Journal of Agricultural Science and Engineering
Vol. 6, No. 2, 2020, pp. 17-25
http://www.aiscience.org/journal/jase
ISSN: 2381-6821 (Print); ISSN: 2381-6848 (Online)

Application of Artificial Neural Networks (ANNs) Based Rainfall-Runoff Model for Flood Forecasting

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Abstract

Artificial neural networks (ANNs) are Soft computing models usually used to emulate the processes of the human nervous system in order to reach successful solutions for the complicated problems in the various fields of sciences and recently, have been widely applied in hydrological modeling. In this study, an ANN was used to model the rainfall-runoff relationship, precisely, to forecast daily runoff as a function of daily precipitation, and self-adjust training was done to produce consistent response with observed outputs. Eight years of input data were divided into two sets as three years (1992-1994) for calibration/training and five years (1995-1999) for validation/testing, collected from catchment located Longyan - China. The two data sets were used to minimize the error and avoiding the overtrained of ANN employed. The ANN rainfall-runoff model assessed and compared with results obtained using existing techniques including coefficient of determination (R^2) and error in volume (VE) as simple linear (black box) model. As an expected for the data used in training and testing, a good matching is obtained in the present case between observed runoff and those computed by ANN model. The obtained results of R^2 and VE prove a success and optimality of ANN model to predict the study catchment runoff from rainfall observed data with fairly high precision performance.

Keywords

Artificial Neural Network, Catchment, Calibration, Validation, Linear Model, Rainfall-runoff Modeling

Received: May 6, 2020 / Accepted: June 4, 2020 / Published online: July 7, 2020

1. Introduction

The application of artificial neural networks (ANNs) to various aspects of hydrological modeling was increased in last period in recent years maybe that is indicated for the model successful [1, 2]. This interest has been motivated by the complex nature of hydrological systems and the ability of ANNs to model non-linear relationships [3, 4]. Although deterministic models strive to account for all physical and chemical processes, their successful employment may be restricted by a need for catchment-specific data and the simplifications involved in solving the governing equations. The use of time-series methods may be complicated by non-stationarity and non-linearity in the data, requiring experience and expertise from the modeller [5]. ANNs offer a relatively quick and flexible means of modelling, and as such applications of ANN modelling are widely reported in hydrological literature [6, 7, 8]

The process of transformation of rainfall into runoff over a catchment is very complex, highly nonlinear, and exhibits both temporal and spatial variability. Many models have been developed to simulate this process. These can be categorized as empirical black box,

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conceptual, and physically based distributed models. Each of these types of models has its own advantages and limitations. Many situations in practice demand use of simple tools such as the linear system theoretic models or black box models. The unit hydrograph is a well known example of this. However, these simpler models normally fail to represent the non-linear dynamics, which are inherent in the process of rainfall-runoff transformation. The adoption of the Artificial Neural Network (ANN) technique for rainfall-runoff modeling has added a new dimension to the system theoretic modeling approach and it has been applied in recent years, as a successful tool to solve various problems concerned with hydrology and water resources engineering [9, 10].

2. Background of the Study Area (Catchment)

The study area is Longyan city, located in Fujian province in the west of china. Longyan city bounded by longitude 115 ° 51 'to 117 ° 45', latitude 24 ° 23 'to 26 ° 02'. The total area of the city 19056 km^2, accounting for 15.7% of the province's land area (Figures 1 and 2). The city consist many rivers as Tingjiang, Jiulong and Minjiang River. The main rivers are Tingjiang and Jiulong River. Rivers city are mountainous areas. Rainfall is the main source of rivers runoff. The city is located in humid areas, the annual runoff coefficient between 0.52-0.62, the multi-year average runoff 994 mm, similar to spatial and temporal distribution of precipitation.

Figure 1. Map of china with different provinces.

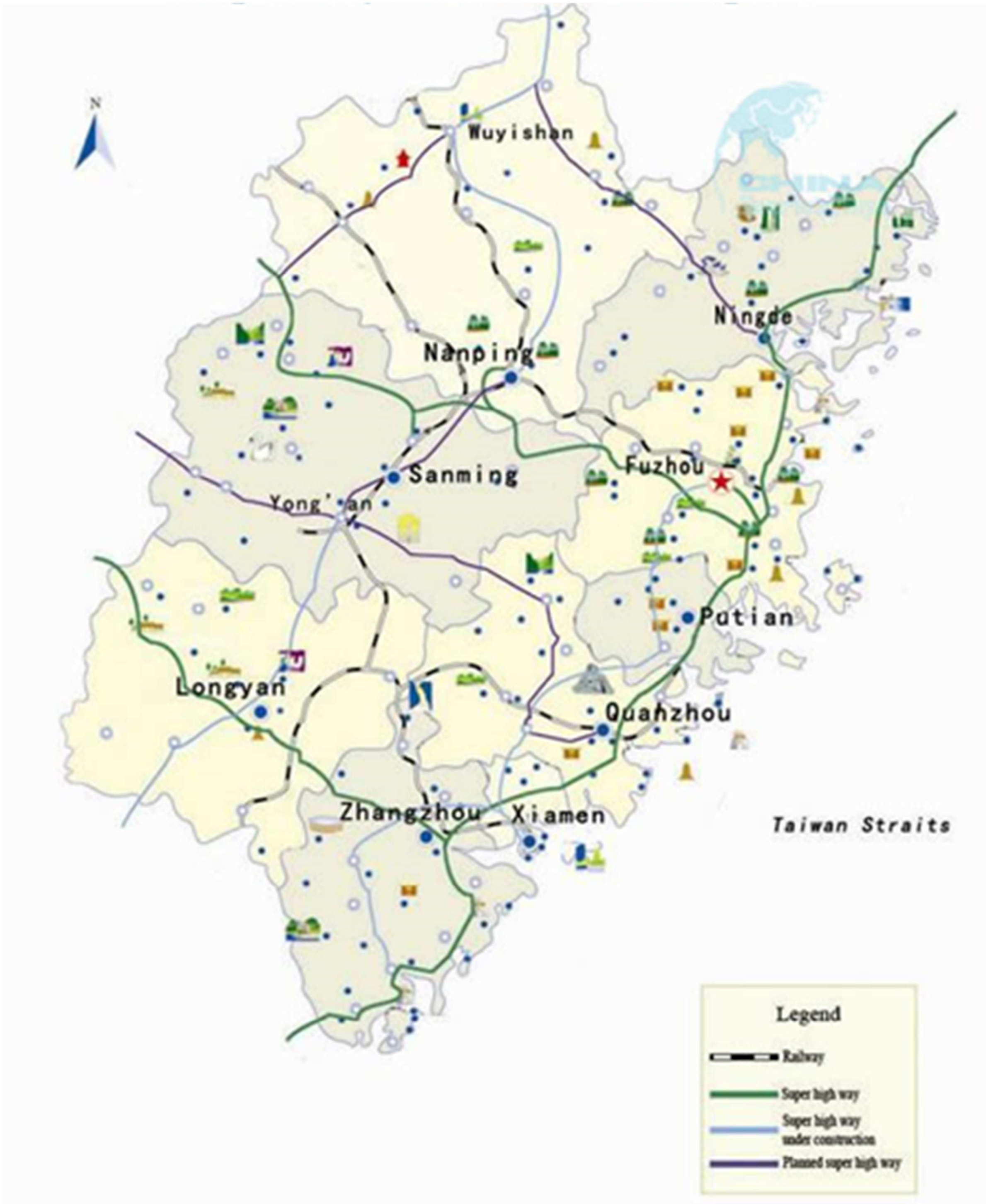


Figure 2. Map of Fujian province and the cities.

3. Rainfall – Runoff Data

The data were collected daily from five meteorological stations in the catchment area for eight years from (1992 – 1999) and divided for two sets three years for calibration/training and five years for validation/testing. The rainfall – runoff data were normalized in the range (0.1 and 0.9) data to accelerate the procedures of the artificial neural network model during the performance of training and testing processes of network, by the following equation:

$$X_{norm} = 0.1+0.8(X_i/X_{max}) \tag{1}$$

Where X_{norm} is the normalized dimensionless variable, X_i is the observed value of the variable and X_{max} is the maximum value in the data set. The logistic sigmoid transfer function can accept X_{norm} values in the range [0, 1]. Thus, the X_{norm}

values calculated as per Eq. (1) remain within this range while X_i (validation) < or = 1.1 X_{max} (training).

4. Methodology

Artificial neural networks are parallel computing systems whose original development was based on the structure and function of the brain. Feed-forward ANNs comprise a system of units, analogous to neurons, which are arranged in layers. Between the input layer and output layer there may be one or more hidden layer. The units in each layer are connected to the units in a subsequent layer by a weight w, which may be adjusted during training. A data pattern comprising the values xi presented at the input layer, i is propagated forward through the network towards the first hidden layer j. Each hidden unit receives the weighted outputs wjixi from the units in the previous layer. These are summed to produce a net value, which is then transformed to an output value upon the application of an activation function. Prior to its application as a model the ANN must be trained [11].

The ANN model implementation was carried out using the MATLAB routines. The connection weights, threshold and the number of neurons in the hidden layer, which can be interpreted as the model parameters, were adjusted during the calibration or training process through minimization of the mean square error (mse) using the Traingdx function in MATLAB which is based on the gradient descent method using the error back-propagation algorithm. For each ANN configuration the training procedure was repeated starting from independent initial condition ultimately ensuring selection of the best performing network. The trend of decrease in the mse in the training and testing sets was used to decide optimal learning. The training was stopped when the mse over the testing set started rising instead of reducing even though the mse over the training set continued to reduce. This is an indication of the network getting overtrained [12].

5. Results and Discussions

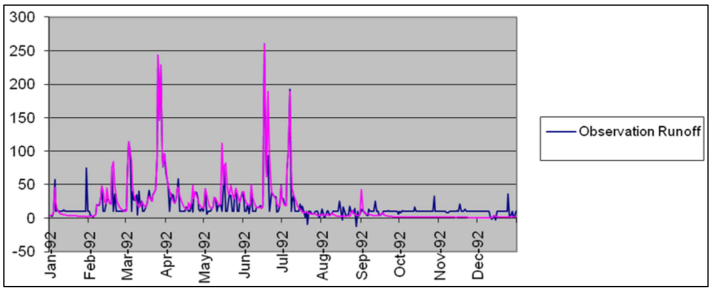
The selection of the final structure of the ANN model, being a trial and error procedure, was started with a minimum number of nodes in the hidden layer and the network was trained until a minimum mse is attained. The number of nodes in the hidden layer was increased gradually until such an increase did not significantly improve the performance of the neural network, ensuring that the finally selected network has minimum complexity and maximum performance [12].

(1) Model calibration:

The three years of data was used to calibration the model are (1992-1993-1994) as the following (Table 1).

Table 1. Model calibration results.

Years	Error in volume VE (%)	Coefficient of determination (R^2)
1992	15.33	0.7918
1993	12.43	0.8388
1994	19.37	0.7124



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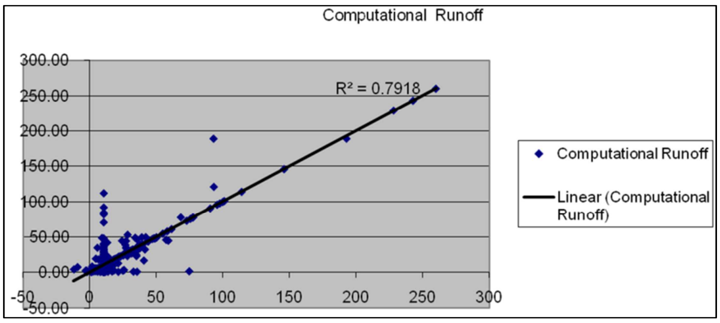

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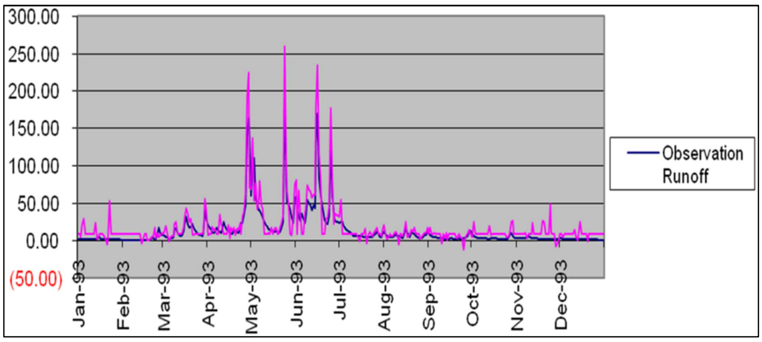
Figure 3. [Data of 1992], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.



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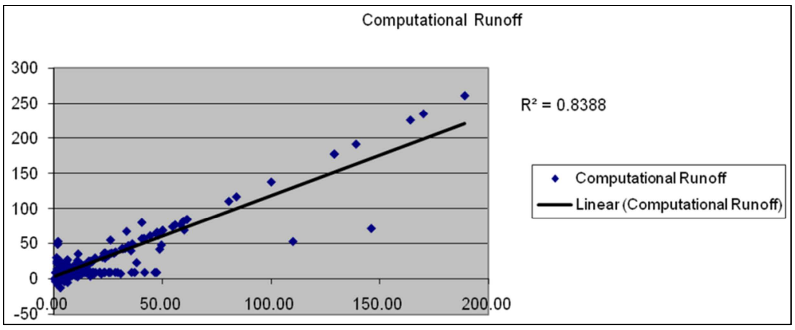

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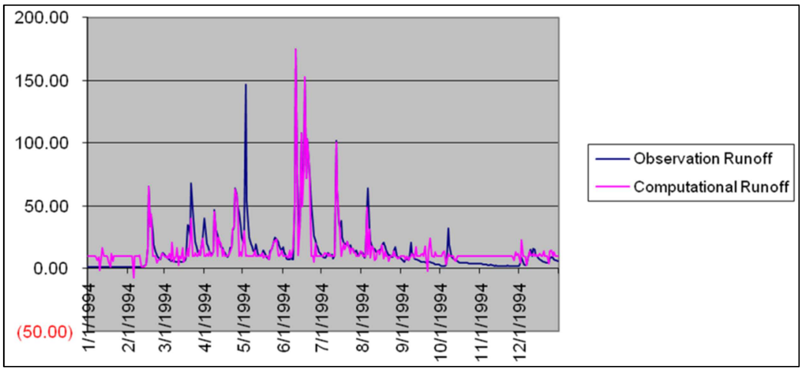
Figure 4. [Data of 1993], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.



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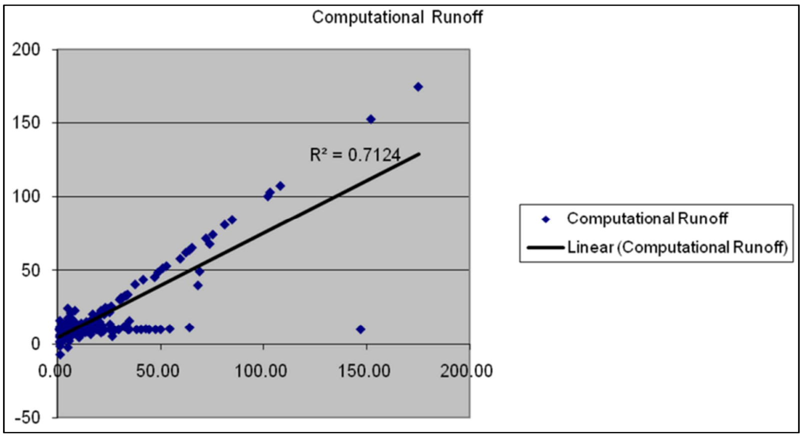

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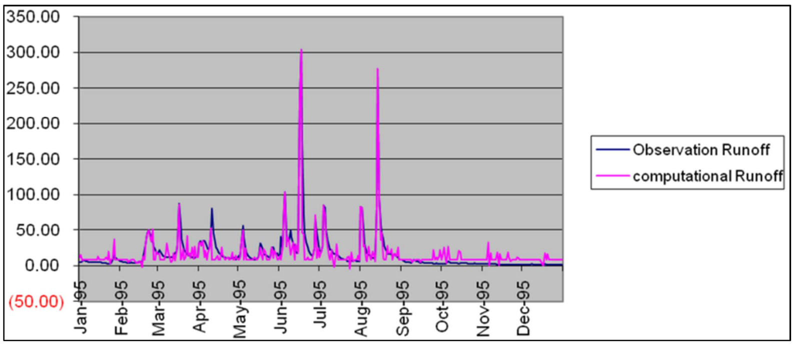
Figure 5. [Data of 1994], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.



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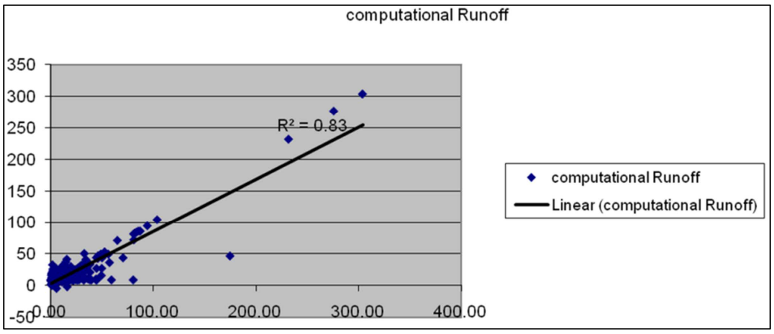

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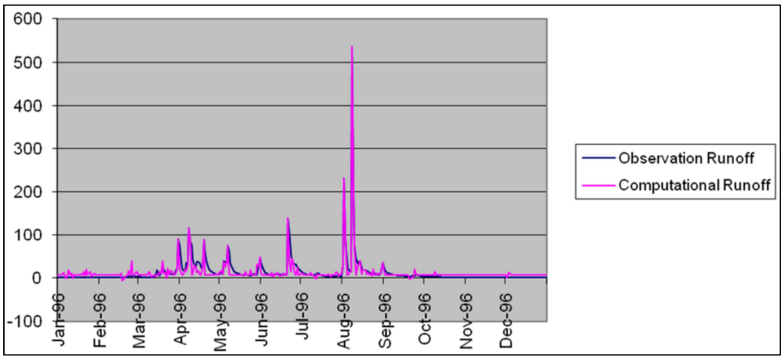
Figure 6. [Data of 1995], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.



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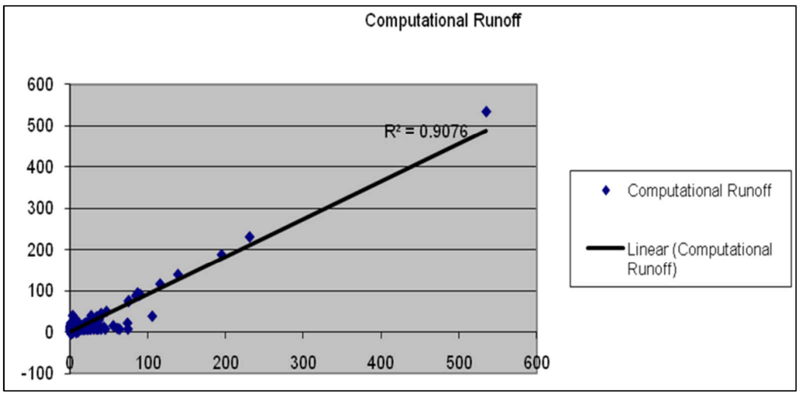

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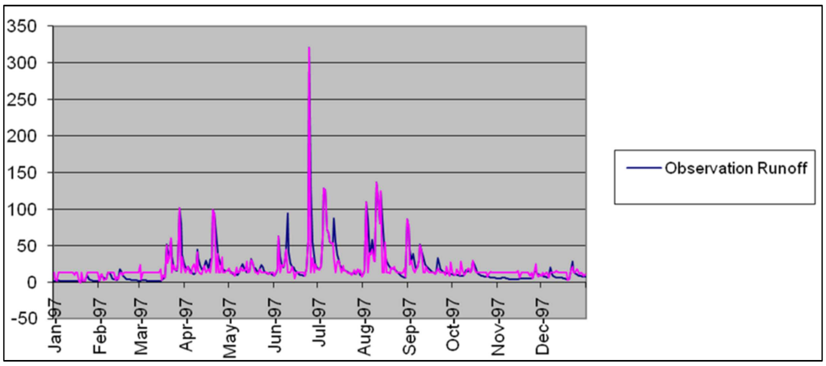
Figure 7. [Data of 1996], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.



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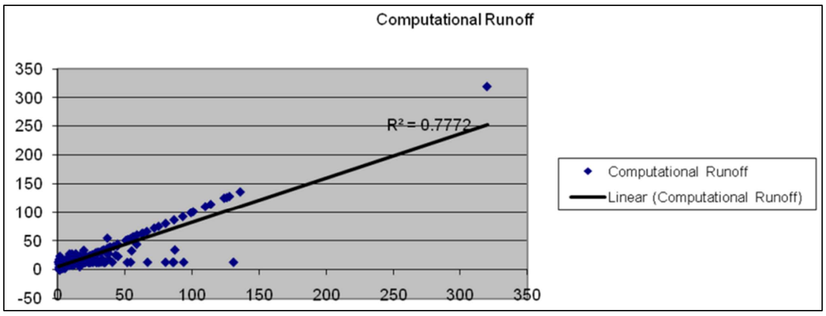

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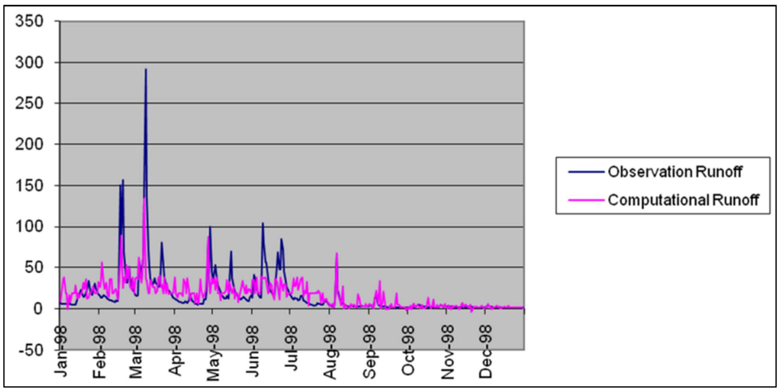
Figure 8. [Data of 1997], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.



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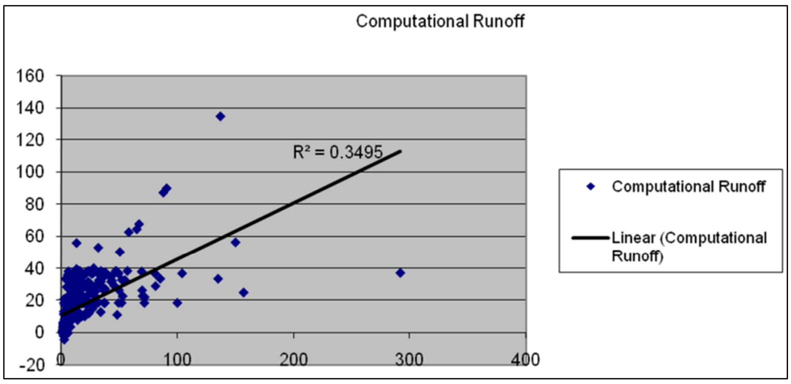

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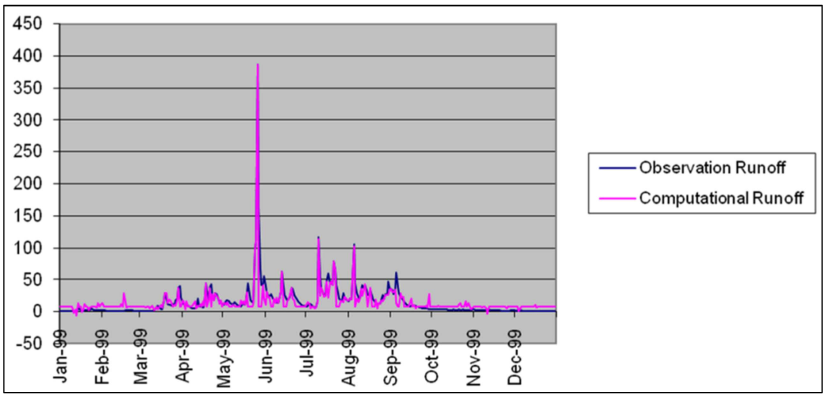
Figure 9. [Data of 1998], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.



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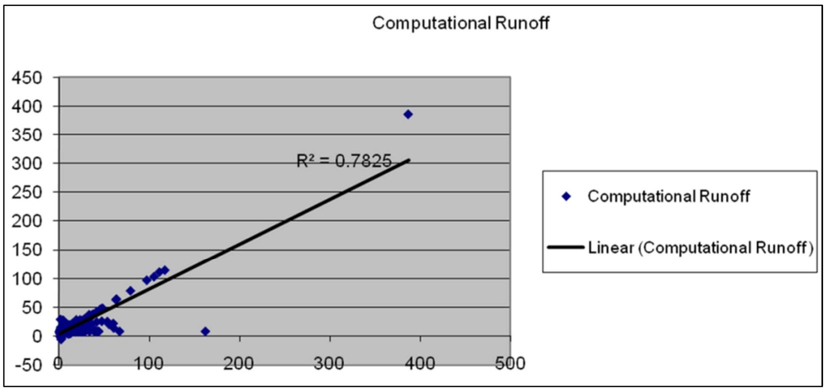

(2)

Figure 10. [Data of 1999], (1) Demonstrated the relationship between the time and observation -computational runoff data. (2) linear model for coefficient of determination.

(2) Model validation:

The second part of the data from 1995 to 1999 was used to validation the model as the following (Table 2).

Table 2. Model validation results.

Years	Error in volume VE (%)	Coefficient of determination (R^2)
1995	12.95	0.83
1996	8.1	0.9076
1997	14.89	0.7772
1998	46.9	0.3495
1999	16.66	0.7825

The results of the model applied in the study were evaluated by estimating the following statistical parameters:

(i) The percentage Error in Volume (VE), is computed according to [13] as:

$$VE = \frac{\sum(Q_{sim}(t) - Q_{obs}(t))}{\sum Q_{obs}(t)} * 100 \quad (2)$$

(ii) The coefficient of determination R^2 between the observed and the simulated flow as given by [14, 15]:

$$R^2 = \frac{\sum((Q_{sim}(t) - \bar{Q}_{sim})(Q_{obs}(t) - \bar{Q}_{obs}))^2}{\sum(Q_{sim}(t) - \bar{Q}_{sim})^2 \sum(Q_{obs}(t) - \bar{Q}_{obs})^2} \quad (3)$$

Where:

$Q_{sim}(t)$ and $Q_{obs}(t)$ are the simulated and observed runoff at time step t.

$\bar{Q}_{sim}$ and $\bar{Q}_{obs}$ are the simulated and observed average runoff

After analysis the results, the present work explained the following:

In the three years that were used for calibration (Table 1), the second year (1993) was obtained good result than the two others years (Figures 3, 4 and 5). The year of (1992) had good result, (Figure 3), when it compared with (1994). According to the previous results, the model was obtained reasonable results when the values of error were decreased.

The results showed in the part of validation (Table 2) and (Figures 6 to 10). The year (1996) had good result than the other years because the output data had good distribution in a linear relation in model, and 1998 had unreasonable result because the non- linearity in the model distribution is highly. Finally, the relationship between the different distributions, values of error and coefficient of determination were very clear in applications of the Artificial neural network model.

6. Conclusions

The application of Artificial neural network model in scopes of the hydrological researches had obtained more successful in last years, and found more acceptances among the researchers, according for the model's accuracy.

The ANN Rainfall-Runoff model applied in this study was obtained almost successful and reasonable results when it's compared and evaluated according to the main parameters of comparison such as coefficient of determination R^2 and error in volume VE as simple linear (black box) model. The internal behavior of an artificial neural network rainfall–runoff model is examined and it demonstrated high efficiency in determination of the runoff from the rainfall data observed and that proved the optimality of the artificial neural network (ANN) model in flood forecasting.

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