OGRIGINAL ARTICLE

MODELING OF THE RELATION BETWEEN RUNOFF AND CLIMATIC PARAMETERS IN ALKABEER ALJANOBEE CATCHMENT IN SYRIA BY USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

Background: Rainfall_Runoff modeling is necessary for hydrologic and hydraulic engineering design, integrated management of water resources, and forecasting flood. **Objectives**: The Objectives of this research was to build amodel of the relation between the runoff and the climatic parameters (rainfall, evaporation, temperature, relative humidity) in Alkabeer Aljanobee river in Syria by using artificial neural networks (ANN). **Methods**: Two type of dynamic neural networks were used, the first type is Focused Time _Delay Neural network (FTDNN), and the second type is NARX network (nonlinear autoregressive exogenous model). Also, Twenty four models were tested, each model had different combinations of inputs with time steps delaystake place in space [0 -3] days, in addition to historical values of runoff with time steps delaystake place in space [-1 -3] days. **Results:** This study reached to that the model which has input layer consists of rainfall, temperature, evaporation, relative humidity at time t=0 through t=-3, in addition to previous runoff at time t=-1 through t=-3, gives the best performance of formed neural networks. The architecture (19-25-1) (19 neurons in input layer and 25 neurons in hidden layer and one neuron in output layer) gives the smallest value of mean squared error (MSE)6.23*10^6, while the correlation of coefficient (R)equals 97.42 % for using data set. **Conclusions**: Thus, this research has shown the capability of using ANN in forecasting runoff depending on climatic variables and their effect on the runoff, the results have also shown that using historical runoff data improve the performance of the network very well.
***Keywords** : Rainfall_Runoff, Dynamic Neural Networks, NARX Network, FTDNN Network.*

1.INTRODUCTION

Rainfall_Runoff relationship is considered as one of the most hydrological complex and hardness phenomenon in understanding, due to the temporal variability in the catchment specification and precipitation patterns, in addition to numbers of parameters that included in the physical processes modeling [1]. Due to the importance of prediction of runoff since it is a basic element of the hydrological cycle elements, and rainfall _runoff modeling also plays an important role in optimizing, planning, and management of the water resources especially in the dry periods [2], Rainfall_runoff modeling has occupied the attention of great number of researchers.

Moradkhani and Sorooshian (2009) introduced a review paper, that presented the different methods of modeling rainfall_runoff relationship, that are lumped method and distributed method, since, this review paper presented ten papers in the applications of lumped method, and twenty papers in the distributed method applications. as well as, it presented a large number of papers, that discussed some problems such as the ways of rectifying the parameters or adjusting the model, the mathematical model of the hydrology systems and the inverse methods, calibration rainfall_runoff relationship as an optimization problem, in addition to methods that were used to solve the problem of inaccuracy in observation and parameters [3] .

The artificial neural network has proved that it is a good tool in simulation the complex processes and the nonlinear systems, which inspired the Hydrologists to use these networks in modeling rainfall_runoff relationship in different places in the world. Rajurkar (2002) used artificial neural network for modeling daily flows during the monsoon flood events for a large size catchment of the Narmada River in India. A linear multiple-input single-output (MISO) model was also coupled with the ANN to provide a better representation of rainfall-runoff relationship in such large size catchments and the result of this model was compared with the results of models of linear and nonlinear MISO. The results showed that (MISO-ANN) model provides a systematic way for forecasting of runoff and improving the accuracy forecast of the runoff for linear and nonlinear MISO model [4].

Also, a study made by Chandwani et al. (2015) presented a number of papers that used one of the following soft computing techniques viz., artificial neural network, genetic algorithms, and fuzzy logic and their application in rainfall-runoff modeling. this paper presented three papers in describing the artificial neural networks, in addition to eleven papers in their applications in rainfall-runoff modeling, as well as, it presented two papers in describing the genetic

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algorithms and five papers in their applications in rainfall-runoff modeling, it also showed three papers in describing the fuzzy logic and four papers in its applications in rainfall-runoff modeling, in addition to five papers in the application of the hybrid system among these techniques in modeling rainfall_runoff relationship. This study showed how artificial neural network learn from experiences or historical data, that made it able to describe functional relationships between rainfall and runoff. While, the genetic algorithm depend on its stochastic research ability for calibrating the rainfall_runoff models. Also, the fuzzy logic emulation of human reasoning and decision making ability can be exploited for modeling problems governed by imprecise information. The paper also presented the importance of hybrid soft computing techniques and its ability in covering up the limitations of the individual methods, thus opens up the avenues for solving new problem [5].

Artificial neural network model was used by several researchers for modeling rainfall_runoff relationship, since, all these studies have reached to the ability of using artificial neural network in modeling this process, and that it is a promising tool in flood forecasting [6,7,8,9,10,11]. Also, many studies proved the superiority of the artificial neural network on the traditional modeling methods [12,13] and on HEC-HMS model [14].

Different types of artificial neural network were used by many studies for modeling rainfall_runoff relationship in different places in the world, like, feed forward back propagations (FFBP), Radial Basis Function(RBF), Recurrent Neural Network (RNN), and all of them reached to that feed forward network gives results better than other network results [15,16,17,18]. Feed forward back propagation network was used for rainfall_runoff modeling by using different training algorithms in the arid areas in Iran [19]. While a study made by Kouk and Nabil (2011) have proved that Recurrent neural network performs slightly better than multilayer perceptron in modeling of the rainfall_runoff relationship in Sungai Bedup Catchment [20]. Alok, Patra, and Das (2013) also suggested in a study made by them for modeling the rainfall_runoff relationship in Brahmani River in India, considering the artificial neural network as a tool of prediction of runoff, since the researcher used two kinds of networks viz., Elman network and Cascade network [21].

Modarres (2009) Also used the artificial neural network for modeling rainfall_runoff in Plasjan basin in the western region of the Zayandehrud watershed, Iran. Thees researcher applied 17 global statistics and 3 additional non-parametric tests to evaluate the ANNs. The study showed that the multilayer perceptron with 4 hidden layers (MLP4) is the best ANN comparing with other MLP networks and empirical regression model [22].

Also, in the study made by Arslan (2011) for modeling rainfall_runoff relationship in KhasaChai basin, twelve model structure were developed with different number of neurons in the hidden layer to investigate the probability impacts of enabling /disabling rainfall-runoff, rainfall, average air temperature,evaporation ,humidity. The researcher reached to that the network which contains nine hidden neurons and nine inputs gives the best performance, depending on the correlation of coefficient and mean squared error in validation stage [23].

2. MATERIALS AND METHODS

2.1 Artificial Neural Network:

Artificial Neural Network is one of the most important method of artificial intelligence fields, Which reflects an important and significant development in the way of human thinking, the idea of ANN talks about simulating the human mind by using the computer, where it is defined as a system for building the information, it has certain properties in similar performance with biological neural networks [24]. Since, ANN have been developed as generalizations of mathematical models of human cognition method and how the nerves process the information [25]. Neuron is considered the base building block for artificial neural network, and it can also be referred to as processing element or node [26]. Theses neurons arrange in layers and each Neuron in certain layer connect with all Neurons in the next layer. 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.The simple model of artificial neural network formed of complex block of processing elements called neurons have the ability to procedure mathematical process [24].

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) [27].Where, the result of the process of updating the weights is called learning process.

In general, artificial neural networks are classified to dynamic and static; the static networks don't have tapped delay lines in input layer and don't have recurrent connections, so the output is calculated directly from the input through feed forward connections. In dynamic networks, the output doesn't depend on the present inputs of the network, but it also depends on the present and previous inputs and outputs [28].

In this study, two types of dynamic networks had been used:

- Focused Time _Delay Neural network (FTDNN) [29]: is the most straightforward dynamic network. These networks are feed forward networks with tapped delay lines at the input, in which the dynamics appears at the input layer of a static multilayer feed forward networks. These networks is considered fitting for forecasting of time series. It's defined by Eq.(1):

$$y(t) = f\big(x(t-1), \ldots \ldots . . x(t-d)\big)(1)$$

Where: $y(t)$ is the output of the network at time t; X(t-1 is the input at time t-1; d is the delay in time.

- NARX network [29]: is a recurrent dynamic network. NARX model is based on the linear ARX model, which is commonly used in time series modeling. NARX network is defined by Eq.(2):

$$Y(t) = f(y(t-1), y(t-2) \ldots . ., y(t-d), \ldots \ldots . . ., x(t-1), x(t-2), \ldots . ., x(t-d)) \ (2)$$

The next value of the output signalis dependedon the previous values of the output signal and previous values of the independent input signal.

These networks have many applications. It can be used as a predictor, in order to predict the next value of the input signal. There are two types of the NARX network, the first type uses the output of the network to fed back the input of the feed forward network, so these networks are used for forecasting of multistep time series. While the second type of NARX network depends on the true output values during training the network instead of feeding backthe estimated output. In this study, the second type of NARX network had been used.

2.2 Study site: For reaching to the research goal, daily time series have been used for rainfall (R), evaporation (E), temperature (T), relative humidity (RH) and discharge variable (Q), the discharge was measuredat the outlet of Alkabeer Aljanobee Catchment which forms a part of the Syrian coast, It also forms the northern board of Lebanon with Syria. It locates in the south of Tartous between two latitudes (34°25`0``) and (34°50`0``) north and two longitudes(35°55`0``) and (36°30`0``) east. The observation period extends from 2004 to 2008, and the rainfall measurement is collected from three stations distributed\ in the catchment, they are (Khalefa station, TlHosh station, Alregbalea station), and the Weighted average is calculated by Thiessen polygons method.

2.3 Data Scaling: Before exporting the data to the artificial networks, they were scaled (i.e. the data values are limited within certain range [0 1] according to Kumare method), that for reducing the error value between network output and the real output and reaching to the optimum solution quietly. So, the whole data was scaled by using Kumare method [30], as per clarified in Eq.(3):

$$p_{(norm)} = 0.5\left[\frac{(p - p_{(mean)})}{p_{(max)} - p_{(min)}}\right] + 0.5(3)$$

Where: P is the original value, p(norm) is the scaled value, p(mean) is the average value, p(min) is the minimum value, p(max) is the maximum value.

2.4 Statistics: The comparison between different models was done by using two statistical indices:

- Mean Squared Error (MSE), that is defined as Eq.(4):

$$MSE = \frac{1}{2 \cdot q}\sum_{i=1}^{i=q}(Yi - a_2)^2(4)$$

  Where: Yi is the observed Q, a_2 is the output of the network, q is the number of observations.
- The coefficient of correlation (R), that is defined as Eq.(5):

$$R = 1 - \sqrt{\frac{\sum_{i=1}^{i=q}(Yi - a_2)^2}{\sum_{i=1}^{i=q}(Yi - \overline{Y})^2}}(5)$$

Where$\overline{Y}$ is the averagevalue of Yi

3. RESULTS

In this study, artificial neural network was formed of input layer contains different combinations of inputs. These networks were built by using MATLAB program and tool boxs (NNTOOL, NTSTOOL) that embedded by it. The number of hidden neurons was determined by experience, because there isn't a standard method in determining this number .In this study, twenty four models were tested with different numbers of neurons in hidden layer as it is shown in table (1). These models are shown the effect of several combinations of climatic variables on the performance of the artificial neural network, which is the value of runoff.

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

Model Number	Number of neurons in the Hidden layer	Model description	Type of network
1	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, Ht)$	FTDNN
2	5,10,15,20,25,30	$Q\ t=f(R_{t-1}, Ev_{t-1}, T_{t-1}, H_{t-1}, Q_{t-1})$	NARX
3	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, Ht, R_{t-1}, Ev_{t-1}, T_{t-1}, H_{t-1})$	FTDNN
4	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, Ht, R_{t-1}, Ev_{t-1}, T_{t-1}, H_{t-1}, Q_{t-1})$	NARX
5	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, Ht, R_{t-1}, Ev_{t-1}, T_{t-1}, H_{t-1}, R_{t-2}, Ev_{t-2}, T_{t-2}, H_{t-2}, Q_{t-1}, Q_{t-2})$	NARX
6	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, Ht, R_{t-1}, Ev_{t-1}, T_{t-1}, H_{t-1}, R_{t-2}, Ev_{t-2}, T_{t-2}, H_{t-2}, R_{t-3}, Ev_{t-3}, T_{t-3}, H_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3})$	NARX
7	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt)$	FTDNN
8	5,10,15,20,25,30	$Q\ t=f(R_{t-1}, Ev_{t-1}, T_{t-1}, Q_{t-1})$	NARX
9	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, R_{t-1}, Ev_{t-1}, T_{t-1})$	FTDNN
10	5,10,15,20,25,30	$Q\ t=f(Rt, Ev_t, Tt, R_{t-1}, Ev_{t-1}, T_{t-1}, Q_{t-1})$	NARX
11	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, R_{t-1}, Ev_{t-1}, T_{t-1}, R_{t-2}, Ev_{t-2}, T_{t-2}, Q_{t-1}, Q_{t-2})$	NARX
12	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, Tt, R_{t-1}, Ev_{t-1}, T_{t-1}, R_{t-2}, Ev_{t-2}, T_{t-2}, R_{t-3}, Ev_{t-3}, T_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3})$	NARX
13	5,10,15,20,25,30	$Q\ t=f(Rt, Evt)$	FTDNN
14	5,10,15,20,25,30	$Q\ t=f(R_{t-1}, Ev_{t-1}, Q_{t-1})$	NARX
15	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, R_{t-1}, Ev_{t-1})$	FTDNN
16	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, R_{t-1}, Ev_{t-1}, Q_{t-1})$	NARX
17	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, R_{t-1}, Ev_{t-1}, R_{t-2}, Ev_{t-2}, Q_{t-1}, Q_{t-2})$	NARX
18	5,10,15,20,25,30	$Q\ t=f(Rt, Evt, R_{t-1}, Ev_{t-1}, R_{t-2}, Ev_{t-2}, R_{t-3}, Ev_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3})$	NARX
19	5,10,15,20,25,30	$Q\ t=f(Rt)$	FTDNN
20	5,10,15,20,25,30	$Q\ t=f(R_{t-1}, Q_{t-1})$	NARX
21	5,10,15,20,25,30	$Q\ t=f(Rt, R_{t-1})$	FTDNN
22	5,10,15,20,25,30	$Q\ t=f(Rt, R_{t-1}, Q_{t-1})$	NARX
23	5,10,15,20,25,30	$Q\ t=f(Rt, R_{t-1}, R_{t-2}, Q_{t-1}, Q_{t-2})$	NARX
24	5,10,15,20,25,30	$Q\ t=f(Rt, R_{t-1}, R_{t-2}, R_{t-3}, Q_{t-1}, Q_{t-2}, Q_{t-3})$	NARX

In order to check the effect of each input on the performance of the network, twenty four models were developed with different numbers of neurons in the hidden layer as we mentioned before. Also, in order to achieve the fitness generalization, in which the network can be able to give good results when it is tested by using similar and no conformable inputs to the inputs that have been used in training the network, early stopping method had been used by dividing the used data collection to three sets which are, training data, validation data, and testing data.

In this study, the model of the artificial neural network of type Focused Time _Delay Neural network (FTDNN) was used for models (1, 3, 7, 9, 13, 15, 19, 21) and NARX (Series-Parallel Architecture) for the rest of the models by using a structure formed of one neuron in output layer fixed at the whole of the study, this neuron represents the runoff, and one hidden layer, in which it was found the optimum size of hidden neurons by testing several architecture of network contained different number of hidden neurons, and the Levenberg-Marquardat algorithmwas also used for training the network.

The table (2) showed the performance of the formed models, since several architecture of artificial neural networks were tested as we mentioned before, in order to reach to the best performance (the minimum value of the mean squared error). Thus, we have reached to that the network of the architecture (19-25-1) (nineteen inputs in the input layer represent temperature, relative humidity, evaporation, and rainfall at time t=0 through t=-3, in addition to previous runoff at time t=-1 through t=-3, and twenty five neurons in the hidden layer, and one neuron in the output layer represents the runoff at the time (t=0)), gives the best performance with mean squared error 6.75*10^-6 (6.93 m^3/sec, without scaling)for the three sets, and correlation of coefficient equals 98.16% for the three sets. And by comparing the performances of the networks (1, 7, 13, 19) with each others, we notice that the performance of the network improves well when the four parameters (rainfall, temperature, evaporation, and relative humidity are used with mean squared error 0.000572, while the performance of the network recedes when three parameters (rainfall, evaporation, temperature) only are used with mean squared 0.000572, and it becomes 0.00143 when rainfall and evaporation are used as inputs, then it becomes 0.00135 when rainfall is used as input, as it is cleared in the figure (1).

Table 2: The table presents the performance of the formed models

Model	Number of hidden layer	Mean Squared error MSE	The coefficient of correlation R	Type of Network
1	5	0.00115	66.6	FTDNN
	10	0.00099	72.31	
	15	0.000843	77.1	
	20	0.000785	78.82	
	25	0.00072	80.86	
	30	0.000572	85.16	
2	5	0.000175	94.35	NARX
	10	0.00011	95.37	
	15	$8.42*10^{-5}$	94.16	
	20	$4.06*10^{-5}$	92.92	
	25	$4.24*10^{-5}$	96.5	
	30	$9.06*10^{-5}$	92.44	
3	5	0.0009	66.14	FTDNN
	10	0.000884	55.81	
	15	0.000782	68.07	
	20	0.000736	70.93	
	25	0.000592	75.78	
	30	0.00052	71.67	
4	5	0.000193	94.51	NARX
	10	0.000157	94.55	
	15	0.000116	94.59	
	20	0.00012	95.78	
	25	$6.96*10^{-5}$	92.81	
	30	$4.21*10^{-5}$	94.59	
5	5	$9.05*10^{-5}$	93	NARX
	10	$4.33*10^{-5}$	96.48	
	15	$8.16*10^{-5}$	95.22	
	20	$7.6*10^{-5}$	95.25	
	25	$4.7*10^{-5}$	94.74	
	30	$8.74*10^{-6}$	94.78	
6*	5	$8.15*10^{-5}$	95.13	NARX
	10	$2.52*10^{-5}$	92.63	
	15	$2.25*10^{-5}$	95.88	
	20	$1.12*10^{-5}$	95.33	
	25	$6.23*10^{-6}$	97.42	
	30	$2.57*10^{-5}$	96.39	
7	5	0.00145	47.79	FTDNN
	10	0.00282	24.32	
	15	0.00123	36	
	20	0.00101	56.54	
	25	0.00127	54.84	
	30	0.0045	68.74	
8	5	0.000216	91.08	NARX
	10	0.000259	91.18	
	15	0.0002	89.55	
	20	0.00019	92.78	
	25	0.00017	84.47	
	30	0.000149	90.42	
9	5	0.000965	66.37	FTDNN
	10	0.000906	63.81	
	15	0.000823	60.65	
	20	0.000873	61.23	
	25	0.000859	69.26	
	30	0.000762	72.56	
10	5	$9.77*10^{-5}$	95.86	NARX
	10	$9.2*10^{-5}$	95.29	
	15	$2.63*10^{-5}$	95.56	
	20	$3.07*10^{-5}$	96.88	
	25	$2.11*10^{-5}$	90.11	
	30	$5.28*10^{-5}$	93.85	

11	5	0.000174	95.57	NARX
	10	4.28*10^-5	96.13	
	15	9.68*10^-5	93.16	
	20	0.000133	92	
	25	0.000159	80.63	
	30	0.000135	90.16	
12	5	8.64*10^-5	94.75	NARX
	10	9.04*10^-5	94.92	
	15	4.54*10^-5	96.76	
	20	5.19*10^-5	94.98	
	25	2.97*10^-5	92.32	
	30	4.63*10^-5	95.13	
13	5	0.00166	40.93	FTDNN
	10	0.00143	36.73	
	15	0.00147	40.9	
	20	0.00167	46.36	
	25	0.00162	13.95	
	30	0.003	13.18	
14	5	0.000398	89.7	NARX
	10	0.000215	91.5	
	15	0.000202	93.1	
	20	0.000167	91	
	25	0.000194	91.4	
	30	0.000172	93.88	
15	5	0.00119	53.28	FTDNN
	10	0.00108	57.34	
	15	0.000967	63.38	
	20	0.00101	62.96	
	25	0.000906	63.48	
	30	0.000984	56.98	
16	5	0.000164	95.14	NARX
	10	0.000135	92	
	15	0.000119	88.3	
	20	0.000105	94.4	
	25	0.0001	95.13	
	30	9.16*10^-5	94.13	
17	5	0.000123	94.47	NARX
	10	0.000106	95.68	
	15	8.93*10^-5	91.25	
	20	4.74*10^-5	94.73	
	25	5.1*10^-5	96.5	
	30	4.01*10^-5	94.6	
18	5	0.00013	94	NARX
	10	0.00011	94.97	
	15	8.74*10^-5	93.7	
	20	5.9*10^-5	95.59	
	25	3.85*10^-5	93.98	
	30	3.61*10^-5	94.7	
19	5	0.00243	18.75	FTDNN
	10	0.0015	42.65	
	15	0.00135	44.47	
	20	0.00151	40	
	25	0.00189	19.77	
	30	0.00137	45	
20	5	0.000215	92.12	NARX
	10	0.000274	92.71	
	15	0.000187	92.48	
	20	0.000219	92	
	25	0.000191	92.33	
	30	0.000142	86.4	
21	5	0.00106	51.03	FTDNN
	10	0.00118	44.85	
	15	0.001	65.5	
	20	0.000993	55.87	
	25	0.00098	60.12	
	30	0.000883	65.02	
22	5	0.000218	94.8	NARX

	10	0.000167	93.23	
	15	0.000141	94.2	
	20	0.000117	93.2	
	25	8.87*10^-5	94	
	30	9.04*10^-5	81.7	
23	5	0.000159	95.16	NARX
	10	0.00011	91.76	
	15	5.08*10^-5	92	
	20	2.38*10^-5	81.6	
	25	9.7*10^-5	94.34	
	30	7.84*10^-5	92.8	
24	5	0.000166	94	NARX
	10	0.000118	93.4	
	15	0.000102	92.77	
	20	9.51*10^-5	95.13	
	25	0.00013	95	
	30	3.05*10^-5	90.29	

*: the best model of the tested networks

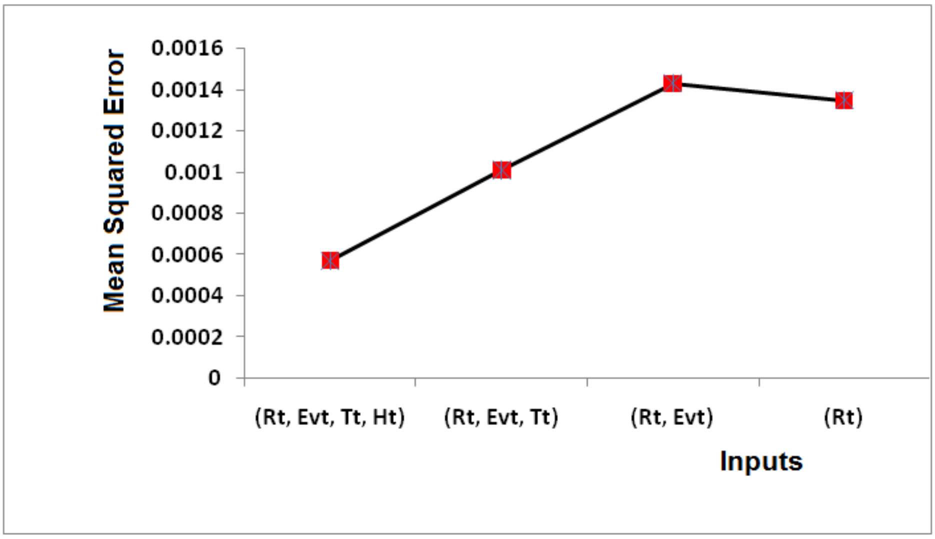

Figure 1: The figure presents the best performance of the network for the models (1, 7, 13, 19)

The formed network is transformed to block by using simulink technique that is available in Matlab programs bundle, in order to check of the performance of the formed model by calculating the error values between the field measurements and the results of the network. The figure (2) showed the formed model by using simulink technique, which couple each of the output of the network and the field value of the runoff in one block named Mux.

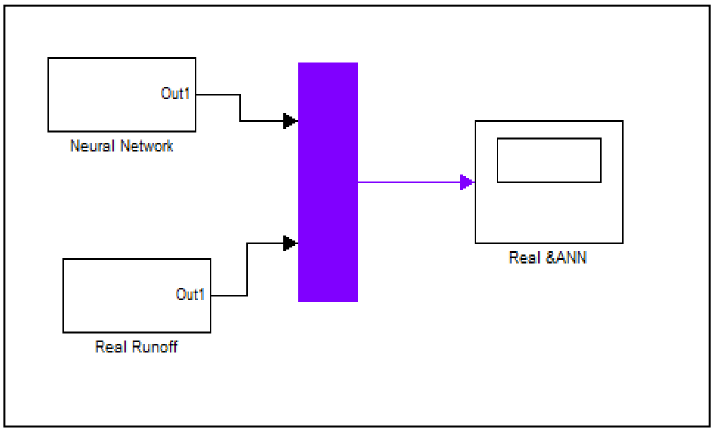

Figure 2: The figure presents artificial neural network block

Then the formed artificial neural network is tested by using testing set, that forms 15% of the data, in order to check the performance of the network and compare the output of the network with the field measurements, as it is cleared in the figure (3), and the correlation was calculated between the measured runoff values and the output of the network, as it is cleared in the figure (4).

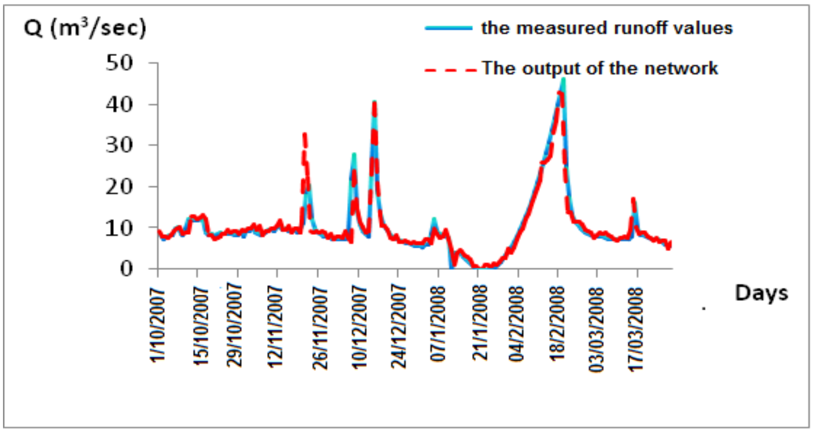

Figure 3: The figure presents the measured daily runoff values and the outputs from NARX network for testing se

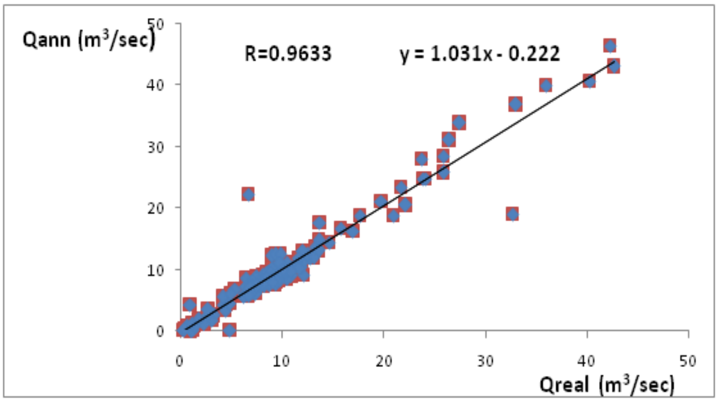

Figure 4: The figure presents the correlation coefficient between the measured daily runoff values and the output of the NARX network for testing set

4. DISCUSSION

The artificial neural network ANN models show an appropriate capability to model hydrological process. In this study, the results show clearly that the artificial neural networks have capability to model rainfall runoff relationship in Alkabeer Aljanobee Catchment, also it showed that Series-Parallel Architecture(NARX) gives performance better than Focused Time _Delay Neural network (FTDNN), in which the network gives its best performance when the four parameters are used at time step t=0 through t=-3, and at time step t=-1 through t=-3 for the runoff (the fifth model), with mean squared error equals 6.75*10^-6, which is very close to the mean squared error value (8.74*10^-6) which the fourth model reached when thirty hidden neurons are used. That showed the effect of the climatic variables on the runoff, and the importance of the historical value of the runoff for improving the performance of the network.

The result that we obtained in this research showed high precision performance, and was better than the result of a lot of researches. For example, Arslan (2011), developed twelve model structure, each one with different number of neurons in the hidden layerto investigate the probability impacts of enabling /disabling rainfall-runoff, rainfall, average air temperature, evaporation, humidity at present and lagged times .For each model the most successful structure was found depending on the value of R and the value of MSE at validation stage, he reached that the model with 9 neurons in the hidden layer (9-9-1) was the best model (R= 0.89851, MSE= 0.008713), this was due to enabling of the rainfall ,average air temperature, humidity, evaporation, at time or month t,t- 1and stream flow data at time t, resulting in improved training which promising an improved prediction [9], Modarres (2009) used six inputs which were Daily rainfall of station(1) at lag time 1-day (R1(t-1)), Daily rainfall of station(1) at lag time 2-days (R1(t-2)), Daily rainfall of station(2) at lag time 1-day (R2(t-1)), Daily rainfall of station(3) at lag time 2-days (R3(t-2)), Daily streamflow at lag time 1-day (Q(t-1)), Daily streamflow at lag time 2-days (Q(t-2)), and one output which was streamflow discharge of the Plasjan River (Qt) at the outlet of the basin (RMSE= 97.15 (MSE=9438.12), R^2=0.9635 (R=0.928)), in which multi-layer perceptron was used in this study [22]. Also, Cigizogluil et al. (2007), used three ANN methods for rainfall-runoff modelling of Turkish hydrometeorologic data, the first type was feed forward back propagation (FFBP) (61 m^3/sec, R^2=0.74 (R=0.86)) and the second type was radial basis function (RBF)(88.1055 m^3/sec R^2=0.29 (R=0.53)), and the third type was generalized regression neural network (GRNN) (107.55 m^3/sec, R^2=0.61 (R=0.78), for testing beriod [16].While in our research MSE equals 4.95 m^3/sec and R equals 0.965, for testing period,also, It is noticed that there is correspondence in performance between the results of the network and the measured values of the runoff for tested data.

The best artificial neural network that we obtained can predict of the daily runoff in Alkabeer Aljanobee Catchment depending on climatic variables, and to make this model able to predict the daily runoff in other places, that have the climatic conditions similar to Alkabeer Aljanobee conditions, we canupdate our network by using the new data for high precision prediction, also if the data aren't available we can use the same network that we obtained to predict the daily runoff in these new places with acceptable accuracy.

5. CONCLUSION

This research presents that:

- ☒ The formed network clearly performances better at using conjoint combinationof climatic variables contains each of temperature, relative humidity, evaporation, and rainfall compared with other combinations that contain some of these variables.
- ☒ NARX (Series-Parallel Architecture) network gives better performance than(Focused Time _Delay Neural network (FTDNN)) network, thus, using historical runoff values in forecasting of featurism runoff values will increase the accuracy of the network performance.
- ☒ There is liner correlation between the output of NARX network and the measured runoff data with correlation of coefficient equals 92.085%, that refers to the capability of using this technique in forecasting of the featurism runoff values in Alkabeer Aljanobee Catchment.
- ❖ It is recommended to use different combinations of the climatic variables and parameters in modeling rainfall_runoff relationship, that contain each of temperature, relative humidity, evaporation, wind, solar radiation, rainfall, land use coefficient, type of soil, and underground flow.
- ❖ It also suggests using NARX network from type (Parallel Architecture) in modeling the relation between the climatic variables and the runoff, then comparing the performance of this network with the performance of NARX (Series-Parallel Architecture) network in modeling this relationship.

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