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*-RESEARCH ARTICLE-*

# Artificial Neural Networks Method for Prediction of Rainfall-Runoff Relation: Regional Practice

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## Abstract

Rainfall and runoff relation is very important on efficient use of water resources and prevention of disasters. Nowadays, different methods of artificial intelligent techniques are applied to determine the rainfall-runoff relations. Artificial Neural Networks (ANN) is used for the present study. Also, Classical methods such as Multiple Linear Regression (MLR) are used. In this study, the data obtained from USA Waltham Massachusetts Stony Brook Reservoir basin was taken. 731 daily data of rainfall, runoff, and temperature were used to generate input data in the Multi Linear Regression and Feed-Forward Back-Propagation Artificial Neural Network models. The results obtained were compared with the actual results.

**Keywords:**
Rainfall, Runoff, Artificial Intelligence, Multi Linear Regressions, Artificial Neural Networks.
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## Introduction

The relevance between rainfall-runoff is one of the primary important parameters for hydraulic science. It is of great importance for engineers to have an accurate project planning and application in water structures planning such as flood control, water supply and hydroelectric power plants, and energy production. Daily, monthly and annual rainfall data can be used during these analyzes. However, due to regional conditions, technical problems in measuring instruments and lack of measurements due to watershed characteristics, it can cause problems in determining relationship of rainfall-runoff data. Therefore, various hydraulic models can be used to determine the rainfall-runoff relationship and to complete the missing measurements. Parametric models take all the details of the process of rainfall into the runoff. The computer program separates this process into all parameters such as leakage, evaporation, superficial and underground flow. The rainfall falling

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into the basin enters the accumulation after these losses. Thus, the basin, which will be measured, is examined with some equations with these accumulation systems and other effective parameters. Recently, artificial intelligence method is a Black Box model that is frequently used in modeling the groundwater level (Demirci et al (2017, 2018a, 2019), Üneş et al (2018a), Kaya et al (2018)), suspended sediment (Demirci and Baltaci (2013), Demirci et al (2015), Tasar et al (2017)), rainfall-runoff relationship (Ünes et al (2018b), Tasar et al (2019)), dam reservoir and lake level (Ünes and Demirci (2015), Ünes et al (2015, 2019a), Demirci and Kaya (2019)), density flow plunging (Üneş (2010)), dam reservoir volume (Unes et al (2017), Demirci et al (2018b), Üneş et al (2019b)), sand bar crest (Demirci et al (2015)), evaporation (Üneş et al (2018c), Tasar et al (2018), Kaya and Tasar (2019)), many different disciplines-areas (Cansiz et al (2009, 2017a, 2017b, 2017c), Dogan et al (2017),Cansiz (2007, 2011), Cansiz and Easa (2011), Cansız and Askar (2018), Dal et al (2019)).

The Artificial Neural Networks model demonstrates the ability to successfully solve complex problems due to its learning and generalization features (Ergezer et al., 2003). McCulloch and W.A. Pitts (1943) determined the fundamentals of initial modeling of artificial neural networks. They modeled simple artificial nerves on electrical circuits. In the last years, there are many studies on the application of ANN to various problems encountered in water resources management.It has been shown that the nonlinear ANN approach is well represented in the rainfall-runoff relationship (Hsu et al., 1995; Mason et al., 1996; Minns and Hall, 1996; Fernando and Jayawardena, 1998).

In this study, 731-day rainfall, temperature and runoff data of the observation station 01104480 in the Stony Brook Reservoir basin of the USA were entered as input and the new runoff values were determined by using the Feed-Forward Back Propagation Neural Network (FFBNN) method and the results were a relatively classical method. It was compared with the linear regression method.

## Material and Methods

### *Artificial Neural Networks (ANN)*

There are three components in the artificial neural network (ANN): artificial neural node (neuron), inter-neuronal connections and learning algorithm. The basic processing element of an ANN is the neuron. Neurons in the neural network receive one or more inputs according to the factors affecting the problem and produce as many outputs as expected from the problem. The connection of neurons through connections creates an artificial neural network structure. In a general artificial neural network system, neurons coming together in the same direction form layers. In an artificial neural network, there are basically three layers, the input, hidden and output layer. In Figure 1, a feed forward ANN structure is given.

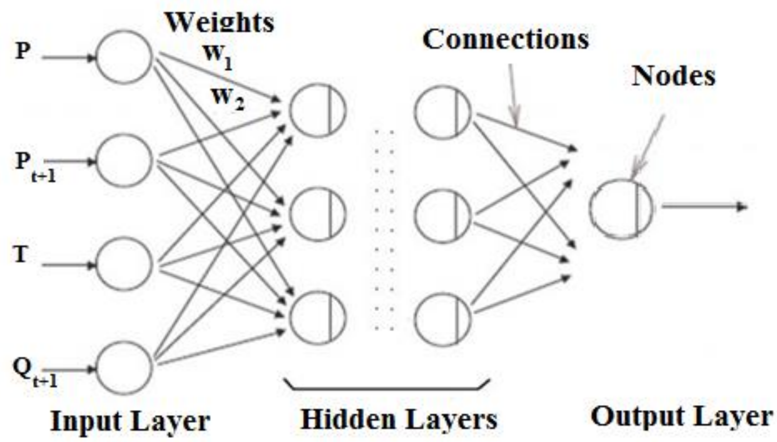



Figure 1. ANN Structure Used in this study

A three-layer feed-forward ANN architecture was given in figure 1. In the Artificial Neural Network, the cells are arranged in layers and the outputs of the cells in a layer are input to the next layer via weights. The input layer transmits information from external environments to the cells in the intermediate (hidden) layer without changing it. Information, intermediate and output layers are processed to determine the network output. With this structure, forward-fed networks perform a non-linear static function. It has been shown that the feed-fed three-layer artificial neural network can approach any continuous function with the desired accuracy, with a sufficient number of cells in the middle layer. The back-propagation learning algorithm, which is the most known algorithm, is used effectively in the training of such neural networks. The network includes both samples and outputs (expected outputs) to be obtained from the samples. The network produces a solution space representing the problem space by making generalizations from the examples shown to it. This solution space can produce results and solutions for the similar examples shown later.

***Multiple Linear Regression***

Multiple Linear Regression (MLR) analysis is performed in order to determine the relationship between two or more variables including cause-effect relationship and to make predictions about that subject by using this relationship.It is a statistical analysis used to convert the interest between one / more variables and one or more estimation variables into numerical values. Regression analysis mainly aims to determine the relationship between variables. It is possible to mention simple regression if one variable is used as the estimation variable, or multiple regression analysis if two or more variables are used as the estimation variables. The aim is to determine the contribution of each estimation variable to the total change in the criterion variable and therefore to estimate the criterion value from the value of the linear combination of the estimation variables.In MLR analysis, dependent variable y, independent variables $x_1$, $x_2$, ..., $x_p$ indicates the relationship between them;

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_j x_j + \cdots + \beta_p x_p + \varepsilon \qquad \textbf{(1)}$$

can be written as. Here, $\beta_0$, $\beta_1$, $\beta_2$, $\beta_j$, .., $\beta p$ are called the regression coefficient. $\beta_j \ (j = 1, 2, \ldots, p)$ is usually referred to as partial regression coefficients. $\beta_0$ is called the breakpoint or constant, and the value of the dependent variable is the value when all x_j variable values are zero. ε is the error term.

***Study Area***

The study area used data from the Stony Brook Reservoir basin near the Waltham Dam in Massachusetts, USA. Station data of 01104480 from the United States Geological Research Institute (USGS) are given in Table 1 and Figure 2. Data includes rainfall, runoff, and temperature information for 731-days between 07.05.2011-07.05.2013. Daily temperature, precipitation and discharge of data fluctuation were given in, respectively, Figure 3, Figure 4, Figure 5.

Table 1. Information on the measurement data and study area used in the paper.

| **Station No** | **Station Name** | **Study Area** | **Latitude** | **Longitude** | **Data Time** |
|---|---|---|---|---|---|
| 01104480 | STONY BROOK RESERVOIR | MA | 42°21'20" | 71°15'56" | 07.05.2011-07.05.2013 |


Figure 2. Study Area (USGS).

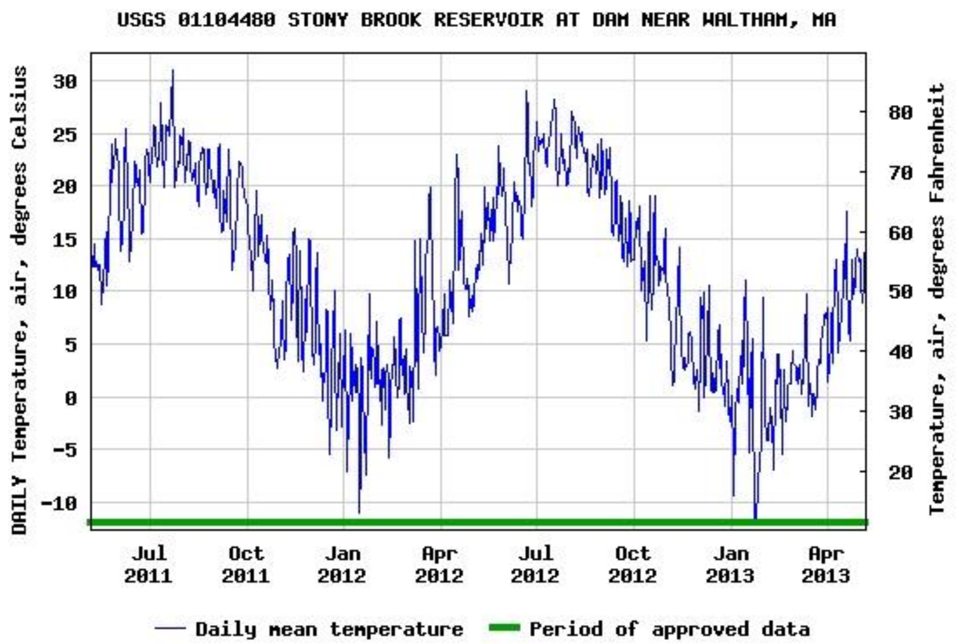



Figure 3. Daily Temperature Amount (° C / ° F) (USGS)

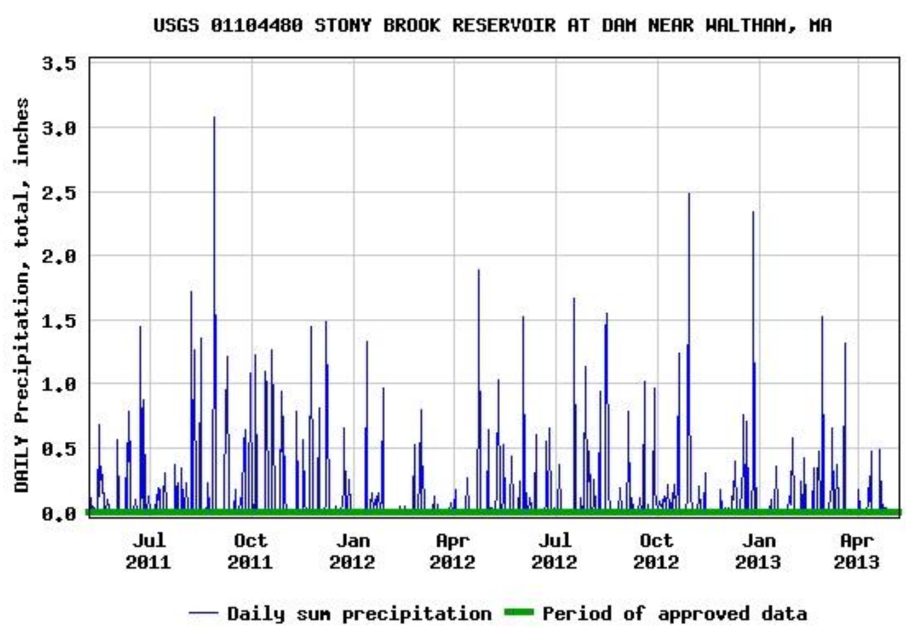



Figure 4. Daily Precipitation (inches) (USGS)

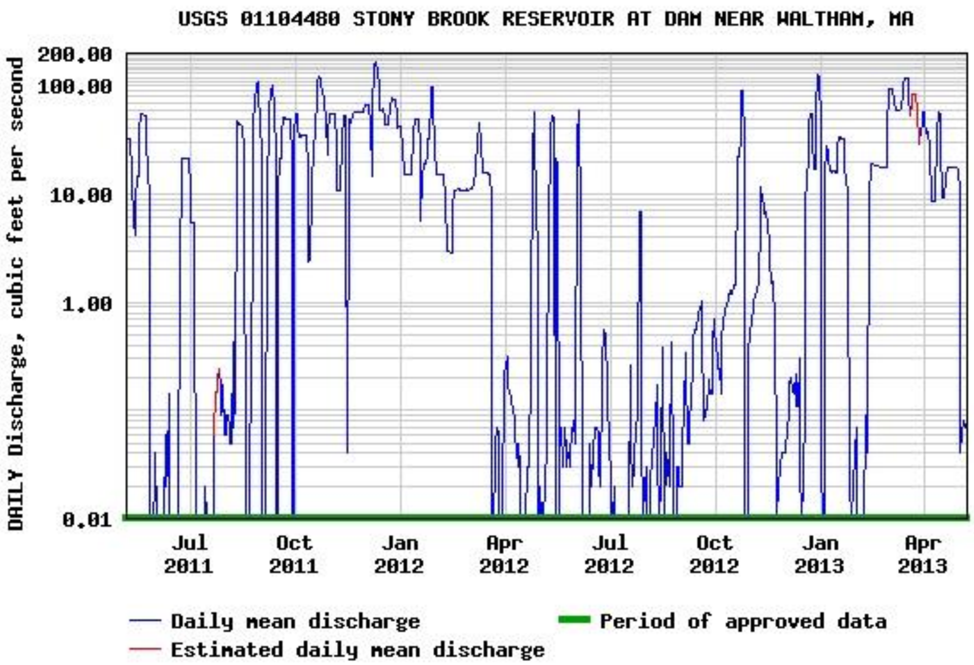



Figure 5. Daily Flow Amount ($ft^3$ / s) (USGS)

**Results**

In the scope of this study for a rainfall-runoff relationship, total 731 data was obtained from the observation station. 550 of these data was used training phase, 181 data was used in the test phase. The estimation results of the models were compared according to the R (Correlation Coefficient), Mean Square Error (MSE) and Mean Absolute Error (MAE) criteria. The Correlation Coefficient (R) shows the regression equation's compatibility with the data. A value between 85% and 100% means that the model complies with our data in terms of performance value.

MAE measures the average size of errors without considering the difference between the estimated value and the actual value. Error rates are expressed in units. It can take value from zero to infinity. The MSE describes how close a regression line is. The smaller the average of the squares, the closer the program is to the actual data. It does this by taking distances between points on the regression line and creating squares.

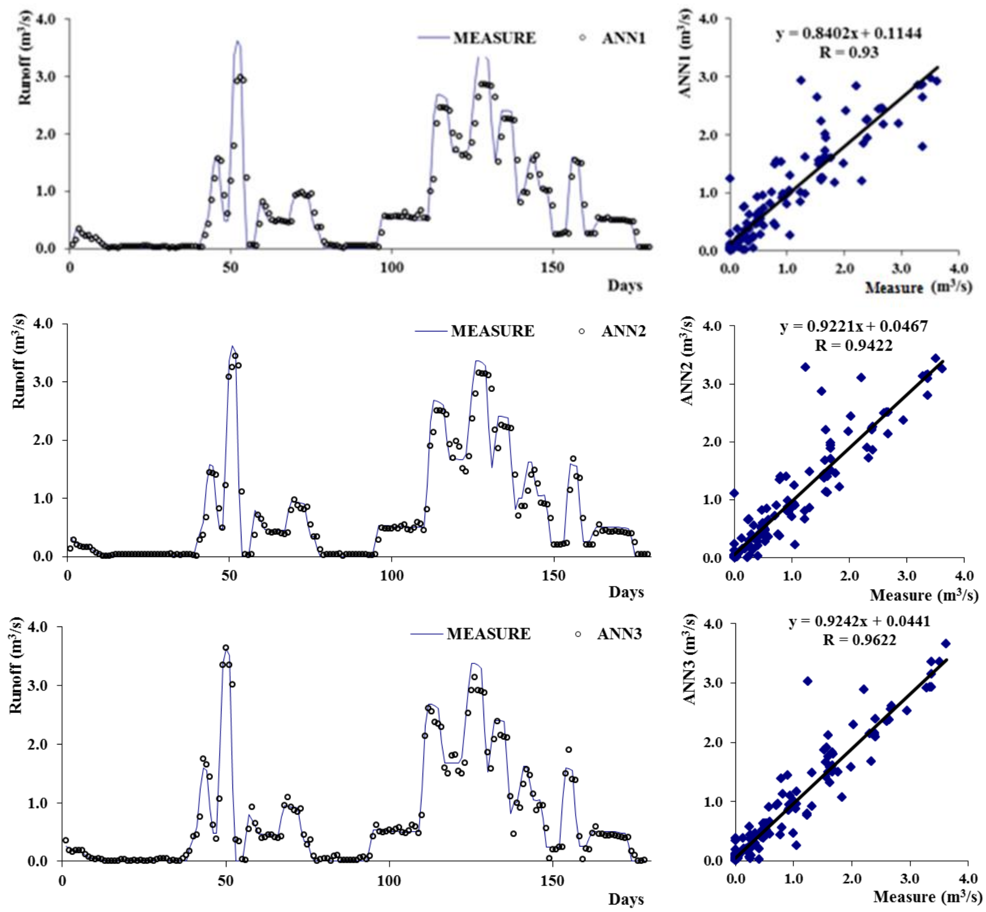
The best result was model 3. The compatibility of the models and the statistical error values are shown in Table 2.

Table 2. Compatibility and statistical error values of results according to models.

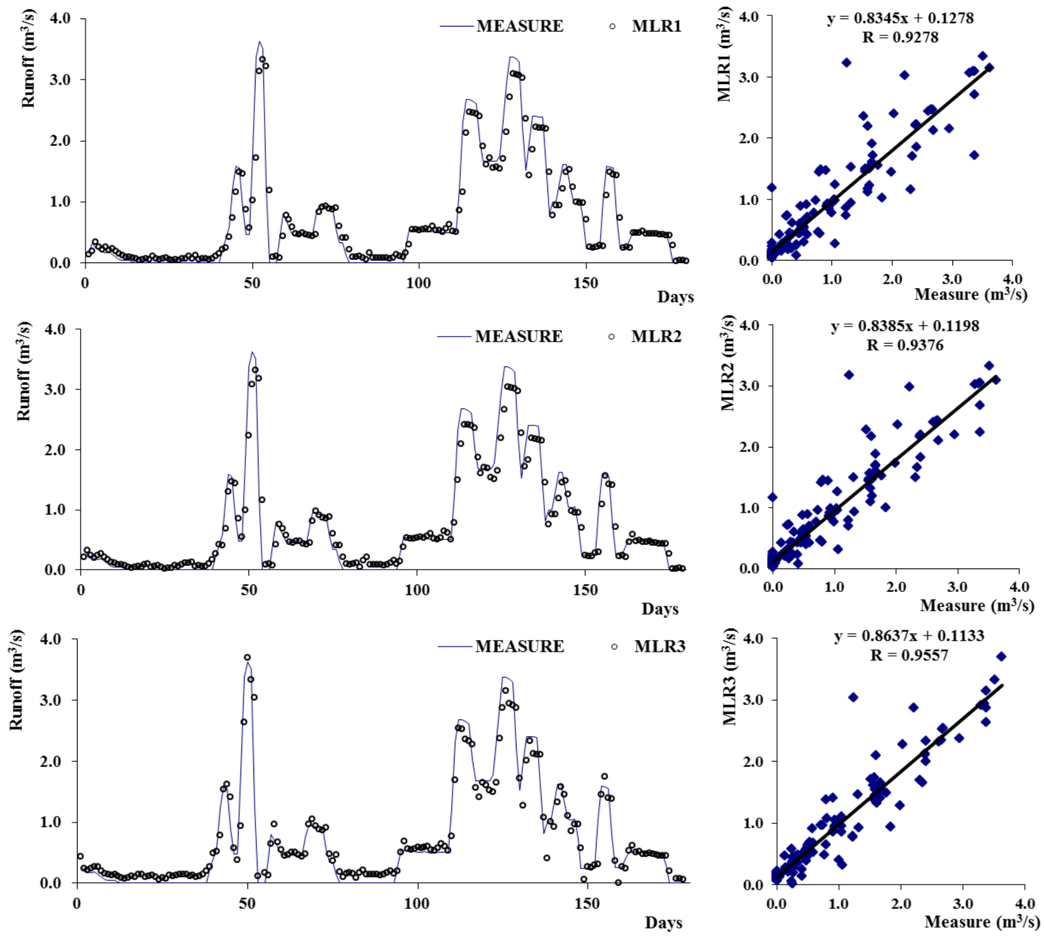
| MODELS | INPUTS | MAE | MSE | R |
|---|---|---|---|---|
| **MLR1** | $P, T, Q_{t+1}$ | *0.1904* | *0.1126* | *0.9278* |
| **MLR2** | $P, P_{t+1}, T, Q_{t+1}$ | *0.1861* | *0.0990* | *0.9376* |
| **MLR3** | $\boldsymbol{P, P_{t+1}, T, Q_{t+1}, Q_{t+2}}$ | ***0.1751*** | ***0.0725*** | ***0.9557*** |
| **ANN1** | $P, T, Q_{t+1}$ | *0.1756* | *0.1195* | *0.9300* |
| **ANN2** | $P, P_{t+1}, T, Q_{t+1}$ | *0.1678* | *0.0917* | *0.9422* |
| **ANN3** | $\boldsymbol{P, P_{t+1}, T, Q_{t+1}, Q_{t+2}}$ | ***0.1389*** | ***0.0602*** | ***0.9622*** |

In this study, runoff was estimated by using rainfall, temperature and runoff (t + 1).

The relationships of the three models with real data are shown in Figure 6 for ANN, and as shown in Figure 7 for MLR.




ANN1, ANN2 and ANN3 model's distribution and scatter charts were shown at testing phase in Fig. 6. The best correlation coefficient was obtained as R = 0.9622 in ANN3 model. In distribution and scatter graphs, ANN predicted values are close to the measured values.




MLR1, MLR2 and MLR3 model's distribution and scatter charts were shown at testing phase in Fig. 7. The correlation coefficient R = 0.9557 was obtained for the test in MLR3 model. The MLR predictions have quite good performance.

## Discussion

In this study, 731-day precipitation, runoff and temperature data of the observation station 01104480 in the Stony Brook Reservoir basin were entered as input in the Multiple Linear Regression and Feed-Forward Back-Propagation Neural Network methods and the new runoff values were estimated. The results were compared to the actual results and the relationship between the models was examined. During modeling, 75% of the 731 data were used in the training phase and the remaining 25% in the test phase. In order to obtain better results with this data, three different cases were studied. Studies have shown that both methods give similar results.

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