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# WATER LEVEL PREDICTION IN 16$^{TH}$ TISHREEN DAM RESERVOIR USING ARTIFICIAL NEURAL NETWORKS

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## ABSTRACT

**Background**: Storage levels prediction ability in dam reservoirs is a critical issue within the dam management system and protection from flood, depending on the values of precipitation and runoff coming into the reservoir over different periods of time. **Objectives:** water level in the 16$^{th}$ Dam reservoir on the North Kebir River in Syria, using artificial neural networks using (ANNs). **Methods:** The daily measured water level used as output of the neural networks. **Results:** The results of this study showed that feed forward back propagation Artificial Neural Networks (FFBP-ANNs) estimated successfully the water level in the dam reservoir, with low values of root mean square errors (RMSE), and high values of correlation coefficients (R). The result also showed that the using of the monthly index improves the accurate of estimation with correlation coefficient (R) of 99.7 %, and root mean square error (RMSE) of 7.28 mm/month for the test period. **Conclusions:** Thus, this research has shown the high reliability of artificial neural networks in estimation of water level in 16$^{th}$ Tishreen dam reservoir where the (1-10-4) feed forward neural network provides a high predictability of water levels dam of the next day, especially during the rainy months.
***Keywords**: Feedforward, Back Propagation, water level, reservoir.*

## 1. INTRODUCTION

Storage levels prediction ability in dam reservoirs is a critical issue within the dam management system and protection from flood, depending on the values of precipitation and runoff coming into the reservoir over different periods of time. Most modern studies have tended to model such phenomena and rely on modern techniques in the process of modeling. Artificial intelligence systems and artificial neural networks have taken great interest in this area because of the great potential of these models in simulating nonlinear and complex relations.

Murase (2007) used six feature groups comprising of water levels, rainfall, evaporation rate, discharges for rivers Malewa and Gilgil and one pair of time harmonics to develop neural network models to forecast water levels for Lake Naivasha in Kenya. The neural network models developed were able to forecast effectively the reservoir levels for the lake [1]. Ishak et al. (2010) studied the ability of Application of Artificial Neural Network (ANN) to predict water level in Tasoh reservoir in Malysia, where they used nine data sets with (2-10) days of inflow time delay. The models showed the ability of feedforward ANN to predict the level with MSE of 0.44 and R of 90.75% for the test dataset [2]. Sztobryn (2010) predicted sea water levels during a next day in the port of Swibno in Poland, using one of the Multilayer Perceptron ANN and obtained the results of models with a performance error of less than 7cm [3]. Bustami et al. (2006) evaluated the daily water level at Sungai Bedup Station in Sarawak, Malaysia, where Back propagation Recurrent Network was used. The results showed that the neural network using 4 days of previous data performed well in simulating and estimating the water level in Bedup basin for one year with (R = 0.96) [4]. Al Aboodi et al. (2009) predicted the Tigris River in Qurna city, south of Iraq using artificial multilayer perceptron networks. Results indicated the ANNs with back-propagation algorithm are a powerful technique to predict the short term stage of Tigris River by a correlation coefficient (0.867- 0.736- 0.649), respectively [5]. In 2011, Rani et al. predicted the water level in Sukhi dam in Gujarat, India, for ten days in a row. The results showed that the feed forward back propagation network provides the best performance and real-time prediction capability with a correlation coefficient (0.97) and RMSE (0.82 m) [6].

## 2. MATERIALS AND METHODS

### 2.1 Study aim and importance

This study aims at predicting the water level in the 16$^{th}$ Dam reservoir on the Al-Kabir Alshimali River, using artificial neural networks. The importance of the research is to preserve the safety of the dam from any dangers caused by flood by predicting the water level in the reservoir early where the necessary measures could be applied, depending on the values of river runoff and climatic factors at the dam station at varying intervals.

## 2.2 Study site & data availability

Al-Kabir Alshimali river flows from the north-west of the coastal mountains, from the highland located at the Turkish border at an altitude of more than 1,100 km to a distance of 89 km and to discharge directly in the Mediterranean Sea at the south of Lattakia. It is bounded by Orontes river basin from east, and by Alsnawbar river basin from the south-east and by several small basins the north-west. The length of the basin is 64 km, its median width is 17 km, the maximum width is 25 km, and the elevation is 680 m, with an area of about 1097 $km^2$. Figure 1 shows an aerial picture of the studied area.

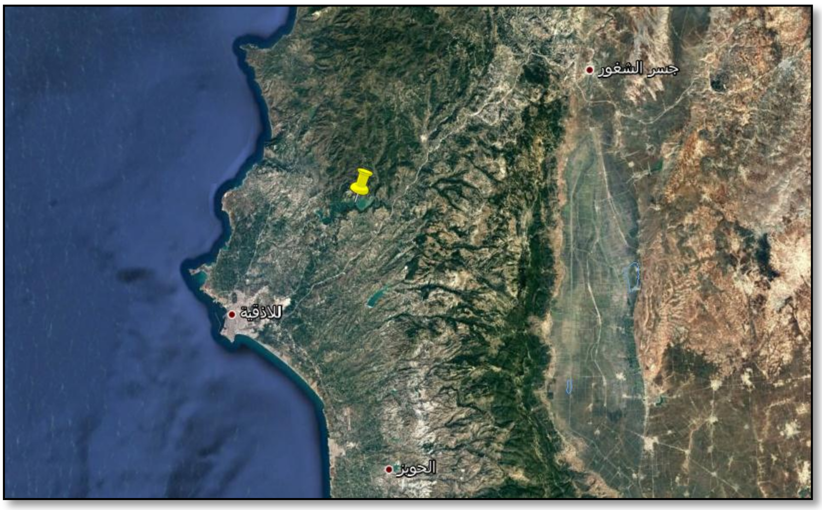


**Figure 1:** The figure presents aerial picture of the studied area

**2.2 Artificial Neural Network:** Artificial neural networks are a kind of black box; this means we do not know its structure but just regard its behavior in practice [7]. The basic computational units in a neural network are the neurons (or perceptrons), which are connected by weighted links called synapses passing signals from one neuron to another [8]. So, ANNs are an attempt at modeling the information processing capabilities of human nervous systems [9]. ANNs learn through experience with appropriate learning exemplars, not from programming [10].

There are several types of ANN which differ in their nomination and properties depending on either the number of layers or construction style or correlation of its units from one layer to another or the type of algorithms that used in its training. Figure 2 illustrate simple model of artificial neural network formed of complex block of processing elements called neurons have the ability to procedure mathematical process [11].

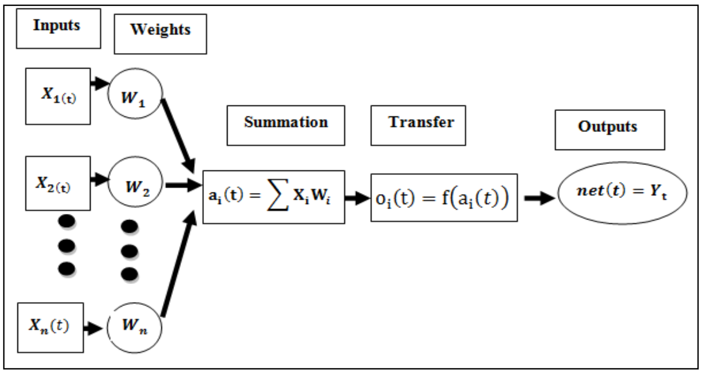


**Figure 2:** The figure presents the structure of artificial neural network.

The network is trained by applying optimum algorithm, which try to minimize the error in the output of the network by adjusting the network weights array and the biases of the neurons. Where the weights between layers don't have fixed value, but they are changing during training, thus if the strength of connection has increased, it's called long term potentiation (LTP), and if it has decreased, it's then called long term depression (LTD) [12].Where, the result of the process of updating the weights is called learning process.

There are two types of neural networks by the learning algorithm classification: Supervised learning and unsupervised learning, and by the structure classification, there are also two types of neural networks: Feed-forward networks and feedback networks [13]. Probably, the feed forward Application of Artificial Neural Network (ANN) is the most common neural network structure used in neural network problems [14].

**2.5 Models Evaluation:** The comparison between different ANNs models was done by using two statistical indices: correlation coefficient (R) and root mean square error (RMSE), which are defined as Eq.(1) and Eq.(2) [15]:

$$R = \frac{\sum_{i=1}^{n}(y_i - \bar{y}).(\hat{y}_i - \bar{\hat{y}})}{\left[\sum_{i=1}^{n}(y_i - \bar{y})^2 . \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2\right]^{\frac{1}{2}}} \qquad (1)$$

$$RMSE = \left[\frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{n}\right]^{0.5} \qquad (2)$$

Where $n$ is the number of observations, $y_i$ is the estimated using the artificial neural networks, $\hat{y}_i$ is the observed $ET_0$ (calculated by the PM method), $\bar{y}$ and $\bar{\hat{y}}$ are the average value for $y_i$ and $\hat{y}_i$.

## 3. RESULTS

The feed forward artificial neural network is configured and trained using MATLAB 2012a programming language. The Levenberg Marquardt back propagation algorithm has been used to deal with large amounts of data, because its ability of providing fast performance and access to the lowest value of mean square error (MSE) used in evaluating the performance of models in the training phase.

The data included daily values of rainfall, flows and water levels during the first four months of each year, in which the levels gradually rise and fall again. In March and April, as shown in figure 3, the highest values of the levels were observed during the study period. March and April of the last year, considered as a test set as it contains the maximum values of the levels that reached (75) meters in 2011.

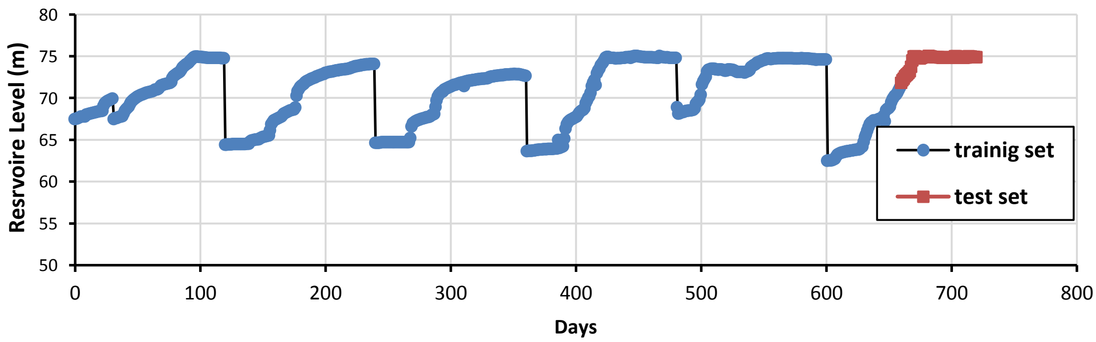


**Figure 3:** The figure presents the time series for dam water level (2006-2011)

Several patterns of training have been developed according to a specific methodology as shown in table 1, to determine the extent of the interconnectivity between them and the previous rainfall and inflow values into the 16 October dam reservoir, in order to determine the number of input to the network by trial and error. In this study, a neural network with one hidden layer containing ten neurons was used. The tan-sigmoid transformation function was also used between the layers by performing a number of performance tests and observing the mean square error (MSE) for the network during training.

**Table 1**: The table presents the Structures of the tested models in this study.

| Model | Input Variables |
|---|---|
| **I** | $S\ (t+1) = f(P_t, Q_t, S_t)$ |
| **II** | $S\ (t+1) = f(P_t, P_{t-1}, Q_t, S_t)$ |
| **III** | $S\ (t+1) = f(P_t, Q_t, Q_{t-1}, S_t)$ |
| **IV** | $S\ (t+1) = f(P_t, P_{t-1}, Q_t, Q_{t-1}, S_t)$ |
| **V** | $S\ (t+1) = f(P_t, Q_t, S_t, S_{t-1})$ |
| **VI** | $S\ (t+1) = f(P_t, P_{t-1}, Q_t, S_t, S_{t-1})$ |
| **VII** | $S\ (t+1) = f(P_t, Q_t, Q_{t-1}, S_t, S_{t-1})$ |
| **VIII** | $S\ (t+1) = f(P_t, P_{t-1}, Q_t, Q_{t-1}, S_t, S_{t-1})$ |

The statistical comparison used in table 2 shows that the third model is the best in performance in the training and testing stages compared to the other models with error less than 10 cm and correlation coefficient (0.995). The model shows the response of the changes in the reservoir dam levels for rainfall values and levels for the previous day and the values of flows for the previous two days.

**Table 2**: The table presents the performance criteria obtained by the best Application of Artificial Neural Networks (ANNs) models.

| Model | Training Set | | Testing Set | |
|---|---|---|---|---|
| | R | RMSE | R | RMSE |
| I | 0.991 | 0.515 | 0.957 | 0.249 |
| II | 0.986 | 0.650 | 0.990 | 0.142 |
| **III** | **0.997** | **0.316** | **0.995** | **0.097** |
| IV | 0.995 | 0.375 | 0.993 | 0.103 |
| V | 0.993 | 0.474 | 0.991 | 0.126 |
| VI | 0.992 | 0.488 | 0.961 | 0.236 |
| VII | 0.995 | 0.384 | 0.996 | 0.102 |
| VIII | 0.996 | 0.361 | 0.992 | 0.113 |

Figure 4 shows a block diagram illustrating the proposed model work mechanism according to the structure (1-10-4), that is, the number of the input nodes is (4) knowing that no processing in the input layer, and the number of neurons in the hidden layer is (10). The dimensions of the input hidden matrix are 4 × 10, we have one neuron in the output layer, and the dimensions of the hidden Output matrix are 1 × 10, using the tan-sigmoid transformation function between the layers, On the mechanism of work of the model in the form of matrices in equations (3), (4) and (5):

$$y_1 = [w_1 * x_1] + b_1 \qquad .............(3)$$

$$H = \frac{2}{[1+\exp^{-2*y_1}]-1} \qquad .............(4)$$

$$y_2 = [w_2 * H] + b_2 \qquad .............(5)$$

Where, ($y_1$) represents the output layer of the first layer, (H) is the output of the hidden layer resulting from the tan-sigmoid activation function, ($y_2$) represents the output of output layer, which is the estimated value of the proposed neural network model, ($w_i$) are the weights among the proposed neural network layers, ($b_i$) bias is added to the output.

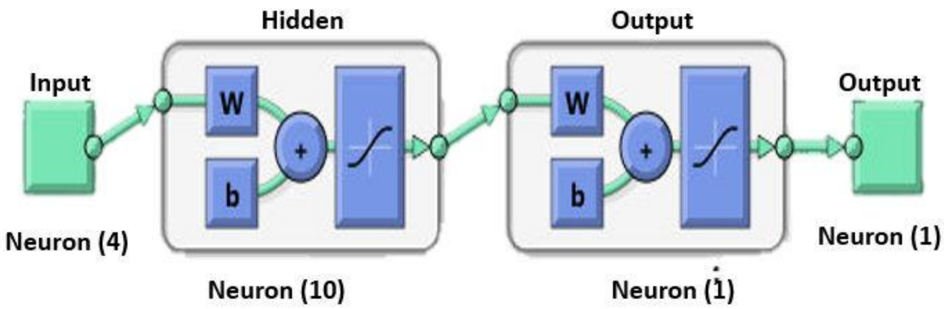


**Figure 4:** The figure presents the block diagram for the design Artificial Neural Network (ANN).

Figure 5 shows the ANN model values with the measured real values of the water levels in the dam lake, which shows the model's ability to predict the high values of the levels in the critical period at high accuracy. The correlation coefficient of the test set is (0.993) Figure 6.

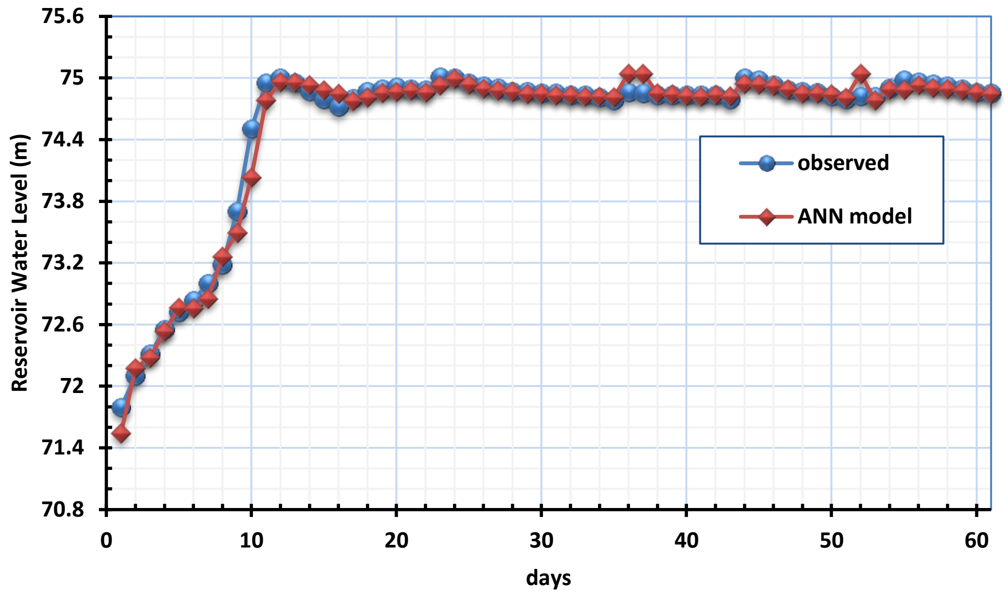


**Figure 5**: The figure presents comparison between (measured and computed by ANN model) water level.

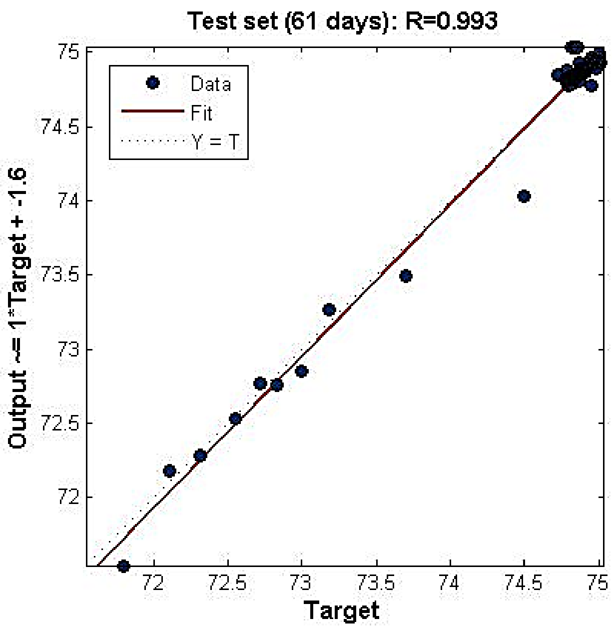


**Figure 6**: The figure presents correlation between (measured and computed by ANN model) water level during all periods.

# 4. DISCUSSION

In this study, Application of Artificial Neural Network (ANNs) models were developed for estimating the water level in 16th Tishreen dam reservoir by using data included daily values of rainfall, flows and levels during the first four months of each year. The data were spilt into three datasets for training, validation and test in the ratio 80:10:10 respectively.

The neural networks were trained with 1–20 nodes in the hidden layer (or layers), with different activation function, training function and adaption learning function. After each training RMSE and R were calculated for training, validation and test periods to find the optimal number of hidden nodes using trial-and-error method. Feed forward back propagation artificial neural network (FFBP ANN) was the best type of ANN models. The results showed that the best suitable network has one hidden layer of 10 neurons, which use tan sigmoid activation function and Levenberg – Marquardt (LM) algorithm with root mean square error (RMSE) of 0.316, 0.097 for training and test periods respectively, correlation coefficient (R) 99.7, 99.5% for the same periods respectively. And for the all dataset R was 99.3%.

The results of this study indicated the ability of the neural networks to predict the water level in the dam reservoir and showed very accurate estimation in comparison with other researches results in the same field. As for example, Bustami et al. (2006) used Back propagation Recurrent Network to evaluate the daily water level at Sungai Bedup Station in Sarawak, Malaysia. The results showed that the neural network using 4 days of previous data performed well in simulating and estimating the water level in Bedup basin for one year with (R = 0.96) [4], where in 2011 Rani et al. predicted the water level in Sukhi dam in Gujarat, India, for ten days. The results showed that the feed forward back propagation network provides the best performance and real-time prediction capability with a correlation coefficient (0.97) and RMSE (0.82 m) [6], while in our research we could predict the water level in 16th dam reservoir using feedforward neural network with R=0.993 and RMSE = 0.097 m which is better than the above mentioned researches.

# 5. CONCLUSION

This paper presents the potential of artificial neural networks for the estimation of the water level in Dam reservoir, where the (1-10-4) feedforward neural network provides a high predictability of water levels in the Lake of 16th Tishreen dam of the next day, especially during the rainy months, which is a critical period when the levels rise to the greatest values with R=0.993, RMSE = 0.097m. The model can therefore be used to make water-discharge decisions and to secure a safe water load for the dam. The results of the proposed models used for examining the response of changes in water levels to the preceding values of precipitation, water levels, and inflow, show a high correlation between the water level and preceding precipitation values of one day and between the one day-preceding water level with the values of inflow for the previous two days, indicating that there is an implicit short memory in the proposed model of hydrological variables (rainfall & inflow). The study recommends using hybrid systems developed from various artificial intelligence methods in order to get more accurate predictions.

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