

Forecasting of River Sediment Amount using Machine Model

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Abstract— Accurate estimation of sediments is important in river structures. The amount of suspended sediments is mostly determined by measurements from observation stations, sediment key curve, artificial intelligence modeling methods. In this study, the estimation of the sediments content was performed by using hydro-meteorological parameters such as river flow, air temperature and precipitation measured between 2011 - 2017 at Omaha Station in Nebraska. For the estimation of sediments amount, Support Vector Machines (SVM) and Generalized Regression Neural Network (GRNN) methods were used. These models were compared by using correlation coefficient (R), mean absolute error (MAE) and root of mean square errors (RMSE). When the measurement and model results were compared, SVM and GRNN models gave consistent results in the estimation of sediments content in rivers. Nevertheless, the SVM method showed slightly better correlation and lower error performance than the GRNN method.

Keywords— Sediment, Prediction, Support vector machine, Generalized regression neural network.

I. INTRODUCTION

In water resources engineering; Accurate estimation of sediment transported in rivers is of particular importance for the design and planning of river structures. Sediments such as rock fragments, gravel and sand carried by rivers are formed by scraping from the river basin or river bed. The sediment movement is complex and differs according to the topography, geological condition and flow characteristics of the basin. Determining the amount of sediment transported in the regulation of transportation network operations such as flood control and transportation in determining the reservoir volume, selection of water intake and type is an important engineering study. If not taken into consideration; It reduces the capacity of the hopper, leads to clogging of the mouth of the intake structure and shortens the economic life of the plants and leads to material losses. Therefore, accurate sediment observations are directly proportional to the development of soil and water resources.

It is not easy to determine because the amount of sediment varies according to many parameters. It is observed that non-linear functions are formed in the complex structure and appropriate and economical methods are used to solve them.

Usually, the amount of sediment is determined by measurements from field observation stations. Although the measured values from the station give healthy results, they are important in terms of time and cost. even, In some rivers, when the flow rate decreases, sediment

measurement is not possible. For these reasons, the estimation of sediment amount is needed in the design of water structures.

In the last years, the artificial intelligence approaches are a technique widely used in water resources engineering and hydrology [1-17].

Thangaraj and Kalaivani [18] estimated the water level in the river using support vector machines. Lafdani et al. [19] investigated their capabilities using Artificial Neural Network (ANN) models to estimate the amount of suspended sediment (SSL) per day in their articles. Afan et al. [20], artificial neural networks (ANN) have been used in their studies to estimate the amount of sediment daily. For this purpose, two different ANN algorithms, feed-forward artificial neural network (FFNN) and radial based function (RBNN) used. They used daily sediment and flow data from the Rantau Panjang station on the Johor River. The results predicted the amount of sediment by the data generated by producing daily flow and sediment time series. When comparing the results, they showed that the FFNN model outperformed the RBNN model in predicting daily sediment.

Taşar et al. [21], in the their articles, artificial neural networks (ANN), M5 tree (M5T) approaches and Multiple Linear Regression (MLR), Sediment rating curve (SRC) using statistical approaches such as daily temperature and flow rate using the estimated daily suspended sediment. The daily data they used was obtained from Iowa station in the USA. They compared these estimation methods with

mean square errors (MSE), mean absolute error (MAE) and correlation coefficient (R) according to three statistical criteria. When comparing the results, they observed that the ANN approach had better sediment prediction than other methods.

Yilmaz et al. [22], have tested various regression models to calculate the amount of sediment in two stations (in Turkey-Coruh). Choubin et al. [23], tried to estimate the amount of sediment using hydro-meteorological data.

They used artificial intelligence method models such as Artificial Neural Networks (ANN) and Adaptive Neural Fuzzy Inference System (ANFIS) for sediment time series modeling.

II. STUDY AREA

In this study, support vector machine (SVM) Generalized Regression Neural Network (GRNN) were used for prediction of sediment on Missouri river. The study area was selected as the Douglas county region in the State of Nebraska in the United States. In this study, data were obtained from Omaha station for near 6 years of water year measurements and data were obtained from USGS [24] and US climate data [25]. Figure 1 shows the general view of the Missouri River at Omaha station and the views of the selected area.

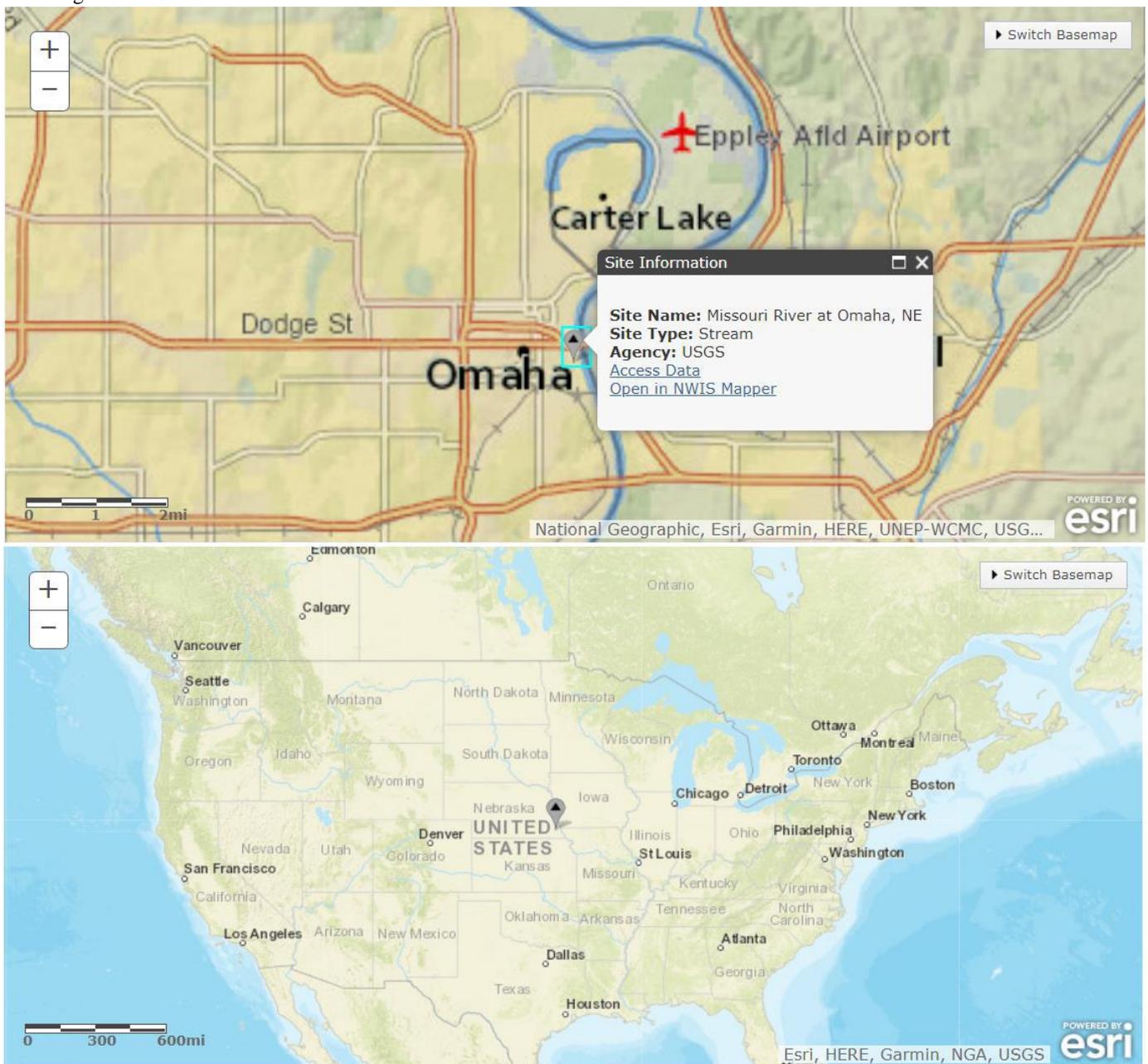


Fig.1: Missouri River at Omaha station [24]

III. METHODS

In this study, estimation of sediment amount was made by using hydro-meteorological parameters such as river flow, air temperature and precipitation measured between 2011-2017 at Omaha Station in Nebraska state of Missouri river. Support Vector Machines (SVM) and Generalized Regression Neural Network (GRNN), which are among the artificial intelligence methods, were used to estimate the sediment amount.

3.1 GENERALIZED REGRESSION NEURAL NETWORK (GRNN)

The GRNN method is a supervised artificial neural network model that is radial-based and usually works as an estimator. The strengths of this algorithm are that they produce consistent and fast results and are easy to model. In this artificial neural network model, one neuron is held in the pattern layer for each sample data in the training data set. Therefore, in studies where the training data set is too high, the layer structure grows in direct proportion to the number of sample data, increasing the number of processes and memory requirement.

3.2 SUPPORT VECTOR MACHINES (SVM)

Founded by Vladimir Vapnik and Alexey Chervonenkis [26] in 1963, Support Vector Machines (SVM) is a supervised learning algorithm based on statistical learning theory. It is mainly used to separate data from two classes in an optimal way. For this purpose, decision limits or in other words hyperplanes are determined. Today, SVMs are used in many classification problems ranging from face recognition systems to sound analysis, from water resource engineering to stock market calculations. In this study, SVM method with Poly Kernel function is used.

IV. METHOD RESULTS

In this section, sediment estimation results of Support Vector Machines (SVM) and Generalized Regression Artificial Neural Network (GRNN) methods are examined. Correlation coefficient (R), root mean square error

(RMSE) and mean absolute error (MAE) were calculated in the evaluation of the results of the models.

The correlation coefficient (R) measures the strength of the linear correlation between the binary values x and y. R value closest to 1 is the most logical and appropriate. Mean absolute error (MAE) measures the average error magnitude. RMSE and MAE are used to diagnose the probability of errors. RMSE, MAE can go from zero to infinity. Lower values mean more useful.

Expressions of the statistical criteria used in the study are given in equations 1-3.

$$R = \frac{n\sum xy - (\sum x)(\sum y)}{\sqrt{(n(\sum x^2) - (\sum x)^2)}\sqrt{(n(\sum y^2) - (\sum y)^2)}} \quad (1)$$

$$MAE = \frac{1}{n} \sum_{j=1}^n |S_{MEASURE} - S_{ESTIMATION}| \quad (2)$$

$$RMSE = \frac{1}{n} \sqrt{\sum_{i=1}^n (S_{MEASURE} - S_{ESTIMATION})^2} \quad (3)$$

Here, n is the number of data and S is the daily suspended sediment / sediment amount, concentration (mg / L).

4.1 GRNN METHOD RESULTS

In GRNN analyze, input and output data files were created by using daily measurement data flow, precipitation, temperature and time series. GRNN model was created by applying testing and training phases. The sediment amount, daily precipitation, flow rate and temperature, which consist of 2139 daily observations used in training phase. The models created in the second step were applied to the inputs of the test data generated from the 535 day observations and the results obtained with the model were compared with the measured values. For GRNN method, scatter and distribution graphs of the test graphs of this method are shown in Figure 2, Figure 3, respectively.

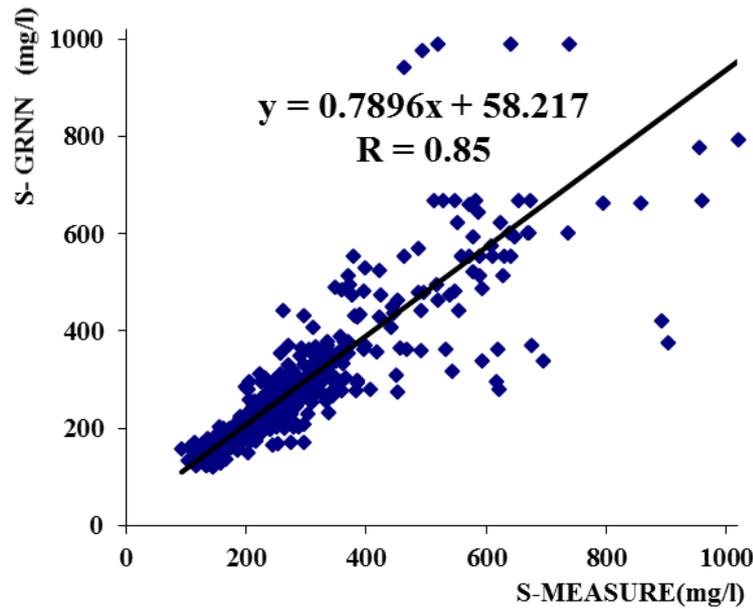


Fig. 2: Measure and GRNN scatter graph for suspended sediment amount test data

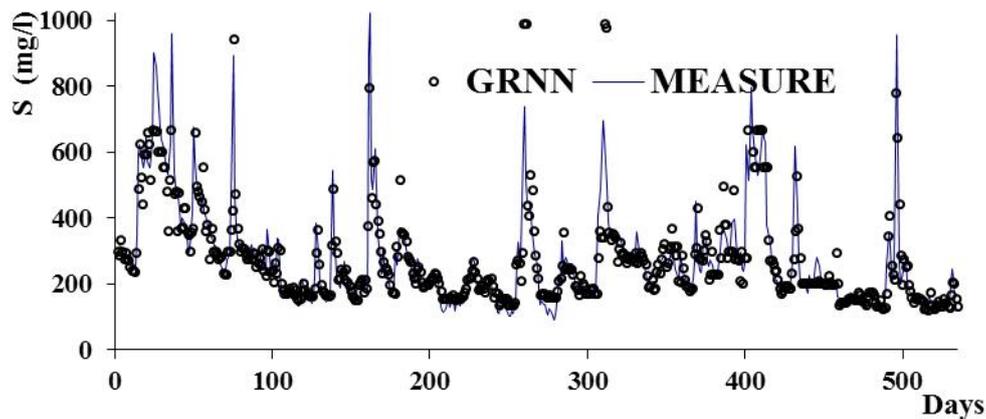


Fig. 3: Measure and GRNN distribution graph for suspended sediment amount test data

Figure 3. shows that distribution of GRNN model test results are quite close to observed values of sediment for the study area. As it is seen in Figure 2, correlation coefficient is calculated as 0.85 for test set of GRNN method.

4.2 SVM METHOD RESULTS

In SVM analyze, input and output data files were created by using daily measurement data flow, precipitation, temperature and time series in SVM model application.

And suspended sediment estimation was made using SVM model. The data sets used in the GRNN model were also used in the SVM model. 2139-day observation data were used in the training phase and 535-day observation data were applied to the model. The model results were compared with the field measured values and the model was evaluated. For SVM method, scatter and distribution graphs of the test graphs of this method are shown in Figure 4, Figure 5, respectively

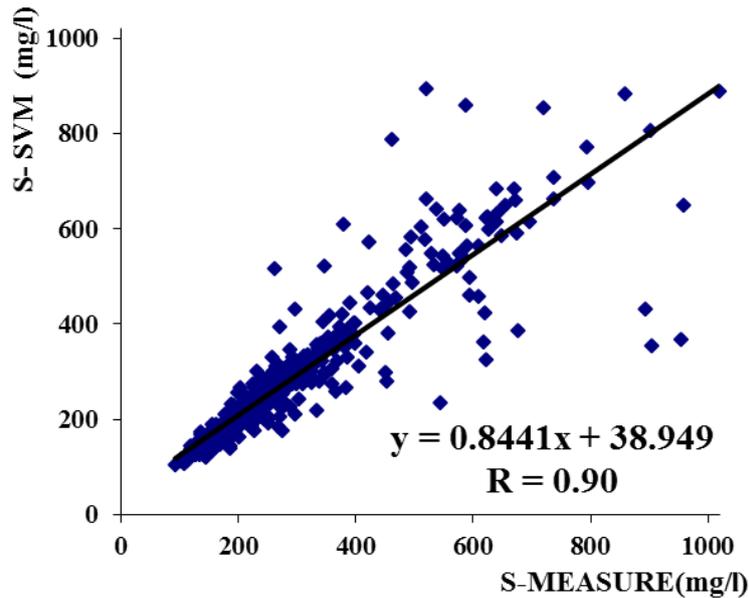


Fig. 4: Measure and SVM scatter graph for suspended sediment amount test data

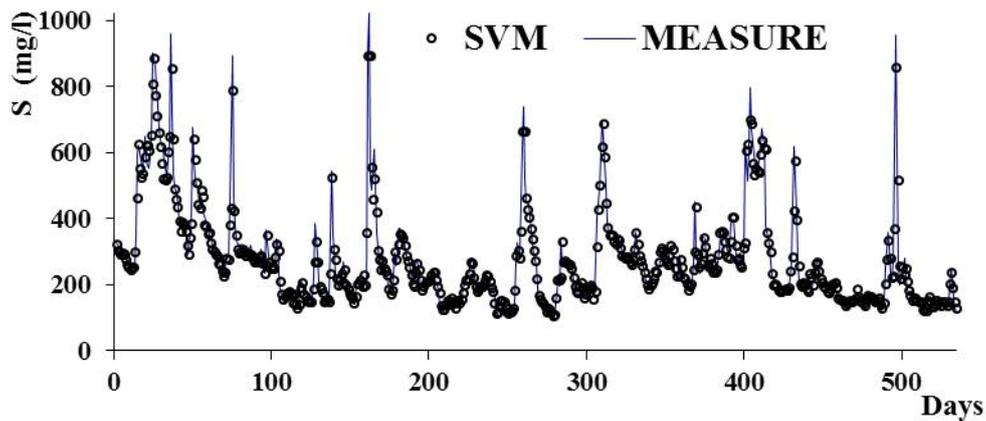


Fig. 5: Measure and SVM distribution graph for suspended sediment amount test data

Results of SVM model show that the correlation coefficient is high and the sediment estimations are closer to the actual values shown in Figure 5. Correlation coefficient is calculated as 0.90 for SVM results as it is seen in Figure 4. The result parameters of the MAE,

RMSE and R obtained from the test data will be shown in table form. The results will be used to compare estimations and performance. The statistical results of the models are given in Table 1

Table 1: MAE, RMSE and R parameter results obtained for test data of GRNN and SVM model

Methods	Method inputs	MAE (Mg/L)	RMSE (Mg/L)	R
GRNN	$Q_t, Q_{t-1}, P_t, P_{t-1}, T_t, S_{t-1}$	39.80	81.53	0.85
SVM	$Q_t, Q_{t-1}, P_t, P_{t-1}, T_t, S_{t-1}$	24.38	55.61	0.90

MAE: Mean absolute error, RMSE: Root mean square error, R: Correlation coefficient.

Q (t): Daily flow, Q(t-1): Daily flow time series, P (t): Daily precipitation, P (t-1): Daily precipitation time series, T (t): Daily temperature, S (t - 1): Daily sediment time series.

According to Table 1, when MAE, RMSE and R statistical criteria were compared, all models were good. All models are evaluated separately; GRNN (39.80 - 81.53 - 0.85) and SVM (24.38 - 55.61 - 0.90) models were found to perform well. Nevertheless, it is observed that the SVM model has a low error rate with high correlation. In addition, the GRNN model are close to SVM prediction performance. When the results were examined, GRNN and SVM models were found to perform better in sediment estimations.

Nevertheless, the SVM method showed slightly better correlation and lower error performance than the GRNN method.

V. CONCLUSION

In this study, daily suspended sediment amount in Missouri River were estimated by using Support Vector Machine (SVM) and Generalized Artificial Neural Network (GRNN) methods. Since the amount of sediment in the river structures actually contains a large number of parameters, the use of the artificial intelligence models, in the solution of this complex problem has enabled us to obtain the most realistic results.

When the SVM model results were compared to the GRNN model, it was observed that the SVM and GRNN model results were close and good.

Since Support Vector Machine applications analyzed for river structures have a low error level and the observed values are close to the estimates, it can be used as an alternative method for the prediction of sediment concentration compared to the classical methods.

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