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Evaluation of the performance of SVR and ANN Models in Sea Water Level Prediction for the Izmir Coast of the Aegean Sea

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Abstract

Prediction of sea water level is a very important phenomenon for making future projections for flood control, human living conditions and coastal planning. However, it is not easy to estimate sea water level due to the influence of atmospheric conditions. Thus, Artificial Neural Networks (ANN) and Support Vector Regression (SVR) methods are used for the prediction of seawater level of Izmir Coast based on the time series data. Coefficient of determination (R^2) and root mean square error (RMSE) are applied as model evaluation criteria in this study. 19 months of seawater level data in the time series were used in this study. The results show that the ANN model can predict the water level with R^2 of 0.84 and 0.68 for 1st and 2nd days, respectively, while the SVR model can predict the water level with R^2 of 0.83 and 0.69 for 1st and 2nd days, respectively.

Keywords: ANN; SVR; sea level prediction; Izmir Menteş coast; Aegean Sea.

1. INTRODUCTION

Seawater levels have increased remarkably around the World because of climate change and human efforts (Yesudian and Dawson, 2021; Jin et al., 2023; Karsavran, 2023). The ecological habitat and economy of coastal regions have been devastatingly influenced by sea level rise (Bernstein et al., 2019; Karsavran, 2023). Therefore, accurate estimation of sea level change is important for coastal areas with increasing populations (Jin et al., 2023; Karsavran, 2023).

Alpar et al. (1997) researched the meteorological effects on sea level along the coast of Izmir. Similarly, Çoşkun and Balas (2018) studied the effect of meteorological conditions on sea level changes in Izmir Bay. The possible impact of different sea level rises on the population of Izmir was explored (Aksoy et al., 2017). In addition, the effect of sea level rise on coastal floods in Izmir Bay was simulated with a soft computer program (Türkseven et al., 2023).

Artificial intelligence (AI) methods offer exceptional noise tolerance and learning performance over traditional methods. For this reason, AI methods are chosen in the examination of coastal areas (Guillou and Chapalain, 2021; Karsavran, 2023). Likewise, Song et al. (2022) reported that sea water level prediction with neural networks was

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successfully used in studies. For example, Imani et al. (2018) used machine learning to predict water level forecasts in Chiayi Beach.

ANN was first applied to predict sea water level by Röske (1997). A neural network method used to estimate the sea water level of the Yellow Sea (Zhao et al., 2019). Besides, Karsavran and Erdik (2021) applied ANN and SVR methods to estimate the sea level of the Bosphorus. SVR and neural network systems were used to estimate sea level fluctuations in Peninsular West Malaysia (Balogun et al., 2021). Additionally, the sea level of the coastal region of China was predicted by neural network methods (Jin et al., 2023). Lastly, Karsavran (2023) used ANN and SVR to forecast the sea level of Sinop.

Even though there are many studies in this field, there is a need to compare the sea level prediction performances of ANN and SVR methods in the Izmir coast. ANN and SVR models are employed to predict the sea water level in this study. Additionally, we assess the future vision of sea level oscillations of Izmir coast.

2. MATERIALS AND METHODS

2.1 Artificial Neural Network

ANN is a small group of individually connected processing units that carry information to interconnects. The multilayer perceptron (MLP), used for predictions in engineering and science, is made up of at least three interconnected layers of neurons (Chau and Cheng, 2002). The first layer is the input layer to receive external data, and the last layer is the output layer to produce MLP results (Karsavran et al., 2023).

The backpropagation algorithm implements two stages of the data flow. First, inputs move to the network from input layer to the output layer. Finally, the network produces an output vector that encounters the desired target vector and an error is estimated using the predetermined error function. At that point, the error signals are back-propagated from the output layer to the previous layers to update their weights based on the Equation 1:

$$\Delta w_{ij}(n) = \alpha^{'} \Delta w_{ij}(n-1) - \varepsilon \left(\frac{\partial E}{\partial w_{ij}} \right) \tag{1}$$

$\Delta(n)$ and $\Delta w_{ij}(n-1)$ are the weight gets among the input and hidden layers during the nth and (n-1)th steps, α' is the momentum factor that increases the training and aids blocking oscillations, and ε is the learning rate that rises the possibility of preventing the training process from being ambushed in a local minimum instead of a global minimum (ASCE Task Committee, 2000; Karsavran et al., 2023).

2.2 Support Vector Regression

SVR is a statistical learning based neural network method used in various engineering regression problems (Patil et al., 2012). SVR has a hyperplane-driven machine learning algorithm to partition data from one dimension into higher dimensional space (Alshouny et al., 2022). It solves the regression problems with Equation 2:

$$f(x) = \sum_{i=1}^{n} w.\phi_i(X) + b \tag{2}$$

w=weight, $\emptyset_i(X)$= Kernel function and b=bias. The optimal objective function is shown in Equation 3:

$$\min R = \frac{1}{2} w^2 + C \sum_{i=1}^{n} (\xi_i + \xi_i^*) \quad (3)$$

The constraint conditions are depicted in Equation 4:

$$Subject\_to \begin{cases} f(x_i) - y_i \le \varepsilon + \xi_i \\ y_i - f(x_i) \le \varepsilon + \xi_i^* \\ \xi_i \ge 0, \xi_i^* \ge 0, i = 1, 2, ..., n \end{cases} \quad (4)$$

ε= allowable error, C= cost factor, ξ_i and ξ_i^* are relaxation numbers. Both will be greater than zero if there are some prediction errors, otherwise both will be zero (Lin et al., 2020; Karsavran and Erdik, 2021).

2.3 Model Evaluation Criteria

Model performances were obtained according to two different numerical error statistics. These are the root mean square error (RMSE) and coefficient of determination (R^2) given in Equation 5 and Equation 6, respectively (Erdik et al., 2009; Wang et al., 2009).

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (WL_f(i) - WL_0(i))^2} \quad (5)$$

$$R^2 = \left[\frac{\frac{1}{n} \sum_{i=1}^{n} (WL_0(i) - WL_0^{'})(WL_f(i) - WL_f^{'})}{\sqrt{\frac{1}{n} \sum_{i=1}^{n} (WL_0(i) - WL_0^{'})^2} \cdot \sqrt{\frac{1}{n} \sum_{i=1}^{n} (WL_f(i) - WL_f^{'})^2}} \right]^2 \quad (6)$$

where $WL_o(i)$ and $WL_f(i)$ are observed and forecasted sea water level, respectively. $WL_0^{'}$ and $WL_f^{'}$ depicts their averages, and n is the number of data.

2.4 Data And Study Area

This research is established on measurements of the Mentes tide measuring station on the coast of Izmir (Figure 1). The sea level data are obtained from the Turkish Sea Level Monitoring System (TUDES, https://tudes.harita.gov.tr/), provided at 15-minute time intervals.

Figure 1. The location of the Menteş Tide Gauge Station.

The sea level data used in this study were taken at 15-minute time intervals for 19 months, from June 2020 to January 2022, and were used as is (Figure 2). Missing data were imputed using the linear interpolation method. In this study, 70% of the total data was used for training and the remaining 30% was used for testing all models (Seo et al., 2015; Karsavran, 2023). The same training and testing data were used for each model run and data splitting was done randomly.

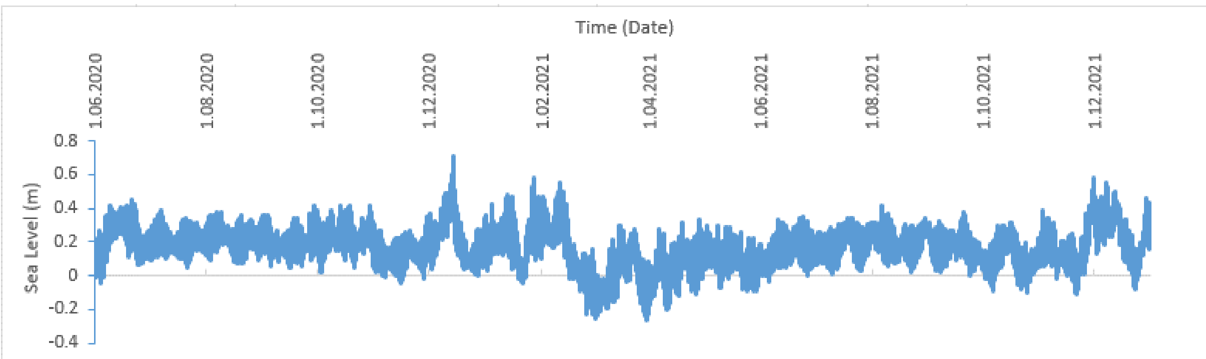

Figure 2. Time series of seawater level in Menteş station.

3. RESULTS AND DISCUSSIONS

In this study, SVR and ANN performances compared for the next 4 days for sea water level prediction of the Izmir coast. First of all, ANN is used to make a decision on the input set combination of the models. The comparison of input sets regarding the prediction results of the ANN model for the next day (t+1) at Menteş Station is depicted in Table 1. Using two values WL(t) and WL(t-1) increased the model performance with an R^2 value of 0.84, while using the next three values (WL(t), WL(t-1)) and WL(t-2) could not increase the performance of the ANN model. As a result, WL(t) and WL(t-1) were used as input sets in all models.

Table 1. ANN model performance for t+1 sea level according to input sets

Input Set	Output Set	RMSE (m)	R^2
WL(t)	WL(t+1)	0.051	0.83
WL(t)WL(t-1)	WL(t+1)	0.051	0.84
WL(t)WL(t-1)WL(t-2)	WL(t+1)	0.051	0.84
WL(t)WL(t-1)WL(t-2)WL(t-3)	WL(t+1)	0.051	0.83
WL(t)WL(t-1)WL(t-2)WL(t-3)WL(t-4)	WL(t+1)	0.051	0.83

After deciding on the input set, sea water level was estimated for 1, 2, 3 and 4 day lead times using the ANN model containing the Vanilla-Standard back-propagation algorithm. Logsig, tansig and purelin activation functions of hidden and output neurons are used. As a result, R^2 is estimated 0.84 and 0.68 for lead times 1 and 2 days, respectively (Table 2).

The Radial Basis Function (RBF) Kernel is employed to predict the water level with specified lead times in SVR. Most studies on the use of SVR in coastal modeling and prediction have shown that RBF has positive performance (Karsavran and Erdik, 2021; Karsavran, 2023). Accordingly, RBF was applied as the Kernel function and the C parameter of the Kernel is 1000 in this study. In addition, ε and σ, which affect the accuracy of the SVR model, are chosen as 0.1 and 0.33, respectively. Finally, R^2 is estimated 0.83 and 0.69 for lead times 1 and 2 days, respectively (Table 2).

Finally, SVR and ANN models have similar performances in predicting sea water level at Mentes Station near Izmir. While, the ANN model predicts sea water level with R^2= 0.84, 0.68, 0.53 and 0.41, the SVR model estimates R^2= 0.83, 0.69, 0.53 and 0.42 for lead times 1,2,3 and 4 days, respectively. The similarity of ANN and SVR model results is due to the short duration of the data measured at the station. Additionally, there is no overfitting in either model. Accordingly, the SVR and ANN models have good performance in sea level prediction for 1 and 2 day lead times in Izmir coast. However, these models are not ideal to be applied for 3 and 4 day lead times due to the dramatic drop in forecast performance.

This research can be used for short-term projections of sea level along the coast of Izmir. Besides, the results and approach proposed in this study may help the analysis of such phenomena in the future.

Table 2. Model performances with respect to lead time prediction WL(t+L)

Inputs (t = day)	Prediction (t = day)	ANN		SVM	
		RMSE (m)	R^2	RMSE (m)	R^2
WL(t)WL(t-1)	WL(t+1)	0.051	0.84	0.051	0.83
WL(t)WL(t-1)	WL(t+2)	0.071	0.68	0.071	0.69
WL(t)WL(t-1)	WL(t+3)	0.087	0.53	0.086	0.53
WL(t)WL(t-1)	WL(t+4)	0.097	0.41	0.097	0.42

4. CONCLUSIONS

In this study, SVR and ANN models were applied to predict the sea level of Izmir coasts for 1, 2, 3 and 4 day lead times. Both models have similar performances in sea level prediction. They have good performance to predict sea level for 1 and 2 day lead times, unlike 3 and 4 day lead times. Thus, both SVR and ANN models can be applied in sea level forecasts for short-term lead times of 1 and 2 days for the coast of Izmir.

Artificial intelligence based SVR and ANN models can be preferred for emergency sea level rise warning system in the future. The results presented here may provide new information for predicting sea level. Particularly, the models preferred in this study can be used for other coasts of the Aegean Sea and the Mediterranean regions, including but not limited to Çanakkale, Muğla and Aydın.

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