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. Artificial Neural Network (ANN) model was applied for Mosul-Dam reservoir which is located on Tigris River, which 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 period of 23 years from 1990 to 2012..The Input data were inflow (I_t), evaporation (E_t), rainfall (R_t), reservoir storage (S_t) and outflow (O_t). The best convergence after more than 1000 trials was achieved for the combination of inflow (I_t), inflow (I_{t-1}), inflow (I_{t-2}), evaporation (E_t), reservoir storage (S_t), rainfall (R_t), outflow (O_{t-1}) and outflow (O_{t-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 (R^2) and MAPE were (0.972) and (17.15) 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.

تشغيل الخزان باستخدام الشبكة العصبية الصناعية (سد الموصل) كحالة دراسية

الخلاصة

يلعب التنبؤ بعملية تشغيل الخزان دورا هاما في ادارة نظم الموارد المائية. في هذه الدراسة ، تم استخدام (ANN) (الشبكات العصبية الصناعية) في محاولة للتنبؤ بالقيم الشهرية للتدفقات الخارجة من خزان سد الموصل وتخمين معادلة مثلى تستخدم في تشغيل الخزان. تم استخدام قاعدة بيانات القياسات الحقيقية لتطوير والتحقق من النماذج. طبق اسلوب التقدم الامامي متعددة الطبقات للمتحسسات (MLPS) مع خوارزمية الانتشار الخلفي المدربة بنجاح في العديد من مشاكل هندسة الموارد المائية. تم استخدام مجموعة البيانات لمدى 23 سنة تغطي (1990-2012) وكانت بيانات المدخلات (I_t)، التبخر (E_t)، سقيط المطر (R_t)،ومخزون الخزان (S_t) والمياه الخارجة (O_t).تم التوصل الى افضل تقارب بعد اكثر من 1000 محاولة لمجموعة من تدفق (I_t) ، تدفق (I_{t-1}) ، تدفق (I_{t-2})، التبخر (E_t)، مخزون الخزان (S_t) ، سقيط المطر (R_t) ، تدفق (O_{t-1}) وتدفق (O_{t-2}) مع مجال الخطأ ، ومعدل التعلم ، ومعدل قوة الزخم ، عدد دورات وعدد الطبقات الخفية 0.001، 1 ، 0.9 ، 50000 ،9 على التوالي وكان معامل التحديد (R^2) وقيمة متوسط نسبة الخطأ المطلقة (MAPE) للقيم المقاسة مع قيم المحاكاة 0.972 و 17.15 على الترتيب. كذلك تم مقارنة نتائج نماذج (ANN) للتدريب والاختبار والمصادقة مع البيانات المقاسة. كانت القيم المتوقعة من الشبكات العصبية مطابقة بشكل جيد للغاية مع القيم المقاسة. ان تطبيق تقنية (ANN) يساعد في قرار تشغيل الخزان والتحديث في المستقبل ، كما انه نموذج اكتشاف مهم للبيانات الناقصة ويمكن من خلاله التنبؤ بدقة بالتدفقات الشهرية.

INTRODUCTION

Reservoir operation is a complex problem that involves many decision variables, multiple objectives as well as considerable risk and uncertainty (Oliveira R. and Loucks, D. P., 1997). 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 (Long, L. N. 2006). In operation study the aim is to optimize the reservoir volume (that is storage) for the 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 (Ismail, K. 2012).

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 (Shahram, K. G. and Huang, Y. F. 2010). Sucharit O. V. (2005) 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. Taesoon K. et al (2009) used Artificial Neural Network (ANN) for inflow forecasting of the 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 the reservoir. He concluded that All of these two models showed a good performance comparison 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 the training process through verification and calibration processes. They used the parameters of Rainfall (R_t) m^3, water level (h_t) m and Inflow (I_t). Debbarma S. et al (2011) 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 indicate 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 a correlation coefficient greater than 0.99. Wan Hussain W. et al (2012) 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 (h_t) m, river water level (h_t) m, inflow (I_t) m^3/sec, No. of gate size of opening, opening duration (T). T. S. Abdulkadir , T.S. et al (2012) carried out management of hydropower reservoirs along the 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 the 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. In this study , a 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.

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 .Mosul Dam is the largest dam in Iraq. It is 113 m in height, 3.4 Km in length, 10 m wide in its crest .At full capacity; the hydroelectric dam holds about 11.1 cubic kilometers (2.7 cu mi) of water and provides electricity to the 1.7 million residents of Mosul. The dam's main 750 megawatts (1,010,000 hp) power station contains four 187.5 megawatts (251,400 hp) Francis turbine-generators .It is ranked as the fourth largest dam in the Middle-East, measured by storage capacity. 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).

Input and Output Parameters:

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

1-Inflow rate (m^3/s)

2-Storage (m^3) , Evaporation (m^3) and Rainfall (m^3) (using area- elevation and storage elevation curves of the Mosul reservoir Fig.(2) and Fig.(3), 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).

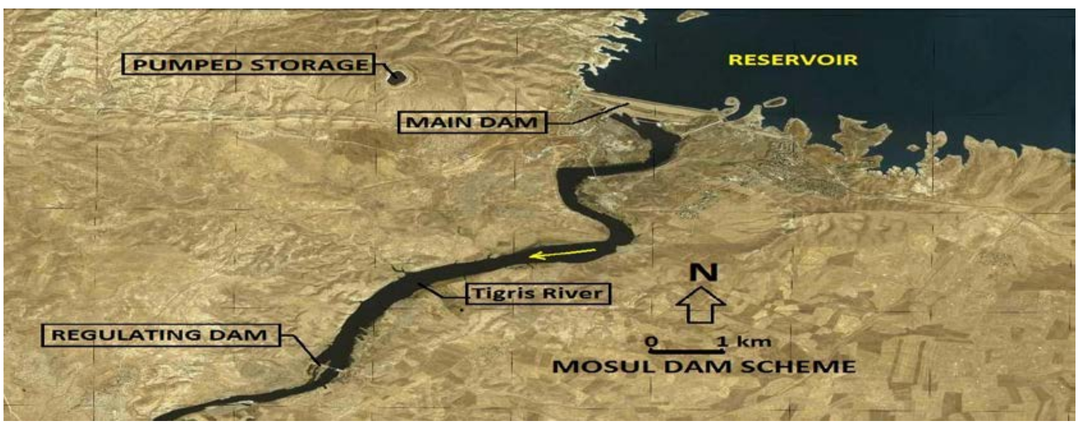
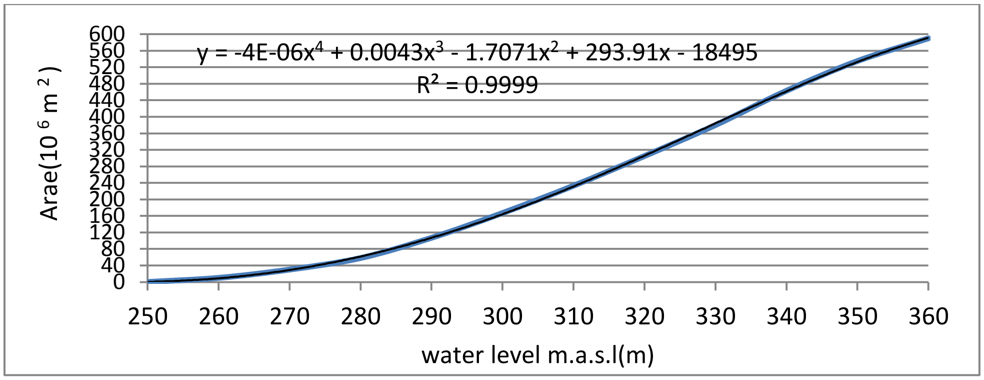
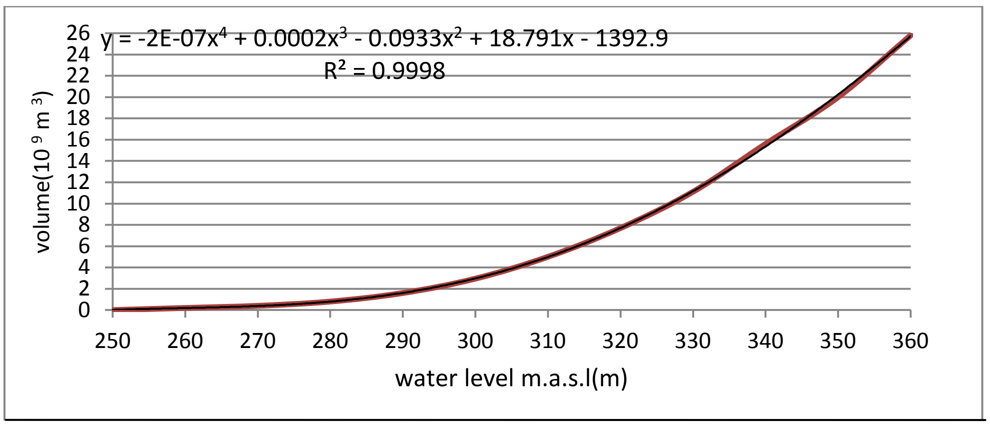


Figure (1): Mosul Dam Scheme Layout

The output of the model is monthly Outflow (m^3/s). These data were collected from Ministry of Water Resources –Iraq, (2013). The data set has a record period of 23 years from 1990 to 2012.



Figure(2): Relationship between water level and reservoir surface area .

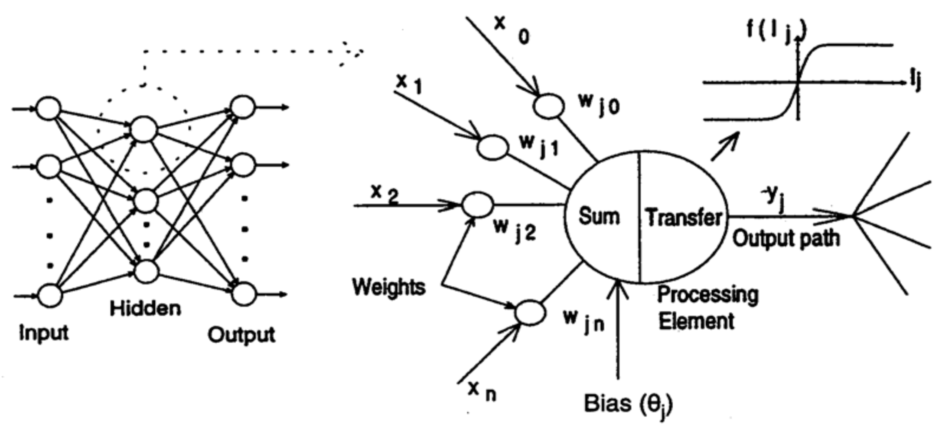


Figure(3): Relationship between water level and reservoir water volume.

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 (Ameri, S. et al 1999). 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. A broad class models that mimic functioning inside the human brain. There are various classes of ANN models and they are different from each other depending on problem types (prediction, classification, clustering), structure of the model and 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 (Brikundavyi, S. et al. 2002; Cigizoglu, H. K. 2003; Jain, A. and Indurthy, P. K. 2003; Kisi, O. 2005). 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 Fig. (4).



Figure(4): 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

into its output value. (Sigmoid (logistic) Function ($f(x) = \dfrac{1}{1+e^{-x}}$), 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% is 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, Gavin J. B. and Holger R. M.(2002). The database used for the ANN model comprises a 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, m^3/sec	78	1715
STORAGE, m^3	3.32E+09	1.09E+10
EVAPORATION, m^3	4694879	1.46E+08
RAINFALL, m^3	0	36419980
OUTFLOW, m^3/sec	115	1947

Scaling of data

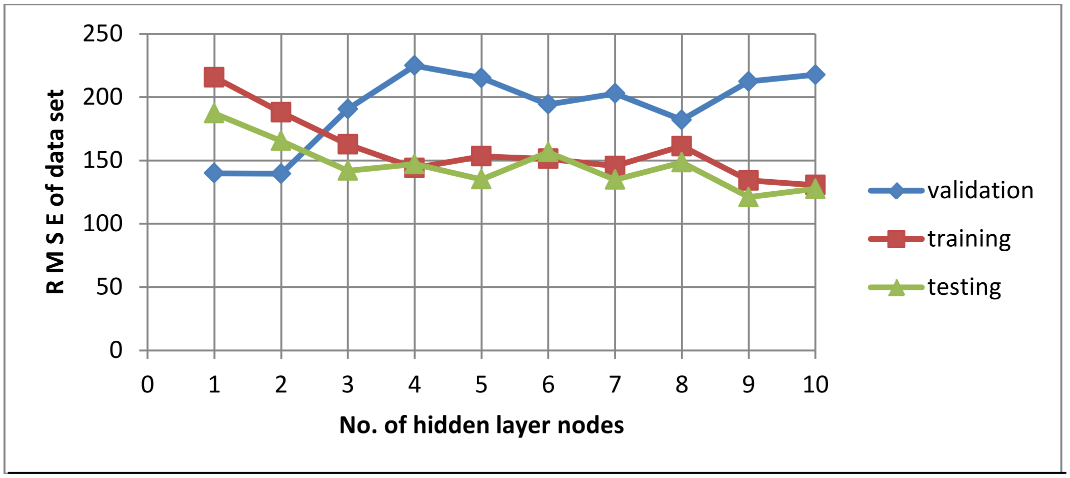
The input and output variables are pre-processed by scaling them between (0 and 1), to eliminate their dimensions and to ensure that all variables receive equal attention during training. The simple linear mapping of the variables extremes is adopted for scaling, as it is the most commonly used methods (Dandy ,G. and Maier, H 2000). As part of this method, for each variable X with minimum and maximum values of X_{min} and X_{max} respectively, the scaled value X_n is calculated as follows:

$$X_n = \frac{X - X_{\min}}{X_{\max} - X_{\min}} \qquad ...(1)$$

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 (I_t), Storage (S_t), Evaporation (E_t), Rainfall (R_t) as an Input and Output (O_t) 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 Fig. (5) and summarized in Table (2) for ANN models.



Figure(5):Performance of the ANN models with different hidden layer nodes (Learning rate = 0.8 and Momentum term = 0.8)

It can be seen from Fig. (5) 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**.** Fig. (5) shows that the network with 9 hidden layer nodes has the lowest prediction error for testing set. However, it is believed that the network with 3 hidden layer nodes is considered optimal, as its prediction error is not far from the network with 5, 7 and 10 hidden layer nodes coupled with a 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 78.131 and 91.301 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 learning term on model performance is shown graphically in Fig.(6). It can be seen that the performance of the

ANN model is relatively insensitive to momentum terms, particularly in the range 0.1 to 0.40.

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

Parameter Effect	Model No.	No. Hidden Nodes	Learning Rate	Momentum Rate	Transfer Function on Hidden Layer	Transfer Function on Output Layer	Performance Measure								
							Coefficient of Determination			RMSE			MAE		
							T	S	V	T	S	V	T	S	V
Default Parameter	MDO-1	1	0.2	0.8	Sigmoid	Sigmoid	0.7743	0.3167	0.4624	215.6881	187.1440	139.8728	160.4452	157.1729	115.8419
	MDO-2	2	0.2	0.8	Sigmoid	Sigmoid	0.8277	0.2510	0.3981	187.9581	165.3784	139.5287	146.7216	132.1209	114.4753
	MDO-3	3	0.2	0.8	Sigmoid	Sigmoid	0.8741	0.4426	0.3573	162.6429	141.9225	190.6081	122.7211	113.9243	163.3652
	MDO-4	4	0.2	0.8	Sigmoid	Sigmoid	0.9019	0.4470	0.3165	144.0784	147.0579	224.8579	115.9335	117.8216	194.4833
	MDO-5	5	0.2	0.8	Sigmoid	Sigmoid	0.8917	0.4032	0.2677	153.3215	135.0516	215.1787	121.5813	112.2399	177.1464
	MDO-6	6	0.2	0.8	Sigmoid	Sigmoid	0.8950	0.4620	0.3896	151.2788	156.5888	194.2595	113.3346	127.6818	170.3823
	MDO-7	7	0.2	0.8	Sigmoid	Sigmoid	0.9006	0.4992	0.3883	145.6221	134.8335	202.9432	114.4748	106.7901	174.1484
	MDO-8	8	0.2	0.8	Sigmoid	Sigmoid	0.8805	0.4788	0.5089	161.3023	148.4588	182.0366	118.2947	117.6964	160.4015
	MDO-9	9	0.2	0.8	Sigmoid	Sigmoid	0.9160	0.4456	0.3015	134.2042	121.0335	212.3347	105.3060	99.4541	177.9698
	MDO-10	10	0.2	0.8	Sigmoid	Sigmoid	0.9207	0.4897	0.2953	130.5746	127.5653	217.6748	102.4151	102.3011	184.5739
Momentum rate	MDO-11	10	0.2	0.1	Sigmoid	Sigmoid	0.8208	0.3375	0.4742	190.5300	190.1097	162.5991	145.7761	160.1159	140.9102
	MDO-12	10	0.2	0.2	Sigmoid	Sigmoid	0.8317	0.3654	0.4539	185.2678	179.5824	170.1132	140.6890	150.9325	148.2717
	MDO-13	10	0.2	0.3	Sigmoid	Sigmoid	0.8408	0.3831	0.4212	180.6178	0.1831	176.8264	135.5788	141.5134	154.5842
	MDO-14	10	0.2	0.4	Sigmoid	Sigmoid	0.8481	0.3965	0.3896	176.8537	159.3380	178.9541	130.8790	131.8998	155.9700
	MDO-15	10	0.2	0.5	Sigmoid	Sigmoid	0.8572	0.4248	0.3745	172.0986	149.2142	179.7707	127.1913	122.3490	156.0407
	MDO-16	10	0.2	0.6	Sigmoid	Sigmoid	0.8691	0.4713	0.3897	165.7229	140.6723	183.3180	124.1632	114.9781	159.1935
	MDO-17	10	0.2	0.7	Sigmoid	Sigmoid	0.8871	0.4993	0.4850	155.7191	148.9972	191.1864	117.4063	120.1875	168.2339
	MDO-18	10	0.2	0.8	Sigmoid	Sigmoid	0.9207	0.4897	0.2953	130.5746	127.5653	217.6748	102.4151	102.3011	184.5739
	MDO-19	10	0.2	0.9	Sigmoid	Sigmoid	0.9472	0.4679	0.1239	108.7804	159.7822	238.4194	77.2694	128.7019	185.9834
	MDO-20	10	0.2	0.95	Sigmoid	Sigmoid	0.9534	0.3904	0.2987	100.5531	301.4266	259.8811	73.4765	241.8653	208.6609
Learning rate	MDO-21	10	0.1	0.8	Sigmoid	Sigmoid	0.8692	0.4719	0.3895	166.0370	142.0606	184.3226	124.3483	116.1857	160.3495
	MDO-22	10	0.2	0.8	Sigmoid	Sigmoid	0.9207	0.4897	0.2953	130.5746	127.5653	217.6748	102.4151	102.3011	184.5739
	MDO-23	10	0.3	0.8	Sigmoid	Sigmoid	0.9450	0.4729	0.1319	109.7440	146.4524	235.8595	80.1113	119.3282	185.1361
	MDO-24	10	0.4	0.8	Sigmoid	Sigmoid	0.9471	0.4685	0.1245	107.6419	163.3289	239.0416	77.3488	131.9782	185.8933
	MDO-25	10	0.5	0.8	Sigmoid	Sigmoid	0.9464	0.4857	0.2007	108.2520	138.0478	210.2933	85.4945	115.0910	170.2387
	MDO-26	10	0.6	0.8	Sigmoid	Sigmoid	0.9363	0.5180	0.4043	117.1541	176.8877	223.7281	93.5270	136.1286	184.2564
	MDO-27	10	0.7	0.8	Sigmoid	Sigmoid	0.9372	0.4750	0.2879	116.3191	194.3592	234.9548	86.7057	157.7170	190.8587
	MDO-28	10	0.8	0.8	Sigmoid	Sigmoid	0.9520	0.3897	0.3160	102.2010	298.1776	259.1837	74.6893	239.7993	208.5825
	MDO-29	10	0.9	0.8	Sigmoid	Sigmoid	0.9560	0.2789	0.1013	97.7535	427.2913	386.7822	73.9881	329.8599	294.7662
	MDO-30	10	1	0.8	Sigmoid	Sigmoid	0.9650	0.2445	0.1250	88.1764	665.3620	252.1528	66.1084	474.8645	201.6033
Transfer Function	MDO-31	10	0.2	0.8	tanh	tanh	0.9554	0.5189	0.2053	135.3439	181.5145	217.3068	114.4252	154.8311	155.0623
	MDO-32	10	0.2	0.8	Sigmoid	tanh	0.9555	0.4285	0.0779	106.5364	112.2362	218.4697	84.8146	99.2972	165.1292
	MDO-33	10	0.2	0.8	tanh	Sigmoid	0.9631	0.4771	0.2303	90.2426	128.7389	214.3385	64.7956	101.8291	170.8846

T = Training, S= Testing, V = Validation

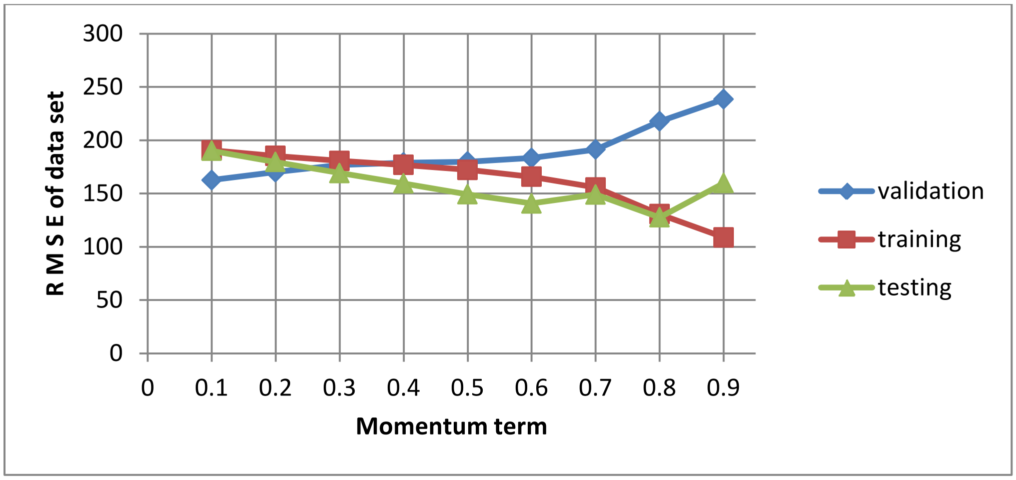
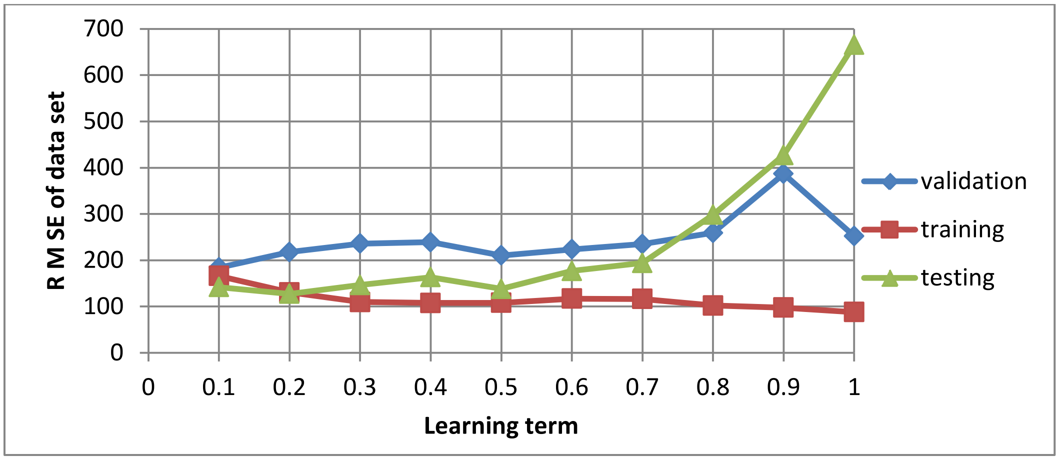


Figure (6):Effect of various momentum terms on ANN performance (Hidden nodes = 7 and learning rate = 0.8)

Fig. (7), 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 0.8 to 1.00 then the prediction errors slightly increase to certain value at 665.362. The figure indicates that the performance relatively insensitive to learning rates before value of 0.7. Thus, the optimum values for momentum term and learning rate used is 0.80 and 0.80 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.



Figure(7):Effect of various learning rates on ANN performance (Hidden nodes = 7 and Momentum term = 0.8)

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 Mosul dam reservoir operation.

input combination	error tolerance	learning rate	momentum rate	neorons in the hidden layers	coefficient of correlation	sum of squared error
senario 1(I(t) O(t) S(t) E(t) R(t))	0.001	0.8	0.8	7	0.8995	104.370
senario 2 (I(t-1) I(t) O(t) S(t) E(t) R(t))	0.001	1	0.5	9	0.9131	139.449
senario 3(I(t-2)I(t-1) I(t) O(t) S(t) E(t) R(t))	0.001	1	0.9	8	0.9638	89.585
senario 4(I(t-2)I(t-1) I(t) O(t-1) S(t) E(t) R(t))	0.001	0.9	0.9	8	0.9528	103.047
senario 5(I(t-2)I(t-1) I(t) O(t-1) O(t-2) S(t) E(t) R(t))	0.001	1	0.9	9	0.9724	78.784

It was noticed that the best convergence was achieved for the scenarios 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 by Garson (1991), 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(I_t) and Outflow(O_{t-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(I_{t-1}), Inflow(I_{t-2}) and Evaporation (E_t), Storage (S_t) and Rainfall (R_t), with a relative importance of 13.71, 13.28, 11.34, 10.84 and 10.43 % respectively. The results are also presented in Fig. (8).

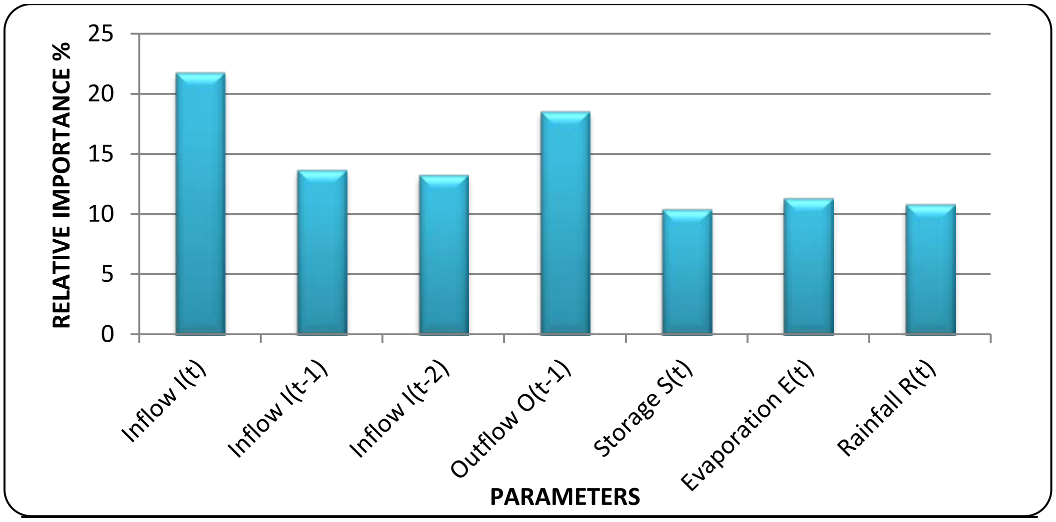


Figure (8) : Relative importance for all input parameters

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 Fig.(9), 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 follows:

$$O_t=\frac{1}{1+e^{(-1.074+2.347\tanh X_1+4.378\tanh X_2-3.727\tanh X_3+7.077\tanh X_4+2.918\tanh X_5+1.415\tanh X_6-6.885\tanh X_7-3.719\tanh X_8-1.555\tanh X_9}} \quad \text{.....(2)}$$

where:

$X_1=\theta_8+W_{81}I_1+W_{82}I_2+W_{83}I_3+W_{84}I_4+W_{85}I_5+W_{86}I_6+W_{87}I_7$

$X_2=\theta_9+W_{91}I_1+W_{92}I_2+W_{93}I_3+W_{94}I_4+W_{95}I_5+W_{96}I_6+W_{97}I_7$

$X_3=\theta_{10}+W_{101}I_1+W_{102}I_2+W_{103}I_3+W_{104}I_4+W_{105}I_5+W_{106}I_6+W_{107}I_7$

$X_4=\theta_{11}+W_{111}I_1+W_{112}I_2+W_{113}I_3+W_{114}I_4+W_{115}I_5+W_{116}I_6+W_{117}I_7$

$X_5=\theta_{12}+W_{121}I_1+W_{122}I_2+W_{123}I_3+W_{124}I_4+W_{125}I_5+W_{126}I_6+W_{127}I_7$

$X_6=\theta_{13}+W_{131}I_1+W_{132}I_2+W_{133}I_3+W_{134}I_4+W_{135}I_5+W_{136}I_6+W_{137}I_7$

$X_7=\theta_{14}+W_{141}I_1+W_{142}I_2+W_{143}I_3+W_{144}I_4+W_{145}I_5+W_{146}I_6+W_{147}I_7$

$X_8=\theta_{15}+W_{151}I_1+W_{152}I_2+W_{153}I_3+W_{154}I_4+W_{155}I_5+W_{156}I_6+W_{157}I_7$

$X_9=\theta_{16}+W_{161}I_1+W_{162}I_2+W_{163}I_3+W_{164}I_4+W_{165}I_5+W_{166}I_6+W_{167}I_7$

In matrix notation, the equation 2 can be written as follows:

$$\begin{Bmatrix} X_1 \\ X_2 \\ X_3 \\ X_4 \\ X_5 \\ X_6 \\ X_7 \\ X_8 \\ X_9 \end{Bmatrix} = \begin{Bmatrix} \theta_8 \\ \theta_9 \\ \theta_{10} \\ \theta_{11} \\ \theta_{12} \\ \theta_{13} \\ \theta_{14} \\ \theta_{15} \\ \theta_{16} \end{Bmatrix} + \begin{bmatrix} w_{81} & w_{82} & w_{83} & w_{84} & w_{85} & w_{86} & w_{87} \\ w_{91} & w_{92} & w_{93} & w_{94} & w_{95} & w_{96} & w_{97} \\ w_{101} & w_{102} & w_{103} & w_{104} & w_{105} & w_{106} & w_{107} \\ w_{111} & w_{112} & w_{113} & w_{114} & w_{115} & w_{116} & w_{117} \\ w_{121} & w_{122} & w_{123} & w_{124} & w_{125} & w_{126} & w_{127} \\ w_{131} & w_{132} & w_{133} & w_{134} & w_{135} & w_{136} & w_{137} \\ w_{141} & w_{142} & w_{143} & w_{144} & w_{145} & w_{146} & w_{147} \\ w_{151} & w_{152} & w_{153} & w_{154} & w_{155} & w_{156} & w_{157} \\ w_{161} & w_{162} & w_{163} & w_{164} & w_{165} & w_{166} & w_{167} \end{bmatrix} \begin{Bmatrix} I_1 \\ I_2 \\ I_3 \\ I_4 \\ I_5 \\ I_6 \\ I_7 \\ I_8 \\ I_9 \end{Bmatrix}$$

$$\{x\}=\{\theta\}+[w]\{I\} \qquad \text{….(3)}$$

Where:

Where : I1=[I_t] Inflow (m^3/sec); I2=[I_{t-1}] Inflow (m^3/sec) initial void ratio; I3=[I_{t-2}] Inflow (m^3/sec);I4= [O_{t-1}] Outflow (m^3/sec); I5=[S_t] Storage (m^3); I6=[E_t] Evaporation (m^3) and I7=[R_t] Rainfall (m^3) .

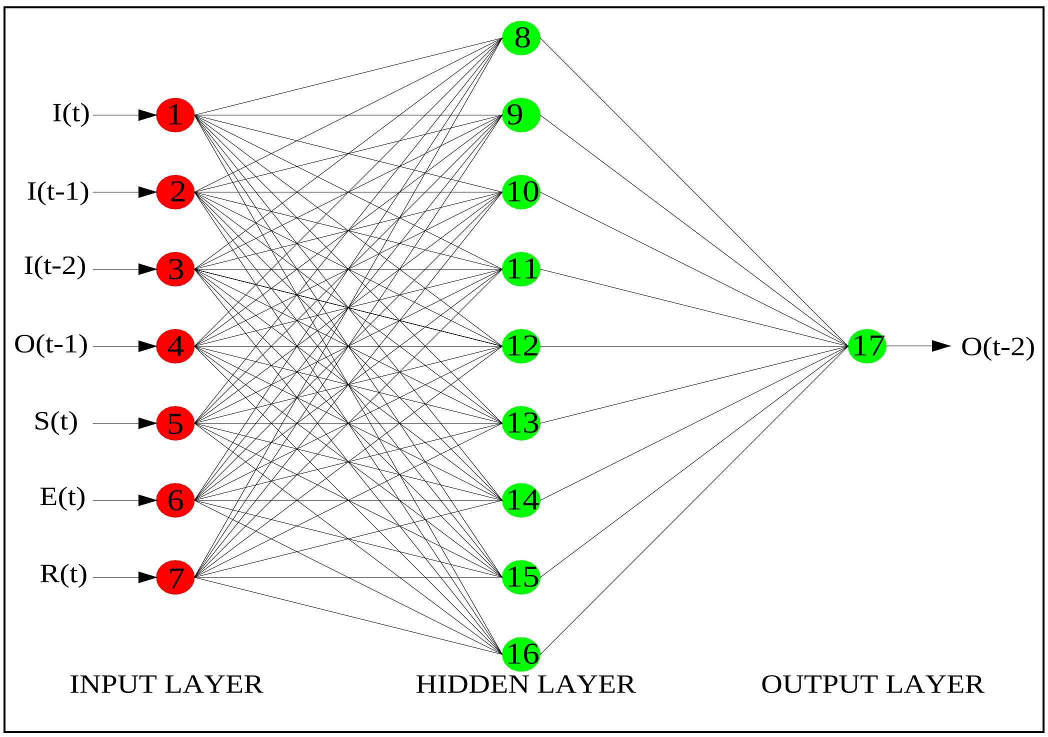


Figure (9) : Structure of the ANN optimal model.

Table (4): Weights and threshold

	HIDDEN LAYER NODES	Wji(weight from node I in the input layer to node j in the hidden layer)							hidden layer threshold θj	
		i=1	i=2	i=3	i=4	i=5	i=6	i=7		
	j=8	-1.49736	4.825626	7.471389	-36.6732	4.116524	-0.0185065	16.393471	7.6586401	
	j=9	-4.9114	6.685559	-0.74298	-0.48428	-1.45668	8.8093857	-0.667483	-6.960548	
	j=10	-15.6154	4.417037	-3.59124	2.189818	-6.32741	5.5191999	-0.379054	-0.31064	
	j=11	3.347161	5.020919	-23.9824	15.32684	-1.95612	-1.4970719	-12.81687	-0.806954	
	j=12	-17.9057	-1.24031	-12.4713	7.681157	0.351216	-0.0916794	-6.013822	2.2622505	
	j=13	8.492627	3.340372	2.809405	-2.87489	-9.30081	-5.1416082	-1.317575	1.668252	
	j=14	-7.93922	-2.33324	1.099041	13.30259	-3.40442	-4.5078332	-8.483068	-1.195907	
	j=15	11.2806	7.515908	-11.8148	8.039722	7.733287	-8.1744236	-6.806613	-6.10127	
	j=16	7.181427	-11.1096	0.393292	-3.70683	-3.68268	-2.3741103	-0.529592	1.5278134	
Output LAYER NODES	Wji(weight from node I in the Hidden layer to node j in the Output layer)									Output layer threshold θj
	i=8	i=9	i=10	i=11	i=12	i=13	i=14	i=15	i=16	
j=18	-2.34745	-4.37877	3.727251	-7.07757	-2.91839	-1.41544	6.8855013	3.7196424	1.5558293	1.074606

It should be noted that, before using Equation (3), all input variables (i.e. [I_t] Inflow (m^3/sec), [I_{t-1}] Inflow (m^3/sec) initial void ratio, [I_{t-2}] Inflow (m^3/sec), [I_{t-1}] Outflow (m^3/sec), [S_t] Storage (m^3), [E_t] Evaporation (m^3) and [R_t] Rainfall (m^3)) need to be scaled between 0.0 and 1.0 using equation (1) and the data ranges in the ANN model training (see Table 1). It should also be noted that the predicted value of Outflow (m^3/sec) obtained from Equation (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 Equation (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 follows:

$$O_t = \frac{1947}{1+e^{(-1.074+2.347\tanh X_1+4.378\tanh X_2-3.727\tanh X_3+7.077\tanh X_4+2.918\tanh X_5+1.415\tanh X_6-6.885\tanh X_7-3.719\tanh X_8-1.555\tanh X_9}}+115 \quad \ldots(4)$$

And

$$X_1 = 29.475 + 10^{-6}(-915I_t + 2949I_{t-1} + 4565I_{t-2} - 20000O_{t-1} + 0.000535S_t - 0.000124E_t + 0.21803R_t) \quad \ldots(5)$$

$$X_2 = -6.615 + 10^{-6}(-3001I_t + 4085I_{t-1} - 454I_{t-2} - 266O_{t-1} + 0.000189S_t + 0.05726E_t + 0.00887R_t) \quad \ldots..(6)$$

$$X_3 = 0.367 + 10^{-6}(-9541I_t + 2699I_{t-1} - 2194I_{t-2} + 1200O_{t-1} - 0.000823S_t + 0.03587E_t - 0.005R_t) \quad \ldots(7)$$

$$X_4 = -0.893 + 10^{-6}(2045I_t + 3068I_{t-1} - 14653I_{t-2} + 8430O_{t-1} - 0.0002543S_t - 0.00973E_t - 0.001705R_t) \quad \ldots(8)$$

$$X_5 = 3.285 + 10^{-6}(-10941I_t - 758I_{t-1} - 7620I_{t-2} + 4220O_{t-1} + 0.000047S_t + 0.0006E_t - 0.008R_t) \quad \ldots.(9)$$

$$X_6 = 1.7 + 10^{-6}(5189I_t + 2041I_{t-1} + 1717I_{t-2} - 15800_{t-1} - 0.00121S_t + 0.03342E_t - 0.0175R_t) \quad ....(10)$$

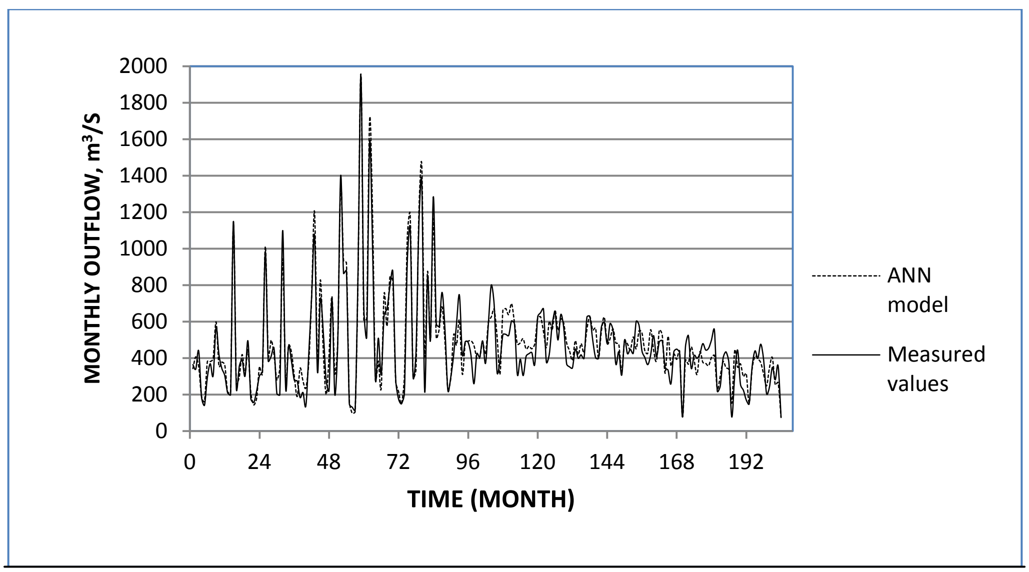
$$X_7 = -1.312 + 10^{-6}(-4851I_t - 1425I_{t-1} + 671I_{t-2} + 73200_{t-1} - 0.000443S_t - 0.0293E_t - 0.1128R_t) \quad ....(11)$$

$$X_8 = -7.035 + 10^{-6}(6893I_t + 4592I_{t-1} - 7219I_{t-2} + 44200_{t-1} + 0.001005S_t - 0.05313E_t - 0.0905R_t) \quad ....(12)$$

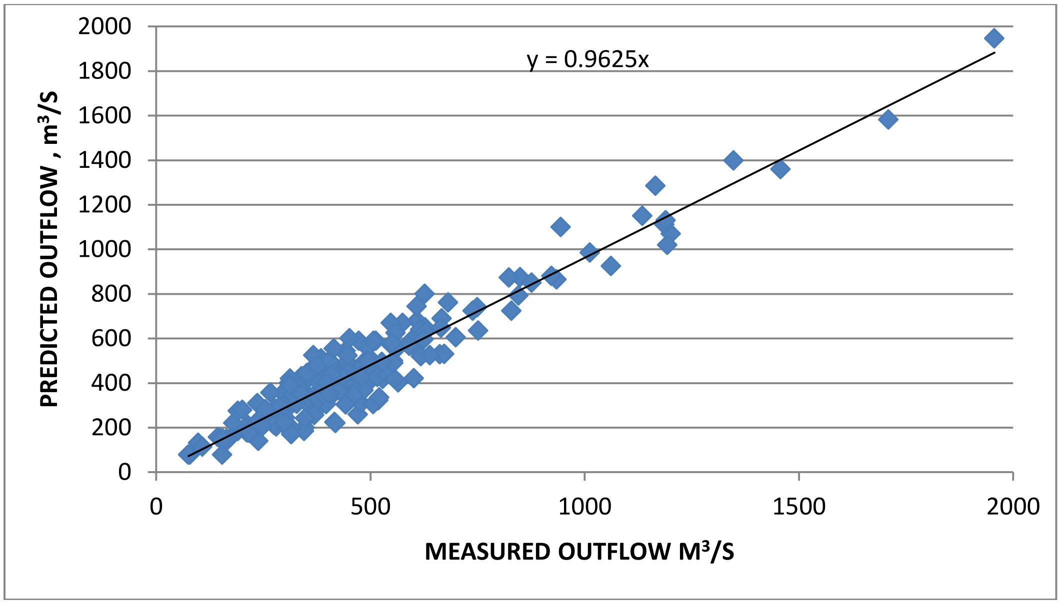
$$X_9 = 2.163 + 10^{-6}(4388I_t - 6788I_{t-1} + 240I_{t-2} - 20400_{t-1} - 0.000479S_t - 0.01543E_t - 0.00705R_t) \quad ....(13)$$

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 (Fig.(10)).The correlation coefficient and MAPE were 0.962 and 17.15% respectively. MAPE is the mean absolute percentage error, Sabah, S. F. and Ahmed; S. (2011) 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 (10 and 11), respectively for the three data sets. It is clear from Figures (10 and 11).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(10): Comparison of predicted and measured values of outflow ,Mosul resevoir-Iraq.



Figure(11) : Predicted vs. measured values of outflow, (Mosul reservoir).

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 (O_t) 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:

-In model architecture, larger values of learning rate and momentum rate gave the 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 the 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.
-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 the 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 done manually, so the constraint should be simplified.

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