MODELING OF DAM RESERVOIR VOLUME USING ADAPTIVE NEURO FUZZY METHOD

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ABSTRACT. – Dam reservoir capacity estimation are important for dam structures, operation, design and safety assessments. Predictions of reservoir volumes must be considered as one of the main part of water resources management. As it is known in water resources management, reservoir capacity has direct effects on choosing irrigation systems, energy production, water supply systems etc. in a study region. In this study, the reservoir capacity of the Stony Brook dam in the USA state of Massachusetts, was tried to be estimated. Data set is taken by U.S. Geological Survey Institute (USGS) website. Reservoir capacity was estimated by Adaptive Neuro Fuzzy (NF) and Multilinear Linear Regression Analysis (MLR). NF model results was compared with MLR results. For the comparison, Mean Square Error (MSE), Mean Absolute Error (MAE) and correlation coefficient statistics were used.

Keywords: Lake level, Prediction, Neuro Fuzzy (NF), Support Vector Machines (SVMs)

1. INTRODUCTION

The control of the water volume in the reservoir of the dam occurs at the right time by accumulating and distributing the water. Due to time-consuming measures and water-borne problems (eg, floods, water supply and thirst), life and property can be lost. That is why proper dam reservoir management is not only a matter of fresh water supply, but also a means of preventing possible damages. One of the basic requirements for managing the dam reservoir is to determine the reservoir water volume and estimate the ups and downs of this volume. The artificial intelligence techniques have been used in hydrology and water resources systems. Adaptive neuro fuzzy (NF) which is one of them has been widely applied in water resources. NF is a combination of an adaptive neural network and a fuzzy inference system. The parameters of the fuzzy inference system are determined by the NN learning algorithms. Since this system is based on the fuzzy inference system, reflecting amazing knowledge, an important aspect is that the system should be always interpretable in terms of fuzzy IF–THEN rules. NF is capable of approximating any real continuous function on a compact set to any degree of

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accuracy (Jang et al. 1997) Keskin et al. (1994) used fuzzy models to estimate daily pan evaporation in Western Turkey. Kazeminezhad et al. (2005) applied NF to forecast wave parameters in Lake Ontario and found NF superior to the Coastal Engineering Manual methods. Kisi (2006) investigated the ability of NF techniques to improve the accuracy of daily evaporation estimation. Kisi and Ozturk (2007) used NF computing techniques for evapotranspiration estimation. Demirci and Baltacı (2013) estimated suspended sediment of Sacremento river in USA using fuzzy logic. Unes (2010a) predicted plunging depth of density flow in dam reservoir using the ANN technique. Unes (2010b), Unes at al. (2015a) used ANN model and Unes and Demirci (2015b) used generalized neural network (GRNN) model for predicting reservoir level fluctuation. Shiri et al. (2011) used NF for predicting shortterm operational water levels.

In this study, the reservoir capacity of the Stony Brook dam in the United States of America was tried to be estimated. The reservoir capacity was estimated using NF and MLR models using temperature, precipitation and flow data and the models were compared with each other.

2. APPLICATION AREA

The application area is the Stony Brook dam in Massachusetts, USA. The Stony Brook dam is located at 42 ° 35 '46.3' (42.5962 °) latitude and 71 ° 26 '18.7' (71.4385 °) longitude in Middlesex County, Massachusetts. The drainage area is 70.7 km2. .The Stony Brook Reservoir reaches roughly 425 million gallons of water at full capacity, with a maximum height of 68.9 feet, the deepest point about 30 feet. Stony Brook is relatively small compared to large basins and is much faster than other dams around.

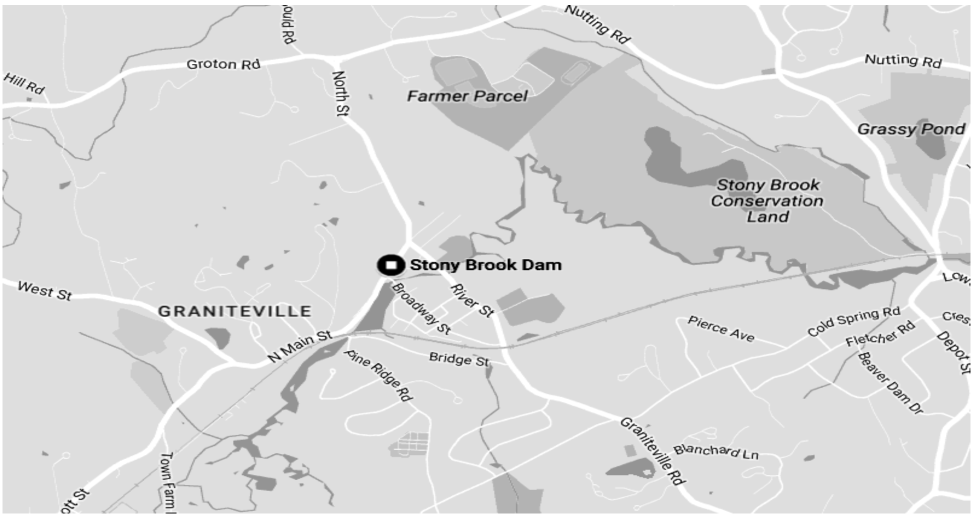

Fig. 1. ***Location of Stony Brook Dam (Google Maps)***

In this study, dam reservoir volume is estimated with using the temperature, precipitation, and flow rate data from the United States Geological Survey Institute (USGS) https://waterdata.usgs.gov/nwis/dv/?referred_module=qw) as input.

Multiple linear regression analysis (MLR) and Neuro Fuzzy (NF) model results for 1-year data are generated. For each model, the mean square error (MSE), the mean absolute error (MAE), and the determination coefficients (R^2) statistics are calculated. The results are also used to compare the performance of model estimations and observations. In this study Stony Brook dam temperature, precipitation, flow rate and past reservoir volume (time, t-1) were taken as input. In NF and MLR models, 255 data of 365 data were applied for training models and the rest 110 data were applied for the test. The results obtained with the model are compared with the measured values.

3. METHODOLOGY

Multi-Linear Regression (MLR) Model

MLR is used to model the linear relationship between a dependent variable and one or more independent variables. It is also used to (understand which among the independent variables are related to the dependent variable, and to) determine the forms of these relationships. The MLR method is generally based on least squares: the model is fit such that the sum-of squares of differences of actual and forecasted values is minimized. Although groundwater problems are a nonlinear problem, statistical MLR model is developed to compare the other models. If there are m independent variables and one dependent variable, the multi-linear regression equation can be generally obtained as,

$$y = a + b_1 x_1 + b_2 x_2 + ... + b_m x_m + e \tag{1}$$

Adaptive Neuro-Fuzzy (NF)

NF identifies a set of parameters through a hybrid learning rule combining backpropaga-tion gradient descent error digestion and a least-squared error method. There are two approaches for fuzzy inference systems, namely the approach of Mamdani and Assilian (1975) and the approach of Takagi and Sugeno (1985). The neuro-fuzzy model used in this study implements Sugeno's fuzzy approach to obtain the values for the output variable from those of input variables.

Sugeno type adaptive neuro-fuzzy (NF) system's structure was shown in Fig. 2. Where, "x, y" ; "A1, A2, B1, B2 " ; "π" ; "N" and "wi" represent, respectively, input parameters, membership functions, rules, weight of parameters after fuzzy rules applied to the system in used modeling.

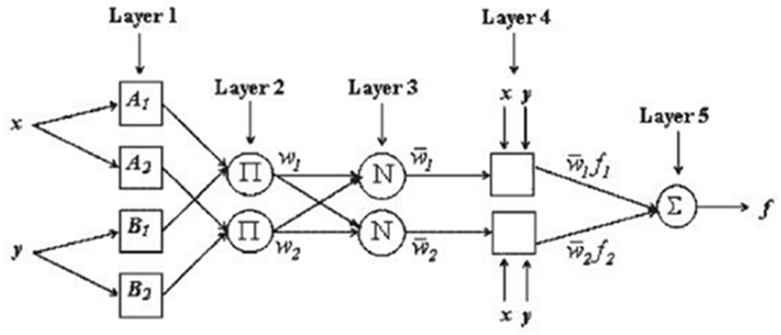

Fig. 2. ***Structure of Sugeno type Adaptive Neuro-Fuzzy (NF) system***

4. RESULTS

MLR Results

Multiple linear regression (MLR) analysis is a type of analysis for estimating a dependent variable depending on 2 or more independent variables. The relationship between multiple independent variables (x_1, x_2, ..., x_n) and a dependent variable (y) is examined in a multiple linear regression.

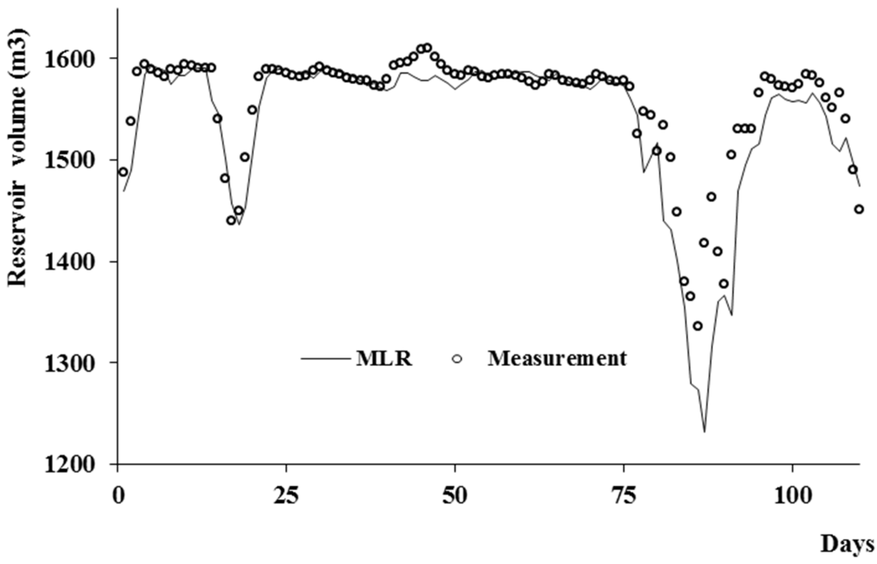

Fig. 3. ***Measurement and MLR distribution graph for reservoir volume test data***

In Figure 3, the daily dam reservoir volume estimates of MLR and measured values are compared. For the test data, the scattering diagram of the MLR estimation results and measured values is given in Fig. 4.

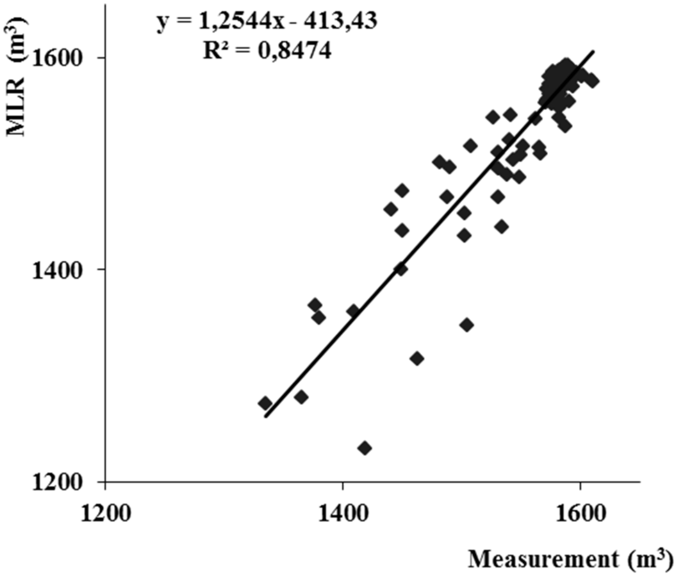

Fig. 4. ***Measurement and MLR scatter graph for dam reservoir volume test data***

In Figure 3, it is observed that there is a very close relationship between the MLR values and the actual measured values when the distribution graph is examined. As shown in Figure 4, the determination coefficient obtained as 0.8474.

Adaptive Neuro-Fuzzy (NF) Results

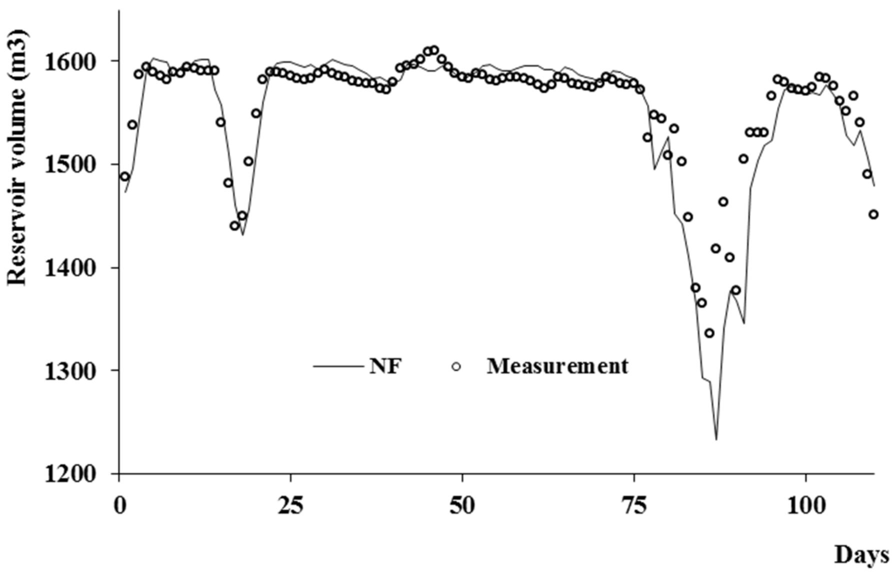

Fig. 5. ***Measurement and NF distribution graph for reservoir volume test data***

In order to develop the dam reservoir models, data were first trained by using 255 day observations. After the training phase was completed, NF was applied to test data from the last 110 observations. In figure 5, reservoir volume estimates and measured values are compared for the test process. Figure 6 shows this relationship in the form of scatter diagram.

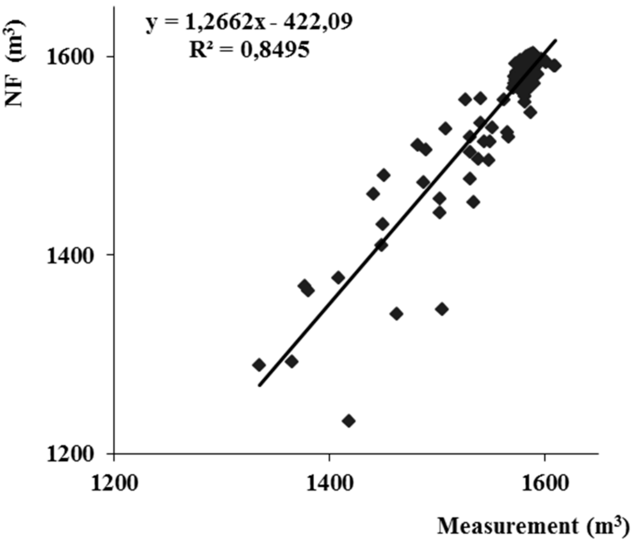

Fig. 6. ***Measurement and NF scatter graph for dam reservoir volume test data***

As can be seen from this figure 5, the observed and estimated dam reservoir volume of the NF model is compatible. As shown in Fig. 6, the correlation coefficient is calculated as $R^2 = 0.8495$ and a very high correlation is obtained.

General Evaluation

The correlation coefficient (R), mean squared error (MSE) and absolute mean error (MAE) were calculated for the performance evaluation of the MLR and NF models. For each model, mean square error (MSE) and mean absolute error (MAE) were calculated. The results are used to compare the performance of the model predictions and the observational data. Comparisons of the MSE, MAE and R^2 parameters obtained from the test data are shown in Table 1.

Table 1. ***Performance comparison of MLR and NF models***

Model	MSE	MAE	R^2
MLR	37.245	21.028	0.847
NF	34.064	19.769	0.849

MSE: Mean squared error, MAE: Absolute mean error, R^2: Determination coefficient

Table 1 shows that MLR and NF model give similar results. The most appropriate model for the test data was the NF model and the highest correlation ($R^2 = 0.849$) and the lowest MSE (37,245), MAE (19,769) were found for each test combination.

5. CONCLUSION

In this study, the Stony Brook dam reservoir volume was tried to be estimated using temperature, precipitation and flow data. MLR and NF models were used to estimate the reservoir capacity and the models were compared with each other.

The multiple linear regression model (MLR), which is often used to describe empirical links, has yielded quite accurate results in solving the problem. The small MSE, MAE values and high correlation for reservoir capacity estimation were able to be obtained. Nevertheless, the performance demonstrated by NF is better than that of the MLR model.

NF is adapting correctly to changing input conditions, such as changes in the planning of water required in the dam reservoir. The reason that NF is more advantageous than conventional methods in predicting reservoir volume is that NF structure incorporates non-linear dynamics of the problem and all data sets. This is very important because similar rapid changes in the time sequence can be observed with reservoir operation management studies.

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