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Research Article

# Comparison of Different Artificial Neural Network Methods in Determining Reservoir Capacity

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**Abstract**
Making estimation of river flow with hydrological and methodological data of the past period and using in water resources project studies have been used for a long time in many studies in our country and in the world. In addition to this, along with frequent drought problems in recent years, it is also important to store and use the water in the reservoirs correctly. This study aims to research how two separate Artificial-Neural-Network-Functions, which are generated based on the study of neural networks in the human brain, can be used in areas with a certain reservoir capacity such as dams or ponds and to provide an example of the most appropriate ANN model for predicting the level changes that will occur depending on the next years. In this context, two separate functions have been evaluated. These are the Gradient-Descent-with-Momentum (GDM) and Levenberg-Marquardt-(LM) training functions. Here, instead of the best results obtained from the models, the best three model outputs were evaluated and the models were considered from a wide frame. Gökçe Dam Basin, which is located in the Marmara region was chosen as the study area. With the different architectures prepared for the period of 31 December 2019 – 1 January 2000, monthly basin capacities for 2019 have been tried to be estimated. 95% of the data belonging to the selected period was used for training and the remaining 5% for testing purposes. The flow rates entering and leaving the dam basin and the average precipitation, evaporation, and dam seepage amount were used as model inputs. While evaluating the model performances, Mean squared error (MSE), Mean absolute percent error (MAPE), Mean absolute error (MAE), and coefficients of determination were taken into consideration. As a result; It can be stated that the LM training models are more successful in estimating the dam basin levels and converge to the real values.
**Key Words:** Artificial Neural Network, Basin Capacity, Estimation Model, Gökçe Dam Basin

## Rezervuar Kapasitesinin Belirlenmesinde Farklı Yapay Sinir Ağı Yöntemlerinin Karşılaştırılması

**Öz**
Geçmiş dönemlere ait hidrolojik ve meteorolojik veriler ile nehir akımı tahminini yapılması ve su kaynakları projelendirme çalışmalarında kullanılması ülkemizde ve dünyada birçok çalışmada uzun süredir kullanılmaktadır. Bununla birlikte son dönemlerde sık sık yaşanan kuraklık sorunlarıyla beraber, haznelere gelen suyun doğru şekilde depolanması ve kullanılması da önem taşımaktadır. Bu çalışmanın amacı, insan beynindeki sinir ağlarının çalışmasından yola çıkılarak oluşturulan iki ayrı Yapay Sinir Ağ Fonksiyonunun baraj ya da gölet gibi belirli bir hazne kapasitesine sahip alanlarda nasıl kullanılabileceğini araştırmak ve gelecek yıllara bağlı olarak oluşacak seviye değişimlerinin tahmini için en uygun YSA modeline ilişkin bir örnek sunmaktır. Bu bağlamda iki ayrı fonksiyon değerlendirilmiştir. Bunlar; Levenberg-Marquardt (LM) ve Gradient Descent with Momentum (GDM) eğitim fonksiyonlarıdır. Burada, modellerden elde edilen en iyi sonuç yerine en iyi üç model çıktısı değerlendirilmiş ve modeller geniş bir çerçeveden ele alınmıştır. Çalışma alanı olarak Marmara bölgesinde bulunan Gökçe Baraj Havzası seçilmiştir. 31 Aralık 2019 – 1 Ocak 2000 dönemi için hazırlanan farklı mimariler ile 2019 yılı aylık havza kapasiteleri tahmin edilmeye çalışılmıştır. Seçilen döneme ait verilerin %95'i eğitim kalan %5' i ise test amaçlı olarak kullanılmıştır. Model girdisi olarak baraj havzasına giren ve çıkan akış debileri ile ortalama yağış, buharlaşma ve baraj sızıntı suyu miktarı kullanılmıştır. Model

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performansları Ortalama karesel hata, Ortalama mutlak yüzde hata, Ortalama mutlak hata ve determinasyon katsayıları bakımından değerlendirilmiştir. Sonuç olarak; LM eğitim modellerinin baraj havzası seviyelerini tahmin etmede daha başarılı olduğu ve gerçek değerlere yakınsadığı ifade edilebilir.

**Anahtar Kelimeler:** Yapay Sinir Ağı, Havza Kapasitesi, Tahmin Modeli, Gökçe Baraj Havzası

## 1. Introduction

Water is an indispensable substance that all living creatures need to survive, which cannot be replaced by another substance and is therefore vital. Water that affects the entire environment regardless of whether it is alive or inanimate, can be considered as the beginning of life. It has realized the effect of a living creature on the water to benefit him physically, socially, and culturally. It has been seen throughout all civilizations since ancient times that this situation has made human society in the historical process, and similar or different civilizations have aimed to make use of water by located near water. Water needs in a region depend on factors such as population density, population growth, life level, productivity increase in agriculture and industry, and economic development. However, the amount of water to be used in water resources such as streams, lakes, groundwater, springs, marine, and artificial rain is limited. At the same time, because water is on the move in the natural hydrological cycle, its amount in a certain place and time also changes (Erkek and Ağıralioğlu, 2013). Hydrology is a basic and applied science that examines the cycle, distribution, physical and chemical properties of water in the earth (earth, underground, and atmosphere), and its mutual relations with the environment and living things (Bayazit, 2013). Water is at the top of the list of natural resources necessary for life to exist. In our earth, water exists in various states (solid, liquid, gas) and rotates in a certain cycle between various parts. Human presence on earth can affect the natural hydrological cycle. With global warming, temperatures are rising, and more water will be needed to protect human and animal health (ensure the continuation of living life). Many economic activities, such as the use of water in agriculture, animal husbandry, and industrial activities, require water as well. The amount of water required in these activities decreases as the soil warms and precipitation decreases, and its quality decreases, and at the same time it poses a significant danger to both the environment and the survival of other creatures **(**Albayrak, 2017). With the changing precipitation regimes recently, water resources management has gained more importance. In this context, estimation studies on subjects such as flow, lake, and dam level are also of great importance. Artificial neural networks, which are one of the methods used in these studies, are successfully used. One of the studies on these issues was used to model changes in lake water level over time due to the rise of the water level of Lake Van and the submergence of coastal parts. In this study, it was concluded that the relationship between the artificial neural network and precipitation and lake water level could be modelled also, dynamic changes in lake water level were examined (Altunkaynak, 2007). In another study, 1796 daily measurement data of Hatay, Antakya Yarseli Dam, and Basin in the Mediterranean region were estimated by using artificial neural network method. The Bayesian arrangement technique was used in the modelling of the artificial neural network. The weight and bias coefficients were renewed using the Levenberg-Marquardt (LM) Training algorithm. It has been determined that the estimation results found in the artificial neural network modelling study give good performance when compared with the data found by the traditional method (Çalım, 2008). After the studies gave successful results, similar studies increased over time. For example, determining the water level changes of Lake Beyşehir, which is the main water source of Konya Plain, which has an important place for our country, by using the artificial neural network method is one of these studies. Artificial neural network and level values were estimated by using inflow, loss flow, precipitation, evaporation, refluent flow of Beyşehir measured by the DSI between 1962 and 1990, and the estimated values obtained were compared with the results obtained traditionally. With this study carried out for Lake Beyşehir, it was aimed to find the lake water level as soon as possible by eliminating the difficulties encountered in evaluating the lake water level measurements made by traditional methods (Yarar and Onüçyıldız, 2009). Again, a study was conducted to estimate the water level of the Dibis Dam, located northwest of Kirkuk, in Iraq, Turkey neighbor.10-year data was used as input data of the artificial neural network. These data are current values entering the dam, current values exiting the dam, precipitation, and initial water level measurements. 80% of these data were used as training data and the remaining 20% were used as test data. Feedforward backpropagation learning algorithm was used for all models in artificial neural network modelling. These analysis models were formed as rainy / non-rainy, initial water level / no initial water level. It was concluded that the initial water level is important data in this study (Abu Salam, 2018). Additionally, different techniques are used in estimation studies besides ANN models. The estimation accuracy of the minimum lake level changes in Bursa Iznik Lake was tried to be tested with models created with autoregressive moving average (ARMA) technique. As input data, daily water level records of Bursa Iznik Lake, between 1955-2002, were used. These 47 years of data were transformed into daily measurements into monthly data, and 46 years of data were used for training of models (AR, MA, and ARMA), and the last one-year data was used for testing and prediction accuracy. It was determined that the analysis results obtained with the ARMA model performed better than other models in estimating the minimum lake level. When the analysis is examined, it has been determined that the minimum water level can be estimated with only its own minimum water level data set without the need for any data set (Özen et al., 2014). In another study, two different neural network models were used to estimate the daily water level of Lake Van. These neural networks are models of feed-forward neural networks (FFNNs) and radial basic functional neural networks (RBNNs). The results of the analysis were compared using the mean square error (MSE) and $R^2$ coefficient of determination, and it was stated that the FFNN algorithm model performed better than the RBFNN algorithm model. According to the estimation results obtained with this study, it was concluded that there will be a decrease in the water level of Lake Van in the future, therefore, the increase of water in the rapidly developing and dense settlements around the coast of Lake Van will not become a threat (Doğan et al., 2016). In another study, using daily flow values in the state of Pennsylvania, the Juniata River, which has an 8687 $km^2$ drainage area without any dam in its basin, was selected by black-box modelling. In the study of the relationship between rainfall and runoff, 2458 data were created by taking the average of the daily total precipitation data of three meteorology stations in the basin of the Juniata River between 01.01.1983-23.09.1989. 2000 (81%) of these data were selected as training and 458 (19%) as test data. In the analysis of these data, flow estimation and rainfall-run-off modelling were performed using the generalized regression neural network (GRNN) method with feed-forward (FFBP).

In the analysis of the models, it was determined that the FFBP method gave better results than the GRNN method. In the results of this study, it was concluded that the GRNN method can be used to estimate flow from stream and precipitation flow, and at the same time, using this method with FFBP for different water sources will be useful in comparing their performance (Alp and CIGIZOĞLU, 2004). In another study, it was tried to be determined by using mathematical estimation models to determine the potential (flows) that may be in the future by using daily flow values of Colombia River between 1950-1960 in America. The Columbia River is in the Pacific Northwest and is approximately 2000km long and its basin drainage area is 250000km2. 3650 days of flow data were used for the analysis of this study, and 60% of this data was used as training data and 40% as test data. In the comparison of these analysis models, network-based fuzzy logic inference system (ANFIS), artificial neural networks (ANN), nonlinear autoregressive model (NAR), and autoregressive integrated moving average model (ARIMA) were used. It has been determined that the estimation results of the ANFIS model give better results than NAR and ARIMA models (Altunkaynak and Başakın, 2018). In another study, the relationship between the monthly average flow values of the rainfall observing station number 2157 and the monthly total precipitation data of the precipitation observing station number 17204, which was measured between 1969-2000 in the Middle Euphrates Basin, has been tried to be determined with Feed-forward back propagation neural network (FFBPNN), generalized regression artificial neural network (GRNN) and radial based artificial neural network (RBANN), which are among the artificial intelligence methods and These results were compared with the multiple linear regression (MLR) method. Within the scope of this study, 266 (70%) of the 380 data of the stations whose data were taken were used as training and the remaining 114 (30%) as test data. These data were analysed as data input for precipitation and flow values according to five different conditions, and the flow values were tried to be estimated according to these situations. It has been determined that the artificial intelligence methods used in the analysis results give more successful results than the MLR method. Of the artificial intelligence methods, the RBANN method has been shown to give more acceptable results in estimation than other methods (Gümüş et al., 2013). Apart from these studies, artificial intelligence models have become very widespread recently, and many similar prediction models are available in the literature. (Dalkiliç and Hashimi (2020), Okkan (2011), Yesilyurt and Dalkilic (2021), Okkan (2012), Damla et al (2020), Temiz et al. (2021), Mulashani et al. (2022), de Faria et al (2021)). With this study, it has been determined that artificial intelligence methods can successfully be found the nonlinear rainfall-flow relationship of basins in the estimation of flow values according to parametric methods without the need for intense data. In a study conducted for Yalova Gökçe Dam, the effect of climate change on the lake water level was examined and the effect of meteorological data on the water level changes in the dam was investigated. For this purpose, daily precipitation in the basin, daily evaporation, lake water level elevations, the inlet flow of the reservoir, and the flow rate from the dam were used, and the monthly and annual changes of these values were examined. As a result, it is predicted that the water level of the Gökçe dam will remain insufficient in the coming years due to the increasing population, as Osman et al. (2017) and Temiz et al. (2021) stated. For this reason, knowing the water change in the dam basin gains importance in terms of preventing possible damages.

## 2. Methodology of Artificial Neural Networks

It is expressed as a highly complex, non-linear, and parallel distributed operating system thanks to the human brain's ability to learn, combine, adapt, and general. Neurons in the human brain communicate through electrical signals they create in a chemical environment.

Therefore, the brain can be considered as the structure of a very dense electrical network. If necessary, commands are produced in the central nervous system and transmitted to the relevant regions. It manages and controls the central nervous system with feedback connections that confirm warnings in these regions (Soycan, 2008).

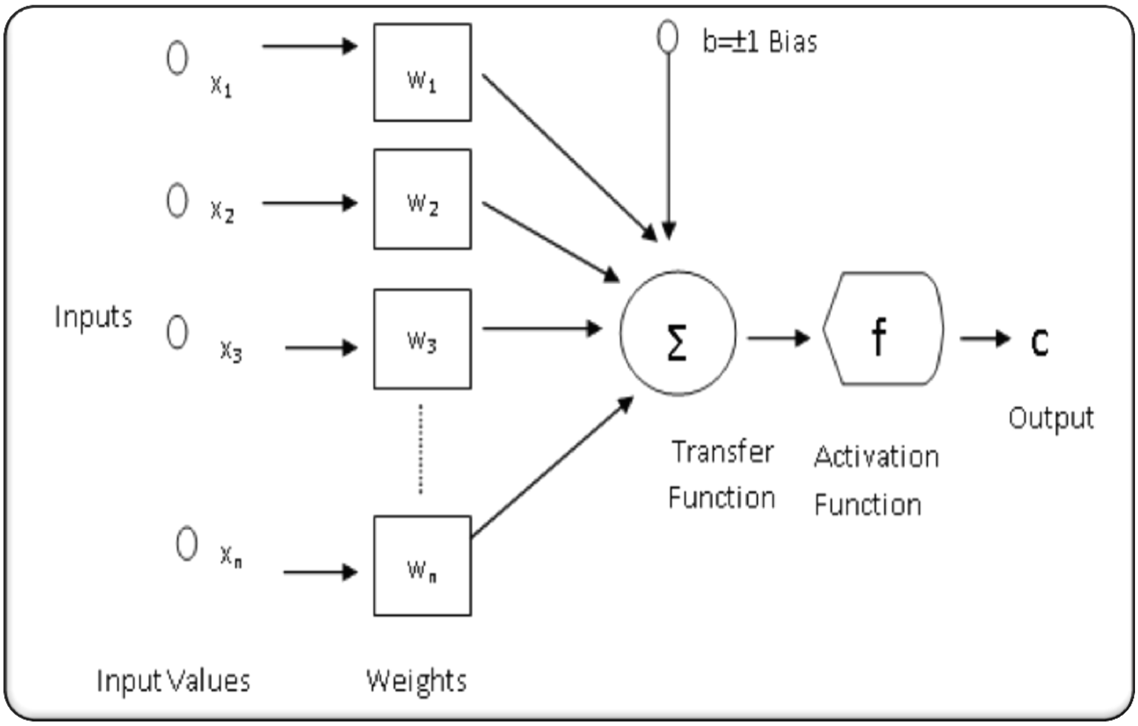


**Figure 1.** Artificial neural network example (Keskenler and Keskenler, 2017).

Artificial neural networks are computer programs that can stimulate the nervous system that makes up the human brain and generate new information from previously learned or classified data with the help of neural sensors and make decisions by making decisions. It is used in many areas such as pattern recognition, system identification, robotic signal processing, nonlinear control areas (Keskenler and Keskenler, 2017). As indicated in Figure 1, artificial nerve cells consist of five main parts. These are inputs, weights, transfer function, activation function, and output.

Inputs are information that enters the cell from other cells or the external environment. These are the data the neural network is asked to learn. Weights refer to the input data or the effect of another processing element in a layer preceding it on this process element. The transfer function is a function that calculates the effect of all inputs and weights on this process element. The activation function is the function that creates the output of the cell by processing the net input obtained by the transfer function (Terzi and Köse, 2012). Artificial neural network systems include multiple nerve cells. If these nerve cells come together, it is not random. For neural network systems to form, cells combine in three layers, and each layer in parallel within itself, forming the neural network. The layer formed by the inputs is the input layer, and the layer where the outputs occur is the output layer. There are hidden layers between these input and lath layers and they may be more than one **(**Kartalopoulos, 1996). To create an output in an artificial neural network, the neural network is pre-trained with certain data, then it reaches a level that can generalize and make decisions with this data given to the network, and then data outputs are formed with this capability. This situation is expressed by equation 1.

$$c = \sum_{i=1}^{n} w_{ij} x_i + b \tag{1}$$

In Equation 1; c, output, xi i. input value of the nerve cell, wij; weighting coefficients, n is the total number of inputs in a cell, b; threshold value and activation function (Terzi and Köse, 2012).

### 2.1. Normalization of analysing data

All the data used in the models used to give successful results were passed through a normalization process. The normalization formula used in Equation 2 is given.

$$\vartheta_N = 0.8x\left[\frac{\vartheta_R - \vartheta_{min}}{\vartheta_{max} - \vartheta_{min}}\right] + 0.1 \tag{2}$$

In addition, in Equation 2, $\vartheta_N$ the result of the value of the normalized data $\vartheta_R$, the data to be normalized, $\vartheta_{min}$ the data with the smallest value to be normalized, $\vartheta_{max}$ the data with the largest value to be normalized.

The normalized estimation data found as a result of the analysis was converted back to the planned water level using equation 3.

$$\vartheta_R = \left(\frac{\vartheta_N - 0{,}1}{0{,}8}\right) x(\vartheta_{max} - \vartheta_{min}) + \vartheta_{min} \tag{3}$$

## 3. Gökçe Dam Basin and Its Data

Yalova Gökçe Dam is one of the important water sources for the Marmara region. It is important in terms of drinking and potable water that it provides to residential areas located around it **(**Doğan et al., 2010). In order to make the 2019 water level estimation of Yalova Gökçe Dam, daily rainfall amount, evaporation values, dam water level values flow into the reservoir and output flow values between 2000-2019, obtained from General Directorate of State Hydraulic Works (DSI) 1st Regional Directorate and Yalova Meteorology Branch Directorate, were obtained. With these data, the water level changes occurring in the Yalova Gökçe Dam reservoir in 2019 were tried to be estimated using the Levenberg-Marquardt (LM) training function and the Gradient Descent with Momentum (GDM) training function.

### 3.1. Gökçe Dam Basin

Drinking, potable and industrial water of Yalova province is supplied from Gökçe dam basin. Construction of this dam began in 1980 and was completed in 1989. Images of the basin are given in Figure 2, and general information about the dam is given in Table 1.


**Figure 2.** General view of the reservoir area and body of Gökçe Dam (Damla, 2020)

With the Gökçe Dam coming into service, groundwater was left for agricultural use and the possibility of salinization of groundwater was planned to be eliminated (DSI Planning Report, 1978).

**Table 1.** Characteristic information of Gökçe Dam reservoir (Damla, 2020)

| | | | |
|---|---|---|---|
| Minimum water level (m) | 43 | Maximum water level (m) | 80 |
| Minimum water volume ($hm^3$) | 1.480 | Maximum water volume ($hm^3$) | 22.306 |
| Minimum reservoir area ($km^2$) | 0.225 | Maximum reservoir area ($km^2$) | 1.237 |
| Operating water level (m) | 79.50 | Precipitation area ($km^2$) | 86.5 |
| Operating water volume ($hm^3$) | 21.791 | Spillway sill top level (m) | 72 |
| Operating reservoir area ($km^2$) | 1.207 | | |

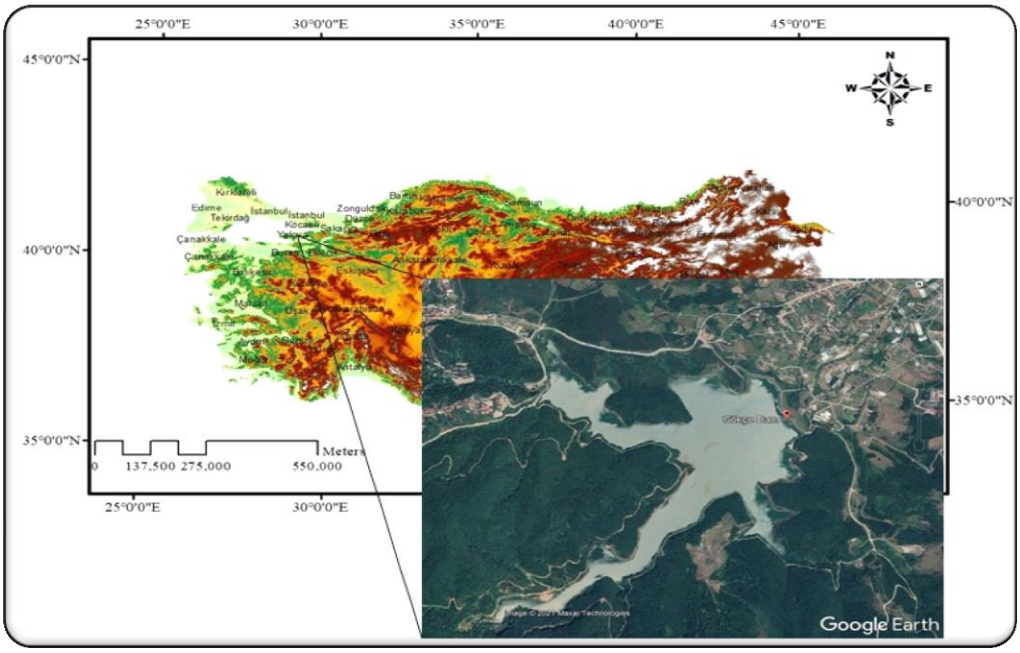


**Figure 3.** Yalova Gökçe Dam Location

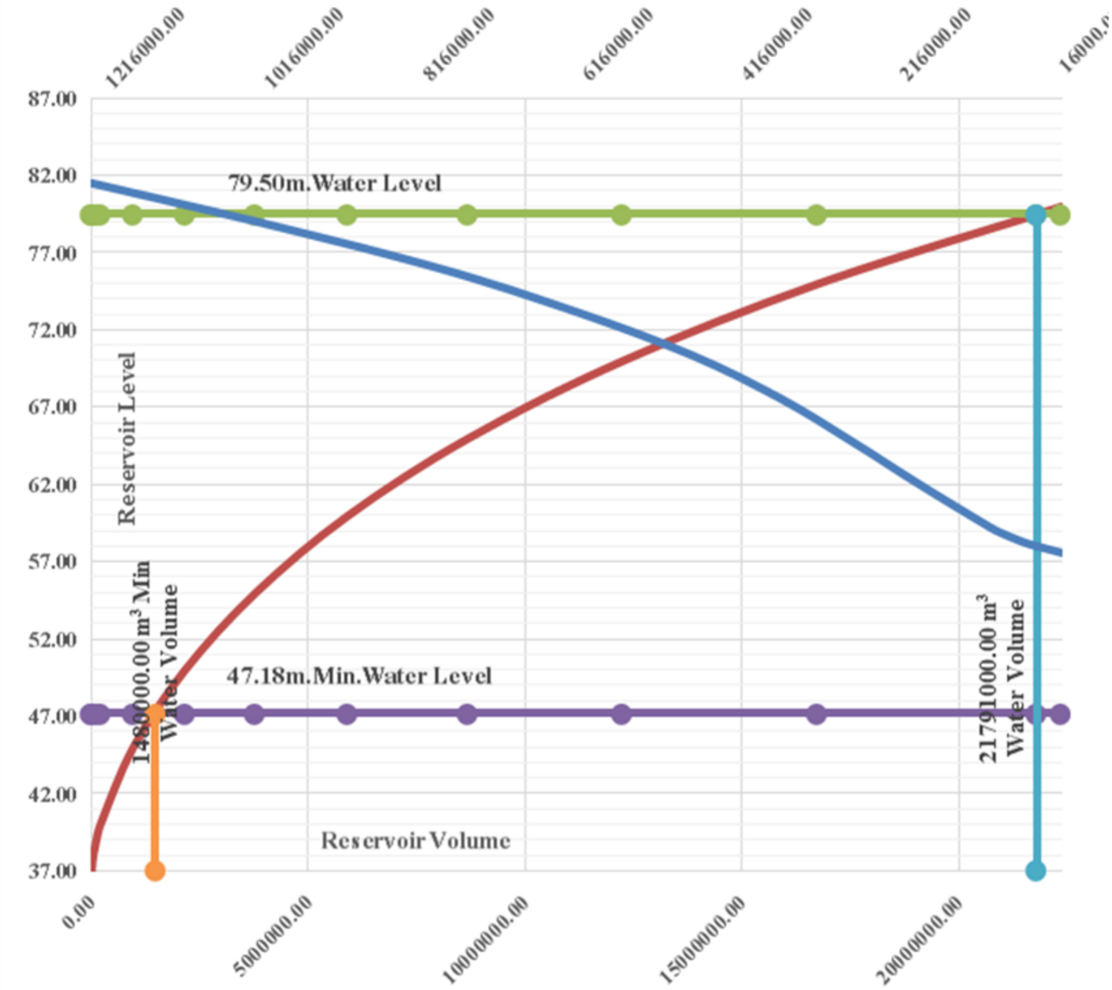


**Figure 4.** Yalova Gökçe Dam Volume Surface Diagram (Damla, 2020)

### 3.2. Gökçe Dam Basin Analysis Data

In this study, the use of Levenberg-Marquardt (LM) Training function and Gradient Descent with Momentum (GDM) training functions, which are artificial neural network functions, was investigated in the estimation of the water level of the Yalova Gökçe Dam. As input data, the flow rate ($m^3$) of the Sellimandıra stream, which forms the water source of the Gökçe Dam, the average rainfall (mm) and evaporation (mm) values of Yalova Province and Çınarçık District in the dam basin, the dam water discharge values ($m^3$), and the amount of seepage water ($10^3$ $m^3$) were used. As output data, water level measurements in the dam reservoir were used. The input and output set, which are used exactly in all models in the study, are given in Figure 4.

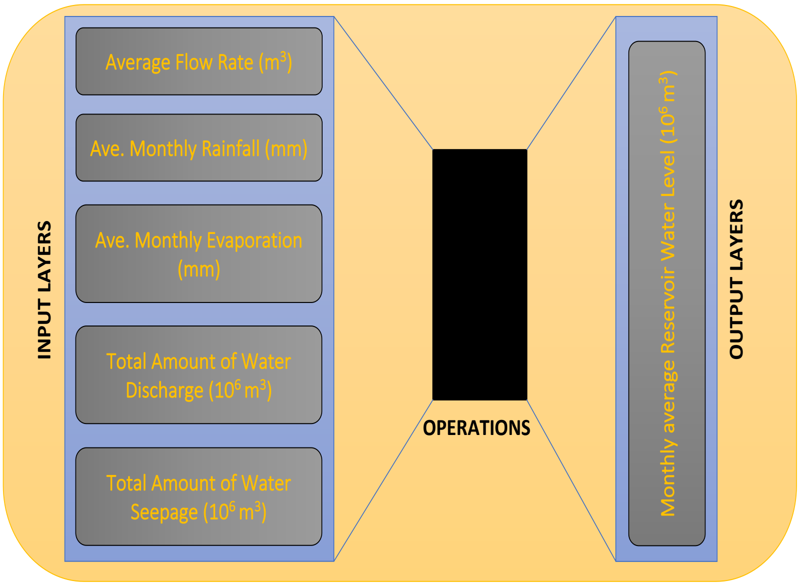


**Figure 5.** Diagram of Input and Output Layers

Since the most effective parameters in determining the water level are flow rate, precipitation, evaporation, water discharge, and seepage, it was preferred to use these data in this study as well. Graphs of these values used are shown in Figure 5.

When the average monthly basin water levels in Figure 6 and the volumes of water evacuated are examined, it is understood that during the dry periods between 2013 and 2015, the water evacuation was carried out due to the rise above the water level of 72.00 m, which is usually sill top elevation of the spillway. For the analysis of the artificial neural network, the LM training function which is a feed-forward backpropagation method, and GDM training function were used. Between 2000 and 2018, 1368 data (95% of the total data) were selected as training data, while 72 data (5% of the total data) of 2019 were used for testing purposes.

Different analysis models were created by making changes in neuron numbers, hidden cell numbers, cycle number, variant coefficient, learning, and momentum coefficients, which are factors that can affect performance in the created artificial neural network.

The performance criteria of these analyses were selected as the determination coefficient, mean square error (MSE), mean absolute percentage error (MAPE), and mean absolute error (MAE) values. Equations of the performance criteria used are given in Equations 4,5,6,7.

$$\boldsymbol{MSE}: \quad \frac{1}{n}\sum_{i=1}^{n} e_t^2 \tag{4}$$

$$\boldsymbol{MAPE}: \quad \frac{\%100}{n}\sum_{i=1}^{n} \left|\frac{e_t}{y_t}\right| \tag{5}$$

$$\boldsymbol{MAE}: \quad \frac{1}{n}\sum_{i=1}^{n} |e_t| \tag{6}$$

$$\boldsymbol{R^2} : 1 - \left(\frac{\sum_{i=1}^{n}(e_t)^2}{\sum_{i=1}^{n} y_t^2}\right) \tag{7}$$

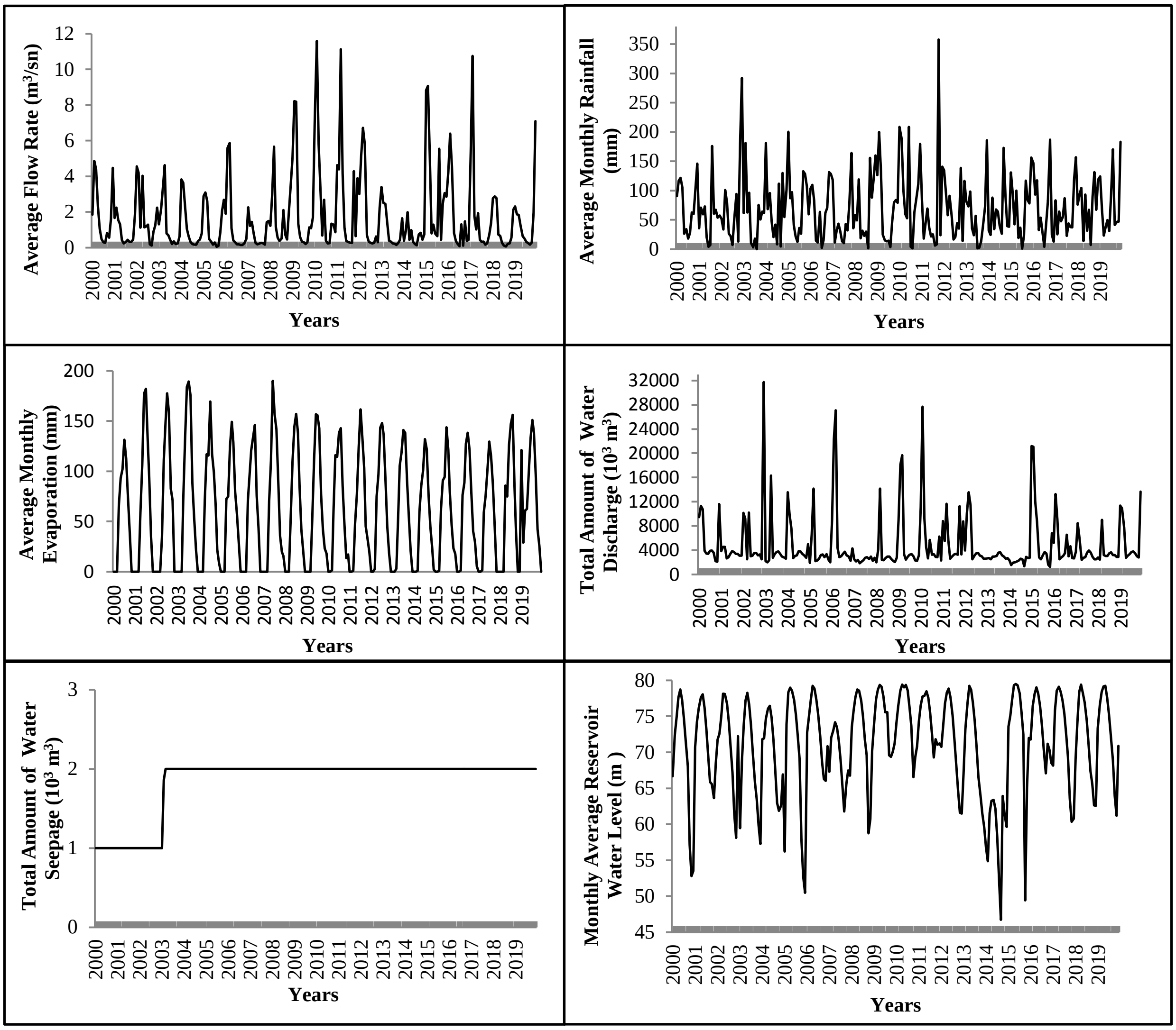


**Figure 6.** Gökçe Dam - Input Values. (Damla et. al., 2020, Temiz et. al., 2021)

## 4. Modelling and Analysis Studies

In this study, many analyses were made with LM and GDM training algorithms, and the best three results from these analyses were evaluated for each function separately, and it was examined not only at the best results of the functions but also at which function, in general, gave successful results. Correlation results were considered as a success criterion.

### 4.1. The most successful results in LM Training function analysis.

Data from 3 trial tests with high cholera (R) value were obtained from 112 analysis models and the relevant results are given below. It can be said that the results of the three models are successful and close to each other.

### 4.1.1. Analysis No: LM-1 Results and Graphics

LM-1 model change options; the number of neurons: 6, number of hidden layers: 9, cycle coefficient: 1000, Variant coefficient: 10000, learning coefficient: 0.80, Momentum coefficient: 0.7, and correlation and validation results of training and test results are given in Figure 7.

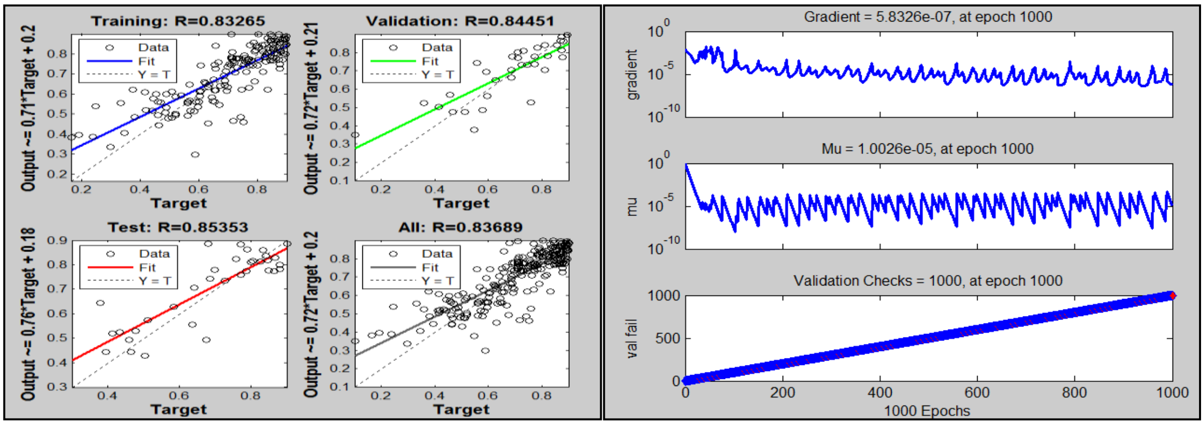


**Figure 7.** LM-1 Correlation (R) Values and Training Graphics

Figures 8 show the relationship between reservoir levels measured monthly for 2019 and predicted levels (LM-1). It can be stated that the estimated values are usually above the actual values and do not reveal the actual values exactly. The curve of determination equation is given in equation 8.

$$y = 0.7497x + 21.113 \tag{8}$$

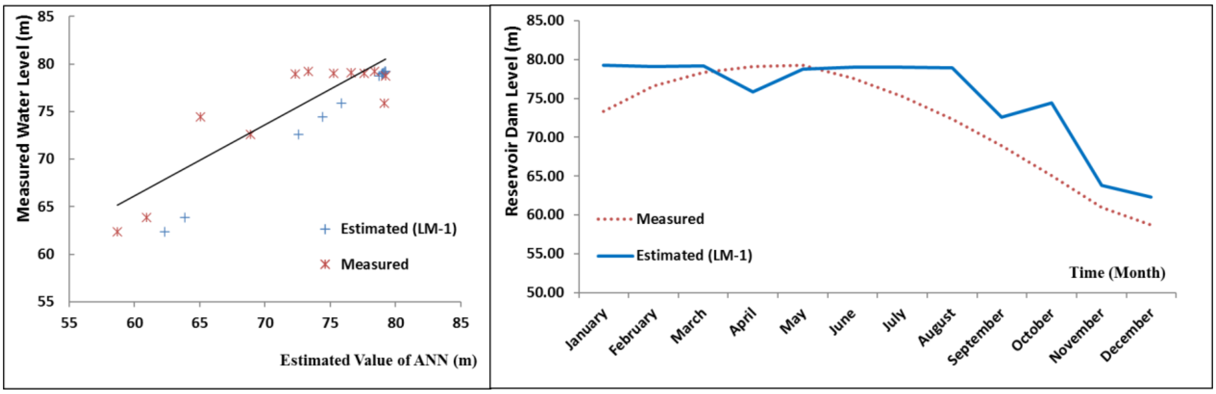


**Figure 8.** LM-1 Water Level - Test Model Curve and Determination Results

### 4.1.2. Analysis No: LM-2 Results and Graphics

LM-2 model change options; the number of neurons: 6, Number of hidden layers: 9, Conversion coefficient: 750, Variant coefficient: 1500, Learning coefficient: 0.80, Momentum coefficient: 0.7 and correlation and validation results of training and test results are given in Figure 9.

Figures 10 show the relationship between reservoir levels measured monthly for 2019 and predicted levels (LM-2). It can be stated that the model results are close to the actual values, except for the winter months. The curve of determination equation is given in equation 9.

$$y = 0.845x + 12.824 \tag{9}$$

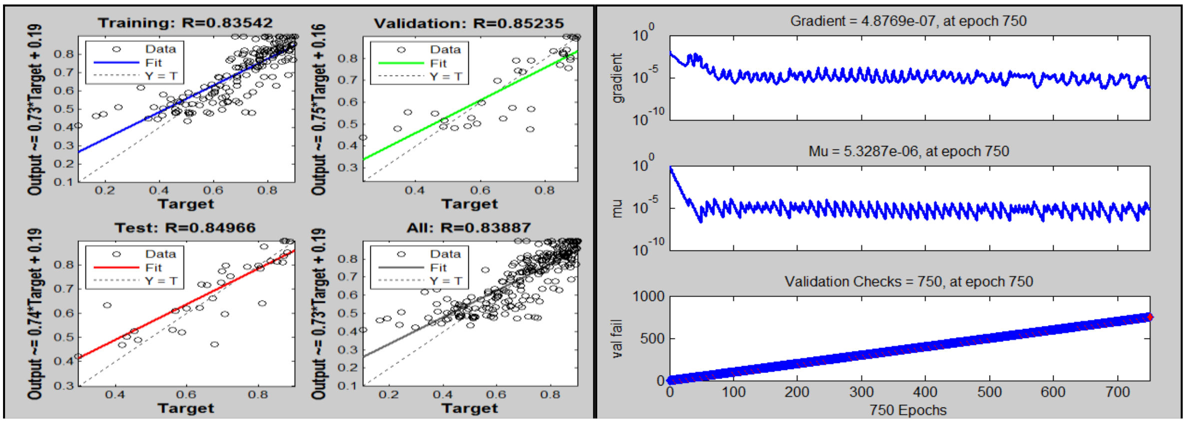


**Figure 9.** LM-2 Correlation (R) Values and Training Graphics.

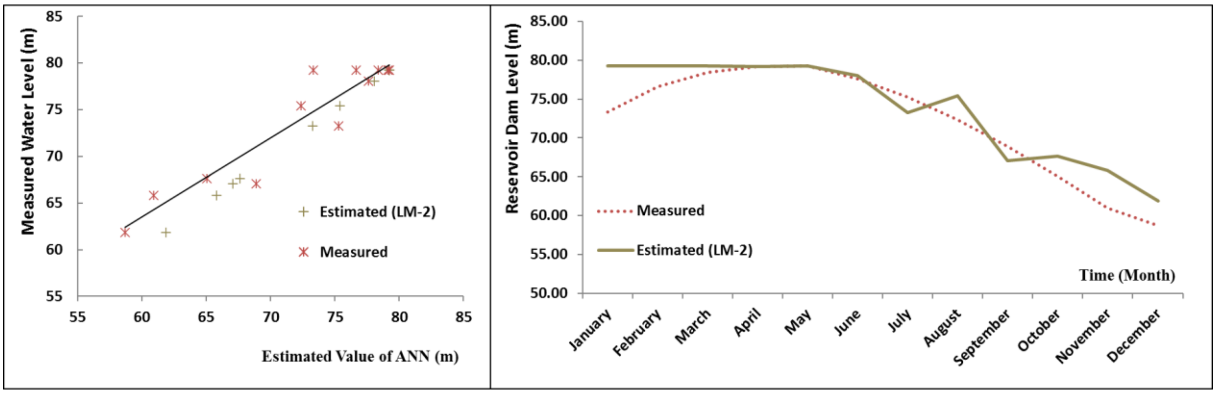


**Figure 10.** LM-2 Water Level - Test Model Curve and Determination Results

### 4.1.3. Analysis No: LM-3 Results and Graphics

LM-3 model change options; the number of neurons: 6, number of hidden layers: 9, cycle coefficient: 750, Variant coefficient: 6500, learning coefficient: 0.80, Momentum coefficient: 0.7, and correlation and validation results of training and test results are given in Figure 11.

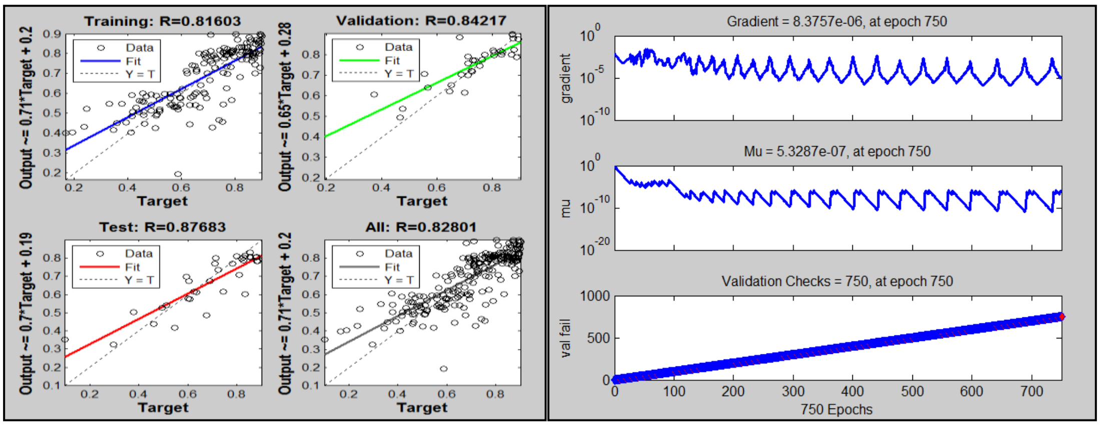


**Figure 11.** LM-3 Correlation (R) Values and Training Graphics.

Figure 12 shows the relationship between monthly measured reservoir levels and predicted levels (LM-3) for 2019. It can be stated that while the model results converge to the real results in the summer months, they give results far from the real values in the other months. The curve of determination equation is given in equation 10.

$$y = 0.7857x + 17.804 \tag{10}$$

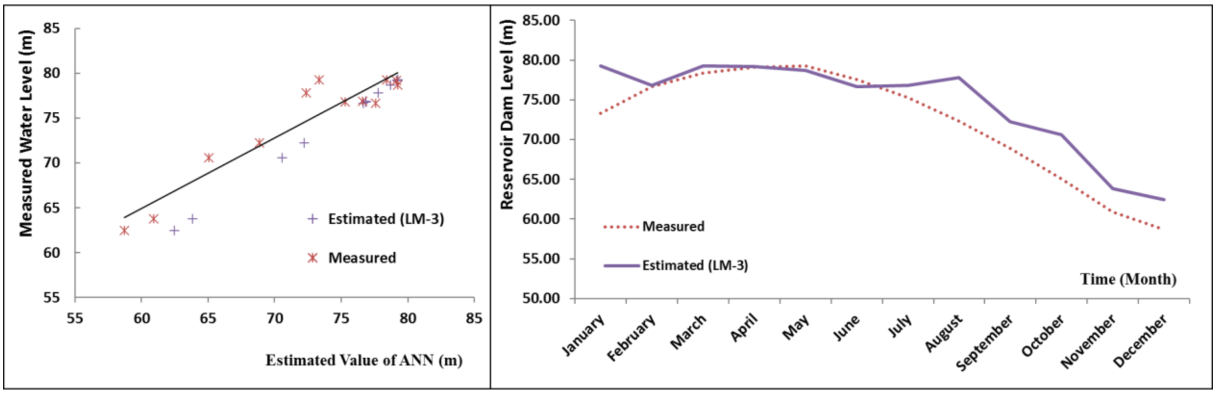


**Figure 12.** LM-3 Water Level - Test Model Curve and Determination Results

### 4.2. The most successful results in GDM educational function analysis.

The data of 3 trial tests (with high correlation (R) values were taken from a total of 74 analysis models, and the relevant results are given below. It can be said that the results of the three models are distant from the expected values, but they give close results to each other.

#### 4.2.1. Analysis No: GDM-1 Results and Graphics

GDM-1 model change options; the number of neurons: 3, Number of hidden layers: 3, Conversion coefficient: 2000, Variant coefficient: 10000, Learning coefficient: 0.80, Momentum coefficient: 0.7, and the correlation and validation results of the training and test results are given in Figure 13.

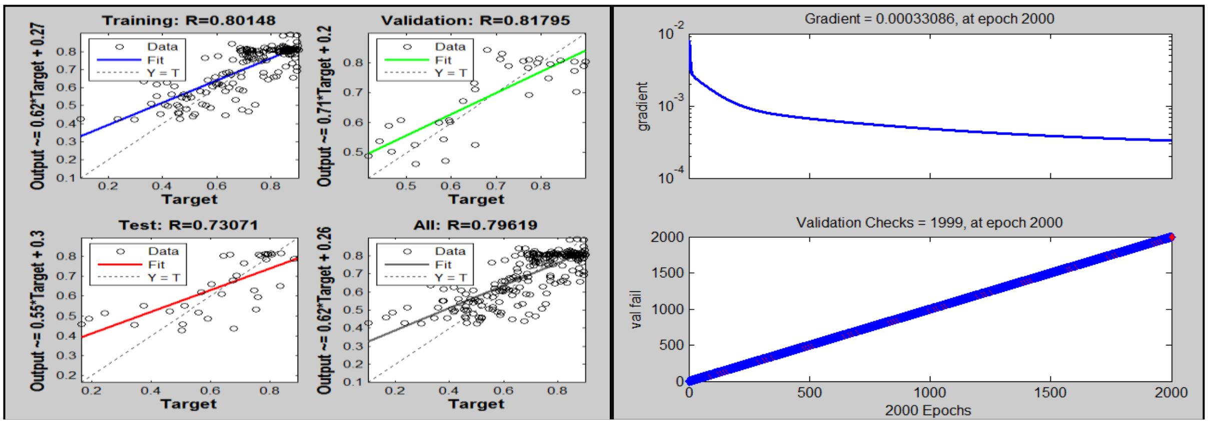


**Figure 13.** GDM-1 Correlation (R) Values and Training Graphics.

Figures 14 show the relationship between reservoir levels measured monthly for 2019 and predicted levels (GDM-1). It is seen that the model results are below the actual results in the summer months and above the real value in the other months. The curve of determination equation is given in equation 11.

$$y = 1.4407x + 36.927 \tag{11}$$

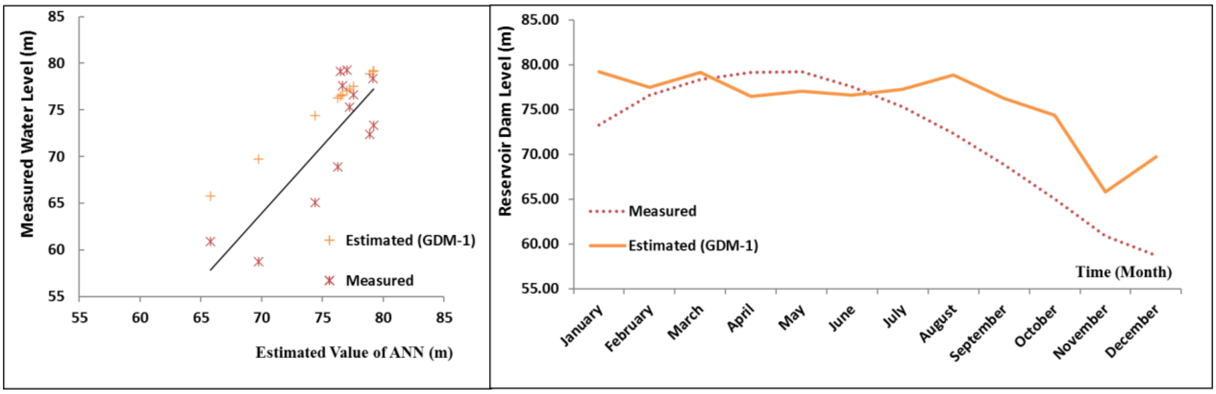


**Figure 14.** GDM-1 Water Level - Test Model Curve and Determination Results

### 4.2.2 Analysis No: GDM-2 Results and Graphics

GDM-2 model change options; the number of neurons: 3, number of hidden layers: 3, Conversion coefficient: 2000, Variant coefficient: 7000, Learning coefficient: 0.80, Momentum coefficient: 0.7 and correlation and validation results of training and test results are given in Figure 15.

Figures 16 show the relationship between reservoir levels measured monthly for 2019 and predicted levels (GDM-2). It is seen that the model results are below the actual results in the summer months and above the real value in the other months. The curve of determination equation is given in equation 12.

$$y = 1.8156x + 64.616 \tag{12}$$

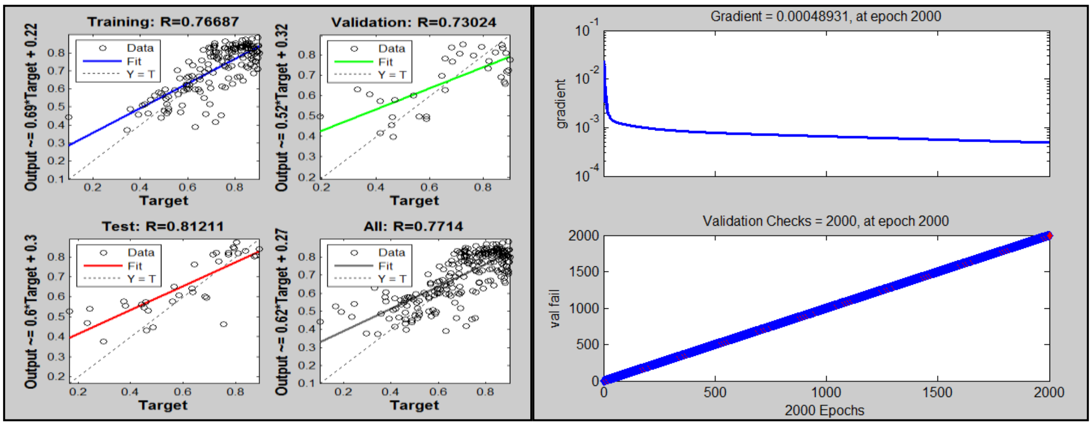


**Figure 15.** GDM-2 Correlation (R) Values and Training Graphics.

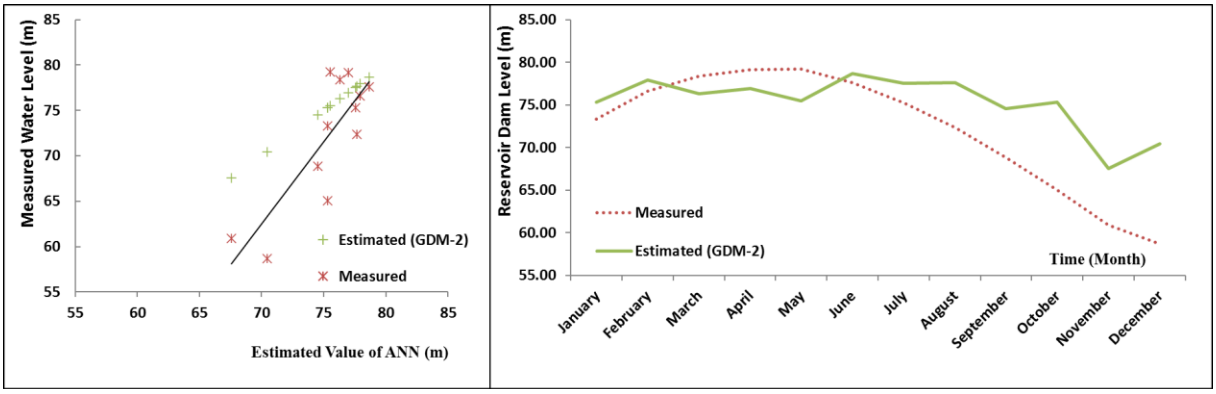


**Figure 16.** GDM-2 Water Level - Test Model Curve and Determination Results

### 4.2.3. Analysis No: GDM-3 Results and Graphics

GDM-3 model change options; the number of neurons: 3, Number of hidden layers: 3, Conversion coefficient: 2000, Variant coefficient: 7000, Learning coefficient: 0.70, Momentum coefficient: 0.7 and correlation and validation results of training and test results are given in Figure 17.

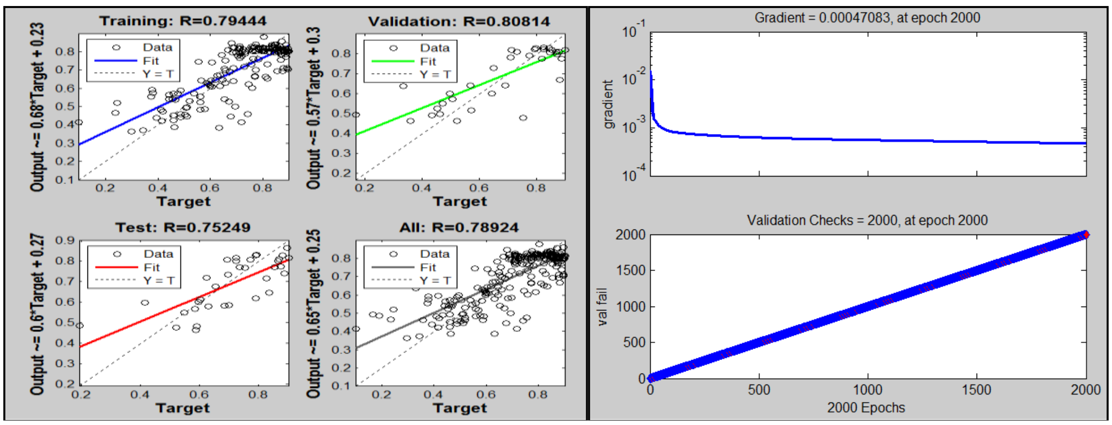


**Figure 17.** GDM-3 Correlation (R) Values and Training Graphics.

Figures 18 show the relationship between reservoir levels measured monthly for 2019 and predicted levels (GDM-3). It is seen that the model results are below the actual results in the summer months and above the real value in the other months. The curve of determination equation is given in equation 13.

$$y = 1.7686x + 61.805 \tag{13}$$

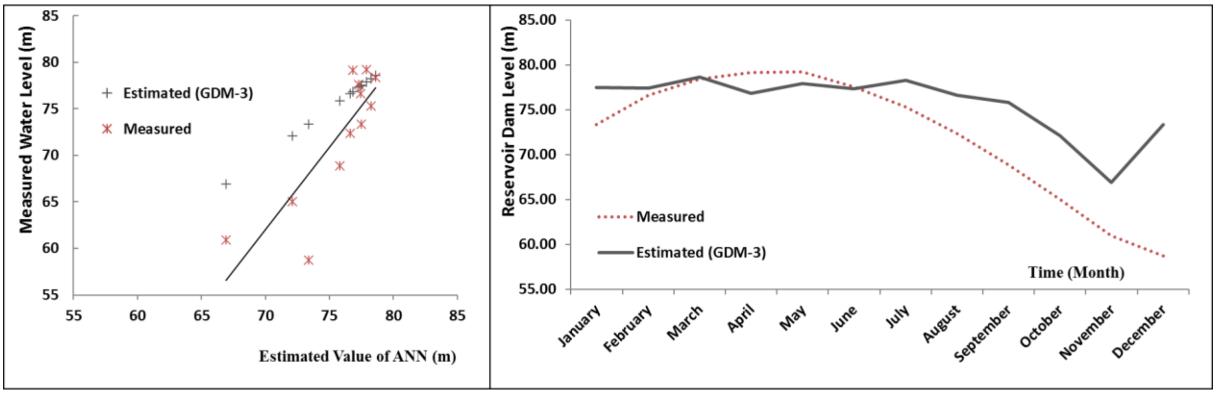


**Figure 18.** GDM-3 Water Level - Test Model Curve and Determination Results

## General Evaluations of the Models

Within the scope of the study, a total of 6 models were evaluated for two separate algorithms, and Tables 2, 3 and 4 were obtained for all model results. It can be stated that all models of the LM algorithm are more successful than the GDM algorithm, therefore, it is appropriate to prefer the LM algorithm in the Gökçe dam water level estimation. In addition, when tables 2 and 3 are evaluated; It has been observed that the coefficient of determination of the LM-2 model is more successful and the MSE, MAE, MAPE values are lower in terms of error rate.

**Table 2.** LM (Trainlm) training function results

| Analysis No | MSE | MAE | MAPE (%) | $R^2$ |
|---|---|---|---|---|
| **LM-1** | 0,02981 | 0,144 | 39,21 | 78,55 |
| **LM-2** | 0,01263 | 0,089 | 29,62 | 89,48 |
| **LM-3** | 0,01685 | 0,101 | 31,92 | 88,25 |

**Table 3.** GDM (Traindm) training function results

| Analysis No | MSE | MAE | MAPE (%) | $R^2$ |
|---|---|---|---|---|
| **GDM-1** | 0,04840 | 0,176 | 67,68 | 65,57 |
| **GDM-2** | 0,48390 | 0,176 | 71,55 | 67,68 |
| **GDM-3** | 0,05081 | 0,166 | 75,56 | 69,78 |

It was concluded that the acceptable determination rate was obtained in LM-2 and in Table 4, a comparison of the level and annual error of the water level in the reservoir of Gökçe Dam was made with the predicted values of water levels. While the actual water level in the reservoir is 72.13 m per year, the value obtained as a result of the model is 73.77 m. Here, the margin of error of the model is approximately 2.3%. With these rates, it is possible to model for later periods whether there will be problems with the amount of water in the future or whether there will be water discharge from the spillway.

**Table 4.** Measured Water Level and Estimated Water Level Values.

| Months | Actual Water Level Value in the Reservoir (m) | Estimated Values of ANN Models (m) | | | | | |
|---|---|---|---|---|---|---|---|
| | | LM-1 | LM-2 | LM-3 | GDM-1 | GDM-2 | GDM-3 |
| **January** | 73.32 | 79.23 | 79.24 | 79.24 | 79.22 | 75.31 | 77.51 |
| **February** | 76.63 | 79.11 | 79.24 | 76.86 | 77.53 | 77.93 | 77.44 |
| **March** | 78.39 | 79.22 | 79.24 | 79.24 | 79.13 | 76.32 | 78.62 |
| **April** | 79.14 | 75.85 | 79.22 | 79.21 | 76.46 | 76.96 | 76.85 |
| **May** | 79.24 | 78.76 | 79.24 | 78.72 | 77.04 | 75.50 | 77.91 |
| **June** | 77.59 | 79.04 | 78.04 | 76.67 | 76.62 | 78.65 | 77.31 |
| **July** | 75.29 | 79.00 | 73.25 | 76.84 | 77.25 | 77.56 | 78.25 |
| **August** | 72.35 | 78.95 | 75.38 | 77.79 | 78.88 | 77.65 | 76.62 |
| **September** | 68.88 | 72.58 | 67.05 | 72.23 | 76.24 | 74.53 | 75.83 |
| **October** | 65.05 | 74.43 | 67.64 | 70.58 | 74.41 | 75.31 | 72.10 |
| **November** | 60.93 | 63.85 | 65.79 | 63.82 | 65.80 | 67.58 | 66.91 |
| **December** | 58.71 | 62.34 | 61.87 | 62.47 | 69.73 | 70.45 | 73.38 |
| **Annual Average** | **72.13** | **75.20** | **73.77** | **74.47** | **75.69** | **75.31** | **75.73** |
| **Average Error** | | **0.043** | **0.023** | **0.033** | **0.049** | **0.044** | **0.050** |

In addition, when the radar diagram in which all the models are considered together is examined; It can be stated that only the LM-2 and LM-3 models can be considered successful in the period when the level is low, and all the models achieve similar results in the period when the level is high.

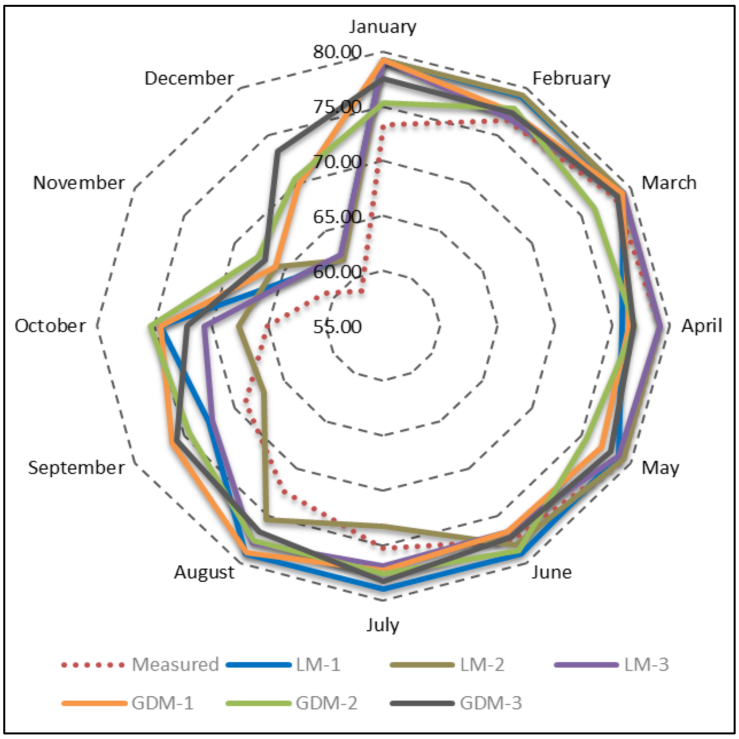


**Figure 19.** Radar diagram layout of the results obtained from the prediction models

## 6. Discussion

In this study, reservoir level modelling was performed with two different ANN functions and the model success of two selected ANN algorithms was evaluated. It can be stated that the LM function gives better results than the GDM function on these models. However, it is necessary to conduct a large number of analyses to get the best results with a particular ANN architecture. Therefore, the most successful three separate analysis results of the models established with two algorithms were evaluated. The main purpose here is not to examine models only with a focus on success, but to reveal the effects of the overall success of models in general. In three separate analyses, both functions approached similar success and prediction values within themselves, and the results of the LM function were more successful than the results of the GDM. In this study, Levenberg-Marquardt (LM) algorithm and Gradient Descent with Momentum (GDM) algorithm were used, and different estimation results can be investigated using different algorithms such as BFGS Quasi-Newton (BFG), Scaled Conjugate Gradient (SCG), One Step Secant (OSS). During the data survey of this study, daily rainfall, evaporation values, dam water level values and flow into the reservoir were found between 1997 and 2019, but the values related to total water discharge between 1997 and 2000 were not obtained. In this case, using artificial neural networks, the total volume of discharge water between 1997 and 2000, which is missing in this study, can be investigated. According to the analysis, water levels can be an indicator of whether there will be problems with the amount of water in the water level in the reservoir of the Gökçe dam in the future, or whether there will be water discharge from the spillway.

## Author Contribution

The study has been prepared from Yunus Damla's Master's thesis. Y. D. (Master Student) carried out the experiments, collected and analyzed the data, and wrote the manuscript. E.K. (Supervisor, Assistant Professor) conceived of the presented idea, supervised the project, revised and approved the manuscript to be published. T.T. (Co-Supervisor, Assistant Professor) carried out the experiments, performed and verified the analytic calculations and numerical simulations.

## Ethics in Publishing

There are no ethical issues regarding the publication of this study.

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