**Reservoir Operation by Artificial Neural Network Model**

 **( Mosul Dam –Iraq, as a Case Study)**

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**Abstract:**

 Reservoir operation forecasting plays an important role in managing water resources systems. This is especially the case for reservoirs because of the among all man-made hydraulic structures in river basins, reservoirs take a key role in redistributing water more evenly both in space and time to prevent damage and increase benefits, either in an economical or in ecological and societal manner. In recent years research on Artificial Neural Networks (ANN) proved to be most convenient and easy tool for modeling and analysis of non-linear events. For the reservoir operation, there is a need to find optimal solution to release water downstream and to keep maximum storage within the reservoir with no or minimum downstream damage during flood peak. ANN model was applied for Mosul-Dam reservoir which locates on Tigris River \_Iraq with the objectives of water resources development and flood control. Feed-forward multi-layer perceptions (MLPs) are used and trained with the back-propagation algorithm, as they have a high capability of data mapping. The data set has a record length of 23 years covering (1990-2012).The Input data were Inflow (It), Evaporation (Et), Rainfall (Rt), reservoir storage (St) and Outflow (Ot).The data were divided into two parts, the first part that has a data for training and testing ANN Model. The remaining data were used for validation. The data set with simulated release for monthly duration was used to Model ANN. The best convergence after more than 1000 trials was achieved for the combination of inflow (It), inflow (It-1), inflow (It-2), Evaporation (Et), reservoir storage (St), Rainfall (Rt), outflow (Ot-1) and outflow (Ot-2) with error tolerance, learning rate, momentum rate, number of cycles and number of hidden layers as 0.001, 1, 0.9,50000 and 9 respectively. The coefficient of determination (R2) and MAPE were (0.972)

and ( 17.15 ) respectively. The results indicate that the Inflow(It) and Outflow(Ot-1) had the most significant effect on the predicted outflow of the reservoir with a relative importance of 21.80 and 18.56 respectively, followed by Inflow(It-1), Inflow(It-2) and Evaporation (Et), Storage (St) and Rainfall (Rt), with a relative importance of 13.71, 13.28, 11.34, 10.84 and 10.43 % respectively. The results of ANN models for the training, testing and validation were compared with the observed data. The predicted values from the neural networks matched the measured values very well. The application of ANN technique and the predicted equation by using the connection weights and the threshold levels, assist the reservoir operation decision and future updating, also it is an important Model for finding the missing data. The ANN technique can accurately predict the monthly Outflow.

**Keywords: ANN , Mosul Reservoir, Iraq , and Outflow.**

**1-Introduction:**

 Reservoir operation is a complex problem that involves many decision variables, multiple objectives as well as considerable risk and uncertainty as in [1]. In addition, the conflicting objectives lead to significant challenges for operators when making operational decisions. Traditionally, reservoir operation is based on heuristic procedures, embracing rule curves and subjective judgments’ by the operator. This provides general operation strategies for reservoir releases according to the current reservoir level, hydrological conditions, water demands and the time of the year.

 Applying optimization techniques for reservoir operation is not a new idea. Various techniques have been applied in an attempt to improve the efficiency of reservoirs operation. These techniques include Linear Programming (LP); Nonlinear Programming (NLP); Dynamic Programming (DP); Stochastic Dynamic Programming (SDP); and Neural Networks as in [2]. In operation study the aim is to optimize the reservoir volume (that is storage) for abstracting sufficient amount of water from the dam reservoir. The monthly inflow of the reservoir is the main data series. It is better to have a data record length as long as possible. In addition to the monthly inflows, the monthly evaporation losses are another main data as in [3].

 Many researchers have applied ANN to model different complex hydrological processes. The ANN methods have good generalization efficiency and are commonly used in practical hydrologic projects. Even when there are missing data values, the ANN methods can be applied to aid in the completion of missing hydrological records as in [4].Reference [5] described how the new prediction technique ANN and optimization technique GA applied to the reservoir operation especially in the flood period. The ANN technique used is based on Multilayer Perception Network and Back-propagation learning typed while GA technique is based from Natural Selection and natural genetics concepts. The application of both techniques to the Pasak Jolasid Reservoir found that the ANN technique can accurately predict the inflow for 7 day in advance with the accuracy of 70 % and GA technique can reduce the overflow during the flood peak reasonably under the determined reservoir rule curve. Reference [6] used Artificial Neural Network (ANN) for inflow forecasting of reservoir up to the next 12 hours. Numerical weather forecasting information (RDAPS), recorded rainfall data, water level of upstream dam and stream gauge site, and inflow of the current time are employed as input layer’s training values, and target value is +3, +6, +9, and +12 hours later inflow to Hwacheon reservoir in South Korea. Comparison result between ANN with RDAPS and without RDAPS showed that RDAPS information is useful for forecasting inflow of reservoir. He concluded that All of these two models showed good performance comparing with the observed records and The performance of ANN model is largely affected by a method of selecting training data sets, and it is also important to maintain accuracy and reliability of training process through verification and calibration processes. They used the parameters of Rainfall (Rt) m3, water level (ht) m and Inflow (It). Reference [7] determined the best model using historical data to predict reservoir inflow one month ahead based on the different techniques of Neural Network. The methods were used to predict inflow in the Majalgaon Reservoir, Jayakwadi Project Stage-II, and Maharashtra, India. The modeling results indicates that reasonable prediction accuracy was achieved for most of model for one month ahead forecast with correlation greater than 0.94. When compared, a 2-4-1 Time-lag Recurrent Network with 2-lag has produced a better performance with correlation co-efficient greater than 0.99. Reference [8] developed The Neural Network model to classify the data that in turn can be used to aid the reservoir water release decision. In this study neural network model 8-23-2 has produced the acceptable performance during training, validation and testing. He concluded that the window sliding has been shown to be a successful approach to model the time delays, while neural network was shown as a promising modeling technique. They used parameters of reservoir water level (ht) m, river water level (ht) m, inflow (It) m3/sec, No. of gate size of opening, opening duration (T). Reference [9] carried out management of hydropower reservoirs along river Niger by forecasting its future storage using Artificial Neural Network (ANN) model. This helps in planning on how it can be fully optimized for hydropower generation, domestic and industrial uses, irrigation and other uses. The networks were trained with monthly historical data of Jebba and Kainji hydropower reservoirs’ inflow, outflow (release), storage and the evaporation loses. The trained networks yielded 95% and 97% of good forecast of training and testing set for Jebba, and 69% and 75% respectively for Kainji reservoir. The correlation coefficients of 0.64 and 0.79 were obtained for Jebba and Kainji reservoirs respectively. This study is devoted to suggest new scenarios for the operation of reservoirs. The Artificial Neural Network was used for analysis old data and forecasting. The computer program Artificial Neural Network package is used for this purpose .Input and Output data of more than twenty years for AL Mosul reservoir as a case study were analyzed and the results were compared with previously monthly operation.

**2-Material and Methods:**

 **Study Area:**

 In this study, ANN model was applied for Al –Mosul reservoir located in Mosul Governorate(Iraq) on Tigris River, 50 Km North of Mosul Town, 80km from the Turkish borders .The scheme included the dam and appurtenant structures, a regulating dam located at the downstream and a pumped storage scheme for additional hydropower generation, Fig. 1.



 **Figure 1. Mosul Dam Scheme Layout**

**Input and Output Parameters:**

 It is generally accepted that data of five parameters have the most significant impact on the dam reservoir operation, and are thus used as the ANN model inputs. These include the following:-

1-Inflow rate (m3/s)

2-Storage (m3) , Evaporation (m3) and Rainfall (m3) ( using area-surface water elevation curve of the Mosul reservoir , the water volume of storage ,evaporation and rainfall can be calculated by multiplying the area by the water depth, evaporation depth and rainfall depth respectively at each month).

 The output of the model is monthly Outflow (m3/s). These data were collected from [10] . The data set has a record length of 23 years covering between (1990-2012).

 **ANNs Technique:**

 ANN’s were inspired by and mimic the biological nervous system. They offer an alternative computing paradigm closer to reality, independent of pre-established rules or models. To fully understand how an ANN works, let’s first get familiar with its components as in [11] . The very basic element of an ANN is called Neuron. Neurons are elemental processors that execute simple tasks. They process the information it receives by applying a mathematical Activation Function that is usually non-linear, to its net input, producing an Output Signal as a result. A Neuron’s net input is basically a weighted sum of all of its inputs. As the biological nervous system, Neurons are connected through Links, which transmit the signals among them. Each Connection Link has an associated weight (W ij)that, in turn, modifies the signal transmitted. Abroad class models that mimic functioning inside the human brain. There are various classes of NN models and they are different from each other depending on :i Problem types (prediction, classification, clustering);ii) Structure of the model ;iii) Model building algorithim.

 For this discussion we are going to focus on, Feed – forward Back Propagation Neural Network which is used for prediction and classification problems as in [12] , [13], [14] and [15]. Often, Neurons are grouped in so-called Slabs. Similarly, Slabs are grouped in Layers. Usually, an ANN comprises three layers: Input, Middle and Output Layer. The Input Layer receives information (set of features representing the pattern) from the environment or surroundings and transmits it to the Middle Layer. At this point, it is important to clarify that every Neuron located in the Input Layer is interconnected with all of the Neurons in the Middle Layer, such that the information processing task is carried out parallel and simultaneously. The same is true for the interconnection between the Middle and Output Layer. It is often said that the Middle Layer is the one that actually analyzes or executes the mapping of the information supplied to the ANN. This layer carries out the pattern recognition task among all input information by re-coding it to generate an appropriate internal representation, so that the essential features of the patterns are retained. The Output Layer receives this analysis and converts it into a meaningful interpretation to communicate it back to the environment. A simplistic schematic of an ANN is depicted in Figure 2.

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 **Figure 2.** **Typical Structure of ANN**

Three properties characterize an ANN:

 1. Architecture: the connectivity pattern among neurons

 2. Algorithm: its method of determining the weights on the connections

 3. Activation Function: a mathematical function that maps a neuron’s net input

in to its output value. (Sigmoid (logistic) Function ( ), the hyperbolic tangent (tanh) function, the sine or cosine function and the linear function ). The model parameters comprise of many transfer functions, learning rate of (0.0-1.0) and momentum rate of (0.0-1.0) . The default values of learning and momentum rates are 0.2 and 0.8 respectively.

 **Division of data**

 The data are randomly divided into three sets (training, testing and validation).In total, 80% of the data are used for training and 20% are used for validation. The training data are further divided into 70% for the training set and 30% for the testing set. These subsets are also divided in such a way that they are statistically consistent and thus represent the same statistical population. To examine how representative the training, testing and validation sets are with respect to each other, T-test and F-test are carried out. These results indicate that training, testing and validation sets are generally representative of a single population as in [16] . The data base used for the ANN model comprises total of (276) individual cases. Ranges of the data used for the input and output variable are summarized in Table 1.

 **Table 1 : Ranges of the data used for the ANN model**

|  |  |  |
| --- | --- | --- |
| Model variables | Minimum value | Maximum value |
| INFLOW, m3/sec | 78 | 1715 |
| STORAGE, m3 | 3.32E+09 | 1.09E+10 |
| EVAPORATION, m3 | 4694879 | 1.46E+08 |
| RAINFALL, m3 | 0 | 36419980 |
| OUTFLOW, m3/sec | 115 | 1947 |

 **Scaling of data**

 The input and output variables are pre-processed by scaling them between (0 and 1), to eliminate their dimensions and to ensure that all variables receive equal attention during training. The simple linear mapping of the variables extremes is adopted for scaling, as it is the most commonly used method as in [17] . As part of this method, for each variable X with minimum and maximum values of Xmin and Xmax respectively, the scaled value Xn is calculated as in (1):

****

 **(1)**

**Model architecture, optimization and stopping criteria:**

 One of the most important and difficult tasks in the development of ANN models is determining the model architecture (i.e. the number and connectivity of the hidden layer nodes). A network with one hidden layer can approximate any continues function, provided that sufficient connection weights are used**.** Consequently, one hidden layer is used in this research. Using the data for Mosul Reservoir, the combination of Inflow (It), Storage (St), Evaporation (Et), Rainfall (Rt).as an Input and Output (Ot) as an Output, was considered for the initial training. This combination was trained with end to the tolerance and the number of cycles as 0.001 and 50000 respectively. The general strategy adopted for finding the optimal network architecture and internal parameters that control the training process is as follows: a number of trials more than 1000 is carried out using the default parameters of the software used with one hidden layer and 1,2,3,…….,10 hidden layer nodes (13 node is the upper limit of hidden layer nodes).

 The network that performs best with respect to the testing set is retrained with different combinations of momentum terms (0-1), learning rates (0-1) and transfer functions in an attempt to improve model performance, since the back-propagation algorithm uses a first-order gradient descent technique to adjust the connection weights, it may get trapped in a local minimum if the initial starting point in weight space is unfavorable. Consequently, the model that has the optimum momentum term, learning rate and transfer function is retrained a number of times with different initial weights until no further improvement occurs. Using the default parameters of the software, a number of networks with different numbers of hidden layer nodes is developed and results are shown graphically in Figure 3 summarized in Table 2 for ANN models

# Figure 3. Performance of the ANN models with different hidden layer

 nodes (Learning rate = 0.2 and Momentum term = 0.8)

 It can be seen from Figure 3 that the number of hidden nodes has little impact on the predictive ability of the ANN model. This is to be expected, as cross-validation is used as the stopping criteria**.** Figure 3 shows that the network with 10 hidden layer nodes has the lowest prediction error for training set. However, it is believed that the network with 10 hidden layer nodes is considered optimal for the validating set, as its prediction error is not far from the network with 6, 8 and 10 hidden layer nodes coupled with smaller number of connection weights. It can also be seen from Table 2 that the results obtained for model during validation are generally consistent with those obtained during training and testing (the error difference in RMSE being 102.81 and 262.13 respectively), indicating that the model is able to generalize within the range of the data used for training, and can thus be used for predictive purposes.

 The effect of the internal parameters controlling the back-propagation (i.e. momentum term and learning rate) on model performance is investigated for the model with seven hidden layer nodes resulting in Table 2. The effect of the momentum term on model performance is shown graphically in Figure 4. It can be seen that the performance of the ANN model is relatively insensitive to momentum terms, particularly in the range 0.1 to 0.6.

 Figure 5, shows that the effect of different learning rates on the model performance. It can be seen that the performance of the ANN model is relatively sensitive to learning rates in the range 0.1 to 0.4 then the prediction errors slightly increase to certain value at 78.30,for the training set. The figure indicate that the performance relatively insensitive to learning rates after value of 0.4. Thus, the optimum values for momentum term and learning rate used is 0.80 and 1.0 respectively. The effect of using different transfer functions is shown in Table 2. It can be seen that the performance of ANN models is relatively insensitive to transfer functions although a slightly better performance is obtained when the linear transfer function is used for input layer, sigmoid transfer function for the hidden layer and the output layer.

Table 2 .Structure and Performance of ANN models developed for Al-Mosul Reservoir Dam Operation



T = Training, S= Testing, V = Validation

**Figure 4. Effect of various momentum terms on ANN performance**

 **(Hidden nodes = 10 and learning rate = 0.2)**

**Figure 5. Effect of various learning rates on ANN performance**

**(Hidden nodes = 10 and Momentum term = 0.8)**

**3- Results and Discussion:**

 It was observed that the performance of ANN is good for learning rate between (0.8-1.0) and the momentum rate of (0.8) and to get the optimized weights for the neural network model, the following combinations of inputs were tried as described below:

|  |
| --- |
| * Scenario 1(I(t) O(t) S(t) E(t) R(t))
* Scenario 2 (I(t-1) I(t) O(t) S(t) E(t) R(t))
* Scenario 3(I(t-2)I(t-1) I(t) O(t) S(t) E(t) R(t))
* Scenario 4(I(t-2)I(t-1) I(t) O(t-1) S(t) E(t) R(t))
* Scenario 5(I(t-2)I(t-1) I(t) O(t-1) O(t-2) S(t) E(t) R(t))
 |

The results of ANN Model under different operation scenarios are shown in Table 3.

 **Table 3. Results of ANN training for dam reservoir operation.**



 Tables 3, shows results at the training for different scenarios for Mosul reservoir operation. It was noticed that the best convergence was achieved for the scenario of (I(t-2)I(t-1) I(t) O(t-1) O(t-2) S(t) E(t) R(t)) with the error tolerance, learning rate, momentum rate, neurons in the hidden layers, coefficient of determination and the sum of squared error as (0.001, 1, 0.9, 9, 0.972 and 78.783) respectively.

 In an attempt to identify which of the input variables has the most significant impact on the Dam Reservoir Operation, a sensitivity analysis is carried out on the ANN model (model MDO-30). A simple and innovative technique proposed as in [18] , is used to interpret the relative importance of the input variables by examining the connection weights of the trained network. For a network with one hidden layer, the technique involves a process of partitioning the hidden output connection weights into components associated with each input node. The results indicate that the Inflow(It) and Outflow(Ot-1) had the most significant effect on the predicted the Dam Reservoir Operation with a relative importance of 21.80 and 18.56 respectively, followed by Inflow(It-1), Inflow(It-2) and Evaporation (Et), Storage (St)and Rainfall (Rt), with a relative importance of 13.71, 13.28, 11.34, 10.84 and 10.43 % respectively. The results are also presented in Figure 6.

 Figure 6. Relative importance for all input parameters

The small number of connection weights obtained for the optimal ANN model (model MDO-30) enables the network to be translated into relatively simple formula. To demonstrate this, the structure of the ANN model is shown in Figure7, while connection weights and threshold levels are summarized in Table 4. Using the connection weights and the threshold levels shown in Table 4, the predicted Outflow of reservoir dam operation can be expressed as in (2):

$$O\_{t=\frac{1}{1+e^{(-1.074+2.347tanhX\_{1}+4.378tanhX\_{2}-3.727tanhX\_{3}+7.077tanhX\_{4}+2.918tanhX\_{5}+1.415tanhX\_{6}-6.885tanhX\_{7}-3.719tanhX\_{8}-1.555tanhX\_{9}}}}$$

 (2)

where:

$$X\_{1=θ\_{8}+W\_{81}I\_{1}+W\_{82}I\_{2}+W\_{83}I\_{3}+W\_{84}I\_{4}+W\_{85}I\_{5}+W\_{86}I\_{6}+W\_{87}I\_{7}}$$

$$X\_{2=θ\_{9}+W\_{91}I\_{1}+W\_{92}I\_{2}+W\_{93}I\_{3}+W\_{94}I\_{4}+W\_{95}I\_{5}+W\_{96}I\_{6}+W\_{97}I\_{7}}$$

$$X\_{3=θ\_{10}+W\_{101}I\_{1}+W\_{102}I\_{2}+W\_{103}I\_{3}+W\_{104}I\_{4}+W\_{105}I\_{5}+W\_{106}I\_{6}+W\_{107}I\_{7}}$$

$$X\_{4=θ\_{11}+W\_{111}I\_{1}+W\_{112}I\_{2}+W\_{113}I\_{3}+W\_{114}I\_{4}+W\_{115}I\_{5}+W\_{116}I\_{6}+W\_{117}I\_{7}}$$

$$X\_{5=θ\_{12}+W\_{121}I\_{1}+W\_{122}I\_{2}+W\_{123}I\_{3}+W\_{124}I\_{4}+W\_{125}I\_{5}+W\_{126}I\_{6}+W\_{127}I\_{7}}$$

$$X\_{6=θ\_{13}+W\_{131}I\_{1}+W\_{132}I\_{2}+W\_{133}I\_{3}+W\_{134}I\_{4}+W\_{135}I\_{5}+W\_{136}I\_{6}+W\_{137}I\_{7}}$$

$$X\_{7=θ\_{14}+W\_{141}I\_{1}+W\_{142}I\_{2}+W\_{143}I\_{3}+W\_{144}I\_{4}+W\_{145}I\_{5}+W\_{146}I\_{6}+W\_{147}I\_{7}}$$

$$X\_{8=θ\_{15}+W\_{151}I\_{1}+W\_{152}I\_{2}+W\_{153}I\_{3}+W\_{154}I\_{4}+W\_{155}I\_{5}+W\_{156}I\_{6}+W\_{157}I\_{7}}$$

$$X\_{9=θ\_{16}+W\_{161}I\_{1}+W\_{162}I\_{2}+W\_{163}I\_{3}+W\_{164}I\_{4}+W\_{165}I\_{5}+W\_{166}I\_{6}+W\_{167}I\_{7}}$$

In matrix notation, the equation 2 can be written as in (3):

 $\left\{\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}X\_{1}\\X\_{2}\end{array}\\X\_{3}\end{array}\\X\_{4}\end{array}\\X\_{5}\end{array}\\X\_{6}\end{array}\\X\_{7}\end{array}\\X\_{8}\end{array}\\X\_{9}\end{array}\right\}=\left\{\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}θ\_{8}\\θ\_{9}\end{array}\\θ\_{10}\end{array}\\θ\_{11}\end{array}\\θ\_{12}\end{array}\\θ\_{13}\end{array}\\θ\_{14}\end{array}\\θ\_{15}\end{array}\\θ\_{16}\end{array}\right\}+\left[\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}w\_{81} w\_{82}w\_{83} w\_{84} w\_{85}w\_{86} w\_{87}\\w\_{91} w\_{92} w\_{93} w\_{94} w\_{95} w\_{96}w\_{97}\end{array}\\w\_{101}w\_{102}w\_{103}w\_{104}w\_{105}w\_{106}w\_{107}\end{array}\\w\_{111}w\_{112}w\_{113}w\_{114}w\_{115}w\_{116}w\_{117}\end{array}\\w\_{121}w\_{122}w\_{123}w\_{124}w\_{125}w\_{126}w\_{127}\end{array}\\w\_{131}w\_{132}w\_{133}w\_{134}w\_{135}w\_{136}w\_{137}\end{array}\\w\_{141}w\_{142}w\_{143}w\_{144}w\_{145}w\_{146}w\_{147}\end{array}\\w\_{151}w\_{152}w\_{153}w\_{154}w\_{155}w\_{156}w\_{157}\end{array}\\w\_{161}w\_{162}w\_{163}w\_{164}w\_{165}w\_{166}w\_{167}\end{array}\right]\left\{\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}\begin{array}{c}I\_{1}\\I\_{2}\end{array}\\I\_{3}\end{array}\\I\_{4}\end{array}\\I\_{5}\end{array}\\I\_{6}\end{array}\\I\_{7}\end{array}\\I\_{8}\end{array}\\I\_{9}\end{array}\right\}$

 {x}={θ}+[w]{I} (3)

Where: Where : I1=[It] Inflow (m3/sec); I2=[It-1] Inflow (m3/sec) initial void ratio; I3=[It-2] Inflow (m3/sec);I4= [Ot-1] Outflow (m3/sec); I5=[St] Storage (m3); I6=[Et] Evaporation (m3) and I7=[Rt] Rainfall (m3) .

 Figure 7. Structure of the ANN optimal model.

 Table 4. Weights and threshold



 It should be noted that, before using Equation 3, all input variables (i.e. [It] Inflow (m3/sec), [It-1] Inflow (m3/sec) initial void ratio, [It-2] Inflow (m3/sec), [It-1] Outflow (m3/sec), [St] Storage (m3), [Et] Evaporation (m3) and [Rt] Rainfall (m3) ) need to be scaled between 0.0 and 1.0 using (1) and the data ranges in the ANN model training (see Table 1). It should also be noted that the predicted value of Outflow (m3/sec) obtained from (2) is scaled between 0.0 and 1.0 and in order to obtain the actual value this collapse potential has to be re-scaled using (1) and the data ranges in Table 1. The procedure for scaling and substituting the values of the weights and threshold levels from Table 4, Equations 2 and 3 can be rewritten as in (4):

$O\_{t=\frac{1947}{1+e^{(-1.074+2.347tanhX\_{1}+4.378tanhX\_{2}-3.727tanhX\_{3}+7.077tanhX\_{4}+2.918tanhX\_{5}+1.415tanhX\_{6}-6.885tanhX\_{7}-3.719tanhX\_{8}-1.555tanhX\_{9}}}+115}$ (4)

And

$X\_{1}=29.475+10^{-6}(-915I\_{t}+2949I\_{t-1}+4565I\_{t-2}-20000O\_{t-1}+0.000535S\_{t}-0.000124E\_{t}+0.21803R\_{t}$) (5)

$X\_{2}=-6.615+10^{-6}(-3001I\_{t}+4085I\_{t-1}-454I\_{t-2}-266O\_{t-1}+0.000189S\_{t}+0.05726E\_{t}+0.00887R\_{t})$ (6)

$X\_{3}=0.367+10^{-6}(-9541I\_{t}+2699I\_{t-1}-2194I\_{t-2}+1200O\_{t-1}-0.000823S\_{t}+0.03587E\_{t}-0.005R\_{t})$ (7)

$X\_{4}=-0.893+10^{-6}(2045I\_{t}+3068I\_{t-1}-14653I\_{t-2}+8430O\_{t-1}-0.0002543S\_{t}-0.00973E\_{t}-0.001705R\_{t})$ (8)

$X\_{5}=3.285+10^{-6}(-10941I\_{t}-758I\_{t-1}-7620I\_{t-2}+4220O\_{t-1}+0.000047S\_{t}+0.0006E\_{t}-0.008R\_{t})$ (9)

$X\_{6}=1.7+10^{-6}(5189I\_{t}+2041I\_{t-1}+1717I\_{t-2}-1580O\_{t-1}-0.00121S\_{t}+0.03342E\_{t}-0.0175R\_{t})$ (10)

$X\_{7}=-1.312+10^{-6}(-4851I\_{t}-1425I\_{t-1}+671I\_{t-2}+7320O\_{t-1}-0.000443S\_{t}-0.0293E\_{t}-0.1128R\_{t})$ (11)

$X\_{8}=-7.035+10^{-6}(6893I\_{t}+4592I\_{t-1}-7219I\_{t-2}+4420O\_{t-1}+0.001005S\_{t}-0.05313E\_{t}-0.0905R\_{t})$ (12)

$X\_{9}=2.163+10^{-6}(4388I\_{t}-6788I\_{t-1}+240I\_{t-2}-2040O\_{t-1}-0.000479S\_{t}-0.01543E\_{t}-0.00705R\_{t})$ (13)

 Equation (4) is long and complex because it contains four independent variables. On the other hand, it can predict accurately the outflow of Mosul reservoir (Figure 9).The correlation coefficient and MAPE were 0.962 and 17.15% respectively. MAPE is the mean absolute percentage error as in [19] ,which was less than 30%.The equation length depends on the number of nodes in the input and hidden layers.

 To assess the validity of the derived equation for the dam reservoir operation, the equations can be used to predict these values on the basis of all, training, and validation data sets used. Then for evaluating resulted ANN model have been compared with those from the simulated mode. The predicted values of the Outflow, are plotted against the measured (observed) values, in Figures (8 and 9), respectively for the three data sets. It is clear from Figures (8 and 9).That the generalization capability of ANN techniques for any data set used within the range of data is used in training the ANN. The models show good agreement with the actual measurements.

 **Figure 8. Comparison of predicted and measured values of outflow**

 **,Mosul resevoir-Iraq.**

**Figure 9. Predicted vs. measured values of outflow, ( Mosul reservoir).**

**4-Conclusions:**

 In this study Artificial Neural Networks (ANNs) are used in an attempt to estimate the optimal formula that used for operation the reservoir. Feed – forward multilayer perceptions (MLPs) are used and trained with the back- propagation algorithm, for forecasting the monthly outflow (Ot) of Mosul reservoir and for a period from (1990 – 2012). An appropriate architecture of ANN model was found by trial and error (more than 1000 trials). To get the optimized weights for the ANN model, five scenarios were used, Based on the results of this study, It can be concluding the following:

 -The better results were obtained by increasing the number of neurons in the hidden layer which increased training times.

-In model architecture, larger values of learning rate and momentum rate gave larger training, testing and validation errors.

-Convert the Evaporation and Rainfall data to volume units, gave a significant impact on the outputs.

-The most effective transfer function in the hidden layers was the sigmoid function.

-The combination (scenario) of inflow (It,It-1,It-2), outflow (Ot-1), storage (St), evaporation (Et) and rainfall (Rt) was found to be the best for the reservoir operation with a coefficient of determination (0.972). This scenario improved the operation of the reservoir.

-The application of ANN technique to Mosul-Reservoir can accurately predict the monthly Outflow (release flow) and assist the reservoir operation decision and future updating.

-The predicted formula of Output flow from Mosul Reservoir can be used efficiently for estimating the missing data.

-During the dividing the available data into their subsets, to represent it statistically consistent and population, high efforts and long times were used.

-ANN model can be always be updated to obtain better results by using available new data and the real values of learning and momentum rates.

- The input for the long-term optimization in ANN model must be used as a daily data to show the peak events.

 A further issues that needs to be given some attention in the future for prediction of outflow from reservoir by ANN model, are to include seepage from the reservoir and the runoff of the catchment area around the reservoir boundary. In the development of ANN model, the output formula must be included in the model output due to high efforts and complexity which were used to predict the mathematical formula for the Outflow from the reservoir and further studies must be achieve to develop a program for the randomly dividing the data set into training, testing and validation processes which were made manually, so the constraint should be simplified.

**ACKNOWLODGEMENT**

This paper is dedicated to the Memory of Mr. Hassan Al Saffar, the one and only oldest Water Resources Engineer in the Department of Water Management, Ministry of Water Resources. Authors would like to thank Assist. Prof. Dr. Hassan Ali, Water and Dams Eng. Dept. , Construction and Building Eng. Dept. for providing the infrastructural support to carry out research activity in this area. The authors also gratefully acknowledge the co-faculty members of the National Center for Water Management, Ministry of Water Resources, for their moral support to complete this manuscript.

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