OKÜ Fen Bilimleri Enstitüsü Dergisi
5(Özel Sayı):80-95, 2022

OKU Journal of The Institute of Science and Technology, 5(Special Issue):80-95, 2022

Osmaniye Korkut Ata Üniversitesi
Fen Bilimleri Enstitüsü
Dergisi

Osmaniye Korkut Ata University
Journal of The Institute of
Science and Technology

Estimating Dam Reservoir Level Change of Istanbul Alibey Dam with The Fuzzy SMRGT Method

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Research Article

Article History:
Received: 07.12.2021
Accepted: 14.01.2022
Published online: 23.02.2022

Keywords:
Dam reservoir level
Prediction
Fuzzy
ANN
Regression

ABSTRACT

Accurate estimation of the dam reservoir level is very important for the planning and operation of water structures. In this study, monthly dam reservoir level data between the years of 1989 and 2020 obtained from the State Hydraulic Works (DSI) was used to estimate the monthly dam reservoir level change. For the monthly dam reservoir level estimation, it has been tried to be estimated using the Simple Membership Functions and Fuzzy Rules Generation Technique (Fuzzy-SMRGT), Artificial Neural Networks (ANN) and the classical Multiple Linear Regression (MLR) methods. Alibey Dam located in Sultangazi district of Istanbul was chosen as the study area. The monthly evaporation, water entering into the lake, consumption of drinking water and amount of water discharged from the dam amounts were used to estimate the monthly Alibey Dam average dam reservoir level. The model results were compared with the actual observation data. When statistical criteria were evaluated, it was seen that artificial intelligence approaches and regression method were successful in estimating the dam reservoir level and gave close estimation results.

İstanbul Alibey Barajının Baraj Rezervuar Seviye Değişiminin Bulanık SMRGT Yöntemiyle Tahmin Edilmesi

Araştırma Makalesi

Makale Tarihçesi:
Geliş tarihi: 07.12.2021
Kabul tarihi:14.01.2022
Online Yayınlanma: 23.02.2022

Keywords:
Baraj rezervuar seviyesi
Tahmin
Fuzzy
ANN
Regresyon

ÖZET

Baraj rezervuar seviyesinin doğru bir şekilde tahmin edilmesi, su yapılarının planlanması ve işletilmesi için çok önemlidir. Bu çalışmada, aylık baraj rezervuar seviyesi değişimini tahmin etmek için Devlet Su İşleri'nden (DSİ) alınan 1989-2020 yılları arasındaki aylık baraj rezervuar seviyesi verileri kullanılmıştır. Aylık baraj rezervuar seviyesi tahmini için Basit Üyelik Fonksiyonları ve Bulanık Kural Oluşturma Tekniği (Fuzzy-SMRGT), Yapay Sinir Ağları (YSA) ve klasik Çoklu Doğrusal Regresyon (ÇDR) yöntemleri kullanılarak tahmin edilmeye çalışılmıştır. Çalışma alanı olarak İstanbul ili Sultangazi ilçesinde bulunan Alibey Barajı seçilmiştir. Aylık buharlaşma, aylık göle giren su, aylık içme suyu tüketimi ve aylık barajdan deşarj edilen su miktarı, aylık Alibey Barajı baraj rezervuar seviyesi ortalamasını tahmin etmek için kullanılmıştır. Model sonuçları gerçek gözlem verileriyle karşılaştırılmıştır. İstatistiksel kriterler değerlendirildiğinde yapay zekâ yaklaşımlarının ve regresyon yönteminin baraj rezervuar seviyesinin tahmininde başarılı olduğu ve yakın tahmin sonuçları verdiği görülmüştür.

To Cite: Er EE., Üneş F., Taşar B. Estimating Dam Reservoir Level Change of Istanbul Alibey Dam With The Fuzzy SMRGT Method. Osmaniye Korkut Ata Üniversitesi Fen Bilimleri Enstitüsü Dergisi 2022; 5(Özel sayı): 80-95.

Introduction

Water has the most important position in human life for sustaining life. However, especially with the global climate change experienced in recent years, the increasing water problems and their solutions have gained more importance. It has become inevitable to take some precautions due to the remarkable decrease in the amount of water usage. For these reasons, it is necessary to take precautions to know the potential of existing water resources and to use more efficiently (Küçükerdem, 2019). It is quitesubstantialto estimate the amount of water entering and leaving the system during the design and operation of water structures. Recently, prominent artificial intelligence models are used to estimate these data (Salam, 2018).

There are many studies in the literature with the development of a prediction model related to water structures and hydrology using artificial intelligence methods. Şener et al. (2014) of the changes in Burdur Lake dam reservoir level using the, regression analysis created prediction models Fuzzy Logic (FL)methods with precipitation and evaporation data. They observed that the FL method gave more successful results than the regression method. Aydemir (2020), estimatedthe dam reservoir level of Terkos Dam Lake with the FL. In his study, the most accurate estimation of water values in the future was investigated by establishing a modeling mechanism with the ANFIS method, with the help of water values from 2001-2012 in Terkos Dam. Üneş (2010), the dam reservoir level was estimated with artificial neural networks. Üneş et al. (2018a) estimated the amount of evaporation in the Cambridge reservoir basin with the ANN method, which is one of the artificial intelligence techniques. Üneş et al. (2018a) created models to predict ground dam reservoir level fluctuations with the ANN with the data of the Minnesota observation well station in the USA. On the other hand, Üneş et al. (2018b) evaluated and compared daily reference evapotranspiration by ANN and empirical methods. Üneş et al. (2019a) estimated the dam reservoir level fluctuations by selecting Millers Ferry Dam on the Alaba River in the USA. It has been observed that FL ANFIS models give better results than classical and other artificial models. Üneş et al. (2019b) estimated modeling of dam reservoir volume using Generalized Regression Neural Network (GRNN), SVM and M5decision tree models. Üneş et al. (2019c) created ground dam reservoir level estimation models with the fuzzy logic method. Üneş et al. (2019d) estimated the artificial neural network method for the estimation of the ainfall-runoff relationship. Demirci et al. (2017) estimated the ground dam reservoir level using the ANN with the data they obtained from the General Directorate of State Hydraulic Works (DSI) in the Kumlu district of the Amik Plain of Hatay (Demirci et al., 2018) estimated the reservoir capacity of the Brook Dam in Massachusetts, USA, using adaptive neuro fuzzy (NF) and multiple linear regression (MLR) models. NF andMLR results were compared to each other.

Arslan et al. (2020) estimated the Keban dam lake level change using adaptive neural fuzzy inference system (ANFIS) and support vector machines (SVM) methods. Kilinc (2004) tried to predict monthly inflows, total evaporations and end-of-month volumes of a reservoir by using the ANN in the operation of dam reservoirs in Istanbul. The estimation results were compared with the results of classical methods. Turhan (2021), a comparative evaluation of the use of artificial neural networks in modeling the precipitation- flow relationship in water resources management. Latif et al. (2021) he studied the reservoir water balance simulation model using machine learning algorithm. Iraji et al. (2020) estimated the reduction in reservoir volume using an artificial neural network. Paul et al. (2019) a comparative study of wavelet transforms and MLR, KNN (K-Nearest Neighbors), ANN and ANFIS models in monthly flow estimation.Other studies on artificial intelligence in the field of hydraulics (Gemici, 2013; Kocabaş, 2013; Ozel 2020).

In this study, monthly evaporation amount (E_t), amount of water coming into the lake (LW_t), drinking water consumption (DW_t) and discharged water amount (DDW_t) from the dam reservoir were used to estimate the monthly dam reservoir level (DRL_t) change of Alibey Dam. Fuzzy-SMRGT + a fuzzy logic method, Multiple Linear Regression methods (MLR) and Artificial Neural Networks (ANN) were used.

Material and Methods

Study Area

In this study, Alibey Dam, which is located in Sultangazi district of Istanbul province of Turkey, was given in Figure 1 it was built between 1975-1983 for the purpose of supplying drinking water, utility water and industrial water. The volume of the dam body, which is an earth-fill type, is 1.900.000 m^3, its height from the river bed is 30,00 m, the lake volume at normal dam reservoir level is 66,80 hm^3, and the lake area at normal dam reservoir level is 4,66 km^2. An average of 39 hm^3 of drinking water is provided annually from the Alibey Dam. The 31-year monthly measurement data of the Alibey Dam, which is of great importance in its region, for the years 1989-2020 were used. Figure 2 shows that the changes in dam reservoir level. The changes in Dam Reservoir level between the years of1989 and 2020.

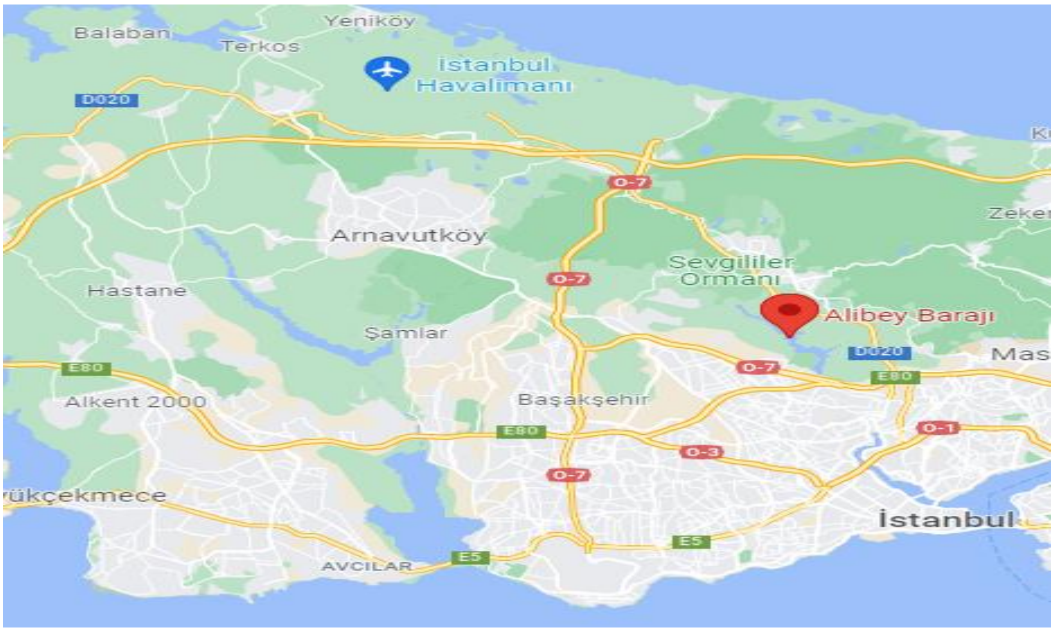

Figure 1. The location of Alibey Dam

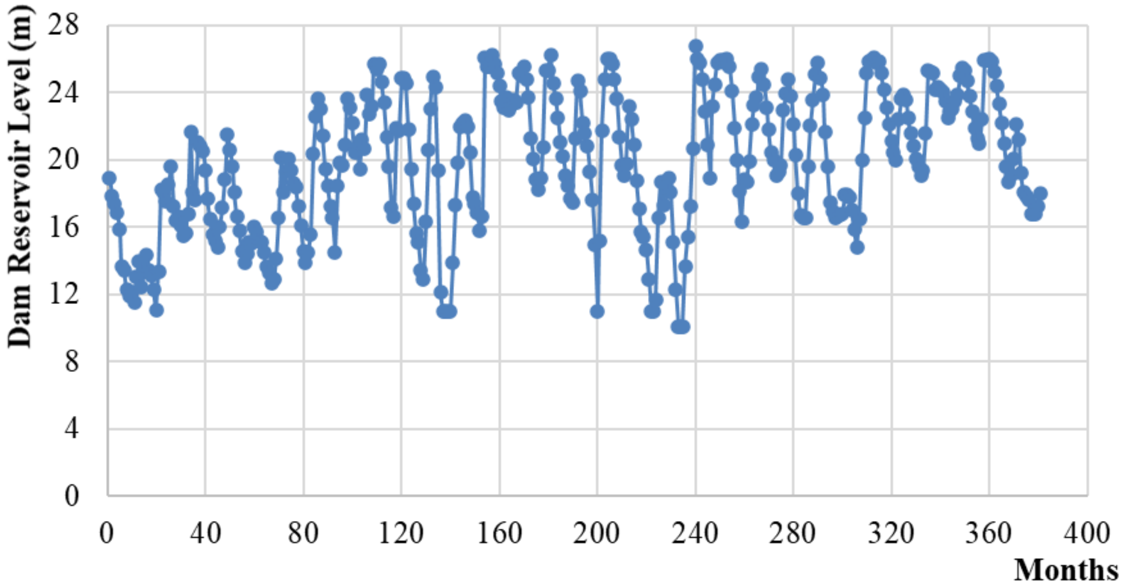

Figure 2. Dam reservoir level (m) variations between 1989 and 2020 years

Multiple Linear Regression (MLR) Method

The multiple linear regression method is a method used to analyze the relationship between one dependent variable and the independent variables. MLR deals with the linear relationship between more than one independent variable and one dependent variable. It is a very common method (Turhan et al., 2016; Tsakiri et al., 2018). If we show the independent variables X and the dependent variable Y, it can be formulated as shown below:

$$Y = A_0 + A_1 * X_1 + A_2 * X_2 \dots . +A_i * X_i + B \quad (1)$$

Artificial Neural Networks (ANN)

ANN is a computer program created by taking advantage of the ability of the human brain to work and think. Thanks to the ANN, solutions are easily offered to complex problems. Although successful results have been achieved in solving the problems, the assignment of weights in the model is based on black box logic. That is, it is not known how the weights are assigned. The ANN is a method used to solve problems that cannot be expressed mathematically and is defined as a black box model. The general formula of the ANN model is given in Equation 2:

$$Y = f(\sum_{i=1}^{n} Xi * Wi + b_i) \quad (2)$$

In Equation 2, Y shows the dependent variable, X values show the independent variables, W model's layer weights and b model's bias value.

Fuzzy Logic

In real life, very complex events cannot be expressed mathematically. All theories and equations are expressed approximately in real life. The logic developed in order to make these uncertainties more understandable verbally is called FL (Uygunoğlu, 2005). This approach was first mentioned by Zadeh in 1965 in his article "Fuzzy Set" (Zadeh, 1996). FL system; It consists of input, database, fuzzification unit, fuzzy inference mechanism, rule base, defuzzification unit and output (Jang, 1997).

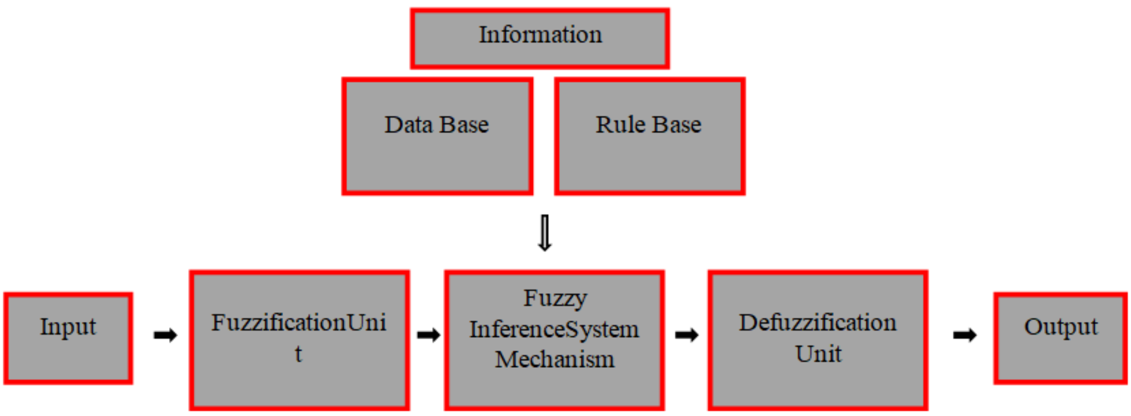

Figure 3. A general fuzzy logic system (Güner, 2014)

Input/Database: Contains input variables affecting the event to be analyzed and all information about them. This information can be numerical or verbal.

Fuzzification Unit: It is the unit in which the necessary transformation is made so that the data coming from the Input/Database section can be processed in the fuzzy extraction mechanism. Membership functions are executed in this unit.

Fuzzy Rule Base Unit: It contains all the rules that can be written as a logical IF-THEN type that binds inputs in the database to output variables.

Fuzzy Inference System Mechanism: This unit is a mechanism that includes all the operations that ensure that the system behaves with a single output by collecting all the partial relations established between the input and output fuzzy sets in the fuzzy rule base. This engine aggregates the implications of each rule and determines how the whole system will output under the inputs.

Defuzzification Unit: It is the unit in which the fuzzy output values (values in the [0-1] Range) are converted to the problem-specific scale at the input.

Output: It is the solution brought by the fuzzy logic system to the problem. It is obtained by passing the fuzzy output formed by the fuzzy extraction mechanism through the defuzzification unit (Uygunoğlu and Ünal, 2005).

In this study, Fuzzy SMRGT method was used in the creation and solution of the Fuzzy Logic model. The fuzzy SMRGT method was first proposed by Fuat Toprak in 2009. The biggest advantage of this method is that the model determines both the fuzzy rule (FRs) base and the membership functions (MFs) together with a very simple technique (Beduk, 2012). On the other hand, since it is completely based on expert opinion, it enables the model to be established without any data. The Fuzzy SMRGT method was first used to calculate the open channel cutoff in the hydraulic field. Afterwards, many studies were carried out in various fields (Hamidi 2013; Toprak, 2013; Toprak, 2015; Altaş, 2018; Bayri, 2018; Çakır, 2018; Derya, 2018; Toprak, 2018).

In the Fuzzy SMRGT method, firstly, the independent variables affecting the dependent variable are determined for the event at hand. Maximum and minimum value ranges are determined for each variable. Then the shape of the membership function is decided. The center and width of the membership functions are determined by their key values for each argument. These key values are the inputs of the fuzzy model. Thus, the Fuzzy SMRGT model is valid for the range of values corresponding to the centroid of the first and last membership function for each independent variable. A table is to give the key values of the outputs and the number of fuzz rules.

$$X_R = X_{\max} - X_{\min} \tag{3}$$

$$UW = \frac{X_R}{n_u} \tag{4}$$

$$EUW = \frac{X_R}{n_u} + A \tag{5}$$

$$A = \frac{UW}{2} \tag{6}$$

$$K_1 = X_{\min} + \frac{EUW}{3} \tag{7}$$

$$K_2 = X_{\max} - \frac{EUW}{3}$$

(8)

$$C_i = \frac{X_R}{2} + X_{\min} \quad (9)$$

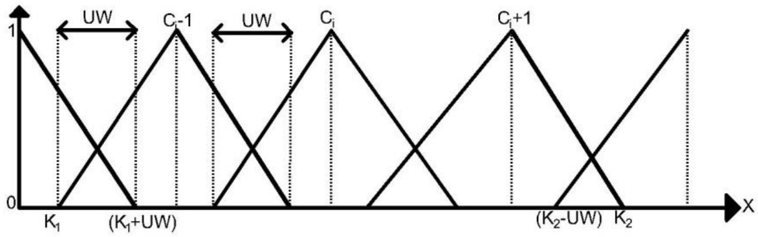

Figure 4. Boundary parameters of the Fuzzy SMRGT method

Table 1. Membership functions and key values range for each parameter

	DDW_t	E_t,	DW_t	LW_t	DRL_{t-1}	DRL_t
N_u	8	8	8	8	8	8
V_{max}	24,62	0,54	15,02	40,01	26,77	26,77
V_{min}	0	0	0	0	10,09	10,09
V_r=V_{max}-V_{min}	24,62	0,54	15,02	40,01	16,68	16,68
U_w	3,07	0,06	1,87	5	2,08	2,08
E_{uw}	4,62	0,10	2,81	7,5	3,13	3,13
K_1	1,54	0,03	0,94	2,50	11,13	11,13
K_1+U_w	4,62	0,10	2,82	7,50	13,22	13,22
C_i-1	6,16	0,14	3,76	10,00	14,26	14,26
C_i-1+E_{uw}-U_w	7,69	0,17	4,70	12,50	15,30	15,30
K_2=Ci-1+E_{uw}	10,77	0,24	6,58	17,51	17,39	17,39
C_i	12,31	0,27	7,51	20,01	18,43	18,43
C_i+E_{uw}-U_w	13,85	0,31	8,45	22,51	19,47	19,47
$K_{3+}U_w$ =C_i+E_{uw}	16,93	0,38	10,33	27,51	21,56	21,56
C_i+1	18,47	0,41	11,27	30,01	22,60	22,60
K_4-U_w	20,00	0,45	12,21	32,51	23,64	23,64
K_4	23,08	0,51	14,09	37,51	25,73	25,73

In this table, the unit width (UW), kernel value (C_i), key values (K_i), range of variation (V_R), base width (E_{UW}) and nu represent the number of right triangles for each membership function.

Table 2. Statistical values of the models

	DDW_t	E_t,	DW_t	LW_t	DRL_{t-1}	DRL_t
			TRAINING			
V_{max}	24,62	0,54	15,02	40,01	26,77	26,77
V_{min}	0	0	0	0	10,09	10,09
SD	9,17	0,017	6,33	35,49	18,07	18,09
SC	5,46	1,24	0,86	2,32	-0,15	-0,15
			TEST			
V_{max}	10,64	0,49	7,06	24,45	26,11	26,11
V_{min}	0	0	0	0,227	14,78	14,78
SD	2,93	0,025	2,61	16,9	10,17	10,03
SC	4,93	0,686	0,2	2,57	-0,34	-0,33

In this table, measured max value (Vmax), measured min value (Vmin), standaid deviation (SD) and skewness coefficient (SC).

Model Result and Evaluations

In this study, monthly dam reservoir level changes were estimated using Fuzzy SMRGT, MLR and ANN methods. The performances of the obtained results were compared. A total of 381 monthly data for the years 1989-2020 of the Alibey Dam for 31 years were used. In the study, 75% of all data wastraining 25% is reserved for testing. 285 months of data were used for training and 96 months of measurement data for testing. In the Fuzzy SMRGT MLR and ANN model applications, the dam reservoir level value was estimated by using the monthly evaporation amount, the amount of water coming into the lake, the consumption of drinking water and the amount of water discharged.

In all models, 285 months of data were trained and 96 months of data were applied in the testing phase. The test results obtained were compared with the dam reservoir level results. The results according to these comparisons are given in Table 1.

To compare the performance of the models used to predict dam reservoir levels, mean absolute error (MAE), root mean squared errors (RMSE), and correlation coefficient (R) were used (Sahoo et al., 2019; Idrees et al., 2021). These statistical criteria are given in equations (10) and (11), respectively.

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\mathrm{DRLt}i_{measured} - \mathrm{DRLt}i_{prediction})^2} \quad (10)$$

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|\mathrm{DRLt}i_{measured} - \mathrm{DRLt}i_{prediction}\right| \quad (11)$$

Where N is the number of data in the test phase and DRL_t represents the dam reservoir level value. Statistical MAE, RMSE and R values of the models used in the study are given in Table 3.

Table 3. Statistical results of models

Model	Model Inputs	MAE	RMSE	R
MLR	E_t, LW_t, DW_t, DDW_t, DRL_{t-1}	0,814	1,071	0,952
ANN	E_t, LW_t, DW_t, DDW_t, DRL_{t-1}	0,830	1,046	0,951
SMRGT	E_t, LW_t, DW_t, DDW_t, DRL_{t-1}	0,803	1,033	0,955

MAE: Absolute mean error, RMSE: Root mean squared R: Correlation coefficient.

When Table 3 is examined, it is seen that MLR model, ANN model and Fuzzy SMRGT model give very close results.

Multiple Linear Regression Model Results

In MLR model applications, the average monthly evaporation (E_t), the water coming into the lake (LW_t), the consumption of drinking water (DW_t), the water discharged from the dam (DDW_t) and monthly average dam reservoir level time series (DRL_{t-1}) amounts were used for the estimation of the monthly average dam reservoir level (DRL_t). The distribution and scatter plots of the MLR model are shown in Figures 4 and 5, respectively. As seen in Figures 5 and 6, when the MLR model is applied for test data, it is seen that the model results are close to the real values and the correlation coefficient is 0,9526.

$$Y = 1{,}01 + 0{,}04 * DDW_t + (-2{,}25) * E_t + 0{,}05 * DW_t + 0{,}09 * LW_t + 0{,}92 * DRL_{t-1} \tag{12}$$

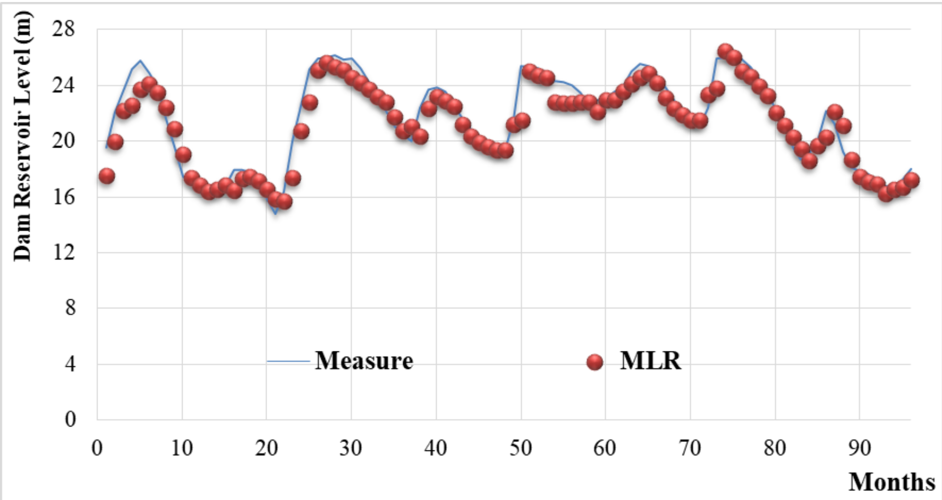

Figure 5. Measurement and MLR distribution plot for monthly average dam reservoir level

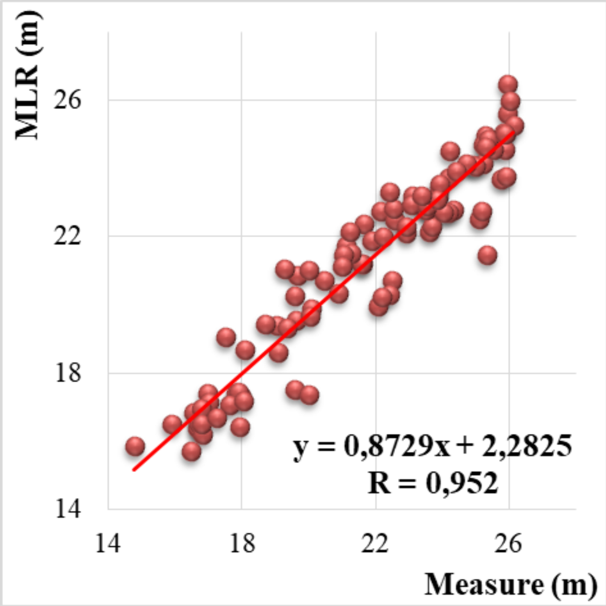

Figure 6. Measurement and MLR scatterplot for monthly average dam reservoir level

Artificial Neural Networks Model Results

In this study, the parameters of the average monthly evaporation (E_t) amount, the amount of water coming into the lake (LW_t), the consumption of drinking water (DW_t) and the amount of water discharged from the dam (DDW_t) obtained and regulated by DSI in ANN model applications, are used for the estimation of the monthly average dam reservoir level (DRL_t). ANN model distribution and scatter plots are shown in Figures 7 and 8, respectively. As seen in Figures 6 and 7, when ANN is applied for test data, it is seen that the model results are close to the real values and the correlation coefficient is 0,951 the fact that the ANN method is very close to the MLR method shows that this method is successful in this study.

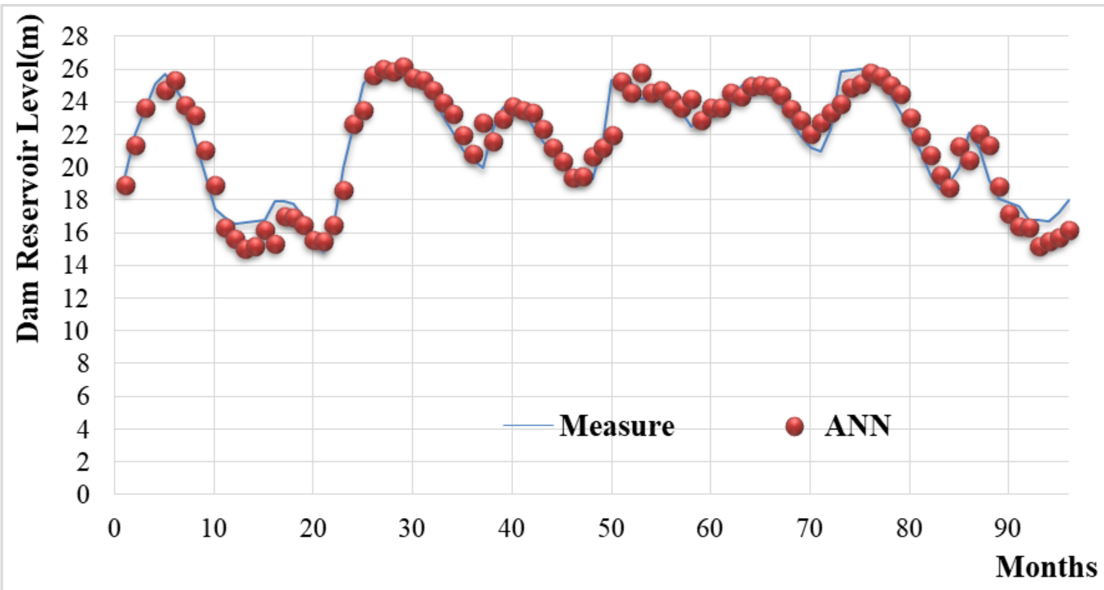

Figure 7. Measurement and ANN distribution plot for monthly average dam reservoir level

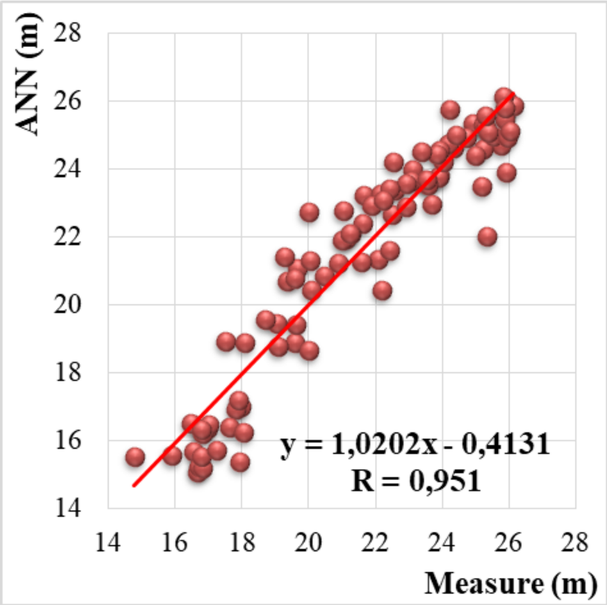

Figure 8. Measurement and ANN scatter plot for monthly average dam reservoir level

Fuzzy SMRGT Model Results

In this study, the parameters of the average monthly evaporation (E_t) amount obtained and regulated by DSI, the amount of water coming into the lake (LW_t), the consumption of drinking water (DW_t) and the amount of water discharged (DDW_t) from the dam were used for the estimation of the monthly average dam reservoir level (DRL_t) in the Fuzzy SMRGT model applications. The Fuzzy SMRGT model distribution and scatter plots are shown in Figures 8 and 9, respectively. As seen in Figures 9 and 10, when applied for Fuzzy SMRGT test data, it is seen that the model results are close to the true values and the correlation coefficient is 0,955. Fuzzy SMRGT method gave slightly better results than ANN and MLR methods. These results show that the Fuzzy SMRGT method can be used.

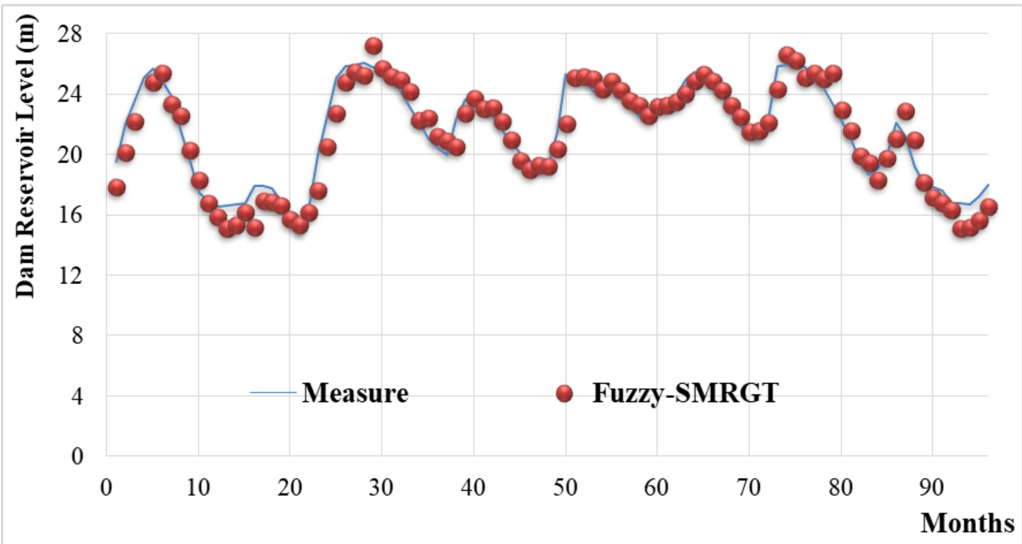

Figure 9. Measurement and SMRGT distribution plot for monthly average dam reservoir level

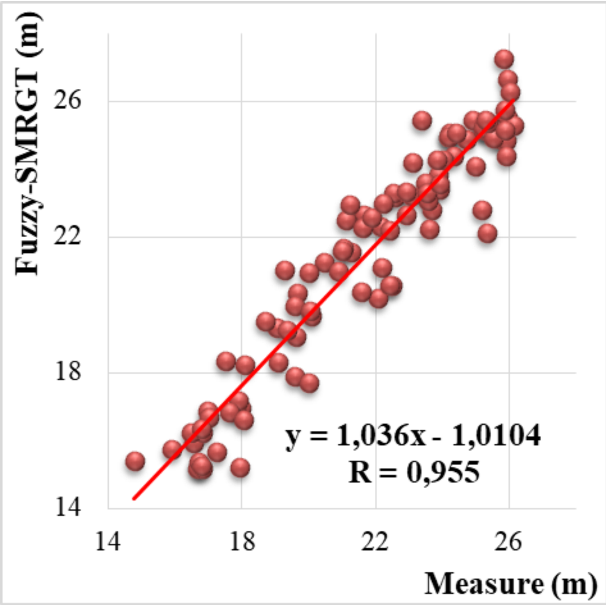

Figure 10. Measurement and SMRGT scatterplot for monthly average dam reservoir level

Result and Discussion

In this study, the monthly average dam reservoir level of Alibey Dam in Sultangazi District of Istanbul between 1989 and 2020 was estimated using the monthly evaporation amount, the amount of water coming into the lake, the consumption of drinking water and the amount of water discharged from the dam. Fuzzy SMRGT, ANNand MLR models were used for dam reservoir level estimation and the models were compared with each other. In the Fuzzy SMRGT, ANN and MLR models, 285 data out of a total of 381 data were applied for training and 96 data were applied for testing. The results obtained with the model were compared with the measurement values. Correlation coefficient (R), (MSE) and (MAE) were calculated for the performance evaluation of Fuzzy SMRGT, ANN and MLR Models. It has been observed that the Fuzzy model gives better results than the ANN model and gives very close results to the traditional MLR model.

The results show that when a Fuzzy SMRGT model is developed for a selected reservoir, monthly reservoir level change, hydroelectric energy calculations and determination of water resources management show that these model results can be used in water resource management studies. In this sense, it is thought that all three models can be used in dam level estimation.Models selected for the level estimation of the Alibey Dam reservoir made correct estimations with results close to each other.In this sense, it is thought that the results of this study can be used by the relevant institutions for future regulation studies for this reservoir.

As a result, Alibey dam is a very important dam in terms of meeting the water needs of the European side of Istanbul. Working with artificial intelligence for the first time on Alibey dam reveals how important this study is. The fact that the Fuzzy SMRGT method gives good results compared to the

ANN and MLR methods shows that the Fuzzy SMRGT method can be preferred in dam reservoir volume studies.

Acknowledgment

In this study, hydrological data measured by the State Hydraulic Works (DSI-TURKEY) was used. The authors thank DSI for measuring and transmitting hydrological data.

Conflict of Interest Statement

The article author declares that there is no conflict of interest.

Contribution Rate Statement Summary of Researchers

All authors declare that they have contributed equally to the article.

*This study was presented as a summary paper at the International Conference on Engineering, Natural and Applied Sciences (ICENAS'21) held online on 24-26 November 2021.

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