Research Article
Turkish Journal of Maritime and Marine Sciences

DOI: 10.52998/trjmms.1342164
Volume: 10 Issue: 1 (2024) 49-56

Comparison of ANN and SVR based models in sea level prediction for the Black Sea coast of Sinop

Sinop'un Karadeniz kıyısı için deniz seviyesi tahmininde YSA ve SVR tabanlı modellerin karşılaştırılması

Türk Denizcilik ve Deniz Bilimleri Dergisi

Cilt: 10 Sayı: 1 (2024) 49-56

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ABSTRACT

Seawater level oscillations are very critical to coastal construction, flood prevention and human living conditions. However, it is difficult to accurately project the daily future for seawater level due to the effects of wind, precipitation and other atmospheric conditions. For this reason, in this paper, artificial intelligence (AI) based Artificial Neural Networks (ANN) and Support Vector Regression (SVR) methods are applied for the estimation of seawater level in Sinop Coast. In addition, Multiple Linear Regression (MLR) is used as a benchmarking model. In this study, coefficient of determination (R^2) and root mean square error (RMSE) were applied as model evaluation criteria. Besides, 15 minutes (approximately 22 months) sea water level data of Sinop Station were collected and used as is. The findings revealed that the ANN model can predict the water level for 1st, 2nd, 3rd, 4th days with correlation coefficients (R^2) of 0.84, 0.67, 0.64, 0.63, respectively, and the SVR model can predict for 1st, 2nd days with correlation coefficients (R^2) of 0.86, 0.66, respectively.

Keywords: ANN, SVR, Artificial Intelligence, Black Sea, Sinop coast

Article Info
Received: 12 August 2023
Revised: 11 December 2023
Accepted: 19 December 2023

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To cite this article: Karsavran, Y. (2024). Comparison of ANN and SVR based models in sea level prediction for the Black Sea coast of Sinop, *Turkish Journal of Maritime and Marine Science* 10(1): 49-56. doi: 10.52998/trjmms. 1342164.

ÖZET

Deniz suyu seviyesi salınımları, kıyı inşaatı, taşkın önleme ve insan yaşam koşulları için çok büyük önem arz etmektedir. Ancak rüzgar, yağış ve diğer atmosferik koşulların etkileri nedeniyle deniz suyu seviyesinin günlük hareketini doğru bir şekilde tahmin etmek zordur. Bu nedenle bu çalışma bünyesinde Sinop Sahili'nde deniz suyu seviyesi tahmini için yapay zeka (AI) tabanlı Yapay Sinir Ağları (YSA) ve Destek Vektör Regresyon (DVR) yöntemleri uygulanmaktadır. Bunların yanında kıyaslama modeli olarak Çoklu Doğrusal Regresyon (ÇDR) kullanılmaktadır. Model değerlendirme kriteri olarak ise determinasyon katsayısı (R^2) ve ortalama karesel hata (RMSE) yöntemleri kullanılmıştır. Bunlarla beraber, Sinop İstasyonu'nun 15 dakikalık (toplamda yaklaşık 22 aylık) deniz suyu seviyesi verileri toplanmış ve olduğu gibi kullanılmıştır. Sonuç olarak bulgular, YSA modelinin sırasıyla 0.84, 0.67, 0.64, 0.63 korelasyon katsayıları (R^2) değerleri ile 1., 2., 3. ve 4. günler için su seviyesini tahmin edebildiğini ve DVR modelinin 1., 2. günler için sırasıyla 0.86, 0.66 korelasyon katsayıları (R^2) değerleri ile tahmin edebildiğini ortaya koymuştur.

Anahtar sözcükler: YSA, DVR, Yapay zeka, Karadeniz, Sinop sahili

1. INTRODUCTION

Sea level has increased greatly in recent times due to human activities. (Woodworth *et al.*, 2021; Yesudian and Dawson, 2021; Jin *et al.*, 2023). The social economy and ecological habitat of coastal areas has been catastrophically affected by sea level rise (Bernstein *et al.*, 2019; Meilianda *et al.*, 2019). Thus, accurate estimation of sea level change has great importance for coastal zones with growing population (Primo de Siqueira and Paiva, 2021; Zhao *et al.*, 2021; Jin *et al.*, 2023).

The Black Sea is an inland sea that receives Europe's largest discharge from the Danube River (Karsavran *et al.*, 2020). It also exchanges water from the Mediterranean through the Bosphorus and the Dardanelles (Karsavran and Erdik, 2021). Accordingly, the daily forecast of the Black Sea level change has great importance.

Artificial Intelligence (AI) methods are commonly utilized in navigation safety, agricultural processes etc. Compared to traditional engineering, AI analysis techniques offer outstanding learning performance and noise tolerance. Therefore, AI methods are more preferred in the analysis of coastal processes and their importance is strengthened by an increasing number of observational datasets (Beuzen and Splinter, 2020; Guillou and Chapalain, 2021).

Röske (1997) was the first to use ANN to estimate sea water level. Also, it has been reported that neural networks for sea level prediction has been successfully applied in studies conducted in recent years (Song *et al.*, 2022). For instance, Imani *et al.* (2017) employed machine learning to estimate the water level projections in the Coast of Chiayi. Zhao *et al.* (2019) applied a neural network approach to predict the sea level of the Yellow Sea. Similarly, the water level of Bosphorus Strait was predicted by using ANN and SVR (Karsavran and Erdik, 2021). Balagun *et al.* (2021) applied SVR and neural network systems to predict sea level fluctuations in the western Peninsular Malaysia. Lastly, Jin *et al.* (2023) used neural network methods to predict sea level in the coastal area of China.

Although there is a great deal of research in this area, there is a lack of comparison of the prediction performances of artificial intelligence methods for the Black Sea coast of Sinop. Our study applies SVR and ANN models to predict sea level of Sinop coast. Based on the performances, we evaluate prediction performance for future projection. In addition, MLR is used as a benchmarking model in this study.

2. METHODOLOGY

2.1. Artificial Neural Network

An ANN is a small group of separately related processing units that transmit information to interconnects. The multilayer perceptron (MLP) technique, that has been used for predictions in

many fields of engineering and science since the 1990s, consists of at least three interconnected layers of neurons (Chau and Cheng, 2002). The input layer is the first layer accepting external data, and the output layer is the last layer producing the results of the MLP. The hidden layer is the layer, where weighted inputs are received by artificial neurons and add a bias value (Karsavran and Erdik, 2021).
Back propagation algorithm performs two stages of data flow. Firstly, the inputs travel to the network from the input layer to the output layer. Lastly, the network generates an output vector that is confronted with the desired target vector and an error is estimated using predetermined error function. At this point, the error signals are propagated back from the output layer to the previous layers to update their weights based on the Equation 1:

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

$\Delta w_{ij}(n)$ and $\Delta w_{ij}(n-1)$ are the weight gains among the input and hidden layers during the nth and (n-1)th steps, α' is the momentum factor that accelerates 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 and Erdik, 2021).

2.2. Support Vector Regression

SVR is a neural network based on statistical learning which is used for a variety of engineering regression problems (Patil *et al.*, 2012). The SVR has a machine learning algorithm that works with hyperplane for splitting data from one dimension to high dimensional space (Alshouny *et al.*, 2022). It solves the regression problems with Equation 2:

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

where w=weight, $\emptyset_i$(X)= Kernel function and b=bias. The optimal objective function is depicted 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 shown in Equation 4:

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

where C= cost factor, ε= allowable error, 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. Multiple Linear Regression

For models with more than one independent variable, the Multiple Linear Regression (MLR) model is applied and it makes the regression model highly flexible. The general MLR is depicted in Equation 5:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad (5)$$

where X_i=independent variable, β_i= regression coefficient, Y= dependent variable. The aim of MLR is to find an approximation function for estimating system outputs (Karsavran and Erdik, 2021).

2.4. Model Evaluation Criteria

The model performances were obtained in terms of two different numerical error statistics. These are coefficient of determination (R^2) and the root mean square error (RMSE) given in Equation 6 and Equation 7, respectively.

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

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(WL_f(i) - WL_0(i))^2} \qquad (7)$$

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.

3. DATA AND STUDY AREA

This study is based on the measurements of the Sinop tide gauge station (Lat:42.02, Lon:35.14) on the southern Black Sea coast (Figure 1). The sea level data are acquired from the Turkish Sea Level Monitoring System (TUDES, https://tudes.harita.gov.tr/), provided at 15-minute time intervals.

The Sinop Station started recording in June 2005. The sea level data used in this study were measured at 15-minute time intervals for 22 months, from July 2016 to May 2018, and were used as is (Figure 2). Missing data were estimated by applying linear interpolation method. In this study, 70% of the total data was used for training and the remaining 30% for testing all models (Karsavran and Erdik, 2021). Data splitting was done randomly and the same training and test data were used for each model run.

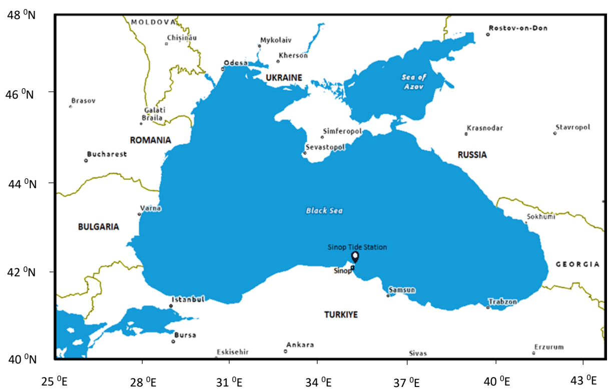

Figure 1. The location of the Sinop Tide Gauge Station

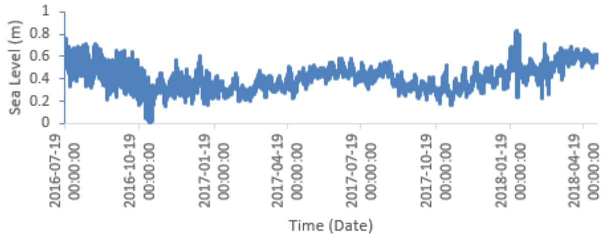

Figure 2. Time series of sea water level in Sinop station

4. RESULTS AND DISCUSSIONS

In this article, ANN and SVR model performances for sea level prediction of Sinop coast are compared for the next 4 days. The code of all models in this study has been written in Python. Firstly, ANN is used to decide on the input set combination of the models. Table 1 shows the benchmark of the input sets on the prediction results of the ANN model for the next day (t+1) in Sinop Station. The use of three values WL(t), WL(t-1) and WL(t-2) increases the model performance with R^2 values of 0.84, while the use of subsequent four values WL(t), WL(t-1), WL(t-2) and WL(t-3) decreases the performance of the ANN model. Finally, the previous variables (WL(t), WL(t-1) and WL(t-2)) were applied as inputs for all models that produced the highest performance.

After the decision on input set, the ANN model including Vanilla-Standart backpropogation algorithm is used to predict the seawater level for lead times of 1, 2, 3 and 4 days. Activation functions logsig, tansig and purelin of hidden and output neurons are applied. As a result, R^2 is 0.84 and 0.65 for lead times 1 (Figure 3) and 2 days, respectively (Table 2).

The Radial Basis Function (RBF) Kernel SVR is applied to predict the water level with specified lead times (Table 2). Most of the studies on the use of SVR in coastal modeling and forecasting have shown positive performance of the RBF (Wang *et al.*, 2009; Karsavran and Erdik, 2021). Therefore, RBF as a Kernel function has been applied and Kernel's C parameter is 1000 in this study. The best performance of SVR is found with R^2 = 0.86 and RMSE = 0.07 for 1 day the lead time (Figure 4).

The results of MLR model for the designated lead times are given in Table 2. The best performance of MLR model is R^2 = 0.68 and RMSE = 0.12 (Figure 5). The underlying residues are normally distributed in MLR models.

In general, ANN and SVR models provide similar prediction results and better prediction performance than MLR model. The SVR predicts the water level with the highest R^2 = 0.86, 0.66 and RMSE = 0.07, 0.12, while ANN is with the highest R^2 = 0.84, 0.65 and RMSE= 0.09, 0.12 in Sinop Station for lead times 1 and 2 days, respectively. Therefore, SVR seems to be the best model to forecast next 1 and 2 days water level in Sinop. However, SVR prediction performance decreases dramatically with R^2 = 0.53, 0.49, while ANN predicts with R^2= 0.64, 063 for lead times 3 and 4 days, respectively. Accordingly, ANN is more ideal than the SVR model in Sinop for forecasting the next 3, 4 days and for long-term forecasting.

This study can be used for long-term projections of the water levels in the coastal region of Sinop. The results of this article and the approach proposed and applied in this study can be used for the analysis of such phenomena.

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)	0.13	0.63
WL(t)WL(t-1)	WL(t+1)	0.09	0.80
WL(t)WL(t-1)WL(t-2)	WL(t+1)	0.08	0.84
WL(t)WL(t-1)WL(t-2)WL(t-3)	WL(t+1)	0.08	0.83
WL(t)WL(t-1)WL(t-2)WL(t-3)WL(t-4)	WL(t+1)	0.08	0.83

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

Inputs (t = day)	Prediction (t = day)	ANN		SVM		MLR	
		RMSE (m)	R^2	RMSE (m)	R^2	RMSE (m)	R^2
WL(t)WL(t-1)WL(t-2)	WL(t+1)	0.08	0.84	0.07	0.86	0.12	0.68
WL(t)WL(t-1)WL(t-2)	WL(t+2)	0.12	0.65	0.12	0.66	0.18	0.25
WL(t)WL(t-1)WL(t-2)	WL(t+3)	0.13	0.64	0.15	0.53	0.20	0.10
WL(t)WL(t-1)WL(t-2)	WL(t+4)	0.13	0.63	0.15	0.49	0.21	0.07

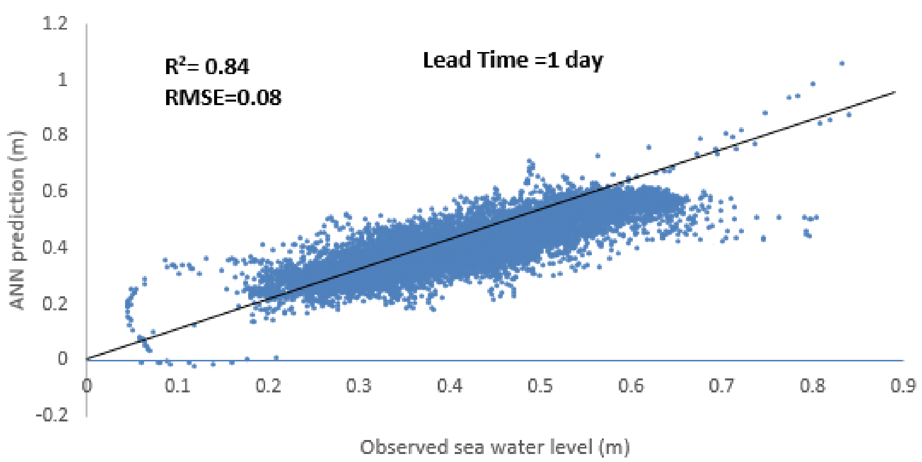

Figure 3. Scatter plot of observed and predicted sea water level for ANN

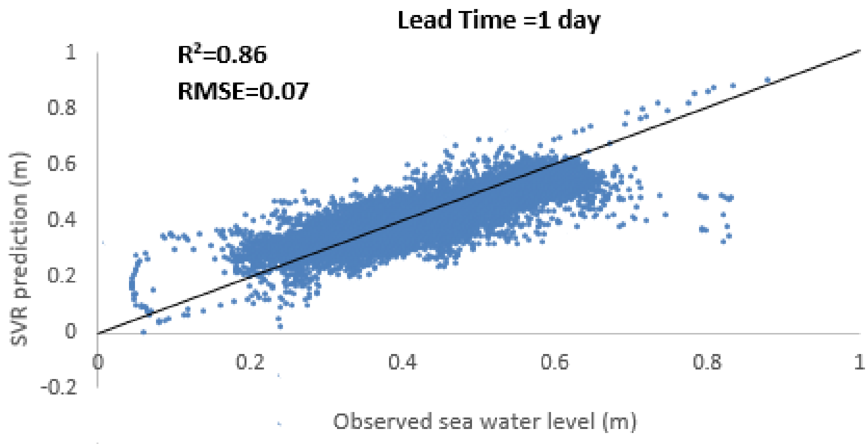

Figure 4. Scatter plot of observed and predicted sea water level for SVR

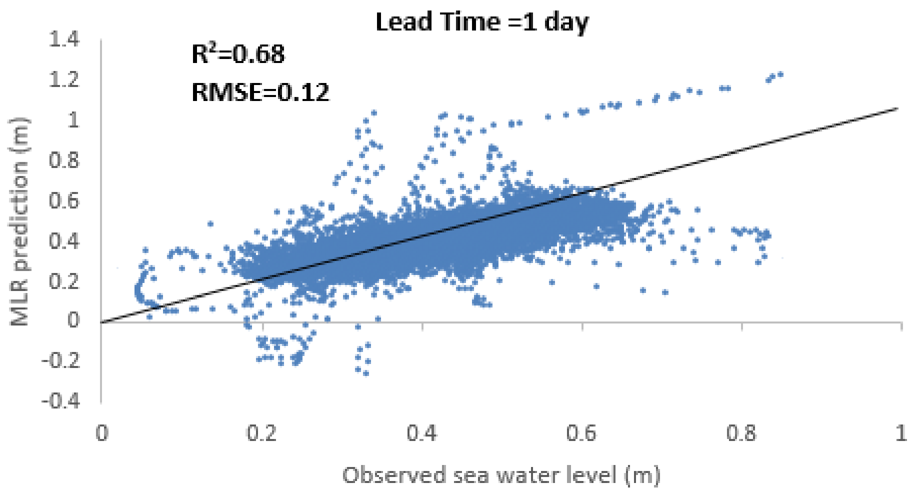

Figure 5. Scatter plot of observed and predicted sea water level for MLR

5. CONCLUSION

In this study, a higher coefficient of determination R^2 was obtained by applying ANN and SVR models to predict the daily water level of the Sinop for next 1, 2, 3 and 4 days. The results depict that SVR has the best performance in prediction of the seawater level in Sinop, while ANN comes close to its prediction performance for the lead times 1 and 2 days. However, ANN produces higher scores than SVR for the lead times of 3 and 4 days for the prediction of seawater level in Sinop. As a result, while the SVR model is more advantageous to be applied for the next 1 and 2 days for water level prediction in Sinop, ANN is more advantageous to be applied for the next 3-4 days and for long-term forecasting.

The SVM model is the main AI method to be used for the sea level surge warning system in Sinop for future studies. I believe that the results presented here may open up new insights in modeling the sea level. More specifically, the methods applied in this study can be used for other coasts of the Black Sea region, including but not limited to Igneada, Istanbul, Amasra, Trabzon.

ACKNOWLEDGEMENTS

Special thanks to Professor Tarkan Erdik for his support in this study. Also, thanks to TUDES for providing the data.

AUTHORSHIP CONTRIBUTION STATEMENT

Yavuz KARSAVRAN: Conceptualization, Methodology, Formal Analysis, Writing-Original Draft, Writing-Review and Editing, Data Curation, Software, Visualization, Supervision.

CONFLICT OF INTERESTS

The author declares that for this article they have no actual, potential or perceived conflict of interests.

ETHICS COMMITTEE PERMISSION

No ethics committee permissions is required for this study

FUNDING

No funding was received from institutions or agencies for the execution of this research.

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