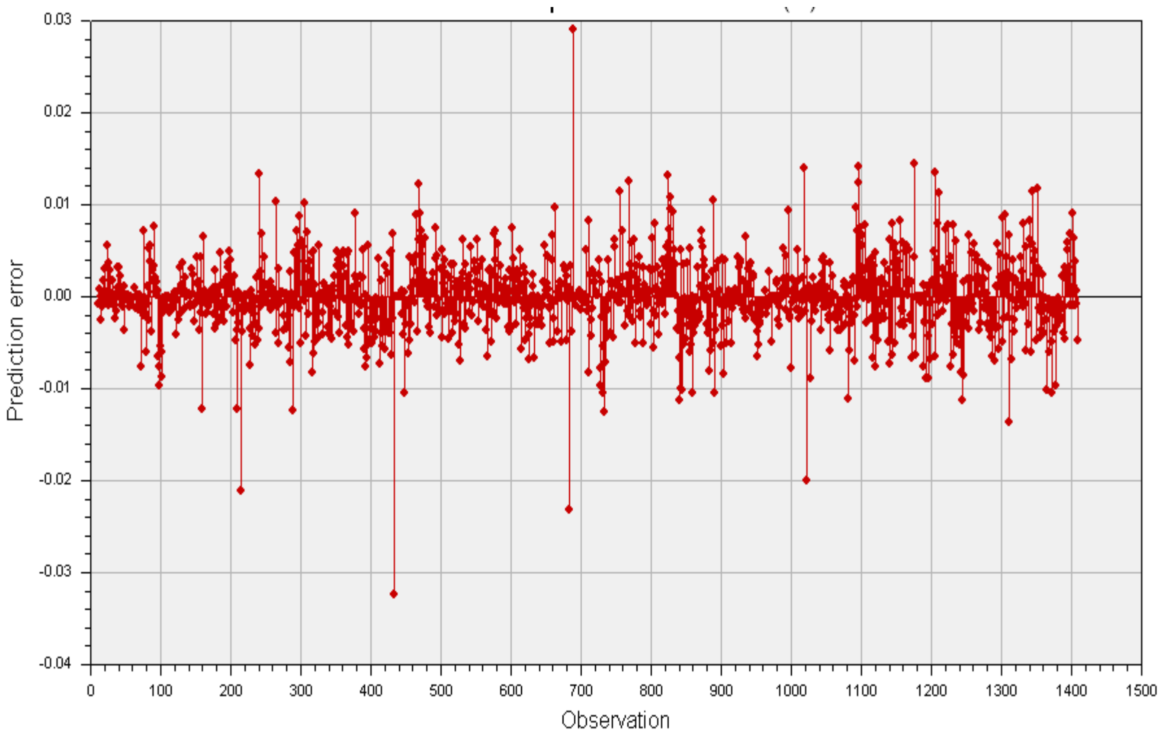

Fig. 2 Residual error between the measured and predicted tidal levels for the GRNN model.

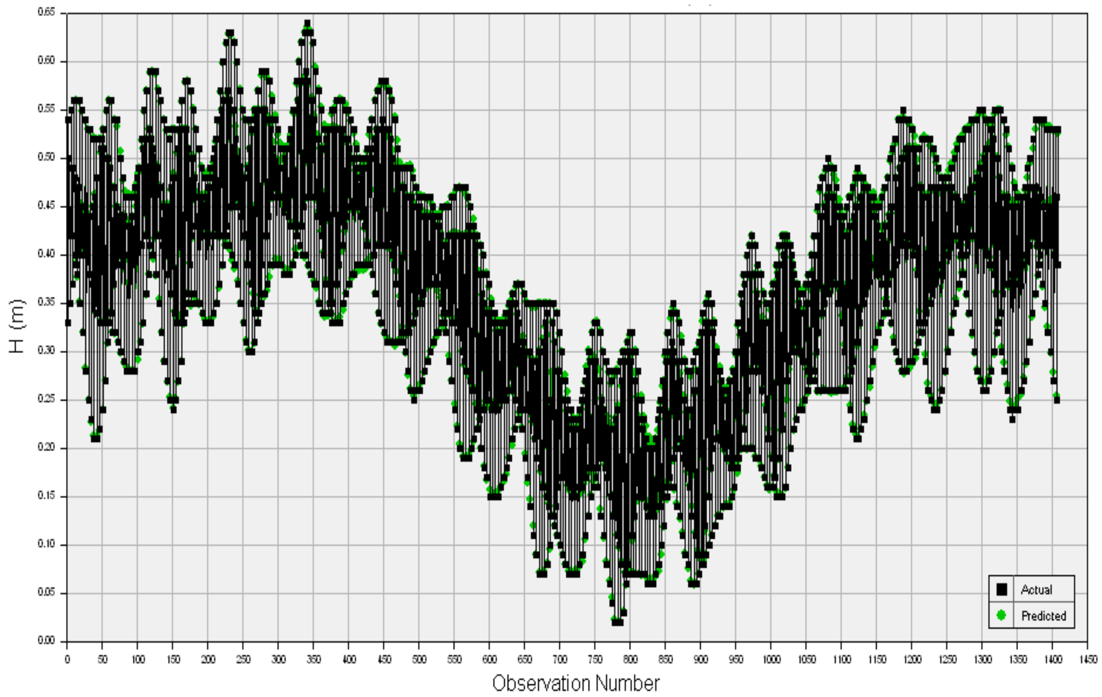

Fig. 3 Tidal level results predicted by the GRNN and the comparison results between the predicted and observed data.

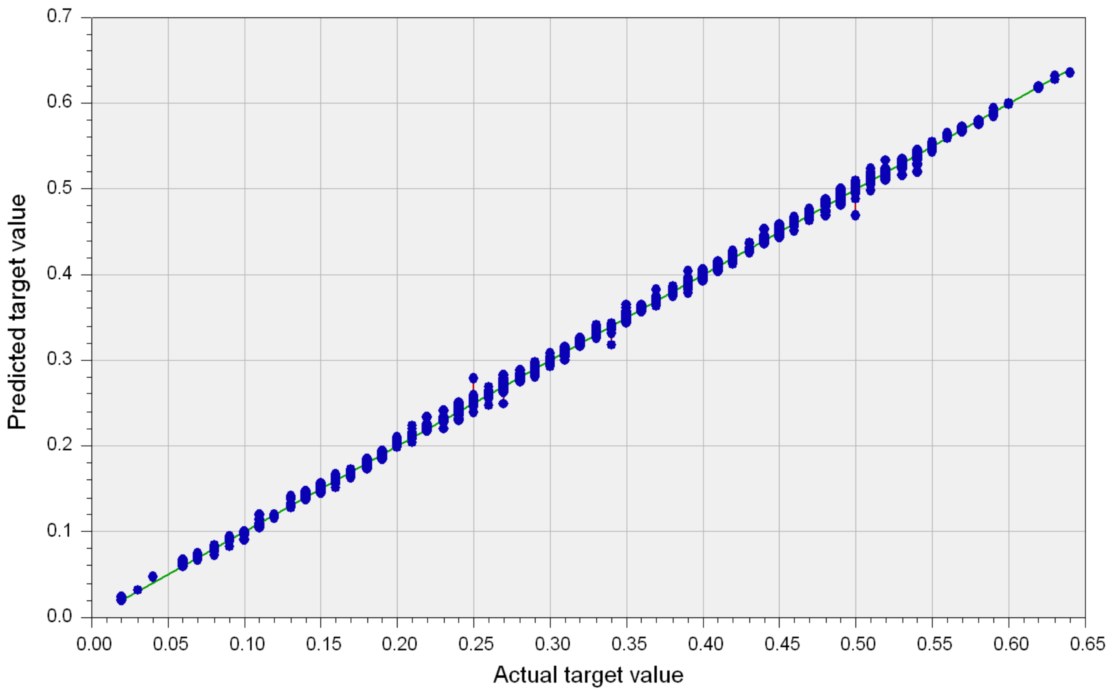

Fig. 4 Scatter plot of tidal levels values measured and predicted by the GRNN.

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